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Globalisation and the Labour Market: An Analysis of Job Stability and Job Security in Britain

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Abstract

Globalisation represents the increased international integration of goods, services, labour, technology, knowledge, ideas and capital of national economics from around the world. It also evokes many opinions in relation to the costs and benefits it can provide. Globalisation can bring greater benefits to countries in the form of greater productivity and output, potentially faster economic growth, increased welfare and even greater incentives to innovate. However, workers fear that globalisation costs more jobs than it creates (Eurobarometer, 69) and it could cause the structure of employment to permanently change over time. Ideally, workers would like to have jobs that last a life time (job security) and jobs that pay a predictable wage (job stability). Yet, should workers become dislocated from their jobs through firm closure or through layoffs, workers hope their prospective re-employment in new jobs is secure and stable with few short-term adjustment costs over time. But, many workers believe 'jobs are not for life' and this is in part attributed towards globalisation – increased trade and advancements in technology, the fall in transportation costs, exchange rate volatility and offshoring are all potential factors that have contributed towards greater competition in world markets for goods and services over the last thirty years. This thesis examines whether job security and job stability have changed over this time. It focuses on whether offshoring and the advancements in technology have increasing made jobs less secure and whether they have increasing made wage levels within jobs more volatile.

Chapters 2 and 3 review the literature: chapter 2 explores the potential forces that could cause labour market insecurity to rise and chapter 3 examines the existing empirical literature to see whether labour market security has declined over time. From these reviews, chapter 2 finds that trade, the advancements in ICT and domestic policy reforms to labour market institutions have caused the structure of employment to change in favour of skilled labour at

the expense of less-skilled workers even though the employment level has not significantly changed over the post 1990s to the latter 2000s. And the empirical evidence from chapter 3 finds that labour market security, which is composed of (a) job security, (b) income volatility within jobs (job stability) and (c) the loss of earnings between jobs has also not changed significantly from the 1970s to the early 2000s.

Chapter 4 examines the effects of industry level offshoring intensity and the advancements in ICT over the post 1990s have increasingly had an impact on the wage levels of individual workers. This chapter finds the impact of service offshoring (measured at the industry level), the potential threat from the advancements of technology that increasingly pose a threat to many more potentially tradable occupations (job tradability measured from the application of Blinder's (2007) occupation tradability index) and the threat of TBTC – particularly from the importance of completing routine intensive job tasks, have all had a negative and significant impact on the wage levels of workers over the period 1992 to 2007.

Chapter 5 examines whether a rise in offshoring intensity could lead to a rise in job insecurity by increasing the probability of becoming unemployed. Using individual level data from 1992-2005, the results show a rise in offshoring (materials and services) and the advancements in ICT did not lower job security, it actually raises the probability of remaining in employment. This chapter also finds workers were more likely to remain in employment with their current employers. But workers employed in potentially the more tradable jobs that are also routine job task intensive appear to have a higher probability of becoming unemployed. Collectively, chapter 4 and 5 suggest that while offshoring may put downward pressure on wage levels, it has had little impact on job security. Workers appear to sacrifice job stability for job security.

Chapter 6 addressed whether there has been a secular decline in job security over the last two decades. Using job tenure and job transitions as measures for job security, this thesis finds medium [longer-term] job tenure shares (job tenure greater than or equal to five [ten] years) declined by 7.95% [8.85%] and 8.70% [7.95%] for men and for women with no children from 1992 to 2006. These declines are not indicative of a rise in job-to-job transitions, but a slender rise in job-to-unemployment and job-to-non-employment transitions over the time frame. Further analysis shows there is no evidence that these latter job transition results have arisen because of a rise in involuntary job separations resulting from redundancies or from firm closures over time.

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List of Abbreviations

ALM	Autor, Levy & Murnane
BDH	Bhagwati-Dehejia Hypothesis
BHPS	British household Panel Survey
BLS	Bureau of Labor Statistics
B&R	Burgess & Rees
CBO	*Congressional Budget Office*
DWS	Displaced Worker Survey
EU	Job-to-Unemployment Transitions
EE	Job-to-Job Transitions
EE1	Job-to-Job Transitions: with job tenure greater than one 1 year
EE2	Job-to-Job Transitions: with job tenure under 1 year
EN	Job-to-Non Activity Transitions
ES	Job-to-Self Employment Transitions
GHS	General Household Survey
G&W	Gregg & Wadsworth
G,K & W	Gregg, Knight & Wadsworth
HRS	Health Retirement Survey
HO	Heckscher-Ohlin Model
HOS	Heckscher-Ohlin-Samuelson Model

ICT	Information Computer Technology
I-O	Input-Output Use Tables
ISCO-88	The International Standard Classification of Occupations version 1988
ISER	Institute for Social and Economic Research
IV	Instrumental Variables
LFS	British Annual Labour Force Survey
NLSY	National Longitudinal Survey of Youth
O*NET	Occupational Information Network
ONS	Office for National Statistics
PSID	Panel Study of Income Dynamics
QLFS	Quarterly Labour Force Survey
R&D	Research & Development
SBTC	Skill Biased Technological Change
SIPP	Survey of Income and Program Participation
SOC	Standard Occupational Classification
TBTC	Task Biased Technological Change
TFP	Total Factor Productivity
WC	Women with dependent children
WC5	Women with dependent children under the age of 5 years
WNC	Women with no dependent children

1

Introduction

"Globalisation is a non-stop economic process. Individuals, companies or governments are always on the lookout for new processes or innovations – and so the economic structure of the world is never stagnant ." ***YaleGlobal Online***

Globalisation – the increased international integration of goods, services, labour, technology, knowledge, ideas and capital of national economies evokes many opinions in relation to the costs and benefits it can provide. As the quote above suggests, the process of creative destruction lies at the heart of economic prosperity and growth. Authors' such as Romer (1992), Grossman and Helpman (1991) and Barro and Sala-i-Martin (1995) have all argued that countries that are more open to the rest of the world have a greater ability to absorb technological advances generated in leading nations, which lead to positive growth and higher output. In other words there are benefits from globalisation. Firms try to maximise profits through innovation and investment by trying to use the right combination of production factors that achieve this goal. Governments try to encourage investment into their countries to create jobs and growth. Whilst workers want jobs that are stable and secure over time.

However, the process of job creation and destruction that can emanate from globalisation and technological advancements has lead to worries of increased vulnerabilities for some workers (OECD, 2007c) and because of the adjustment costs which workers could face from this process. This increasing vulnerability for workers is reflected in the rise in press references to outsourcing and job security and insecurity over the last two decades. Amiti & Wei (2005) show press references to 'outsourcing' has increased in the U.S. and U.K. ([see figure 1.1A in appendix 1] and Mankiw & Swagel (2006a,b) [see figure 1.2A in appendix 2]) over the post 1990s time frame. And Green (2003) shows that press references to 'job security' and 'insecurity' have increased dramatically over the same time period in the U.K. than in the U.S. [see figure 1.3A in appendix 3].

From these changes, less skilled workers fear they will face increasing job insecurity and instability as their jobs and skills become increasingly substitutable with foreign labour from less developed countries that are able to offer their skills at a fraction of what it would cost to produce output in developed countries. By sourcing production inputs from foreign markets, the demand for less skilled labour falls, but productivity levels rise with lower prices that can lead to higher sales, which can promote job creation. However, newly created jobs may encapsulate the latest technologies which require higher skills that may not match the skills of those workers displaced from their jobs (Mortensen & Pissarides, 1998).

What is meant by job security and job stability and why are changes to them important? Job security and job stability refer to two different aspects of an employment relationship. Job security refers to how long jobs last and this also reflects the probability of job endings. Job endings can be of two types: First, they can be voluntary job separations initiated by the employee to raise their welfare to exploit better work opportunities; and the second type is a non-voluntary job separation that is initiated by firms through mass layoffs or through firm closure. Job security is typically measured by exploring changes to job tenure, job transitions, job retention rates and the inflow and outflow rates from employment and non-employment over time. Job stability refers to the stability of continuing jobs. Job stability depends on a number of within job characteristics such as the number of hours that are worked, wage movements and the prospects of promotion. Job stability is typically measured by exploring changes to wages and its volatility over time. Changes to job security can have important implications for job stability. More specifically, the returns to wages from general and specific experience can be significant; Topel (1991) finds substantial returns to wages from job seniority: ceteris paribus, 10 years of job seniority raises the wage of a typical male worker by over 25 percent. Thus, what this implies is that any change to job security can mean that the returns from job seniority can have a significant impact on job stability.

A rise in competition between domestic and foreign workers can make jobs less secure if domestic firms are able to threaten workers with the possibility of transferring their production operations to other countries. This can also cause jobs to be less stable. But if workers value their jobs they could be forced to accept lower pay if there are few good job opportunities available over the long-term. These changes depend on the relative skill intensities of the industries (Geishecker & Görg, 2005) and whether firms face import competition from foreign firms in their sectors. It is evident that less skilled workers employed by firms within less skill intensive sectors that face import competition may experience greater job insecurity and job instability, with fewer job opportunities within these sectors compared to other sectors that are expanding. With rising economic growth, displaced workers from contracting sectors may not necessarily see the benefits from globalisation and the advancements that technology can bring to their lives, if their way of life and the traditions of the types of jobs that may have been completed in local areas of developed countries start to disappear. Globalisation could also permanently raise job insecurity if labour markets are continually adjusting to changing demands for goods and services.

This can explain why there exists a "globalisation paradox" between the likely benefits and the costs cited amongst proponents and adversaries of globalisation (OECD, 2007b). There is an agreed consensus amongst academics that trade leads to higher welfare for a country overall through higher living standards and higher economic growth but not all workers will benefit, especially less skilled workers. Traditional trade theory suggests trade and globalisation should encourage competition amongst various economic agents and this should benefit both consumers and producers through lower prices, but it is also a source of increased job insecurity. Ex-Prime Minister Tony Blair, acknowledged that[1], "..., China competes with us and can take jobs away. But our exports to China have also trebled since 1996, creating more jobs here", but with these benefits of globalisation there was also "a deep and abiding insecurity". Hence, there is the possibility that the benefits associated with globalisation may not benefit all workers.

Widely quoted results from public opinion polls reflect the above disparities on the benefits and costs from globalisation. From a recent public opinion poll published by Eurobarometer 69 (Spring 2008) noted that, "despite recognised economic benefits [from globalisation], Europeans are slightly inclined to see globalisation as a threat to their national companies". 39% of Europeans (37% of British respondents) thought globalisation represented a good opportunity for their country's companies thanks to the opening up of markets; whilst 43% of Europeans (U.K.: 42%) thought globalisation represented a threat to employment and companies in their countries[2]. Another poll, the German Marshall Fund (GMF) (December 2006) reports 78% of Americans and 76% of Europeans believe free trade leads to lower prices and more product choice for consumers[3]. The same poll reports globalisation fears weakened compared to the previous year (American views: 52% vs. 46%; UK views: 53% vs. 47%), but there were anxieties over jobs over the period 2005/2006: 57% of Americans, 65% of British and 62% of French respondents reported that foreign direct investment creates jobs. However, 59% of Americans, 58% of French respondents reported that freer trade costs more

[1] Reported by George Jones, Political Editor of the Telegraph Newspaper, published on 23rd March, 2004. This speech was made at Goldman Sachs.

[2] Similar views are reflected within Eurobarometer 66, published in December 2006 comparing Spring and Autumn poll results: (1) globalisation represents a good opportunity for home countries: 37% vs. 40%; (2) globalisation represents a threat to employment and home countries: 47% vs. 41%.

[3] Similar views are reflected by a PEW public opinion poll taken in 2007 supporting key features of economic globalisation, reflecting positive views on trade (U.S.: 59%, Britain: 78%), foreign companies (U.S.: 45%, Britain: 49%) and free markets (U.S.: 70%, Britain: 72%).

jobs than it creates compared to only 44% in the U.K. The GMF poll also reports 59% of both Americans and Europeans believe China's growing economy to be a threat because of the competition that is created from low-cost Chinese products and from U.S. and Europeans firms re-locating to China. The U.K. however expressed opinions whereby more respondents saw China as an opportunity than those who viewed it as a threat. Public opinions on globalisation also vary by socio-economic groups; the negative views expressed on the potential effects globalisation may have on employment increase with age (although positive views decrease with age) and manual workers and the unemployed were more likely to have a negative view (Eurobarometer 66).

Two key recent developments to trade patterns have been proposed as possible reasons why workers in developed countries might become increasingly vulnerable. The first is related to the increasing presence of 'BRIC' (Brazil, Russia, India and China) countries accounting for a greater share of the world's labour supply (45% of the world's labour supply) compared to the OECD (20% of the world's labour supply) where competition has been concentrated at the sector level. This is where firms transfer some of their labour-intensive production stages abroad (OECD, 2007c). And secondly, ongoing developments of ICT have enabled the 'great unbundling' of service related job tasks (Baldwin, 2006). Technology including the fall in telecommunication costs has made it easier to fragment the production process further, where job tasks in service sectors that were not affected by outsourcing during the 1990s, are increasingly at risk of being offshored (OECD, 2007c; Amiti & Wei, 2005, 2006). For example, many service sector jobs from call centres have been transferred to India. Additionally, many high-skilled white-collar jobs in accountancy and radiology are at risk of being offshored in a global market place, where high-skilled labour in other geographic locations are able to provide their services electronically without face-to-face contact with customers at a fraction of the cost (Blinder, 2007).

This thesis has the following structure: Chapter 2 provides a detailed synopsis of the theoretical and empirical literature that assesses the potential forces that could cause labour market security to change over time. Structural changes resulting from changes in tastes and technology can lead to changes in the costs of production. Forces stemming from globalisation, technological innovations and domestic labour market policies such as offshoring, outward FDI, product market competition, a fall in transportation costs, improvements in telecommunications, the dynamic nature of comparative advantage and reforms to labour market institution policies encouraging labour market flexibility can affect the rate of job creation and destruction over time. This review assesses whether these forces can lower the employment level and exert downward pressure on wages to potentially raise labour market insecurity over time.

Chapter 3 assesses the empirical evidence from (a) job security, (b) income volatility within jobs (job stability) and (c) the earnings losses following job displacement between jobs, which represent a trio of components that I define as labour market security. This review assesses whether the magnitude of losses has increased over time to substantiate claims for a rise in labour market insecurity.

Chapters 4 and 5 examine whether offshoring and technological advancements as proposed by the routinization hypothesis [Autor *et al.,* (2003)] have had a negative impact on pay [job stability] (chapter 4) and job security (chapter 5). Chapter 4 contributes to the growing literature that has examined the impact of offshoring and technology on the wage levels for individual workers in Britain for the period 1992-2007 using a Mincer wage regression approach. If structural changes in tastes and technology are allowing forces associated with globalisation and technology to affect the job creation and destruction rates over time (or the demand for labour), this chapter examines whether they can cause wage levels (the price level) to rise or fall over time for different groups of skilled workers. This chapter examines the effects from industry level offshoring intensity (services and materials), from the potential tradability of jobs by creating a British version of Blinder's (2007) occupation tradability index and by exploring the implications of the task biased technological change hypothesis (TBTC) proposed by Autor *et al.*, (2003) on wage levels.

Chapter 5 examines whether a rise in the offshoring intensity and the impact from the TBTC hypothesis can lower job security over time. This chapter uses discrete time survival analysis to estimate a single risks model to study the impact offshoring and task biased technological change have on the probability of making job-to-unemployment transitions over time. Additionally, this chapter estimates competing risk models to examine the impact of offshoring and the TBTC hypothesis on other competing job transition states.

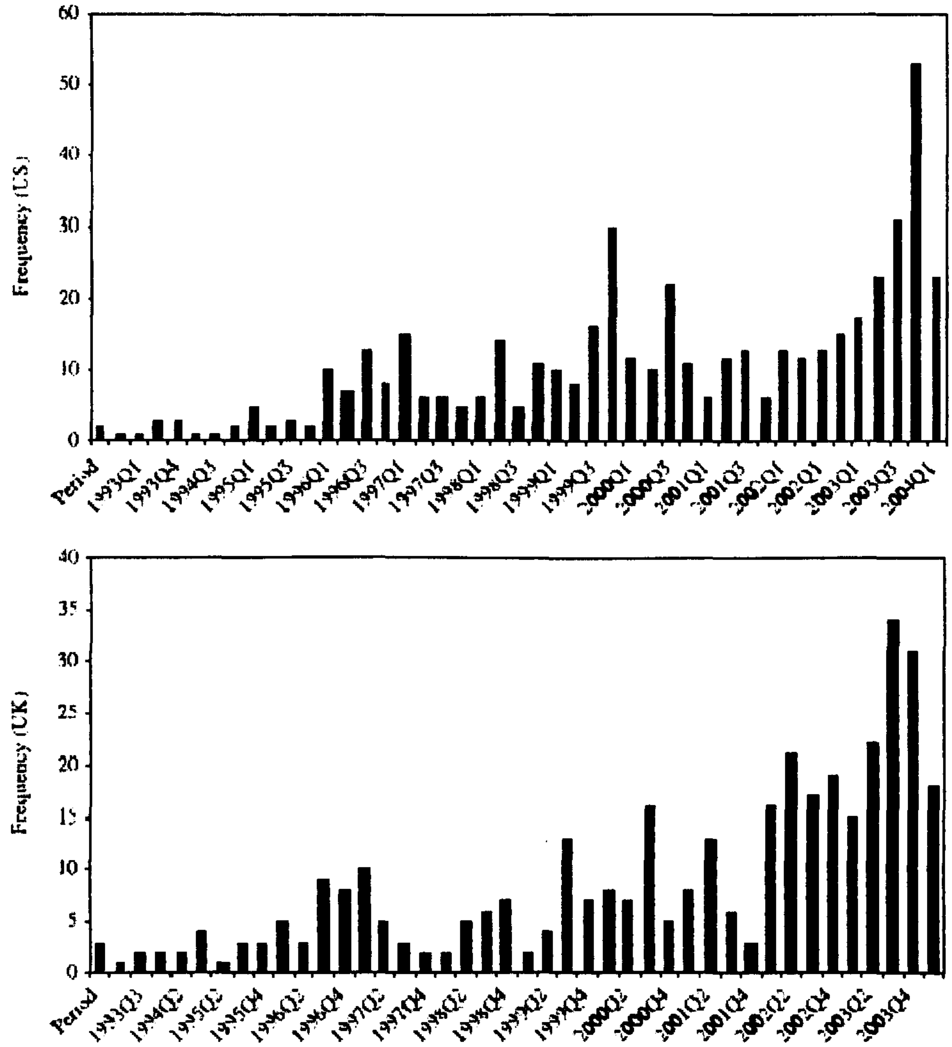
Chapter 6 assesses the job security trends for the period 1991-2007. This chapter examines the changes to job security using two different measures of job security using the QLFS and the BHPS data sets. The first measure examines the changes from median job tenure and the changes from three job tenure groups: short, medium and long-term. For the second measure of job security, I examine the trends from three different job transition states: job-to-job, job-to-unemployment and job-to-inactivity transitions over time. For each of these measures of job security, I apply Gregg & Wadsworth's (2002) methodology to assess the changes in job security trends over time.

Finally, chapter 7 provides the concluding comments from this thesis.

1.2 Appendices

Appendix 1

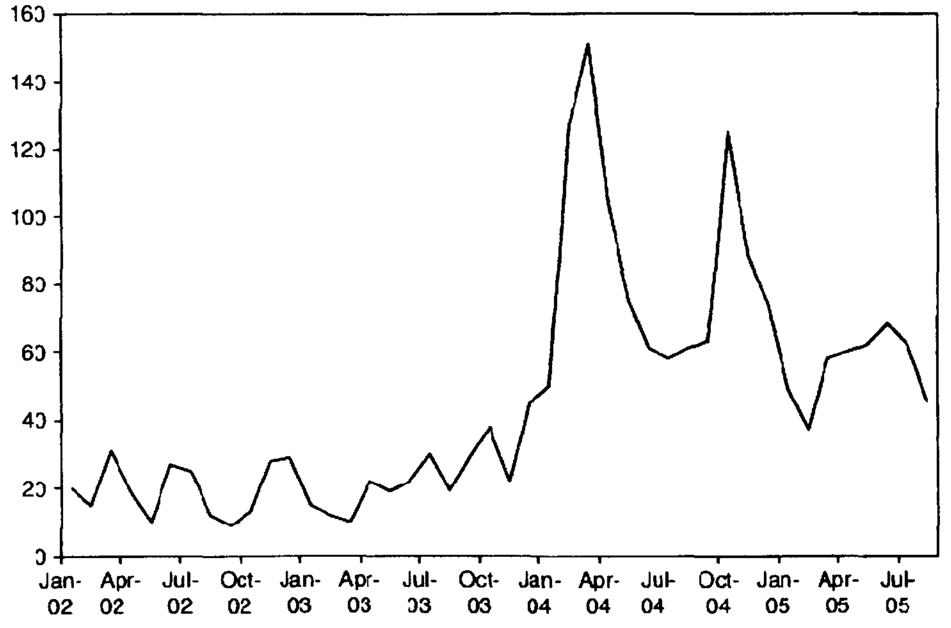
Figure 1.1A: Press references to outsourcing in the U.S. and U.K.



Source: This is figure 1 from Amiti & Wei (2005).

Appendix 2

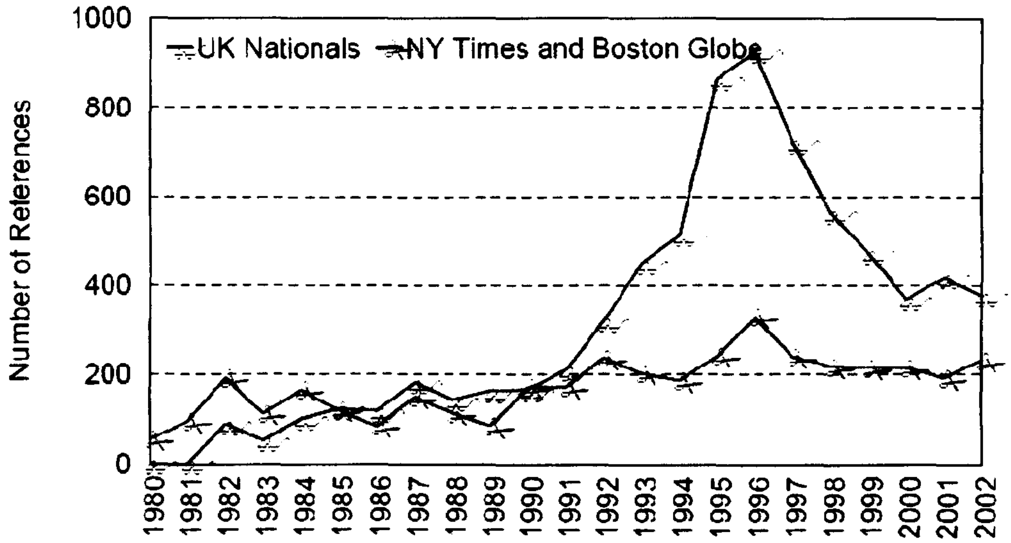
Figure 1.2A: Press references to outsourcing in the U.S.



Source: This is figure 1 from Mankiw & Swagel (2006a,b).

Appendix 3

Figure 1.3A: Press references to Job Security and Insecurity in the U.S. and U.K.



Source: This is figure 1 from Green (2003).

2

The Potential Causes of Increased Labour Market Insecurity: Theory & Evidence

2.1 Introduction

Labour market flows are determined by the simultaneous creation and destruction of jobs that occurs every day within the labour market. Job creation occurs due to the entry of new firms and through employment growth from incumbent firms. Similarly, job destruction takes place through the exit of firms and through the contraction of workforces within existing firms. They are necessary processes to achieve innovation and growth, where job destruction leads to the creation of new jobs which embody the latest technology and improve productivity. Although this process of creative destruction is necessary for economic prosperity, it requires the movement of workers between jobs which can lead to a number of adjustment costs. For example, when jobs are destroyed, workers become involuntarily unemployed and they will have to search for new jobs which require a period of search.

This chapter proposes that labour market security[1] can be thought to be comprised of three parts: (a) job security, (b) the volatility of income within jobs and (c) the changes to earnings levels between jobs. A worker may experience a sense of labour market security if their job is

[1] Milberg & Winkler (2009) use the term 'real' economic security to ascertain the trends from the following components: (a) real wage growth; (b) income inequality; (c) labours' share of national income; (d) the incidence of longer term unemployment and (e) the number of workers displaced by foreign trade and investment. This chapter does not consider all of these factors but a trio of measures which I define as labour market security.

secure, their labour income is stable and there are sufficient opportunities for re-employment if the worker should separate from their job (whether this is voluntary or firm initiated).

From the first component of labour market security, job security refers to how long jobs last. This can reflect the probability of a job ending, which depends on the exit type from employment. An exit from employment may be voluntary, where the worker initiates the job separation by quitting or involuntary where the employer initiates the job separation through mass layoffs or plant closures. This latter form of job separations can be driven by job destruction which can result from structural changes in tastes and technology. Firms may destroy jobs if the demand for a product made by labour falls or workers are laid off because their jobs were temporary. High rates of job destruction and job creation can lower job security over time if workers are not able to retain a job for a sustained length of time and where their employment histories consist of numerous jobs. The question is whether job security has declined over time to have made workers worse off.

The second component of labour market security is income volatility. The volatility of income within jobs is called job stability. The stability of jobs can vary with the movements of the business cycle, which can affect the number of hours worked. Changes to the number of hours that are worked can affect income levels. For instance during favourable economic conditions, the number of hours that are worked may be above average and labour income will therefore be higher than the average. But during unfavourable economic conditions, the number of hours that are worked may be below the average number of hours that may typically be completed and thus labour income will be lower than the average if wages are linked to the number of hour of work. The stability of jobs can also be tied to firm performances and firm sales. Additionally, income volatility can result from globalisation, where greater competition from foreign firms and foreign workers and the advancements in technology can affect the costs of production which could also affect income volatility. The changes brought by technology may make it difficult for workers to transfer their skills to new capital which embodies the latest technology. Thus, firms may have to decide whether it is profitable to undertake renovation costs to train workers to use the latest capital. If the renovation costs are too high, with few prospects for growth to recoup the costs, then firms may not undertake training their existing workforce. This decision may lead to the loss of labour income in the short run, where old jobs are increasingly marginalised while old jobs may be competed away by new jobs that embody the latest technology in the long run. The question is whether income volatility has increased over time and whether this has made workers worse off over time.

The third component of labour market security examines the change to the earnings levels between jobs. Changes to labour income can result from job dislocation, where spells in unemployment can lead to a fall in real income. During this period, workers may experience unemployment scarring between jobs. This is where the incidence of unemployment can lower the trajectory of wage levels from new jobs and it can increase the probability of experiencing future spells of unemployment. This can be due to two reasons. The first is if workers have been unemployed for a long time, they will lower their reservation wage levels to try to obtain employment. And second, workers lose human capital accumulation when they become unemployed. Thus, if firms are uncertain about the quality of the workers they are hiring, they may offer short term jobs with low pay to better ascertain the quality of the worker and their skills. Many short term positions are more often destroyed rather than maintained, but short term jobs can also be stepping stones to permanent jobs. Workers can therefore become stuck in a cycle of low pay and short term employment. The mere threat of job destruction can also affect the stability of jobs and threaten long-term job security. The question is whether workers must accept lower wages and lower quality jobs to return to employment, and whether the earnings losses following job displacement has increased in magnitude over time.

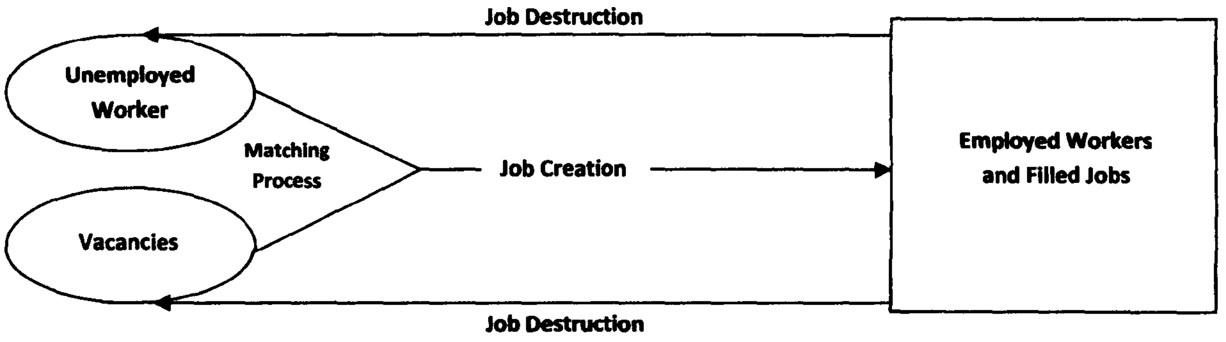
The key focus with respect to labour market security is whether the three components: (a), (b), and (c) have changed over time. For instance, the earnings losses following job loss can be large in the short run and the long run. However, the key issue is whether the magnitude of these losses has become larger. This chapter explores the potential reasons why labour market security components: (a), (b), and (c) might change. This review does not seek to explore one off changes in relative demand for different worker groups. But to explore the reasons that may cause structural changes to the demand for labour over time. We use a flow model of job search with job creation and destruction to examine these structural changes to the demand for labour over time.

This chapter examines the potential reasons that might cause labour market insecurity to rise in theory coupled with empirical evidence. This chapter has the following structure: Section 2.2 outlines a basic theoretical model of job creation and destruction. Section 2.3 explores the forces that could cause the job creation and destruction rates to change. Section 2.4 provides the empirical evidence from the forces outlined in section 2.3. Finally, section 2.5 provides the concluding comments.

2.2 Job Creation and Destruction

The concept of job creation and destruction was pioneered by the various theoretical works of Dale Mortensen and Christopher Pissarides. These concepts were presented within a series of selected papers by Mortensen & Pissarides (1994, 1998, & 1999) and a book by Pissarides (2000) to illustrate the impact upon unemployment. This section draws heavily from their work to describe the job flow process.

Figure 2.1: Job Flows and Worker Flows



Source: Rocheteau (2006).

The process of job creation and destruction is best understood from figure 2.1 which presents the flow of jobs. From this diagram there are three important forces which affect the level of employment and the dynamics of labour market security. These forces are job creation, job destruction and the matching process. At any point in time, there are stocks of employed workers and filled jobs. The flow of job creations adds to the stock of employed workers within filled jobs where these jobs can be temporary or long term permanent jobs. And the stock of unemployed workers is replenished by the flow of job destruction. This process of job creation and destruction is more complicated than figure 2.1 demonstrates. This process is outlined in more detail from the Mortensen-Pissarides Model (1994) of equilibrium unemployment.

2.2.1 Job Creation and Job Destruction: A Basic Model

From the Mortensen-Pissarides (1994) model of equilibrium unemployment, firms and workers must spend resources before job creation takes place. The model assumes firms and workers are homogenous and wealth maximisers. From the workers perspective they must spend their time and resources to search for new jobs. From the firm's perspective, they have jobs that are in one of two states: (1) filled and producing or (2) vacant and searching. Firms must decide on the type of technology and the product value that is to embody the new jobs. It is assumed that firms always choose a high value for the level of productivity and the latest level of technology to embody the new jobs. Once job creation has taken place, firms have no choice over either. Firms must then advertise the jobs to attract unemployed workers; on the job search does not exist in the model. The most productive jobs offer higher wages as job vacancies make use of the latest technology available within the market; thus new jobs offer higher wages. Each job is characterised by a fixed irreversible technology and produces a unit of a differentiated product which has a price that is $p + \sigma\varepsilon$. The price simply reflects the productivity of the job where p is the aggregate component of productivity that does not affect the dispersion of prices. Parameter σ represents the price variance and the parameter ε represents the idiosyncratic component of the price of productivity for a specific job, where $\varepsilon_u > \varepsilon > \varepsilon_d$, which are the upper and lower limits. The process that changes the idiosyncratic component of the price is a Poisson process with an arrival rate λ. When the idiosyncratic component changes, new values of ε are drawn from a fixed distribution. Modelling the arrival process as Poisson implies persistence in job specific shocks. Exogenous events that affect the persistence or distribution of idiosyncratic shocks (these are assumed to be micro-level shocks) shift λ and σ respectively. Events that affect the productivity of all jobs by the same amount and in the same direction (these are assumed to be macro-level shocks) is reflected by changes to the common price component p. Firms create jobs that are equal to the upper portion of the price distribution: $p + \sigma\varepsilon_u$.

Higher values of σ raises price dispersion, implying profitable jobs become more profitable and the less profitable jobs become less profitable. Thus, a higher σ necessitates a rise in the reservation productivity – this is a threshold or a level of productivity that must be achieved for a job to continue. If the reservation productivity threshold is not achieved, then marginal jobs that are less profitable are destroyed. This implies that a rise in σ raises the job destruction rate. A rise in λ raises the level of persistence, meaning the rate at which idiosyncratic shocks affect jobs; these shocks can be good or bad. If the shocks are bad, this raises the option value of jobs because job-specific product values are less persistent. This means jobs are less likely to be destroyed as the level of ε_d decreases, but this also lowers the rate of job creation. Additionally, a higher discount rate r reduces the profitability of jobs at all prices in the future. This reduces the option value of waiting for improvements in productivity and therefore jobs are more likely to be destroyed. Thus, this raises the level of ε_d. Finally, the business cycle can lead to an overall change in the price of jobs by affecting the aggregate component of productivity p. If net aggregate productivity shocks are positive, represented by a rise in p, the effect would be a rise in the rate of job creation and the rate of job destruction. Conversely, a negative productivity shock increases the rate of job destruction, but the model assumes the rate of job creation remains unchanged. Thus, job destruction rates are more volatile than job creation rates.

Job creation takes place when vacant jobs advertised by firms are matched with unemployed workers according to the prevailing matching[2] technology at a negotiated wage. The model assumes there is unemployment in the steady state because during the matching process and prior to all unmatched job-worker pairs meeting, some existing job matches are destroyed. This leads to a flow into unemployment. Existing jobs are destroyed only if the idiosyncratic component of their productivity falls below some reservation level where $\varepsilon_d < \varepsilon_u$. However, filled jobs are not necessarily destroyed because there is a cost associated with recruiting and maintaining vacancies.

Once job destruction takes place, workers move from employment to unemployment and firms either withdraw from the market place or re-open new vacancies which embody the latest technology. This implies that job destruction forces workers to separate from their employment non-voluntarily. Job destruction leads to a flow into unemployment and this can affect the employment level that can result from job specific (idiosyncratic) shocks at the

[2] See Petrongolo & Pissarides (2001) for a survey of the matching function.

Poisson rate λ. These specific shocks may be caused by structural shifts in labour demand as it is a derived demand. This can lead to changes in the relative price of the goods produced by jobs or the change can be caused by productivity shocks that change the unit costs of production. These changes in labour demand can result from shocks that may be associated with shifts in tastes and technology. These shifts in tastes and technology can result from product market competition, product and process innovation, new production diffusion processes, the entry and exit of products and product life cycles (Blanchflower & Burgess, 1996). They can also result from other factors such as globalisation and be influenced by domestic labour market policies. The former relates to the processes of offshoring, technological change, falling transportation costs and international trade which can affect the costs of production, exchange rate volatility and the kaleidoscopic nature of comparative advantage. Domestic labour market policies include unemployment insurance benefits, employment protection legislation and other policies related to taxation and subsidies received by firms.

This basic model of job creation and destruction provides useful insights as to how firms create new jobs and destroy jobs and how they can potentially affect labour market security over time. Labour market security can fall and potentially make workers worse off, if there are high rates of job creation and destruction over time. This can lower job security because higher rates of job creation and destruction can raise the probability of job endings where jobs will not last a life time. Additionally, higher rates of job destruction that could be caused by structural changes in tastes and technology can raise job instability over time. But this can also raise the costs of job displacement between jobs, where the prospects of obtaining a temporary job that could lead to a permanent job will diminish over time as the least profitable jobs will always be destroyed. Hence, the earnings losses between jobs that can result from job displacement and from unemployment scarring could rise over time and make workers worse off. The next section explores the potential factors that could cause structural changes in tastes and technology which can affect the job creation and job destruction rates. Changes in tastes and technology are arguments that could be made with respect to the rise in globalisation over the last 30-40 years.

2.3 Forces which cause changes in Job Creation and Job Destruction

2.3.1 The Impact of Technology

Mortensen & Pissarides (1998) extend their equilibrium unemployment model to explore the impact of technological progress embodied in new capital equipment. Firms face three choices regarding the deployment of the new technology: First, firms commit to the new level of technology at the date of job creation where this technology is irreversible. Second, firms may pay a fixed renovation cost to update technology[3] embodied within existing capital and continue to produce using existing labour within existing jobs from time to time. Third, firms may close existing jobs and exit production. This leads to job destruction and workers become displaced and unemployed.

The arrival of new technology signifies that firms will have to update existing jobs or destroy them as new jobs drive out old jobs by bidding away workers. The authors' note that workers may fear the arrival of new technology because capital embodied with the latest technology may lead to greater labour productivity. This may threaten existing jobs because: (1) the level of technology encapsulated within existing capital used by existing jobs may not be as productive as the new level of technology. New jobs utilising new technology are more profitable. (2) Firms may not want to undertake the cost of renovation investment to update existing capital and provide existing labour within existing jobs the required training to use the

[3] This may take the form of updating existing capital equipment with the latest production processes and training existing workers to use the new technology.

new technology. Therefore existing jobs may be destroyed. This uncertainty over the arrival of new technology may raise job insecurity fears.

Whether firms choose to update the technology utilised by existing jobs depends on: (a) the rate of technological progress; (b) the size of the idiosyncratic component for productivity and (c) the size of the structural renovation costs with growth productivity. First, the rate of technological progress plays a part in determining the length and life of old and new jobs. With high rates of technological progress, firms may not want to create new jobs or invest money into updating existing jobs as these jobs will have shorter life-spans. Thus, firms may not be able to re-coup the investment costs before these jobs are destroyed. However, slower rates of technological progress will lead to longer lasting jobs as they are profitable for longer which will lower job creation and job destruction rates.

Secondly, the model assumes each job-worker pair has an idiosyncratic component for output productivity. The model predicts that if employers have a high idiosyncratic output, firms update the technology for existing jobs because the high idiosyncratic match productivity signifies a good employer-employee relationship. This is a valuable resource firms will not destroy, and they will preserve the resource by updating it from time to time where the frequency of the renovation updates increases the idiosyncratic component of the match product between firms and workers. This will ensure job security for those workers. However, if the firm-worker pairs have low idiosyncratic output, then jobs will be destroyed sooner as they are not profitable. This will raise job insecurity for those workers who have a low idiosyncratic component for the match product. However, this is a difficult concept to measure in practise.

Finally, the decision to update existing jobs rather than destroy them depends on the size and cost of the structural change and the level of productivity. The model predicts that if the size of implementing the updates to existing jobs is sufficiently small and the growth in productivity is rising over time, the value of existing jobs rises as productivity growth rises. Thus, existing jobs would be updated, job destruction would fall and the unemployment level would fall. However, if updating existing capital requires substantial structural change where the renovation costs are large, it may not be profitable for existing job matches to continue and existing jobs would be destroyed as productivity grows. The increased job destruction rate implies a higher unemployment level.

Mortensen & Pissarides (1998) note that whilst new technology may stimulate job creation and the destruction of old jobs, this does not imply that the economy will achieve a higher level of employment or the same employment level as before once old jobs are replaced by new jobs. This is because different firms of different sizes within different sectors may pursue different job creation and job destruction policies. The model assumes that if there is perfect factor mobility, then new technology would induce some sectors to expand and other sectors to contract. Jobs within declining sectors would be destroyed and jobs within expanding sectors would take their place. With costless mobility of labour and capital between two sectors, the model shows if both sectors have high and equal productivity growth, resources from the sector with high renovation costs would shift to the sector where costs were low. However, with costly factor mobility, the migration of employers and employees to the expanding sector may be costly and subsequently the unemployment level may be higher in the short run, whilst firms relocate to different sectors and unemployed workers search for new employment.

2.3.1.1 The Origins of Technological Innovations and its Impact on Labour Market Security

Understanding the origins of the technology-skill and capital-skill complementarity is important because this evolution can have important implications on the demand for different types of labour and the elasticity of labour demand over time. It began in the U.S. during the

1830s to the 1880s; Atack *et al.*, (2005) estimate that capital-to-labour ratios in manufacturing establishments increased by at least 75 percent after taking into account the change in the price of capital over this period. Along with this increase, there was a change in the mode of the production process. Prior to the process of capital deepening (defined as the rise in the capital-to-labour ratio, where lesser skilled workers are substituted by capital), most manufacturing took place in artisan shops, which were small, owner-operated work establishments with few work assistants. Most goods that were produced in artisan shops were made to order (e.g. jewellery, watch makers, engravers, etc.) and required little in the way of capital. On average, workers in artisan shops were highly skilled and produced the entire goods with no division of labour using modest tools that could be applied in different lines of work. As the manufacturing sector grew and shifted away from artisan shops with no power source towards factories (1830s to 1880s), many of the job tasks moved away from skilled workers from artisan shops toward less skilled blue collar workers using more specialised machinery with steam and water power. The production processes further evolved towards assembly lines in the early 1900s and towards continuous- and batch- process methods (1890s and beyond) lead to a rise in the demand for blue collar workers with a high school education in many high-skilled industries from 1909 to 1929 (Goldin & Katz, 1998). Goldin & Katz (1998) further find that blue collar workers in 1940 were in greater demand as a result of capital deepening (the substitution of lesser skilled workers with the fall in the cost of capital), the diffusion of new technologies such as electric motors using purchased electricity instead of steam and water power (due to a fall in the price of purchased electricity) and with the introduction of continuous- and batch- process production methods lead to a further rise in the demand for high-skilled production and white collar 'machine maintenance' workers at the expense of lesser skilled workers in hauling, conveying and assembly tasks in the twentieth century. These factors have contributed towards technology-skill and capital-skill complementarity.

Another reason for the rise in the demand for blue collar workers was due to many more workers becoming educated with the expansion of schools in the U.S. Many workers with a high school level education entered ordinary white collar occupations as clerks, bookkeepers, secretaries and other sales positions during the early nineteenth century because a high school graduate became a reasonable priced input in the production process. This may have fuelled skill biased technological change whilst lesser skilled labour became increasingly substituted by the introduction of capital.

More recent innovations in technology such as the adoption of computer processors in workplaces, the fall in telecommunication costs and with many workers choosing to go to university, many white-collar jobs in bookkeeping and in human resources are now termed medium skilled occupation. These workers have at most high school diplomas, are employed in these jobs that are now considered to be at risk from being replaced by computer software (task biased technological change[4]) but these are job tasks that are also likely to be offshored abroad (Acemoglu & Autor, 2010 & forthcoming). Many jobs in engineering are now termed high-skilled white collar jobs which are less likely to be replaced by computer software or be offshored abroad for the moment, but this could change in the future. These continued innovations in technology and changes to the production processes have raised the demand for skilled labour, and they can contribute towards a change in the demand towards skilled labour, which can lead to greater wage inequality between skilled and less skilled labour and a rise in job insecurity and the own wage elasticity of labour demand for lesser skilled labour over time.

[4] See subsection 2.3.3.5 for the theory and subsection 2.4.7 for the empirical evidence for the TBTC hypothesis proposed by Autor *et al.*, (2003).

2.3.2 The Impact of Policy

Job creation and destruction rates can also be affected by employment subsidies and taxation. The equilibrium unemployment model is extended by Pissarides (2000) to examine the impact of six policy instruments: (1) tax subsidy; (2) the marginal rate of tax; (3) the replacement rate (unemployment compensation); (4) employment subsidies received by firms; (5) hiring subsidies received by firms and (6) firing taxes paid by firms. With the absence of policy instruments, and assuming there are no idiosyncratic productivity shocks, no stochastic search intensity and excluding unemployment compensation, the supply of jobs are variable and determined by profit maximisation. The destruction of jobs takes place at a constant rate λ. With the introduction of policy instruments, job creation and destruction rates can change over time.

Within this model the creation of new jobs are advertised by firms. When unemployed workers arrive to fill job vacancies to commence a working relationship following the completion of a signed contract, firms receive a hiring subsidy in addition to the value from the jobs. This hiring subsidy adds a flow to the firm's revenue. After workers have been taken on, the benefit to the firms from the continuation of the employment are the value of the jobs only as no further hiring subsidies is received by firms. The hiring subsidies work to creative incentives for firms to create new jobs because this decreases the reservation productivity value of jobs from the matching process and this decreases unemployment. Hiring subsidies also raise the number of jobs that are destroyed as older jobs are replaced by new jobs that embody the latest technology. They can also potentially crowd out employment from firms that do not receive the aid to create jobs and thus this could potentially push firms not being aided to fail[5].

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[5] For further details regarding the evaluation of public policies on employment, see chapter 8 in Cahuc & Zylberberg (2006) for the issues and references therein.

Once workers have been hired, firms are liable for paying a firing tax[6] if they are unable to re-negotiate wages with workers. The extent of job creation and destruction depends on the negotiated wage, which affect firms' production costs and the reservation productivity level for maintaining a continuing job. Firing taxes discourage job creation because once jobs have been created, firms are liable to pay firing taxes which reduces the overall expected value from jobs. Firing taxes also discourage job destruction as they reduce the reservation productivity value of jobs which makes it expensive to destroy existing jobs. The overall impact upon unemployment and job security from this model is ambiguous and is a matter to be determined empirically.

Employment subsidies and tax subsidies reduce job destruction because they reduce the reservation productivity level for a given level of labour market tightness. The model predicts higher subsidies decreases the unemployment level. Finally, unemployment compensation and wage taxes discourages job creation as the former policy increases the costs of production and the latter policy reduces the cost of leisure as leisure is untaxed and is preferable to work if wage taxes are high. These policies also increase job destruction as they increase the reservation productivity levels for jobs as they reduce the expected profits from new and continuing jobs. The model predicts that unemployment compensation and wage taxes unambiguously increase the unemployment rate.

2.3.3 The Impact of Globalisation

Globalisation refers to the increasing integration of the world economy, particularly through international trade and the flow of capital, ideas, migration, the transfer of culture and technology and the development of transnational regulation. It is a complex process that has facilitated trade openness, technological innovation and finance transfers that generate a

[6] Firing taxes can be thought of as redundancy pay. This is paid to workers who are displaced from employment. The size of this cost can vary between firms, but it can be linked to the number of years of service at firms and skill levels.

wide range of benefits and costs through affecting the rate of job creation and destruction that can be the result from structural changes in tastes and technology.

Economists agree that globalisation encourages flexible borderless markets for goods, services and labour which can generate greater competition and trade between many different nations. This should encourage job creation where these benefits are in line with those predicted by the Heckscher-Ohlin-Samuelson Model (HOS) of international trade. This model encapsulates the traditional view of international trade and it assumes each country uses the same technology to produce the same goods but they differ with respect to factor endowments which determine the patterns of trades. This model predicts that trade is determined by the characteristics of each country. With two types of goods that are produced by two countries, the country that is capital abundant will produce and export this good because they have a comparative advantage in producing this good. Whilst the labour abundant country will produce and export the labour intensive good but import those goods that are relatively scarce – the capital intensive good. Without trade, each country will produce both types of goods. But when international trade takes place, theory predicts that trade openness should create jobs in industries that produce goods making intensive use of the relative abundant factor of production. This will destroy jobs within industries that produce goods using the relatively less abundant factor of production. As the model makes full employment assumptions with perfect information and with no labour market frictions, there is no unemployment – meaning workers who lose their jobs in the declining sector due to job destruction are able to find immediate employment at the market wage in other sectors. This implies there is no rise in job insecurity or change to labour market security.

Therefore, free trade can raise aggregate welfare for a country relative to autarky, where there are aggregate efficiency and productivity gains. One can conclude that both producers and consumers benefit from free trade at the aggregate level. Globalisation can bring greater benefits to countries which allow their firms to engage in offshoring and from the outward FDI activities of MNEs in the form of greater productivity and output, potentially faster economic growth, increased welfare and even greater incentives to innovate (Mann, 2003; OECD, 2003; Mankiw & Swagel, 2006a; Amiti & Wei, 2006b; Olsen, 2006; Crinò, 2009a, c; Ritter, 2009).

However, globalisation can severely polarise the labour market winners and losers (Brown, 2003). One cannot conclude that every individual consumer and producer will benefit from free trade because the aggregate gains from free trade can conceal the redistributive effects. The assumptions of perfect labour mobility and frictionless labour markets, where each country produces the same goods with the same technology are not realistic assumptions. Firms are likely to have many stages of production that employ many different types of workers with different skill intensities, not just one type of labour. Additionally, the matching process is more likely to differ between industries as firms search to find workers that fit their needs. This will cause frictions in the labour market, where workers may not be able to regain immediate employment after job loss.

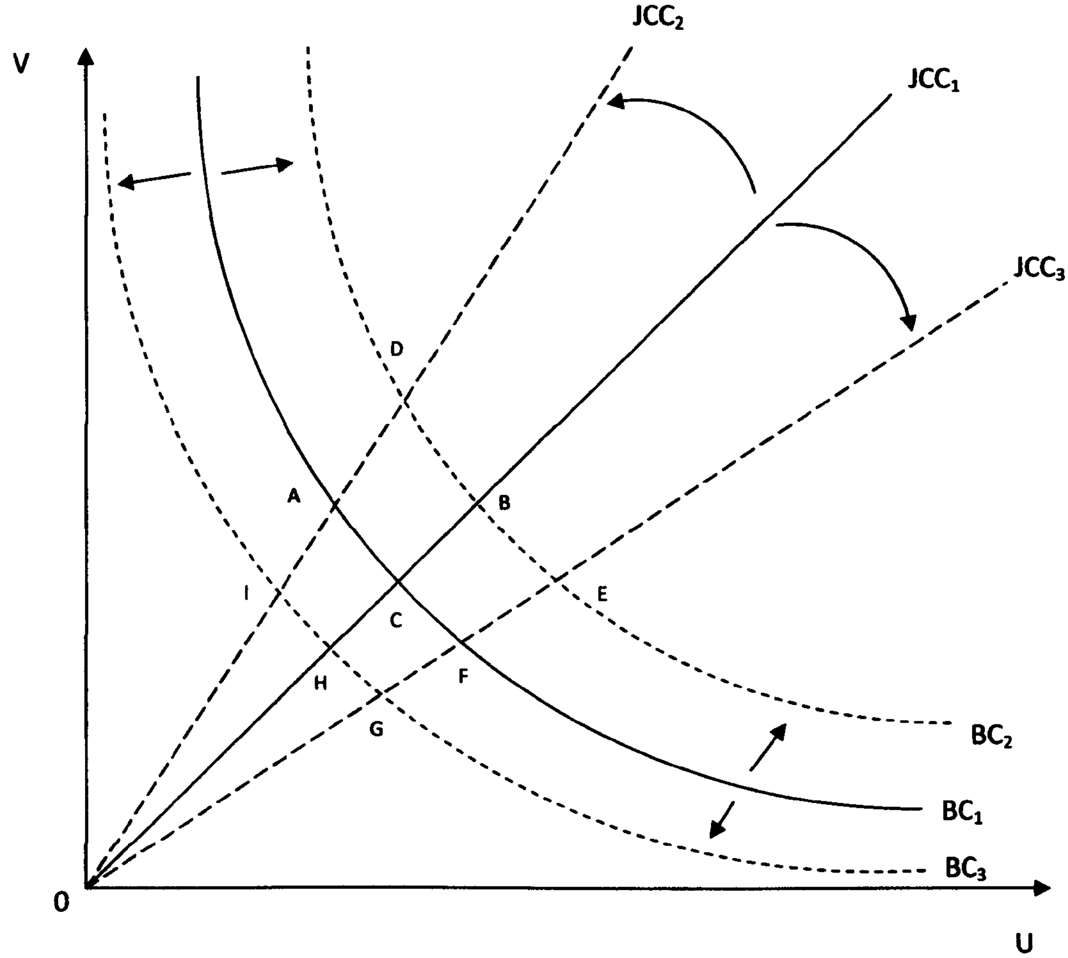
Globalisation and trade can change the economic trading environment (Davidson & Matusz, 2004), where they can create benefits (as outlined above) and they can raise the anxiety levels for workers from advanced industrialised countries. For the latter, anxiety from trade and globalisation may manifest itself as fears of job loss, where workers may not be able to compete with the imports that are produced by cheaper foreign labour. Globalisation may destroy jobs and lower job creation in some or all operations that are performed in-house by firms. This may exert downward pressure on average wage levels and raise unemployment and possibly increase job turnover rates and raise the substitutability of domestic workers with the use of foreign labour over time. Globalisation and trade can change the mixture of employment opportunities between good jobs and bad jobs available to domestic workers.

They could also affect the number of job opportunities that are available over time and this can raise labour market insecurity fears.

Figure 2.2 examines how job creation and destruction rates can be affected by globalisation when it affects the price of productivity for jobs: $p + \sigma\varepsilon$ in vacancies (V) and unemployment space (U). Curve JCC represent the job creation condition which is drawn through the origin and curve BC represents the Beveridge curve, which is convex to the origin in vacancy-unemployment space. If the job creation condition curve, JCC_1 rotates to the left to JCC_2 – this is a rise in the job creation rate. However, if JCC_1 rotates to the right, then the job creation rate falls. If the Beveridge curve shifts outwards to BC_2, this implies a fall in matching efficiency between vacancies and the unemployed. But if the Beveridge curve shifts towards the origin, this signifies a rise in matching efficiency. The equilibrium is determined at the interaction of the job creation condition and the Beveridge curve – this is at point C.

Shifts in the JCC and BC curves can result from positive and negative macro- and micro-economic shocks. For instance, net productivity shocks can result from macro-shocks that can change the general level of all goods prices. The price of all goods can also change from expectations about future economic conditions. Positive net productivity shocks represented by an increase in the common price p and a fall in the reservation productivity level (ε_d) increases the job creation rate. This causes the job creation condition to pivot upwards to JCC_2. The Beveridge curve shifts inwards towards the origin and the job destruction rate increases due to a rise in labour market tightness, which improves workers employment options. The new equilibrium is point I from point C, where the unemployment rate falls and the vacancy rate rises according to the diagram.

Figure 2.2: Changes to the Rate of Job Creation and Destruction



Accordingly, the price dispersion parameter σ could also rise because of greater competition from foreign firms. This can raise both of the job creation and job destruction rates. If domestic firms are able to compete with foreign firms because they are able to offshore their intermediate stages of production abroad where they have no comparative advantage in producing some of these goods compared to other stages of production. Then its impact in the vacancy-unemployment space shifts the Beveridge curve out and rotates the job creation condition curve upwards – the new equilibrium is point D from C. Equilibrium vacancies increase but the effect on the unemployment rate is ambiguous. This is because offshoring the assembly stages of production predominately completed by unskilled labour raises the job destruction rate in import and non export competing firms. These domestic firms may destroy jobs to lower production costs or even close down within declining sectors. However, domestic firms that are able to compete with foreign firms within expanding sectors can create new jobs for skilled and unskilled labour. With perfect information and labour mobility, unemployed workers can search for jobs that match their skills and obtain new jobs immediately. Therefore, the unemployment rate may not rise if there are high job reallocation rates in these sectors. And there is no rise in job insecurity if workers are able to find jobs as there is no uncertainty in the models. Thus, the exact impact on the unemployment rate is ambiguous.

Similarly, a reduction in persistence shown by a fall in λ (this is the arrival rate of idiosyncratic shocks to jobs) can raise and lower the job creation and job destruction rates for a given reservation productivity level (ε_d) between industries. This could be caused by the changing kaleidoscopic nature of comparative advantage or exchange rate volatility. But its impact on the unemployment level is once again unclear.

Alternative models that incorporate job-search with unemployment in imperfectly competitive labour markets can cause job security to fall as workers are not able to find jobs immediately. The following section examines the Davidson & Matusz (2003, 2004 & 2008) model of job turnover with imperfect labour markets.

2.3.3.1 Job Search, Unemployment & Job Turnover

Davidson & Matusz's (2003, 2004 & 2008) model incorporates job search, unemployment and job turnover. They are all factors that can affect production costs and job turnover rates which can determine patterns of comparative advantage enjoyed by firms. They can also affect the rate of job creation and destruction and the decisions made by workers to reallocate their employment to other industries which can affect their labour market security.

This model makes several assumptions. First, there is imperfect information, where it takes time for unemployed workers and firms with vacancies to meet and establish a working relationship. This may depend on a number of factors. First, workers and firms are not homogenous. Workers can differ by ability and they must choose between two types of jobs that require different levels of skills. There are jobs that do not require many skills and offer low pay and they are less durable. And there are jobs that require training and pay is relatively high where these jobs are durable. Labour markets are not frictionless and workers may not be perfectly mobile. Job search takes time once workers have completed their training from education for example, where job search and training can be costly. Firms can operate in two sectors: a high tech sector and a low tech sector which have different job turnover rates.

The matching process between workers and vacancies advertised by firms are easier in some industries than in others. For instance, jobs that require less skills or experience may be easier to fill compared to vacancies advertised in other industries that require high skills and where the production process is complex. To fill these latter vacancies, it may take firms more time to hire the right person that meets their criteria to fill the job. Therefore the matching process can be difficult to solve. Finally, the model assumes that once firms and workers establish a working relationship, job security is uncertain because random fluctuations in labour demand can be caused by basic shifts in comparative advantage.

Due to this uncertainty, workers cycle between periods of employment and unemployment, where job turnover rates determine the length of employment spells in each sector. Whether workers have secure jobs in employment or they experience spells of unemployment, this depends on their decision to choose occupations based on their future income streams. Jobs in the low-tech sectors are easy to find where they require specific skills. But they are not durable as they have high job turnover rates. Whereas jobs in the high-tech sector are relatively hard to find as they require a period of training before workers can qualify to carry out these jobs. The matching process for these jobs is also hard to solve as firms may have specific requirements. But these jobs are durable with low job turnover rates and these workers have general work skills.

As jobs are hard to come by in the high-tech sector, high-skilled workers may obtain employment in the low-tech sector. They are assumed to produce more output than low ability workers. When a job separation occurs, worker become unemployed, workers must re-train if they have specific employment skills for a particular job (e.g. a baker versus a sales assistant: each occupation has very specific skill). But if they have general skills, they may be able to obtain re-employment and not have to re-train if they are re-employed in the same sector (e.g. professional jobs such as teachers or accountants). If workers choose to change sectors, they will require training to obtain jobs in the new sector. Therefore becoming unemployment, searching for a job and re-training can be costly if workers seek employment in another industry.

Firms that have high job turnover rates with less durable jobs have to pay compensating wage differentials to workers. This is to convince them that the jobs in this sector are worth searching for. Higher compensating wage levels push up the costs of production which affect prices. Thus, customers turn to foreign produced goods if the goods produced domestically are more expensive. These price changes can affect patterns of trade. This model assumes that when job turnover rates are sector and country specific, a fall in the rate at which jobs are created or a rise in the job destruction rate in a particular sector-country pair raises the costs of production for a particular good. This raises its price and reduces a country's comparative advantage in that particular good. This model suggests that unemployment, job search and job turnover are determinants of comparative advantage, with particular emphasis on the job turnover rates influencing the patterns of trade. This is because different industries in different countries have different labour market structures and labour market institutions where job turnover rates vary significantly across these industries and where the length of unemployment spells can vary from country to country. It is these differences that may have a significant influence on the patterns of comparative advantage.

The implications from this model are that countries should have a comparative advantage in industries that have low job turnover rates. This would imply that jobs in the high-tech sector are durable with secure jobs; they are more likely to have a comparative advantage as they have lower job destruction rates. But jobs in the low-tech sector are less durable and they have higher job turnover rates. This implies that jobs in this sector are less secure as firms are not likely to have a comparative advantage in this sector if they have to pay workers compensating wage differentials to attract and retain workers in that industry. Thus, changes in the costs of production along with job turnover rates determine the basic nature of comparative advantage enjoyed by firms when they trade. And therefore job security is essentially determined by the job turnover rates within specific sectors and whether workers choose to reallocate to other sectors to obtain employment. One off changes to the demand for labour for specific groups is unlikely to lead to a change in job security. However, if the demand for labour continually changes then job security can be lowered if workers continually have to seek re-employment.

2.3.3.2 Kaleidoscopic Comparative Advantage

The nature of comparative advantage enjoyed by firms can also change over time with globalisation. Bhagwati & Dehejia (1993) name this the '*kaleidoscopic*' nature of comparative advantage. Their hypothesis is that volatility in employment and income is the result of greater internationalisation of world financial markets combined with the growth of transnational production by multinational enterprises (MNEs). Together with the diffusion of production know-how, this has exposed firms to much fiercer competition. This has narrowed the margin of comparative advantage enjoyed by many industries in developed countries. Small shifts in production costs can cause comparative advantage to shift suddenly from one country to another and hence cause the comparative advantage to be more 'kaleidoscopic' between countries. That is, one country may have comparative advantage in good X and another in good Y one day and the next day it may suddenly be reversed (Bhagwati & Dehejia, 1993; Bhagwati, 1995; Beaulieu *et al.*, 2004). There are three consequences from this hypothesis:

1. For labour there could be greater job turnover between industries and this could lead to greater frictional unemployment.
2. Greater labour turnover could flatten the growth profile of earnings for workers most affected due to less skill accumulation.
3. Less skilled labour will be affected more than skilled labour assuming that skilled workers have greater transferability of workplace acquired skills than less skilled workers. This could lead to an increasing wage-differential between the two groups of workers. Although this is a weak implication from this theory.

Thus, the kaleidoscopic nature of comparative advantage may lead to an increase in job instability and insecurity if there is little potential for productivity growth for firms to recoup any sunk costs they may have invested into their operations to reap the potential benefits from globalisation.

2.3.3.3 Exchange Rate Volatility & Product Market Competition

Borderless markets can raise international competition and expose more firms to real exchange rate changes (Gómez-Salvador *et al.*, 2004) and greater product market competition (Fenoll, 2009). This can further affect costs of production and job turnover rates. Campa & Goldberg (2001) identify three sources of currency exposure that can potentially affect job turnover. First, a currency appreciation increases the relative production costs of domestic firms relative to foreign firms through *export exposure*. This reduces the price competitiveness of goods produced by domestic firms, lowering export sales which intern raises the reservation productivity level. A rise in the reservation productivity level signifies firms may lay off workers through job destruction and lower job creation rates. The second source of currency exposure is through *import competition*. An appreciation of the exchange rate implies foreign imports are now cheaper, making foreign produced goods cheaper and allowing foreign firms to gain market share. Domestic firms that may not engage in trade may also be affected by the presence of foreign competition in the domestic market. This second effect can again lead to job destruction and lower job creation rates. Finally, the third source of currency exposure counteracts the first two through *cost exposure of imported intermediate imports*. Firms which rely on intermediate inputs may regain competitiveness through importing intermediate inputs. Firms may lower their costs of production and this may lower the number of jobs that are destroyed.

2.3.3.4 Footloose Multinationals and Offshoring

Job security can fall if employment within foreign owed firms is more volatile. This is because foreign-owned plants that may be owned by MNEs operate in many countries, where they may be able to shift production operations between countries should the operating conditions change in the host country. It can also be argued that the rise in FDI investment by MNEs can contribute towards raising employment risk (Scheve & Slaughter, 2004) as they are footloose – they can react to changes in the host country and shift production to another country and never be fully rooted in the host country. Another argument is that foreign-owned firms are more likely than domestically owned plants to exit the market. This raises job uncertainty and it can raise worker turnover if jobs are destroyed.

Offshoring refers to the relocation of production stages abroad either through arm's length supply through market transactions (international outsourcing) or within the boundaries of the firm (vertical FDI) (Jabbour, 2010). This relocation can be the material and immaterial stages of production. Job and labour market security can fall if firms are able to offshore stages of the production process that they are not able to provide at a competitive price in comparison to foreign firms who may have a comparative advantage in producing certain goods and services compared to domestic firms. Although labour market security can be affected by offshoring, not all workers are equally likely to be affected.

Footloose MNEs, outward FDI and offshoring can change the organisational structure of the production process and the composition of the labour force between skilled and unskilled labour. Firms employ many different types of labour: they may be skilled and employed within knowledge based jobs or less skilled labour employed within manual and repetitive jobs. Borrowing terminology from Hijzen *et al.,* (2007b), take for example a firm which has three distinct areas of operations to produce and distribute goods. These areas are (1) development: which employs skilled labour in knowledge based jobs, (2) assembly: which employs less-skilled labour to assemble together inputs into final products and (3) sales: which typically employs skilled labour to carry out sales transactions and provide after sales care services. In the past firms would have carried out all of these activities in house and in one particular country using local labour where all output would have been produced domestically.

However, globalisation and the advancements of telecommunication technology can give firms access to international markets where firms may take on the opportunity to establish production facilities in other countries where labour is cheaper. This can allow firms to produce intermediate inputs abroad, whilst also maintaining production in the domestic market. Primarily, the motivation for offshoring production stages is to reduce costs, but this decision can depend on the sector and the form of the relocation that takes place (OECD, 2007a). For instance, the primary motivation for small and medium sized enterprises (SMEs) to offshore production is due to pricing; whilst the decision to relocate headquarters of large MNEs is due to tax (OECD, 2007a). In terms of the example, firms may choose to set up assembly operations overseas where foreign intermediate inputs are used in addition to domestic assembly operations. Scheve & Slaughter (2004) note the cross-border flows of foreign direct investment have grown much faster than the cross-border flow of goods and services within the last couple of decades. These decisions have contributed towards the fragmentation of the production process, where the *'multinationalisation of production'* (Scheve & Slaughter, 2004) has contributed towards making workers feel much less secure about their employment spells (Davidson & Matusz, 2008).

The *'multinationalisation of production'* can be related to the changing nature of production costs that can cause MNEs to become footloose. This can mean, through vertical FDI, MNEs can change the geography of their production operations between plants due to changes in local production costs (Inui *et al.*, 2009) in the host country. For example, if there are two countries: the North (a developed country which is capital abundant) and the South (a developing country which is labour abundant) that produce and assemble intermediate goods in both countries. A rise in production costs in the North can enable MNEs to switch production to the South to lower the costs of production for a final good. The decision to switch production to other plants in other geographic locations may not necessarily be due to a rise in local production costs. Decisions to move productions can also be due to tax, government subsidies, and labour disputes. MNEs being able to switch their production operations to other plants can lower job security.

The decision to establish overseas production networks can lead to a rise in job instability as it enables firms to prevent wage rises for domestic workers as they are a credible threat to domestic employment, where foreign labour is cheaper. The threat of job loss by moving operations overseas can suppress wage increases. Additionally, changes in foreign labour markets can also affect the structure of the production process in the domestic labour market. The fragmentation of the production process can destroy jobs and lower wage increases for domestic workers. This process also increases the substitutability of domestic workers, which can increase the elasticity of labour demand. This can increase the volatility of wages and employment in the future (Greenaway *et al.*, 2008). Other reasons for workers to accept lower wage levels may relate to the fact that if workers do lose their jobs, it may take a considerable amount of time and resources to receive other job offers. Labour markets are far from perfectly competitive where a worker who refuses a job will not be able to instantaneously get a job offer from another firm (Cahuc & Zylberberg, 2006). Therefore, workers may retain their jobs with lower pay.

Traditionally, jobs most at risk of being offshored have come from manufacturing industries which have employed low-skilled labour; firms tend to move their assembly operations offshore and other operations in which they do not have a comparative advantage. Deardorff's (2005) model predicts that with the advent of international offshoring in final good Z and intermediate activity Y, whilst maintaining the production of good X using skilled labour, the wage levels for skilled labour would rise and fall for unskilled labour when trade takes place. This model predicts international offshoring benefits skilled labour at the expense of unskilled labour, as the work activities carried out by non-skilled labour (this is intermediate activity Y in terms of the model) are offshored to the South as the North has no comparative advantage in activity Y. The North does not offshore intermediate activity X as it has a comparative advantage in X with superior technology. Thus, offshoring leads developed countries to retain those jobs with activities that the North has a comparative advantage over the South.

2.3.3.5 Job Polarization

Technological innovation may also contribute towards displacing workers from their jobs and raise job and labour market insecurity. The current wave of globalisation differs with respect to previous waves because international trade has been facilitated by the decline in the real price of information technology. The fall in the real price of computer capital has allowed firms to substitute computer capital for labour in performing workplace job tasks (Acemoglu & Autor, 2010 & forthcoming). But technology can also lead to higher productivity as it can benefit workers whose job tasks complement technology. This can lead to more productive workers and higher productivity.

The advancements in information and telecommunications technology have allowed firms to trade many more goods and services were previously not at risk from being offshored (Garner, 2004)[7]. The Economist (2010)[8] notes during the 1970s and 1980s, employment in middle-skilled occupations grew – occupations relating to sales, bank clerks, factory supervisors and secretaries. But during the 1990s, the growth in these middling-skilled occupations started to decline. This is because instead of simply trading finished goods and services, there has been a move towards trading certain job tasks through offshoring and outsourcing. This process has applied to job tasks that are information based which have in recent years become easy to deliver at low cost via the internet from foreign labour market locations over the last two decades (Acemoglu & Autor, 2010 & forthcoming). The combination of technology and trade in tasks has contributed towards job polarization – the simultaneous growth in the share of employment in high-skill high-wage occupations and growth in low-skill low-wage occupations with a fall in the share of employment from middling jobs (Goos & Manning, 2003, 2007).

[7] Other reasons for greater service offshoring opportunities can be due to economic factors such as lower production costs from low-income countries but also because of comparative advantage. This has led to the relocation of labour–intensive service activities such as medical diagnostics of computer-tomography images or X-rays can be easily offshored abroad. Sharp declines in shipping and long distance telephone calls have contributed towards more production stages becoming vertically integrated in goods and services production. And the final reason relates to deregulation of service industries and trade liberalisation by developed and some developing countries during the early 1990s. See Garner (2004) for further details.

[8] This Economist article can be found at the following link:
URL: http://www.economist.com/node/16990700?story_id=16990700&fsrc=rss.

Authors' Autor, Levy & Murnane (2003) present the *'Routinization'* hypothesis [also known as the 'ALM' hypothesis and the 'Task Biased Technological Change Hypothesis (TBTC)]. It is nuanced explanation of how new technology can have an impact on labour demand, in particular how the composition of job tasks performed by occupations can be affected by the use of computer technology. The ALM hypothesis is based on three concepts that describe the task content of occupations that are required to perform jobs and its relationship with computer capital: (1) **Routine Job Tasks**- Computer capital can substitute for workers carrying out a limited and well defined set of routine cognitive and manual job tasks; those that can be accomplished by following explicit rules and procedures. (2) **Non-Routine Abstract Job Tasks** – Computer capital complements workers in carrying out problem solving and complex communication activities. Job tasks are not well structured and require non routine cognitive skills to perform them. Computers are not able to substitute for these job tasks as yet. (3) **Non-Routine Manual Job Tasks** – The capability of computers to substitute for workers carrying out cognitive and interpersonal job tasks is limited. Job tasks demand flexibility, creativity, generalized problem-solving and complex communications in a less than fully predictable environment.

The evidence from the ALM hypothesis suggests that jobs within industries that heavily used routine intensive skills had seen the greatest adoption of computers. This reduced the relative demand for routine intensive skills in those industries. Jobs that are characterised by routine cognitive and manual job tasks, such as record keeping and performing calculations (for instance a bank clerk), clerical work, or a job which requires repetitive sorting and monitoring (such as assembly workers in manual jobs) are jobs that can be substituted by technology. However non-routine cognitive and interactive job tasks require workers to engage in high degree abstract reasoning; these are skills that are complementary to technology but cannot be replaced by technology at this point in time (e.g. a surgeon). Jobs that require a high intensity of non-routine manual job tasks have limited opportunities for technology to substitute or complement these jobs as they consist of job tasks that require a certain degree of flexibility in an unpredictable environment. Examples include truck drivers, security guards, and construction workers[9].

Building on the work by Autor *et al.*, (2003), Goos & Manning (2003, 2007) argue that the routinization hypothesis has a subtle impact upon the demand for labour across the skill spectrum. That is jobs that can be routinized are not distributed uniformly across the wage distribution. They identify non-routine job tasks which compliment technology, which include skilled professional and managerial jobs are likely to be situated at the upper end of the wage distribution, where there is likely to be a rise in these types of jobs. These jobs are referred to as lovely jobs. On the other hand, non-routine manual job tasks account for most unskilled jobs such as in cleaning and personal help related occupations such as bar staff and child care providers or truck drivers are not likely to be affected directly by technology. This is because these jobs require situational adaptability and in-person interactions that are not likely to be performed by computer capital technology such as software. The impact of technology in other parts of the economy is likely to lead to a rise in employment for unskilled jobs (Manning, 2004). These types of jobs tend to occupy the lower end of the wage distribution and are referred to as lousy jobs. Jobs which exhibit routine-cognitive and routine-manual job tasks tend to occupy the middle of the wage distribution and are referred to as middling jobs. These jobs are likely to be substituted by computer capital and they are likely to experience a fall in relative demand. It is this fall in relative demand for 'middling' jobs which are substituted by technology that the authors' call this process job polarization.

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[9] The "trade in tasks" view does not only affect manufacturing jobs but also many jobs are in high skill service occupations (Grossman & Rossi-Hansberg, 2008; Ritter, 2009). For example, jobs within development and sales can be delivered via telephone or remotely via the internet because of a decline in shipping and long-distance telephone costs over the last fifty years. This means firms can now offshore not only their assembly operations but also their development and sales operations. The decision to offshore skilled jobs from development and sales operation can only take place if firms are able to invest in knowledge capital (Markusen, 2005) abroad, where these jobs can easily be monitored at low cost and where there are prospects for productivity growth. Jobs will be destroyed within the domestic market if the costs of establishing production networks abroad are cheaper than maintaining jobs at home. Thus, the fears of globalisation not only affect low-skilled jobs but they can also affect high-skilled service jobs that were previously insulated by offshoring. This can further raise employment volatility and job insecurity.

Table 2.1: Tradable Job Task Characteristics

Study	Job Task Characteristics
Bhagwati (1984)	Long distance arm's length vs. Face-to-face delivered services.
Leamer & Stroper (2001)	Codifiable vs. Tacit Information.
Autor, Levy & Murnane (2003)	'Routinization' Hypothesis: Routine tasks are repetitive and can be replaced by a computer.
Levy & Murnane (2004)	Routine vs. Non-Routine Tasks.
Bardhan & Kroll (2003); Kroll (2005)	(1) No face –to-face contact with customers. (2) Work via remote communications. (3) Tasks reducible to set of instructions. (4) Information the major component of the 'product'. (5) Low set-up barriers. (6) Low social networking requirements. (7) High wage differential compared to the receiving country.
Blinder (2006, 2007)	Remote Delivery vs. Physical Contact.

Source: Author's own compilation and part adapted from Grossman & Rossi-Hansberg (2008)

Table 2.1 lists the job task characteristics reported by various published and non-published working papers which are most likely to be offshored. Job tasks which appear to be most offshorable or tradable must be able to be delivered at long distance arm's length without degradation in the quality of the service as opposed to job tasks which require close proximity to the customer (Bhagwati 1984; Blinder 2006, 2007). Authors' Leamer & Stroper (2001), Levy & Murnane (2004) and Grossman & Rossi-Hansberg (2008) note the degree to which job tasks can be broken down into a series of codifiable job tasks, which can be described by a series of written set of rules and procedures can be substituted by machines or computer software (Acemoglu & Autor, 2010 & forthcoming). These job tasks can be easily monitored and they are most likely to be offshored (Grossman & Rossi-Hansberg, 2007). Job tasks which are non-routine in nature, have a large degree of tacit information and require visual and motor processing which cannot be described by a set of rules or be replaced by computer capital at present, they are least likely to be offshored as monitoring these job tasks may not be possible or too costly. Bardhan & Kroll (2003), Kroll (2005) provide an array of task and trading environment characteristics which enable job tasks to be offshored.

Thus, structural changes in tastes and technology that can be facilitated by globalisation can raise job insecurity and job instability as technology can substitute for labour that are employed by occupations that have a high importance for routine intensive job tasks that follow well defined rules that can be performed using computer software or machines. On the other hand, workers who are employed in middling jobs perform routine intensive job tasks that are highly substitutable with foreign labour, who are able to deliver these job task services remotely from foreign labour market locations. This can raise the elasticity of labour demand, which is discussed in the next section.

2.3.3.6 The Elasticity of Labour Demand

Rodrik (1997) noted the labour demand elasticities could rise with globalisation. A rise in international trade through greater offshoring, induced through greater product market competition, a fall in trade protection, greater competition from less developed countries and technology will increase the own-wage elasticity of labour demand. This is because borderless markets for goods, services and labour allow firms greater access to foreign markets. Firms may decide to establish production networks abroad through outward FDI or outsource parts of their domestic operations abroad to take advantage of cheaper labour costs. Offshoring and outward FDI investment establish production networks outside the domestic market where firms may have access to cheaper factors of production. This increases the substitutability of domestic workers with foreign workers, which raises the elasticity of labour demand. This rise can raise job insecurity.

Similarly, the deregulation of labour market policies and the kaleidoscopic nature of comparative advantage will raise the elasticity of labour demand. The deregulation of employment protection policies lowers the cost of job destruction, which in turn will allow firms greater flexibility to create and destroy jobs without facing large costs in response to changing economic trading conditions, where the relative benefits of comparative advantage can change over time. A rising elasticity of labour demand will increase the responsiveness of wages and employment through potential labour demand shocks caused by structural changes in tastes and technology (Hijzen & Swaim, 2008).

2.3.4 Worker Heterogeneity

Workers are not homogeneous; they can differ by their human capital characteristics (whether acquired through training or innate) that contributes to their productivity. Worker heterogeneity within the labour market may have important implications for the job security for different groups of workers.

Mortensen & Pissarides (1999) extend their equilibrium unemployment model to allow workers to differ by their skill endowment. This new model examines the impact of skill-biased technology shocks and the role labour market policies have upon the unemployment level. The model assumes there are high-skilled and low-skilled workers. The labour market policies that are explored are unemployment insurance benefits (UI) and employment protection policies (EP).

Unemployment compensation and other forms of welfare payments are paid to workers when they are involuntarily displaced from employment. The generosity of these payments determines the extent of job search intensity carried out by workers. Generous UI payments discourages job search because it decreases the cost of unemployment. This also discourages job creation because higher UI payments are acquired through raising the costs of production in the form of higher taxes which are then collected by the state. Employment protection policies are policies which reduce the efficient allocation of resources as they restrict the ability of firms to adjust their workforces in response to changing economic conditions. EP policies can be thought of as job security policies, where they serve three economic goals (Cahuc & Zylberberg, 2006): (1) to preserve employment and discourage job destruction; (2) to reduce the risk of employment and income fluctuations for existing wage earners and (3) to encourage firms to take the social value of jobs into account. However, strict EP policies may not serve any of the three goals if they increase actual or implicit firing costs. This will also discourage job creation in response to technology shocks or changing patterns of labour demand, as they leave firms with unwanted workers (Mortensen & Pissarides, 1999).

The model assumes there is a fully segmented labour market separated by skill where each market has a separate matching function. When employers create vacancies in this model, they must specify the skill requirement for the job, where this decision is irreversible. Employers only hire those worker whose skill levels are at or above those required to perform the jobs. This is because qualified workers (those who have the required skill level or above) generate the required future profit stream that is equal to the asset value of the job. Less skilled workers are not accepted for employment as their skill endowment does not match the skill level required for the job; they are assumed to produce nothing if hired. The wage in each sub-market is determined by a process of bargaining under perfect information, where wages are continuously negotiated with the advent of structural changes. If wage negotiations cannot be reached between workers and firms, firms are liable to pay firing costs. The cost of firing workers increases with skill, so it is more costly to fire skilled workers than unskilled workers.

Strict EP and generous UI policies have an impact on each sub-market for each skill group when structural changes affect the demand for labour. They have the following predicted impact on job creation and destruction rates for each skill group: First, higher UI payments increase production costs which subsequently raise the reservation productivity value for all jobs in each sub-market. This increases the job destruction rate which also raises the unemployment rate for all workers. However, the unemployment rate for less skilled workers increases more than that for skilled workers because the model assumes skilled workers are more costly to fire than unskilled workers. The job creation rate remains unchanged. Second, strict EP policies decrease the option value of jobs because high firing taxes prevent firms from terminating jobs. This decreases the unemployment rate where the fall in the unemployment rate for unskilled workers is less than that for more skilled workers. Third, with strict[10] EP and generous UI policies, the model predicts the average unemployment rate will rise more in response to structural changes than if UI and EP policies were less generous and weak and the duration of unemployment would be longer but less frequent. Finally, the fourth prediction from the model shows that as low skilled labour represents a smaller fraction of the employed work force, wage dispersion would increase in response to a skilled biased shock when UI and EP policies are less generous and weak.

Thus, the rate of job creation and destruction determines the equilibrium level of unemployment which subsequently has important implications for labour market security. Structural changes in tastes and technology can alter job creation and job destruction rates. Job creation and destruction rates are higher with weaker job protection policies, and this would imply job security would be lower because firms can adjust their work forces. Job stability can be lower if firms want to reduce their production costs but do not want to reduce their work forces during unfavourable trading conditions. Workers may accept lower pay and a shorter working week to remain employed rather than become unemployed. But firms could still shed their work force and close down if their business operations do not improve. And finally, the costs associated with job displacement can be higher. Although job creation rates are higher, job destruction rates are also higher and this would imply workers who are displaced from employment can obtain another job quickly, but there is no guarantee that these newly created jobs will be permanent jobs in the future if firms hire workers

[10] Strict EP policy relates to how costly it would be for firms to let go of workers to adjust their labour force in response to changing economic conditions. If employment protection policies are strict, this means workers can make a claim for unfair dismissal from employers if they have been employed by them for 12 months or more. On the other hand, weak EP policy can relate to an unfair dismissal policy which may require workers to be employed by firms for at least 24 months. Thus, the former policy is strict in the sense that the cost of firing workers are higher if firms are not able to adjust their worker forces over the short term in response to changing economic conditions as opposed to the latter policy. The latter policy is weak because firms can dismiss workers within the 24 month period. In reality the right to make a claim for unfair dismissal is more complicated compared to the assumptions made by this model and the policies.

temporarily. Additionally, the incidence of unemployment can lead to unemployment scarring where becoming unemployment can increase the probability of becoming unemployed in the future with lower future earnings trajectory if workers become stuck in a cycle of temporary jobs with low pay and eventually out of the labour force.

If labour market policies were geared towards protecting jobs, labour market security would be higher as jobs would be more secure, labour income would be less volatile and the earnings losses from job displacement between jobs would be smaller in theory. However, theory predicts that less skilled workers would be worse off if labour market policies protected jobs. The job creation and destruction literature does not provide predictions as to whether less skilled workers would be worse off if labour market policies did not protect jobs; but this is the most likely scenario as it is less costly to destroy less skilled jobs than it is to destroy jobs for skilled labour. Current labour market policies in the U.K. provide minimal protection for existing jobs[11]. These policies allow for greater labour market flexibility towards changes in tastes and technology which affect labour demand. Thus, this chapter asks whether there is evidence that technological change, globalisation and changes in labour market policy have had a significant impact on job security.

In summary, this section shows job creation and destruction rates can change from forces associated with technological change, labour market policy changes and globalisation. They can potentially affect job turnover rates, which can subsequently affect trade patterns. The theoretical literature suggests if job turnover rates are high for a particular industry, then firms within these sectors have to pay workers high compensating wage differentials to attract workers to work within these industries and to retain workers. But these higher costs raise the costs of production which can affect the price and the comparative advantage for a

[11] UI payments are paid to workers for a period of six months only. There are minimal EP policies which restrict employers' ability to adjust their work forces in response to changing economic condition. But workers do have the right to claim unfair job dismissal if they have been employed with an employer for 12 months or more.

particular good. Higher prices force customers to switch to foreign goods that are cheaper. Thus, a rise in production costs, and a fall in sales may cause firms to outsource parts of their production process overseas or in the case of MNEs change the geographic location of production. This can increase job turnover rates. Higher job turnover rates can lead to unemployment and workers must search for other jobs or re-train to obtain employment in other industries. These one off changes in labour demand will not increase job insecurity or job instability. However, a rise in the number of job reallocations with job search and unemployment can increase labour market insecurity. They can lower job security, because jobs are less durable; they can raise job instability if workers prefer to remain in employment and thus accept lower pay. They can also raise the earnings losses post job loss if there are frequent spells of unemployment and job search.

2.4 The Empirical Evidence

This section provides the empirical evidence which sheds light on the potential forces outlined in section 2.3 that could lead to changes to the three components of labour market security.

2.4.1 Job Creation & Destruction

The job flow literature has established a number of facts in relation to the creation and destruction of jobs: First, the 15 percent rule: there are a large number of jobs that are simultaneously destroyed and created in all major industrial countries within different industrial sectors regardless of the business cycle. These rates are more or less similar for all industrialised countries. Roughly, on a national scale, around 15 percent of jobs are destroyed each year and roughly 15 percent of new jobs are created each year (Davis & Haltiwanger, 1999). Recent estimates suggest approximately 53,000 jobs are created and 51,000 jobs are destroyed by the services and manufacturing firms in the U.K. economy every week for the period 1998 to 2005 (Hijzen *et al.*, 2007)[12]. On average, this is a 15.2% job creation rate and a 14.5% job destruction rate over the 1998 to 2005 period. Their estimates are in line with the 15 percent rule. Additionally, their results also show a decline in the job creation and destruction rates over time: for 1998 the job creation rate for the manufacturing and services sector was 17.2% and the corresponding job destruction rate was 17.5%. In 2001, the job creation rate was 15.6% and the job destruction rate was 13.8%. By 2005, the job creation rate was 14.8% and the job destruction rate was 14.2%. For other countries, the job creation and destruction rates are also similar; Davis *et al* (1997) report gross annual rates of job creation and destruction averaged 9.2% and 11.3% for the U.S. manufacturing industry between 1972 and 1986. These rates show the relative decline in the manufacturing sector over this period, which are somewhat less than the 15 percent rule. These reported rates for the manufacturing sector are generally true for most developed countries, where for Norway, the respective job creation and job destruction rates for the period 1976-1986 were 7.1% and 8.4% respectively. However, these rates for the manufacturing sector for developing countries are somewhat higher than the 15 percent rule. Estimates reported by Davis *et al.*, (1997) show for Morocco, the job creation and destruction rates for the manufacturing sector for the period 1984-1989 were 18.6% and 12.1% respectively. For France, Cahuc & Zylberberg (2006) note roughly 10,000 jobs are created and destroyed each day. Roughly this is around 10-12% per day or around 11.4% and 12% of all jobs from 1978-1984 for the private non-farm sector for France (Davis *et al.*, 1997)[13]. These estimates show very little change to these rates over time.

Second, there is a negative relationship between job creation and job destruction over the business cycle, where job creation rates are pro-cyclical and job destruction rates are counter cyclical. Job destruction rates are found to be more volatile over the business cycle than job

[12] Job creation and destruction rates are on average higher for the services sector than for the manufacturing sector, where the manufacturing sector tends to have higher job destruction rates than job creation rates.
[13] See table 2.2 from Davis *et al.*, (1997) for estimates for other countries.

creation rates. Third, job reallocation rates, defined as the sum of job creation and job destruction rates, are inversely related to capital intensity, where more jobs are destroyed and created by the service sector than by the manufacturing sector (Gómez-Salvador *et al.*, 2004; Hijzen *et al.*, 2007). Fourth, job reallocation intensity depends on firm specific characteristics where job creation rates are negatively associated with firm age and size. Finally, job reallocation rates are persistent over time, such that observed job flows cannot be accounted for by temporary lay-offs or recall procedures; they depend on structural changes in tastes and technology – or what Joseph Schumpeter refers to as "creative destruction".

2.4.2 Globalisation and Wages

2.4.2.1 The Causes of Wage Inequality: the Trade vs. Technology Debate

Research from the empirical literature for various developed countries shows that wage inequality - the gap between the skilled and non skilled labours' wage bill share have increased over the last four decades (See Machin (2010) for a detailed description for these trends). In brief, Machin (2011) notes wage inequality between skilled and non skilled labour widened rapidly throughout the earnings distribution during the 1980s. These changes continued throughout the 1990s, where they were a little muted. The post 2000 time frame saw wage inequality in the upper tail continue to rise, but the lower tail wage inequality changed very little. Similar patterns have also been observed by the U.S.; Katz & Autor (1999) note the wages of college educated workers relative to non-college educated workers rose dramatically during the period 1979-1995[14]. During this period, there was an observed increase in the supply of skilled labour, where the increase in the wage premium was driven by demand side factors. Similar trends have also been observed by other developed countries: see Berman *et al.*, (1998) and Machin & Van Reenen (2007) for further details.

[14] The real wage for the latter group declined over the same time frame.

There exists a large body of literature that has sought to explain these observed changes to the wage structure over time. Katz & Autor (1999) note there are a number of explanations that have been explored and tested to explain these observed changes to the wage structure; they include the following explanations, though the authors' note these explanations are not exclusive.

The first explanation lies with technological change. The new technology revolution over the last 30 years has been associated with the spread of computer technology in micro-processors in the work place (Mincer, 1991; Bound & Johnson, 1992; Berman *et al.*, 1994; Autor *et al.*, 1998). This hypothesis suggests the new technology is biased towards skilled labour (skill biased technological change, SBTC) because the newly created jobs that incorporate the new technology complement their skills but more educated workers are also more likely to have an advantage in using ICT more effectively and may be able to cope better with the uncertainty surrounding the use of new technology. With the fall in ICT costs, and greater investments through higher R&D intensities into new technologies, this could shift demand towards more skilled labour (Machin & Van Reenen, 2007). Technology can also lead to job polarization whereby technology such as computer software can substitute for jobs that are intensive in routine job task functions (task biased technological change, TBTC); this can shift the demand for labour away from lesser skilled workers (Machin, 2010).

The second explanation focuses on the impact of globalisation. This explanation relates to increased international trade and greater outsourcing of domestic production processes in manufacturing and services abroad to developing countries. Globalisation can lower the employment level and shrink the relative demand for less skilled workers in manufacturing and service industries which can lead to fall in the wage premium paid to these workers (Wood, 1994, 1995, 1998; Borjas & Ramey, 1995; Feenstra & Hansen, 1996; Goos *et al.*, 2010; Crinò 2009a; Bottini *et al.*, 2009).

The third explanation relates to policy changes affecting the strength of labour market institutions. Policy changes can relate to the decline in unionisation, changes in minimum wage legislation; they can also include UI and EP policy changes that could affect wage inequality over time. The argument here is that countries that have experienced a fall in the strength of labour market institutions (for instance a fall in the presence of unions, a real decline in minimum wage levels and/or less generous UI and weak EP policies) may effectively remove protection for less skilled wage workers. This may lead to a fall in relative wages and thus a rise in wage inequality (Machin, 2010).

The debate about the causes for the change in the wage structure and for the increase in the demand for more skilled workers has primarily focused on the first two explanations: namely the trade hypothesis vs. the technology hypothesis.

The technology hypothesis as an explanation for the shift towards more skilled labour lies with skill biased technological change (SBTC). This explanation notes that the change in the wage structure is attributed to a rise in the demand for skilled labour because new technologies can lead to higher productivity. Newly created jobs or newly renovated jobs require workers with the right skill intensities (skilled workers) who complement the new technology. This can lower wages for other less skilled workers or this can cause job displacement for those workers who do not have the right skills to use the new technology (Machin, 2008). More recent trends have re-examined the implications of the SBTC hypothesis with the proposition of the routinization hypothesis by Autor *et al.*, (2003). This hypothesis provides an explanation for the polarization of jobs in many developed countries (Autor *et al.*, 2006; Goos & Manning, 2007). It proposes that many middle skill jobs have been lost because technology such as computer software can substitute for routine intensive job tasks. Many of these routine intensive job tasks are also the most offshorable job tasks (Acemoglu & Autor, 2010; Grossman & Rossi-Hansberg, 2008) which have been facilitated by the fall in telecommunication costs.

This can have a negative impact on the wages for less skilled labour assuming that the relative price effect and the labour supply effect dominate the productivity effect from the trade-in-tasks model proposed by Grossman & Rossi-Hansberg (2008).

The trade hypothesis relates to increased international trade as the explanation for the rise in wage inequality which stems from the Heckscher-Ohlin Model (HO) of international trade as to why less skilled workers may have fared less favourably from the benefits of trade compared to skilled workers. In terms of a North and South model setting, the HO model assumes the North is a relatively skill abundant developed country (e.g. U.S. or U.K.) and the South is a relatively labour abundant developing country (e.g. China or India). The HO theorem predicts that when two countries move from autarky to free trade, the owners of a country's relatively abundant factors gain from free trade but the owners of the scarce factors lose out. This theorem predicts that less skilled workers from the North now have to compete with less skilled labour from the South within similar industries. Thus, with the influx of cheaper goods produced using less skilled workers from the South, this can put downward pressure on their wages as there is a shift downwards in the demand for less skilled labour in the North. A similar argument can be made for outsourcing; firms in the North outsource their intermediate stages of production that are completed by less skilled workers to the South in the same industry. This can lead to fall in the demand for less skilled labour in the North and put downward pressure on wages.

Another result from the HO model is the Stolper-Samuelson theorem that is relevant to this analysis. This theorem relates relative factor prices to relative product prices through the zero profit condition. The Stolper-Samuelson theorem states that an increase in the relative price of a good will increase the real return to the factor used intensively in the production of that good and will decrease the return to the other factor. This theorem implies that when the North moves from autarky to free trade, the fall in trade costs with the removal of trade barriers will raise the relative price for the skilled intensive good in the North, which implies a higher wage premium for skilled worker.

The empirical evidence from the trade hypothesis is mixed. While the HO model provides coherent and testable explanations for the potential rise in wage inequality over time, Desjonqueres *et al.*, (1999) and Berman *et al.*, (1998) find the predictions from the HO model are at odds with the data and Machin (2010) notes the observed trends are better explained by technology variables in favour of the SBTC hypothesis.

First, according to the trade based explanation from the HO model, we should observe an increase in the relative demand for skilled labour in the North that can be the result from an increase in specialisation resulting from shifts in the sectoral distribution of employment *between* industries to the skill intensive industries when each country moves towards free trade. And with the rise in the relative price of skill, the model predicts there should be a *within* industry shift in employment towards less skilled labour. The empirical evidence from Desjonqueres *et al.*, (1999) decompose the changes in within-industry employment shares from 1981-1991. Their results show most of the shift in employment occurred *within* industries[15] was towards skilled labour (skill upgrading). They also found within non-tradable sectors such as hotels & restaurants and wholesale & trade, there was an increase in the education employment premium – indicating a shift in employment towards skilled workers. Desjonqueres *et al.*, (1999) conclude their evidence from the *within* industry shifts is consistent with the SBTC hypothesis but is at odds with the HO trade theory.

Second, the Stolper-Samuelson theorem implies that if wage inequality were to increase in a developed country through its impact on domestic product prices, the price of the skilled intensive products relative to unskilled intensive products should increase when trade takes

[15] Earlier work by Berman *et al.*, (1994) also show that the increase in the relative demand for skilled labour occurred *within* industries rather than *across* industries.

place[16]. Empirically, researchers have tried to establish whether rising wage inequality is the result of the North experiencing a fall in prices for unskilled intensive products relative to skilled intensive products (Slaughter, 1999). Using product price regressions[17], authors Leamer (1998) and Baldwin & Cain (1997) found the relative product prices for unskilled intensive sectors fell during the 1970s for the U.S. However, Bhagwati (1991), Lawrence & Slaughter (1993), Leamer (1998) and Baldwin & Cain (1997) find no clear trend in relative prices during the 1980s. This evidence is not consistent with the trade based explanation.

Feenstra & Hanson (1996, 1999, and 2003) take another stance to find support for the trade hypothesis by noting that trade in intermediates might be responsible for the increase in the skill premium. This is because trade in intermediates differs from trade in final goods. They note that a substantial part of the increase in international trade might be associated with a vertical disintegration of production processes within industry (i.e. offshoring). Offshoring raises the demand for skilled labour in the North because firms within industry offshore the relatively less skill intensive stages of production to foreign labour markets. The relative demand for labour is not only affected in import competing industries, but in all industries that use foreign inputs. Thus, offshore outsourcing may affect the relative demand for labour *between* industries but also *within* industries.

Feenstra & Hanson (1995) estimate product price regressions to explore the impact of offshoring on wage bill shares for skilled and non-skilled workers. They compute a broad material offshoring[18] measure for 450 manufacturing industries for the period 1979-1987, where skilled and non-skilled workers are proxied by non-production and production workers.

[16] Deardorff (1994) provides a survey describing the many theoretical statements for the Stolper-Samuelson theorem.

[17] Slaughter (2000) provides a review of nine papers that have explored the impact of trade and technology contributing towards increased wage inequality using product price regressions. The majority of the empirical studies have used the correlation version of the Stolper-Samuelson theorem. Product price regressions consist of changes in goods prices that are regressed on share-weighted changes in the prices of their inputs (that is the factor prices for labour and capital). Under zero-profit conditions, the coefficients reflect the implied change in factor prices following the change in industry prices. This approach implements a general equilibrium framework to test the Stolper-Samuelson theorem from the HO model using industry level data.

[18] Broad offshoring measures the values of all imported intermediate inputs of an industry. Narrow offshoring measures the value of intermediate inputs that are purchased from the same industry as the goods being produced; this captures the idea of production being transferred abroad that could have been produced by a domestic firm.

Their results show the growth in imports as measured by broad material offshoring accounted for 15%-33% of the rise in the share of non-production labour costs. These results are further confirmed by their 1996 paper which found offshoring accounted for 31%-51.3% of the rise in the non-production labour's share of the wage bill for the period 1972-1992. Similarly, Becker *et al.*, (2008) examine the onshore composition of job tasks to skill levels within German MNEs. They found offshoring predicts an increase in the wage-bill shares for high-skilled labour.

In another paper, Feenstra & Hanson (1999) study the impact of offshoring and technology on U.S. wage inequality. This paper endogenise prices and total factor productivity (TFP is the measure for technology) in a two stage mandated-wage approach[19]. They to not estimate product price regressions because they argue the conventional price regressions approach is fully specified; they become an identity, which can no longer be used to make inferences about the implied factor price changes. In the first stage of the mandated-wage approach, industry prices and TFP are regressed onto the expenditure on computers and offshoring[20]. And in the second stage, the estimated coefficients from the structural variables from the first stage are then used in the second stage as the dependent variable in the mandated wage regressions (see Slaughter (2000) and Baldwin (2008) for a detailed synopsis on this method). Feenstra & Hanson (1999) find offshoring has sizable effects on wage inequality in the U.S. They find offshoring can explain about 11% to 15.2% rise in the wage bill share of skilled labour, whilst expenditure on computers can explain up to 31.5% of the increase in the wage bill share.

[19] The mandated wage regression approach is a method that has been built upon the contributions of Jones (1965), Hilton (1984), Leamer (1995, 1998) and Baldwin & Cain (1997, 2000). This framework interprets the estimated coefficients on the factor shares in an equation as "mandated" changes in factor costs that are compatible with zero profit conditions in the presence of changes in product prices and technology.

[20] Expenditure on computers and offshoring are known as the structural variables.

Third, the HO model predicts that wage inequality should fall in developing countries because the North experiences a relative supply increase in skilled labour. Desjonqueres *et al.*, (1999) find the changes in the relative employment shares of non-production to production workers rose for a number of developing countries within industries, which should lead to an increase in wage inequality. Additionally, Wood (1997) finds an increase in wage differentials in Latin America from the mid-1980s onwards. See further evidence outlined by Milner *et al.*, (2005). The fact that wage premiums are found to increase in the 'South' is at odds with HO model.

To help explain the rise in the wage premium in the North and the South, Feenstra & Hanson (1995) develop a theoretical model of vertical specialisation. The Key point from this model is that international outsourcing de-locates unskilled intensive production processes from the viewpoint of the North, but these production processes are skilled intensive from the view point of the South. This may explain the rise in the skill premium in the North and the South. Feenstra & Hanson (1995 & 1997) are able to demonstrate that the *within* industry shift for skilled labour in Mexico have increased due to outsourcing.

This empirical evidence suggest that the trade hypothesis has little support but the SBTC seems to fit the observed trends from the data (Machin, 2008) in explaining the shift in the demand for labour towards skilled labour. However, there are two potential caveats: First, Desjonqueres *et al.*, (1999) and Machin (2008) note that most of the data from the empirical studies were based on data prior to 1995 when China started to emerge as a major exporter. And second, Acemoglu (2002a, 2002b) notes that trade could partially induce skill biased technological change.

More recent research exploring the impact of offshoring on wages has used individual level data using the Mincer wage regression approach. This research was originally explored and developed by Mincer (1958, 1962 and 1974), Schultz (1960, 1961) and Becker (1962, 1994) to explore human capital theory. In brief, the human capital theory suggests that individuals who invest their time in further education and forgo earnings that could be earned in the labour market must be rewarded or compensated with higher earnings levels when they enter the labour market with higher skills and qualifications. This is because higher skills and qualifications can equate to higher productivity which can be profitable for firms to employ and to pay higher wages. On the other hand, screening theory advocated by Arrow (1973) and Spence (1973, 1974) suggest that individuals who hold higher degrees and qualifications have superior innate abilities and are more productive. The human capital and screening theories both note that differences in education levels and decisions to undertake further training can lead to differences in wage premiums between skilled and non-skilled workers. In a similar vein, Mincer wage regressions can be used to examine the impact offshoring and technology can have on wage levels. Specifically, if offshoring enables firms to relocate intermediate production processes largely completed by less skilled labour abroad, this relocation can have a negative impact on their wage levels. Similarly, technological innovations benefit skilled workers because they complement their skills, which should have a positive impact on their wage levels but have a negative impact on the wage levels of less skilled workers. This approach can be used to quantify the magnitude or the returns to wages from offshoring and technology.

Evidence from the Mincer wage regression approach suggests skilled labour benefit with higher wage levels compared to less-skilled labour when firms engage in offshoring; but the quantitative impact appears to be small. For instance from Germany, Geishecker & Görg (2008a) find a 1% rise in broad and narrow material offshoring intensities lower hourly wage levels on average by 0.9% in manufacturing industries. For different skill groups, a 1% rise in narrow (broad) offshoring intensity lowers the hourly wage levels for the lowest skill group by

1.5% (1.3%). For high-skilled workers, a 1% rise in narrow (broad) offshoring intensity raises hourly wage levels by 2.6% (1.9%).

For the U.K., Geishecker & Görg (2008b) investigate the impact of service and material offshoring for male workers employed in manufacturing industries for the period 1992-2004[21]. Their results show service and material offshoring lowered the hourly wage levels for workers on average by 0.7% and 0.8% from a 1% in service and material offshoring intensity respectively. By skill group, a 1% rise in material offshoring intensity lowered the hourly wage levels for medium and lower skilled workers by 0.85% and 1.95%. But a 1% rise in service offshoring intensity lowered hourly wage levels for low and medium skilled workers by 1.32% and 1.14% respectively. For high-skilled worker, a 1% rise in service offshoring intensity raised hourly wage levels by 4.5%. These findings are consistent with the predictions from Deardorff's (2005) model. Similar empirical evidence is also reported by Hummels *et al.*, (2009) and Munch & Skaksen (2009) for Denmark. Munch & Skaksen (2009) examine the impact of domestic and foreign material offshoring on the hourly wage levels for Danish manufacturing workers for the period 1993-2002. Their results show domestic offshoring raised the hourly wage levels for less skilled labour but foreign outsourcing raised the hourly wage levels for skilled labour. They also found male workers appeared to be unaffected by foreign outsourcing compared to women, where a 1% rise in foreign outsourcing reduced their hourly wage levels by 0.131%.

However, the impact of offshoring on the wage levels of skilled labour depends on whether offshoring takes place to high income countries or to low income countries. Hummels *et al.*, (2009) found that an exogenous shock to outsourcing from a low income country depressed the wage levels for medium and low skilled workers but raised wages for high-skilled workers. However, if the exogenous shock to outsourcing occurred from high income countries, the

[21] This is the only paper that I have found so far which has examined the impact of service offshoring on wage levels; the empirical research has so far only examined the impact of material offshoring.

wage levels for medium and low skilled workers rose but depressed the wage levels for high-skilled workers. Similar evidence is also found by Geishecker *et al.,* (2007). Their results show outsourcing to central and Eastern European countries (CEEC) lowered wage levels for skilled workers in Germany and the U.K. But if outsourcing took place to non-CEEC, this lowered the wage levels for non-skilled workers only in Germany and U.K. For Denmark, outsourcing to CEEC's had a negative and significant impact on lowering the wage levels for lower skilled workers only.

The empirical evidence from this section has shown that skilled labour benefit from offshoring but less skilled workers suffer lower wage levels. The estimated coefficients show that the quantitative impact appears to be quite small at present. This could however change in the future.

2.4.3 Globalisation and the Composition of Employment

2.4.3.1 The Impact on Job Security

A small selection of papers have explored whether job security as measured by the probability of job loss, a job separation and the probability of making a job-to-unemployment transition have increased because of offshoring or because of exchange rate volatility[22]. Four papers have examined the implications for job security from material offshoring; there are no papers which have explored the implications from service offshoring. If job reallocation rates have increased, and assuming the job destruction rate is higher than the job creation rate, one should find a fall in job security through higher job displacement rates and frequent job to job transitions rates. There is however no clear consensus from the literature as to the effects offshoring and exchange rate volatility have had on different skill groups; but the empirical literature does confirm low skilled workers face greater job insecurity.

[22] This review is limited to Europe and two European countries; to the best of my knowledge there are no papers that have explored the job security implications from offshoring for the U.S.

The empirical evidence does suggest that the rise in material offshoring intensity and the rise in exchange rate volatility have raised the probability of a job separation, but the impact so far has been small. For Germany, Geishecker (2008) finds a 1% rise in international outsourcing (narrow) in the manufacturing sector leads to a 6% rise in the probability of non-participation in the labour market. With a 2.28% rise in international offshoring (narrow) for the period 1991-2000, this translates to a 13% rise in the probability of non-participation in the labour market. Geishecker's (2008) results also show employment security declining with increasing duration dependence, meaning longer tenured workers are more likely to exit employment due to international outsourcing. Bachmann & Braun (2008) also examine the effects of international outsourcing on job security in Germany for the manufacturing and service sectors. Their results show jobs security to be greater in the service sector than for the manufacturing sector. Their estimates show from a 1% rise in offshoring in the manufacturing sector increases the hazard of leaving employment and entering non-employment by 2.6% which is a lower estimate compared to Geishecker (2008). Medium skilled workers were found to have higher job-to non-employment hazards, but skilled workers in the services sectors had the most secure jobs.

For Denmark, the impact from international outsourcing on job displacement is smaller compared to Germany. Munch (2008) finds that a 1% rise in offshoring (broad) raises the job separation probability by 0.451%. Additionally, results from a competing risks model found offshoring (broad) raises the unemployment risk and lowers the job change hazard rate. However, the quantitative impact from offshoring based upon these reported results are modest as the impact is analysed over a period of 12 years and not annually. Hummels *et al.,* (2009) find doubling the offshoring intensity (material offshoring) increases the job separation probability by 5-10%, but the results vary little by skill groups.

Exchange rate volatility also has a significant impact on the probability of job displacement. The OECD (2007b) finds that a depreciation of the industry specific exchange rate (a fall in foreign competition) reduces the probability of job-to-unemployment and job-to-non-employment transitions. With an appreciation in the industry specific exchange rate (a rise in foreign competition) raises the job-to-unemployment hazards for workers with job tenure under 5 years and it increases the job-to-job hazard for low-tenured and medium skilled workers.

Fenoll (2009) finds that product market competition also raises job insecurity through the appointment of temporary work contracts in Spain. Fenoll (2009) reports that a one standard deviation increase in international competition measured by the price-cost margin decreases the probability that a worker employed on a temporary work contract to be made permanent in a given year by more than 40% with a 3% rise in the probability of becoming unemployed. There is empirical evidence on the other hand which shows product market competition does raise the employment and wage levels which does signify job security and stability; see Nicoletti & Scarpetta (2005), Griffith *et al.,* (2007) and Fiori *et al.,* (2008) for empirical country-level analysis on the incidence of product market competition on employment and wages. But the evidence from Fenoll (2009) relates specifically to the labour market policies pursued by Spain; these results cannot be generalised to other countries.

Has offshoring lead to a fall in the demand for labour that could signify there has been a rise in job insecurity? The answer is no; the change to the employment level has been small and limited to less skilled labour. This empirical evidence is reviewed below, which shows this evidence mirrors the empirical evidence from studies that have examined the impact of offshoring and exchange rate volatility on the probability of becoming unemployed/not participating in the labour market from this section.

2.4.3.2 The Impact on the Employment Level

The impact that offshoring has had on the demand for labour has been summarised in vast detail by Bottini *et al.*, (2007) and Crinò (2009a). The general findings from Bottini *et al.*, (2007) indicate material offshoring has lead to a fall in the demand for less skilled workers, where the effects of material offshoring have also lowered the probability of staying in the manufacturing sectors: Anderton *et al.*, (2002) found material offshoring lowered the employment level and wage bill shares for low skilled labour for the U.K., U.S. Sweden and Italy. Similarly, for the European Union, Falk & Wolfmayr (2005) found imported intermediate inputs from low-wage countries had a significant negative impact on total employment and for less skilled labour. For Sweden, Ekholm & Hakkala (2008) found offshoring of intermediate inputs to low-income countries shifted labour away from workers with an intermediate level of education and towards workers with a high level of education. But offshoring to high income countries had the opposite impact. Ekholm & Hakkala (2008) report no evidence of any particular shift in the employment level for workers with the lowest education level from offshoring, but R&D intensity was found to shift labour demand away from workers with the lowest education level towards workers with the highest education level.

Whilst there have been job losses for less skilled workers, the number of job losses appear to be small as other researchers have found offshoring to have had little impact on the demand for labour. Castellani *et al.*, (2008) found no evidence of a fall in the employment level for Italy, but there was some evidence of skill-upgrading when offshoring occurred to Eastern European countries. Marin (2004) found vertical FDI towards Eastern Europe lead to a small number of job losses in source countries. Hijzen & Swaim (2007) found offshoring within the same industry reduced the labour demand intensity of production but it did not affect the overall industry employment level. They report inter-industry offshoring had no impact on labour demand intensity, which could possibly have a positive impact on industry employment. The authors' interpret their results to suggest the productivity gains from offshoring could be large enough to offset job losses due to production relocation from material offshoring. The only paper not to report similar trends is by Ando & Kimura (2007). They found material offshoring to East Asia from Japan lead to higher employment only in manufacturing firms.

Head *et al.,* (2007) note the scope for job displacement from service offshoring could rise over time, although there is at present limited evidence. Bottini *et al.,* (2007) and Crinò (2009a) suggest the impact from service offshoring on total employment has also been small where the impact essentially depends on the skill intensities within service jobs. They note that the shift in the composition of the work force has benefited highly skilled labour. Amiti & Wei (2005, 2006) find a small change in the composition of employment for U.K. sectors engaged in service offshoring were found not to have slower job growth rates compared to non-outsourcing sectors. For the U.S. manufacturing sectors, offshoring of service inputs had little impact on the employment level. Görg & Hanley (2005) found the impact of service and material offshoring had a negative impact on plant-level labour demand for the Irish electronics sector where the impact was stronger from outsourcing materials than from outsourcing services. But Van Welsum & Reif (2006) found no evidence of a fall in the employment level for 14 OECD countries from service offshoring. Hijzen *et al.,* (2007b) report the offshoring of intermediate service inputs in the U.K. did not destroy jobs; the import of intermediate services lead to faster employment growth compared to firms that did not engage in service offshoring. These findings imply the demand for labour and the probability of becoming unemployed/out of the labour force has been small because offshoring can create jobs in addition to the jobs that are destroyed. Thus, the impact on the employment level is small at present but this could change in the future.

There are few papers that have explored the impact of service offshoring on the composition of white-collar employment in light of the fact that many high-skilled service sector jobs such in radiology and accountancy are potentially at risk from being offshored because of technological advancements. First, Liu & Trefler (2008) examined the effects of service offshoring from China and India had on the wage levels and job security for U.S. white-collar workers. They found service offshoring had no significant impact on labour income losses for high school educated workers or for college educated workers. Service offshoring also had a limited impact on the probability of switching industries and occupations for the different education groups. Crinò (2009c) examined the change in the skill structure of labour demand for the U.S. resulting from service offshoring for the period 1997-2002. Crinò estimated the elasticity of demand with respect to service offshoring for each occupation; each of these estimate were then used to evaluate the impact of service offshoring upon broad aggregates of occupations with high, medium and low levels of education attainment. Crinò's results showed service offshoring raised the relative demand for high-skilled white collar workers and reduced the demand for medium and low skilled white collar employment by a relatively small margin. Crinò (2007) also reports similar results for the European Union for the period 1990-2004. Further analysis by Crinò (2010) finds service offshoring did not affect the employment level for workers employed within Italian firms that engaged in service offshoring but service offshoring did change the composition of the workforce in favour of high-skilled workers.

Whilst the main focus from the literature has primarily centred upon the number of jobs that could potentially be lost due to offshoring, few papers have sort to explore the flip side of offshoring – that is the "inshoring" of services. Inshoring refers to the opposite process of offshoring, where firms located outside of Britain relocate their operations to firms located in Britain (Kirkegaard *et al.,* 2006). Inshoring will be in line with a developed country's comparative advantage. There is empirical evidence from two papers that have explored offshoring and inshoring effects on employment and wage levels for Denmark and the U.S.

For Denmark, Kirkegaard *et al.,* (2006) found the employment effects of offshoring and inshoring were limited to less than 1 percent of all jobs lost to offshoring or gained by inshoring. They also report inshoring was concentrated among highly skilled and specialised job functions, whilst medium skilled administrative jobs, customer relations and trade functions experienced both job inshoring and outflow. For the U.S., Liu & Trefler (2008) found the net effects from offshore outsourcing and inshoring were positive. However the effects had a tendency to be negative for workers without a college degree or for less-skilled white-collar jobs.

2.4.3.3 Material Offshoring vs. Service Offshoring: Does it Matter?

Should it matter that job are being lost because materials are being offshored compared to services? Much of the literature that has been reviewed in this section has provided evidence from material offshoring; there are few papers which have explored the impact from service offshoring. However, going back to the question, whether it should matter if materials are being offshored compared to services, the simple answer is: No it should not matter. This answer is based on a U.S. policy brief published by Jensen & Kletzer (2008). Their policy brief makes a number of important points for the U.S., but these points should also be important for the U.K. This brief makes two key points from economic theory. The first relates to the law of comparative advantage, which suggests that whilst the number of jobs that could be offshored from the U.S. to low-wage and labour abundant countries could amount to 15-20 million jobs, many of the jobs (about 40 percent) from the manufacturing sector have long been considered to be at risk. About one-third of the jobs are estimated to be at risk of being offshored from tradable service activities.

The second key point is the U.S. is a net exporter of services; therefore there should be gains for high skill and high wage jobs through the export of services, which is in line with U.S. comparative advantage as it is a high-skilled capital intensive country. The U.S. also maintains a significant manufacturing presence of high-skilled capital intensive goods such as medical and scientific equipment. This is consistent with U.S. comparative advantage where manufacturing activities have moved towards skill intensive products and capital intensive production techniques. The risk to jobs depends on whether firms within industries face import competition. Jobs are less likely to be at risk if firms within industries face little import competition. Import competition from low income countries is less likely to be a concern within industries that are capital intensive. Jensen (2009) notes that workers employed within the apparel industry are more likely to face competition from low-income countries and are less likely to export. By contrast, the aircraft building industry is less likely to face competition from low-income countries and they are more export intensive. There is likely to be a similar trend that also determines the number of jobs that could potentially be lost in the future within the service sectors. Thus, it does not matter whether jobs are lost because of material offshoring or service offshoring, the evidence from by Jensen & Kletzer (2008) and Jensen (2009) suggest job creation and destruction is dependent on the nature of comparative advantage and the degree of import competition that is faced by industries from low income countries.

The main point from this policy brief is there is evidence of a pattern between material offshoring and service offshoring. The trend for the manufacturing sector may be an indicator as to which jobs may be lost within the service sector. For the manufacturing sector, many low skill jobs have been offshored and a similar pattern is expected for the service sector. The authors' expect many jobs will be at risk from tradable service activities which are relatively low-skilled and with low pay. Higher skilled and higher wage jobs remain to be a source of potential exports for the U.S. However jobs which may be composed of these higher-skilled activities may be at risk in the future if there is a process that enables knowledge capital such as 'know how' to be invested in developing countries. These countries will then be able to challenge the comparative advantage of developed countries in the future.

2.4.4 Kaleidoscopic Comparative Advantage

There is at present very little evidence for the Bhagwati-Dehejia hypothesis (thereafter referred to as BDH). Davidson & Matusz (2008) suggest there is some support for some elements from the hypothesis, but more research is needed to explore the other implications from the hypothesis. Empirical evidence from Beaulieu *et al.*, (2004) found trade volatility can lead to greater labour turnover and greater jobless spells for less skilled workers in Canada. They also found mixed evidence for less skilled workers having less skill accumulation compared to skilled workers, which is one of the predictions from the BDH. However, Davidson & Matusz (2008) doubt the rise in labour turnover is linked to globalisation. A second caveat with this theory relates to skilled workers having greater transferability of workplace acquired skills to other jobs than less skilled workers. Davidson & Matusz (2008) note that whilst this is a valid assumption which they have made within their own work, other researchers argue that this assumption may not be true in all cases. They provide the example of auto-workers as high wage workers having acquired specific skills within the auto-industry. These skills may or may not transfer to other high-wage sectors of the economy. Further empirical research is required to determine whether there is empirical support for this assumption.

2.4.5 Footloose Multinationals and Offshoring

MNEs are termed footloose because of their ability to change the geography of production to other plants in other countries. The question is whether job security in foreign owned plants or affiliates is lower because MNEs have greater flexibility in choosing where to locate production compared to domestically owned plants? The empirical evidence is not conclusive.

There is a vast literature that explores the relationship between firm exit and foreign-ownership of firms. This literature reports the exit of firms from a market is related to its age, the industry in which the firms operate and the size of the industry and whether these plants export their output. Empirical studies show that plant failure rates decline with plant size, and the age of the plant (Dunne *et al.*, 1988, 1999), and new firms are more likely to fail (Wagner, 1994; Mata & Portugal, 1994; Audretsch & Mahmood, 1995; and Disney *et al.*, 2003). Görg & Strobl (2003) and Bernard & Sjöholm (2003) find foreign–owned plants by MNEs in Ireland and foreign-owned plants in Indonesia were larger compared to domestically owned plants but they also had higher exit rates. Similarly, Bernard & Jensen (2007) find U.S. plants that were owned by MNEs had higher exit rates even though these plants were larger, older and more productive. But Alvarez & Görg (2005) find plants that were part of MNEs that were domestic market orientated in Chile were more footloose compared to foreign-owned plants that export did not have higher exit rates.

Having established many foreign owned plants in developed countries have higher exit rates, the question is whether workers employed by these plants face greater job turnover and a rise in job insecurity. The theoretical literature on firm ownership and job turnover suggests this relationship depends on human capital accumulation spillovers and training that is provided by foreign-owned firms. Human capital spillovers is defined as spillovers when workers accumulate human capital and training from foreign owned plants and then move between foreign and domestically owned plants. Fosfur *et al.*, (2001) note there is little conclusive evidence between these spillovers and worker mobility. Glass & Saggi (2002) suggest from their theoretical model that job security for workers employed by foreign-owned plants should be high because foreign-owned plants offer workers higher wages to prevent mobility from spillovers.

From empirical evidence, Andrews *et al.*, (2007) find foreign-owned plants in Germany had lower plant closure rates and lower job separation rates. When plants were compared by size and profitability, they found foreign-owned plants had higher closure and job separation rates compared to other plants. But these results were found to be small and not indicative of job security and job stability being substantially lower from these plants. They conclude that globalisation has not lead to an insecure labour market – at least for Germany.

Becker & Muendler (2008) also find secure jobs for German workers employed in plants owned by MNEs. Using a linked employer-employee data set they examine how a foreign expansion (FDI) affects domestic employment and job security. They found outward FDI expansion retains more domestic jobs, which are secure and not disrupted by trade compared to employment in domestic plants. They note that the job destruction rate would have been greater had the expansion not taken place. They also suggest that outward FDI activity raises domestic-worker job retention, more amongst highly educated workers. They conclude that FDI expansion may present attractive career paths for domestic workers which may reduce job losses and it provides better job security (Prendergast, 1999). Similarly, the empirical evidence reviewed by Crinò (2009a) shows that whilst domestic and foreign workers are substitutes in the MNEs technology, the strength of the relationship is weak. The nature of substitution depends on whether each group of workers are substitutes or complementary to each other in the production process and the nature of this relationship depends on the type of FDI investment.

The substitutability between domestic and foreign labour is found to be driven by affiliate firms to MNEs in high-income countries, which results from horizontal FDI that has two purposes: (1) to serve the domestic market and (2) to try to avoid trade barriers and transportation costs in the foreign market. The substitutability is found to be much weaker with respect to employment in affiliate firms in low income countries, which are the result from vertical FDI. The empirical evidence reviewed by Crinò (2009a) also shows that substitutability can switch to complementarity between foreign and domestic labour in the long run because of the substantial costs involved in achieving optimal levels of employment in foreign labour markets – see Crinò (2009a) for further details.

So far this literature review has shown there is very little evidence to suggest job security is lower in MNEs[23]. But Scheve & Slaughter (2004) find a negative relationship between FDI undertaken by MNEs and lower perceived economic security for workers in the U.K. One important implication from this latter study is that higher rates of FDI should raise the elasticity of labour demand for less skilled workers from developed countries because their skills are substitutable compared to skilled labour. This evidence is reviewed in the following section.

2.4.6 The Elasticity of Labour Demand

The OECD (2007a) notes that the elasticity of labour demand has increased over time, raising the potential substitutability of domestic workers with foreign labour. This can increase job insecurity because workers are substitutable with foreign labour which implies domestic workers can lose their jobs if firms decide to shift their intermediate stages of production overseas. Additionally, this rise in the own wage elasticity of labour demand can raise job

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[23] The lack of evidence between job security and job mobility is also supported by studies which have examined the impact of offshoring and MNE activity on employment. Empirical reviews by Mankiw & Swagel (2006a), Ebenstein *et al.*, (2009) and Crinò (2009a) suggest offshoring and MNE activity does not have a conclusive impact on employment because the evidence is mixed. Research from the U.S. by Borga (2005), Desai *et al.*, (2005a,b), and Slaughter (2003) find the expansion of U.S. multinationals activities abroad stimulated job growth within the domestic labour market. But other research by Brainard and Riker (2001), Hanson *et al.*, (2003), Muendler and Becker (2009), Harrison and McMillan (2009) and Harrison *et al.*, (2007) found jobs abroad do replace domestic jobs; but these numbers have been small. Harrison & McMillan (2006) explored the employment changes between parent and affiliates for the U.S. Their results showed jobs from low-wage countries were substitutes for U.S. jobs, but jobs from high-income countries were complementary to U.S. jobs. Their analysis also showed vertical FDI was associated with lower employment within the U.S. regardless of whether the destination country was a high or low income country. Mankiw & Swagel (2006a) note offshoring will create winners and losers, where there is evidence for job dislocation, but net jobs can be created within the domestic and foreign labour markets. Their review concludes outsourcing and generally foreign activity has been associated with increased employment for the U.S. and where, 'foreign activity does not crowd out domestic activity; the reverse is true'.

instability because firms can threaten workers with the potential destruction of their jobs if they do not accept lower wages to keep their jobs.

The empirical evidence reviewed below from firm level and industry level studies show the rise in the own wage elasticity of labour demand has become more elastic for less skilled workers, whilst the own wage elasticity of labour demand has remained unchanged for skilled labour over the 1980s and 1990s. The evidence suggests that the rise in the elasticity of labour demand for less skilled workers is due to globalisation and trade. Globalisation and trade in many of the developed countries has enabled firms to access many more markets for goods and services but also for labour as ICT innovations and the fall in transportation costs have allowed firms to offshore their intermediate stages of production. Policy changes to labour market institution towards greater labour market flexibility have also contributed to this rise, although this evidence is limited to Europe and requires further empirical research.

Firm-level studies have sought to explore whether labour demand elasticities are greater within MNEs due to greater access to productions networks compared to domestically owned plants. Fabbri *et al.,* (2003) estimated manufacturing wide-elasticities for production workers in the U.S. and U.K. were unity in absolute value by the mid 1980s. They found that the labour demand elasticities had become more elastic over the 1990s as MNE activities expanded within both countries.

From European evidence, Görg *et al.,* (2009) also found workers employed by MNEs had higher labour demand elasticities compared to domestic plants for the Republic of Ireland. However, Barba Naveretti *et al.,* (2003) found workers employed by MNEs had less elastic labour demand elasticities than workers employed by domestic firms for eleven European countries, whilst Hakkala *et al.,* (2007) found wage elasticities did not differ for different types of firms from Sweden.

The industry level evidence has tried to estimate the change in the absolute value of the own wage elasticities of labour demand over time from globalisation and trade. Slaughter (2001) found the elasticity of labour demand for production workers became more elastic for 5 out of 8 manufacturing industries in the U.S. The absolute elasticity was approximately 0.5 in 1975 and by 1991, the absolute value of the elasticity had increased to 1.0 for production workers. For non-production workers, the elasticity of labour demand remained less elastic across all industries where estimates ranged from -0.5 and -0.8. The overall impact from trade is however only significant with the inclusion of industry fixed effects and it disappears with the inclusion of time controls. Slaughter (2001) reports that the time series of labour demand elasticities for both types of labour are largely explained by time.

Senses (2006) found U.S. manufacturing plants operating in industries that heavily outsourced unskilled labour experienced a rise in the conditional labour demand elasticities for the 1980-1992 period. The absolute value for the own-wage elasticity of labour demand was 0.2-0.7 from 1980-1987, and stable at 0.80 by the 1988-1990 period. Post 1990, the absolute value of the elasticity was 1.2 by 1992, but it declined in absolute value to 0.6 by 1995. Senses (2006) notes the decline in labour demand elasticities from industries which engage in offshore outsourcing may be the result from a decline in the share of unskilled labour which may dominate the outsourcing effect.

For European countries, Bruno *et al*, (2004) estimated labour demand elasticities via the substitution effect for six European countries including Japan and the U.S. Their analysis found that import penetration raised the elasticity of labour demand for the U.K., but the elasticity did not increase for all countries in absolute terms.

Riihimäki (2005) found increased European integration intensified trade competition in Finland which then raised the labour demand elasticity for the period 1975-2002. For production worker the elasticity was -0.65 by the end of the 1990s. For non-production workers, the elasticity did not decline, but remained stable at -0.5 over the same period. The estimated scale effect on the labour demand elasticities was greater for production workers. Their paper also found firms which had better advantages from economies of scale decreased the elasticity of substitution between differentiated products. Additionally, Riihimäki (2005) notes that if increased integration leads to a rise in input substitutability and/or outsourcing, this could cause labour demand elasticities to become more elastic. Similarly, Molnar *et al.*, (2007) found outward FDI from manufacturing sectors with strong commercial links to non-OECD countries had increased the long-run wage elasticity of labour demand. For the service sector there was no evidence.

Finally, Hijzen & Swaim (2008) found intensive offshoring (material) had lead to an average labour demand elasticity that was 30-40% larger in absolute value than the counter-factual elasticity for a large sample of OECD countries. This study also found EP policies had weakened the link between offshoring and higher labour demand elasticities. Countries which employed strict EP policies lead to less elastic labour demand elasticities. The results from this study therefore suggests that job security implications from offshoring essentially depends on the generosity of EP policies; jobs would be much more stable and secure if EP policies were strict[24].

2.4.7 Job Polarization

The empirical evidence for job polarization is well documented for many developed countries: for Britain (Goos & Manning, 2003, 2007), the U.S. (Autor *et al.*, 2006; Acemoglu & Autor, 2010 & forthcoming); for Germany (Black & Spitz- Oener, 2007; Dustmann *et al.*, 2010) and for a number of European countries (Goos *et al.*, 2008, 2009a,b & 2010). They show a simultaneous

[24] Similar evidence has also been found by Hasan *et al.*, (2007); they found labour demand elasticities became more elastic after reforms lead to greater trade liberalisation in India. Labour demand elasticties were found to be less elastic for industries within states that were protected from the reforms. The labour demand elasticities were found to be more elastic within states that offered weak employment protection against greater trade reforms.

growth in employment for high-wage high-skill occupations such as managers, professional and technical occupations and for low wage occupations in personal service occupations that involve helping and caring for others. But employment shares in middling jobs in manufacturing and routine service jobs have declined over time, thus raising job and labour market insecurity for these workers.

A number of papers have sought to examine which skill groups are most affected by job polarisation and how they vary by personal level characteristics. Spitz-Oener (2006) reports analytical and interactive job task inputs are most associated with workers with high educational qualifications. For workers with medium level qualifications are associated with all job tasks. And workers with low educational qualifications are most associated with routine manual and cognitive job tasks and non-routine manual job tasks. Black & Spitz-Oener (2007 & 2010) find job polarization was more pronounced for women compared to men; the employment share in middle occupations shrunk by 52% for females compared to 23% for men. Similar evidence is also documented by Acemoglu & Autor (2010 & forthcoming) for the U.S.

With the hallowing out of the employment level for routine intensive occupations, workers have allocated themselves to high-skilled jobs and to low-skilled jobs. Yet the transfer of workers to these abstract and manual intensive occupations at the extreme ends of the skill distribution depends on age and education levels. Autor & Dorn (2009) found a fall in the share of employment in commuting zones which specialised in occupations intensive in routine job tasks from 1980 to 2005 in the U.S. The hallowing out of employment primarily generated movement towards low-skill non-routine jobs situated towards the bottom tail of the skill distribution. Their results showed prime-aged and older workers obtained employment within low-skilled non-routine jobs and workers aged 16-29 years obtained employment in high-skilled jobs towards the upper tail of the wage distribution. Further analyses by educational qualifications found college educated workers were able to obtain high and low-skilled, non-routine jobs, but high-skilled jobs situated at the top end of the skill distribution were concentrated amongst young college educated workers. Thus, there is scope for job insecurity for displaced workers from routine-intensive occupations.

The effects of job polarization can also vary by personal characteristics such as race and immigration. Peri & Sparber (2007) present a simple model where the immigration of foreign born low-skilled labour specialise in occupations that require manual job tasks such as cleaning, cooking or building work. The immigration of foreign born nationals causes native born workers to reallocate their labour supply as they have better knowledge of local networks, rules, customs and language proficiency that they pursue jobs that require interactive job tasks such as coordination, organisation, and communication. Autor & Handel (2009) report the job tasks completed by workers with similar levels of education were related to race, gender and language proficiency. They found female workers carried out far fewer analytical job tasks and far more interpersonal and routine job tasks than equally educated male workers. By race, black workers were found to perform a disproportionate number of interpersonal job tasks. And by language, Spanish language workers carried out fewer analytic and interpersonal job tasks and substantially more repetitive, physical and cognitive job tasks compared to equally educated worker within similar occupations.

The key question for the job polarization hypothesis has been whether technology and globalization have contributed towards the polarization of employment which can raise job insecurity. Recent cross country empirical evidence shows job polarization is driven by ICT developments. Two pieces of research provide evidence. First, Michaels *et al.*, (2010) use industry level data from 11 countries (U.S., Japan and nine European countries) between 1980 and 2004. They found industries within countries that had faster growth of ICT lead to an increase in relative demand for highly skilled educated workers and a bigger fall in the relative demand for middle skilled workers (workers employed in routine-intensive occupations). They found technology accounted for up to a quarter of the growth in the demand for college educated workers since 1980. They also found trade openness to be associated with job polarization, but once the role of technology was accounted for, trade openness had no significant impact on job polarization.

The second piece of research comes from Goos *et al.*, (2010). They found the routiniztion hypothesis proposed by Autor, Levy & Murnane (2003) to be the single most important factor explaining the shifts in the employment structure of 16 European countries. They also found some evidence to show offshoring can explain job polarization, although its impact is much smaller than the routinization hypothesis.

So far, the empirical evidence has shown the decline in middling jobs has been facilitated by ICT developments. There is research from Bloom *et al.*, (2009) which shows that although technology may explain the polarization of employment in middling jobs, technology may have been facilitated by globalisation. Bloom *et al.*, (2009) examine the impact of the growth of Chinese import competition on technical change (measured by IT, patent counts and citations, TFP and R&D) for over 200,000 European firms. They found that once China entered the World Trade Organization, import competition from China led to both within firm technology upgrading by industry and between firm reallocation of employment towards more technology intensive plants. This innovation was an attempt to move up the value chain. They estimate that between 2000 and 2007, 15%-20% of technology upgrading in Europe can be explained as responses to Chinese import competition. This evidence shows that job polarization has been driven by ICT which has in part been facilitated by globalisation. This evidence also shows technology upgrading on the part of firms have created jobs that require skilled labour. This may explain why skilled labour has benefited more from technological improvements compared to non-skilled labour. But this could change in the future.

2.4.8 The Impact of Policy on Labour Market Security

From sections 2.2 and 2.3, the extensions to the Mortensen & Pissarides (1994) equilibrium unemployment framework showed different labour market policies can affect the rate of job creation and destruction. Generous UI and strict EP policies encourage labour market security as the former policy provides insurance against the loss of labour income and the latter policy ensures job security because it protects workers from losing their jobs (Mortensen & Pissarides, 1999). These policies reduce the sensitivity to job destruction as firms are not able to adjust their demand for labour to their profit maximising level when a structural shock occurs due to firing restrictions. Government regulations may present firms with high adjustment costs if workers are made redundant, thus firms forgo the adjustment. The down side to these policies are, if redundant workers are not laid off to reduce the costs of production, abnormal profits could deteriorate, where some firms may accumulate losses up to the point where they could become bankrupt. These policies may ensure jobs last longer and preserve labour market security among existing firms in response to structural changes in tastes and technology. But jobs will eventually be destroyed later on where the least efficient firms most affected by the structural changes go out of business (Moser *et al.*, 2010; Cahuc & Zylberberg, 2006). Thus, UI and EP policies are favourable if they reduce the rate of job destruction more than they reduce the rate of job creation.

These policies can also prolong unemployment spells for workers who have become displaced because it prevents firms from adjusting labour demand in response to structural changes; this will discourage job creation. This is because *insider* workers benefit from higher wages and secure jobs whilst *outsider* workers face slower job reallocation prospects. The resulting unemployment spells are less frequent compared to the deployment of weak EP and less generous UI policies.

The effect these labour market institutions can have on labour market security varies by country to country because different countries have different policies; this will therefore have a different effect on labour market security. But reforms to UI and EP policies which encourage greater labour market flexibility may potentially lead to an increase in labour market insecurity over time. The forth coming paragraphs discusses the empirical evidence which examine the impact of UI and EP policies on employment and unemployment levels and the effect EP and UI policy reforms may potentially have upon labour market security.

2.4.8.1 UI and EP Policies

Addison & Teixeira (2003) and the OECD (2004) provide comprehensive literature reviews which show the impact of EP policies on employment and unemployment varies widely across studies. These two papers provide an in-depth analysis of EP policies which the reader is referred to for further details. The main findings from the literature shows the generosity of EP policies lower employment rates[25] (Lazear, 1990; Nickell, 1997) and with significant union coverage, this policy raises the unemployment rate and the average jobless duration in response to adverse macroeconomic shocks as EP policies reduce both job creation and destruction (OECD, 1993; Scarpetta, 1996; Nicoletti & Scarpetta, 2001; Belot & Van Ours, 2000, 2004; Cahuc & Zylberberg, 2006). They also have a tendency to create a dual labour marketd where 'insider' workers maintain higher wages and secure jobs. This is at the expense of 'outsider' workers who become stuck with less secure jobs which may be temporary with low pay (OECD, 2004) and with low job reallocation prospects. However, many of these findings are based upon static measures of EP policy indicators. When time-varying measures for EP and UI policy indicators are employed to account for reforms to labour market institutions, there is evidence showing little change to the employment and unemployment rates in association with macroeconomic shocks (Blanchard & Wolfers, 2000).

[25] Many workers may abandon job search as EP policies protect existing jobs and prolongs the duration of unemployment. These workers may leave the labour market and become inactive; thus the employment rate falls.

Similarly, empirical studies show generous unemployment compensation lowers job search intensity and prolongs unemployment duration (for the U.S.: Katz & Meyer, 1990; Newton & Rosen, 1979; Moffitt & Nicholson, 1982; for the U.K.: Nickell 1979a, 1979b; for Canada: Ham & Rea, 1987 and for Germany: Hunt, 1995). This is because UI lowers the cost of unemployment and discourages the relative incentives of paid employment as workers raise their reservation wage levels as leisure is untaxed (Mooi-Reçi & Mills, 2008; Devine & Kiefer, 1991; Holmlund, 1998; Nickell 1997; Narendranathan *et al.*, 1985; Johnson & Layard, 1986). This can lead to negative productivity, loss of human capital and a sluggish economy (Mooi-Reçi & Mills, 2008; Abbring *et al.*, 2005; Arulampalam *et al.*, 2000; Belzil, 1995; Narendranathan & Elias, 1993; Heckman & Borjas, 1980). Benefit restrictions may lead to shorter spells of unemployment duration near towards the month of benefit exhaustion, where there is a subsequent rise in job search intensity (van Ours & Vodopivec, 2006; Katz & Meyer, 1990; Card & Levine, 2000; Carling *et al.*, 1996; Røed & Zhang, 2003).

However, job search theory assumes that unemployed job seekers may require time to find jobs which match their skills and the UI acts to cover search costs (Mortensen, 1977; Devine & Kiefer, 1991; Lippman & McCall, 1979). This lowers the opportunity cost of job search and allows time for job search that is for "the right job" (Burdett, 1979), which may smooth income risks and consumption variability (Acemoglu & Shimer, 2000). Less generous UI benefits may not encourage good job searches as workers may be forced to accept jobs that are of lower quality which may not suit their skills if benefit payments are low. This may not be a sign of great efficiency and the quality of the resulting job matches may be low, which may do nothing to raise the quality and quantity of goods and services produced from production (Cahuc & Zylberberg, 2006). Mooi-Reçi & Mills (2008) point to evidence which suggests generous UI can accelerate economic recovery after unemployment as it improves job matching and it additionally heightens earnings after re-employment for certain groups of workers (Belzil, 1995; Burgess & Kingston, 1976; DiPrete, 2002; DiPrete & McManus, 1996; Gangl, 2004). Research by Acemoglu & Shimer (2000) showed the U.S. suffered low productivity with low unemployment and low quality job matches from short job searches during the 1990s. Simulations from their paper reveal that if UI payments were slightly more generous and unemployment duration was slightly longer, this would have been beneficial for workers to search for better jobs which matched their skills. Their results also indicate that better job matches would have led to higher productivity in work, where this could have increased the overall production of goods and services in the long-run. Similarly, Gangl (2004) reports UI protects workers against earnings losses, downward occupational mobility and from entering unstable employment. Pollman-Schult & Büchel (2005) support these findings by showing that whilst lower unemployment rates were achieved in West Germany through a reduction in UI, this was at the expense of subsequent job matching and quality.

However, generous UI and strict EP policies can come at a cost of *'eurosclerosis'*. *Eurosclerosis* was a term coined to describe European patterns of high unemployment and slow job creation with periods of slow economic growth during the late 1970s and 1980s. During this same period, the U.S. experienced a period of economic expansion accompanied by high job growth. Research by Mortensen & Pissarides (1999) shows through calibrated models, the U.S. would have experienced European style unemployment during the late 1980s and early 1990s if it had employed generous UI and strict EP policies. They also found European unemployment was longer but less frequent than for the U.S. and where income inequality was also found to be greater in the U.S. than in Europe. Thus, strict EP and generous UI policies ensure labour market security but they come at the expense of lower economic growth and lower job creation rates. This evidence suggests that although EP and UI policies may protect jobs, the increased duration of unemployment along with the eventual destruction of existing jobs and lower job creation rates has a larger impact upon the economy though lower economic growth.

2.4.8.2 Recent Policy Reforms in Britain

The U.K. has pursued a number of UI and EP policy reforms during the 1980s and the 1990s. Two of the most recent reforms took place over the latter half of the 1990s. The first policy reform relates to EP policy, where the qualifying period to claim unfair dismissal from employment was reduced from 24 months to 12 months. This reform was introduced by the 1999 Unfair Dismissal and Statement of Reasons for Dismissal (Variation of Qualifying Period) Order. This policy change raises the potential firing costs faced by firms, but lowers the probability of becoming unemployed and thus job destruction. This policy ensures job security for existing jobs, but it can also lower the rate of job creation.

The second policy reform was to the unemployment insurance system. Under the old benefit system, UI was paid to workers who became displaced. This was essentially money that was paid to workers as a form of entitlement for money they had contributed towards whilst working; payments were made for a period of 12 months (Manning, 2009). This system was overhauled and was renamed 'Job Seekers Allowances' (JSA). The 'Job Seekers Allowances', as the name suggests is an allowance that was granted to workers who agree to search actively for employment. Payments were no longer made to workers because they had become unemployed or to alleviate the cost of income loss; there was more emphasis upon agreeing to look for work to obtain the benefits. The new JSA system took effect in October 1996 where this new system reduced the benefit coverage period from 12 months to 6 months and where the benefits paid roughly ten per cent less than its predecessor. For further details about the JSA reforms see Manning (2009), Petrongolo (2009) and a Times Online article dated July 2009[26] for details regarding the current level of benefit entitlements received by unemployed labour. The effect of this policy change should lower workers' reservation wage levels; it should raise the opportunity cost of unemployment and encourage greater job search

[26] Here is the link to this article: http://www.timesonline.co.uk/tol/money/reader_guides/article5572594.ece.

intensity. Job search theory predicts that whilst workers may only have at most 6 months to search for a job, they may have to accept the first available job. These jobs may not be the right job and they may pay significantly less post-unemployment. The net impact from this policy reform is uncertain, but it could decrease unemployment durations and increase job creation.

These policy reforms are designed to encourage greater labour market flexibility, and to encourage greater job creation and destruction but also to protect workers from unfair job dismissal. On the other hand, these policy reforms appear to lower labour market security as they no longer protect existing jobs and workers no longer receive benefit payments to maintain their living standards. So the question is whether less generous UI and stricter EP policy have lead to greater job creation and destruction?

The EP policy reform has been examined by Marinescu (2008). Using survival analysis, Marinescu (2008) found the policy change significantly reduced the firing hazard by 27% for workers with up to 11 months of job tenure and by 29% for workers with 12-23 months of job tenure relative to workers with 24-48 months of job tenure. Unemployment duration did not rise after the policy change however the author notes there was a significant 11% rise in the probability of exiting unemployment towards a permanent job with more than 16 hours of work a week. As the policy change only applies to full-time employed workers, Marinescu (2008) found no evidence of a rise in the probability of unemployment duration. The results also show workers looking for full time jobs were 8.6% more likely to exit unemployment after the policy change. But workers under the age of 26 benefited less as they were only 3% more likely to exit unemployment after the policy change. This policy change had no significant impact upon wages, yet there was an increase in training offered to workers. Workers with 12-23 months of job tenure received more training compared to workers with 24-48 months of job tenure; but workers with 0-11 months of job tenure did not receive increased on the job training. The fall in the firing hazard and a fall in unemployment duration was attributed to firms employing greater monitoring and screening procedures to lower the burden of higher potential firing costs.

The UI policy reforms have been examined by Manning (2009) and by Petrongolo (2009). Manning (2009) found the short run impact of the JSA reforms did not encourage job search. The reforms successfully lead to a large outflow out of claimant status for workers who had low levels of job search intensity, but there was no evidence to show employment rates had increased. The short-run impact of the policy simply led to some level of savings for the state. This result suggests 6 months of JSA payments may not be sufficient to find adequate jobs.

Petrongolo (2009) examined the long term effects of JSA reform using longitudinal data from social security records (LLMBD) for a sample of male workers aged 16-64 years. Using a difference-in-difference approach, Petrongolo (2009) found the new reforms successfully lead to an outflow of workers claiming unemployment related benefits, but the reforms increased the incidence of other benefits. Workers who started unemployment spells after the introduction of the JSA system as opposed to starting unemployment spells six months earlier were 2½-3% more likely to move from unemployment to incapacity benefit spells six months after unemployment exit. The reforms also had a negative and significant impact on post unemployment annual earnings. Workers commencing unemployment spells under the new reforms were 4-5% less likely to have positive earnings in the following year. Results show that an initial loss of labour income amounting to £900 on annual earnings could persist for 4-5 years after the unemployment shock. Finally, the new reforms were not successful in allowing workers to obtain employment within longer lasting and secure jobs[27]. The author

[27] Tatsiramos (2004) explored the effects of UI on unemployment and subsequent employment duration for the U.K., Germany and France. This paper found benefit recipients in Germany and France had lower exit rates from unemployment than the U.K. But with generous UI payment in both France and Germany compared to the U.K., recipients were able to search for longer during the first year of unemployment and were more likely to obtain greater employment security.

concludes the job search requirements under the new reforms appeared to raise the non-monetary search costs of remaining on UI rather than enhancing job finding rates.

From the two policy reforms, the evidence suggests that the labour market became more flexible. The EP policy reform shows labour market security did not fall as the probability of becoming unemployed did not rise. But the introduction of the 1996 JSA reforms appears to lower labour market security – where this impact appears to be small. Under the new JSA system, workers are not able to obtain secure jobs post-unemployment and workers are more likely to have lower post-unemployment earnings which can persist for up to 4-5 years after the initial unemployment shock. This policy reform did successfully lower the number of JSA benefit claimants but it also increased the number of workers who started to claim other forms of benefits. To ascertain the overall impact of these policy changes, further research is required.

2.5 Conclusion

The process of creative destruction improves productivity to achieve economic prosperity and growth. Newly created jobs which embody the latest technology are more productive whilst old or existing jobs are destroyed because rising reservation productivity levels dictate old jobs are not profitable. Structural changes stemming from technological change, globalisation and changes to domestic labour market policies can affect the rate of job creation and destruction over time.

The survival of jobs and the creation of new jobs depend on whether firms are able to adapt to the structural changes. If firms cannot cope with the changes, then firms will shut down or exit production from the goods and services that are not profitable to provide. Changes to tastes and technology can lead to job loss which can in turn impose a number of adjustment costs for workers and raise labour market insecurity. This chapter has sought to establish whether the forces stemming from globalisation, technology and domestic labour market policies can potentially increase job and labour market insecurity over time. From this review, the following conclusions are drawn:

- Job creation and destruction rates have observed the 15 percent rule over time. Roughly 15 percent of jobs in existence are destroyed each year and 15 percent of new jobs come into existence. There is evidence from the U.K. showing these rates have fallen over time. At present there is evidence which suggest these rates have not changed job security but this could change in the future if these rates change.
- Material offshoring has raised the wage bill share for non-production workers at the expense of non-skilled labour in developed countries in line with a developed country's comparative advantage. This is a trend that may continue with service offshoring. However, the impact on wage levels has been small and it depends on the offshore destination, where non-skilled labour can benefit from offshoring with non-CEECs. But it is not clear whether the magnitude of earnings losses could rise over time for less skilled workers.
- Material offshoring and exchange rate volatility have raised the probability of job loss for less skilled labour, but these estimates are very small. Service offshoring has had small negative impact on the employment level for less skilled labour but it has benefited skilled labour from white collar occupations, although this may change over time with further technological innovations. Additionally, there is limited evidence for the Bhagwati-Dehejia Hypothesis for the kaleidoscopic nature of comparative advantage as more research is required.
- Empirical evidence shows MNEs are footloose in the sense that they have higher exit rates from production than domestic firms and thus can potentially lower job security. But evidence shows MNEs provide jobs that are secure and pay well to prevent human

capital spillovers. The estimates for the elasticity of substitution between domestic and foreign labour from low income countries is found to be weak. Additionally, outward FDI activity raises job retention rates amongst skilled labour and provides employment that are more secure compared to domestic plants, thus raising job security.

- The elasticity of labour demand for less skilled labour has become more elastic over time. The evidence suggests that this rise appears to be due to globalisation and trade but also from policy reforms to labour market institutions that can lead to flexible labour markets can also lead to this rise. This suggests that job insecurity and job instability could rise over time as domestic workers become more substitutable with foreign labour. But also the policy changes to labour market institutions may not protect these workers from the potential adjustment costs associated with structural changes and from job loss.
- Advancements in technology has lead to the polarization of middling jobs consisting of routine intensive job tasks that are situated in the middle of the skill distribution over the last 30 years in Britain, Europe and U.S.A., thus potentially contributing towards raising job insecurity and earnings losses between jobs. Technological innovations in the future could potentially raise job insecurity for occupations intensive in non-routine job tasks, although this is not possible at present.
- Finally, recent labour market policy reforms to EP and UI policies in the U.K. have the potential to raise labour market insecurity. Empirical evidence shows EP reforms have raised job security, but UI reforms over the latter 1990s have potentially lowered labour market security.

Overall, the findings from this review suggest offshoring (material and services) and outward FDI establish foreign production networks which directly substitute for domestic labour and have raised the elasticity of labour demand, particularly for less skilled labour. They have raised the job reallocation rates which could potentially lower job security, yet this impact on the employment and wage levels and on the own wage elasticity of labour demand has been small. There are three potential reasons why the impact may be small. First, part of the reason is the empirical literature has failed to account for the inshoring of production and service activities and their impact on wages and employment. Secondly, offshoring and outward FDI may sustain job which would possibly have been destroyed if they did not take place. Third, workers may simply accept lower pay to retain employment, because labour markets are not perfectly competitive. Workers may not be able to instantaneously court frequent job offers without spending considerable resources and time to search for another job offer.

Thus, the empirical evidence from forces stemming from globalisation, technology and domestic labour market policies can affect labour market security over time; although the present empirical evidence show they have not significantly affected employment and wage levels; this could change in the future. The next chapter assess whether labour market security has fallen over time.

3

Has Labour Market Security Declined? The Empirical Evidence

3.1 Introduction

Chapter 2 provided a detailed synopsis of the potential forces that could cause the rate of job creation and job destruction to change over time thereby causing labour market security to change by affecting the: (1) the employment level, (2) the wage level and (3) increasing the elasticity of labour demand. From that review, forces such as exchange rate volatility, product market competition, advancements in communications and technology, the fall in transportation costs, engaging in offshore outsourcing activities and establishing external production networks through outward FDI in foreign labour markets along with employment protection policies and unemployment insurance benefits have not significantly affected the employment, wage and the elasticity of labour demand for all workers equally over the last three decades. For the U.K., the empirical evidence suggests that these forces can lower labour market security over time, but their impact has so far been small and limited to low-skilled labour where: (1) the demand for low-skilled labour has fallen over time; (2) their wage levels have also declined over time in certain cases where low-skill intensive production processes have been offshored to developing countries and (3) their elasticity of labour demand has become more elastic over time due to trade and globalisation.

This second part of the literature review presents a detailed account of whether there is empirical evidence from the three components of labour market security to show if they have declined over time. The three components that make up labour market security are: (a) job security, (b) income volatility within jobs (job stability) and (c) the earnings losses from job displacement between jobs. Rising labour market insecurity can be reflected through shorter employment spells with uncertainty over future employment. The variability in income may lead to lower national welfare and a fall in output and the earnings losses from job displacement can lead to unemployment scarring on future wage levels and re-employment. Unemployment scarring describes the negative impact that spells of unemployment can have on future re-employment and wage levels. The empirical evidence shows experiencing a spell of unemployment can lower wage levels upon re-employment. This is because unemployed workers lose some of their general labour market experience by not being in paid employment and therefore their re-employment wage levels are lower than their pre-displacement wage levels. But by being in a state of unemployment, this can also increase the probability of becoming unemployed in the future. This can subsequently lower earnings levels further following re-employment over time. The second part of this literature review establishes whether there is empirical evidence to support these suppositions. The question is whether job insecurity, income volatility within jobs and the earnings losses between jobs have increased in magnitude over time to make workers worse off.

Why is job security and job stability so important to workers? The established empirical literature suggests that changes to job security can have important implications for job stability. The empirical research also shows that they have important implications for individual welfare and well being for two important reasons.

First, changes to job security can potentially impact job stability; in particular any changes to job tenure can potentially affect the returns to wages and to the potential incomes losses workers can incur through job loss for the following reasons. Job tenure is accumulated through employment, which is in turn an accumulation from general employment and firm specific employment tenure that workers develop throughout their lives from education and from their employment in the labour market. The returns from general and firm specific tenure give a picture of the overall wage growth over the life cycle which is important for individual wellbeing. It also provides important insights for the overall wage distribution (Farber, 1999b; Sulis, 2009). And it provides a way to test the implications from the human capital accumulation and job search models and their potential impact on labour market security over time. Sulis (2009) suggest the definition for general and firm specific employment tenure is important to the evaluation of active labour market programs that may be employed to try to aid workers to gain employment through training and acquiring transferable skills. Thus, it is important to understand the contributions of general and specific labour market experiences.

Early studies that have estimated the returns to wages from general and specific employment tenure have been the subject of an intense debate as the empirical research has shown that OLS regressions estimating the returns from experience and specific job tenure can potentially be biased due to unobserved heterogeneity. This means that the estimated coefficients are biased because they are correlated with the error term. Early studies based on U.S. data found that the returns to experience and specific tenure were large when individual heterogeneity was not accounted for (Sulis, 2009). And when previous labour market experience is controlled for, the returns to wages from experience and specific seniority are found to be substantially reduced (Mincer & Jovanovic, 1981). The reasoning for this bias is discussed by Topel (1991); see the paper for further detail.

Many empirical papers have taken different approaches to account for the bias from unobserved heterogeneity: Abraham & Farber (1987) use an instrumental variables (IV) approach to account for the bias. They present IV estimates using a residual from a regression of tenure on completed job duration as instruments for tenure. Altonji & Shakotko (1987) take another approach; they use deviations of tenure from the average sample observation on job matches as instruments for tenure. Both of these empirical papers find the IV estimates for the returns to (general) experience and firm specific tenure that is far less than the OLS estimates. Topel (1991) takes a different approach and uses the estimated returns to prior experience at the start of a job as an estimator to provide an estimate for the lower bound on the returns to job specific tenure. Topel (1991) finds substantial returns to wages from job seniority: ceteris paribus, 10 years of job seniority raises the wage of a male worker by over 25 percent. Thus, the returns from job seniority can have a significant impact on job stability.

Second, workers fears about job insecurity and the prospects of experiencing unemployment can have a negative impact on job stability, in particular wage growth, where previous spells of unemployment can impact job stability. Campbell *et al.*, (2007) find that high fears of unemployment are found to lead to lower levels of wage growth for men, but there is little significance for women in Britain. If workers value job security, they may sacrifice job stability which may be reflected through a fall in wage growth.

This chapter has the following structure. Section 3.2 presents an overview of the empirical findings for the job security trends from the U.K. and North America. Section 3.3 discusses the empirical evidence for income volatility within jobs and section 3.4 presents and discusses evidence from the earnings losses associated with job displacement between jobs. Finally, section 3.5 provides the concluding comments.

3.2 Trends in Job Security: 1970s to 1990s

3.2.1 U.K. Evidence

The British literature has primarily sought to measure job security via elapsed job tenure with current employer. The North American literature has sought to measure job security by calculating job retention probabilities over time at similar points along the business cycle. The aim from both of these measures of job security has been to establish whether the length of jobs (U.K. literature) or the job retention rates (U.S. literature) have changed over time. If they have declined over time, they indicate a fall in job security.

From the British literature, the trends from two different measures of job security have been explored; these are (a) median and average elapsed job tenure in years and months and (b) the proportion of job tenure less than one year and greater than or equal to five and ten years over time. Table 3.1 presents the findings from the changes in median elapsed job tenure for the U.K. This table shows there has been a decline in job security in the region of approximately 2%-30% at the aggregate level using the Labour Force Survey (LFS) and the General Household Survey (GHS). But a broader picture for the main trends from reported median elapsed job tenure by the empirical literature are summarised by figures 3.1 - 3.4.

Figure 3.1[1] presents the trends from reported median job tenure in years and months from three empirical papers[2] using the LFS and the GHS from the 1970s to 2000. The first point to note is median job tenure fluctuations is counter cyclical to the business cycle. To better ascertain the movements of elapsed jobs tenure and the economic climate over this period, figure 3.2 presents trends from macroeconomic activity. This figure shows from the latter period of the 1970s to the early 1980s, the U.K. economy was in a recession - the reported unemployment rate was 4% in 1971, reaching a peak of 11.9% by 1984. GDP growth rates

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[1] Abbreviation Key of authors' names: G&W: Gregg & Wadsworth; G,K&W: Gregg, Knight & Wadsworth.

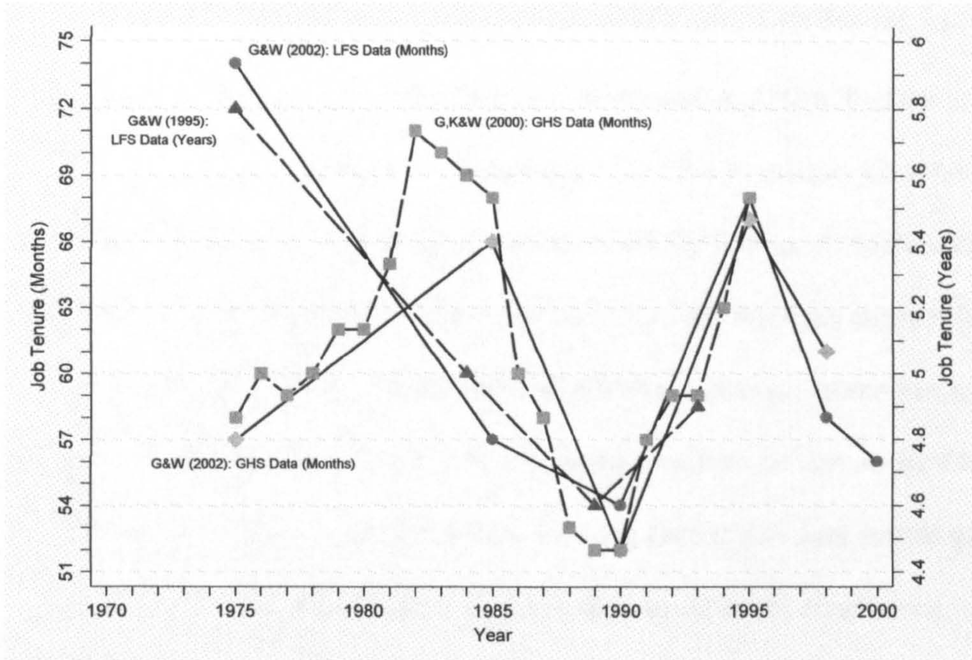
[2] Papers being referred to are by Gregg & Wadsworth (1995, 2002) and Gregg *et al* (2000).

were negative during the early 1970s and output per worker was lower during the mid 1970s and early 1980s compared to the 1960s[3]. During recessionary periods, fewer workers tend to quit their jobs as there are fewer vacancies and fewer better job opportunities to be exploited. What this implies is job layoffs tend to dominate quits and hence average job tenure tends to rise. This is demonstrated in figure 3.1 where trends from the GHS show rising median job tenure from the mid-1970s to the early 1980s. Post 1984, the U.K. economy experienced a recovery and it was a period of growth, where the unemployment rate declined to a low of 7% by 1990. The employment rate rose and where GDP growth rates and output per worker became stable. This was a period where workers were more likely to quit their jobs and search for better work opportunities; thus quits tend to dominate layoffs and one observes average job tenure to fall. Figure 3.1 shows all reported median job tenure fluctuations show a downward trend over this period. Median job tenure was approximately 51-54 months by 1990 from a high of around 71 months for the year 1983.

Fluctuations in median job tenure in years and months seem to have similar cyclical movements over the post 1980 period apart from observations reported for the year 1975. The reported median job tenure figures by Gregg & Wadsworth (1995, 2002) show from the LFS, job tenure was approximately 6 years or around 74 months as reported from the graph. But reported median job tenure figures from the GHS are less than 5 years or 60 months for 1975. No explanations are provided as to why these differences may exist between the two data sets and there is no way to check the differences between the two data sets as there is no data available to measure job tenure from the LFS for the period 1977-1984. Thus, the analysis involving observations for 1975 should be treated with caution.

[3] There is no data available for redundancy rates from ONS for the mid 1970s to the early 1990s. From the data that is available, the figure shows a downward trend over time up to the point of the most recent recession.

Figure 3.1: Comparisons of Reported Elapsed Median Job Tenure



Source: Figure compiled by the author. Abbreviation key for author's names G&W: Gregg & Wadsworth; G,K&W: Gregg, Knight & Wadsworth.

Table 3.1 presents the changes in median job tenure from the data plotted by figure 3.1. This table tries to reconcile the changes in median job tenure over comparable periods over time. From this table, Gregg & Wadsworth (1995) report for the period 1975-1993, median job tenure declined by approximately 20% (LFS data); this is verified by my calculations from the table. From Gregg *et al.,* (2000), the calculations show median job tenure rose by 15% according to the GHS for the period 1975-1995 for a near comparable period to their earlier paper which had utilised the LFS. But the differences between the two data sets can be accounted for by the large variation in value for median job tenure from 1975. If I exclude the value for 1975[4], the results from Gregg & Wadsworth (1995) indicate a 2% fall in median job tenure for the period 1985-1993. Whilst the results from Gregg *et al.,* (2000) suggest there

[4] Data for the Labour Force Survey is available from UKDA for the period: 1975, 1977, 1979, 1981, 1983 and 1984-1991. From the first survey in 1975, it asks respondents the length of time they have spent in present employment. The name of the data variable from the data set is called 'LENGEMPA', where data is recorded and available in discrete bands. For years 1977-1981, the survey does not ask for any sought of information on the length of time spent in present employment. For the period 1983-1984, the survey does ask for length of time spent in present employment; the name of the data variable is 'LENEMP', but this variable is not available from the 1983 or 1984 data files. For 1985, there is data available from a variable called 'EMPLEN', which provides details for length of time in present employment. Thus, there is no data available from the LFS for the period 1977-1984 for length of time in present employment. This absence explains why Gregg & Wadsworth (1995, 2002) do not provide calculations for median job tenure for these intermediate periods.

was no change in median job tenure for the period 1985-1995 with the GHS data. Gregg & Wadsworth (2002) report calculations for median job tenure using both the LFS and the GHS, but the results still differ widely for similar periods that are analysed from their paper. For the period 1975-2000, calculations from the LFS suggest a 32% fall in median job tenure, whilst calculations from the GHS reports a 6.5% rise for the period 1975-1998. If reported changes in median job tenure are considered for the period 1985-1998, the reported changes in median job tenure show they have different signs and imply different changes to median job tenure from the two data sets over this period. The LFS suggest median job tenure rose by 1.72%, whilst the GHS results indicate an 8% fall. Thus, by using each of the data sets to gather the changes in median job tenure over time, they can lead to different conclusions, especially when there is an outlier[5].

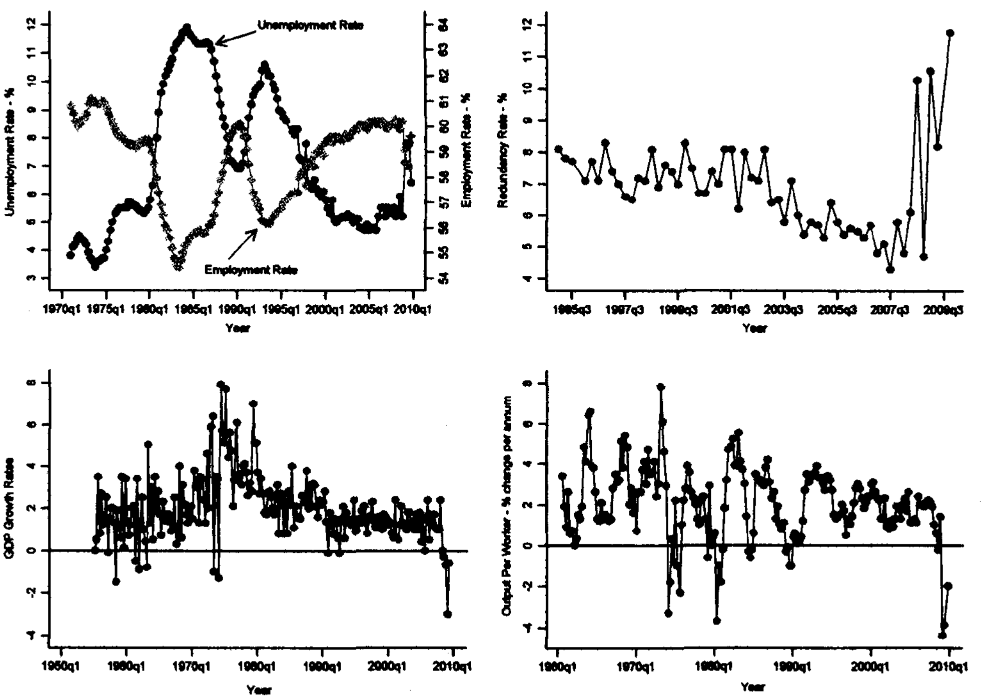
Table 3.1: Changes in Median Elapsed Job Tenure (Aggregate Trends)

Empirical Paper	Period	Median Tenure Trends	
		LFS Data	GHS Data
Gregg & Wadsworth (1995)	1975-1993	-20%	-
	1985-1993	-2%	-
Gregg *et al* (2000)	1975-1995	-	+15%
	1985-1995	-	No Change
Gregg & Wadsworth (2002)	1975-2000	-32%	+6.5% (1975-1998)
	1975-1995	-9%	+14%
	1985-1998	+1.72%	-8%

Source: Table compiled by the author.

[5] In other analysis, Gregg & Wadsworth (2002) estimate multivariate regressions to examine the changes in elapsed job tenure over time. These results are discussed in the forth coming paragraphs, but I believe it is important to note, that from this analysis, Gregg & Wadsworth (2002) exclude the observation for 1975 from the LFS data and only use data for the period 1985-1998. This may be because the data value for the 1975 observation could be a potential outlier. This one observation from the 1970s could distort the results if the aim is to explore secular changes from short, medium and long term job tenure shares over time.

Figure 3.2: Trends from Macroeconomic Activity



Source: Figure compiled by the author. Appendix 1 provides details of data sources used to construct these graphs.

Figure 3.3 compares median job tenure reported by Gregg & Wadsworth (1995) with average elapsed job tenure for men and Women from Burgess & Rees's (1996) paper[6]. Gregg & Wadsworth (1995) report a 20% decline in job security since 1975 (accounting for a 14% fall for all employees). Burgess & Rees (1996) report a slight decline in job tenure of approximately 10% at the aggregate level (trends not presented). At the disaggregate level, the average job tenure trend for men and women from Burgess & Rees (1996) results are redrawn for comparison with figures reported by Gregg & Wadsworth (1995). Figure 3.3 shows there are similar cyclical variations over time from the reported job tenure figures in

[6] The empirical literature does not signify whether reported median job tenure in months is better than being reported in years. My opinion on this matter is that, reported median job tenure in months is slightly more accurate than reporting median job tenure in years, which may suffer from rounding. This is because median job tenure in months provides a more accurate figure than in years. For example, if reported median job tenure in months is 62 months, this may translate to 5 year or even 6 years if this figure is rounded down or rounded up. This discrepancy between median job tenure reported in months and years can be small or big, where the former discrepancy is true in this instance. To illustrate this point, figure 3.1 compares the reported median job tenure in years and months provided by Gregg & Wadsworth (1995, 2002). The reported median job tenure from the two papers using the LFS data is very similar over time and they have similar cyclical variations over time.

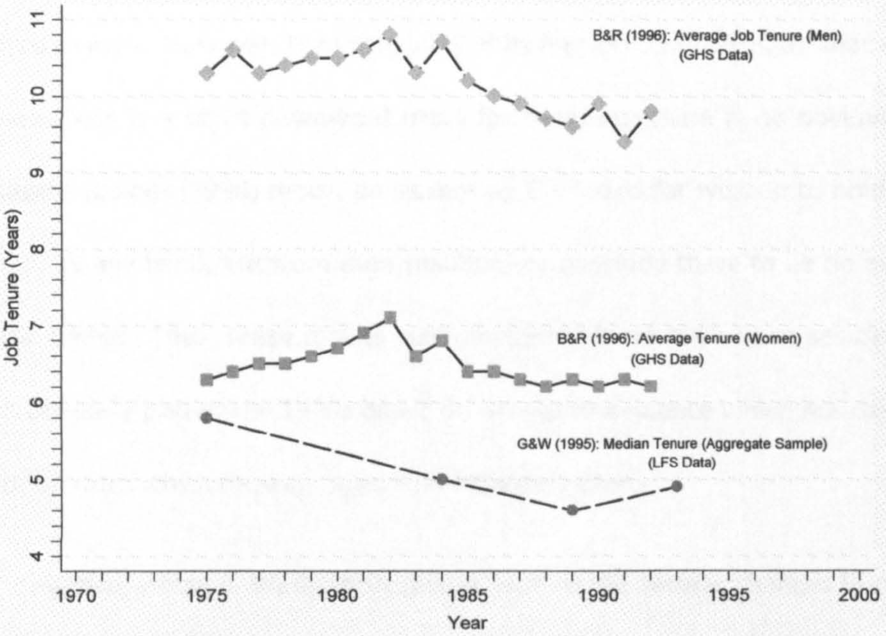
years to the trends from figure 3.1 and between the two papers[7]. But there is some evidence of a secular fall in average job tenure. For men, there is a slight fall in average job tenure from 1985 onwards, with elapsed job tenure falling to 9.4 years in 1991 from 10.8 years in 1982. For women, there is also a decline in average job tenure after 1982; but their average job tenure trends remained stable from 1986 to 1992. Empirical evidence from other research tells a similar story – that there is some evidence that average job tenure has fallen over the 1980s to the 1990s. Booth *et al.*, (1999) found job separation hazards were higher for more recent cohort of workers than for earlier cohorts over the period 1915 to 1990 –implying job security had fallen. But they found men to have higher job insecurity than women and the rise in job insecurity was more marked in the lowest occupational classifications over time for both men and women. Burgess & Rees (1997) also found marginally shorter jobs for men in 1992 than for women compared to the mid 1970s; but both men and women have continued to have stable and secure employment from the latter 1970s to the early 1990s. This empirical evidence suggests that although elapsed job tenure has declined for men, workers generally have secure employment spells with no great tendency to become unemployed over time.

Figure 3.4 presents reported and fitted job retention probabilities for job tenure less than 1 year and greater than or equal to 5 years taken from Gregg & Wadsworth (2002) and from Burgess & Rees (1998). Firstly, the reported probabilities from Gregg & Wadsworth (2002) are simply calculations of job tenure proportions from the raw data. No controls are imposed for the cycle or for personal and job characteristics. Their calculations for the probability of job tenure less than 1 year shows a slight upward trend and a slight downward trend for the

[7] At most, median job tenure in years reported by Gregg & Wadsworth (1995) fell by one year over a 17 year period. And average job tenure for men and for women reported by Burgess & Rees (1996) shows job tenure declined for men (similar to the aggregate trends reported from figure 3.1) but there is little change for women. This plot may show little cyclical variation over time because of the way this graph has been drawn. If this graph focused on each reported measure for job tenure for each gender separately, they would reflect similar cyclical variations over time as presented by figure 3.1. For example, from figure 3.1, papers that have used the GHS show rising median job tenure over the latter part of the 1970s to the early periods of the 1980s. From figure 3.3, the average job tenure reported by Burgess & Rees (1996) for men and women also show rising job tenure over this very period. From the early 1980s to 1990, figure 3.1 shows a decline in median job tenure from the GHS; this very trend is reflected by the average job tenure for men and for women over this time frame.

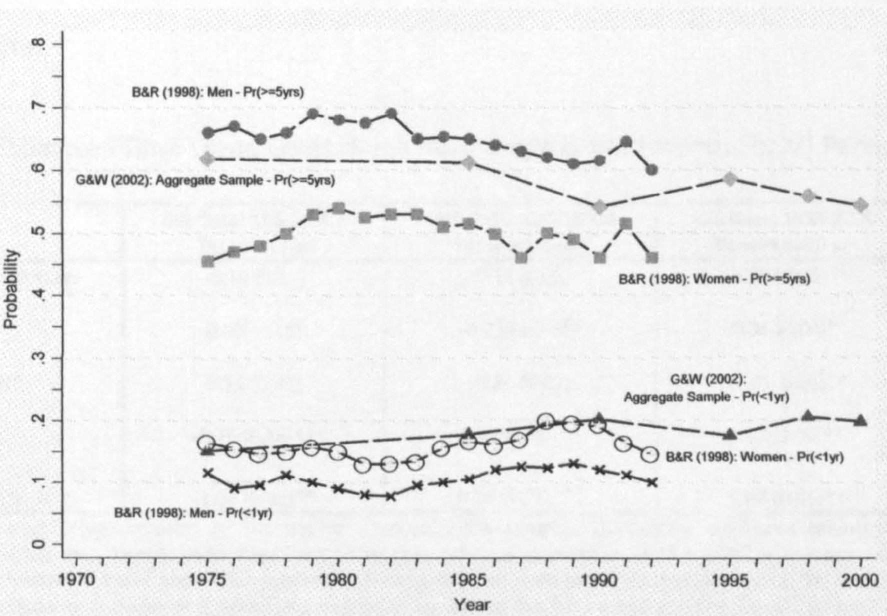
probability of job tenure greater than or equal to 5 years. These trends signify a slight fall in job security.

Figure 3.3: Comparisons of Reported Job Tenure in Years



Source: Figure compiled by the author. Abbreviation key for author's names G&W: Gregg & Wadsworth; B&R: Burgess & Rees.

Figure 3.4: Comparisons of Reported and Fitted Probability of Job Tenure <1yr & >=5yrs



Source: Figure compiled by the author. Abbreviation key for author's names G&W: Gregg & Wadsworth; B&R: Burgess & Rees.

Burgess & Rees (1998) estimate the probability of job tenure greater than or equal to 5 years and less than 1 year, controlling for the cycle, personal and job characteristics. From these results, the trends for the probability of job tenure less than 1 year shows no obvious changes for men or for women; but women have a higher probability of holding a job for less than one year compared to men. However, the probability of having job tenure greater than or equal to 5 years shows there is a slight downward trend for men, but there is no obvious trend for women. Burgess & Rees (1998) report an increasing likelihood for women to hold long-term jobs for the 25-35 age band, but from their results they conclude there to be no evidence for shorter job tendency. Thus, these results seem to signify there have been secure jobs from the 1970s to the early part of the 1990s based on this latter evidence which has examined job tenure retention rates which have changed very little over time.

From other evidence, Gregg & Wadsworth (2002) explore the secular changes in elapsed job tenure via multivariate regression analysis. Their reported results are displayed by table 3.2, where control variables are employed to account for individual and job related characteristics and for the business cycle to examine the changes from three different job tenure bands per year over time.

Table 3.2: Estimated Time Trend Coefficients from Gregg & Wadsworth (2002) Paper

	LFS Data: 1985-2000 Tenure <1 yr	GHS Data: 1975-1998 Tenure >=5 yrs	LFS Data: 1985-2000 Tenure >=10 yrs
All Workers	-0.10 (0.17)	-0.14 (0.06)	-0.20 (0.03)**
Men	0.09 (0.15)	-0.29 (0.06)**	-0.36 (0.04)**
WNC	0.11 (0.20)	-0.24 (0.07)	-0.26 (0.05)**
WC	-0.76 (0.14)**	0.40 (0.09)**	0.42 (0.06)**
WC5	-1.32 (0.12)**	0.58 (0.10)**[8]	0.47 (0.06)**

Source: Table compiled by the author. Asterisks are assumed to indicate significant time-trend coefficients. Identification Key: WNC = women with no dependent children; WC = women with dependent children and WC5 = women with dependent children under the age of 5 years. Time-trend coefficients and standard errors are multiplied by 100 so the time-trend coefficients can be read as yearly percentage point changes. Bootstrapped standard errors are presented within the parentheses.

[8] For women with children under 5 years, the analysis commences from 1979-1998 for the GHS.

At a glance, these estimated time-trend coefficients show for job tenure less than 1 year, there are significant per year declines for women with dependent children/children under the age of 5 years. For job tenure greater than or equal to 5 years there is a significant decline for men and a rise for women with dependent children/children under the age of 5 years. For job tenure greater than or equal to 10 years, their results show significant declines across all workers, for men and women with no dependent children, but there are gains for women with children/children under the age of 5 years. Gregg & Wadsworth (2002) attribute this rise in job tenure to the introduction of maternity legislation[9].

To sum up the empirical evidence: the evidence from table 3.2 indicates there has been a small decline in job security from the 1970s to 2000. For example, job tenure greater than or equal to 5 years for men declined by 0.29 per cent per year (table 3.2). This translates to 6.96% [0.29 × 24] fall for the period 1975-1998. It is hard to quantify what this figure means in terms of what impact this has had on average elapsed job tenure. This is because we are looking at what happens to the number of workers who have at least 5 years of job tenure or more. The negative time-trend coefficient simply illustrates that there are fewer people each year who have at least 5 plus years of job tenure. One could argue that if on average elapsed job tenure is at most 60 months (or 5 years), elapsed job tenure declined by at most 4 months – which is a very small fall over 24 years.

There has also been a secular decline in long term job tenure shares and a secular rise in the short term job tenure shares under one year for men and for women with no children[10]. The evidence also shows a slight decline in average job tenure for men and women from the mid

[9] From the analysis of age and education specific regressions (results not shown here) their paper finds evidence of a rise in short term job tenure (<1 year) shares across all education groups for men and with similar secular trends for women with no children. Across age groups, there was some evidence of a secular rise in job tenure less 1 year for the 16-24 age group for both men and women with no children. For women with children/children under the age of 5 years there were declines across all age and education groups for elapsed job tenure <1 year. From the analysis of tenure shares greater than or equal to 10 years, there were significant declines across all age and education groups for men and for women with no children, whilst there were increases for women with dependent children across many education and age specific regressions.

[10] These are results from table 3 from Gregg & Wadsworth (2002); the reported results refer to estimated results from the GHS which are not presented within table 3.2 from this literature review.

1970s to the early 1990s [evidence from figure 3.3: Burgess & Rees, 1996]. These results also reaffirm the findings reported by figure 3.4. Part of the reason for this fall may relate to the changing industrial structure, with the decline in the manufacturing industries and the rise in the services industry along with the advancements in ICT, where these factors have contributed towards a changing employment relationship between workers and firms in the domestic labour market. Other reasons relate to a rise in the number of job-to-job transitions that may result from a decline in the number of staff contracts that are offered to workers and replaced by flexible job contracts. In my opinion these changes have affected job tenure, but they have not lead to a substantial change in job security over time. They do not signify that workers have increasing become worse off over time by having to continually search for new jobs such that the rates of job tenure under one year have risen by 30-40% over the last 30 years. However this empirical evidence does show a secular decline in job security from the 1970s to 2000, for men and women with no dependent children. But many of the reported results from median elapsed job tenure and the changes observed from the raw data job tenure proportions fail to account for personal and job characteristics along with the business cycle, which makes many of the observed changes to elapsed job tenure untenable bar results from multivariate regression analysis.

3.2.1.1 Recent Trends in Job Security in Britain: 1985-2009

Faggio *et al.*, (2011) explore an array of job security measures: the median, short and long term job tenure, trends from temporary jobs and the inflow and outflow rates from employment and non-employment over the period 1985 to 2009 using the LFS. They note that whilst aggregate job tenure has largely remained unchanged over the last 30 years, the aggregate trends disguise important compositional effects that have changed over time. Their analysis notes that average median job tenure is much lower for men (a fall of approximately 18 months) than for women where average job tenure rose over the time frame. Reported figures show that in 1985, the average median job tenure was approximately 7 years for men and 4 years for women. In 2009, the figure for men was 5.5 years and 5 years for women. These average tenure trends depend on long term and short term job tenure trends over time.

They found the share of long term jobs (defined as jobs that have lasted at least 10 years) fell over time as a share of all employees aged 35 years and over: In 1985, the share of long term jobs among all employees aged 35 plus years was 46.1% and by 2009 this share had fallen to 38.3%. This fall is concentrated entirely among men: In 1985 this share was 56.5% and by 2009 this share had fallen to 40.7%. This fall was greater for younger men aged less than 50 years than for those aged over 50 years. Long term job shares among men aged 35-44 years fell by 16 percentage points to 41%; whilst long term job tenure for workers aged 55-64 years was 49% in 2009. These results suggest that there is a lower chance for younger male workers to move into longer term jobs compared to the past. Long term jobs rose for women with young children: In 1985 their share was 9.2% and by 2009 this share was 17%. This rise is primarily attributed to maternity leave legislation and family friendly policies (Burgess *et al.*, 2008).

Short term job shares defined as jobs that last less than one year as a percentage of all employees show little change over time. In 1985, this share among all employees was 18.5% and in 2009 this share had fallen slightly to 14.9%; this suggests there is matching efficiency. Amongst men and women, more women have had short term jobs over time than men. But the difference among men and women has narrowed over time. The marked decline has been the greatest for women with young children under the age of five years: in 1985 this share was 40% and in 2009 this share was 17%. There is little trend by education groups but younger workers aged 16-24 years have a higher share of short term job tenure (around 40%) than workers aged 55-64 years (under 10%).

There is no rise in the share of temporary jobs over the last 25 years. And from their final measure of job security – they examine the movements into and out from employment. They find a fall in the flow out of employment which suggests a fall in the rate of job loss over time. The inflow rate is found to be higher in bad times (around 8%) than during goods time (around 6%). There is also a difference amongst men and women. For men, the outflow rate from employment is pro-cyclical, where these trends have been quite high over the most recent recession; and for women there is a downward trend over time. Overall, the employment inflow rate shows little change over time.

The authors' conclusion from their results suggests that job tenure for men has fallen over time because of a rise in job-to-job moves. This conclusion does seem plausible as the employment inflow rate from non employment has changed little for all employee during the time frame, where for men especially there appears to be a general downward trend. But it is unclear what proportion of this trend is accounted for by the inflow rate into employment from unemployment as these trends are not presented. And the rise in long term job tenure for women is due to a fall in the rate of job loss and fewer job-to-job moves.

3.2.2 North American Evidence

The North American literature reviews the empirical results from the U.S. and from Canada. The U.S. literature for job security has typically sought to establish whether media concerns regarding the disappearance of life-time jobs can be merited. A summary of the main findings from the North American literature review are displayed by table 3.3, which are now discussed briefly.

Jaeger & Huff Stevens (1999)[11] find a statistically significant rise in the fraction of male workers with job tenure of less than 10 years. They also find the share of men aged 40 years and older with job tenure of less than ten years began to rise in the mid 1980s. They report no evidence of a similar rise for workers with less than one year of job tenure from 1976-1996 using the Panel Study of Income Dynamics (PSID). This evidence suggests there has been no fall in job security for the U.S. for the period 1976-1996 analysed by the authors'. However, although their multivariate regression results accounts for individual and job level characteristics, their analysis does not account for the business cycle which does make the evidence less tenable. But their results are supported by the findings from other papers' which are discussed in the following paragraphs.

Hall (1982) provides one of the first papers for the U.S. empirical literature, analysing the importance of lifetime jobs. From table 3.3, part (a), the analysis from the Current Population Survey (CPS) across all U.S. workers back in 1978 shows median job tenure was 3.6 years with eventual job tenure[12] of 7.7 years. Around 40% of workers held jobs for over 5 years, whilst eventual job tenure calculations suggest that approximately 60% of workers would go on to have jobs which would have eventual tenure of 5 plus years. These numbers indicate stable and long-tenured employment over time. Similarly, Ureta (1992) finds comparable evidence to Hall (1982) when accounting for potential biases in Hall's (1982) methodology[13].

[11] They also provide a review of the U.S. evidence and the issues associated with conflicting evidence from differing data sets; see their paper for further details.

[12] Eventual job tenure refers to projections of how long workers will remain employed in their current jobs.

[13] Ureta (1992) utilises the methodology used by Hall (1982) to establish whether there are any potential biases that could signify the method used by Hall (1982) could lead to unreliable results for actual and observed job tenure calculations in 1978. Ureta's (1992) analysis show Hall's calculations underestimate the true job retention rates for job tenure levels below 20 years and they over estimate job retention rates over 20 years. This underestimation is due to the secular rise in the arrival of women to the labour force during the 1960s and 1970s. Whereas the over estimation is associated with men. Ureta (1992) notes the participation rate for men declined over the 1970s and 1980s. But the over estimation is likely to be associated with men who remain in the labour force are on average more likely to have high levels of job tenure and more stable jobs. However, calculations from Ureta (1992) show when these biases are corrected for, persons with actual job tenure for 5+ years remain marginally unchanged between each paper. But estimates for actual job tenure of 20+ years show corrected estimates are much lower than from Hall (1982). However, the underlying results do show with the corrections, there remain high percentages of 5+ and 20+ years of eventual job from Ureta's (1992) calculations using CPS from 1978.

Farber (1995) similarly explores whether there is evidence for the disappearance of lifetime jobs over the period 1973 to 1993. The results [presented in table 3.3, part (b)] show from the exploration of the median and the 0.9 quantile of all jobs in duration were stable and long-tenured if not near life-time jobs. From the median regression, the coefficient for employed males represents an average decline over the 20-years period of 0.358 years in the median, whilst for women there was an average increase of 0.664 years in the median. Similar patterns are also shown by the 0.9 quantile regression, where these results show there to be a small increase on average in the 0.9 quantile of job durations for males by approximately 0.3 years. For women there was a substantial and significant increase of around 1.5 years on average in the 0.9 quantile, which is a larger rise than from the median. The overall results suggest there to be no evidence for the disappearance of life-time jobs in the U.S.

Other research has explored 4-year and 8-year job retention rates over time. The objective is to view whether these job retention rates at similar points along the business cycle, but at different points in time have changed over time. Swinnerton & Wial (1995) explore changes in job security via 4-year job retention rates for the 1980s: 1983-1987 and 1987-1991[14]. Their results indicate lower job retention rates over the latter part of the 1980s than for the early part of the 1980s (the average annual unemployment rate in the U.S. in 1983 was 9.6%) for all workers. Their results by gender also show lower job retention rates for men than for women, who had seen a very small decline. Swinnerton & Wial (1995) interpret these results as, "suggesting a secular decline in job stability during the 1980s".

Diebold *et al.,* (1997) also explore 4-year job retention rates over the same period of the 1980s as Swinnerton & Wial's (1995) paper and their results only indicate a small decline of 0.01 or 1 percent for all workers. Their results by gender also show a modest decline for men. Diebold *et al.,* (1997) report that the large decline in job security reported by Swinnerton & Wial (1995)

[14] If the unemployment rate is taken to be a measure of the business cycle, these two sets of periods comprising of 4 years reflect similar stages in the US business cycle.

are to a large extent accounted for by (1) inconsistent classification of the self-employed (by Swinnerton & Wial (1995)) and (2) the failure to account for non-responses to the tenure questions. Their disaggregated results by job tenure show stable job retention rates for those with 9+ years of job tenure; whilst by age, workers aged over 40 years showed no statistically significant decline in job retention rates. These results seem to present very little evidence for the end of life-time jobs.

Neumark *et al.,* (1999) explored 8-year job retention rates from the early 1980s to the mid 1990s. Some of the results are reported in table 3.3, part (f). In contrast to Diebold *et al.,* (1997), calculations from 8-year job retention rates reveal evidence of a decline in job security through to the mid-1990s. Diebold *et al.,* (1997) reported 4-year job retention rates that were roughly stable over the 1980s; but the results for the 8-year job retention rates from Neumark *et al.,* (1999) reveal a significant difference of around -0.02 [15] or 2 per cent, with significant declines for men and for women. The disaggregated results showed a decline in job retention rates by age (although there was no change for those aged 55+ years) and by job tenure there were significant declines in job security for more tenured workers (those with 2-9 and 9-15 years of job tenure) with increases in job security for those with two years of job tenure or less. Although the 8-year job retention rates show a significant decline, this decline is however quite small.

Many workers believe that large corporations can be footloose if they are able to transfer jobs to other divisions overseas or to outsource them domestically. Allen *et al.,* (1999) find little evidence to show jobs were less secure in large private corporations in the U.S. in the 1990s. Their data sample consisted of 51 firms that were clients of Watson Wyatt Worldwide. Their results [presented in table 3.3, part (e)] show stable jobs in the private sector over the early part of the 1990s: average job tenure for the sample in period t-5 was 12.6 years with an

[15] This figure refers to column 3 from table 3.3, part (f) from this chapter.

estimated average rise of 0.8 years over the next 5 years. There were over 50% and over 25% of employees with job tenure over 10 and 20 years respectively, where approximately 61% of employees in period t-5 would be with the same employer 5 years later.

Huff Stevens (2005) explored snap shots of job tenure taken at the end of workers careers (specifically men) from 1969 to 2002. Table 3.3, part (g) presents a few of the main findings from measures of average and median job tenure. These findings show stability in the prevalence of long-term relationships for men in the U.S. In 1969, average job tenure in the longest job for males aged 58-62 years was 21.9 years; in 2002, the comparable figure was 21.4 years. Similar trends were also observed by median job tenure figures. For all years, it was found more educated men had higher job tenure than less educated men. Among non-white men, average job tenure remained below measures comparable to white men. Long term relationships were found to be an important feature of the U.S. labour market in 2002 as much as it was in 1969. But, an important limitation with this study is that it examines job tenure from the experiences of men at the end of their careers. As evidence from Neumark *et al.*, (1999) show a small decline in 8-year job retention rates from the 1980s to the early 1990s, it is likely that younger workers from this present time will have different labour market experiences by the time they are 60 years old compared to the Huff Stevens's (2005) sample (Winship, 2009).

Finally, Brochu (2009) documents the trends for one year job retention probabilities for Canada; these trends are presented within table 3.3, part (h). From this table, the job retention probabilities show little change post 1990 for all groups. At the start of the period, men had higher one year retention probabilities compared to women; but after 1989, women continued to have slightly higher one-year job retention rates, where these rates stabilised. This estimated stability in the one year retention rates after 1989 is interpreted by Brochu (2009) to be a rise in job security as over this very same period the unemployment rate continued to decline. From other results reported by Brochu (2009), there were stable trends for the one year job retention rates by age groups and there were no changes in the one year job retention rates over the sample period. Evidence of job security was also found by Heisz (2005)[16].

The empirical evidence from the U.S. literature suggest there is no end to the existence of life-time jobs; they show stable job retentions rates over the 1980s (4-year job retention rates) and there is some evidence of a decline in job retention rates over the 1990s (8-year job retention rates) for men and for women and for more tenured workers. The literature also shows workers employed in large corporation in the private sector had secure jobs over the 1990s, and there is the existence of long-term job tenure spells in 1962 and 2002 for men reported by Huff Stevens (2005). However, much of this research compares cross sections of data, where average job tenure or job retention rates are compared at particular snap shots in time – at similar points along the business cycle. Most of this evidence also fails to take account the individual or job characteristics that might influence job security over time as well as for the business cycle[17]. Research by Battu *et al.*, (2002) show individual and job characteristics are factors that can influence the potential accumulation of job tenure over time. Battu *et al.*, (2002) report that gender and the presence of dependent children can influence the type of job contract workers may be offered by their employers. These factors have not been incorporated into much of the literature on job retention rates at particular points in time and therefore due to these reasons, it is difficult to assess whether job security

[16] Heisz (2005) also finds similar evidence. Using the Canadian Labour Force Survey for the 1976 to 2001 period, Heisz found no evidence of a fall in job security. There was some evidence of a decline in one year job retention rates over the 1980s for young workers and for workers with high school level education or less, but this rose over the 1990s. Overall the evidence from Canada suggests there has been little change in job security as there is no evidence of any increasing or decreasing trends from the one job retention probabilities covering the 1990s.

[17] Marcotte (1999) is the exception to this case. He estimates one year job retention rates for men over the period 1976-1992 using the PSID. These rates were then used to estimate a series of job retention probability models that account for individual and job characteristics and also the unemployment rate for economic conditions. He finds that job security declined for black men and for men who dropped out of high school and for workers with some post secondary education but no college education. From Marotte's paper and the reported results it is not clear whether job security declined over the 1976-1992 period for all workers as the analysis from Marcotte (1999) focuses on the changes to job security for specific education, age and race groups.

has declined over time[18]. However, the incidence of job loss rates may shed light on the security of jobs in the U.S. over the 1970s to year 2000.

The incidences of job loss are also important to the job security debate. If job loss rates have changed very little over time, this may corroborate the story told by the job retention rate literature. If however, the incidence of job loss has increased over time, this evidence may be at odds with the job retention rate literature. However, the job loss literature does tell a similar story to the job retention rate literature, which is job loss rates have not grown over the last 40 years. Gardner (1995) found the incidence of job loss in 1981-1982 period were comparable to the 1991-1992 periods using the Displaced Worker Survey (DWS). But other results from Gardner (1995) show the incidence of job loss by industry and occupations had changed over this period. She found there was a decrease in the incidence of job loss among blue collar workers in manufacturing industries and a rise in the incidence of job loss amongst white collar workers and workers employed in the non-manufacturing industries. Additionally, older workers had a higher incidence of job loss in the 1990s compared to the previous decade.

Farber (1996, 1998, 2001, 2003, & 2009) provides an extensive array of evidence which has explored the incidence of job loss rates and costs associated with job displacement using the DWS over time. From earlier papers, Farber (1996, 1998) does find the incidence of job loss was higher during the 1990s than for the 1980s, where the incidence of job losses was higher for older and more tenured workers. Similarly, research by Aaronson & Sullivan (1998) found the incidence of job loss through job displacement was 0.3 percentage points higher during the 1990-1991 recession compared to the 1982 recession. But this percentage change is less

[18] Valletta (1999) finds that the relationship between employers maintaining general employment contracts for workers that account for performance incentive problems for workers and firms with imperfect monitoring changed over the 1976-1993 period for the U.S. Valletta (1999) finds that this relationship is also responsive to economic conditions. Using the PSID, he finds the negative relationship between job tenure and probability of job dismissal weakened over time – meaning firms appear not to maintain general employment work contracts and even long-tenured workers may face the risk of job loss. However, the fourth coming paragraphs from the job loss literature show that although job loss rates increased in the U.S. during the 1990s, they have not increased in magnitude over time. Thus, these results may have been relevant during the 1990s, but they are not consistent with more recent evidence that examines the changes in job security beyond the 1990s.

than a half a percentage point and this does not signify a rise over time. Farber (2003) suggests the higher incidence of job loss in the 1990s were due to a slower decline in the job loss rates during the early 1990s expansion relative to the decline in the expansion of the 1980s.

In later a paper, Farber (2005) finds the evolution of job loss rates to be counter cyclical to the business cycle, but these job loss rates did not show that they had increased over time. The evidence shows that these rates fluctuated between 8 and 13 percent between 1981 and 2003. Farber (2005) did find that the aggregate job loss rate masks the patterns of job loss rates over time for different groups of workers. He finds job loss rates were higher for less educated workers (workers with less than 12 years of education) compared to other education groups but these job loss rates did not show a rise over time. Additionally, although highly educated worker with 16+ years of education had lower job loss rates compared to other workers with lesser years of education, the job loss rates for this group of workers has been rising over time: for the 1981-1983 period, the job loss rate for highly educated workers was approximately 7%; for the 1989-1991 period the job loss rate was 8%; by the 2001-2003 period their job loss rate had increased to 10% – although this rate is still quite small. Additionally, Farber (2005) found workers aged 20-29 years had higher job loss rates compared to other age groups; and workers aged 50-64 years had lower job loss rates. But the job loss rates by age once again do not show there has been a rise for the different age groups over time.

From a more recent paper, Farber (2009) interprets the rise in job loss rates and the fall in long term job retention rates over the 1990s as a rise in job insecurity for that period. When these rates are examined over the period 1984 to 2008 using the DWS, Farber (2009) finds there has not been an increase in job loss rates over this time frame that would account for a decline in job tenure and long-term employment rates. Farber (2009) finds the decline in job tenure and long-term employment is restricted to the private sector with evidence of a rise in job tenure and long-term employment for public sector workers over the period 1984-2008[19]. There is also no evidence of changes in job loss rates for either sector that could account for the observed results. A probable explanation for the fall in long-term job tenure rates may rest with the fact that whilst job loss rates have not increased over time, there is evidence which shows job tenure from long-term employment is falling and this may be due to higher job loss rates for high-tenured workers relative to low-tenured workers in the private sector. Second, Farber (2009) suggests that job loss rates may not be captured by the DWS because the scope to establish changes from the survey questions is limited and they are not able to capture the observed trends.

From other research exploring the quality of jobs following job loss, Farber (1997) finds the quality of jobs available for less skilled workers declined over the 1979-1996 period. However the quality of jobs available to higher skilled workers changed very little. And there is little evidence of a rise in the rate of part-time jobs within new and old jobs. Gottschalk & Moffitt (1999) find no evidence for job endings to be increasingly followed by a non-employment spell. And Hamermesh (1987) reported the present value of social loss attributed to the workers' share of firm specific human capital to be around $7,000 (1980 dollars).

In summary, I interpret the empirical evidence from the North American literature to show that job security has not declined over the last 40 years. The U.S. literature on job loss shows there has not been a rise in the incidence of job loss from the early 1980s to the early 2000s. What this literature does show is job retention rates have been stable and job loss rates are counter cyclical to the business cycle. Although the job retention literature does suggest there has been a decline in 8-year job retention rates over the 1990s, the differences between the job retention rates from the 1980s and the 1990s are small (see table 3.3, part (f) for the

[19] These results contrast with the findings from Allen *et al.,* (1999) who found evidence of job security in large private corporations during the 1990s.

details). Overall, the findings from the job loss literature show there is no evidence for the disappearance of life-time jobs; on the contrary job retention rates have been stable over time and the incidence of job loss has not increased over the last 40 years.

But changes to the length of employment spells may reflect elements of voluntary job separations where workers try to seek better opportunities to improve their within job benefits. However, concerns regarding the end of lifetime jobs may in part reflect the anxieties of labour market changes (partly related to the movements to the business cycle, changes in expectations of economic conditions or concerns of globalisation) that may only be partially related to changes in the overall length of employment spells. This anxiety may in part reflect concerns of how long jobs will last, which is likely to stem from concerns of firm-initiated (involuntary) job separations. Neumark & Polsky (1998) suggest the distinction between voluntary and involuntary job separations is important as workers who quit their jobs are likely to improve their welfare but involuntary job separations may make workers worse off. Thus, their argument is, if the proportion of involuntary job separations has risen over time but overall job separations have remained stable, this may make workers feel less secure and more anxious about their jobs; hence reflecting concerns for job insecurity. The job security literature for the U.K. provides no evidence of a rise in firm-initiated quits. Partly this is due to lack of data that allows for this distinction. For the U.S., evidence from Davis (2008) finds there has been a fall in the uptake of Federal unemployment assistance for workers who become involuntarily separated from their jobs (see next section for further details).

In summary, the analysis of the British and North American literature reviews have been examined from the view of establishing whether the length of an employment spell or time individuals spend within their current employment has declined over time. This chapter interprets the empirical findings as providing some evidence of a decline in job security at the aggregate level for the U.K. has been small; though recent evidence analysing the period 1985-

2009 by Faggio *et al.*, (2011) suggests that long term (short term) job tenure has fallen (rose) over time for men (women with young children). For North America, there is evidence of a fall in job security during the early 1990s, but over time, there is no evidence of a decline in job security.

Table 3.3: North American Estimates for Changes in Job Security

a) **Hall (1982):** Eventual & Actual job tenure distribution estimate for all U.S. workers' in 1978

Years	Eventual Tenure (%)	Actual Tenure (%)
0-2	23	39.9
2-5	18.5	20.2
5-20	29.9	30.4
20+	28	9.5
Median Tenure: 3.6 years		
Median Eventual Tenure: 7.7 years		

b) **Farber (1995):** Annual change in median job tenure for all employed individuals aged 21-64, 1973-1993

Median Regression: **Males:** -0.0179 years **Females:** +0.0332 years
0.9 Quantile Regression: **Males:** +0.0138 years **Females:** +0.0734 years

c) **Swinnerton & Wial (1995):** Changes in 4-year job retention rates, 1983-87 vs. 1987-91

	1983-1987	1987-1991	Change
All workers	0.547	0.488	-0.059
Men	0.586	0.504	-0.082
Women	0.501	0.471	-0.03

d) **Diebold, Neumark & Polsky (1997):** Changes in 4-year job retention rates, 1983-1987 vs. 1987-1991

	1983-1987	1987-1991	Change
All workers	0.537	0.527	-0.010*
Men	0.578	0.554	-0.024*
Women	0.487	0.494	0.007
Tenure Groups:			
0 to <2	0.335	0.346	0.011*
2 to <9	0.568	0.522	-0.046*
9 to <15	0.806	0.805	-0.001
15+	0.671	0.712	0.041*
Age Groups:			
16-24	0.290	0.254	-0.036*
25-39	0.577	0.558	-0.019*
40-54	0.685	0.675	-0.010
55+	0.487	0.486	-0.001

Results reported are corrected for heaping and business cycle. Estimated changes statistically significant at the 5% indicated by *.

e) **Allen, Clark & Schieber (1999):** Tenure in the early 1990s in period t-5

	Period t-5	Growth per year for 5 yrs
Average Tenure	12.6 yrs	0.8 yrs
% of employees with 10+ yrs of tenure	54.5%	4.1 percentage points rise
% of employees with 20+ yrs of tenure	25.6%	0.6 percentage points rise
5 year retention rate	60.7% of employees in the same firm stayed with the same employer 5 years later	

f) **Neumark, Polsky & Hansen (1999):** Changes in 8-year job retention rates, 1983-91 vs. 1987-95

	1983-1991	1987-1995	Change
All workers	0.386	0.370	-0.016*
Men	0.420	0.379	-0.041*
Women	0.345	0.325	-0.020*
Age Groups:			
16-24	0.190	0.154	-0.036*
25-39	0.454	0.404	-0.050*
40-54	0.527	0.484	-0.043*
55+	0.188	0.188	0.000
Tenure Groups:			
0 to <2	0.183	0.216	0.034*
2 to <9	0.433	0.384	-0.049*
9 to <15	0.650	0.617	-0.033*
15+	0.485	0.477	-0.008

Results reported are corrected for heaping. Estimated changes statistically significant at the 5% indicated by *. Information displayed in this table is taken form tables: 3 and 5.

g) **Huff Stevens (2005):** Tenure on longest job for men aged 58-62 years; Completed tenure in years 1969-2002

	1969	1975	1980	1992	2002
Mean	21.9	23.8	24.1	22.8	21.4
Median	21	24	24	23	21

h) **Brochu (2009):** One year job retention rates for Canada; Period analysed is 1977-2003

	1977	1983	1989	1992	1995	1998	2001	2003
All	0.79	0.81	0.775	0.82	0.815	0.82	0.825	0.83
Men	0.81	0.82	0.78	0.81	0.80	0.81	0.825	0.815
Women	0.77	0.80	0.77	0.82	0.82	0.815	0.82	0.83

Source: Table compiled by the author. Part of the table has been adapted from Neumark & Polsky (1998).

3.2.3 Recent Evidence for Job Security

Steven J. Davis (2008) asserts there is considerable evidence from the American empirical literature which suggest recent job loss rates (for the post 2000 periods) are considerably lower compared to the 1990s, the 1980s or even the 1970s. His paper explores new evidence from a selective set of 'unwelcome' job separations which are, "employer-initiated separations that lead to unemployment, temporary or persistent drop in earnings, and other significant costs of job loss". This new evidence has been gathered from five different indicators of 'unwelcome job losses' using various data sources. The first source of evidence comes from the Federal-State Unemployment Insurance Program, which is a form of benefit that is provided to experienced workers who may become involuntarily unemployed and meet various other requirements to receive the benefit. Davis (2008) examines this data for new claims for unemployment benefits from the Federal State Unemployment Insurance Program from January 1967 to January 2007. The evidence from new claims post January 2002 shows there has been a downward trend in the uptake of this benefit. Prior to the 1980s there was a rising trends in new claims for the insurance benefit. Other indicators that are also explored provide support for this view and are briefly discussed below.

Evidence from studies which explore unemployment inflow rates for the U.S. provides unanimous evidence in support for a fall in job loss trends with similar percentage point drops. Davis *et al.,* (2008) assess evidence from monthly unemployment inflow, outflow and escape rates for the period 1976 to 2006. They find the unemployment inflow rate fell from a peak of approximately 4 percent[20] of employment in 1983 to approximately 2.3 percent of employment by 2006. Shimer (2007) examines the employment exit probability and the employment-to-unemployment (EU) transition probability over time. Both of these probabilities present similar fluctuations over time, where prior to 1980, both sets of probabilities rose over time. But after the early 1980s period there has been a continued decline in these probabilities. Elsby *et al.,* (2007, 2009) explore the ins and outs of cyclical unemployment for the U.S. They find declining inflow probabilities for the post 1980 period. At its peak, the inflow rate was approximately 5 percent in 1982; by 2005 the inflow probability had fallen to approximately 2.7 percent.

Whilst the above papers present support for declining trends at the aggregate level, there is also support from results at the disaggregated level. Fujita & Ramey (2006) examine the cyclicality of job loss (job-to-unemployment flows) and hiring flows (unemployment-to-

[20] The monthly inflow rate into unemployment was 3.15 percent of employment in 1976.

employment flows) for the U.S. They examine the trends for job loss and hiring flows using CPS short panels from 1976 to 2006. They examine: (a) total job loss trends and (b) net job loss trends with four interest groups, which are (1) all workers aged 16+ years; (2) the young aged 16-24 years; (3) prime-age (aged 25-54) and (4) prime aged males aged 25-54 years. Fujita & Ramey (2006) found young workers have higher total and net job loss flows compared to the other interest groups. They also found over the post 1980 period there had been a gradual decline in the job loss flows for all interest groups. Their results from the hiring flows also show a downward trend over time for all interest groups; although this flow does rise during NBER recessionary periods[21]. These results also reaffirm Davis's (2008) assessment of fewer job loss flows during the most recent decade that has passed compared to the 1980s and the early to mid-1990 period. They also support the findings from the job loss literature which was discussed in the last sub-section.

Finally, Stewart (2000, 2002) explored trends in job security using the March CPS data. Stewart (2000) found men tend to have higher job-to-unemployment (EU) transitions compared to women and there were lower trends for all workers. All trends show there was an overall decline in EU job loss trends after 1983 where there was a clear downward trend, whilst prior to 1983 there were rising EU job loss trends.

For the U.K., the evidence from other indicators is quite sparse, but Petrongolo & Pissarides (2008) explore the ins and outs of European unemployment studying the contribution of inflows and outflows to the dynamics of unemployment. For the U.K. their paper finds the unemployment inflow rate was a big factor that accounted for the unemployment dynamics during the 1980s, but its contribution to unemployment has had little effect for the late 1990s or for the post 2000 period. In other words, with a declining unemployment rate over the post 1993 period, there is little evidence that points to a rising inflow rate that contributes to the

[21] See appendix 3 for details about the NBER dated recession periods.

unemployment dynamics over this period. Hence, one could say that with the inflow rate into unemployment accounting for very little change over the late 1990s and post 2000 time frame, this lack of inflow would suggest that job security has changed very little if fewer jobs are ending and resulting in a state of unemployment. Another angle through which job security trends can also be assessed is from the job creation and job destruction literature. The most recent paper that has explored job creation and destruction rates for the U.K. has been by Hijzen *et al.,* (2007). They explore the job creation and job destruction rates from firm-level evidence for the services and manufacturing sectors. Viewing the job creation and job destruction rates (table 2 from their paper) on the whole show little evidence of rising job destruction rates for the period 1998-2005. Their results show these rates have declined over time; see chapter 2, section 2.4.1 for further details.

Figure 3.5: Claimant Count Trends

Source: Author's own compilation. Appendix 2 provides the details for the data source used to construct this graph.

The final evidence for the U.K. is presented by figure 3.5. This figure plots the claimant count from the third quarter of 1983 to the first quarter of 2010, where the number of claimants that are registered to claim job seekers allowances following job loss. This figure loosely provides an indication for the number of claimants seeking assistance following involuntary job loss[22]. This graph shows after the early 1990 recession, the number of claimants declined between 1993 and the early 2008 period. There has only been a rise over the most recent economic downturn. This evidence shows there is no rising tendency for becoming unemployed or for job insecurity.

To sum up, the recent evidence shows there is no evidence of a rise in job insecurity for the U.S. over the last two decades. This recent evidence is limited for the U.K., but from this limited evidence there is no increasing tendency for becoming unemployed. Additionally, this evidence shows job retention rates and unemployment inflow rates have not become volatile over this time frame.

3.3 Trends in Income Volatility

Income volatility refers to the variance of income and whether this variance is changing over time (Jensen & Shore, 2008). The variance can become bigger or smaller over time. If the variance is getting bigger, this means that income volatility is increasing over time; but if the variance is getting smaller, this implies income volatility is declining over time[23]. Income volatility can be affected by the business cycle and by forces associated with globalisation, such as international trade, product market competition, the dynamic nature of comparative advantage, advancements in telecommunication technology, offshore outsourcing activities and out ward FDI can all put pressure on the wage levels of domestic labour. But to date there has been little empirical research to establish conclusively whether these forces have influenced income volatility over time (Gottschalk & Moffitt, 2009).

Income volatility can be affected by transitory shocks and by permanent shocks. These shocks can have a transitory or a permanent impact on income levels over time. The transitory

[22] The reform after 1995 restrict the eligibility to claim allowances for a period of 6 months if workers have (a) voluntarily left paid employment; (b) discharge for misconduct; (c) refusal of suitable work; and (d) because of labour disputes. The trends from this graph after 1996 do not show a rising trend. See Wu (2000) for further details.

[23] It is important to note here that rising income volatility is not necessarily a bad thing. What is interesting is whether this trend is increasing or decreasing over time.

change to income can result from a change in the number of hours that are worked where the loss or gain in income may not go away immediately by the next time period. The worker's earnings level may take three or four years to reach their natural income level. They can also change temporarily because of the business cycle and from forces associated with globalisation. For example, the increase in the variance of transitory earnings could result from skill-biased technological change which may temporarily increase income inequality. From a theoretical model developed by Violante (2002) concludes that advancements in technology can make it more difficult for workers to transfer their skills to more recent 'vintages' of capital. Thus, workers can experience transitory wage losses within jobs that can differ amongst workers (Gottschalk & Moffitt, 2009). Through calibrations, Violante (2002) shows this mechanism can account for a 30% transitory surge in residual inequality in the U.S. One of the implications from this theory is that this technology mechanism can also lead to large wage losses through job dislocation which can lead to permanent wage losses over time.

A permanent income change can imply an income change that may never go away even after a number of years (Gottschalk & Moffitt, 2009). Permanent changes to income can also be associated with globalisation. For example, consider the job polarization hypothesis, where advancements in technology can replace job tasks completed by workers that are routine and codifiable in nature. These job tasks are also the most offshorable because routine job tasks can be delivered from offshore foreign locations via telephone or via the internet. Consider a call centre manager aged 45 years, who has spent 15 years working for a firm for the most part of his/her life, is laid off as the firm decides to permanently downsize their operations in the U.K. and offshore the call centre operations to India. As a result of the downsizing, the worker may have to transition to another industry. At the age of 45, to seek employment in another industry is not easy as he/she will require re-training. Empirical evidence from Autor & Dorn (2009) found older college educated workers were most likely to transition to jobs located at the bottom end of the skill distribution. The earnings level from these jobs will be lower compared to the old job. In terms of the example, the worker used to earn say, £30,000 and he/she may probably never be at that level of income after job loss. With a new job, the worker may earn £24,000. This new income level may climb to £26,000, but the permanent loss of income is £4,000, which may never be recovered (Gottschalk & Moffitt, 2009).

The impact of transitory and permanent income shocks which cause income volatility has been presented in a theoretical model by Gamber (1988) which explores income volatility resulting from firm level volatility. The model is a long-term contracting model with bankruptcy constraints. Firms and workers must decide on a two-period wage contract, where the firms face both transitory and permanent shocks to its revenue function. The objective of the contract is to smooth workers incomes. The model predicts that there is an asymmetric response of the wage to permanent and transitory shocks. If the risk neutral firms are insuring risk-averse workers, the model predicts the real wage responds more to a given permanent shock than to a temporary shock of the same size. Firms appear to absorb transitory shocks but try to insure against permanent shocks. Permanent shocks are assumed to persist for two periods, whilst temporary shocks persist for only one period. Gamber (1988) finds that real wages respond more to permanent shocks than to transitory shocks[24].

Income volatility can lead to consumption volatility and volatility in household income levels. Households and individuals may not be able to maintain their standards of living or economic status to which they are accustomed to because of income uncertainty and this may cause a rise in precautionary savings[25]. Hacker & Jacobs (2008a) note increased income instability can reduce individual and household welfare. Additionally, many households may borrow money

[24] Guiso *et al.*, (2005) find evidence in support of these predictions for Italy.

[25] Lise (2006) develops a model which examines on-the-job-search and precautionary savings. This model suggests that the decision to save money depends on the dynamics of the wage ladder resulting from the search process. The model assumes there is an important asymmetry between the incremental wage increases generated by on-the-job-search (climbing the ladder) and the drop in income associated with job loss (falling off the ladder). The model assumes that low wage workers are more likely to dis-save if expected wage growth is not much higher than unemployment benefits. As workers wages rise, the incentive to save increases; and the potential for wage loss in the future makes it increasingly important to insure against large income losses in the future. High-wage workers are more likely to save for the future as this mode of behaviour is driven by the prospect of falling of the work ladder.

to insulate their spending patterns from earnings volatility (Milberg & Winkler, 2009). There has been a rise in unsecured debt (credit card finance) to supplement lost earnings, which many household utilise during transitory periods of low income (Sullivan, 2002). This raises concerns over indebtedness, bankruptcy, home repossessions with household expenditure and consumption volatility. See Hacker & Jacobs (2008b), Dynan *et al.,* (2008), Winship (2009) and Nichols & Zimmerman (2008) for empirical trends in household income volatility; and for household consumption volatility see Gorbachev (2009) and Davis & Kahn (2008). Whilst these are important implication from income instability, these factors are not the focus of this of this review.

Winship (2009) provides a vast review of the literature for income volatility, income mobility and income dispersion for the U.S. at the individual level and at the household level. The main findings from this review are discussed below. The literature for income volatility has focused on transitory and permanent income volatility trends. For income mobility, this literature has tried to assess the non-directional and directional movement of the income variance along the income distribution over time[26]. It determines how well off individuals are over time, whether they are becoming well off (moving up the income distribution) or becoming worse off (moving down the income distribution) because of changes in the permanent and transitory variances of income. And the literature for income dispersion examines whether the standard deviation of income as a whole is increasing over time.

[26] Income mobility is defined as a, 'change in the relative rank, or relative position, in the income distribution' (Gottschalk & Moffitt, 2009). This strand of the literature examines the movements of income from one period to the next for each individual in the population. It tries to determine the changes in their rank or to determine the probability of such changes in the relative position. For example, an increase in the variance of transitory income can lead to an increase in short-term income mobility. This increases the chance that an individual will change their relative position with someone else – both upwards and downwards. But as the effect on income is temporary, in the long-run there is no effect on the chance that an individual will change their relative position in the distribution of income. A permanent change on the other hand has a permanent impact on income where this increases the prospects of long-term mobility of moving upwards or downwards along the long-run income distribution. But if permanent changes to income have occurred, this diminishes the chances for individuals to change their relative position in the future because the permanent and temporary shocks to earnings can cause individuals to be further away from their original position in the distribution (Gottschalk & Moffitt, 2009).

3.3.1 Permanent & Transitory Income Volatility Trends

The question this literature tries to establish is whether permanent and transitory income volatility has increased over time (can make individuals worse off) or has it decreased over time (can make individuals better off) and can this be attributed to forces associated with globalisation.

From the income volatility literature, research by Gottschalk *et al.,* (1994) find the dispersion of growth in permanent earnings variance for males grew by 41% from 1970 to the 1980s, where the transitory variance also grew by 42% over the same period for the U.S. Prior to the 1990s, the authors' note that whilst the compositional changes from the labour force accounted for a 12% rise in transitory earnings, the aggregate data suggested that the increased variability had nothing to do with increased instability from the labour market or from industry. Shin & Solon (2008) extended the period of analysis using the PSID for men and found that whilst earnings volatility was counter cyclical to the business cycle, their evidence was consistent with Gottschalk *et al.,* (1994): they found a secular rise in earnings volatility during the 1970s. Post 1970, their paper found little evidence of any form of change in earnings volatility however, post 1998, they note there be a slight rise in earnings volatility. Most recent research carried out by Gottschalk & Moffitt (2009) found increasing earnings instability[27] during the 1970s and 1980s, with little change in the 1990s; but there is evidence of slight rise over the most recent decade.

Part of the reason why there may have been no trend in earnings during the early 1990s is due lack of wage growth during this period. The analysis from Aaronson & Sullivan's (1998) paper suggest that an increase in job displacement rates during the early 1990s recession, along with rising anxiety over job security may have limited wage growth by about three tenth to seven

[27] Gottschalk & Moffitt (2009) interpret income instability to refer to transitory income volatility.

tenths of a percentage point per year during the 1990s. This evidence is consistent with their being little evidence of rising income volatility over the early 1990s.

Yet, Jensen & Shore (2008) report income volatility may be related to risk. They note that research which has examined income volatility trends over time have failed to take into account individual heterogeneity, where this research has effectively been estimating an increase in average income volatility over time. Their research accounts for individual heterogeneity when they decompose the increase in average income volatility over time. Their analysis agrees with previous research which shows using the PSID, the permanent and transitory variances of average income have increased for all individuals all along the income distribution. They found the mean of the permanent and transitory variances increased by 73 and 93 percent over the sample. The most important findings from their paper show average volatility of incomes is driven by sharp changes in income by those with the most volatile incomes. These changes are attributed to the 'right tail' of the income distribution. They found self-employed workers and workers with very high tolerances for risks have the most volatile incomes in the population. They found the permanent and transitory variances at the right tail (the 95th percentile) increased by 71 and 154 percent respectively. For all other individuals along the income distribution, from the 1st to the 75th percentile, their results show the permanent and transitory income variances were stable over the 1970s to the early 2000 time frame. They also found individuals with more years of education and married male workers were less likely to have more volatile income over time. But older individuals were more likely to have volatile incomes. Jensen & Shore's (2008) research shows average income volatility has not increased for the vast majority of individuals and this implies average income volatility has not increased over this time frame, but has effectively remained stable for most individuals.

What these results suggest is that the impact from any form of policy changes to labour market institutions or from changes to industry trading conditions appears to have had little or no impact on the volatility of income for the vast majority of individuals in the U.S. However, forces associated with globalisation could have raised the income volatility for those who are self-employed or for those individuals who identify themselves with high risk tolerances are prone to having their income levels being more volatile over time. This is a supposition that has yet to establish empirical support, but this may be a plausible explanation as to why their income levels may be more volatile over time.

To establish whether transitory income volatility can be caused by the volatility from firms' trading environment, Comin *et al.,* (2009) explore whether transitory earnings volatility is linked to the volatility in firm performance for publically traded companies. The authors' find firm-level volatility in sales has caused wage levels to be volatile over time if firms tie wage levels to firm performance. Comin *et al.,* (2009) find the rising turbulence in firm sales over the past three decades in the U.S. had raised wage volatility. The transitory volatility of wages along with sales were strong during the 1980s within large companies that were service oriented compared to manufacturing oriented firms. The authors' suggest there is a causal relationship between firm sales and wage volatility which may be the result of large firms not being able to monitor the work tasks completed by workers as they become more complex. Firms may therefore tie wages to firm performance such as sales, which may cause wage levels to be more volatile over time.

Davis *et al.,* (2006) also find firm level volatility of publicly traded firms had increased by three quarters from 1978 to 1999. But they also found the volatility for privately held firms (which are typically small firms) declined by one third from 1978-2001. Pistaferri (2009) comments that the research by Comin *et al.,* (2009) may not be capturing wage volatility at the individual level as their analysis simply regresses the transitory variance of average wages in the firm against the transitory variance of firm sales. Pistaferri (2009) also notes the data used for the analysis (COMPUSTAT data) was not ideal and therefore this is one of the reasons why there has been little evidence to date exploring the link between income volatility and firm-level volatility. Thus, this evidence signifies that transitory income volatility being linked to firm-level volatility is questionable and it does not show that workers have become worse off over time due to forces associated with globalisation. More research is required to establish a link.

The empirical evidence from industry level studies is still in their infancy, but from the research that is available, it does suggest that the forces associated with globalisation have had little impact on income volatility. Bach (2008) finds the unconditional volatility of labour and capital incomes had declined for European countries where the transitory component of income volatility changed very little over time. Bach (2008) finds that the volatility of labour income did not change much during the 1980s or 1990s. But there was some evidence to suggest the relative volatility of incomes for low-skilled workers had increased in some industries and countries. Income volatility was found to be associated with variables measuring bargaining power of workers; but the impact from the trade variables appeared to have no impact on the volatility of income or capital over time.

Krishna & Senses (2009) find trade leads to income risk for the U.S. The authors' found import penetration had a statistically significant association with labour income risks. Their paper reports that a 10 percentage point increase in import penetration was associated with an increase in the standard deviation of persistent income shocks of about 10-20%. The persistent income risk was estimated to account for a 4-11% decline in life-time consumption.

Finally, another explanation for the rise in income volatility can be due to job displacement. For workers who become displaced, the transitory variance of their income can be more volatile in the immediate aftermath following job displacement. Huff Stevens (2001) finds job displacement did raise the variance of transitory earnings during the 1970s and 1980s. This means displaced workers had a higher variance of transitory earnings than non-displaced workers. However, little is known about the transitory variance trends over the last two decades – over the 1990s and 2000s. Additionally, Huff Stevens (2001) acknowledges that rising job displacement can only explain part of the overall rise in earnings instability as displaced and non-displaced workers experienced a rise in earnings instability during the 1980s.

For the U.K. there are no papers available to my knowledge which have explored the trends in transitory income fluctuations or have distinguished between the permanent and transitory variance of income. But, Nickell *et al.*, (2002) find the probability of substantial year on year real hourly pay reduction (of 10% or more) for continuously employed men rose by 20-30% from the early 1980s to the mid 1990s. Devereux & Hart (2006) find income volatility for the U.K. may be the result of changing employers. They find the wages for external job movers exhibited high wage cyclicality that was 30-40% more than job stayers (10-15%). They also reported internal wage cyclicality did exist but was not as great as for external job movers.

To sum up, has income volatility increased over time – the answer to this question is yes and no. Average income volatility has not increased over time for the vast majority of individuals with income between the 1st and 75th percentiles; but it has increased for individuals with the most volatile income above the 90th percentile. Secondly, can the rise in income volatility be attributed to forces associated with globalisation – the answer to this question is no. This is because this literature is still in its infancy and it does not provide conclusive results which agree income volatility has increased over time because of forces associated with globalisation. At present the existing literature suggests their impact has been negligible.

3.3.2 Income Mobility and Income Dispersion

Another strand of the literature examines income mobility. This literature tries to establish whether individuals have moved up the income distribution (they have become better off) or whether changes in transitory and permanent components of income volatility have moved them down the income distribution (that is they have become worse off) over time. To gage the change in income mobility, this strand of research estimates the probability that family/individual incomes have experienced a 20–50 percent drop (or a gain) in their income levels over time. This is taken to be a measure of downward (upward) mobility. Non-directional income mobility examines the absolute share of upward and downward mobility changes to income over time to assess the overall absolute change in income mobility. And the literature on income dispersion looks at changes in the dispersion of absolute income mobility – that is the spread or the standard deviation over time. All studies which have examined these measures of income volatility for the U.S. have been reviewed by Winship (2009).

Winship (2009) finds the changes in income mobility are inconclusive as the empirical evidence cannot conclusively find that individuals have become better off or have become worse off over time. His review of this literature does suggest that absolute income mobility – non-directional, downward and upward income mobility increased during the 1970s. But there is difficulty with trying to reconcile the estimates from various data sets that have been used to measure income mobility over the post 1970s. Some of these findings are outlined below.

Hacker (2006) examines downward income mobility using the PSID and finds the predicted probability of a 20 percent drop in income between two years increased from 4 percent to 11 percent between 1970 and the early 2000s. Similar findings are also reported by Jacobs (2007), Hacker & Jacobs (2008), Gosselin (2008), Dynan *et al.*, (2008), Rose & Winship (2009) and Gosselin & Zimmermen (2008). But research by Orszag (2008) for the Congressional Budget Office (CBO), reports downward income mobility has changed very little over time and Acs *et al.*, (2009) report adults experiencing a 25% drop in their income between successive four month waves over the course of a year rose from 40 percent in 1996 to 46 percent in 2001 and then fell to 36 percent in 2004. Similar rate changes are reported with a 50% and a 75% drop in income over time.

The differences amongst the results may be explained by the use of three different data sets amongst the different papers that are mentioned. Research by Jacobs (2007), Hacker & Jacobs (2008), Rose & Winship (2009), and Gosselin & Zimmerman (2008) have all used the PSID. Whereas papers by Orszag (2008) have used the social security administrative data on continuous work history sample (CWHS); Dahl *et al.*, (2008) and Acs *et al.*, (2009) use SIPP – Survey of Income and Program Participation panels which are maintained by the CBO. The differences between the results may relate to the fact that the administrative data are not subject to recall bias from respondents with survey data such as the PSID. Secondly, administrative data has income for individuals who have very high incomes that may not be present in survey data. However, the disadvantage of using survey data is it does not have data for all individuals – namely individual who are not part of the social security system, the self-employed and unreported income. But Dahl *et al.*, (2008) note this may relate to less than 10 percent of the sample which may make little difference to the overall results which show using administrative data, income mobility has changed very little over time.

Most of the research that has examined upward income mobility agrees there has been a rise in upward income mobility during the 1970s and the 1980s, but it fell during the early 2000s (Gosselin (2008), Dahl *et al*, (2008), Orszag (2008)). But Rose & Winship (2009) find little evidence of any change in upward income mobility over time using the PSID. Similarly, research that has examined non-directional mobility (this refers to the share of upward and downward mobility) from the 1960s to the early 1990s has roughly remained the same (Duncan *et al*, 1993). Other papers show absolute income mobility has changed little over the 1990s to the post 2000 time frame compared to the early 1980s to 1990s (Hertz (2006, 2007); Dahl *et al.*, (2008); Nichols & Zimmerman (2008) and Orszag (2008)).

The review of literature relating to income dispersion is equally inconclusive. Research by Dynan *et al.*, (2008) finds the standard deviation from two-year percent changes in income increased by 30 percent from the 1970s to the early 2000s. But other studies disagree there has not been a continuous increase in income dispersion over time. The empirical research agrees that income volatility did increase over the 1970s, it changed little over the 1980s and rose slightly over the 1990s and post 2000 periods. See Orszag (2008), Nichols & Zimmerman (2008), Gundersen & Ziliak (2008) Blundell *et al.*, (2008) for further details.

The literature for income volatility suggests there has been a rise in income volatility over the last decade based on U.S. data, but little is known as to why the transitory and permanent income trends have increased. There is recent evidence which suggests income instability may result from trade, job displacement and firm-level sales associated with business cycle movements to some extent. But there is no conclusive evidence which shows that the forces associated with globalisation are responsible for this volatility over time. The most plausible explanation from the income volatility literature suggests average income volatility has not increased for all individuals (those with income from the 1st to the 75th percentile); but permanent and transitory income volatility has increased for those with income above the 90th percentile, who may be self-employed and have high tolerances for taking risks. Equally, there is very little evidence that shows these changes to income mobility and income dispersion has made individuals worse off over time.

3.4 Job Displacement Costs

This final section presents the empirical evidence which explores the earnings losses that may result from job displacement and spells of unemployment.

3.4.1 Unemployment Scarring & Wages

The incidents of unemployment can be scarring for future employment spells and for employment earnings between jobs. A worker can become displaced from employment through firm closure or from firm downsizing which can be the result from forces associated with globalisation. Job displacement can lead to a number of adjustment costs; Fallick (1996) notes job displacement disrupts the lives of displaced workers, it diminishes hard-earned expectations and it leads to a waste of human capital. Job displacement can have two potential costs: (1) unemployment scarring and (2) a lower trajectory of earnings following re-employment.

Job displacement can cause unemployment scarring as spells of unemployment can lead to future unemployment spells. An individual's future risk of unemployment may be related to their past history of unemployment (Arulampalam *et al.*, 2001). The cycle of unemployment followed by re-employment into temporary and possibly unstable jobs may occur as job loss leads to a loss of firm-specific human capital. Unemployment can lead to the loss of general work skills and it can prevent the accumulation of human capital. Böheim & Taylor (2002) find post-unemployment jobs in the U.K. have shorter survival times where only one half of jobs last for 12 months and the incidence of unemployment is found to be scarring such that it increases the future incidence of unemployment.

The incidence of unemployment can lead to lower re-employment earnings because the range of jobs to which workers skills are transferable is an important question for displaced workers (Fallick, 1996). The less transferable are the skills towards future jobs, the greater will be the loss of wages upon re-employment if human capital is specific to a particular industry or following the change of industries from job displacement. Indeed, from the perspective of job signalling, the past incidence of unemployment may be interpreted by an employer as low productivity (Phelps, 1972; Lockwood, 1991; Pissarides, 1992; Blanchard & Diamond, 1994). Thus, less secure jobs with low re-employment wages may be offered by an employer to prospective employees to better ascertain the quality of the job match. Many of these jobs may be temporary and may lead to further cycles of unemployment with no pay and re-employment with low pay. Pissarides (1992, 1994) notes that unemployed workers are more likely to enter 'bad' jobs which have low start up costs, low pay, low productivity and have higher rates of job destruction. Alternatively, Arulampalam *et al.,* (2000) suggest the unemployed may experience future incidence of unemployment as unemployed workers lower their reservation wages with the passage of time; they are more willing to accept lower quality jobs which are more likely to be destroyed. But Arulampalam *et al.,* (2001) find that although interruptions to spells of employment with unemployment can lead to a loss of labour income, this may also lead to longer term 'scars' from future unemployment spells and re-employment within unstable jobs. A higher incidence of future unemployment may lead to longer spells of job search but workers may also drift into economic non-activity. This may potentially exacerbate future inequality through poverty and social exclusion.

3.4.1.1 Empirical Evidence

The evidence from unemployment scarring has primarily focused on men, where little is known how unemployment scarring affects the earnings level for women. One possible reason for this lack of research may be because women have career interruptions to start families which may affect the quality of data that is available for analysis. From the literature, Arulampalam *et al.,* (2000) find strong evidence of state dependence effects with respect to previous unemployment incidence for mature men. Roughly 40% of the observed persistence in the unemployment probability was by state dependence. In other work, Arulampalam (2001) reports the wage scars for men re-entering employment following unemployment face a wage penalty of 5.7% during the first year of unemployment.

The first spell of unemployment and the duration of unemployment can be very damaging to wage levels in future employment spells. The impact from unemployment on earnings levels occurs in two parts, which relates to the incidence and the duration. Gregory & Jukes (2001) examine the impact of unemployment scarring on British men for the period 1984-1994. They report the incidence of unemployment merely has a temporary average impact upon earnings following re-employment. This earnings set back is estimated to be 10% on initial engagement, which is largely eroded away after two years of continuous re-employment. The first spell of unemployment causes the most damage on the earnings levels for men; this wage scar is estimated to be 21.5%. The duration of unemployment is found to have the most damaging impact on earnings levels which can have a permanent long lasting impact. The authors' find that a one year spell of unemployment adds a further 10 percentage point penalty upon wages. These costs are most significant for older and high seniority workers.

Youth unemployment can also lower earnings levels in adulthood employment. Gregg (2001) and Gregg & Tominey (2005) examine how the experiences of youth unemployment and repeated spells can impact the earnings level on re-employment in adulthood and the role of education in preventing or promoting the wage recovery. Gregg (2001) found men, who experienced an extra 3 months of unemployment in youth before the age of 23, experienced an extra 2 months out of employment between the ages of 28-33. Gregg & Tominey (2005) also find unemployment experienced in early youth can result with a wage scar with a magnitude of 13-21% by the age of 42. Wages scars of 9-11% can persist for up to 20 years later even without further spells of unemployment. This study also lends further support to the fact that extensive youth unemployment can lead to further incidences of unemployment risk up to the age of 33, which further inhibit wages. The authors' report upgrading education qualifications can enhance earnings recovery, but they are not frequently undertaken[28].

The literature on unemployment scarring predominately features British empirical evidence and some evidence from Europe. This evidence shows that the incidence of unemployment can lead to lower earnings levels post unemployment and where the incidence of unemployment can increase the future occurrences of unemployment spells. The earnings losses that can result from unemployment can cause wage scars that can be big during the first year. And additionally, the length of time spent unemployed can further lower earnings levels post unemployment. Youth unemployment can also have a detrimental effect on the earnings levels of workers in adulthood. Yet, it is unclear from this literature whether the impact on the earnings level and the subsequent wage scars that can result from re-employment following a spell of unemployment have grown over time. This is because most of the findings from the British empirical literature are based on a small number of papers that were published during the first half of the 2000s. I call this literature the first wave of findings. There is currently no new empirical evidence from a second wave of research to determine whether workers who have lost their jobs over recent time, have experienced wage scars that have increased in magnitude over time compared to earlier estimates.

There is no empirical evidence from the U.S. literature that has examined the impact of unemployment scarring on wage and earnings levels. Much of the research has tended to focus on the long-term earnings losses that can result from job displacement. The job loss literature has already shown the incidence of job loss has not increased over time. But the

[28] Evidence from the European evidence shows the impact of unemployment scarring is not limited to experienced labour or men; Gartell (2009) finds a wage scar of 30% for graduates who registered as being unemployed five years after graduation compared to those graduates who did not register as being unemployed upon graduation for Sweden. Lupi & Ordine (2002) find the impact of unemployment scarring on wages was greater for Southern and more developed regions of Italy compared to the Northern and less developed regions. Other research also shows that unemployment insurance benefits can mitigate the income losses that can be caused by unemployment by encouraging workers to seek and search for better jobs that are not unstable (Gangl, 2004; Mooi-Reçi, 2009). Additionally, Mooi-Reçi (2009) finds unemployment scarring was more persistent amongst women for the Netherlands.

question is whether the earnings losses from job displacement have increased over time to signify that workers have become worse off. The forth coming section tries to establish this fact.

3.4.2 The Earnings Losses from Job Displacement

The earnings losses for displaced workers are well established; for earlier reviews see Fallick (1996) and Kletzer (1998). From a more recent review, Couch & Placzek (2010) re-examine the U.S. literature on the earnings losses from job displacement and note that the estimates from a number of high quality studies agree job displacement can lead to sustained income losses for many years following job displacement. Yet they note the magnitude of the earnings losses from the empirical research can vary by the data sets used for analysis, whether a comparison group is employed in the analysis, whether demographic groups are examined, or whether comparisons are made of workers switching industries to find post-displacement re-employment, among other factors. Table 3.4 has been taken from Couch & Placzek (2010); this table summarises the main findings from papers which have used a range of different data sets from the U.S. literature. A few of these papers are discussed below along with other papers not featured within table 3.4.

Studies which have used the DWS agree the impact of job loss on earnings levels can be substantial, which may typically reflect the loss of firm specific human capital from the employment relationship. This impact is substantial for older and high seniority workers. Topel (1990) finds the earnings level for blue collar workers fell by 40 percent in the short run, caused by a fall in labour supply[29]. Topel (1990) additionally finds the loss of labour income in the first year amounts to 17 percent. And four years after job displacement, the earnings levels are still 16 percent lower, and where the long run costs can have substantial effects on life-time wealth among older and experienced workers. Farber (1993, 1995) finds the costs of

[29] This is a fall in the number of hours that are worked and because of unemployment.

job displacement can cause post displacement income to be 11%-12% lower after 1-3 years following job displacement. Research by Carrington (1993) finds the earnings losses can be substantial following job loss if workers switch industries. Similar findings are also reported by Huff Stevens (1997) and Couch *et al.*, (2009). The impact is less if workers are re-employed within the same industrial sector (Neal, 1995).

Figure 3.6 plots the earnings losses reported by table 3.4. For each data set, the graph shows the period of coverage used by each study and the percentage of long-term earnings losses that are reported following job displacement. This graph is an attempt by this chapter to reconcile whether the magnitude of the earnings losses following job displacement, have increased or remained unchanged over time from the use of different data sets reported by the literature. This figure shows the reported earnings losses from studies that have used the DWS can amount to 8-16% following job displacement after 1-5 years from data covering the period 1979 to 1998.

Studies that have used the PSID report earnings losses that are of a similar magnitude to papers that have used the DWS. Ruhm (1991) finds earnings levels were 14-18 percent lower in the first year after job loss and workers who were out of work an additional week continued to earn 10-13% less than non-displaced workers 4 years after job displacement. Huff Stevens (1997) finds the effects of job displacement can be quite persistent resulting with earnings and wage levels being approximately 9% below their expected levels more than six years after job loss because of additional job loss in years following the initial incidence of job displacement. The costs can also be substantial in the short run, where earnings levels can be 30 percent lower in the first year. If workers avoid additional spells of job displacement, the earnings losses are only 1-4% lower six years after job loss. Overall, figure 3.6 shows that the earnings losses following job loss according to the PSID data covering the period 1968-1986 can amount to 10-13% after 4-6 years following job displacement; these estimates are similar in magnitude to the DWS estimates.

Couch (1998), Chan & Huff Stevens (1999) and Chan & Huff Stevens (2004) examine the effects of job displacement for older workers using the Health and Retirement Surveys (HRS). They find the earnings losses can be larger on average for older workers than for prime-aged workers reported from the DWS and PSID. The earnings levels can be 19-34 percent lower in the first year and they can be 23-47 percent lower over six years after job displacement. Figure 3.6 shows that these earnings losses are above average compared to the earnings losses reported by the DWS covering a similar period of data analysis. However, one of the reasons why these estimates are above average compared to the PSID and the DWS is because this survey relates to older individuals whom may have had near life-time jobs at some stage during their employment.

Using the National Longitudinal Survey for Youth (NLSY), Kletzer & Fairlie (2003) find the earnings losses for young workers are short term. The short run fall in annual earnings 5 years after job displacement were found to be between 8-13% for men and 7-12% for women. But the earnings losses of younger displaced workers in the long-term can be similar to those with greater labour market experience (Couch & Placzek, 2010). These estimates also show from figure 3.6, the earnings losses are comparable and consistent in magnitude with the PSID and the DWS.

Figure 3.6 and table 3.4 show the earnings losses following job displacement from the DWS, PSID and the NLSY have similar magnitudes which lay in the region of 7-16% following job displacement after 1-6 years from 1968 to 1998. They have not increased in magnitude over time. These estimates suggest that workers who became displaced during the 1990s were no more worse off compared to workers who had become displaced during the 1970s or 1980s according to the estimates from these three data sets.

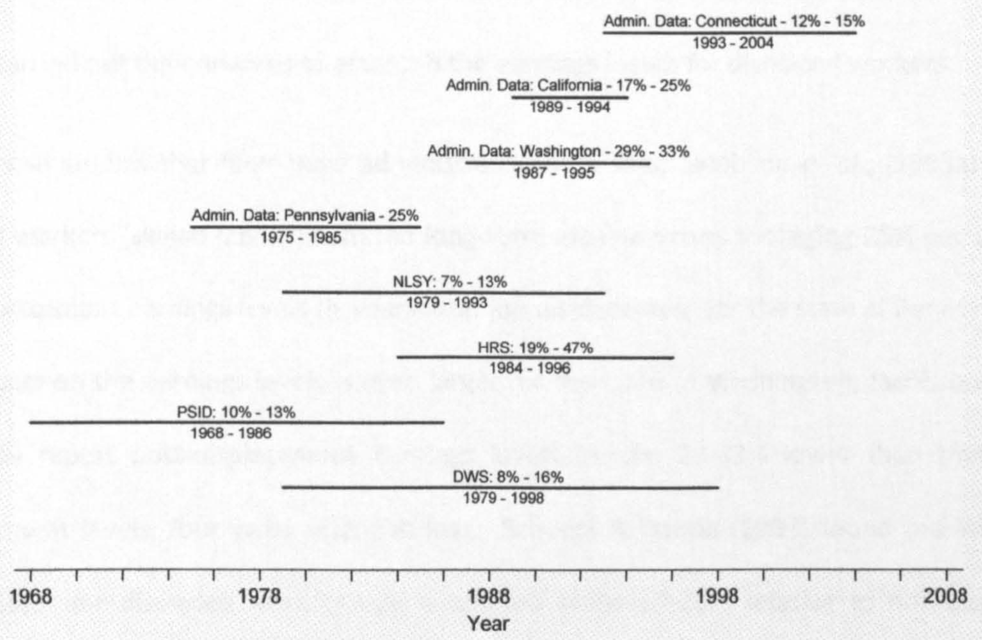
Table 3.4: Studies of Job Displacement, Mass Layoffs and Earnings Losses

	Sample description				Percent earnings losses		Larger percent losses		
Data source	Years	Age	Workers	Comparisons	First year	Last (yrs)	Female	Age	Switch
Panel A. Displaced worker surveys									
Topel (1990)	81 to 86	20 to 60	Displaced	No	17	16 (4)		+	+
Farber (1993)	82 to 91	20 to 64	Displaced	No		8 (1–2)	—	+	
			Displaced	Yes		11 (1–2)			
Farber (1997)	81 to 95	20 to 64	Displaced	No		9 (1–3)	—	+	
			Displaced	Yes		12 (1–3)			
Carrington (1993)	79 to 98	21 to 63	Displaced	No		12 (1–5)		+	+
Neal (1995)	79 to 90	20 to 61	Displaced	No					+
Panel B. PSID									
Ruhm (1991)	69 to 82	21 to 65	Displaced	Yes	14–18	10–13 (4)			
Stevens (1997)	68 to 86	HH heads	Separators	Yes	28–31	7–11 (6)			+
			Displaced	Yes	30	11–12 (6)			
Panel C. HRS									
Couch (1998)	85 to 92	50 to 60	Displaced	No		30–39 (1)	+	+	
Chan and Stevens (1999)	84 to 96	over 49	Displaced	No		19 (1)			
				Yes		24 (1)			
Chan and Stevens (2004)	92 to 98	over 49	Displaced	Yes	48–50	23–47 (6+)	—		
Panel D. NLSY									
Fairlie and Kletzer (2003)	79 to 93	14 to 36	Displaced	Yes	16–19 (male)	8–13 (5)	—		
					33 (female)	7–12 (5)			
Panel E. Administrative records									
Pennsylvania:									
Jacobson, LaLonde, Sullivan (1993a)	75 to 85	20 to 50	M. Layoff	Yes	40	25 (6)	—	+	+
			Separators	Yes	26	0 (6)			
Jacobson, LaLonde, Sullivan (1993b)	75 to 85	20 to 50	UI	Yes	66	24 (6)			
Washington:									
Jacobson, LaLonde, Sullivan (2005a)	87 to 95	22 to 60	UI	No	43–66	29 to 33 (4)			
Connecticut:									
	93 to 04	20 to 50	M. Layoff	Yes	32–33	12 to 15 (6)			
			M. Layoff	No	27	0 (6)			
			Separators	Yes	32–33	7 to 9 (6)	+	+	+
			UI	Yes	49	32 (6)			
			UI	No	47	22 (6)			

Source: This is table 1 from Couch & Placzek (2010). ***Notes:*** '+' denotes a larger impact and '-' an equivocal result. UI indicates the data sample was used to calculate earnings losses from records that are kept by states to calculate unemployment insurance benefits if a worker loses employment.

However, many of the studies that have used administrative data sets to examine the earnings losses for workers from specific states in the U.S. show the estimated earnings losses can be sensitive to the economic cycle and whether each of the states were heavily industrialised and had a disproportionate number of job losses from the manufacturing sector. The type of job displacement (a mass-layoff or a plant closure) can also affect the magnitude of earnings losses in the long run. For example, Gibbons & Katz (1991) develop an asymmetric information model about layoffs. This model suggests that workers displaced from employment because of mass-layoffs experience larger post-displacement earnings losses compared to workers displaced from employment because of plant-closure. This is because when firms are able to choose which workers they lay-off, they tend to lay-off workers who are less productive and have low ability. But with plant closures, all workers are laid-off regardless of the productivity or ability levels. As lay-off rates tend to be greater during a recession, workers who become displaced from mass-layoffs tend to have lower productivity and therefore their earnings losses should be larger in poorer economic conditions than during favourable economic conditions (Couch *et al.*, 2009).

Figure 3.6: Comparison of Earnings Losses from U.S. Studies



Source: Graph compiled by the author. The information used to compile this graph was taken from table 3.4.

To reconcile the findings from the existing literature that have used administrative data sets, figure 3.1A located in appendix 3 shows a rising national civilian unemployment rate during the late 1970s to the mid 1980s. When Jacobson *et al.*, (1993a, b; 2005a) carried out their analysis, the average unemployment rate for the state of Pennsylvania was 8.6% for the period 1976-1985 and for the state of Washington, the average unemployment rate was 6.4% for the period 1987-1995. And during the late 1980s to the early 1990s there was a falling national unemployment rate when Schoeni & Dardia (1996) carried out their analysis for the state of California, although the unemployment rate was high during the early stages of the 1990s. The average unemployment rate for the state of California was 7.7% for the period 1989-1994. Additionally, figure 3.2A from appendix 4 compares the unemployment rates across each of these states with the national average civilian rate in the U.S. This graph shows for the states of Washington and Pennsylvania, both of these states had higher unemployment rates compared to the national average for the civilian work force during the mid 1970s and late 1980s. And the state of California had a higher unemployment rate during the early 1990s compared to the national average. These figures show there were unfavourable economic conditions during the time when Jacobson *et al.*, (1993a, b; 2005a) and Schoeni & Dardia (1996) carried out their analysis to establish the earnings losses for displaced workers.

From these studies that have used administrative data sets, Jacobson *et al.*, (1993a) found tenured workers (skilled labour) suffered long-term income losses averaging 25% per year of pre-displacement earnings levels six years after job displacement for the state of Pennsylvania. The impact on the earnings levels is even larger for the state of Washington; Jacobson *et al.*, (2005a,b) report post-displacement earnings levels can be 29-33% lower than their pre-displacement levels, four years after job loss. Schoeni & Dardia (1996) found the long run wage losses for displaced workers was estimated to be 17-25% relative to non-displaced workers, 4 years after job displacement for the state of California for the period 1989 to 1994 [30,31].

The earnings losses from the states of Pennsylvania (Jacobson *et al.*,1993a,b), Washington (Jacobson *et al.*, 2005a) and California (Schoeni & Dardia, 1996) appear to be very large in the

[30] Schoeni & Dardia (1996) also find the short run decline in income amounted to 60%. This was attributed to reductions in weeks and hours of work.

[31] Research by Morissette *et al.*, (2007) find income losses following job loss can be big for Canada, consistent with U.S. findings. They find high seniority displaced male workers experienced long-term earnings losses that ranged between 18%-35% of their pre-displacement earnings. For females, they find the income losses range between 25% and 35%.

long-term based on data from the early 1980s and 1990s. These periods had higher unemployment rates compared to the national average during the time frame these papers' carried out their analysis, which can be classed as unfavourable economic conditions. Couch & Plazek (2010) argue that the *'generalisability'* of these results is called into question as they cannot be generalised to all periods of economic conditions. This point in illustrated by research carried out by Wachter *et al.*, (2009) who find the long-term earnings losses were smaller during the latter period of the 1990s. Their research used administrative wage data for the state of California that were matched with the DWS for the period 1994 to 2000 where economic conditions were favourable[32]. Their results show the longer-term earnings losses following job displacement were 12%-16% lower than pre-displacement income levels. These estimates are in line with papers which have used the PSID, DWS and the NLSY.

Additionally, Couch *et al.*, (2009) examine the earnings losses for displaced workers from mass-layoffs at different points along the business cycle. They use administrative data for the state of Connecticut spanning the period 1993 to 2004. They find the long-term earnings losses for workers displaced from employment because of a mass layoff during a recessionary period were 1.7 and 3.9 times larger than for those workers observed in a period of sustained economic growth. To quantify these figures, if a worker losses their job in a mass layoff in an economic expansion, their earnings losses in the sixth year after job displacement amount to 7.2 percent. But if the job loss occurs during poor economic conditions, the earnings losses equate to 18.2 percent. Regardless of gender, age and firm size, their results show workers experience larger long-term earnings losses when a mass layoff event occurs during poor economic conditions.

The second issue relating to whether the results from administrative studies can be generalised over time relates to the fact that many states have increasingly seen the

[32] Figure 3.2A from appendix 4 shows a falling unemployment rate for the state of California over the 1994 to 2000 period. The average unemployment rate was 6.6% for the period 1994-2000.

expansion of employment in the service sector since the 1970s. These changes to the composition of employment may influence the estimated earnings losses in the U.S. over time (Couch & Placzek, 2010)[33]. Previous research reports the long-term earnings losses are significantly less for workers displaced from the services sector than from the manufacturing sector (Carrington & Zaman 1994; Jacobson *et al.*, 1993a).

Couch & Placzek (2010) address these issues and examine the earnings losses from job displacement for the state of Connecticut from 1993 to 2004. Figure 3.2A from appendix 4 shows the state of Connecticut has had a lower unemployment rate compared to the national average over time, where the average unemployment rate for Connecticut was 4.4% for the period 1993 to 2004. The state of Connecticut's unemployment rate has also been lower over time compared to the states of Washington, California and Pennsylvania. And the unemployment trends from figure 3.2A also signify that over this period the economic conditions were much more favourable and more robust for the state of Connecticut compared to the other three states.

Their analysis reports the estimated earnings losses were half the magnitude of the Pennsylvania study by Jacobson *et al.*, (1993a). They found initial earnings losses resulting from mass-layoffs ranged from 32-33 percent in the first year of job displacement. The earnings losses from mass layoff remained 12-15 percent lower six years after job displacement. They also found the earnings losses were substantial for women, for older and more experienced workers, and these estimates are in line with findings from the DWS, PSID and NLSY. The difference between the reported magnitudes of earnings losses between the Connecticut study and the Pennsylvania study may relate to the fact that Connecticut has a more robust economy compared to Pennsylvania which has a higher unemployment rate

[33] For Jacobson *et al.*, (1993a) – table 1, panel A from their paper shows the total number of separators from the manufacturing sector was twice as big compared to the non-manufacturing sector in Pennsylvania. From Jacobson *et al.*, (2005a) – the state of Washington represents a large number of individuals were employed within manufacturing sectors. Schoeni & Dardia (1996) examine the earnings losses of displaced workers who worked for the durable goods manufacturing sector and were affected by recent downsizing.

compared to Connecticut. Secondly, the Connecticut study analysed the earnings losses during favourable economic conditions compared to the Pennsylvania study which analysed the losses during unfavourable economic conditions. This could account for the difference in the magnitudes from each of the papers. Another possible explanation for the bigger estimated magnitude from the Pennsylvania study may simply reflect the skill mismatch amongst workers that were trying to regain employment following job displacement (Couch & Placzek, 2010).

To sum up, the earnings losses following job displacement after one year can be substantial. But reconciling the earnings losses from studies which have used administrative data sets suggest the magnitude of the earnings losses are sensitive to economic conditions, the type of job displacement from employment and to the changes in the composition of the labour force over time. When these factors are taken into consideration, the results from the literature show that the earnings losses can be substantial during unfavourable economic conditions and smaller over favourable economic conditions. Additionally, the earnings losses are larger for workers who become displaced from employment because of a mass layoff event compared to plant closure events. On the whole, the magnitude of the earnings losses following job displacement over the long-term has not become bigger over time. The magnitude of the earnings losses suffered by workers who became displaced over the last decade has been similar to the survey data estimates for those workers who became displaced over the 1970s, 1980s and the 1990s.

From other research, the estimated wage losses from job displacement are consistent with the literature that has quantified the level of earnings losses over time. Polsky (1999) finds the odds of receiving a large wage cut rose from 9% for the 1976 to 1981 period to 17% for the 1986 to 1991 period. Farber (2005) found full-time job losers with new full-time jobs earned 13% less on average on their new jobs than on their lost jobs. Full-time job losers who find new full-time jobs earned up to 17% less on average on their new jobs than they would have had, had they not been displaced. And Abbring *et al.*, (2002) find no evidence of a decline in mean wages for workers in the U.S. following job displacement using the DWS. They suggest that workers who become displaced may have tried to seek immediate employment to avoid earnings losses and therefore their results may reflect slower wage growth over time.

Moving on to the job displacement literature from the U.K. and Europe, this literature is not as well established as the U.S. Yet the research from the U.K. and Europe suggests the size of the earnings losses following job displacement can be large and small.

The U.K. evidence suggests the earnings losses are quite smaller compared to the U.S. Gregg & Wadsworth (2000) find the average hourly wage gap between entry and continuing jobs rose by 15 percentage points from 1980 to 1990 and by 8 percentage points between 1994 and 1997. This evidence show the wage losses were higher during the 1980-1990 period where the unemployment rate was higher and there were unfavourable economic conditions compared to the 1994-1997 period, where the unemployment rate was lower and economic conditions were favourable (see figure 3.2 for details for the U.K. unemployment rate). Booth *et al.*, (2002) note that labour market flexibility comes at a cost, as many temporary job holder have lower levels of job satisfaction, with less job-related training and lower wage levels. However, temporary jobs are found to be stepping stones towards permanent jobs. Nickell *et al.*, (2002) find the real wage losses resulting from job loss for men rose by around 40% from the early 1980s to the early 1990s. The wage losses were found to increase for older workers and for the higher skill group – consistent with the findings reported by the U.S. literature.

Borland *et al.*, (2002) found there were large wage penalties experienced by displaced workers with longer seniority and for those workers who were out of work for 12 months or more using the British Household Panel Survey (BHPS) for the period 1991-1996. Comparing income before and after job loss, they estimate the weekly wage losses for re-employed workers were approximately 14%. The earnings losses for full time workers was 10%. These wage losses are quite similar to the reported figures by the U.S. studies during favourable economic conditions. But longer-term estimates are not available because of a small sample in comparison to the administrative data sets from the U.S. (Hijzen *et al.*, 2010).

Finally, Hijzen *et al.*, (2010) examine the earnings losses for displaced workers using the New Earnings Survey for the period 1994 to 2003 for the U.K. This period of analysis relates to favourable economic conditions. They find the income losses five years after job displacement were in the range of 18%-35% per year for workers displaced through firm closure, and the income losses were in the range of 14%-25% for workers displaced through mass layoff. These results contrast with the findings from the U.S. literature which finds the earnings losses associated with mass-layoffs are much larger compared to displacement associated with firm closure events. But this evidence is consistent with the evidence from Europe. Their estimates are associated with periods of non-employment. The authors' note the extent of income loss depends on how long it takes displaced workers to re-enter employment. Other notable results from their paper show that older workers, more tenured workers, men, skilled labour and workers employed by manufacturing sectors have higher earnings losses associated with job displacement[34].

For Europe, the empirical evidence suggests the costs from job displacement can be big and small. For the latter evidence, Huttunen (2005) finds the earnings levels of displaced workers in 1991 were on average 2.5% lower in the first year of displacement and only 1-2% lower on average seven years after job displacement for Norway. Appelqvist (2007) reports re-

[34] Older workers lose 39% of their pre-displacement earnings per year compared to 32% for younger workers. More tenured workers lose 38% of their pre-displacement earnings per year compared to less tenured workers (13%). Male workers lose 39% of their pre-displacement earnings per year compared to only 29% for females. Making a distinction between the types of industry workers are displaced from; workers lose 39% of their pre-displacement earnings per year if displaced from the manufacturing sector compared to 33% for workers displaced from service orientated industries – consistent with findings from the U.S. And skilled labour loses 36% of their pre-displacement earnings per year compared to 31% for less skilled labour.

employed workers displaced in 1992 suffered an 8-9½% fall in monthly wages after job displacement for Finland. In comparison, workers who became displaced in 1997, their monthly re-employment wages were unaffected. Appelqvist (2007) suggests the impact of job displacement on earnings levels for Europe may depend on the sensitivity to subsequent macroeconomic shocks.

For the former evidence, Bender *et al.*, (1999) find evidence of large wage losses for Germany and France. Workers who remained unemployed more than a year after job loss earned 5% less in France and around 13-20% less in Germany upon re-employment. Couch (2001) finds annual earnings declined by 13.5% during the first year of job displacement, with post-displacement earnings 6.5% lower than pre-displacement earnings for German workers. Similarly, Carneiro & Portugal (2003) found the average hourly earnings for men and women to be 11% and 9% below the expected counter factual level had displacement not occurred in Portugal. The average hourly earnings for workers, who had experienced non-employment, experienced an additional average hourly wage penalty of 4-6 percentage points. The earnings differentials between displaced and non-displaced workers were found to be largely associated with the loss of job tenure within the firm.

In summary, the earnings losses from job displacement are somewhat smaller in magnitude from the U.K research compared to the U.S. The U.K. research suggests the earnings losses can be big and small[35]. However, it is unclear whether the magnitude of the earnings losses have grown or remained unchanged over time. This is because it is difficult to reconcile the estimates from survey data that have explored wage changes at hourly and weekly intervals compared to estimates by Hijzen *et al.*, (2010) that have used an administrative data set to examine the earnings losses post 1990 at annual intervals.

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[35] The losses are big in the sense that the earnings losses from plant closures are larger during a favourable economic climate. They are small in the sense that the earnings losses in the first year are somewhat smaller.

3.5 Conclusion

This chapter examined whether there is empirical evidence to support claims there has been a rise in labour market insecurity over time. The empirical evidence from three components of labour market security comprised of (a) job security), (b) income volatility within jobs (job stability) and (c) the earnings losses between jobs resulting from job displacement were reviewed by this chapter. From this literature review, I find there is little evidence to suggest there has been a rise in labour market insecurity for the U.K. or for the U.S. over the last four decades. Further details regarding this conclusion are provided below.

From the first component of labour market security – job security, this review found there has been a secular decline in job security from the 1970s to the 1990s for the U.K. The empirical evidence shows *à la* Gregg & Wadsworth (2002) there has been a secular fall in medium (job tenure greater than or equal to 5 years) and long term (job tenure greater than or equal to 10 years) job tenure shares for men and for women with no children. But this fall has been small over time. And recent evidence from Faggio *et al.*, (2011) note that long term (short term) job tenure has continued to fall (risen) for men (women with young children) over the 1985-2009 time frame. From the North American literature, there was no evidence of a decline in job retention rates over the period of the 1970s to the latter 1990s. Recent evidence by Davis (2008) also shows there has been a decline in job loss rates over the last decade compared to the 1970s, 1980s or the 1990s; a decline in state assistance for displaced workers and a decline in the unemployment inflow rates. Additionally, research by Farber (2001, 2005 & 2009) shows job loss rates have not increased over the last four decades. The empirical evidence suggests there are stable job that can be thought of as life-time jobs that have not become shorter over time.

The second component of labour market security explored income volatility within jobs over time. This component of labour market security examined three strands of empirical research based on U.S. findings. These three strands of research related to (1) changes in the permanent and transitory variances of individual income levels over time; (2) changes in income mobility over time and (c) changes in the dispersion of income levels over time. The empirical evidence from the first strand showed there has been a rise in the permanent and transitory variances of individual level income from the 1970s to 1990, with little change of over the 1990s with a rise once again after 1998 over the most recent decade. The overall change in income volatility suggests that permanent and transitory variances of income have increased over time. But this rise cannot be interpreted as a rise in average volatility for the vast majority of individuals. When the average income volatility accounts for individual heterogeneity, the rise in the average volatility is driven by the changes in the income levels from those with the most volatile incomes at the right tail of the income distribution. These individuals are most likely to be self-employed and they may have high tolerances to take risks. They have experienced greater changes to their income levels than compared to the average population. There is also little conclusive empirical evidence which shows that the rise in income volatility is associated with forces with globalisation. Further empirical research is required to provide clarity. The evidence from the second and third strands of research show the changes to income mobility and income dispersion are not conclusive. This empirical research disagrees as to whether they have increased or declined over time.

Finally to the last component, there are substantial costs associated with unemployment scarring in the event of job loss for the U.K., where the re-employment wages can be substantially lower than the pre-employment wage levels. Unemployed workers are more likely to be re-employed within jobs that are shorter in duration and very few jobs after job loss last for up to 12 months. The post-displacement earnings losses can be substantial in the long-run following job displacement, where the earnings losses can be greater from plant closures than from mass-layoff events for the U.K. The opposite conclusion is reached from the U.S. literature. The evidence from the U.K. suggests the magnitude of the earnings losses depends on the length of time spent out of employment. But as this literature is in its infancy and is not as well established as the U.S. evidence, it is unclear whether the earnings losses from job displacement and from unemployment scarring have increased over time to signify that workers have become worse off over time.

The evidence from the U.S. literature shows the post job displacement income losses can be substantial in the long-run and the short-run. They can be substantial during recessionary periods of the business cycle and somewhat less during favourable economic conditions. The earnings losses are found to be larger for workers displaced during mass-layoff events than from plant closures. The earnings losses can be substantial for older and high-seniority workers. But this literature does show that the magnitude of the earnings losses have not become bigger over the last four decades.

To sum up, the empirical evidence signifies that life time jobs may not be getting shorter for U.S. or for U.K. workers. Income volatility has grown for risk tolerant individuals over the last 10 years but has remained unchanged on average for workers who do not have highly volatile income levels in the U.S. And the costs of job loss can be substantial in the short-run and long-run that are the result from mass-layoffs. The earnings losses can be larger during recessionary conditions than during favourable economic conditions. This literature suggests that the magnitude of the earnings losses following job displacement ranges between 8-16%, 4-6 years after job loss; this magnitude has not increased over the last four decades and thus workers have not become worse off over time. Thus, my conclusion from this review is there is no evidence that signifies there has been a rise in labour market insecurity for the U.S or for the U.K. over the last four decades.

3.6 Appendices

Appendix 1

Data Sources

List of data sources used to create figure 3.2 were obtained from the Office for National Statistics (ONS) from the U.K. The names of data series that have been used are as follows:

- Output per Worker: Series A4YN; Output per worker for the whole economy; % change per annum, seasonally adjusted.
- GDP Growth Rates: Series IHYN; GDP quarter on quarter growth, seasonally adjusted.
- Redundancy Rate: Series BEIR; LFS ILO Redundancy rate, seasonally adjusted.
- Unemployment Rate: Series MGSX; LFS Unemployment rate for U.K., aged 16 and over, seasonally adjusted.
- Employment Rate: Series MGSR; LFS Employment rate for U.K., aged 16 and over, seasonally adjusted.
- Retail Price Index: Series CZBH; Quarterly index of numbers; Percentage change in RPI over 12 months.

Appendix 2

Data Sources

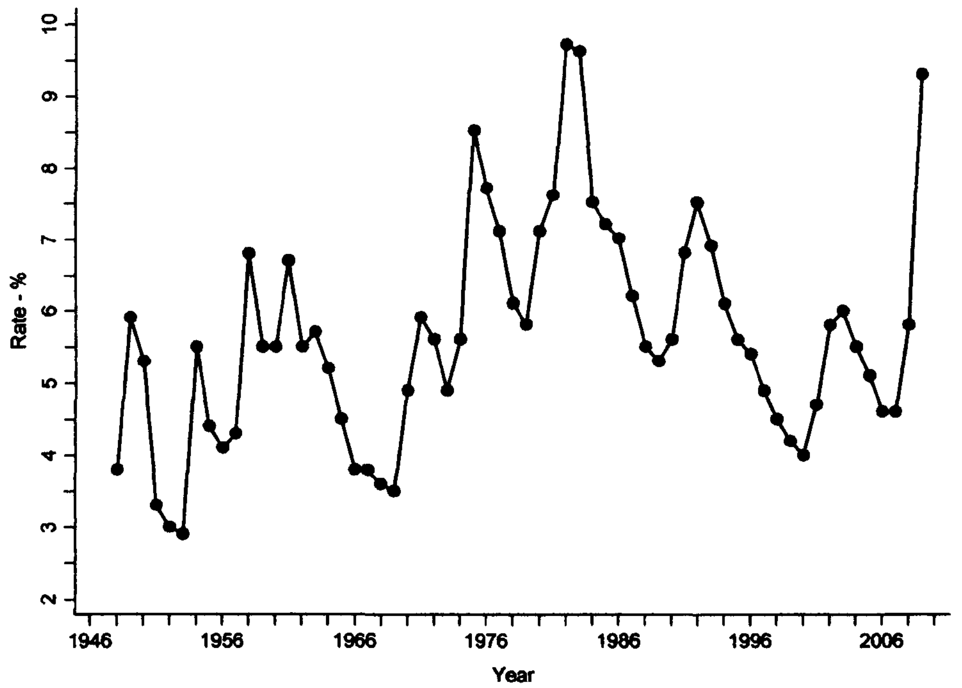
This appendix provides the data source used to construct figure 3.5. The data for this graph was obtained from the Office for National Statistics (ONS) from the U.K. The name of the data series used is the following:

- Total Claimant Count; NSA in thousands. Data series name: BCJA.

Appendix 3

U.S. Unemployment Trends

Figure 3.1A: U.S. National Average Unemployment Rate for Civilian Labour Force



Source: Figure compiled by the author. Data obtained from the Bureau of Labor Statistics. The national average unemployment rate for the civilian labour force consists of persons aged 16 years and over.

For the periods of recession noted by the U.S. economy over time in relation to figure 3.1A relate to:

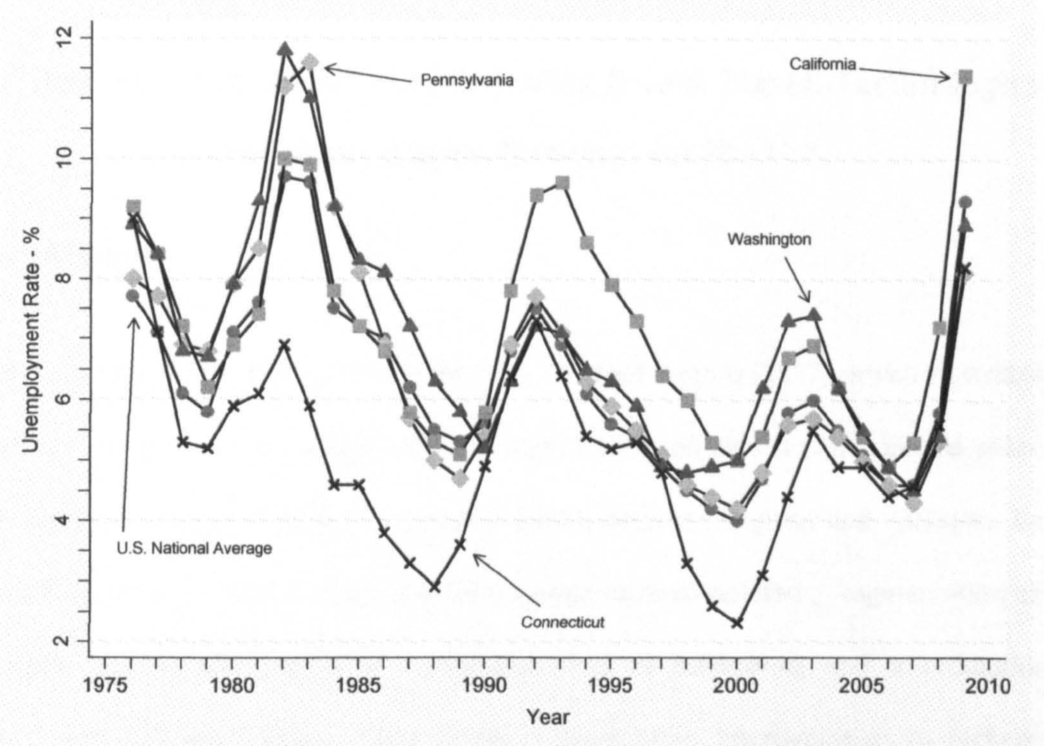
1948- 1949	1953-1954	1957-1958	1960-1961	1969-1970	1973-1975
1980	1981-1982	1990-1991	2001	2007-2009 (estimate)	

The NBER provides details of the peak to trough recession dates. These are available from http://www.nber.org/cycles.html.

Appendix 4

U.S. Unemployment Trends for California, Connecticut, Pennsylvania and Washington

Figure 3.2A: U.S. National Average & State Unemployment Rate for Civilian Labour Force



Source: Figure compiled by the author. Data was obtained from the Bureau of Labor Statistics. The national average unemployment rate for the civilian labour force consists of persons aged 16 years and over. The unemployment rate for each of the states relates to state wide unemployment rates.

4

An Analysis of the Effects of Offshoring & Task Biased-Technological Change on Wages: Evidence for the U.K.

4.1 Introduction

Grossman & Rossi-Hansberg (2007) cite the work of David Ricardo (1817), which illustrates the principle of comparative advantage. This principle illustrated almost two hundred years ago the exchange of one good (wine) for another (cloth) between England and Portugal. Goods were completed at a single location and were traded once completed. Fragmentation of the production process was expensive during that time as monitoring and co-ordination of workers' activities were costly. Two hundred years later, improvements in technology, telecommunications and transportation have reduced co-ordination costs and they have allowed the production process and the specialisation of job tasks to become fragmented. Domestic firms from developed countries have taken advantage of this opportunity to offshore production stages to developing countries. Traditionally, the purchase of intermediate inputs took place in domestic markets. But with the fragmentation of the production process, offshoring and outsourcing allow domestic firms to purchase inputs from foreign markets and more importantly to have access to wider markets around the world, not just for inputs but also for labour[1]. Offshoring can affect the rate of job creation and job

[1] A recent example of fragmentation of the production to take place in the U.K. relates to a wave of strikes that took place in February 2009 at the Lindsey Oil Refinery located in North Lincolnshire. The dispute centred upon a contract to extend the diesel refining capacity at the refinery owned by oil giant Total. The contract was awarded to a Californian-based engineering group Jacobs in June 2006 for completion in 2009. Jacobs subcontracted to an Italian firm, IREM after a tender process. The terms of the contract between Jacobs and IREM stated IREM would be using its existing Italian and Portuguese workforce for the job.

destruction through structural shifts in labour demand that may result from changes in tastes and technology (Mortensen & Pissarides, 1994). Offshoring allows firms the flexibility to allocate their work activities more efficiently that maximise their profits (Jabbour, 2010). This process enables firms to offshore job tasks that they lack comparative advantage and expertise to produce and maintain and inshore those job tasks they have a comparative advantage and expertise to produce.

The consequences of offshoring have received much attention from the media. Amiti & Wei (2005) and Mankiw & Swagel (2006a,b) show the number of press references to outsourcing steadily increased throughout the 1990s and the early 2000 period for the U.S. and the U.K. Responses for the U.S. heightened during the 2004 U.S. presidential election, where offshoring became synonymous with the public debate on job loss which was a hotly debated issue [see Mankiw & Swagel (2006a,b) for further details on the political and economic issues on offshoring and Bhagwati *et al.*, (2004) and Baldwin (2006) for a summary of the offshoring debate].

The attention from the media references reflects the anxiety felt by many workers. That is, offshoring parts of the production process to developing countries can lead to adjustment costs, particularly for less skilled workers. There is also the fear that offshoring raises labour market insecurity because domestic labour may be substituted by foreign labour. A rise in offshoring to foreign labour markets can raise the rate of job destruction, assuming this is greater than the rate of job creation. The fall in demand for domestic labour can exert downward pressure on wage levels. This downward pressure can also culminate from the threat of offshoring made by firms during wage negotiations. Thus, offshoring can lower job security and job stability and it can raise job reallocation rates. With a rise in the number of

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British workers and unions were unhappy about this aspect of the contract as they felt key infrastructure projects at power stations and oil refineries were in a long line of key projects that were being awarded to foreign workers. EU law states nationals of member states are automatically allowed to live and work in Britain. This strike lead to wave of sympathy strikes across the U.K. More details of this story can be found at the following links: http://news.bbc.co.uk/1/hi/business/7860622.stm; and http://news.bbc.co.uk/1/hi/uk_politics/7866614.stm.

jobs that may be at risk from being offshored, many workers may become unemployed. The post-displacement costs of unemployment on future employment and income can potentially be substantial in the long run. But the empirical evidence does show these costs are somewhat less for the U.K. than they are for the U.S. Chapter 3 from this thesis provided a review of this literature. This review found that although the magnitude of the earnings losses associated with job displacement can be substantial during recessionary economic conditions and less during favourable economic conditions, this magnitude has not increased over time. See chapter 3 for further details of this review.

Traditionally, offshoring has reflected the transfer of assembly jobs completed by low skilled labour employed within the manufacturing industries. The prime motivation for firms has been to lower the costs of production by substituting domestic workers for cheaper foreign workers. This offshoring strategy is possible because domestic firms from developed countries may not have a comparative advantage in the production of goods that are labour intensive compared to developing countries (Deardorff, 2005). The scope for savings is greater with transferring low-skill production stages because less-skilled labour in developed countries are scarce and more expensive compared to developing countries which have an abundance of labour but less capital (Crinò, 2009b).

The international transaction of services may also be inputs in the production process and they are a recent innovation that has taken place over the last 20 years. Service offshoring has often been equated to call centres in the U.K. where jobs have been offshored to India. The most recent fears about job loss reflect the loss of high-skilled white collar jobs from the service sector. Many high-skilled jobs were previously considered impervious to international competition (Amiti & Wei, 2005). But more recently, highly skilled jobs such as radiologists, architects and even accountants are occupations that are at risk of being offshored with the improvements in telecommunications and technology. Many of the services provided by these occupations can be delivered remotely via the internet as some of these occupations do not require face-to-face contact with the customer (Blinder, 2007). More recently for the U.K., in July 2009 the British Council announced a number of jobs in IT and finance areas would be cut and replaced by local staff in India where the civil service hoped to locate jobs. Many workers had felt civil service jobs would be unaffected as these were jobs in Government that may present potential national security risks if performed by other organisations other than British nationals[2].

The potential number of jobs that could be destroyed because of offshoring has been well documented by the literature. Published reports by the OECD (2007a) and the National Academy of Public Administration (thereafter referred to as NAPA) (2006) summarise details of papers which provide upper and lower estimates for the total number of jobs that could be destroyed within the U.S. economy and worldwide. The reported numbers for potential job losses from service offshoring vary widely amongst the reported papers [see OECD (2007a) and the NAPA (2006) for further details]. Blinder (2006, 2007) refers to service offshoring as the third industrial revolution and estimated approximately 28-42 million jobs were potentially at risk from being offshored; for the manufacturing sector, Blinder estimates roughly 14 million jobs could potentially be lost. That represents 20%-30% of total U.S. employment in 2004. Whereas research by Jensen & Kletzer (2005), Garner (2004), van Welsum (2004) and Bardhan & Kroll (2003) estimated between 9 and 23 million jobs could be offshored from the U.S. McKinsey Global Institute (2005) reported 160 million jobs worldwide were potentially at risk of being offshored to developing countries. But the actual number of job losses to date has been small. Bronfenbrenner & Luce (2004) find there were 48,000 job losses for the first quarter of 2004 for the manufacturing sector in the U.S., whilst Brown (2004) finds the total number of job losses for the year 2004 was 16,073 for the service and manufacturing sectors

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[2] The full details for this story can be found at the following link to The Times News paper: http://www.timesonline.co.uk/tol/news/politics/article6731151.ece; and http://www.timesonline.co.uk/tol/news/politics/article6731114.ece.

for the U.S. This amounts to less than one percent of total job losses due to offshoring. Similarly, McKinsey Global Institute (2005) found the total number of job losses due to offshoring of service activities amounted to 565,000 job losses worldwide for 2005. For Europe, the evaluation of jobs lost due to offshoring was conducted by the European Restructuring Monitor (ERM) and was published in 2006 by the European Foundation for Improvement of Living and Working Conditions. This report finds job losses due to offshoring represented a small fraction from total job losses. Total job losses for the U.K. in 2005 was over 200,000, where the number of jobs lost due to offshoring was a fraction of the total, at 6,764 job losses or 3.38%[3,4].

There is a comprehensive review of the literature which has examined the effects of offshoring on the employment level, job security, wage inequality, the wage level and more recently the skill composition of domestic employment. Reviews exploring the impact from material offshoring activities, service offshoring activities and the foreign activities of MNEs have been provided by Feenstra & Hanson (2003) (material offshoring); Crinò (2009a) (for material and service offshoring) and Barba Navaretti and Venables (2004) (for foreign activities from MNEs) and more recently by Bottini *et al.*, (2007). These reviews show material offshoring has lead to a fall in domestic demand for less skilled workers. The effects of material offshoring have lowered the employment level and the wage bill shares of less skilled labour in the U.S. and Europe (Anderton *et al.*, 2002; Falk & Wolfmayr, 2005; Ekholm & Hakkala, 2008; Harrison & McMillan, 2006). These job losses have been small and the evidence from other studies indicate that material offshoring has had little impact on the employment level (Castellani *et*

[3] These results are reported from table 7, page 42 from the ERM report.

[4] There are however a number of methodological shortcomings with the ERM research that must be mentioned. The ERM database for measuring offshoring is based on daily monitoring of press reports (general and specialist) in different EU countries. Monitoring of press reports relate to reviews of newspapers reporting indiscriminately on current offshoring processes, offshoring that is being performed and announcements of possible layoffs that may relate to offshoring. This monitoring by ERM only relates to businesses restricting operations that satisfy the following criteria:

1. Offshoring affects at least one EU-27 member country;
2. Offshoring announcements relate to the elimination (announced or actual) job losses of at least 100 jobs;
3. Offshoring relates to firms employing at least 250 workers – that is at least 10% of the work force.

These criteria may underestimate the actual number of jobs that may be lost due to offshoring and this may provide an inaccurate picture of offshoring related implications for job loss in the EU (Escalonilla & Peralta, 2009).

al., 2008; Marin, 2004; Hijzen & Swaim, 2007; Ando & Kimura, 2007). Bottini *et al.*, (2007) and Crinò (2009a) find service offshoring has had a small impact on the total employment level as the impact essentially depends upon the skill intensities within service jobs. But the shift in the composition of the work force has benefited highly skilled labour (Crinò 2007, 2009c & 2010).

The empirical literature also shows offshoring has had a positive impact on the wages for skilled labour. There have two approaches that have taken by the empirical literature to examine the impact that offshoring in intermediate inputs (materials and services) can have on wages. The first approach takes an industry level approach to test the implications of the Stolper-Samuelson theorem from the Heckscher-Ohlin model of international trade. This literature relates to the trade vs. technology debate about the causes for the change in the wage structure that could explain the increase in the demand for more skilled workers which may have contributed significantly towards the growing inequality in wages between skilled and non-skilled workers over the last 30 years. The impact of technology relates to the skill biased technological change hypothesis which notes that new technology is complementary with skilled labour than with non-skilled labour who may lack the necessary skills to adapt to the changes. To test the impact that trade and technology can have on wage inequality, the empirical literature has taken product prices (the trade approach) and the relative wages between skilled and non-skilled workers (the technology approach) as the dependent variables and have estimated either product price regressions or mandated wage regressions to examine the impact offshoring and technology can have on the wage bill shares of production workers at the industry level over time. This approach has been taken by Feenstra & Hanson (1996, 1999, and 2003), Machin (2010) and others authors – see chapter 2 for further details.

The second approach uses individual level data to examine the impact offshoring intermediate inputs can have on individual wage levels by estimating Mincer wage regressions. This latter approach has traditionally been used to determine the magnitude of the positive returns to wages from education noted by human capital theory (Becker, 1962, 1994; Mincer, 1958, 1962 and 1974), job search theory (Jovanovic, 1979), screening and signalling theories (Arrow, 1973; Spence, 1973). In brief, each of these theories explains why there is a positive relationship between education and earnings. Human capital theory advocates that education contributes to an individual's productivity. Hence, firms will hire skilled labour to maximise profits and in return they will pay higher wages to the more productive workers[5]. Geishecker & Görg (2008a,b), Hummels *et al.,* (2009) and Munch & Skaksen (2009) have take this latter approach.

Feenstra & Hanson (1995, 1996 & 1999) for the U.S. and Geishecker & Görg (2008a,b), Hummels *et al.,* (2009) and Munch & Skaksen (2009) for European countries find material offshoring increases the wage bill share for skilled labour but it lowers the wage levels for less-skilled labour. However, the impact from offshoring on the wage levels for skilled labour depends on whether offshoring takes place to high income countries or low income countries. Offshoring to high income countries tends to have a negative effect on the wage levels for skilled labour than for non-skilled labour. But if offshore outsourcing takes place to low-income countries, there is a negative impact on the wage levels for less-skilled labour (Hummels *et al.,* 2009; Geishecker *et al.,* 2007).

One of the important reasons why skilled labour has benefited from increased employment and a rise in wage levels has resulted from an outward shift in the demand for skilled labour

[5] The latter explanation for the positive relationship relates to screening, job search and signalling theories. The screening argument is that though the price (the wage) and years of education are information that are available in the labour market, employers have imperfect information about the potential productivity of prospective employees and therefore it may take time to find the right employer-employee match. This theory notes that if potential employees have the potential ability to be productive, they will have high levels of education. Thus, employers use education as a 'screen' to increase the probability of hiring workers who have the right education level that employers wish to hire to maximise profits. Able workers will realise that employers have imperfect information about the potential productivity of workers and they will acquire high education qualifications to signal to employers' their ability. The underlying point from these theories is that high ability workers will succeed with further education whilst low-skilled workers with low ability will not be able to succeed past the screening process. The difference between the theories for the positive relationship between wages and education is that the human capital theory advocates that education is a signal of productivity thus higher education leads to higher wages. But the job search, screening and signalling theories all note that it is not schooling that leads to any productivity enhancing skills, but in a world with imperfect information, schooling allows employers to identify which workers are potentially the most productive.

from within industry demand changes. Crinò (2009a) notes that the relative demand for skilled labour shifted outwards because industries raised the relative skill intensities of production. They did not gain skilled labour from the expansion of skilled-intensive sectors at the expense of lower employment shares for less-skill intensive sectors (Berman *et al.*, 1994, 1998; Machin, 1996; Bernard and Jensen, 1997; Dunne *et al.*, 1997; Osburn, 2001). Advancements in technology tend to complement skilled labour because they have general and specific human capital accumulation that can more easily be applied to new jobs. This is because the 'general' skills they have are more adaptable to new jobs that encompass the latest technology. Less skilled labour are not the beneficiaries because they have specific human capital accumulation that is more specific to particular types of jobs (Ritter, 2009).

This chapter makes three contributions to the empirical literature. For the first contribution, I follow Geishecker & Görg (2008b), to examine the impact of material and service offshoring intensities, measured at the industry level, on wages using the British Household Panel Survey (BHPS). My analysis differs with the work by Geishecker & Görg (2008b) on two fronts: First, I extend the analysis period from 1992-2005 to 1992-2007; second, they examine the effects of material and service offshoring on the wage levels for men only. This chapter examines the impact of the service and material offshoring intensities for men and women throughout this period. The gender dimension is important because offshoring can affect men and women differently. Munch & Skaksen (2009) find foreign outsourcing in Demark had a significant negative impact on the wage levels for women but no significant impact on the wage levels for men. Although, Geishecker & Görg (2008b) find that foreign outsourcing can have a significant and negative impact on wage levels for men in the U.K.

This chapter takes the Mincer wage regression approach to examine the impact of offshoring on wage levels and departs from the method that has been employed by the empirical literature that has examined the trade vs. technology debate to explain the rise in wage inequality between skilled and non-skilled workers. This latter approach has used industry level data to estimate product price regressions, mandated wage regressions and relative wage regressions to help explain the observed trends in wage inequality through the changes in the wage bill shares between skilled and non-skilled workers over time. The Mincer wage regression approach simply tries to quantify the magnitude of the impact on wage levels when firms engage in the offshoring of intermediate inputs.

My second contribution to the empirical literature is a British version of an occupation tradability index created by Blinder (2007) for the U.S. Blinder (2007) identifies occupations which are able to deliver their services remotely, are not tied to specific labour market locations and do not require face-to-face contact with the customer are potentially tradable occupations. Workers who may occupy the most tradable occupations may face competition from foreign workers and domestic firms may demand fewer workers from the most tradable occupations, if parts of their domestic operations are outsourced abroad. With less demand for workers in the most offshorable occupations, this should lead to a fall in the wage level for these workers. Since this index has not been used with British data, this chapter is the first to examine the wage penalty experienced by the most tradable occupations in the U.K. Additionally, this contribution is important as this index can potentially be a useful resource that could be made available to other researchers.

Finally, my third contribution to the literature examines the impact of the 'routinisation' hypothesis[6] (Autor *et al.*, 2003) upon wage levels. Specifically, I follow Autor *et al.*, (2003) and Goos *et al.*, (2009a,b) and construct four job task variables using data from O*NET, where these variables measure the importance of different types of job tasks completed by occupations. These variables are used to examine the impact of technology substituting away job tasks completed by workers on the wage level. This is an alternative exploration of how

[6] This hypothesis is also known as the ALM hypothesis and the Task Biased Technological Change hypothesis (TBTC).

the composition of job tasks completed by occupations may affect the wage levels of workers over time. To my knowledge, there is only one other paper that has explored how the type of job tasks performed by occupations can have an impact on wage levels; this is a working paper by Hummels *et al.*, (2009) using Danish matched employer-employee data. This chapter would be the first to explore the impact of the task biased technological change (TBTC) hypothesis on individual level wages for the U.K. Additionally, the techniques and data that are used may also potentially be a useful resource for other researchers.

Few papers have explored the gender differences with the TBTC hypothesis. Black & Spitz-Oener (2007, 2010) are one of the few papers to examine the implications of the TBTC hypothesis in explaining gender pay differences. Their analysis for Germany for the period 1979 to 1999 finds job polarization was more pronounced for women than for men. They found the employment share in middle skill occupations shrunk by 52% for females compared to 23% for men; similar changes are also documented by Acemoglu & Autor (2010 & forthcoming). This is explained by a change in the work content of job tasks performed by women and men. Women experienced larger relative increases in non-routine interactive tasks and non-routine analytical tasks, but also a marked decline in routine tasks, with little change for men over this period. These changes to the composition of work tasks completed by women are the key to explaining the narrowing of the gender pay gap in the recent decades in Germany. The empirical analysis from this chapter differs somewhat from the methodology that was undertaken by Black & Spitz-Oener (2007, 2010) in that I do not seek to explore the change in work tasks completed by men and women on the pay gap. But my analysis seeks to explore the impact that these job tasks may have on the wage levels at the individual level. To preview these results, table 4.8 from this chapter shows that female workers are more likely to have lower wage levels from work tasks that are intensive in routine and non-routine manual job tasks. The impact from non-routine abstract job tasks and service job tasks exert a positive impact on wage levels, though the estimated coefficients are not statistically significant. These results suggest that if female workers compute fewer routine and non-routine manual job tasks as part of their work tasks, this could explain the narrowing of the wage gap between men and women found by Black & Spitz-Oener (2007, 2010).

This chapter has the following structure: Section 4.2 provides details of the data used to measure service and material offshoring intensities; how to construct the Binder (2007) occupation tradability index and how to create the task biased technological change job task variables proposed by the Autor, Levy & Murnane (2003) hypothesis. Section 4.3 outlines the data and the estimation strategy. Section 4.4 provides the results and section 4.5 provides the concluding remarks.

4.2 Measuring Offshoring, Occupation Tradability and TBTC

This section defines offshoring and provides details of the four variables that will be used to measure occupation tradability, service offshoring intensity, material offshoring intensity and TBTC.

4.2.1 Defining Offshoring

Offshoring is a term that is often used quite interchangeably with *outsourcing*. Offshoring refers to the relocation of production stages abroad either through arm's length supply through market transactions (international outsourcing) or within the boundaries of the firm (vertical FDI) (Jabbour, 2010). This relocation can be the material and immaterial stages of production. *Material offshoring* refers to the offshoring of manufacturing tasks e.g. assembly and intermediate production goods. *Immaterial offshoring* or *services offshoring* refers to the offshoring of business services e.g. front office services such as call centres and customer services, back office services such as human resources, IT services (Roland Burger Strategy Consultants, 2005). *Outsourcing* does not imply that production stages are relocated to another country. It could imply outsourcing to an external firm which is located within the same developed country.

4.2.2 Blinder (2007) Occupation Tradability Index

To identify the most tradable occupations, Blinder (2007) creates a subjective offshorability index which measures the potential tradability for U.S. occupations. The aim for creating this index was to provide an estimate for the future numbers of jobs that could be lost due to offshoring over the future 10-20 years.

To create this index, Blinder (2007) assumes that there is extrapolating normal technical progress, meaning there are no significant or sudden improvements to technology[7]. Blinder (2007) creates an occupation tradability index for a total of 817 occupations that are examined from the O*NET database[8]. This index is an ordinal scale where values assigned to occupations range from 0-100, where increasing values indicate a high degree of occupation tradability.

When exploring which occupations may or may not be offshorable, Blinder (2007) keeps in mind two key characteristics:

1. Whether jobs must be performed at a specific U.S. labour market location (e.g. working on a farm or at an amusement park).
2. Whether jobs require face-to-face personal communication and/or contact with the end user of the service (e.g. taxi driver or a surgeon).

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[7] With little change in technology, the index categorises each occupation according to an offshorability criterion which distinguishes between the most and least offshorable job. This assumption allows the index to remain unchanged over time and allows there to be little change in the composition of occupations available in the U.S. This index therefore enables Blinder (2007) to estimate the number of jobs that could be offshored according to the identification criteria that is used to identify the index; details of this criterion follow. If this assumption was not made, the index would have to be continually adjusted to account for new technological developments to gage the potential number of jobs that could be lost.

[8] Further details regarding the O*NET database can be found in appendix 3.

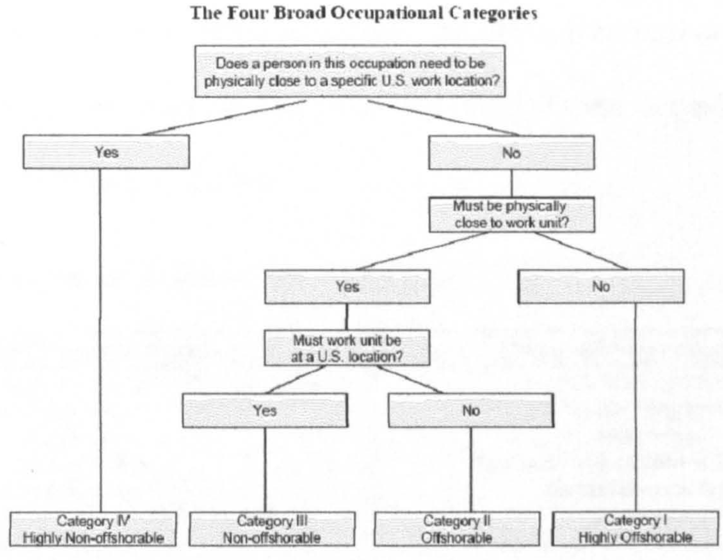
The main principle behind creating the index is the more personal a service is and for which the job requires significant face-to-face contact to prevent a degraded quality of service, these jobs are the least likely to be offshored abroad. To identify which occupations may be more tradable compared to others, Blinder (2007) follows the identification criterion shown by figure 4.1 below bearing these two characteristics in mind.

Using O*NET data, Blinder views the task content and work activities for each occupation. Based upon their descriptions, figure 4.1 provides a series of questions that enable a route to categorise each occupation title into one of four categories which assign the degree of offshorability.

From figure 4.1, there are four categories for the most to the least offshorable occupations. If workers are employed within occupations that are not required to be physically present at specific work locations or units, this signifies highly offshorable occupations. Category I describes these highly offshorable class of occupations with index values in the range of 76-100. If however workers are employed within occupations which have to be physically close to specific work locations, these are highly non-offshorable occupations. Category IV describes these highly non-offshorable occupations with index values in the range of 0-25.

There are two further intermediate classes for defining potential occupation offshorability. Category II describes the offshorable class of occupations with index values in the range of 51-75. These occupations do require a worker employed within an occupation to be physically close to U.S. work locations, but they do not require the job to be at a work unit at a specific U.S. location. The final category for offshorable occupations is Category III. This category describes the non-offshorable class of occupations with index values in the range of 26-50. These occupations do require the job to be physically close to a work unit located at specific U.S. locations. Blinder (2007) identifies 291 potentially offshorable occupations with values in the range of 25-100. The large remainder of the occupations with values in the range of 0-24 are discarded from analysis.

Figure 4.1: Decision Tree: Identifying Tradable & Non-Tradable Occupations[9]



4.2.2.1 Blinder (2007) Index using British Data

To create an occupation tradability index using British data, I mapped the Blinder (2007) index onto the British Household Panel Survey (BHPS) using a crosswalk between U.S. SOC codes and ISCO-88 codes[10]. From mapping the U.S. SOC codes to ISCO-88 codes identifies 219 potentially offshorable occupations for the British version of the offshorability index[11]. The complete list of occupations is presented in table 4.1A in appendix 1.

[9] This is figure 1 taken from Blinder (2007), page 18.

[10] The crosswalk between U.S. SOC and ISCO-88 codes was provided by the National Cross Walk Center, Des Moines, Iowa. The file provides a detailed crosswalk between U.S. SOC codes at the 6-digit level to ISCO-88 codes at the 4-digit level. The crosswalk can be obtained from the following link: ftp://ftp.xwalkcenter.org/DOWNLOAD/xwalks/.

[11] The British version of the index provides 219 occupations compared to 291 occupations that Blinder (2007) identifies from the U.S. version of this index. The reason for there being fewer occupations within the British index is there are some occupation codes in the U.S. SOC classification system that are represented by a single ISCO-88 occupation group. For example, consider table FN1 below:

Occupation	SOC code	Rank	Offshorability Index	ISCO88	ISCO88 Description
Computer Systems Analysts	151051	21	93	2131	Computer systems designers and analysts
Database Administrators	151061	60	75	2131	Computer systems designers and analysts
Network and Computer Systems Administrators	151071	211	50	2131	Computer systems designers and analysts
Network Systems and Data Communications Analysts	151081	27	92	2131	Computer systems designers and analysts
Computer Specialists, All Other	151099	30	90	2131	Computer systems designers and analysts

This table details the U.S. SOC codes for a list of 5 different computer related occupations. When the crosswalk was applied, this list of 5 occupations relate to one single ISCO-88 occupation group. With multiple occupations, the offshorability index value from the original index was averaged to generate a new index value for the ISCO-88 occupation group. This is one example of many that exist within the mapping. This process therefore reduces the number of occupations within the British version of this index.

Table 4.1 provides details for the 10 most and least offshorable occupations from the British index. From the list, the least offshorable occupations include medical doctors, nursing associate professionals, psychologist, carpenters and joiners among others which require workers to be at specific locations to perform their work tasks. Among the most offshorable list, there are many computer related occupations. All of these occupations do not require significant face-to-face contact with the customer and many of these occupations' work tasks could be provided remotely from abroad.

Table 4.1: The 10 Least & Most Offshorable Occupations

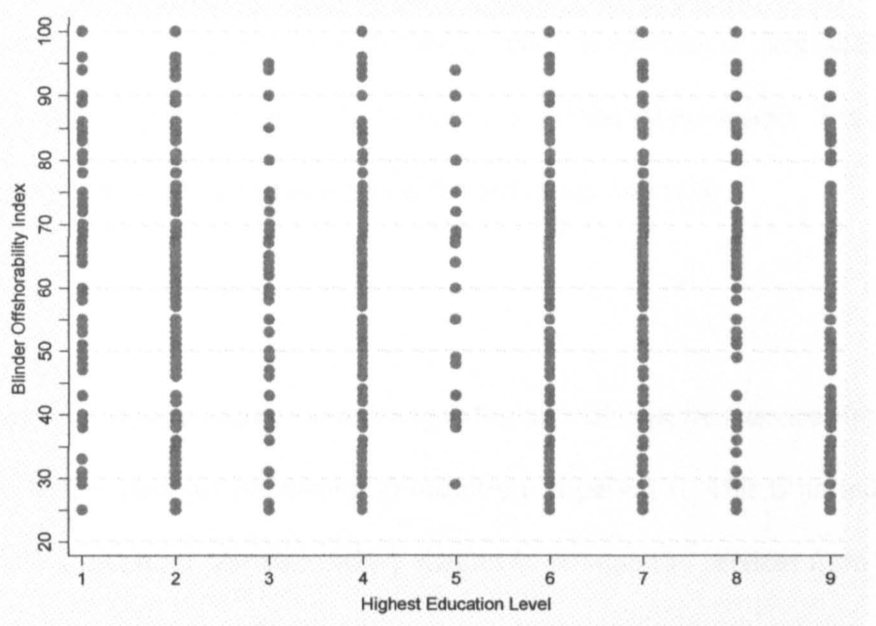
10 Least Offshorable Occupations	10 Most Offshorable Occupations
College, University & Higher Education Teaching Professionals	Data Entry Operators
Nursing Associate Professionals	Computer Programmers
Psychologists	Statisticians
Medical Doctors	Door-to-Door & Telephone Salespersons
Senior Government Officials	Stenographers & Typists
Philosophers, Historians & Political Scientists	Bookkeepers
Special Education Teaching Professionals	Word-Processor & Related Occupations
Carpenters & Joiners	Draughtspersons
Child-Care Workers	Social Work Associate Professionals
Religious Professionals	Computing Professionals not elsewhere classified

Source: Author's own compilation from the BHPS data.

A major point from Blinder (2005, 2006) is that occupations which are and are not offshorable can be found all along the skill spectrum. Figure 4.2 illustrates this point in graphical form. Taking the highest education qualifications reported by respondents from the BHPS survey as a measure for skill, this figure shows offshorable and non-offshorable jobs lay all along the skill distribution. The implication from this graph is the correlation between skill and offshorability should therefore be low. Blinder (2007) argues the relationship between skill and offshorability should be zero as it is not obvious which, "skill or education level that typifies a job and its vulnerability to offshoring"[12]. Estimates from table 4.2A in appendix 2 shows the correlation between wages and the index are close to zero.

[12] Table 4.2A from appendix 2 presents the estimates for the Spearman's Rank correlation coefficients for the period 1992-2007. Three different variables are used to measure skill. These variables are: wages, years of education and average years of education. The Spearman's Rank correlation tests the null hypothesis of independence between the offshorability index and skill; the alternative hypothesis states the relationship between the offshorability index and skill does not equal to zero. From the table, skill measures years of education and average years of education provide estimates that are very close to zero, where few coefficients are significant for skill measure years of education. And from the average years of education skill measure, there are

Figure 4.2: Potential Occupation Tradability & Skill[13]



Source: Author's own compilation from the BHPS. The skill measure is taken to be the highest education qualification reported by respondents. The index values range from 25-100. See footnote 13 for details relating to the highest education categories from the graph.

4.2.3 Offshoring Intensity

For the second measure of offshoring, two measures of industry level offshoring intensity are created. These two measures capture the idea that workers who are employed in jobs within industries that engage in offshoring may be more likely to lose their jobs and/or have lower wage levels compared to workers employed within industries that do not engage in offshoring related activities. The two measures of offshoring intensity are outlined below. The first is service offshoring intensity and the second is material offshoring intensity.

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quite a few more significant coefficients. The estimated coefficients from these skill measures do suggest there is no relationship between offshorability and skill for some years; but for other years, the estimated results reject the null hypothesis. With wages as a measure of skill, there are significant coefficients for all years, where the size of the estimated correlation coefficient increases in size every year. The highest estimate is 0.2279 for 2006. These coefficients are positive which suggest the most offshorable jobs have higher pay. These findings contrast with Blinder (2007) who finds no correlation between skill and offshorability. However, this conclusion is based on a single year of data, unlike my results which show across a number of cross sections of years, this relationship may or may not exist.

[13] The education classification codes have been taken from BHPS User Manual Volume B Codebook: 1: Higher Degree; 2: First degree; 3: Teaching QF; 4: Other higher OF; 5: Nursing QF; 6: GCE A Levels; 7: GCE O Levels or equivalent; 8: Commercial OF; 9: CSE Grade 2-5, Scot Grade 4-5, Apprenticeship, Other QF, No QF, Still at school - No QF.

4.2.3.1 Service Offshoring Intensity

To measure service offshoring at the industry level, I follow Geishecker & Görg (2008b), who define service offshoring as a more direct measure of imported service inputs. The definition used to measure service offshoring intensity is defined by equation (1):

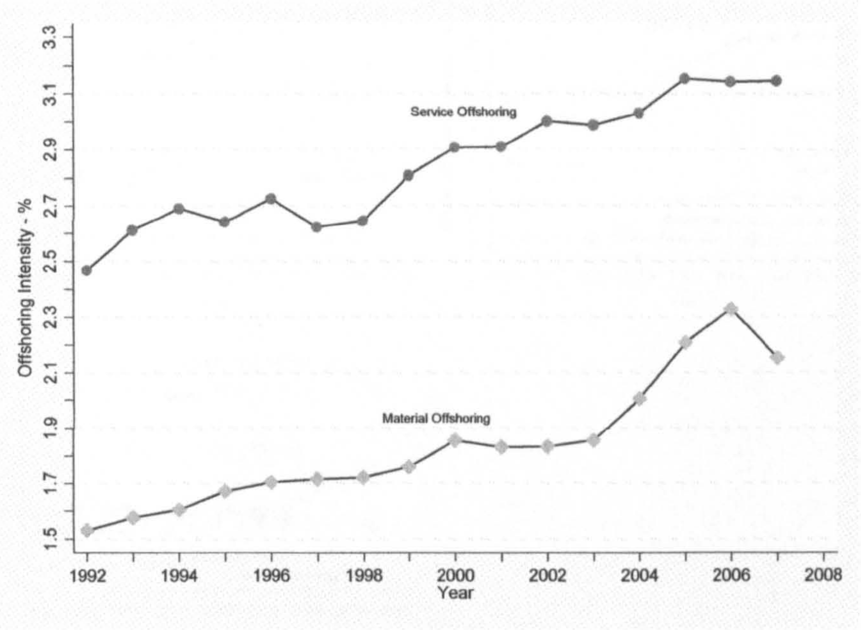
$$\mathbf{OSS_{i,t}} = \frac{\mathbf{IMP_{i^*,t}}}{\mathbf{Y_{i,t}}} \tag{1}$$

Equation (1) defines service offshoring intensity as the ratio of imported services from industry i in period t, to the value of production in industry i in period t. This is an industry level service offshoring measure. Variable $\mathrm{IMP}_{i^*,t}$ measures all imported services from industry i^* at time t and variable $Y_{i,t}$ measures industry output from industry i at time t. Data used to measure equation (1) is from the annual input-output supply and use tables from the Office for National Statistics (ONS) in the U.K. The input-output supply and use tables provide a breakdown of information which relate to the transactions of all goods and services between industries and final consumers for the U.K. economy for one year. These tables provide details for the whole economy by 108 industries and 123 products. From this information, I use 2-digit SIC92 division level information to construct $\mathrm{OSS}_{i,t}$. At the time of writing this chapter, annual input-output supply and use tables are available for the period 1992-2007.

Figure 4.3 shows the average service and material offshoring[14] intensities across all industries. From this figure, service offshoring and material offshoring intensities show rising trends over time. The service offshoring intensity is higher than material offshoring intensity for the entire period.

[14] The material offshoring intensity measure is outlined below in section 4.2.3.2.

Figure 4.3: Average Services and Material Offshoring Intensity across Industries

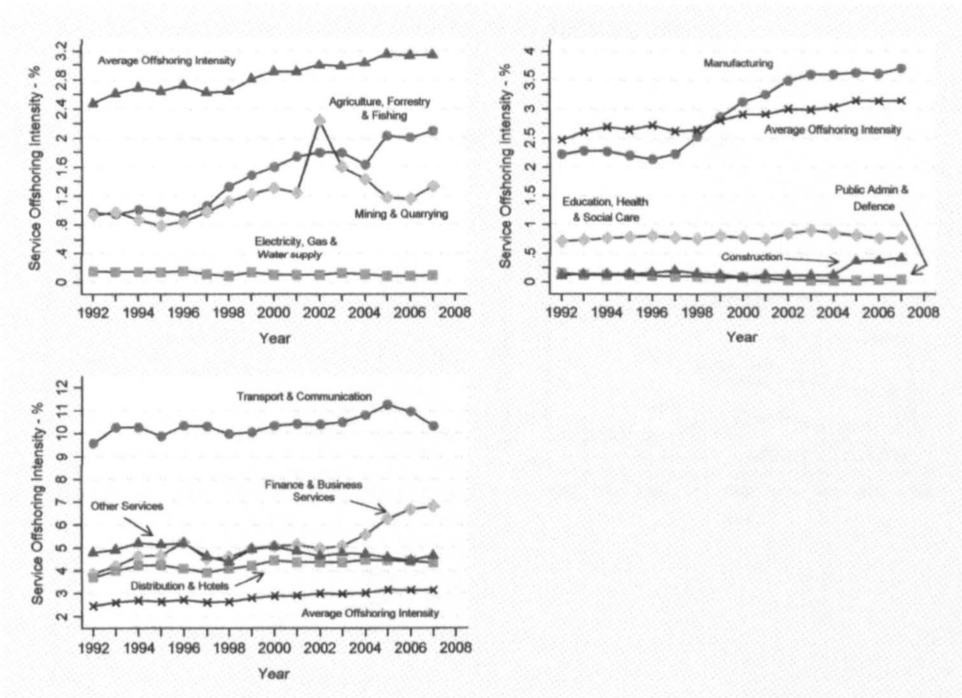


Source: Author's own compilation.

From 1992-2007 service offshoring intensity rose by approximately 27%; the material offshoring intensity rose by approximately 29%. The graph also shows a sharp rise in material offshoring post 2003 from 1.9% to approximately 2.3% by 2006. But these average offshoring intensities across all industries are quite small over time.

Figure 4.4 compares the trends in service offshoring intensity by industry groups. From this figure, the OSS intensity for industries agriculture, forestry & fishing, mining & quarrying, electricity, gas & water supply, construction, public administration & defence, education, health & social work have trends that lay below the average offshoring intensity across all industries. Whereas for industries: distributions & hotels, transport & communication, finance & business services and other services have higher offshoring intensities compared to the average. The manufacturing sector also has a higher OSS intensity post 2000 compared to the average.

Figure 4.4: Service Offshoring Intensity by Division Industry Groups



Source: Author's own compilation.

The industry with the highest OSS intensity is transport & communications compared to the other industries, fluctuating between the bands of 10-11% for the period 1992-2007.

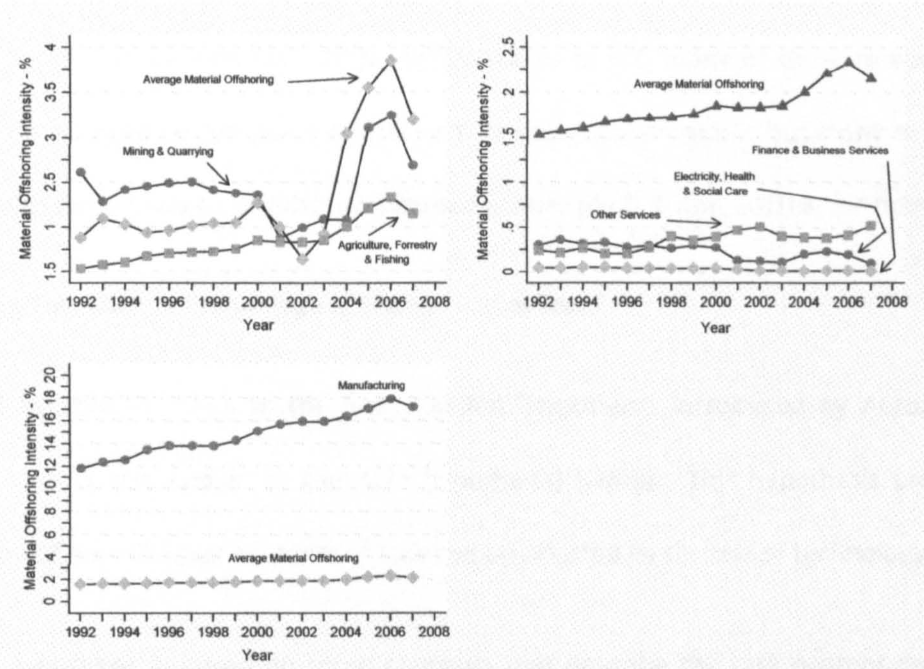
4.2.3.2 Material Offshoring Intensity

To calculated material offshoring intensity, I again follow Geishecker & Görg (2008b). The formula to calculate material offshoring is the following:

$$\mathbf{OSM_{i,t}} = \frac{IMP_{i^*,t} \times \Omega_{i,i^*,t}}{Y_{i,t}} \qquad (2)$$

Where $\mathrm{IMP}_{i^*,t}$ represents imported intermediate inputs from the foreign industry i^*. $\Omega_{i,i^*,t}$ denotes the share of domestic and foreign inputs from an industry i^* that is consumed by industry i. The material offshoring intensity is calculated using aggregate data on imports of manufactured goods; this information is then allocated to their use share in domestic industries from the input-output data available from ONS. This is a narrow measure of offshoring in the sense that it represents the transfer overseas of the production activities that could be carried out by a domestic firm (Feenstra & Hanson, 1999).

Figure 4.5: Material Offshoring Intensity by Division Industry Groups



Source: Author's own compilation.

Figure 4.5 presents the material offshoring intensities for six industries at the division level. From this figure, the manufacturing sector has the highest material offshoring intensity. From 1992 to 2007, this intensity rose by nearly 5-6 percentage points. The top right graph presents trends for three industries which have the lowest material offshoring intensity. The finance & business services sector has the lowest trend, which is very close to zero over time, as is the trend from the electricity, health & social care sectors.

4.2.4 Task Biased Technological Change: Concept & Measurement

An alternative view of exploring the number of jobs that could be offshored, is to think of each job as bundles of tasks or activities that are associated with an occupation and completed by workers. It is these bundles of tasks that may be broken down into separate components, re-categorised into new bundles of job tasks where some job tasks are produced cheaper abroad and other job tasks are produced by continuing occupations in the domestic country. It is this alternative view of breaking down the production process into a series of job tasks which provides an alternative explanation to offshoring 'jobs' abroad. The task biased technological change (TBTC) hypothesis explains how the adoption of technology can have an impact on the job tasks completed by workers. With improvements in ICT, many of these re-bundled job tasks can be replaced by computer capital such as computer programs but many of these job tasks are also more likely to be offshored abroad (Acemoglu & Autor, 2010 & forthcoming).

4.2.4.1 The Task Biased Technological Change Hypothesis

The TBTC hypothesis refers to the 'routinization' hypothesis introduced by Autor, Levy & Murnane [this is also known as the ALM hypothesis] (2003). This hypothesis provides an explanation of how the task contents of jobs can be affected by the use of technology.

The ALM hypothesis is based on three concepts that describe the task content required to perform jobs: routine job tasks, non-routine abstract job tasks and non-routine manual job tasks. Autor *et al.*, (2003), Leamer & Stroper (2001), Levy & Murnane (2004) and Grossman & Rossi-Hansberg (2008) note the degree to which job tasks can be broken down into a series of codifiable job tasks that may be repetitive and routine in nature are most likely to be offshored. Routine job tasks require methodical repetition of procedures that can be described by a series of written set of rules and procedures (Grossman & Rossi-Hansberg, 2007), where such job tasks can be easily monitored; they are also most likely to be replaced by computer capital such as software (Acemoglu & Autor, 2010 & forthcoming). Job tasks which are non-routine in nature, have a large degree of tacit information and require visual and motor processing which cannot be described by a set of rules are least likely to be automated at present but they are also least likely to be offshored as monitoring of such tasks may not be possible or too costly.

The ALM hypothesis does not signify which job tasks are the most offshorable, but indicates which job tasks are complements to, or substitutes to the use of ICT. What this hypothesis does imply is routine-intensive job tasks are most likely to be replaced by computers. Thus, with improved ICT, these job tasks can easily be provided remotely from an offshore location domestically or from foreign labour market locations.

4.2.4.2 The Job Polarization Hypothesis

Goos & Manning (2003 & 2007) argue the ALM hypothesis has a subtle impact on the demand for labour across the skill spectrum. That is occupations that have a high importance for completing routine-intensive job tasks are not distributed uniformly across the skill distribution. They identify non-routine intensive job tasks compliment technology, which include skilled professional and managerial jobs are likely to be situated at the upper end of the skill distribution, where there is likely to be a rise in these types of jobs. On the other hand, non-routine intensive manual job tasks that account for most unskilled jobs such as cleaning and personal help occupations are not likely to be affected directly by technology. But they suggest that the impact of technology in other parts of the economy is likely to lead to a rise in employment for these unskilled jobs (Manning, 2004). These types of jobs tend to occupy the lower end of the skill distribution. Jobs which exhibit routine-cognitive and routine-manual job tasks tend to occupy the middle of the wage distribution. These jobs are likely to be substituted by technology and are they are also likely to experience a fall in relative demand. It is this fall in relative demand for 'middling' jobs the authors' call this process job polarization.

4.2.4.3 Measuring TBTC: Principal Component Analysis

To measure TBTC, I follow Goos *et al.,* (2008, 2009a,b) to construct four variables using data from the Occupational Informational Network or O*NET for short.[15,16]. O*NET is a database of occupation information. It is a career exploration database which provides job seekers, firms, students and many other groups, a tool for identifying the relevant skills required by workers in each U.S. occupation. The O*NET database provides several hundred task rating scales which describe key skills, job tasks and characteristics for approximately 800 occupations based on U.S. SOC 2000 codes. This information comes from occupational analysts and sampled workers, whom complete a task questionnaire. To use this information, I use a crosswalk provided by the National Cross Walk Center, to convert the U.S. SOC codes to ISCO-88 codes. The four job task variables I construct are: (1) Routine Job Tasks; (2) Non-Routine Abstract Job Tasks; (3) Non-Routine Manual Job Tasks and (4) Service Job Tasks.

Each of these job task variables has been constructed from a series of task activities which may be completed by occupations. They describe the importance of each job task activity has to each US SOC occupation available within the O*NET files. The 'Survey Booklet Locations' file which is available within the O*NET file bundle provides details of 419 variables which describe job task activity characteristics related to: abilities, work context, work activities, skill and knowledge information that relate to specific features of occupations. From this file, I selected 95 of these task activity variables.

From each of the task activity descriptions, each occupation has a task rating scale – which is a value from 1-5 to measure the importance each task activity has to each occupation and the percentage of time a job activity may play in the work-context of an occupation. A value of 1 signifies there is low importance or low work context importance of a task activity to an

[15] Appendix 3 provides details for the O*NET database.

[16] I have used O*NET Version 13.0. At the time of writing this chapter, the latest version available is Version 14.0 dated July 2009.

occupation; a value of 5 signifies high importance of a task activity to an occupation. Appendix 4 provides further explanations about the importance rating for a selection of the task activity variables that I have selected and how they relate to occupations.

Appendix 5 provides details of all the task activity variables I have used to construct each of the four TBTC variables. To preview some of these variables that has been used: for the routine job task measure includes 'arm-hand steadiness', 'importance of repeating same task', 'clerical' and 'interacting with computers'. For non-routine abstract job tasks, examples include 'initiative', 'leadership', 'complex problem solving' and 'making decisions and solving problems'. For non-routine manual job tasks, examples of variables used are 'handling and moving objects', 'operating vehicles, mechanized devices or equipment' and spend time using your hands to handle, control or feel objects, tools, or controls'. Finally for service job tasks, examples of task activity variables I have used are 'customer and personal service', 'establishing and maintaining interpersonal relationships', 'service orientation' and 'face-to-face discussions'.

The first three of these tasks variables have been discussed in detail in the last section; they relate to occupations that may occupy specific positions of the skill distribution. However, service job tasks differ from the other job task variables because this job task variable consists of activities that are non-routine and they do not relate to one specific part of the skill distribution but they may be performed by workers with different levels of education (Goos *et al.*, 2008).

To create these four job task variables, I follow Goos *et al.*, (2008, 2009) and Autor *et al.*, (2003) to construct a single principal component[17] across each SOC in O*NET, which has been

[17] Principal component analysis is a multivariate technique which linearly transforms an original set of variables which may possibly be correlated with each other into a smaller set of uncorrelated variables. This smaller set of uncorrelated variables is called principal components. The smaller set of uncorrelated variables is much easier to understand and to use in further analysis. The first principal component accounts for much of the variability in the data as possible whilst the succeeding components account for much of the rest of the variability. This technique was originally proposed by Karl Pearson in 1901 and independently

collapsed to the ISCO-88 level. Each principal component has been weighted by U.S. employment in each SOC cell[18]. Each of the principal components is extracted as the eigenvectors of the correlation matrix. This method is the equivalent to calculating the principal components from the original variables after each of the task variables have been standardized to have unit variance (Everitt & Dunn, 2001)[19]. Tables' 4.4A - 4.7A in appendix 6 presents the principal component eigenvalues (also known as component loadings) and the proportion of the variance accounted for by each component[20].

Table 4.2a and figure 4.6 provide a more insightful picture of how each of the TBTC variables is distributed across occupations as shown by the wage distribution and table 4.2b shows the mean for each TBTC measures for each one digit ISCO-88 occupation groups. Table 4.2a presents the mean ranked hourly wage for each ISCO-88 2-digit level occupations deflated to 1995 prices. Additionally, following Goos *et al.*, (2008), figure 4.6 presents four lowess smoothing plots for each of the job task variables distributed across the wage distribution. The mean ranked hourly wage from table 4.2a should provide a picture for which job tasks have more importance for each occupation group according to figure 4.6 above the zero line[21].

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developed by Hotelling (1933) (Dunteman, 1989). This technique has also been used in regression analysis to solve multi-collinearity problems between two or more independent variables.

[18] I have used the May 2008 release from the Bureau of Labor Statistics, U.S.

[19] The process of standardizing potential variables to be used as principal components is very important if one has data for variables measured in different units. For example, length, temperature, blood pressure and anxiety rating have different units of measurements. If these variables are derived from the covariance matrix, the derived components will depend on the arbitrary choice of unit measurements. If the unit of measurement of say length is changed from meters to centimetres, this will alter the derived components. Also if there are large differences between the variances of the original variables, those variables with large variances will dominate the early components (Everitt & Dunn, 2001).

[20] I have not presented the eigenvectors for each component because there are 19 plus variables that have been used to construct each principal component. Table 4.4A presents component loadings for routine job tasks. The first principal component has the largest variance of 8.4413 which accounts for $\left(\frac{8.4413}{19} * 100\right)$ 44.43% of the variance from the 19 variables used to measure routine tasks. Each subsequent component accounts for less of the variance ranging between 17.03% and 0.14%. Table 4.5A presents component loadings for non-routine abstract job tasks. The first component accounts for $\left(\frac{18.6198}{36} * 100\right)$ 51.72% of the variance from the 36 variables used. Table 4.6A presents component loadings for non-routine manual job tasks. The first principal component for manual tasks accounts for $\left(\frac{11.5588}{20} * 100\right)$ 57.79% of the variance from the 20 variables used to measure *non-routine manual* job tasks. And finally from table 4.7A, the first component for service job tasks accounts for $\left(\frac{10.7328}{23} * 100\right)$ 46.66% of the variance from the 23 variables used to measure service job tasks. For each of the job task variables, the first components explain 44.43% to 57.79% of the variances.

[21] Figure 4.6 perhaps lacks the finesse shown from a similar figure created by Goos *et al.*, (2008), but these graphs present the main trends from the BHPS data.

From figure 4.6, non-routine abstract job tasks appear to be concentrated towards the upper and middle portion of the wage distribution. Abstract job tasks are not important at the lower end of the distribution. Routine job tasks are required by occupations which occupy the lower and middle portion of the wage distribution. This graph verifies routine job tasks are required by occupations which are situated in the middle portion of the wage distribution. Service job tasks relate to occupations which lay at the bottom and upper portion of the wage distribution. The middle portion of the wage distribution signifies a lack of service related job tasks required by occupations. Finally, manual job tasks are required by occupations which occupy much of the bottom and middle portion of the wage distribution. Manual job tasks are not very important towards the upper portion of the wage distribution.

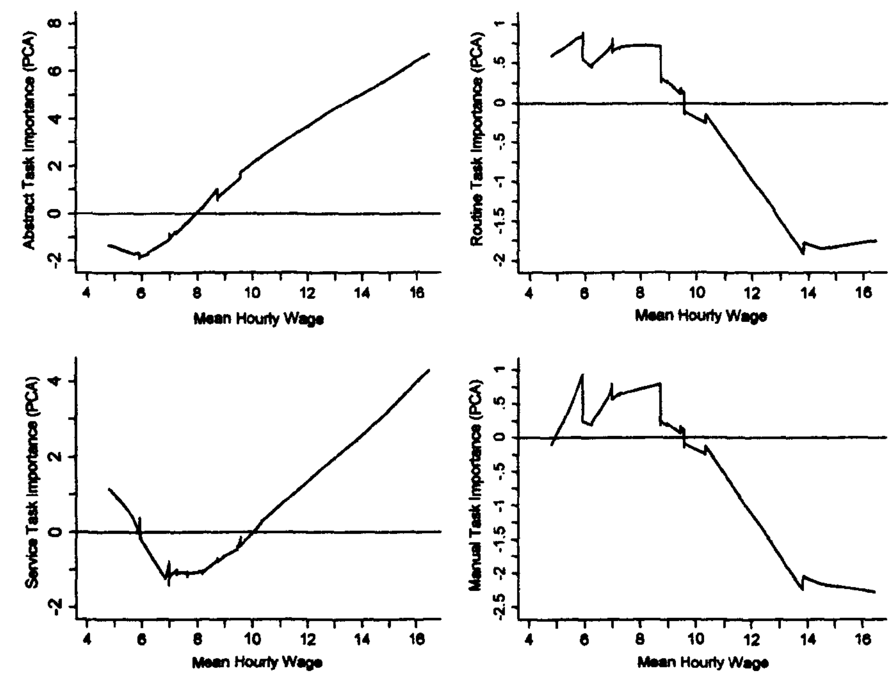
From all four of these plots, the abstract and service job task graphs show these tasks are important to high paid occupations situated towards the middle and upper portion of the wage distribution. These occupations appear to be located mainly within the service sector. From the routine and manual job task graphs, each of these job tasks is important to occupations situated towards the middle portion of the wage distribution. Routine and manual job tasks appear to be highly important for occupations located within the manufacturing industry. For the lower portion of the wage distribution, the low paid jobs in services require more service related job tasks than routine job tasks. These findings are in accordance with those reported by Goos *et al.,* (2008).

Table 4.2a: ISCO 2-Digit Occupations ranked by Mean Hourly Wage with ISCO occupation descriptions

Rank	ISCO 2-Digit	Mean Wage	ISCO Description
1	52	4.79	Models, Salespersons & Demonstrators
2	92	4.98	Agricultural, Fishery & Related Labour
3	33	5.22	Teaching Associate Professionals
4	61	5.65	Market-Oriented Skilled Agricultural & Fishery Workers
5	51	5.92	Personal & Protective Services Workers
6	74	5.97	Other Craft & Related Trades
7	91	6.03	Sales & Service Elementary Occupations
8	42	6.24	Customer Services Clerks
9	93	6.24	Labourers in Mining, Construction, Manufacturing & Transport
10	82	6.84	Machine Operators & Assemblers
11	41	6.96	Office Clerks
12	83	7.24	Drivers & Mobile Plant Operators
13	13	7.61	General Managers
14	73	8.04	Precision, Handicraft, Printing & Related Trades Workers
15	71	8.16	Extraction & Building Trades Workers
16	72	8.72	Metal, Machinery & Related Trades Workers
17	81	8.93	Stationary-Plant & Related Operators
18	32	9.44	Life Science & Health Associate Professionals
19	34	9.54	Other Associate Professionals
20	31	10.32	Physical & Engineering Science Associate Professionals
21	23	12.61	Teaching Professionals
22	24	12.92	Other Professionals
23	21	13.24	Physical, Mathematical & Engineering Science Professionals
24	12	13.82	Corporate Managers
25	22	14.46	Life Science & Health Professionals
26	11	16.45	Legislators & Senior Officials

Source: Author's own calculations from the BHPS. Mean hourly wages are deflated to 1995 prices. Mean hourly wages refer to ISCO 2-Digit Occupation Groups.

Figure 4.6: Routine, Abstract, Manual and Service Task Importance for 26 Occupations ordered by mean hourly wage for UK



Source: Author's own compilation. ISCO occupations ranked by Mean Hourly Wage deflated to 1995 prices.

Table 4.2b: Mean TBTC Measures for 1-Digit ISCO-88 Occupation Groups

Occupations	Routine Tasks	NR-Abstract Tasks	NR-Manual Tasks	Service Tasks
Legislators, Senior Officials & Managers	-1.7319	4.4188	-1.7345	2.9671
Professionals	-1.8265	4.7828	-2.1842	1.6459
Technicians & Associate Professionals	-0.4980	3.0113	-0.7178	1.1471
Clerks	-2.0066	-0.9172	-2.7730	-0.1755
Service Workers , Shop & Market Sales Workers	0.3624	-0.8078	0.1913	1.5496
Skilled Agriculture & Fishery Workers	3.2768	-2.1922	4.2452	-2.9924
Craft & Related Trades Workers	4.4849	-0.5996	5.5930	-3.9185
Plant & Machine Workers	5.0896	-3.0739	5.2262	-5.5867
Elementary Occupations	2.7146	-6.0428	2.8909	-4.1439

Source: Author's own calculations from the BHPS. Note that NR = Non-Routine.

Table 4.2b shows the mean task values from each of the TBTC variables for each one-digit ISCO-88 occupation group. The TBTC hypothesis notes that non-routine abstract job tasks have more importance in professional occupations such as managers and other professional occupations such as scientists and solicitors compared to lower skilled occupations in services and clerical workers in offices and in physical manual jobs. This should therefore suggest that the mean for non-routine abstract tasks should be larger for the former group of occupations than for the latter group.

Table 4.2b shows that the mean for non-routine abstract tasks are larger for skilled occupation groups such as legislators, senior official, managers, professionals and technical occupations. Whereas, this mean is smaller for less skilled occupations for clerks, service related occupations and for physical manual occupations in plants and agriculture. Similarly, the mean for routine tasks are greater for less skilled occupations in service related and physical manual occupations than for skilled professional occupations. The estimated means for non-routine manual tasks tell a similar story to the routine job task means. And the mean for service tasks are larger for high-skilled occupations and service related occupations than for clerks or physical manual occupations. These calculations are in line with the predications from the ALM hypothesis.

4.3 Data & Empirical Strategy

Section 4.3.1 provides details of the data set that has been used to carry out analysis followed by section 4.3.2 which provides details of the empirical strategy used in this chapter.

4.3.1 Data

The British Household Panel Survey (BHPS) data has been used for analysis in this chapter. The BHPS is a nationally representative annual survey, carried out by the Institute for Social and Economic Research at the University of Essex, of each adult member of a nationally representative sample of more than 5,000 private households (with a total of approximately 10,000 individual interviews) randomly selected south of the Caledonian Canal. The first wave of the BHPS was conducted during the autumn of 1991, and annually thereafter (Taylor *et al.*, 2006). For this chapter, I use data covering the period 1992-2007, consisting of individuals aged 16-65 years in paid employment.

The summary statistics for this sample of data are presented within table 4.3. From this table, the average age of the sample is approximately 38 years with job tenure averaging less than five years per worker. The average hourly wage is over £8.50[22]. The average service offshoring intensity (OSS) over the sample is 2.17% and the average material offshoring intensity is 2.97%. The summary statistics for other variables that are used are presented within table 4.3. Further details relating to these variables and their measurement will be discussed in more detail in the coming subsections.

[22] This figure may seem quite high for the average hourly wage; however the income data that was used to create hourly pay includes income from employment, overtime payments and bonus pay that individuals may have paid.

Table 4.3: Summary Statistics

Variable	Observations	Mean	Standard Deviation
Real Hourly Wage	58978	8.6300	6.2702
log(Real Hourly Wage)	58978	1.9995	0.5466
Age	58978	37.9076	11.6848
Age Squared	58978	1573.521	922.7971
White Collar Occupations	58978	0.5894	0.4919
Ethnicity: White	58978	0.1003	0.3003
Female	58978	0.5109	0.4999
Male	58978	0.4891	0.4999
Married/Cohabitating	58978	0.7259	0.4461
Single	58978	0.1975	0.3981
Divorced	58978	0.0604	0.2383
Separated	58978	0.0162	0.1262
Dependent Children in HH	58978	0.4095	0.4918
Job Tenure	53457	4.9834	5.7688
Job Tenure Squared	53457	58.1129	151.5575
Experience	58978	19.8390	12.5340
Experience Squared	58978	550.6832	577.6714
High Skill Education Group	58978	0.0282	0.1656
Medium Skill Education Group	58978	0.5942	0.4911
Low Skill Education Group	58978	0.3776	0.4848
Firm Size < 25	58978	0.3322	0.4710
Firm Size 25-99	58978	0.2601	0.4387
Firm Size 100-999	58978	0.3005	0.4585
Firm Size >=1000	58978	0.1053	0.3069
Private Sector	58978	0.7002	0.4582
Public Sector	58978	0.2534	0.4350
Industry Output	58978	188029.4	114733.3
R&D Expenditure	49290	1538.085	2937.761
R&D Intensity	58978	0.3694	0.7085
Hours Worked (Week)	58978	34.5031	10.2608
Hours Worked (Month)	58978	138.0124	41.0433
Service Offshoring Intensity (OSS)	58978	2.1766	2.4781
Material Offshoring (OSM)	58978	2.9666	5.8110
Blinder Offshorability Index	58978	33.7946	33.0357
Offshorability Dummy (OI)	58978	0.2592	0.4382
Years of Education	58978	13.0866	3.2972
Years of Education Squared	58978	182.1297	78.3209
Annual Unemployment Rate	58978	6.7582	1.9063
Net Exports	58978	-4310.91	17293.3
Union	58978	0.2492	0.4325
Routine Job Tasks	58707	0.1461	2.9887
Non-Routine Abstract Job Tasks	58707	0.6414	3.8309
Non-Routine Manual Job Tasks	58978	0.0267	3.7444
Service Job Tasks	58707	-0.0684	3.4650
Offshoring: Blinder Index Values	58978	0.4452	0.4970
Offshoring: Blinder Index Values 25	58978	0.0129	0.1129
Offshoring: Blinder Index Values 26-35	58978	0.0415	0.1995
Offshoring: Blinder Index Values 36-45	58978	0.0664	0.2490
Offshoring: Blinder Index Values 46-55	58978	0.0758	0.2647
Offshoring: Blinder Index Values 56-65	58978	0.1153	0.3193
Offshoring: Blinder Index Values 66-75	58978	0.1506	0.3577
Offshoring: Blinder Index Values 76-85	58978	0.0473	0.2123
Offshoring: Blinder Index Values 85+	58978	0.0449	0.2071

Source: Author's own calculations from the BHPS: 1992-2007.

4.3.2 Empirical Strategy

This section is composed of two parts. Each section will outline the empirical strategy that is undertaken by this chapter to answer each of the contributions outlined in section 4.1.

4.3.2.1 OLS Cross Section Regression Analysis

To estimate the impact of offshoring, TBTC and occupation tradability on wage levels over time, Mincer wage equations are estimated for each cross section of data. This estimation strategy is outlined by equation (3). This equation is estimated separately for each year of data to explore the wage loss for the most offshorable jobs and the impact of TBTC on wage levels each year over time. This first estimation strategy is pursued because it was noted in section 4.1 that the potential number of jobs that could be lost due to offshoring were very high estimates compared to the actual number of jobs that have been lost due to offshoring related activities to date. These estimates may provide firms with a credible threat point where they may able to put downward pressure on the wage levels of workers – assuming wage levels are negotiated each year. The time dimension enables one to gather if there are continuous negative or positive, increasing or decreasing effects upon wages over time. The model that I estimate is outlined by equation (3) below:

$$\log(Wage)_{i,j,t} = \beta_0 + \beta_1 \mathrm{INDIV}_{i,t} + \beta_2 \mathrm{JOB}_{i,t} + \beta_3 \mathrm{INDUS}_{j,t} + \beta_4 \mathrm{OI}_o + \beta_5 \mathrm{OSS}_{j,t} + \beta_6 \mathrm{OSS}_{j,t} * \mathrm{OI}_o + \beta_7 \mathrm{OSM}_{j,t} + \beta_8 \mathrm{OSM}_{j,t} * \mathrm{OI}_o + \beta_9 \mathrm{Task}_o + \mathrm{Y}_{j,t} + \varepsilon_{i,j,t} \quad (3)$$

Where i = 1,...,n; o = occupation o; j = industry j; t = 1992,...,2007. The dependent variable $\log(\mathrm{Wage})_{i,j,t}$ is the log real hourly wage for worker i, in industry j at time t. It is defined as the gross real hourly pay deflated to 1995 prices, based on income data which includes overtime pay and bonuses over the year. Variable INDIV accounts for individual level variables which include age, age squared, three dummy variables for marital status, a child dummy variable, a female dummy and two education dummy variables[23]. Variable JOB accounts for job characteristics such as experience and experience squared; a dummy variable for union membership, eight ISCO occupation dummy variables, three firm size dummy variables and a dummy variable for public sector employment. Variable INDUS accounts for industry level variables which include industry dummy variables, research and development intensity[24] and net exports[25], which account for potential job creation and job destruction effects that may influence wage levels (Kletzer, 2000, 2004; Klein *et al.*, 2004 and Davidson & Matusz, 2005 highlight the importance of export orientation and international competition as being important determinants). Control variables also include regional dummy variables and industry level output, $Y_{j,t}$, measured at the major group level. OI is a dummy variable which has a value of one if the Blinder index has a value greater than or equal to 65[26]. The estimated impact on the wage levels for the most tradable occupations should provide an estimate of whether the impact is negative and significant from one year to the next and whether the size of the coefficient has changed over time. Variables OSS and OSM are the service and material offshoring intensities measured from I-O data for the period 1992-2007. Variable Task represents the four job task variables which measure routine, non-routine abstract, non-routine manual and service job tasks.

The inclusion of the routine job task variable (from the subset of Task variables) enables one to explore whether routine job tasks yields a negative impact on wages over time. By

[23] To construct the education groups, I follow Geishecker & Görg (2008b), who follow the International Standard Classification of Education (ISCED). High-skilled workers are identified with second stage of tertiary education. Medium-skilled workers are classified with upper secondary education, post secondary but non-tertiary education and first stage of tertiary education. Low skilled workers are identified with pre-primary education, primary education and lower secondary education.

[24] Research and development intensity is measured as follows: $\frac{R\&D}{Y}$, where R&D is industry expenditure on research and development and Y is the output level from each industry. Data for R&D was obtained from the U.K. Business Enterprise Research and Development (BERD) publication available from ONS. Missing data from BERD was supplemented by data from the OECD ANBERD. This data is available by product groups. To obtain R&D expenditure by industry groups, I used an unpublished concordance provided by ONS to allocate the R&D expenditure by product groups into industry groups. Data for industry output is available from Input-Output supply and use tables available from ONS.

[25] Net exports are measured by subtracting imports from exports: (exports – imports). This data relates to the export and import of goods and services which is available from ONS.

[26] I do not include the index itself as this would include all values for the least and potentially more tradable occupations. I am only interested in the impact on wages from the most tradable occupations. But including the index itself may complicate the interpretation of the coefficient in relation to the impact on wages.

construction, each task variable does not change over time; if a job requires repetitive motion, this will be part of a series of activities performed by a job. If the tasks performed by a job changes, this will be a new occupation compared to the old occupation. Hence, as with the Blinder offshorability dummy variable (OI), the year to year estimates from the routine job task variable should provide evidence of whether the impact on wages are negative and whether these estimates are negative and significantly increasing in absolute value over time.

Additionally, the impact of offshoring may vary with individual heterogeneity. The empirical literature reports women rather than men are more likely to be employed by tradable occupations that have a high importance to complete routine job tasks (Black & Spitz-Oener, 2007, 2010) [27]. Additionally, research by Peri & Sparber (2007) shows the immigration of foreign born low-skilled labour specialise in occupations that require manual job tasks such as cleaning, cooking or building work. This causes native born workers to reallocate their labour supply as they have better knowledge of local networks, rules, customs and language proficiency, hence they pursue jobs that require interactive tasks such as coordination, organisation, and communication. Thus, being employed within a potentially tradable occupation and occupations which complete a high percentage of routine job tasks is likely to differ amongst different individual workers. These differences among workers may have a different impact on the wage levels of different workers. This is explored with the interaction of the offshoring dummy variable OI with the education dummy variables and with gender, race and white-collar worker groups.

Finally, variable OI is also interacted with OSS and OSM to examine the impact on the wages for workers employed within potentially tradable occupations and employed within industries that engage in service and material offshoring activities. It is predicted that workers who are employed in potentially tradable occupations and within industries that have high service and

[27] They found job polarization was more pronounced for women compared to men; the employment share in middle occupations shrunk by 52% for females compared to 23% for men.

material offshoring intensities, should have lower hourly wage levels compared to workers that are employed within firms and industries that do not engage in offshoring activities. Wages for workers employed within the most tradable jobs and employed by firms within industries that engage in offshoring activities are more likely to have lower wage levels because firms can threaten domestic workers with the potential transfer of jobs to offshore locations to prevent higher wage levels.

For each year equation (3) has been estimated, the standard errors have been clustered by four-digit industry SIC codes[28]. This procedure estimates robust standard errors that are corrected for within cluster correlations. This is important, as argued by Moulton (1990) who illustrates estimated coefficients may be biased downwards due to the estimation of industry level measured variables such as OSS and OSM on individual level wages.

4.3.2.2 Panel Regression Analysis

A firm's decision to engage in offshoring at any given time may be influenced by technological change, wage negotiations and the prevailing labour market and industry conditions over time. Firms are more likely to offshore low-skill intensive production activities as these activities are cheaper to produce abroad. Additionally, these decisions may be driven by technological innovations, which can allow firms the flexibility to offshore those tasks that can be provided cheaply from abroad. The impact of offshoring measured at the industry level implies OSS and OSM may be endogenous because firms may decide to offshore parts of their production processes if the cost of producing intermediate or final goods and services are more costly to provide in the domestic market compared to employing foreign labour. Hence, there may be a problem of reverse causality, meaning the error term is correlated with the offshoring intensity variables. Thus, ceteris paribus, the failure to control for this correlation will provide estimated coefficients that are inconsistent and they may be biased downwards.

[28] This is SIC80 for the period 1992-2001 and SIC92 for the period 2002-2007.

The annual OLS estimates for OSS and OSM may not represent the correct specification due to these reasons unlike for variable OI that is fixed over time. The panel model does not control for endogeneity, it merely allows one to account for unobserved heterogeneity at the individual and industry level that cannot be measured adequately with observed data. Therefore, I follow Geishecker & Görg (2008a,b) and Munch & Skaksen (2008) and estimate equation (4):

$$\log(Wage)_{i,j,t} = \beta_0 + \beta_1 \mathrm{INDIV}_{i,t} + \beta_2 \mathrm{JOB}_{i,t} + \beta_3 \mathrm{URATE}_t + \beta_4 \mathrm{OI}_o + \beta_5 \mathrm{OSS}_{j,t} + \beta_6 \mathrm{OSM}_{j,t} + \beta_7 \mathrm{INDUS}_{j,t} + \beta_8 \mathrm{Task}_o + \mathrm{Y}_{j,t} + \mathrm{T}_j + \mu_t + \alpha_i + \varepsilon_{i,j,t} \tag{4}$$

Where i = 1,...,n; o = occupation o; j = industry j; and t = 1992-2007. The dependent variable $\log(\mathrm{Wage})_{i,j,t}$ is the log real hourly wage for worker i, in industry j at time t. URATE is the annual unemployment rate which accounts for the business cycle. Variable INDIV accounts for individual level variables which include age, age squared, three dummy variables for marital status, a child dummy variable, a female dummy and two education dummy variables. Variable JOB accounts for individual job characteristics which include experience and experience squared, a union membership dummy, eight ISCO occupation dummy variables, three firm size dummy variables and a dummy for public sector employment. The model also includes region dummy variables. Variables OSS and OSM measure industry-level service and material offshoring intensities constructed from I-O data for the period 1992-2007. OI is a dummy variable which has a value of one if the Blinder index has a value greater than or equal to 65. Variable Task represents the four task variables. Variable INDUS accounts for industry level variables which are industry dummy variables, industry level output $\mathrm{Y}_{j,t}$ is measured at the major group level is used to account for differences in industry size, research and development intensity is used to proxy for technological progress and net exports are used to account for potential job creation and job destruction effects from trade. Following Geishecker & Görg (2008b), I include variable T_j which controls for industry specific time trends; Year effects μ_t and individual specific effects α_i are also included in the model. Individual specific effects control for potential unobserved individual heterogeneity that cannot be measured from available data; for example individual ability may affect the wage level and therefore equation (4) is estimated by panel fixed effects to provide consistent estimates of the betas[29]. Variables R&D intensity and industry specific time trends ensure the inclusion for industry specific technological progress. Finally, ε is a random disturbance term.

A first point of note with equation (4) as was the case with equation (3) is the combination of individual and industry level information may lead to contemporaneous correlations within the error term and this may result with bias within the estimated standard errors (Moulton, 1990). Following the standard approach taken by the literature, I follow Geishecker & Görg (2008b) and Crinò (2009b) and adjust the standard errors by clustering on 2-digit industry codes common across the sample of data[30]. As equation (4) includes industry level dummy variables, the effects from the impact of the offshoring intensity coefficients are identified through within-industry variation over time.

A second potential problem that may affect the estimation is the potential endogeneity of OSS and OSM. This problem may arise if wages and offshoring decisions are chosen simultaneously or because of time-invariant industry characteristics that may influence both variables and hence lead to inconsistent estimates (Crinò, 2009b). Geishecker & Görg (2008b) note this issue should not pose a problem to the results as equation (4) has a large range of industry-level data and individual-level wage data that should mitigate offshoring being endogenous. And with the inclusion of industry level fixed effects, this allows for the control

[29] The Hausman Specification test was applied to determine whether a fixed effects model was more appropriate or whether a random effects model was more appropriate. This test suggests the appropriate model to use for estimation is a fixed effects model.

[30] There are two sets of industry SIC codes available within the BHPS data. There is information on SIC80 codes for years 1991-2001 and SIC92 codes available for years 2002-present. There is no standard common convergence criterion that may be used to transfer one set of SIC codes to the other. Therefore, I obtained an unpublished convergence file from the Classifications Division at ONS, which provides a convergence index for industries between SIC80 and SIC92 codes. This file does not provide a one-to-one mapping between the two industry classifications; they provide partial correlations based on the title of each industry between the two classifications. The file only provides a guide between each SIC classification. Thus, from this index, I constructed a common two-digit SIC80 classification across the sample of data that would allow the standard errors to be clustered in the panel model.

of time invariant effects such as production technology within different industries. Following Geishecker & Görg (2008b) and Crinò (2009b), I test the assumption of exogeneity for OSS and OSM using an instrumental variable GMM approach of equation (4) by using the first two lags of each offshoring variable OSS and OSM in separate regressions as instruments.

4.4 Results

The results from the two specified models from section 4.3.2 are discussed in the following order in the forth-coming subsections: Section 4.4.1 provides the OLS results and Section 4.4.2 presents the panel regression estimates.

4.4.1 The Wage Levels for Potentially Offshorable Occupations

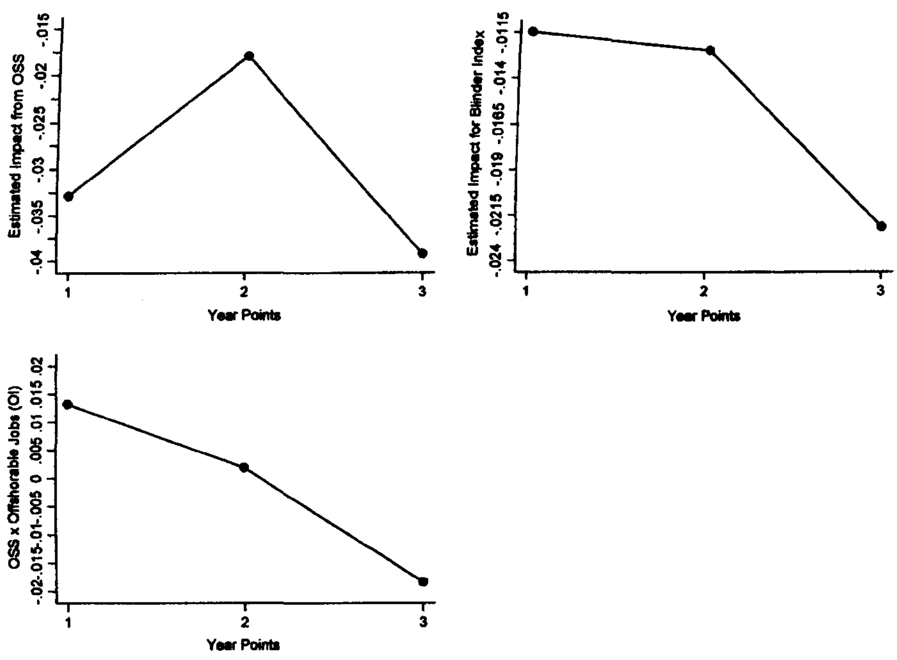
Figure 4.7 presents OLS estimates which plot the estimated impact from variables OI, service offshoring intensity, OSS and the interactions of OI and OSS upon wages. Each graph presents the estimated average trends from three-year point estimates. Each of the three-year point estimates represents the average impact on wages from a group of years. For example, year point '1' represents the average estimated impact on wages for the period 1992-1997; year point '2' represents the average estimated impact on wages for the period 1998-2002. And year point '3' represents the average estimated impact on wages for the period 2003-2007. I have plotted the average estimated coefficients from the three year points to examine the general trend from OI, OSS and OSM on wage levels over time instead of plotting each coefficient for each year.

From figure 4.7, the top right graph shows the estimated average impact on wages for the most tradable occupations as defined by the Blinder (2007) occupation tradability index. The estimated trend is negative over time, where workers who are employed within the most tradable jobs have become worse off. From the first and second year points, workers earned approximately 1.15% less per hour compared to workers not employed in the most tradable jobs for the period 1992-2002. By the third year point, workers employed in the most tradable jobs earned approximately 2.2% less per hour than workers employed in the least tradable jobs. However, table 4.8A from appendix 7 lists the estimated coefficients for each year. These estimates show most of these coefficients are insignificant for this particular plot.

The top left graph shows the impact of OSS intensity on wage levels. The first year point illustrates that workers earned approximately 3.5% less per hour on average from a 1% rise in OSS intensity. The second year point shows workers earned approximately 1.75% less per hour. By the third year point, the average point estimate shows that a one per cent rise in service offshoring intensity lowered the hourly wage level for workers employed in industries that engage in service offshoring by approximately 4%. This graph suggests that workers have become worse off over time resulting from the decline in wage levels. Additionally, the estimated coefficients from table 4.8A from appendix 7 shows that all of the year estimates which make up year point '3' are statistically significant and negative over time.

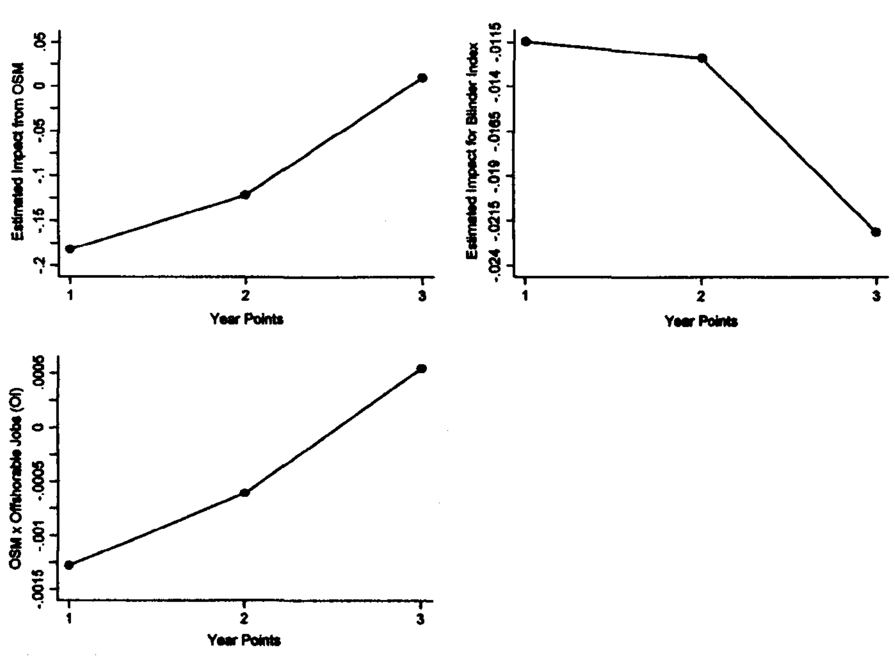
This final graph from figure 4.7 plots the estimated impact on wage levels from the interaction of OSS and OI: that is workers employed in the most tradable occupations and employed in industries that engage in service offshoring. This interaction captures the idea that these workers are more likely to have lower wage levels over time. From this graph, year points 1 and 2 show hourly wages were positive during the 1990s and the early 2000 time frame. For the latter part of the 2000s covered by year point 3, hourly wage levels were on average lower for workers compared to year points 1 and 2. However, table 4.8A shows that most of these estimated coefficients from these regressions are largely insignificant over time, and thus signifying that workers employed within the most tradable jobs and within industries that engage in service offshoring have not become significantly worse off over time through having lower wage levels.

Figure 4.7: Estimated Impact of Blinder Index and OSS upon Wages



Source: Compiled by the author. Year point indicators: 1 = 1992-1997; 2 = 1998-2002 and 3 = 2003-2007. See appendix 7, table 4.8A for a list of the estimated coefficients for each year and their significance.

Figure 4.8: Estimated Impact of Blinder Index and OSM upon Wages



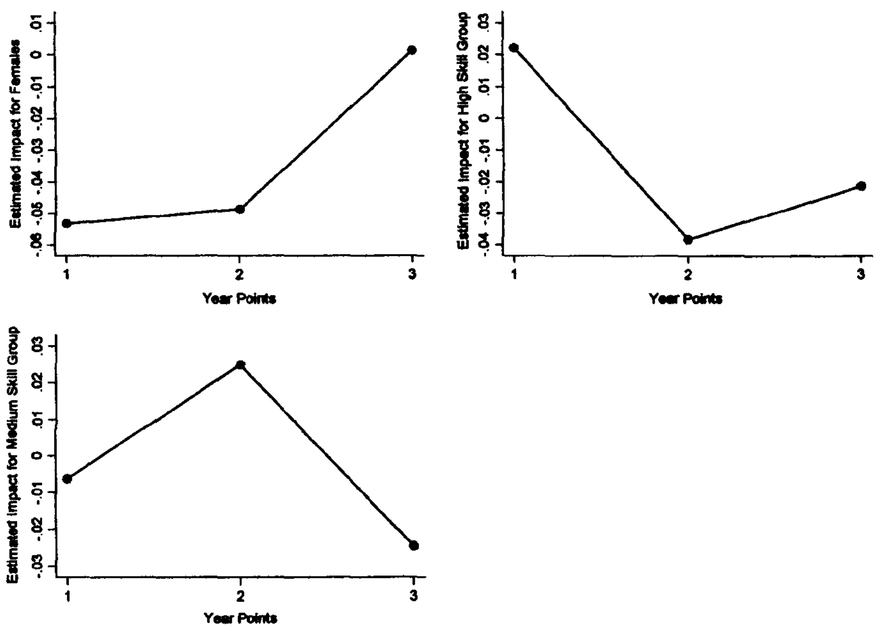
Source: Compiled by the author. Year point indicators: 1 = 1992-1997; 2 = 1998-2002 and 3 = 2003-2007. See appendix 7 table 4.9A for a list of the estimated coefficients for year and their significance.

Figure 4.8 explores the impact of OSM and OI over time. The top left graph shows that a rise in material offshoring intensity does not have a negative impact on the wage levels for workers employed within industries engaging in material offshoring over time. Although the graph does show the impact of OSM on wage levels was negative during the 1990s and early 2000s, year point 3 suggests there has been a positive impact on wage levels post 2000. Similarly, the interaction of OSM and OI show workers employed in the most tradable jobs and within industries that engage in material offshoring, their wage levels have not changed significantly over time. Additionally, table 4.9A from appendix 7 shows the estimated coefficients for each year are largely insignificant from these regressions over time.

Figures 4.9 and 4.10 examine how the wage levels for the most tradable jobs vary by worker and skill heterogeneity such as gender, race, educational attainment and white-collar employment over time. From figure 4.9, for female workers employed in the most tradable jobs, they have not experienced a fall in their wage levels over time. Although, year points one and two do show the wage levels were lower during the 1990s and the early 2000 time frame, but this is not shown for most recent year point on average.

For highly educated workers employed within the most tradable jobs, the top right graph shows this group of workers have had lower wage levels over time. And for medium skilled workers employed in the most tradable jobs, the bottom left graph shows the average impact on their wage levels has been negative for the latter part of the 2000 period shown by year point three. But, the estimated coefficients that make up the three year points for all of plots from figure 4.9 are presented in table 4.10A in appendix 7. These coefficients show the estimated coefficients for females, highly skilled and medium skilled workers are largely insignificant over time and they imply workers have not become worse off over time.

Figure 4.9: Estimated Impact of Blinder Index on Worker and Skill Heterogeneity



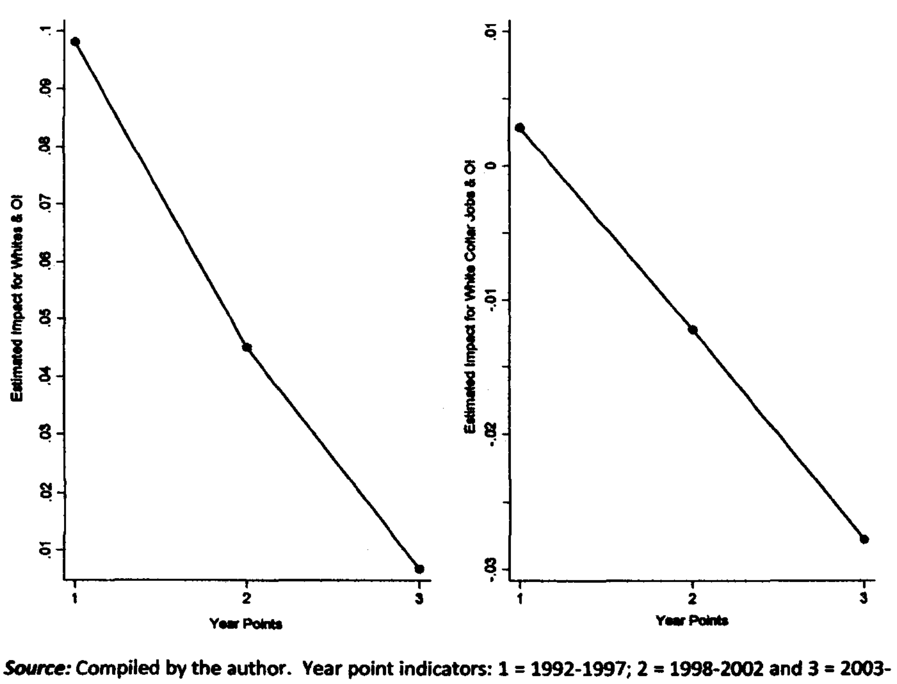
Source: Compiled by the author. Year point indicators: 1 = 1992-1997; 2 = 1998-2002 and 3 = 2003-2007. See appendix 7 table 4.10A for a list of the estimated coefficients for each year and their significance.

Figure 4.10 shows white workers employed by the most tradable jobs have had positive wage levels that are falling over time – the general trend is negative. Additionally, the impact on the wage levels for the most tradable white-collar jobs also shows a negative impact on hourly wage levels over time. However, the estimated coefficients for each graph are displayed in table 4.11A in appendix 7; they show most of the estimated coefficients are insignificant over time.

Figure 4.11 presents the estimated impact on the hourly wages from the four task variables, which explores the impact of the TBTC hypothesis. The two tasks variables which are of particular interest are routine job tasks and service job tasks. Routine job tasks are most likely to be replaced by technology but are also job tasks that can be offshored abroad. And service job tasks relate to activities that can be carried out by occupations situated at the upper and lower tails of the skill distribution. The importance of service job tasks for occupations situated at the upper tail of the skill distribution were unaffected by the first wave of offshoring which took place during the early 1980s and 1990s. More recently with the advancements in ICT, these occupations previously unaffected by offshoring may now face the possible risk of job loss and the potential threat of lower wage levels.

The first graph from figure 4.11, presents estimated coefficients which plot the impact upon wages for occupations which necessitate routine job tasks. This graph shows that with a one standard deviation increase in the importance of routine job tasks lowered wage levels on average by 0.75% and 0.55% during year point one and year point three. The impact on wages is negative over time but there are very few estimated coefficients that are statistically significant – these coefficients can be viewed in table 4.12A in appendix 7.

Figure 4.10: Estimated Impact of Blinder Index on White-Collar Jobs and Race

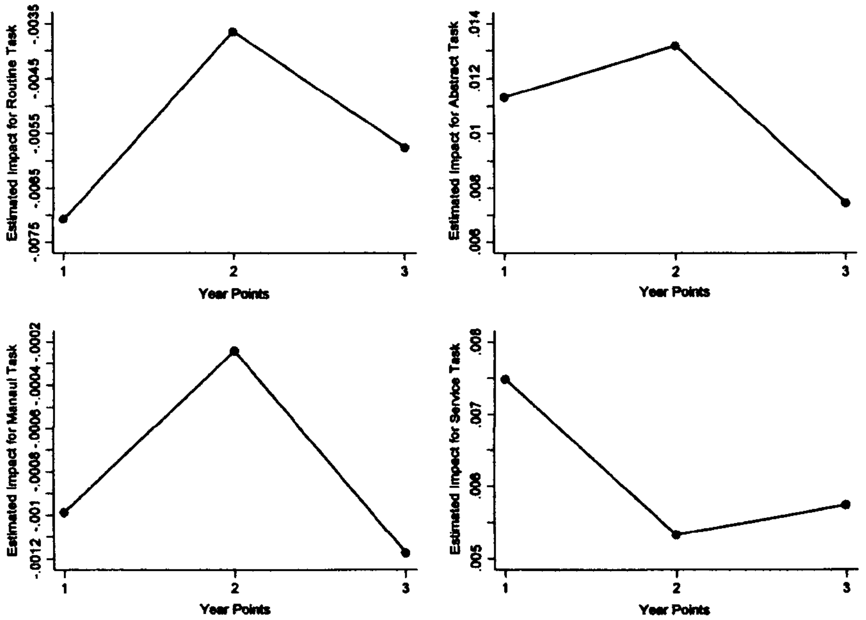


Source: Compiled by the author. Year point indicators: 1 = 1992-1997; 2 = 1998-2002 and 3 = 2003-2007. See appendix 7 table 4.11A for a list of the estimated coefficients for each year and their significance.

For non-routine abstract job tasks, a one standard deviation increase in the importance of non-routine abstract job tasks have had a positive and significant impact on hourly wages over the sample period. For occupations which require non-routine manual job tasks, the impact has been negative over time but also the magnitude from the impact has been very small and many of the estimated coefficients are largely insignificant. Finally to the final graph, a one standard deviation increase in the importance of service job tasks has a positive impact on the wage levels over time. However, the majority of the estimated coefficients are insignificant – see appendix 7 table 4.12A.

To sum up, this section has examined the impact of industry level offshoring intensity, a dummy variable which captures the most tradable jobs according to the Blinder's (2007) occupation tradability index and the TBTC hypothesis has had on individual level wage each year on average over time. The results from this section show industry level service offshoring intensity has on average had a negative and significant impact on the wage levels of workers who are employed within industries that engage in service offshoring over the three year points. Coefficients which measure the impact from material offshoring intensity at the industry level (OSM), workers employed in the most tradable jobs (OI), and workers employed in the most tradable jobs and employed within industries that engage in material and service offshoring have not had a significant and negative impact on their wage levels on average over time. Also, the effects from being employed within the most tradable jobs are independent of race, gender, white-collar employment and educational attainment. What these graph do show is that workers who are employed within occupations which have a high importance for non-routine abstract job tasks have had a positive and significant impact on their wage levels on average over time. The impact from routine and service intensive job tasks are insignificant over time; these results suggest that workers employed in jobs that are intensive in these job tasks have not significantly become significantly worse off.

Figure 4.11: Estimated Impact of Task Biased Technological Change upon Wages



Source: Compiled by the author. Year point indicators: 1 = 1992-1997; 2 = 1998-2002 and 3 = 2003 - 2007. See appendix 7 table 4.12A for a list of the estimated coefficients for each year and their significance.

4.4.2 Panel Regression Estimates

4.4.2.1 Results for Service Offshoring Intensity: OSS

Table 4.4 presents the results from the estimation of equation (4). Columns (1) and (2) from this table presents the baseline model where industry specific time trends are excluded from column (1) but are included in column (2). These two columns also exclude variables which explore skill heterogeneity.

From table 4.4, the estimated coefficients from individual level variables have their expected signs for all but one variable. From the estimated coefficients, the hourly wage increases with age (both variables: age and age squared are significant at the 1% level from all specifications of equation (4)), albeit at a decreasing rate reflecting the concave nature of the relationship. Being married yields a positive influence on hourly wages compared to the reference group of separated individuals. Individuals who are single or divorced earn lower hourly wages compared to the reference group (being a window), but these coefficients are not significant.

Having a dependent child lowers hourly pay, but again the estimated coefficient for this variable is not significant. Experience yields a concave relationship, where hourly pay rises up to a point where the returns to wages yield lower returns with increasing labour market experience.

Education is an important determinant to hourly pay and the results show individuals with a high level of education earn approximately 12% more towards their hourly pay than lower educated workers. Medium skilled workers earn less than lower educated workers according to the estimated coefficients; however these coefficients are small and not statistically significant. Female workers tend to earn less than male workers; the estimated coefficients for females show their hourly wages are approximately 18% lower.

Workers who are members of a trade union have higher hourly pay compared to non-union workers; the estimated coefficients show union workers have hourly earnings that are approximately 10% higher than for non-union workers. Controlling for external labour market conditions, the estimated coefficient from the annual unemployment rate has a negative influence. This is consistent with the findings from the literature where good economic conditions yield a lower unemployment rate and hence higher hourly pay, whilst the converse is true during bad economic conditions.

From the industry control variables, employment within smaller sized firms lead to lower hourly wages compared to the reference group for a firm size greater than a thousand. Public sector workers have higher hourly wages compared to workers employed within the private sector. Variables industry output, research and development intensity and net exports exert negligible returns to hourly wages. Crinò (2009b) suggests the inclusion of industry control variables in Mincer wage equations could be imprecisely estimated, as much of the effects from these variables may be absorbed by the industry and time variables[31]. The signs from these variables show hourly wages increase with industry output and net exports but fall with rising research and development intensity.

Finally, industry level service offshoring intensity (OSS) is significant and negative from columns (1) and (2) at the 10% and 1% significance levels; this result is consistent with OLS results reported in section 4.4.1. From column (1), where industry specific time trends are not included, a 1% rise in OSS intensity lowers hourly wages by 1.56%. With the addition of industry specific time trends, a 1% rise in OSS intensity lowers hourly wages by 1.91%. These findings are consistent with those reported by Görg & Geishecker (2008b), but the estimated coefficients from this chapter are smaller[32].

Moving onto the bottom part of table 4.4 presents the exogeneity test statistics obtained from the estimation of equation (4) via the instrumental variable GMM approach using the first two lags of OSS as instruments. The Hansen *J*-statistic presents results for instrument validity whilst the *C*-Statistic presents results for OSS exogeneity. The Hansen *J*-statistics for instrument validity are low, which suggests that lagged values of the current service offshoring variable are relevant instruments for present period service offshoring. Secondly, the *C*-statistic tests the null hypothesis for the exogeneity of OSS; these results show from columns (1) and (2), the null hypothesis of exogeneity cannot be rejected.

Columns (3), (4) and (5) supplement the baseline model from columns (1) and (2) with the addition of interaction variables to explore skill heterogeneity. Columns (3) and (4) incorporate the inclusion of variable OI which is the dummy variable constructed from the

[31] Crinò (2009b) includes time dummies, not a linear time trend.

[32] As a robustness check, I examined the interaction of variables OSS with a linear time trend to explore the impact from these coefficients over time. Appendix 15 table 4.20A provides the estimated coefficients from this exercise. They show from column (1) the impact of OSS has a significant and negative impact on wages. When OSS is interacted with a linear time trend, this coefficient is very small, positive and statistically significant. Therefore, the impact of OSS over time is negative but at a decreasing rate – signifying that workers are not becoming worse off over time. Additionally, a similar exercise was carried out with OI. From column (2) of table 4.20A, variable OI has no significant impact on wages. The interaction between OI and a linear time trend is also not significant – thus verifying the OLS results.

Blinder (2007) occupation tradability index; column (3) excludes industry specific time trends and column (4) includes industry specific time trends. The results from columns (3) and (4) present similar estimated coefficients which show the potentially most tradable occupations earn 3.62% and 3.53% less hourly pay than non-tradable occupations; these results are similar to those reported by OLS regressions from the last section.

With the interaction of OSS and the occupation tradability dummy variable OI, the estimated coefficients are positive and significant at the 5% level. These results suggest that individuals employed in potentially tradable occupations within industries that engage in service offshoring yields a positive impact on hourly pay[33]. It was predicted that workers employed in tradable occupations within industries that engage in service offshoring should experience a negative impact on their hourly pay compared to workers employed within industries that do not engage in high levels of service offshoring. These estimated results provide no support for this prediction. This result appears to support the theoretical literature, where service offshoring benefits the economy through higher productivity (Crinò, 2009a) and thus this appears to translate into higher pay. These results also contrast with the OLS results reported in the previous section which found workers employed within industries that engage in service offshoring and who are employed within the most tradable jobs have lower hour pay over time – however the estimated coefficients were largely insignificant over time.

Column (5) from table 4.4 examines skill heterogeneity and service offshoring. The estimated results are presented with the interaction between service offshoring intensity, OSS and education dummy variables for high-skilled and medium-skilled workers; the reference category is low-skill workers. For high-skilled workers, the estimated coefficient is small and positive but not significant. For medium-skilled workers, the estimated coefficient is negative and small but not significant. These results suggest that for high skilled workers, service

[33] The Hansen *J*-Statistic and the *C*-Statistic results for columns (3) and (4) reach similar conclusions to results for columns (1) and (2).

offshoring has a positive impact upon hourly wages. For medium skilled workers, service offshoring has a negative impact on hourly wages implying that firms offshore medium skilled service activities that may be in favour of high skilled labour, but the estimated result is not significant. These results differ with respect to the reported results from Görg & Geishecker (2008b) who find positive coefficients for both skill groups.

Table 4.4: Regression Results: Service Offshoring and Skill Heterogeneity

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Age	0.0875	0.0874	0.0876	0.0874	0.0874
	*(0.0094)****	*(0.0094)****	*(0.0094)****	*(0.0094)****	*(0.0095)****
Age Squared	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0232	0.0226	0.0231	0.0225	0.0224
	*(0.0128)**	*(0.0128)**	*(0.0129)**	*(0.0129)**	*(0.0127)**
Single	-0.0577	-0.0589	-0.0580	-0.0591	-0.0591
	*(0.0163)****	*(0.0160)****	*(0.0164)****	*(0.0161)****	*(0.0159)****
Divorced	-0.0190	-0.0193	-0.0187	-0.0190	-0.0194
	(0.0175)	*(0.0174)*	*(0.0178)*	*(0.0176)*	*(0.0174)*
Child	-0.0104	-0.0112	-0.0103	-0.0110	-0.0111
	(0.0075)	*(0.0076)*	*(0.0075)*	*(0.0076)*	*(0.0076)*
Experience	-0.0286	-0.0284	-0.0285	-0.0284	-0.0285
	*(0.0039)****	*(0.0039)****	*(0.0039)****	*(0.0039)****	*(0.0039)****
Experience Squared	0.0001	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)**
Union	0.0972	0.1003	0.0959	0.0991	0.1002
	*(0.0184)****	*(0.0184)****	*(0.0178)****	*(0.0177)****	*(0.0184)****
Unemployment Rate	-0.0115	0.0044	-0.0119	0.0037	0.0043
	*(0.0038)****	*(0.0027)*	*(0.0037)****	*(0.0027)*	*(0.0027)*
Edu: High Skill	0.1209	0.1190	0.1196	0.1176	0.1155
	*(0.0332)****	*(0.0323)****	*(0.0333)****	*(0.0324)****	*(0.0332)****
Edu: Medium Skill	-0.0033	-0.0034	-0.0034	-0.0036	0.0017
	(0.0089)	*(0.0088)*	*(0.0090)*	*(0.0090)*	*(0.0124)*
Female	-0.1818	-0.1817	-0.1807	-0.1807	-0.1817
	*(0.0109)****	*(0.0110)****	*(0.0112)****	*(0.0113)****	*(0.0111)****
Firm Size: <25	-0.1806	-0.1791	-0.1804	-0.1790	-0.1791
	*(0.0264)****	*(0.0256)****	*(0.0270)****	*(0.0262)****	*(0.0257)****
Firm Size: 25-99	-0.0840	-0.0834	-0.0837	-0.0831	-0.0834
	*(0.0229)****	*(0.0222)****	*(0.0233)****	*(0.0226)****	*(0.0223)****
Firm Size: 100-999	-0.0149	-0.0151	-0.0143	-0.0145	-0.0150
	(0.0212)	*(0.0205)*	*(0.0215)*	*(0.0208)*	*(0.0205)*
Firm: Public	0.0479	0.0410	0.0469	0.0398	0.0409
	*(0.0214)***	*(0.0221)**	*(0.0215)***	*(0.0220)**	*(0.0221)**
Industry: Output	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	-0.0064	-0.0031	-0.0081	-0.0040	-0.0033
	(0.0169)	*(0.0092)*	*(0.0175)*	*(0.0096)*	*(0.0091)*
Net Exports	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Offshoring: OSS	-0.0156	-0.0191	-0.0172	-0.0210	-0.0178
	*(0.0087)**	*(0.0063)****	*(0.0093)**	*(0.0070)****	*(0.0070)***
Offshoring: Blinder Index >=65	-	-	-0.0362	-0.0353	-
	-	-	*(0.0115)****	*(0.0123)****	-
Offshoring: OSS*Blinder Index>=65	-	-	0.0076	0.0077	-
	-	-	*(0.0033)***	*(0.0037)***	-
Offshoring: High Skill*OSS	-	-	-	-	0.0028
	-	-	-	-	*(0.0101)*
Offshoring: Medium Skill*OSS	-	-	-	-	-0.0022
	-	-	-	-	*(0.0032)*
Constant	0.4297	0.3007	0.4455	0.3157	0.2985

	*(0.1792)***	*(0.1571)**	*(0.1789)***	*(0.1566)***	*(0.1575)**
Industry Specific Time Trends	No	Yes	No	Yes	Yes
Region Controls	Yes	Yes	Yes	Yes	Yes
Occupation Controls	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Observations	58978	58978	58978	58978	58978
R^2	0.4926	0.4956	0.4927	0.4957	0.4956
Exogeneity Tests for OSS					
H_o: Instrument Validity					
Hansen *J*-Statistic	0.538	0.544	0.622	0.586	0.491
Hansen *J*-Statistic *(p-value)*	*(0.4631)*	*(0.4607)*	*(0.4302)*	*(0.4439)*	*(0.4835)*
H_o: Regressor is Exogenous					
C-Statistic	2.176	1.084	2.109	1.057	1.135
C-statistic *(p-value)*	*(0.1402)*	*(0.2978)*	*(0.1464)*	*(0.3039)*	*(0.2867)*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10.*

4.4.2.2 Results for Material Offshoring Intensity: OSM

Table 4.5 presents the estimated coefficients from the estimation of equation (4) with particular focus on the material offshoring intensity, OSM. As with the results from table 4.4, most of the estimated coefficients that control for individual, job and industry levels characteristics have similar estimated coefficients that were presented by table 4.4. The main variables of interest here are OSM and its interactions with OI and the different education groups.

From table 4.5, the estimated coefficients for the industry level material offshoring intensity (OSM) are all negative and insignificant from each of the columns (1) to (5). Additionally, the estimated coefficients from the interaction between OI and OSM are negative from columns (3) and (4), although they are all insignificant. Finally, the interaction of OSM with the high education dummy variable shows high-skilled workers employed in industries that engage in material offshoring have positive hourly wage levels (column (4)). For medium-skilled workers employed in industries that engage in material offshoring, their estimated coefficients are not significant, though it is positive (column (5)). These results once again differ with the reported results from Görg & Geishecker (2008b) who find a significant and negative impact of OSM intensity for workers with different skill intensities. My results may differ with the reported results from Geishecker & Görg (2008b) on three fronts. First, this chapter examines the impact of offshoring on the wage levels for men as well as for women; their sample concentrates exclusively on men. Secondly, the lack of significance could be due fewer women being employed within the manufacturing sector; women are more likely to be employed in service sector jobs than in manual blue-collar jobs (Acemoglu & Autor, 2010). Third, although the estimated coefficients are insignificant, which could be due to multi-collinearity, they do show the estimated impact from material and service offshoring have a similar impact on the wage levels of skilled and non-skilled workers. The Hansen *J*-statistics for each column accept the null hypothesis for lagged values of the current material offshoring intensity as relevant instruments for present period material offshoring. And the *C*-Statistic tests show OSM is exogenous in the estimation of equation (4).

Table 4.5: Regression Results: Material Offshoring and Skill Heterogeneity

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Age	0.0878	0.0876	0.0877	0.0876	0.0876
	*(0.0096)****	*(0.0096)****	*(0.0096)****	*(0.0096)****	*(0.0096)****
Age2	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0228	0.0219	0.0226	0.0216	0.0216
	*(0.0126)**	*(0.0126)**	*(0.0127)**	*(0.0126)**	*(0.0125)**
Single	-0.0585	-0.0603	-0.0589	-0.0606	-0.0605
	*(0.0163)****	*(0.0158)****	*(0.0164)****	*(0.0158)****	*(0.0158)****
Divorced	-0.0197	-0.0199	-0.0199	-0.0201	-0.0198
	(0.0175)	*(0.0173)*	*(0.0177)*	*(0.0174)*	*(0.0172)*
Child	-0.0100	-0.0111	-0.0099	-0.0110	-0.0111
	(0.0075)	*(0.0076)*	*(0.0075)*	*(0.0076)*	*(0.0076)*
Experience	-0.0287	-0.0284	-0.0285	-0.0283	-0.0283
	*(0.0040)****	*(0.0039)****	*(0.0040)****	*(0.0039)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0001)**
Union	0.0982	0.1004	0.0975	0.0998	0.1007
	*(0.0186)****	*(0.0187)****	*(0.0182)****	*(0.0183)****	*(0.0187)****
Unemployment Rate	-0.0145	-0.0005	-0.0147	-0.0008	-0.0005
	*(0.0026)****	*(0.0036)*	*(0.0025)****	*(0.0035)*	*(0.0036)*
Edu: High Skill	0.1186	0.1172	0.1177	0.1163	0.0985
	*(0.0332)****	*(0.0324)****	*(0.0332)****	*(0.0324)****	*(0.0289)****
Edu: Medium Skill	-0.0036	-0.0036	-0.0033	-0.0034	-0.0060
	(0.0089)	*(0.0088)*	*(0.0089)*	*(0.0088)*	*(0.0085)*
Female	-0.1842	-0.1840	-0.1827	-0.1827	-0.1836
	*(0.0114)****	*(0.0114)****	*(0.0118)****	*(0.0118)****	*(0.0114)****
Firm Size: <25	-0.1851	-0.1831	-0.1854	-0.1834	-0.1832
	*(0.0230)****	*(0.0236)****	*(0.0232)****	*(0.0238)****	*(0.0235)****
Firm Size: 25-99	-0.0853	-0.0845	-0.0852	-0.0844	-0.0846
	*(0.0220)****	*(0.0219)****	*(0.0223)****	*(0.0222)****	*(0.0218)****
Firm Size: 100-999	-0.0148	-0.0149	-0.0144	-0.0145	-0.0149
	(0.0217)	*(0.0212)*	*(0.0219)*	*(0.0213)*	*(0.0212)*

Firm: Public	0.0604	0.0548	0.0595	0.0541	0.0548
	*(0.0313)**	*(0.0305)**	*(0.0315)**	*(0.0305)**	*(0.0304)**
Industry: Output	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)****	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0001	0.0028	0.0005	0.0031	0.0024
	(0.0149)	*(0.0086)*	*(0.0150)*	*(0.0087)*	*(0.0085)*
Net Exports	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Offshoring: OSM	-0.0009	-0.0053	-0.0007	-0.0049	-0.0058
	(0.0045)	*(0.0059)*	*(0.0046)*	*(0.0062)*	*(0.0059)*
Offshoring: Blinder Index >=65	-	-	-0.0151	-0.0124	-
	-	-	*(0.0115)*	*(0.0112)*	-
Offshoring: OSM*Blinder Index>=65	-	-	-0.0007	-0.0008	-
	-	-	*(0.0014)*	*(0.0014)*	-
Offshoring: High Skill*OSM	-	-	-	-	0.0081
	-	-	-	-	*(0.0025)****
Offshoring: Medium Skill*OSM	-	-	-	-	0.0007
	-	-	-	-	*(0.0014)*
Constant	0.4020	0.3437	0.4132	0.3550	0.3465
	*(0.1739)***	*(0.1632)***	*(0.1744)***	*(0.1631)***	*(0.1641)***
Industry Specific Time Trends	No	Yes	No	Yes	Yes
Region Controls	Yes	Yes	Yes	Yes	Yes
Occupation Controls	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes
Observations	58978	58978	58978	58978	58978
R^2	0.4891	0.4932	0.4889	0.4931	0.4936
Exogeneity Tests for OSM					
H_o: Instrument Validity					
Hansen *J*-Statistic	1.113	1.016	1.083	1.026	1.036
Hansen *J*-Statistic *(p-value)*	*(0.2914)*	*(0.3136)*	*(0.2980)*	*(0.3112)*	*(0.3086)*
H_o: Regressor is Exogenous					
C-Statistic	0.390	0.025	0.434	0.032	0.034
C-statistic *(p-value)*	*(0.5321)*	*(0.8746)*	*(0.5100)*	*(0.8586)*	*(0.8530)*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10.*

4.4.2.3 Offshoring & Individual Heterogeneity

Table 4.6 presents the results from the estimation of equation (4) augmented with variables that explore the implications of offshoring for different subsets of worker groups. To explore the effects of offshoring on individual heterogeneity, I focus on three characteristics: gender, white-collar occupations and race. From table 4.6, the interaction between female and OSS is negative and significant at the 10% level. This result shows the impact of service offshoring has a more negative impact on the wage levels for female workers. Column (2) presents a positive yet insignificant coefficient for white-collar occupations. Finally, column (3) presents a positive and insignificant coefficient from the interaction between OSS and white individuals. Although this latter result is insignificant, it is in line with the OLS results from section 4.4.1, which found little significance between occupation tradability and race. These results also lay in accordance with the literature (e.g. Simister, 2000 and Cancio *et al.*, 1996) which finds non-white individuals tend to earn less compared to white individuals employed within similar occupations due to a segmented (Bonacich, 1972) or dual (Doeringe & Pione, 1971) labour market where non-whites disproportionately occupy less desirable low paying jobs. These estimated coefficients show the effects of service offshoring are not important to individual heterogeneity. They support the results reported by Crinò (2009b) who finds service offshoring intensity does not vary with individual level heterogeneity; Crinò (2009b) suggests the impact is homogenous across different individual workers.

Finally, the estimated results in columns (4), (5) and (6) show the impact from material offshoring. These results suggest that its impact is homogenous by sex, race and job type.

Table 4.6: Offshoring and Individual Level Characteristics

Dependent Variable: Log of Real Hourly Employment Wage	OSS			OSM		
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Offshoring	-0.0173	-0.0209	-0.0126	-0.0047	-0.0048	-0.0056
	*(0.0064)****	*(0.0085)***	*(0.0086)*	*(0.0060)*	*(0.0061)*	*(0.0061)*
Offshoring*Female	-0.0038	-	-	-	-	-
	(0.0022)	-	-	-	-	-
Offshoring*White Collar	-	0.0027	-	-	-0.0009	-
	-	*(0.0048)*	-	-	*(0.0018)*	-
Offshoring*White	-	-	-0.0067	-	-	0.0001
	-	-	*(0.0044)*	-	-	*(0.0025)*
Constant	0.3005	0.3042	0.1988	0.3441	0.3415	0.2573
	*(0.1568)**	*(0.1544)**	*(0.1627)*	*(0.1634)***	*(0.1642)***	*(0.1688)*
Observations	58978	58978	58978	58978	58978	58978
R^2	0.4957	0.4957	0.4961	0.4935	0.4932	0.4937
Exogeneity Tests for Offshoring						
H_o: Instrument Validity						
Hansen *J*-Statistic	0.599	0.572	0.329	1.037	1.019	0.993
Hansen *J*-Statistic *(p-value)*	*(0.4389)*	*(0.4494)*	*(0.5663)*	*(0.3084)*	*(0.3127)*	*(0.6087)*
H_o: Regressor is Exogenous						
C-Statistic	1.023	1.025	1.315	0.031	0.022	0.008

C-statistic *(p-value)*	*(0.3118)*	*(0.3113)*	*(0.2516)*	*(0.8599)*	*(0.8832)*	*(0.9294)*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. OSS - Industry level service offshoring intensity; OSM – industry level material offshoring intensity. A white collar occupation is a dummy variable equal to one for occupations: Legislators, Senior Officials, Managers, Professionals, Technicians, Associate Professionals and Clerks. See appendices 8 and 9 which provide the full list of estimated coefficients.

4.4.2.4 Wages and the Task Biased Technological Change Hypothesis

Table 4.7 presents the effects from the four job task variables created to measure the TBTC hypothesis upon wages. These variables are routine job tasks, non-routine abstract job tasks, non-routine manual job tasks and service job tasks. Job tasks may have an important impact on wage levels as these job tasks may either be complemented by or be adversely affected by technological innovations. The ALM hypothesis finds ICT can substitute for human labour in occupations which have a high importance for completing routine job tasks; can be a complement with abstract job tasks and is neither a complement nor a substitute for manual job tasks. For service job tasks there is a mixture of complementarity and substitutability between certain service job task characteristics and technology as technology complements 'establishing and maintaining interpersonal relationships', but will not complement 'face-to-face discussions'. The reason behind this explanation is that an occupation which is required to complete these activities may have to be present at specific labour market locations, e.g. a child minder has to be physically present to supervise young children but may use mobile technology to inform parents of their children's welfare. For routine job tasks, the impact on wage levels should be negative. For abstracts job tasks, the impact should be positive; for manual job tasks, it is unclear whether the impact will be positive or negative and finally for service job tasks, the impact on wages should be positive[34].

[34] Goos *et al.*, (2008, 2009) find service job tasks yields a positive influence on labour demand in Europe. Thus, a positive influence on labour demand should transpire to a positive impact upon the returns to earnings.

Table 4.7 presents the estimated coefficients from equation (4). From column (1), routine job tasks have a significant and negative impact on wage levels, where a one standard deviation increase in the importance of routine job tasks causes hourly wages to fall by 0.52%.

Column (2) presents the estimated impact from non-routine abstract job tasks. The estimated coefficient is positive and significant at the 1% level implying that a one standard deviation increase in the importance of abstract job tasks raises hourly pay by 0.92%. For non-routine manual job tasks, column (3) presents a positive coefficient indicating a positive impact on wages; however the coefficient is not significant. Column (4) presents the impact of service job tasks on wages. This estimated coefficient is positive and significant at the 5% level, implying that a one standard deviation increase in the importance of service job tasks raises hourly pay by 0.58%. Finally, column (5) presents the estimated coefficients from equation (4) which now includes all job task variables[35]. From column (5), abstract job tasks continue to have a significant and positive impact on wage levels, whilst all other job task variables are not significant, with the service job task variable now a negative coefficient.

Table 4.7: Task Biased Technological Change & Wages

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Routine Job Task	-0.0052	-	-	-	-0.0101
	*(0.0022)***	-	-	-	*(0.0094)*
Non-Routine Abstract Job Task	-	0.0092	-	-	0.0087
	-	*(0.0023)****	-	-	*(0.0042)***
Non-Routine Manual Job Task	-	-	0.0005	-	0.0073
	-	-	*(0.0033)*	-	*(0.0082)*
Service Job Task	-	-	-	0.0058	-0.0015
	-	-	-	*(0.0022)***	*(0.0044)*
Constant	0.3444	0.3964	0.3396	0.3628	0.3899
	*(0.1664)***	*(0.1577)***	*(0.1669)***	*(0.1626)***	*(0.1584)***
Observations	58707	58707	58978	58707	58707
R^2	0.4942	0.4958	0.4933	0.4942	0.4956

Note: All regression models present robust standard errors clustered by 2-digit SIC level within the parentheses. *Significance Level: ***p<0.01, **p<0.05 and *p<0.10.* Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. See appendix 10 for the full list of estimated coefficients.

[35] It is important to note here that the task variables are not dummy variables. Thus, there is no reference category that must be excluded from estimation.

In summary, routine job tasks are associated with occupations that lie in the middle of the wage distribution (Goos *et al.*, 2003, 2007); these results imply that firms are likely to substitute routine job tasks with computers, but they are also the most offshorable job tasks where a fall in demand for occupations which require routine job tasks may yield a fall in wages. Occupations which require abstract job tasks lie at the top end of the wage distribution, where firms appear to employ computers to complement occupations which require this job task. Occupations which require abstract job tasks are more likely to be associated with high-skilled workers and therefore it would appear that industries are more likely to reward occupations which require abstract job tasks with higher pay at the expense of occupations that require routine job tasks. For occupations which require non-routine manual job tasks which lie at the bottom end of the wage distribution, there appears to be little change to their wage levels from these job tasks. This result is to be expected as computers appear to be neither a complement nor a substitute for human labour at the bottom portion of the wage distribution. For occupations which require service job tasks, computers appear to complement these job tasks, which therefore has a positive impact on wages. The results from table 4.7 show the importance of the type of job tasks completed by occupations are important factors that affect the wage levels of workers in addition to service offshoring over time. These results are similar to the results reported by the OLS regressions and they support the TBTC hypothesis posed by Autor *et al.*, (2003).

4.4.2.5 Wages, Task Biased Technological Change and Individual Heterogeneity

Next, I examine task bias technological change associated with individual heterogeneity. Individual heterogeneity is examined with the interaction of the female, white individuals and white-collar occupation dummy variables with the four task variables. Equation (4) was estimated with the addition of these interaction variables. The estimated results are presented within tables 4.8, 4.9 and 4.10.

From table 4.8, for females, routine job tasks and non-routine manual job tasks have a negative and significant impact on wage levels. From abstract and service job task interactions, the impact on wages are positive but not significant. These results are not consistent with the reported findings from the literature review. Spitz-Oener (2006) and Black & Spitz-Oener (2007, 2010) found women gradually completed more analytical job tasks than routine job tasks compared to men in Germany over time; therefore this should translate to a positive impact on their wage levels and hence these changes to the types of job tasks performed by women contributed towards narrowing the gender pay gap between men and women in Germany. This chapter's job task measures are not dynamic but are fixed over time; therefore, my results suggest that if women have jobs that are more intensive in routine and manual job tasks as part of their work responsibilities, their impact on wage levels are bound to be negative. But if they were dynamic TBTC variables, I believe the results this chapter would be in line with the reported findings from Spitz-Oener (2006) and Black & Spitz-Oener (2007, 2010).

From table 4.9, for white-collar occupations, the interaction between white-collar jobs and non-routine manual job tasks yields a small and significant negative impact on wages. The interactions between other job task variables are not significant.

The results from this section show the impact from the job task variables are important determinants of wages and they also vary across different individual workers. This evidence supports the findings reported by Autor & Handel (2009) who found female workers carried out far fewer analytical job tasks and far more interpersonal and routine job tasks than equally educated male workers.

Table 4.8: Task Biased Technological Change and Individual Characteristics - Gender

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Routine Job Task	0.0035	-	-	-
	(0.0035)	-	-	-
Female*Routine Job Task	-0.0151	-	-	-
	*(0.0040)****	-	-	-
Non-Routine Abstract Job Task	-	0.0077	-	-
	-	*(0.0029)****	-	-
Female*Non-Routine Abstract Job Task	-	0.0027	-	-
	-	*(0.0027)*	-	-
Non-Routine Manual Job Task	-	-	0.0064	-
	-	-	*(0.0051)*	-
Female*Non-Routine Manual Job Task	-	-	-0.0121	-
	-	-	*(0.0033)****	-
Service Job Task	-	-	-	0.0041
	-	-	-	*(0.0024)**
Female*Service Job Task	-	-	-	0.0035
	-	-	-	*(0.0028)*
Constant	0.3198	0.3936	0.3153	0.3604
	*(0.1669)**	*(0.1581)***	*(0.1664)**	*(0.1630)***
Observations	58707	58707	58978	58707
R^2	0.4958	0.4959	0.4947	0.4945

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. See appendix 11 for the full list of estimated coefficients.

Lastly, table 4.10 presents the interactions from the job task variables with race. The estimated coefficients show there is little significance between job tasks and white individuals. Although the estimated coefficient from column (4) shows white workers employed in occupations that have a high importance for service related job tasks can have a negative impact on their wage levels.

Table 4.9: Task Biased Technological Change and Individual Characteristics – White Collar Jobs

Dependent Variable: Log of Real Hourly Employment Wage				
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Routine Job Task	-0.009	-	-	-
	(0.0077)	-	-	-
White-collar*Routine Job Task	0.0058	-	-	-
	(0.0128)	-	-	-
Non-Routine Abstract Job Task	-	0.0092	-	-
	-	*(0.0043)***	-	-
White-collar*NR-Abstract Job Task	-	0.0000	-	-
	-	*(0.0062)*	-	-
Non-Routine Manual Job Task	-	-	0.0079	-
	-	-	*(0.0033)**	-
White-collar*NR-Manual Job Task	-	-	-0.0126	-
	-	-	*(0.0037)****	-
Service Job Task	-	-	-	0.0055
	-	-	-	*(0.0053)*
White-collar*Service Job Task	-	-	-	0.0004
	-	-	-	*(0.0067)*
Constant	0.3549	0.3963	0.3134	0.3623
	*(0.1526)***	*(0.1477)***	*(0.1627)**	*(0.1537)***
Observations	58707	58707	58978	58707
R^2	0.4944	0.4958	0.4936	0.4942

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. See appendix 12 for the full list of estimated coefficients.

Table 4.10: Task Biased Technological Change and Individual Characteristics – Race

Dependent Variable: Log of Real Hourly Employment Wage				
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Routine Job Task	-0.0097	-	-	-
	(0.0063)	-	-	-
Non-Routine Abstract Job Task	-	0.0121	-	-
	-	*(0.0042)****	-	-
Non-Routine Manual Job Task	-	-	-0.0027	-
	-	-	*(0.0065)*	-
Service Job Task	-	-	-	0.0128
	-	-	-	*(0.0049)***
White*Routine Job Task	0.0048	-	-	-
	(0.0052)	-	-	-
White*NR-Abstract Job Tasks	-	-0.0030	-	-
	-	*(0.0033)*	-	-
White*NR-Manual Job Tasks	-	-	0.0034	-
	-	-	*(0.0045)*	-
White*Service Job Task	-	-	-	-0.0074
	-	-	-	*(0.0040)**
Constant	0.2794	0.3297	0.2732	0.2991
	(0.1690)	*(0.1596)***	*(0.1680)*	*(0.1647)*
Observations	58707	58707	58978	58707
R^2	0.4949	0.4965	0.4940	0.4950

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05 and *p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. See appendix 13 for the full list of estimated coefficients.

4.4.2.6 TBTC & Blinder (2007) Occupation Tradability Index

This penultimate section examines whether workers employed within the most tradable jobs earn lower pay than other least tradable jobs as defined by the Blinder (2007) occupation tradability index. Following Blinder (2007), I create nine dummy variables which take a value of one for specific values from the job tradability index. These dummy variables were added to equation (4), where table 4.11 presents the results; the reference category relates to category IV, which relates to the highly non-offshorable jobs. See section 4.2.2 and figure 4.2.1 for a reminder of the index and the categories.

From the top half of table 4.11, workers employed within highly offshorable jobs with index values in the range 76-85 earn 15.05% less per hour compared to highly non-offshorable jobs. This figure is very close to a figure reported by Blinder (2007) using a single year of data for the U.S. Similarly, non-offshorable jobs with index values 26-35 earn almost 8% less than highly non-offshorable jobs and workers employed within occupations which have an index value of 25 earn 6.23% more than the reference group.

The second half of table 4.11 examines whether the most tradable jobs are the most offshorable because these jobs have a high degree of importance for completing routine-type job tasks. For this exercise, I simply interact each of the Blinder index dummy variables with the routine job task variable that was created via principal component analysis. From the bottom half of table 4.11, the estimated coefficients show for the most offshorable jobs with index values of 86+ and 76-85 interacted with routine job task variable have hourly wages that are lower. These results demonstrate that routine job tasks completed by workers employed within highly tradable job are more likely to have lower wage levels. The estimated coefficients from the interactions with the routine job task variable with the lesser offshorable job dummy variables are not significant.

Table 4.11: Blinder Index & Task Biased Technological Change

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	**Estimated Coefficients**
Offshoring: Blinder Index Values 25	0.0623
	*(0.0336)**
Offshoring: Blinder Index Values 26-35	-0.0795
	*(0.0362)***
Offshoring: Blinder Index Values 36-45	0.0258
	(0.0293)
Offshoring: Blinder Index Values 46-55	0.0042
	(0.0310)
Offshoring: Blinder Index Values 56-65	0.0045
	(0.0180)
Offshoring: Blinder Index Values 66-75	-0.0110
	(0.0254)
Offshoring: Blinder Index Values 76-85	-0.1505
	*(0.0400)****
Offshoring: Blinder Index Values 86+	-0.0385
	(0.0259)
Routine Tasks	0.0000
	(0.0033)
Blinder Index Values 25*Routine Job Task	0.0521
	(0.0312)
Blinder Index Values 26-35*Routine Job Task	0.0060
	(0.0131)
Blinder Index Values 36-45*Routine Job Task	-0.0229
	*(0.0078)****
Blinder Index Values 46-55*Routine Job Task	0.0102
	(0.0107)
Blinder Index Values 56-65*Routine Job Task	0.0109
	*(0.0043)***
Blinder Index Values 66-75*Routine Job Task	-0.0030
	(0.0059)
Blinder Index Values 76-85*Routine Job Task	-0.0560
	*(0.0088)****
Blinder Index Values 86+*Routine Job Task	-0.0205
	*(0.0063)****
Constant	0.3749
	*(0.1645)****
Observations	58707
R^2	0.4961

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. This regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. Reference group for the Blinder Index are all occupations that have a value of zero; these are the non-tradable occupations. See appendix 14 for the full list of estimated coefficients.

4.4.2.7 Monetary Magnitudes

Finally, table 4.12 provides a simple exercise to estimate the monetary impact from service offshoring intensity (OSS), the most tradable occupations (OI) and the importance of completing routine job tasks has on the wage level per hour, over one week, one month and one year. To estimate the monetary impact, the estimated coefficients have been taken from tables 4.4 and 4.7. For service offshoring, a 1% rise in service offshoring intensity lowers hourly wages by 1.91%-2.10%; the estimated monetary fall in the average hourly wages over the sample at 1995 prices ranges from £0.16- £0.18, if the average hourly pay is £8.63. Assuming the average number of hours worked per week is 37.5 hours, the monetary loss in pay over one week is £6.18-£6.80. Over one month, the monetary loss is £24.72- £27.20. Annually, a 1% rise in service offshoring lowers annual pay by £321.36-£326.40.

For the most tradable occupations, the monetary loss is slightly bigger. According to the estimated coefficient from table 4.4, hourly pay is lower by 3.53% compared to the least tradable occupations. Per hour, this translates to a £0.30 fall if the average hourly pay rate is taken to be £8.63. Per week, this is a fall of £11.42 and per month the fall in pay amounts to £45.70. Annually, the fall in pay for the most tradable occupations is estimated to be £548.35.

Table 4.12: Monetary Estimates

Average Hourly Wage at 1995 Prices: £8.63[Ω]		
Hours Worked per Week: 37.5		
Service Offshoring Intensity	**Tradable Occupations**	**Routine Tasks**
-1.91% - -2.10%[α]	-3.53%[α]	-0.52%[β]
Fall in Hourly Wage		
£0.16-£0.18	£0.30	£0.04
Fall in Pay: One Week		
£6.18-£6.80	£11.42	£1.68
Fall in Pay: One Month		
£24.72-£27.20	£45.70	£6.73
Fall in Pay: One Year		
£321.36-£326.40	£548.35	£80.78

Source: Author's own calculations. α: represents estimated coefficients taken from table 4.4. β represents estimated coefficient taken from table 4.7. Ω – Average hourly wage statistic taken from table 4.3.

For occupations which are intensive in routine job tasks, the monetary impact is small from a one standard deviation change; however the monetary loss could be big if occupations have a very high importance for completing routine job tasks. A one standard deviation increase in the importance for routine job tasks lowers hourly wages by 0.52%. Per hour, the fall in the hourly wage is £0.04 for an average hourly wage of £8.63. Per week, the fall in pay is £1.68; per month this fall in pay translates to £6.73. Annually, the monetary impact from a one standard deviation increase in the importance for routine job tasks lower pay by £80.78.

4.5 Conclusion

This chapter has examined the effects of offshoring and how the advancements of technology can affect the wage levels of British workers for the period 1992 to 2007. Using the British Household Panel Survey, the estimation of Mincer wage regressions examined how industry level material and service offshoring intensity, and the advancements of technology could potentially make some jobs previously unaffected by offshoring more offshorable and affect individual level wages. The potential threat of engaging in offshoring can provide firms with the impetus to lower wage rises because of the potential threat of substituting domestic labour with foreign workers. Additionally, the impact from the TBTC hypothesis –technology substituting away routine job tasks performed by labour are also job tasks that are most likely to be offshored. The results from this chapter show the impact from service offshoring at the industry level, the potential threat from the advancements of technology that increasingly pose a threat to many more potentially tradable occupations and the threat of TBTC – particularly from the importance of completing routine job tasks, all have had a negative and significant impact on the wage levels of workers.

The results from this chapter show skilled workers benefit from offshoring (materials and services) activities at the expense of lesser skilled labour and where the affects of offshoring does not discriminate by gender or race. These findings are consistent with the reported results from the empirical literature (Feenstra & Hanson (1995, 1996 & 1999) and Crinò (2009c) for the U.S. and Geishecker & Görg (2008a,b), Hummels *et al* (2009) and Munch & Skaksen (2009) for European countries.

From the preferred specifications, the results show that a one percent rise from industry level service offshoring intensity lower hourly wage levels by 1.91%-2.10%. The monetary magnitude from this estimation can imply a fall in pay that could amount to £321.36 - £326.40

over the course of one year. This fall in pay can be substantial for workers who are employed by firms that engage in service offshoring. However, industry level material offshoring intensity exerts no significant impact on the wage levels of workers, though the estimated coefficients are negative for less skilled workers and positive for skilled workers. These results suggest that material offshoring and service offshoring have a similar impact on wage levels though they differ by their statistical significance.

According to Blinder's (2007) occupation tradability index, workers employed within the most offshorable jobs earn 3.53% less per hour compared to workers who are employed by lesser tradable jobs. The monetary loss over the space of one year can be substantial, amounting to £548.35. Finally, from the TBTC hypothesis, a one standard deviation increase in the importance of routine job tasks lowers hourly wage levels by 0.52%. The monetary loss can amount to £80.78 over twelve months. This loss could potentially be greater for occupations which have a very high importance for completing routine job tasks. Finally, workers employed within the most tradable jobs, which also have a high importance for completing routine intensive job tasks have lower wage levels over time compared to other jobs that are not as potentially tradable.

This chapter has shown that offshoring, being employed in the most tradable jobs and completing routine intensive job tasks can lower job stability but can they lower job security? The forth coming chapter examines whether these forces have raised job insecurity by increasing the probability of becoming unemployed over the last two decades.

4.6 Appendices

Appendix 1

Table 4.1A: Complete List of Offshorable Occupations

ISCO88	ISCO88 Description	ISCO Offshorability Index	Number
2141	Architects, town and traffic planners	25	1
2453	Composers, musicians and singers	25	2
3415	Technical and commercial sales representatives	25	3
4142	Mail carriers and sorting clerks	26	4
7311	Precision-instrument makers and repairers	26	5
7414	Fruit, vegetable and related preservers	27	6
8271	Meat- and fish-processing-machine operators	27	7
8277	Tea-, coffee-, and cocoa-processing-machine operators	27	8
8155	Petroleum- and natural-gas-refining-plant operators	29	9
8161	Power-production plant operators	29	10
8229	Chemical-products machine operators not elsewhere classified	29	11
8274	Baked-goods, cereal and chocolate-products machine operators	29	12
9333	Freight handlers	29	13
3472	Radio, television and other announcers	30	14
4131	Stock clerks	31	15
8275	Fruit-, vegetable- and nut-processing-machine operators	31	16
3228	Pharmaceutical assistants	32	17
2432	Librarians and related information professionals	33	18
3139	Optical and electronic equipment operators not elsewhere classified	34	19
3224	Optometrists and opticians	34	20
8340	Ships' deck crews and related workers	34	21
3132	Broadcasting and telecommunications equipment operators	35	22
7112	Shotfirers and blasters	35	23
8222	Ammunition- and explosive-products machine operators	35	24
7111	Miners and quarry workers	36	25
7113	Stone splitters, cutters and carvers	36	26
7121	Builders, traditional materials	36	27
7129	Building frame and related trades workers not elsewhere classified	36	28
8111	Mining-plant operators	36	29
8113	Well drillers and borers and related workers	36	30
4115	Secretaries	38	31
1226	Production and operations department managers in transport, storage and communications	39	32
1233	Sales and marketing department managers	40	33
8224	Photographic-products machine operators	41	34
8163	Incinerator, water-treatment and related plant operators	42	35
1316	General managers in transport, storage and communications	43	36
3111	Chemical and physical science technicians	43	37
4141	Library and filing clerks	43	38
7421	Wood treaters	43	39
8112	Mineral-ore- and stone-processing-plan operators	44	40
3213	Farming and forestry advisers	44	41
2412	Personnel and careers professionals	46	42
3133	Medical equipment operators	46	43
7344	Photographic and related workers	47	44
3113	Electrical engineering technicians	47	45
3114	Electronics and telecommunications engineering technicians	47	46
3116	Chemical engineering technicians	47	47
3211	Life science technicians	48	48
3212	Agronomy and forestry technicians	48	49
1142	Senior officials of employers', workers' and other economic-interest organisations	49	50
1232	Personnel and industrial relations department	49	51
1235	Supply and distribution department managers	49	52
3422	Clearing and forwarding agents	49	53
2419	Business professionals not elsewhere classified	50	54
3414	Travel consultants and organisers	50	55
3417	Appraisers, valuers and auctioneers	50	56
4133	Transport clerks	51	57
2421	Lawyers	51	58
3141	Ships' engineers	52	59
1317	General managers of business services	52	60
3131	Photographers and image and sound recording equipment operators	52	61
1234	Advertising and public relations department managers	53	62
3119	Physical and engineering science technicians not elsewhere classified	53	63
2455	Film, stage and related actors and directors	54	64
3439	Administrative associate professionals not elsewhere classified	54	65
4214	Pawnbrokers and money-lenders	54	66
2111	Physicists and astronomers	54	67
1227	Production and operations department managers in business services	55	68
1228	Production and operations department managers in personal care, cleaning and related service	55	69
1236	Computing services department managers	55	70
1237	Research and development department managers	55	71

1311	General managers in agriculture, hunting, forestry/ and fishing	55	72
1313	General managers in construction	55	73
1314	General managers in wholesale and retail trade	55	74
1315	General managers of restaurants and hotels	55	75
1318	General managers in personal care, cleaning and related services	55	76
1319	General managers not elsewhere classified	55	77
3416	Buyers	55	78
7415	Food and beverage tasters and graders	55	79
8162	Steam-engine and boiler operators	55	80
7423	Woodworking machine setters and setter-operators	57	81
7437	Upholsterers and related workers	57	82
8141	Wood-processing-plant operators	57	83
8285	Wood and related products assemblers	57	84
8251	Printing-machine operators	58	85
1222	Production and operations department managers in manufacturing	58	86
3419	Finance and sales associate professionals not elsewhere classified	59	87
6142	Charcoal burners and related workers	59	88
7331	Handicraft workers in wood and related materials	59	89
7341	Compositors, typesetters and related workers	59	90
7342	Stereotypers and electrotypers	59	91
7343	Printing engravers and etchers	59	92
7345	Bookbinders and related workers	59	93
8121	Ore and metal furnace operators	59	94
8252	Bookbinding-machine operators	59	95
1312	General managers in manufacturing	59	96
2149	Architects, engineers and related professionals not elsewhere classified	60	97
3152	Safety, health, and quality inspectors	60	98
4190	Other office clerks	60	99
8240	Wood-products machine operators	61	100
4223	Telephone switchboard operators	62	101
7422	Cabinet makers and related workers	63	102
3421	Trade brokers	64	103
4132	Production clerks	64	104
8281	Mechanical-machinery assemblers	64	105
2143	Electrical engineers	64	106
7313	Jewellery and precious-metal workers	64	107
8171	Automated-assembly-line operators	64	108
8286	Paperboard, textile and related products assemblers	64	109
9321	Assembling labourers	64	110
4215	Debt-collectors and related workers	65	111
7211	Metal moulders and coremakers	65	112
7241	Electrical mechanics and fitters	65	113
3432	Legal and related business associate professionals	65	114
2113	Chemists	66	115
2114	Geologists and geophysicists	66	116
7424	Basketry weavers, brush makers and related workers	66	117
8282	Electrical-equipment assemblers	66	118
8283	Electronic-equipment assemblers	66	119
4222	Receptionists and information clerks	67	120
8290	Other machine operators and assemblers	67	121
3123	Industrial robot controllers	68	122
3411	Securities and finance dealers and brokers	68	123
7141	Painters and related workers	68	124
7224	Metal wheel-grinders, polishers and tool sharpeners	68	125
7323	Glass engravers and etchers	68	126
7324	Glass, ceramics and related decorative painters	68	127
7413	Dairy-products makers	68	128
8122	Metal melters, casters and rolling-mill operators	68	129
8124	Metal drawers and extruders	68	130
8139	Glass, ceramics and related plant operators not elsewhere classified	68	131
8142	Paper-pulp plant operators	68	132
8143	Papermaking-plant operators	68	133
8151	Crushing-, grinding- and chemical-mixing machinery operators	68	134
8153	Chemical-filtering- and separating-equipment operators	68	135
8154	Chemical-still and reactor operators (except petroleum and natural gas)	68	136
8159	Chemical-processing-plant operators not elsewhere classified	68	137
8172	Industrial-robot operators	68	138
8211	Machine-tool operators	68	139
8212	Cement and other mineral products machine operators	68	140
8221	Pharmaceutical- and toiletry-products machine operators	68	141
8223	Metal finishing-, plating- and coating-machine operators	68	142
8253	Paper-products machine operators	68	143
8272	Dairy-products machine operators	68	144
8273	Grain- and spice-milling-machine operators	68	145
8276	Sugar production machine operators	68	146
8278	Brewers-, wine and other beverage machine operators	68	147
2147	Mining engineers, metallurgists and related professionals	69	148
8131	Glass and ceramics kiln and related machine operators	69	149
8284	Metal-, rubber- and plastic-products assemblers	69	150
3431	Administrative secretaries and related associate professionals	69	151
7212	Welders and flamecutters	69	152

7321	Abrasive wheel formers, potters and related workers	69	153
7322	Glass-makers, cutters, grinders, and finishers	69	154
8231	Rubber-products machine operators	69	155
7222	Tool-makers and related workers	69	156
8232	Plastic-products machine operators	70	157
2145	Mechanical engineers	70	158
7213	Sheet-metal workers	70	159
8123	Metal-heat-treating-plant operators	70	160
8152	Chemical-heat-treating-plant operators	70	161
9322	Hand packers and other manufacturing labourers	70	162
7223	Machine-tool setters and setter-operators	70	163
4114	Calculating-machine operators	71	164
2146	Chemical engineers	72	165
2411	Accountants	72	166
3115	Mechanical engineering technicians	72	167
3442	Government tax and excise officials	72	168
4221	Travel agency and related clerks	72	169
8261	Fibre-preparing-, spinning- and winding machine operators	73	170
2144	Electronics and telecommunications engineers	73	171
7434	Furriers and related workers	73	172
2112	Meteorologists	74	173
2451	Authors, journalists and other writers	74	174
2211	Biologists, botanists, zoologists, and related professionals	74	175
7435	Textile, leather and related pattern-makers and cutters	75	176
1231	Finance and administration department managers	75	177
7332	Handicraft workers in textile, leather and related materials	75	178
7346	Silk-screen, block and textile printers	75	179
7431	Fibre preparers	75	180
7432	Weavers, knitters and related workers	75	181
7433	Tailors, dressmakers and hatters	75	182
7436	Sewers, embroiderers and related workers	75	183
7441	Pelt dressers, tanners and fellmongers	75	184
7442	Shoe-makers and related workers	75	185
8262	Weaving- and knitting-machine operators	75	186
8263	Sewing machine operators	75	187
8264	Bleaching-, dyeing- and cleaning-machine operators	75	188
8265	Fur and leather-preparing-machine operators	75	189
8266	Shoemaking- and related machine operators	75	190
8269	Textile-, fur- and leather-products machine operators not elsewhere classified	75	191
4122	Statistical and finance clerks	75	192
3122	Computer equipment operators	76	193
2452	Sculptors, painters and related artists	78	194
2121	Mathematicians and related professionals	80	195
3121	Computer assistants	80	196
4121	Accounting and bookkeeping clerks	80	197
2131	Computer systems designers and analysts	81	198
3471	Decorators and commercial designers	83	199
2212	Pharmacologists, pathologists, and related professionals	83	200
3433	Bookkeepers	84	201
3434	Statistical, mathematical and related associate professionals	84	202
3412	Insurance representatives	85	203
2148	Cartographers and surveyors	86	204
5113	Travel guides	86	205
2441	Economists	89	206
2139	Computing professionals not elsewhere classified	90	207
3460	Social work associate professionals	90	208
2444	Philologists, translators and interpreters	93	209
4112	Word-processor and related operators	94	210
3118	Draughtspersons	94	211
4144	Scribes and related workers	94	212
4211	Cashiers and ticket clerks	94	213
4111	Stenographers and typists	95	214
4143	Coding, proof-reading and related clerks	95	215
9113	Door-to-door and telephone salespersons	95	216
2122	Statisticians	96	217
2132	Computer programmers	100	218
4113	Data entry operators	100	219

Source: Author's own compilation from mapping Blinder's (2007) job tradability index on British data.

Appendix 2

Table 4.2A: Spearmen's Rank Correlation Coefficients between Three Skill Measure and Blinder's Index

	Skill Measures					
Year	Wages		Years of Education		Avg. Years of Education[36]	
1992	0.0816	***	-0.0010		-0.0317	**
1993	0.0758	***	-0.0062		-0.0408	**
1994	0.1055	***	-0.0049		-0.0318	**
1995	0.1194	***	-0.0031		-0.0175	
1996	0.1133	***	-0.0081		-0.0298	*
1997	0.1265	***	0.0001		-0.0202	
1998	0.1235	***	-0.0228		-0.0430	***
1999	0.1454	***	-0.0166		-0.0371	**
2000	0.1247	***	-0.0154		-0.0368	**
2001	0.1194	***	-0.0333	**	-0.0471	***
2002	0.0838	***	-0.0061		-0.0232	
2003	0.1451	***	0.0182		0.0018	
2004	0.1243	***	-0.0098		-0.0232	
2005	0.1008	***	0.0247		0.0103	
2006	0.2279	***	0.0573	***	0.0426	**
2007	0.2090	***	0.0474	**	0.0311	

Source: Results compiled by the author. Spearman's Rank Correlation coefficients are presented. Significance Level: ****p<0.01; **p<0.05; *p<0.10.* The null hypothesis tests the independence between the skill measures and the Blinder Occupation Tradability Index; that is there is no correlation. Data used is the BHPS data.

Appendix 3

O*NET Database

O*NET stands for the 'Occupational Information Network'. It is a project that was created by the U.S. Department of Labor, through the Employment and Training Administration (ETA) to provide a successor to the Dictionary of Occupational Titles (DOT) which had provided details of occupations since the 1930s. The objective for the O*NET project is to maintain and develop occupation descriptions that are available from the system. The O*NET project is a database which provides public standard descriptions of occupations in the U.S.

The database contains details of 949 occupational titles[37] of which at least 812 occupations have or will have data available for the titles. Missing information for some occupation titles

[36] Average Years of Education are defined as follows from Blinder (2007): E1 = Fraction with high school qualifications or less; E2 = fraction with some college; E3 = fraction with a bachelor's degree or higher. Additionally two scalar measures for average years of education are constructed: E4 = E3-E1 and E5 = 10E1 +14E2+18E3. Measures E5 is used in this estimation.

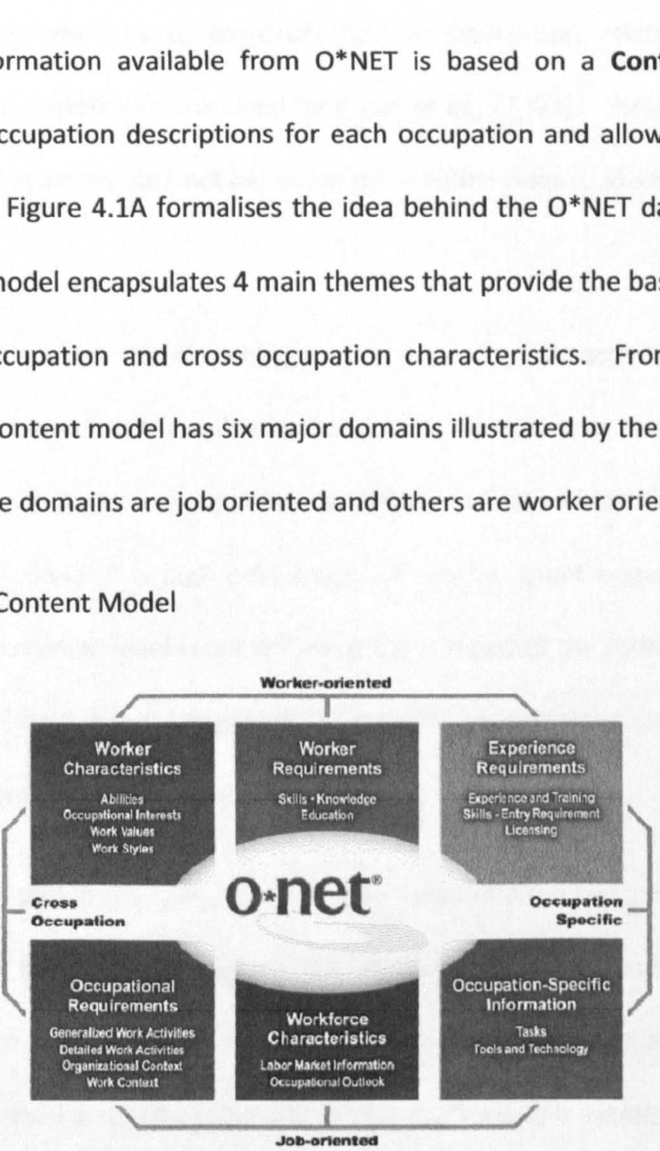
[37] The version of O*NET that I have used is Version 13.0, but the latest version available is July 2009 is Version 14.0.

are due to there being no information available for the titles as information may not have been collected or the information may not be possible to be collected because some of the titles were created using O*NET-SOC classifications. The O*NET-SOC classifications are based upon the U.S. SOC system, however there may be some occupation titles that provide a little more detail compared to the available U.S. SOC titles.

O*NET Occupation Information

The occupation information available from O*NET is based on a **Content Model**, which provides common occupation descriptions for each occupation and allows for a comparison across occupations. Figure 4.1A formalises the idea behind the O*NET database. The outer ring of the content model encapsulates 4 main themes that provide the basis for O*NET which are: worker, job, occupation and cross occupation characteristics. From these four outer characteristics, the content model has six major domains illustrated by the six different square boxes. Some of these domains are job oriented and others are worker oriented.

Figure 4.1A: O*NET Content Model



Source: O*NET Occupations Reference Guide

Each of these domains is made up of a series of elements that refer to a series of worker, job, occupation and experience characteristics which may influence the domain. For example, the Worker Characteristics domain consists of four elements which are Abilities, Occupational

Interests, Work Values and Work Styles. Each of these elements refers to characteristics or work activities that may influence the performance and capacity to acquire knowledge and skills required to carry out effective work performance.

For each element, O*NET provides 11 rating scales which provide a measure for a number of characteristics/work activities that describe how these characteristics/work activities relate to each O*NET-SOC. From these 11 rating scales, I use the ***importance*** level and the ***context*** level required to perform jobs to construct four variables that relate to the Task Bias Technological Change Hypothesis proposed by Autor *et al.,* (2003). These variables measure routine job tasks, non-routine abstract job tasks, non-routine manual job tasks and service job tasks.

The context level measures the percentage of time a job task activity may relate to an occupation and is measured from a rating scale of 1 to 5. For example, the percentage of time may relate to how much time an occupation may engage in face-to-face discussions within the context of an occupation. If a high percentage of time is spent engaging in face-to-face discussions, then the context level score will be at the top end of the rating scale near to 5. If a small percentage of time is spent engaging in face-to-face discussions, the context rating will be towards the bottom end of the rating scale near to 1.

The importance level provides a rating for the importance of a job task activity. For example, the importance level may seek to measure how important manual dexterity may be to the performance of a job. The importance level is measured from a five point scale, where 1 denotes the item (manual dexterity) is not important and 5 which is extremely important[38].

From the O*NET occupation database, I have selected elements from three of the six domains. These domains are worker characteristics, worker requirements and occupational

[38] The following link is one of many resources that are available which provides greater depth of details of the O*NET database: ftp://ftp.xwalkcenter.org/download/onet10/ONET10UserGuide.pdf

requirements. From each of these domains, I have used the elements which provide the importance level and the context level rating scales for selected job task activity descriptions. Appendix 5 provides details of each work task activity that has been used to perform principal component analysis.

Appendix 4

Explaining the O*NET 'Importance Rating'

Table 4.3A lists the importance scale ratings for five occupations in relation to the four job task variables I have constructed to measure TBTC. Each of the job task variables are constructed from a list of potential job task activities which are associated with routine, non-routine (manual and abstract) and service job tasks. For each occupation there is an importance rating in the range of 1-5 to indicate the importance each activity has to each occupation.

Table 4.3A: Task Importance from O*NET Classifications

ISCO-88 Occupations	Mining & Quarrying Labourers	Medical Doctors	Economists	Computer Programmers	Domestic Helpers & Cleaners
Routine Tasks					
Manual Dexterity	4.13	4.00	1.00	2.13	2.50
Spend Time Making Repetitive Movements	3.42	2.38	2.03	3.47	4.31
Clerical	1.69	2.52	2.25	2.61	2.17
Abstract Tasks					
Analytical Thinking	2.83	4.57	4.80	4.27	2.86
Attention to Detail	4.09	4.96	4.62	4.27	4.27
Leadership	3.18	4.06	3.90	3.03	2.99
Manual Tasks					
Performing General Physical Activities	3.04	2.64	1.17	1.66	3.00
Multi-limb Co-ordination	4.38	3.38	1.00	1.00	2.38
Handling & Moving Objects	3.67	3.84	1.16	1.64	2.69
Service Tasks					
Face-to-Face Discussions	4.24	5.00	4.59	4.84	3.87
Service Orientation	2.79	4.20	2.87	2.54	2.53
Selling & Influencing Others	1.84	2.44	2.71	2.43	1.42

Source: Author's own compilation.

For example, the medical profession is a high skilled profession where routine, abstract, manual and service related job task activities are important functions that are required to be performed by this occupation group. The importance ratings for medical doctors are quite high for the majority of the job task activities listed by this table. For instance, medical doctors are required to use their medical training to prescribe medicines, make diagnosis and perform operations to aid patient welfare. Many of these functions require analytical thinking to try to diagnose illnesses; they need to have attention to detail to make sure the correct doses of medication are prescribed to patients. Many of these activities are listed under abstract job tasks have an importance scale rating greater than 4. Doctors also have face-to-face consultations (service related job activities) with patients; they use their limbs (manual job tasks) to check the physical welfare of patients and are required to fill out forms to keep a record (clerical related job task activities) for patients' medical histories. It must be noted that the importance scale rating is specific to each occupations and cannot be compared to other occupations.

In comparison to medical doctors, computer programmers perform a number of abstract related job task activities. This is reflected by all job task activities listed under abstract job tasks in table 4.3A to have an importance scale rating greater than 3. There are few routine related job tasks performed by computer programmers, and there is little importance for manual dexterity or clerical related job task activities. There is also little need for manual job tasks such as multi-limb co-ordination or service tasks related to service orientation or selling and influencing people.

For mining and quarrying labourers, manual job tasks such as performing general physical activities, multi-limb co-ordination and handling and moving physical objects have a greater importance rating for this occupation compared to economists or computer programmers. Thus, many of these job task activities related to manual job tasks have an importance scale rating greater than 3.

Appendix 5

Selection of Variables used to construct the Job Task Variables

For each TBTC variable, I have selected the following task activity variables from the following domains: Worker Characteristics, Worker Requirements and Occupational Requirements. Variables selected from these domains are available from the O*NET database bundle. From these files I have selected 95 task activity variables, where some variables are used more than once. All variables that I have used to construct each task measure are listed below:

Routine Tasks

Arm-hand steadiness; Manual dexterity; Finger dexterity; Control Precision; Wrist finger speed; Reading Comprehension; Operation Monitoring; Operation and Control; Repairing; Clerical; Estimating the quantifiable characteristics of products, events or information; Processing Information; Interacting with Computers; Documenting/Recording Information; Performing administrative activities; Spend time making repetitive motions; Degree of automation; Importance of repeating same task; Pace determined by speed of equipment. **Number of Variables: 19.**

Non-Routine Abstract Tasks

Originality; Deductive reasoning; Inductive reasoning; Mathematical reasoning; Memorization; Speed of Closure; Flexibility of closure; Selective attention; Achievement/Effort; Persistence; Initiative; Leadership; Stress tolerance; Adaptability/Flexibility; Attention to detail; Independence; Innovation; Analytical thinking; Reading comprehension; Mathematical skills; Critical thinking; Active learning; Monitoring; Complex problem solving; Judgment and decision making; Management of personnel resources; Administration and management; Mathematical knowledge; Evaluating information to determine compliance with standards; Making decisions and solving problems; Thinking creatively; Developing objectives and strategies; Interpreting the meaning of information for others; Communicating with supervisors, peers or subordinates; Coordinating the work activities of others; Dependability. **Number of Variables: 36.**

<u>**Non-Routine Manual Tasks**</u>

Multi-limb coordination; Response orientation; Rate control; Reaction time; Static strength; Dynamic strength; Peripheral vision; Depth perception; Equipment selection; Performing general physical activities; Handling and moving objects; Operating vehicles, mechanized devices or equipment; Deal with unpleasant or angry people; Spend time standing; Spend time climbing ladders, scaffolds or poles; Spend time walking and running; Spend time kneeling, crouching, stooping or crawling; Spend time keeping or regaining balance; Spend time using your hands to handle, control, or feel objects, tools, or controls; Spend time bending or twisting the body. **Number of Variables: 20.**

<u>**Service Tasks**</u>

Speech clarity; Cooperation; Social orientation; Self control; Active listening; Speaking; Social perceptiveness; persuasion; Service orientation; Management of material resources; Sales and marketing; Customer and personal service; Communication and media; Judging the qualities of things, services, or people; Communicating with persons outside the organisation; Establishing and maintaining interpersonal relationships; Assisting and caring for others; Selling or Influencing others; Resolving conflicts and negotiating with others; Performing for or working directly with the public; Face-to-face discussions; Deal with external customers; Concern for others. **Number of Variables: 23.**

Appendix 6

Table 4.4A: Principal Component Eigenvalues and Proportion of Explained Variance for Routine Job Tasks

Principal Component	Eigenvalue	Proportion of Variance explained Individually	Cumulative explained Variance
1	8.4413	0.4443	0.4443
2	3.2354	0.1703	0.6146
3	2.5019	0.1317	0.7462
4	1.0245	0.0539	0.8002
5	0.8091	0.0426	0.8427
6	0.5988	0.0315	0.8743
7	0.5042	0.0265	0.9008
8	0.4028	0.0212	0.9220
9	0.3176	0.0167	0.9387
10	0.2267	0.0119	0.9506
11	0.2013	0.0106	0.9612
12	0.1716	0.0090	0.9703
13	0.1420	0.0075	0.9777
14	0.1375	0.0072	0.9850
15	0.0934	0.0049	0.9899
16	0.0613	0.0032	0.9931
17	0.0553	0.0029	0.9960
18	0.0488	0.0026	0.9986
19	0.0265	0.0014	1.0000

Source: **Author's own calculations using the BHPS data. This table presents un-rotated eigenvalues for each component. As there are 19 variables used to create a single component for routine tasks, the principal component loadings or eigenvectors are not presented. Eigenvalues, proportion of individually explained variance and cumulative explained variance present values adjusted to 4-decimal places.**

Table 4.5A: Principal Component Eigenvalues and Proportion of Explained Variance for Abstract Job Tasks

Principal Component	Eigenvalue	Proportion of Variance explained Individually	Cumulative explained Variance
1	18.6198	0.5172	0.5172
2	4.3243	0.1201	0.6373
3	2.9573	0.0821	0.7195
4	1.8605	0.0517	0.7712
5	1.4093	0.0391	0.8103
6	1.1796	0.0328	0.8431
7	1.0566	0.0293	0.8724
8	0.6197	0.0172	0.8896
9	0.5126	0.0142	0.9039
10	0.4360	0.0121	0.9160
11	0.4177	0.0116	0.9276
12	0.3552	0.0099	0.9375
13	0.2816	0.0078	0.9453
14	0.2576	0.0072	0.9524
15	0.2357	0.0065	0.9590
16	0.2003	0.0056	0.9645
17	0.1569	0.0044	0.9689
18	0.1364	0.0038	0.9727
19	0.1193	0.0033	0.9760
20	0.1084	0.0030	0.9790
21	0.1026	0.0028	0.9819
22	0.0890	0.0025	0.9843
23	0.0866	0.0024	0.9868
24	0.0687	0.0019	0.9887
25	0.0598	0.0017	0.9903
26	0.0550	0.0015	0.9918
27	0.0529	0.0015	0.9933
28	0.0500	0.0014	0.9947
29	0.0374	0.0010	0.9957
30	0.0325	0.0009	0.9966
31	0.0299	0.0008	0.9975
32	0.0230	0.0006	0.9981
33	0.0206	0.0006	0.9987
34	0.0182	0.0005	0.9992
35	0.0148	0.0004	0.9996
36	0.0142	0.0004	1.0000

Source: **Author's own calculations using the BHPS data. This table presents un-rotated eigenvalues for each component. As there are 36 variables used to create a single component for non-routine abstract tasks, the principal component loadings or eigenvectors are not presented. Eigenvalues, proportion of individually explained variance and cumulative explained variance present values adjusted to 4-decimal places.**

Table 4.6A: Principal Component Eigenvalues and Proportion of Explained Variance for Manual Job Tasks

Principal Component	Eigenvalue	Proportion of Variance explained Individually	Cumulative explained Variance
1	11.5588	0.5779	0.5779
2	2.6894	0.1345	0.7124
3	1.6332	0.0817	0.7941
4	0.9374	0.0469	0.8409
5	0.7766	0.0388	0.8798
6	0.6025	0.0301	0.9099
7	0.4512	0.0226	0.9325
8	0.2855	0.0143	0.9467
9	0.2360	0.0118	0.9585
10	0.2042	0.0102	0.9687
11	0.1700	0.0085	0.9772
12	0.1241	0.0062	0.9835
13	0.0890	0.0044	0.9879
14	0.0715	0.0036	0.9915
15	0.0535	0.0027	0.9942
16	0.0342	0.0017	0.9959
17	0.0276	0.0014	0.9972
18	0.0258	0.0013	0.9985
19	0.0171	0.0009	0.9994
20	0.0122	0.0006	1.0000

Source: Author's own calculations using the BHPS data. This table presents un-rotated eigenvalues for each component. As there are 20 variables used to create a single component for non-routine manual tasks, the principal component loadings or eigenvectors are not presented. Eigenvalues, proportion of individually explained variance and cumulative explained variance present values adjusted to 4-decimal places.

Table 4.7A: Principal Component Eigenvalues and Proportion of Explained Variance for Service Job Tasks

Principal Component	Eigenvalue	Proportion of Variance explained Individually	Cumulative explained Variance
1	10.7328	0.4666	0.4666
2	2.9327	0.1275	0.5942
3	2.4895	0.1082	0.7024
4	1.6873	0.0734	0.7758
5	0.9932	0.0432	0.8189
6	0.7256	0.0315	0.8505
7	0.6382	0.0277	0.8782
8	0.5397	0.0235	0.9017
9	0.4725	0.0205	0.9222
10	0.2983	0.0130	0.9352
11	0.2697	0.0117	0.9469
12	0.1954	0.0085	0.9554
13	0.1739	0.0076	0.9630
14	0.1586	0.0069	0.9699
15	0.1257	0.0055	0.9754
16	0.1041	0.0045	0.9799
17	0.0989	0.0043	0.9842
18	0.0888	0.0039	0.9880
19	0.0666	0.0029	0.9909
20	0.0639	0.0028	0.9937
21	0.0577	0.0025	0.9962
22	0.0500	0.0022	0.9984
23	0.0369	0.0016	1.0000

Source: Author's own calculations using the BHPS data. This table presents un-rotated eigenvalues for each component. As there are 23 variables used to create a single component for service tasks, the principal component loadings or eigenvectors are not presented. Eigenvalues, proportion of individually explained variance and cumulative explained variance present values adjusted to 4-decimal places.

Appendix 7

Table 4.8A: OLS Results for Single Year Regressions

Year	OSS	OI	OSS x OI
1992	-0.0235	-0.0385	0.0220
	(0.0128)	*(0.0181)***	*(0.0087)***
1993	-0.0474	-0.0337	0.0017
	*(0.0135)****	*(0.0176)**	*(0.0076)*
1994	-0.0236	-0.0056	0.0158
	(0.0133)	*(0.0186)*	*(0.0091)**
1995	-0.0131	-0.0138	0.0105
	(0.0114)	*(0.0165)*	*(0.0073)*
1996	-0.0468	0.0093	0.0151
	*(0.0123)****	*(0.0150)*	*(0.0056)****
1997	-0.0427	0.0136	0.0144
	*(0.0129)****	*(0.0182)*	*(0.0069)***
1998	-0.0065	-0.0076	0.0112
	(0.0092)	*(0.0142)*	*(0.0067)**
1999	-0.0327	0.0035	0.0118
	*(0.0112)****	*(0.0158)*	*(0.0061)**
2000	-0.0197	-0.0115	-0.0052
	*(0.0109)**	*(0.0202)*	*(0.0072)*
2001	-0.0084	-0.0061	0.0144
	(0.0089)	*(0.0164)*	*(0.0060)***
2002	-0.0219	-0.0402	-0.0229
	*(0.0116)***	*(0.0169)***	*(0.0162)*
2003	-0.0367	-0.0117	-0.0026
	*(0.0140)****	*(0.0174)*	*(0.0184)*
2004	-0.0229	-0.0105	-0.0097
	*(0.0131)***	*(0.0173)*	*(0.0237)*
2005	-0.0248	-0.0535	-0.0539
	*(0.0136)***	*(0.0219)***	*(0.0319)**
2006	-0.0576	-0.0171	-0.0321
	*(0.0126)****	*(0.0219)*	*(0.0376)*
2007	-0.0538	-0.0180	0.0068
	*(0.0163)****	*(0.0255)*	*(0.0304)*

Source: Compiled by the author. All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects, industry controls, job characteristics, individual characteristics and industry level variables. OSS = Industry level service offshoring intensity; OI = Dummy variable equal to one if occupations have a value greater than or equal to 65 according to the Blinder (2007) offshorability index.

Table 4.9A: OLS Results for Single Year Regressions

Year	OSM	OSM x OI
1992	-0.1336	-0.0007
	(0.0984)	*(0.0029)*
1993	-0.3749	0.0019
	*(0.1082)****	*(0.0028)*
1994	0.0120	-0.0001
	(0.0102)	*(0.0030)*
1995	-0.0920	0.0024
	(0.1038)	*(0.0025)*
1996	-0.5074	-0.0059
	*(0.1437)****	*(0.0022)****
1997	-0.0002	-0.0052
	(0.0077)	*(0.0026)***
1998	-0.0404	-0.0019
	(0.0913)	*(0.0023)*
1999	-0.3626	-0.0001
	*(0.1305)****	*(0.0025)*
2000	-0.2184	-0.0013
	*(0.1160)**	*(0.0026)*
2001	0.0072	0.0004
	(0.0062)	*(0.0021)*
2002	0.0075	-0.0001
	(0.0098)	*(0.0021)*
2003	0.0036	-0.0010
	(0.0087)	*(0.0025)*
2004	0.0169	0.0013
	*(0.0087)**	*(0.0025)*
2005	0.0142	-0.0012
	(0.0111)	*(0.0022)*
2006	0.0041	-0.0008
	(0.0069)	*(0.0028)*
2007	0.0052	0.0044
	(0.0094)	*(0.0030)*

Source: Compiled by the author. All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*.. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects, industry controls, job characteristics, individual characteristics and industry level variables. OSM = Industry level material offshoring intensity; OI = Dummy variable equal to one if occupations have a value greater than or equal to 65 according to the Blinder (2007) offshorability index.

Table 4.10A: OLS Results for Single Year Regressions

Year	Female x OI	High x OI	Medium x OI
1992	-0.0447	0.0560	-0.0804
	(0.0336)	*(0.1809)*	*(0.0312)***
1993	-0.0729	-0.0044	-0.0061
	*(0.0349)***	*(0.1477)*	*(0.0315)*
1994	-0.0685	0.1723	-0.0057
	*(0.0356)**	*(0.1084)*	*(0.0314)*
1995	-0.0681	-0.0469	-0.0025
	*(0.0280)***	*(0.1101)*	*(0.0326)*
1996	-0.0489	0.0723	0.0344
	(0.0332)	*(0.1583)*	*(0.0293)*
1997	-0.0175	-0.1172	0.0224
	(0.0317)	*(0.1137)*	*(0.0292)*
1998	-0.0546	0.1397	0.0283
	*(0.0269)***	*(0.0733)**	*(0.0277)*
1999	-0.0849	0.0577	0.0433
	*(0.0288)****	*(0.1066)*	*(0.0293)*
2000	-0.0570	-0.1177	0.0203
	*(0.0308)**	*(0.0657)**	*(0.0296)*
2001	-0.0086	-0.1043	0.0223
	(0.0300)	*(0.0851)*	*(0.0283)*
2002	-0.0385	-0.1672	0.0107
	(0.0350)	*(0.0858)**	*(0.0302)*
2003	-0.0056	-0.2357	0.0173
	(0.0293)	*(0.1096)***	*(0.0319)*
2004	-0.0082	-0.0365	-0.0132
	(0.0338)	*(0.1249)*	*(0.0366)*
2005	0.0502	-0.0844	-0.0566
	(0.0392)	*(0.1220)*	*(0.0347)*
2006	-0.0402	0.1345	-0.0063
	(0.0417)	*(0.1160)*	*(0.0397)*
2007	0.0098	0.1152	-0.0645
	(0.0424)	*(0.1291)*	*(0.0466)*

Source: Compiled by the author. All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects, industry controls, job characteristics, individual characteristics and industry level variables. OI = Dummy variable equal to one if occupations have a value greater than or equal to 65 according to the Blinder (2007) offshorability index. High = Dummy variable equal to one for college level of education. Medium = Dummy variable for intermediate level of education.

Table 4.11A: OLS Results for Single Year Regressions

Year	White Ethnicity	White Ethnicity x OI	White Collar Jobs x OI
1992	0.0407	0.1038	-0.0077
	(0.0289)	*(0.0571)**	*(0.0366)*
1993	0.0295	0.0806	-0.0428
	(0.0377)	*(0.0756)*	*(0.0390)*
1994	0.0277	0.0842	0.0261
	(0.0360)	*(0.0650)*	*(0.0390)*
1995	0.0796	0.0991	-0.0142
	*(0.0299)****	*(0.0584)**	*(0.0395)*
1996	0.0504	0.1635	0.0319
	*(0.0304)**	*(0.0602)****	*(0.0369)*
1997	0.0519	0.0572	0.0236
	(0.0381)	*(0.0658)*	*(0.0405)*
1998	0.0636	0.0930	0.0008
	*(0.0307)***	*(0.0644)*	*(0.0384)*
1999	0.0906	-0.0583	0.0112
	*(0.0386)***	*(0.0713)*	*(0.0374)*
2000	0.1084	-0.0047	0.0004
	*(0.0355)****	*(0.0691)*	*(0.0403)*
2001	0.0533	0.0545	-0.0253
	(0.0344)	*(0.0642)*	*(0.0330)*
2002	0.1306	0.1401	-0.0483
	*(0.0448)****	*(0.0876)*	*(0.0321)*
2003	0.0830	0.1801	-0.0407
	*(0.0480)**	*(0.0927)**	*(0.0398)*
2004	0.0973	0.0218	-0.0153
	*(0.0384)***	*(0.0850)*	*(0.0373)*
2005	0.1000	0.0281	-0.0552
	*(0.0357)****	*(0.0717)*	*(0.0419)*
2006	0.0557	-0.1366	-0.0197
	(0.0435)	*(0.0887)*	*(0.0527)*
2007	0.0517	-0.0599	-0.0081
	(0.0450)	*(0.1150)*	*(0.0536)*

Source: Compiled by the author. All regression models present robust standard errors clustered by the 2-digit SIC level within parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects, industry controls, job characteristics, individual characteristics and industry level variables. OI = Dummy variable equal to one if occupations have a value greater than or equal to 65 according to the Blinder (2007) offshorability index. A white-collar occupation is a dummy variable equal to one for occupations Legislators, Senior Officials, Managers, Professionals, Technicians, Associate Professionals and Clerks.

Table 4.12A: OLS Results for Single Year Regressions

Year	Routine Tasks	Non Routine Abstract Tasks	Non Routine Manual Tasks	Service Tasks
1992	-0.0111	0.0119	-0.0005	0.0145
	*(0.0041)****	*(0.0027)****	*(0.0042)*	*(0.0037)****
1993	-0.0005	0.0087	0.0032	0.0075
	(0.0052)	*(0.0035)***	*(0.0051)*	*(0.0042)**
1994	-0.0056	0.0128	0.0011	0.0077
	(0.0056)	*(0.0044)****	*(0.0049)*	*(0.0037)***
1995	-0.0018	0.0098	0.0005	0.0016
	(0.0056)	*(0.0037)****	*(0.0046)*	*(0.0042)*
1996	-0.0098	0.0077	-0.0056	0.0054
	*(0.0049)***	*(0.0032)***	*(0.0043)*	*(0.0041)*
1997	-0.0136	0.0171	-0.0046	0.0081
	*(0.0048)****	*(0.0036)****	*(0.0042)*	*(0.0042)**
1998	-0.0053	0.0140	-0.0020	0.0043
	(0.0041)	*(0.0032)****	*(0.0033)*	*(0.0030)*
1999	-0.0052	0.0152	0.0000	0.0054
	(0.0044)	*(0.0026)****	*(0.0037)*	*(0.0034)*
2000	-0.0008	0.0092	0.0018	0.0039
	(0.0038)	*(0.0031)****	*(0.0036)*	*(0.0035)*
2001	-0.0044	0.0117	-0.0031	0.0064
	(0.0049)	*(0.0037)****	*(0.0037)*	*(0.0039)*
2002	-0.0025	0.0159	0.0021	0.0067
	(0.0049)	*(0.0040)****	*(0.0039)*	*(0.0035)**
2003	-0.0001	0.0128	0.0033	0.0090
	(0.0049)	*(0.0040)****	*(0.0037)*	*(0.0037)***
2004	-0.0030	0.0130	-0.0012	0.0064
	(0.0059)	*(0.0031)****	*(0.0043)*	*(0.0034)**
2005	-0.0065	0.0078	-0.0013	0.0088
	(0.0047)	*(0.0035)***	*(0.0041)*	*(0.0032)****
2006	-0.0101	0.0008	-0.0028	0.0013
	*(0.0056)**	*(0.0037)*	*(0.0044)*	*(0.0042)*
2007	-0.0090	0.0029	-0.0039	0.0031
	(0.0064)	*(0.0041)*	*(0.0051)*	*(0.0044)*

Source: **Compiled by the author. All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ******p<0.01*, *******p<0.05* **and ****p<0.10*. **Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects, industry controls, job characteristics, individual characteristics and industry level variables. See appendix 3 for further details about the O*Net database; appendix 4 explains the importance ratings and appendix 5 provides a list of the variables used to create the job task variables via principal component analysis.**

Appendix 8

Table 4.13A: Offshoring (OSS) and Individual Level Characteristics

Dependent Variable: Log of Real Hourly Employment Wage			
Coefficients	*(1)*	*(2)*	*(3)*
Age	0.0872	0.0874	0.0875
	*(0.0095)****	*(0.0094)****	*(0.0095)****
Age2	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0221	0.0227	0.0225
	*(0.0128)**	*(0.0128)**	*(0.0129)**
Single	-0.0596	-0.0587	-0.0582
	*(0.0161)****	*(0.0160)****	*(0.0158)****
Divorced	-0.0199	-0.0191	-0.0192
	(0.0175)	*(0.0174)*	*(0.0173)*
Child	-0.0113	-0.0111	-0.0099
	(0.0075)	*(0.0076)*	*(0.0076)*
Experience	-0.0283	-0.0284	-0.0286
	*(0.0039)****	*(0.0039)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)*
Union	0.1004	0.1003	0.0999
	*(0.0184)****	*(0.0183)****	*(0.0186)****
Unemployment Rate	0.0044	0.0044	0.0044
	(0.0027)	*(0.0027)*	*(0.0027)*
Edu: High Skill	0.1198	0.1191	0.1243
	*(0.0323)****	*(0.0324)****	*(0.0326)****
Edu: Medium Skill	-0.0031	-0.0034	-0.0024
	(0.0089)	*(0.0088)*	*(0.0087)*
Female	-0.1731	-0.1816	-0.1815
	*(0.0113)****	*(0.0109)****	*(0.0111)****
Firm Size: <25	-0.1792	-0.1793	-0.1785
	*(0.0257)****	*(0.0256)****	*(0.0258)****
Firm Size: 25-99	-0.0836	-0.0837	-0.0827
	*(0.0222)****	*(0.0220)****	*(0.0224)****
Firm Size: 100-999	-0.0151	-0.0153	-0.0140
	(0.0205)	*(0.0203)*	*(0.0206)*
Firm: Public	0.0402	0.0407	0.0416
	*(0.0224)**	*(0.0220)**	*(0.0222)**
Industry: Output	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	-0.0045	-0.0022	-0.0023
	(0.0093)	*(0.0087)*	*(0.0091)*
Net Exports	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*
Offshoring: OSS	-0.0173	-0.0209	-0.0126
	*(0.0064)****	*(0.0085)***	*(0.0086)*
Offshoring: Female*OSS	-0.0038	-	-
	*(0.0022)**	-	-
White Collar Job	-	0.2902	-
	-	*(0.0219)****	-
Offshoring: White Collar*OSS	-	0.0027	-
	-	*(0.0048)*	-
White	-	-	0.0799
	-	-	*(0.0144)****
Offshoring: White*OSS	-	-	-0.0067
	-	-	*(0.0044)*
Constant	0.3005	0.3042	0.1988
	*(0.1568)**	*(0.1544)**	*(0.1627)*
Observations	58978	58978	58978
R^2	0.4957	0.4957	0.4961
Exogeneity Tests for OSS			
H_o: Instrument Validity			
Hansen J-Statistic	0.599	0.572	0.329
Hansen J-Statistic *(p-value)*	*(0.4389)*	*(0.4494)*	*(0.5663)*

H_o: Regressor is Exogenous			
C-Statistic	1.023	1.025	1.315
C-statistic *(p-value)*	*(0.3118)*	*(0.3113)*	*(0.2516)*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. OSS = Industry level service offshoring intensity. A white-collar occupation is a dummy variable equal to one for occupations Legislators, Senior Officials, Managers, Professionals, Technicians, Associate Professionals and Clerks.

Appendix 9

Table 4.14A: Offshoring (OSM) and Individual Level Characteristics

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	***(1)***	***(2)***	***(3)***
Age	0.0876	0.0877	0.0878
	*(0.0096)****	*(0.0096)****	*(0.0096)****
Age2	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0219	0.0220	0.0217
	*(0.0126)**	*(0.0125)**	*(0.0127)**
Single	-0.0602	-0.0602	-0.0597
	*(0.0157)****	*(0.0158)****	*(0.0156)*
Divorced	-0.0196	-0.0197	-0.0197
	(0.0172)	*(0.0171)*	*(0.0172)*
Child	-0.0114	-0.0110	-0.0098
	(0.0076)	*(0.0076)*	*(0.0076)*
Experience	-0.0283	-0.0284	-0.0286
	*(0.0039)****	*(0.0039)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**
Union	0.1001	0.1000	0.1000
	*(0.0188)****	*(0.0186)****	*(0.0189)****
Unemployment Rate	-0.0006	-0.0005	-0.0005
	(0.0036)	*(0.0036)*	*(0.0035)*
Edu: High Skill	0.1173	0.1173	0.1220
	*(0.0322)****	*(0.0323)****	*(0.0327)****
Edu: Medium Skill	-0.0035	-0.0035	-0.0028
	(0.0088)	*(0.0088)*	*(0.0087)*
Female	-0.1781	-0.1843	-0.1840
	*(0.0123)****	*(0.0113)****	*(0.0114)****
Firm Size: <25	-0.1833	-0.1831	-0.1826
	*(0.0236)****	*(0.0236)****	*(0.0238)****
Firm Size: 25-99	-0.0845	-0.0845	-0.0838
	(0.0219)	*(0.0220)****	*(0.0222)*
Firm Size: 100-999	-0.0150	-0.0150	-0.0139
	(0.0213)	*(0.0212)*	*(0.0214)*
Firm: Public	0.0550	0.0548	0.0555
	*(0.0304)**	*(0.0304)**	*(0.0305)**
Industry: Output	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0026	0.0027	0.0034
	(0.0086)	*(0.0087)*	*(0.0084)*
Net Exports	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*
Offshoring: OSM	-0.0047	-0.0048	-0.0056
	(0.0060)	*(0.0061)*	*(0.0061)*
Offshoring: Female*OSM	-0.0022	-	-
	*(0.0011)**	-	-
White Collar Job	-	0.3034	-
	-	*(0.0282)****	-
Offshoring: White Collar*OSM	-	-0.0009	-
	-	*(0.0018)*	-
White	-	-	0.0646
	-	-	*(0.0146)****
Offshoring: White*OSM	-	-	0.0001
	-	-	*(0.0025)*
Constant	0.3441	0.3415	0.2573
	*(0.1634)***	*(0.1642)***	*(0.1688)*
Observations	58978	58978	58978
R^2	0.4935	0.4932	0.4937
Exogeneity Tests for OSM			
H_o: Instrument Validity			
Hansen *J*-Statistic	1.037	1.019	0.993
Hansen *J*-Statistic *(p-value)*	*(0.3084)*	*(0.3127)*	*(0.6087)*
H_o: Regressor is Exogenous			
C-Statistic	0.031	0.022	0.008
C-statistic *(p-value)*	*(0.8599)*	*(0.8832)*	*(0.9294)*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. OSM = Industry level material offshoring intensity. A white collar occupation is a dummy variable equal to one for occupations Legislators, Senior Officials, Managers, Professionals, Technicians, Associate Professionals and Clerks.

Appendix 10

Table 4.15A: Task Biased Technological Change & Wages

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Age	0.0879	0.0870	0.0876	0.0877	0.0869
	*(0.0097)****	*(0.0095)****	*(0.0095)****	*(0.0097)****	*(0.0092)****
Age2	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0198	0.0185	0.0219	0.0197	0.0185
	(0.0127)	*(0.0128)*	*(0.0125)**	*(0.0127)*	*(0.0130)*
Single	-0.0621	-0.0626	-0.0603	-0.0622	-0.0625
	*(0.0154)****	*(0.0155)****	*(0.0157)****	*(0.0155)****	*(0.0157)****
Divorced	-0.0216	-0.0231	-0.0198	-0.0210	-0.0229
	(0.0168)	*(0.0167)*	*(0.0173)*	*(0.0168)*	*(0.0166)*
Child	-0.0104	-0.0109	-0.0111	-0.0113	-0.0107
	(0.0076)	*(0.0078)*	*(0.0077)*	*(0.0077)*	*(0.0079)*
Experience	-0.0285	-0.0279	-0.0284	-0.0283	-0.0278
	*(0.0039)****	*(0.0038)****	*(0.0038)****	*(0.0039)****	*(0.0036)****
Experience2	0.0001	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)**
Union	0.1015	0.0994	0.1000	0.0979	0.0977
	*(0.0186)****	*(0.0179)****	*(0.0168)****	*(0.0181)****	*(0.0148)****
Unemployment Rate	-0.0002	0.0002	-0.0006	-0.0004	0.0004
	(0.0036)	*(0.0033)*	*(0.0035)*	*(0.0035)*	*(0.0033)*
Edu: High Skill	0.1114	0.1137	0.1175	0.1147	0.1153
	*(0.0329)****	*(0.0318)****	*(0.0322)****	*(0.0312)****	*(0.0312)****
Edu: Medium Skill	-0.0043	-0.0039	-0.0036	-0.0036	-0.0037
	(0.0089)	*(0.0087)*	*(0.0087)*	*(0.0089)*	*(0.0086)*
Female	-0.1859	-0.1809	-0.1837	-0.1861	-0.1790
	*(0.0112)****	*(0.0112)****	*(0.0114)****	*(0.0110)****	*(0.0105)****
Firm Size: <25	-0.1828	-0.1812	-0.1832	-0.1842	-0.1814
	*(0.0240)****	*(0.0246)****	*(0.0234)****	*(0.0239)****	*(0.0244)****
Firm Size: 25-99	-0.0838	-0.0841	-0.0845	-0.0850	-0.0847
	*(0.0226)****	*(0.0225)****	*(0.0218)****	*(0.0229)****	*(0.0219)****
Firm Size: 100-999	-0.0145	-0.0145	-0.0149	-0.0145	-0.0149
	(0.0217)	*(0.0218)*	*(0.0213)*	*(0.0225)*	*(0.0212)*
Firm: Public	0.0561	0.0539	0.0551	0.0559	0.0514
	*(0.0302)**	*(0.0293)**	*(0.0301)**	*(0.0312)**	*(0.0266)**
Industry: Output	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0021	0.0033	0.0018	0.0023	0.0035
	(0.0089)	*(0.0084)*	*(0.0089)*	*(0.0088)*	*(0.0084)*
Net Exports	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Routine Task	-0.0052	-	-	-	-0.0104
	*(0.0022)***	-	-	-	*(0.0094)*
Non-Routine Abstract Task	-	0.0092	-	-	0.0089
	-	*(0.0023)****	-	-	*(0.0042)***
Non-Routine Manual Task	-	-	0.0005	-	0.0074
	-	-	*(0.0033)*	-	*(0.0083)*
Service Task	-	-	-	0.0058	-0.0019
	-	-	-	*(0.0022)***	*(0.0045)*
Constant	0.3444	0.3964	0.3396	0.3632	0.3893
	*(0.1664)***	*(0.1577)***	*(0.1669)***	*(0.1626)***	*(0.1583)***
Observations	58707	58707	58978	58707	58707
R^2	0.4942	0.4958	0.4933	0.4942	0.4956

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls.

Appendix 11

Table 4.16A: Task Biased Technological Change and Individual Characteristics - Gender

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.0885	0.0870	0.0882	0.0878
	*(0.0097)****	*(0.0094)****	*(0.0096)****	*(0.0097)****
Age2	-0.0008	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0193	0.0185	0.0219	0.0198
	(0.0125)	*(0.0127)*	*(0.0125)**	*(0.0126)*
Single	-0.0621	-0.0632	-0.0595	-0.0623
	*(0.0151)****	*(0.0153)****	*(0.0157)****	*(0.0154)****
Divorced	-0.0213	-0.0231	-0.0195	-0.0209
	(0.0166)	*(0.0166)*	*(0.0172)*	*(0.0169)*
Child	-0.0100	-0.0105	-0.0109	-0.0111
	(0.0077)	*(0.0076)*	*(0.0078)*	*(0.0077)*
Experience	-0.0287	-0.0279	-0.0287	-0.0282
	*(0.0040)****	*(0.0037)****	*(0.0039)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0001)**
Union	0.1005	0.0988	0.0999	0.0973
	*(0.0183)****	*(0.0176)****	*(0.0165)****	*(0.0179)****
Unemployment Rate	0.0003	0.0003	-0.0001	-0.0003
	(0.0036)	*(0.0034)*	*(0.0035)*	*(0.0036)*
Edu: High Skill	0.1118	0.1142	0.1176	0.1148
	*(0.0327)****	*(0.0317)****	*(0.0325)****	*(0.0312)****
Edu: Medium Skill	-0.0035	-0.0034	-0.0028	-0.0034
	(0.0086)	*(0.0085)*	*(0.0084)*	*(0.0088)*
Female	-0.1910	-0.1836	-0.1911	-0.1874
	*(0.0102)****	*(0.0101)****	*(0.0107)****	*(0.0106)****
Firm Size: <25	-0.1834	-0.1814	-0.1840	-0.1843
	*(0.0242)****	*(0.0245)****	*(0.0232)****	*(0.0240)****
Firm Size: 25-99	-0.0842	-0.0843	-0.0852	-0.0850
	*(0.0223)****	*(0.0224)****	*(0.0214)****	*(0.0230)****
Firm Size: 100-999	-0.0143	-0.0145	-0.0153	-0.0143
	(0.0216)	*(0.0218)*	*(0.0208)*	*(0.0225)*
Firm: Public	0.0557	0.0534	0.0556	0.0557
	*(0.0296)**	*(0.0293)**	*(0.0294)**	*(0.0312)**
Industry: Output	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0018	0.0033	0.0018	0.0022
	(0.0088)	*(0.0084)*	*(0.0089)*	*(0.0087)*
Net Exports	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Routine Task	0.0035	-	-	-
	(0.0035)	-	-	-
Female*Routine Task	-0.0151	-	-	-
	*(0.0040)****	-	-	-
Non-Routine Abstract Task	-	0.0077	-	-
	-	*(0.0029)****	-	-
Female*Non-Routine Abstract	-	0.0027	-	-
	-	*(0.0027)*	-	-
Non-Routine Manual Task	-	-	0.0064	-
	-	-	*(0.0051)*	-
Female*Non-Routine Manual	-	-	-0.0121	-
	-	-	*(0.0033)****	-
Service Task	-	-	-	0.0041
	-	-	-	*(0.0024)**
Female*Service Task	-	-	-	0.0035
	-	-	-	*(0.0028)*
Constant	0.3198	0.3936	0.3153	0.3604
	*(0.1669)**	*(0.1581)***	*(0.1664)**	*(0.1630)***
Observations	58707	58707	58978	58707
R^2	*0.4958*	*0.4959*	*0.4947*	*0.4945*

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls.

Appendix 12

Table 4.17A: Task Biased Technological Change and Individual Characteristics – White Collar Jobs

Dependent Variable: Log of Real Hourly Employment Wage

Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.0879	0.0870	0.0874	0.0877
	*(0.0096)****	*(0.0095)****	*(0.0095)****	*(0.0097)****
Age2	-0.0007	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0202	0.0185	0.0210	0.0197
	(0.0127)	*(0.0128)*	*(0.0126)*	*(0.0127)*
Single	-0.0616	-0.0626	-0.0611	-0.0622
	*(0.0157)****	*(0.0156)****	*(0.0158)****	*(0.0156)****
Divorced	-0.0212	-0.0231	-0.0206	-0.0211
	(0.0170)	*(0.0167)*	*(0.0173)*	*(0.0170)*
Child	-0.0104	-0.0109	-0.0109	-0.0113
	(0.0076)	*(0.0077)*	*(0.0077)*	*(0.0077)*
Experience	-0.0285	-0.0279	-0.0283	-0.0282
	*(0.0039)****	*(0.0038)****	*(0.0038)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)*	*(0.0000)**
Union	0.1012	0.0994	0.1018	0.0978
	*(0.0180)****	*(0.0180)****	*(0.0164)****	*(0.0186)****
Unemployment Rate	-0.0001	0.0002	-0.0002	-0.0004
	(0.0036)	*(0.0033)*	*(0.0035)*	*(0.0035)*
Edu: High Skill	0.1120	0.1137	0.1154	0.1147
	*(0.0323)****	*(0.0316)****	*(0.0334)****	*(0.0312)****
Edu: Medium Skill	-0.0043	-0.0039	-0.0033	-0.0036
	(0.0090)	*(0.0087)*	*(0.0086)*	*(0.0091)*
Female	-0.1855	-0.1809	-0.1821	-0.1861
	*(0.0111)****	*(0.0113)****	*(0.0116)****	*(0.0109)****
Firm Size: <25	-0.1822	-0.1812	-0.1842	-0.1843
	*(0.0250)****	*(0.0245)****	*(0.0230)****	*(0.0246)****
Firm Size: 25-99	-0.0836	-0.0841	-0.0849	-0.0851
	*(0.0230)****	*(0.0224)****	*(0.0212)****	*(0.0236)****
Firm Size: 100-999	-0.0142	-0.0145	-0.0160	-0.0145
	(0.0223)	*(0.0216)*	*(0.0203)*	*(0.0228)*
Firm: Public	0.0555	0.0539	0.0562	0.0559
	*(0.0293)**	*(0.0290)**	*(0.0287)**	*(0.0312)**
Industry: Output	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0022	0.0033	0.0022	0.0023
	(0.0087)	*(0.0084)*	*(0.0089)*	*(0.0085)*
Net Exports	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Routine Task	-0.0090	-	-	-
	(0.0077)	-	-	-
Non-Routine Abstract Task	-	0.0092	-	-
	-	*(0.0043)***	-	-
Non-Routine Manual Task	-	-	0.0079	-
	-	-	*(0.0033)**	-
Service Task	-	-	-	0.0055
	-	-	-	*(0.0053)*
White-collar	0.2798	0.4141	0.3169	0.4558
	*(0.0272)****	*(0.0644)****	*(0.0343)****	*(0.0310)****
White-collar*Routine Task	0.0058	-	-	-
	(0.0128)	-	-	-
White-collar*NR-Abstract	-	0.0000	-	-
	-	*(0.0062)*	-	-
White-collar*NR-Manual	-	-	-0.0126	-
	-	-	*(0.0037)*	-
White-collar*Service Task	-	-	-	0.0004
	-	-	-	*(0.0067)*
Constant	0.3549	0.3963	0.3134	0.3623
	*(0.1526)***	*(0.1477)***	*(0.1627)**	*(0.1537)***
Observations	58707	58707	58978	58707
R^2	0.4944	0.4958	0.4936	0.4942

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. *Significance Level*: ****p<0.01, **p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls.

Appendix 13

Table 4.18A: Task Biased Technological Change and Individual Characteristics – Race

Dependent Variable: Log of Real Hourly Employment Wage				
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.0880	0.0871	0.0877	0.0878
	*(0.0097)****	*(0.0094)****	*(0.0095)****	*(0.0097)****
Age2	-0.0007	-0.0007	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****	*(0.0001)****	*(0.0001)****
Married	0.0199	0.0185	0.0220	0.0197
	(0.0127)	*(0.0128)*	*(0.0125)**	*(0.0127)*
Single	-0.0611	-0.0618	-0.0593	-0.0614
	*(0.0154)****	*(0.0155)****	*(0.0156)****	*(0.0155)****
Divorced	-0.0213	-0.0227	-0.0195	-0.0206
	(0.0168)	*(0.0167)*	*(0.0173)*	*(0.0168)*
Child	-0.0093	-0.0098	-0.0101	-0.0101
	(0.0077)	*(0.0078)*	*(0.0078)*	*(0.0077)*
Experience	-0.0287	-0.0282	-0.0286	-0.0285
	*(0.0039)****	*(0.0037)****	*(0.0038)****	*(0.0039)****
Experience2	0.0001	0.0001	0.0001	0.0001
	*(0.0000)**	*(0.0000)**	*(0.0000)**	*(0.0000)*
Union	0.1014	0.0992	0.0999	0.0977
	*(0.0188)****	*(0.0180)****	*(0.0170)****	*(0.0183)****
Unemployment Rate	-0.0002	0.0001	-0.0005	-0.0004
	(0.0036)	*(0.0033)*	*(0.0035)*	*(0.0035)*
Edu: High Skill	0.1141	0.1157	0.1202	0.1166
	*(0.0333)****	*(0.0321)****	*(0.0326)****	*(0.0317)****
Edu: Medium Skill	-0.0042	-0.0039	-0.0036	-0.0036
	(0.0090)	*(0.0087)*	*(0.0087)*	*(0.0089)*
Female	-0.1859	-0.1811	-0.1837	-0.1859
	*(0.0113)****	*(0.0112)****	*(0.0114)****	*(0.0111)*
Firm Size: <25	-0.1829	-0.1813	-0.1833	-0.1844
	*(0.0241)****	*(0.0246)****	*(0.0234)****	*(0.0239)*
Firm Size: 25-99	-0.0837	-0.0839	-0.0844	-0.0848
	*(0.0227)****	*(0.0226)****	*(0.0220)****	*(0.0230)****
Firm Size: 100-999	-0.0142	-0.0142	-0.0147	-0.0143
	(0.0218)	*(0.0218)*	*(0.0214)*	*(0.0225)****
Firm: Public	0.0564	0.0542	0.0553	0.0564
	*(0.0302)**	*(0.0293)**	*(0.0302)**	*(0.0312)**
Industry: Output	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Industry: R&D Intensity	0.0027	0.0039	0.0023	0.0030
	(0.0088)	*(0.0083)*	*(0.0088)*	*(0.0087)*
Net Exports	0.0000	0.0000	0.0000	0.0000
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
White	0.0644	0.0670	0.0659	0.0630
	*(0.0141)****	*(0.0131)****	*(0.0133)****	*(0.0146)****
Routine Job Task	-0.0097	-	-	-
	(0.0063)	-	-	-
Non-Routine Abstract Job Task	-	0.0121	-	-
	-	*(0.0042)****	-	-
Non-Routine Manual Job Task	-	-	-0.0027	-
	-	-	*(0.0065)*	-
Service Job Task	-	-	-	0.0128
	-	-	-	*(0.0049)***
White*Routine Job Task	0.0048	-	-	-
	(0.0052)	-	-	-
White*NR-Abstract Job Tasks	-	-0.0030	-	-
	-	*(0.0033)*	-	-
White*NR-Manual Job Tasks	-	-	0.0034	-
	-	-	*(0.0045)*	-
White*Service Job Task	-	-	-	-0.0074
	-	-	-	*(0.0040)**
Constant	0.2794	0.3297	0.2732	0.2991
	(0.1690)	*(0.1596)***	*(0.1680)*	*(0.1647)*
Observations	58707	58707	58978	58707
R^2	0.4949	0.4965	0.4940	0.4950

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Each regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls.

Appendix 14

Table 4.19A: Blinder Index & Task Biased Technological Change

Dependent Variable: Log of Real Hourly Employment Wage	
Coefficients	**Estimated Coefficients**
Age	0.0873
	*(0.0095)****
Age2	-0.0007
	*(0.0001)****
Married	0.0175
	(0.0127)
Single	-0.0627
	*(0.0156)****
Divorced	-0.0219
	(0.0166)
Child	-0.0103
	(0.0073)
Experience	-0.0281
	*(0.0039)****
Experience2	0.0001
	*(0.0000)**
Union	0.1027
	*(0.0163)****
Unemployment Rate	-0.0018
	(0.0036)
Edu: High Skill	0.1030
	*(0.0313)****
Edu: Medium Skill	-0.0068
	(0.0091)
Female	-0.1900
	*(0.0112)****
Firm Size: <25	-0.1851
	*(0.0230)****
Firm Size: 25-99	-0.0833
	*(0.0221)****
Firm Size: 100-999	-0.0125
	(0.0214)
Firm: Public	0.0599
	*(0.0301)**
Industry: Output	0.0000
	(0.0000)
Industry: R&D Intensity	0.0026
	(0.0093)
Net Exports	0.0000
	(0.0000)
Offshoring: Blinder Index Values 25	0.0623
	*(0.0336)**
Offshoring: Blinder Index Values 26-35	-0.0795
	*(0.0362)***
Offshoring: Blinder Index Values 36-45	0.0258
	(0.0293)
Offshoring: Blinder Index Values 46-55	0.0042
	(0.0310)
Offshoring: Blinder Index Values 56-65	0.0045
	(0.0180)
Offshoring: Blinder Index Values 66-75	-0.0110
	(0.0254)
Offshoring: Blinder Index Values 76-85	-0.1505
	*(0.0400)****
Offshoring: Blinder Index Values 86+	-0.0385
	(0.0259)
Routine Tasks	0.0000
	(0.0033)
Blinder Index Values 25*Routine Task	0.0521
	(0.0312)
Blinder Index Values 26-35*Routine Task	0.0060
	(0.0131)
Blinder Index Values 36-45*Routine Task	-0.0229
	*(0.0078)****
Blinder Index Values 46-55*Routine Task	0.0102

	(0.0107)
Blinder Index Values 56-65*Routine Task	0.0109
	*(0.0043)***
Blinder Index Values 66-75*Routine Task	-0.0030
	(0.0059)
Blinder Index Values 76-85*Routine Task	-0.0560
	*(0.0088)****
Blinder Index Values 86+*Routine Task	-0.0205
	*(0.0063)****
Constant	0.3749
	*(0.1645)****
Observations	58707
R^2	0.4961

Note: All regression models present robust standard errors clustered by the 2-digit SIC level within the parentheses. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. This regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls. Reference group for the Blinder Index are all occupations that have a value of zero; these are the non-tradable occupations.

Appendix 15

Table 4.20A: Regression Results for Service Offshoring, Occupation Tradability and the interaction with a linear time trend.

Dependent Variable: Log of Real Hourly Employment Wage		
Coefficients	*(1)*	*(2)*
Age	0.0872	0.0876
	*(0.0094)****	*(0.0096)****
Age2	-0.0007	-0.0007
	*(0.0001)****	*(0.0001)****
Married	0.0222	0.0217
	*(0.0129)**	*(0.0126)**
Single	-0.0594	-0.0606
	*(0.0161)****	*(0.0158)****
Divorced	-0.0194	-0.0200
	(0.0177)	*(0.0174)*
Child	-0.0114	-0.0109
	(0.0076)	*(0.0076)*
Experience	-0.0284	-0.0283
	*(0.0039)****	*(0.0039)****
Experience2	0.0001	0.0001
	*(0.0000)**	*(0.0000)**
Union	0.1011	0.0995
	*(0.0189)****	*(0.0184)****
Unemployment Rate	0.0103	-0.0010
	*(0.0026)****	*(0.0035)*
Edu: High Skill	0.1192	0.1164
	*(0.0324)****	*(0.0325)****
Edu: Medium Skill	-0.0036	-0.0034
	(0.0088)	*(0.0088)*
Female	-0.1810	-0.1829
	*(0.0111)****	*(0.0118)****
Firm Size: <25	-0.1786	-0.1834
	*(0.0256)****	*(0.0237)****
Firm Size: 25-99	-0.0833	-0.0844
	*(0.0221)****	*(0.0221)****
Firm Size: 100-999	-0.0151	-0.0146
	(0.0205)	*(0.0213)*
Firm: Public	0.0402	0.0544
	*(0.0225)**	*(0.0310)**
Industry: Output	0.0000	0.0000
	(0.0000)	*(0.0000)*
Industry: R&D Intensity	0.0021	0.0020
	(0.0092)	*(0.0089)*
Net Exports	0.0000	0.0000
	(0.0000)	*(0.0000)*
Offshoring: OSS	-0.0418	-
	*(0.0055)****	-
Offshoring: OSS*Time Trend	0.0024	-
	*(0.0004)****	-
Offshoring: Blinder Index >=65	-	-0.0129
	-	*(0.0144)*
Offshoring: Blinder Index >=65*Time Trend	-	-0.0004
	-	*(0.0010)*
Time Trend	0.0021	-0.0029
	(0.0049)	*(0.0067)*
Constant	0.2799	0.3518
	*(0.1634)**	*(0.1649)***
Observations	58978	58978
R^2	0.4956	0.4933

Note: **Own calculations from BHPS data. Standard errors are presented in the parentheses and are clustered by the 2-digit industry classifications. Significance level key: ****p<0.01, **p<0.05* and **p<0.10*. This regression controls for industry specific time trends, regions, occupation controls, individual fixed effects and industry controls.**

5

Offshoring, Task Biased Technological Change & Job Insecurity: Evidence from the U.K.

5.1 Introduction

In the previous chapter, it was shown that the impact of service offshoring (measured at the industry level), the potential threat from the advancements of technology that increasingly pose a threat to many more potentially tradable occupations from the application of Blinder's (2007) job tradability index and the threat from the routinization hypothesis (Autor *et al*,. 2003) – particularly from the importance of completing routine intensive job tasks, have all had a negative and significant impact on the wage levels of workers over time. The previous chapter also found service and material offshoring to benefit skilled labour whereas the potential wage losses for workers employed by jobs that are potentially tradable and which have a high importance for computing routine intensive job tasks could be large over time. From this chapter, I examine whether these forces associated with globalisation: - the impact from offshoring (material and services), the potential tradability of jobs that may result from the improvements in information technology and the routinization hypothesis have all contributed towards lowering job security over the last two decades.

There is a belief among many workers in developed countries that the impact from globalisation [through trade, offshoring and through the advancements in ICT] destroys many more jobs than it creates (Eurobarometer 69) and this therefore raises the fear of job loss and lowers the potential for job security over time. But many economists argue that globalisation and the improvements from ICT can lead to a structural change in the composition of employment rather than to change the employment level. The process of creative destruction ensures economic prosperity and growth from structural changes in tastes and technology that can emanate from globalisation (Cahuc & Zylberberg, 2006), where old jobs are bid away by new and more productive jobs which encapsulate the latest technology. Thus, firms must decide which stages of production are best produced abroad or in the domestic economy to be able to compete with rival firms in a global market place. However, the job creation and destruction literature reviewed in chapter 2 found the job creation and destruction rates for most developed countries have observed the 15 percent rule over time (Davis *et al.,* 1997; Cahuc & Zylberberg, 2006). What this means is 15 percent of old jobs are roughly destroyed each year and roughly 15 percent of new jobs come into being as a share of jobs. This implies there should be very little change to the employment level and thus implying that the forces associated with globalisation can create and destroys similar number of jobs over the most recent phase of globalisation that has occurred over the last two decades; see chapter 2 for further details.

Technology advancements can also affect job security. Technological advancements can in theory allow firms to raise the demand for skilled labour as newly created jobs embody the latest technology (Mortensen & Pissarides, 1994, 1999). However, the decision to update existing capital and to train the existing workforce to be able to use the new technology depends on the size of the renovation costs, the growth in productivity and the rate of technological progress. If the rate of technological progress is slow and there is potential for growth, firms may decide to continually undertake investment into capital and train their workforces, thus implying job separations could be low. However, if renovation costs are high and technological progress is not slow then firms may decide not to undertake the cost of updating existing capital or train their workforces. This can lead to job separations and a fall in job security. Theoretically, it is unclear whether the advancements in technology could raise job separations or lower job separations and its impact on the unemployment level is equally unclear; this is matter to be determined empirically.

Not all workers are likely to be affected equally by the structural changes. Economic theory from the HOS model of international trade suggests output in one industry will fall and rise in another. And when trade takes place, theory predicts that firms are most likely to scale back production of the goods that are labour intensive in the domestic market; these stages are produced more efficiently by developing countries. These are production stages that firms in developed countries do not have a comparative advantage to produce. This can potentially lower job security for less skilled workers as their jobs are lost to foreign labour. Although the theory of job creation and destruction suggests that it is less costly to destroy less skilled jobs than it is to destroy skilled jobs (Mortensen & Pissarides, 1999); theoretical models examining the impact of offshoring on the labour market implications are not conclusive and the impact on labour depends on the assumptions made about the nature of comparative advantage enjoyed by domestic firms and the size of the open economy. Deardorff's (2005) model predicts that less skilled workers are more likely to suffer job and wage losses compared to skilled labour because firms offshore those stages of production in which they lack comparative advantage.

However, Grossman & Rossi-Hansberg (2008) find that offshoring of 'L-tasks' (these are job tasks that are performed by workers with little education or training in comparison to 'H-tasks' that must be performed by workers who have greater educational accomplishments and training) may actually benefit less skilled workers if the productivity effect from a fall in offshoring costs, dominates the relative price effect and the labour supply effect. However, if the relative price and labour supply effects dominate, less skilled workers are worse off as they may suffer a fall in relative wage levels and possibly job loss. These outcomes are based on the assumption that the developed country is small; it is unclear what the implications could be if the size of the open economy were large.

It has also been suggested that the ICT advancements may cause some service activities performed by high-skilled occupations that were previously not at risk from being offshored, may now be at risk (Amiti & Wei, 2005, 2006). Markusen (2005) suggests that skilled workers may suffer job loss if knowledge capital can be invested in developing countries; but this may happen in the longer term. These recent concerns relate to the 'great unbundling' of job tasks (Baldwin, 2006). The 'great unbundling' refers to the greater tendency to trade in tasks through outsourcing and offshoring[1] certain job tasks instead of trading final goods and services to other countries and even locally where they can be provided at low cost. This process has applied to information-based job tasks that have become costless and instantaneous to transport (Acemoglu & Autor, 2010 & forthcoming). Blinder (2007), Grossman & Rossi-Hansberg (2007) and Autor *et al.*, (2003) suggest job tasks that are routine and codifiable in nature, which can be easily replaced by computer technology, that require little face-to-face contact with customers and where job tasks do not have to be performed at specific work locations are job tasks that can be easily offshored abroad. These job characteristics can relate to low-skilled jobs such as machinists and call centre workers as well as high-skilled jobs such as accountants, computer software programmers and car plant assembly workers. Although the empirical evidence has shown material and service offshoring have had a positive impact on the employment levels for skilled labour; see chapter 2 for further details. This may be because skilled workers have more firm-specific and general human capital accumulation that is valued and retained by firms over and beyond than that is received by less skilled labour (Ritter, 2009).

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[1] See section 5.2.1 below for the definitions for offshoring and outsourcing.

The empirical literature which has examined the impact of technology and offshoring on job security is still in its infancy. From the few papers that have examined this area, the research has shown technology and offshoring raise job reallocation rates and reduce job security; but this impact has been small and limited to less skilled labour.

From the U.S., Zavodny (2003) examines how the usage of technology can affect job turnover. Zavodny (2003) uses a number of variables to measure technological intensity at the industry level: These are: (1) computer usage rates; (2) the number of scientists and engineers employed as a fraction of total employment in all sectors; (3) research and development expenditure as a fraction of sales; (4) computer investment as a fraction of new investment and (5) the annual growth rate of total factor productivity. She finds a negative relationship between job separations and technology for young adults, where many of the job separations account for voluntary job separations over the 1980 to 1998 time frame. Other results from Zavodny (2003) also suggest less skilled workers are more likely to experience a non-voluntary job separation in technology intensive industries than more educated workers. Skilled labour are found to be more likely to quit technology intensive sectors because they have more general human capital accumulation that allows them to easily switch employers within industries than other workers.

Similarly, Aaronson & Housinger (1999) find industry specific technological innovation affects the probability of job displacement and re-employment. They find job displacement due to the elimination of job positions were more likely in high-tech industries. But there is little evidence to suggest there is a positive correlation between technology and plant closings. And there is also no support for the displacement-technology relationship having a disproportionate impact on less skilled labour or older workers.

Job security also differs among men and women classed by their skill intensity. Royalty (1998) reports job security transitions, defined as staying on in current employment among more educated men and women were similar for the U.S. But these transitions differed amongst women with less education.

From Europe, Geishecker (2008) and Bachmann & Braun (2008) find a 1% rise in material offshoring intensity from the manufacturing sector raises the probability of non participation in the labour market by 6% and 2.6% respectively for Germany. For Denmark, the impact of international outsourcing on job displacement is smaller compared to Germany. Munch (2009) finds that a 1% rise in material offshoring raises the job separation probability by 0.451% over 12 years. Similarly, Hummels *et al.*, (2009) find doubling the material offshoring intensity increased the job separation probability by 5-10%, but this varied little by skill groups. These empirical estimates suggest the impact from material offshoring intensity has had a small impact on raising the probability of becoming unemployed/out of the labour force.

This chapter makes three contributions to the empirical literature. First, I follow Geishecker (2008) and Munch (2009) and analyse the effects of international offshoring on job security for the U.K. Job security is measured by different employment transitions. To my knowledge, this is the first paper from the U.K. to analyse the effects of offshoring (materials and services) on job security using the British Household Panel Survey (BHPS). Additionally, this chapter is one of the first papers to examine the impact of service offshoring on job security; the empirical literature has so far only examined the impact of material offshoring on job security. My second contribution to the empirical literature examines the impact of the task biased technological change (TBTC) hypothesis on job security. The existing literature has focused on exploring the impact from industry level measures of technology which have been merged with individual level data to examine the relationship between technology and job security. This chapter is the first to examine whether the importance of the type of job tasks performed by workers can have an impact on job security. My third contribution to the empirical literature is the application and the creation of a British version of Blinder's (2007) job tradability index to job security.

The structure of this chapter is as follows: Section 5.2 provides a brief outline of the variables that will be created to measure offshoring intensity, the potential tradability of jobs and task biased technological change. Section 5.3 provides details of the data set that will be used for analysis and the empirical strategy that will be used to examine the impact of offshoring, TBTC and the potential tradability of jobs on job security. Section 5.4 provides the results and section 5.5 provides the concluding comments.

5.2 Measuring Offshoring Intensity, Job Tradability & Task Biased Technological Change

5.2.1 Defining Offshoring

Offshoring and outsourcing are terms that were defined in chapter 4. To reiterate these definitions, this thesis defines these terms as follows: Offshoring refers to the relocation of production stages abroad either through arm's length supply through market transactions (international outsourcing) or within the boundaries of the firm (vertical FDI) [Jabbour, 2010]. Offshoring can relate to material stages of production such as intermediate production stages in the manufacturing process such as car assembly; and offshoring can also refer to service related job tasks in business services. For example, they can refer to front office services such as call centres and customer services or back office services such as human resources and IT services (Roland Burger Strategy Consultants, 2005). *Outsourcing* on the other hand does not imply that these production stages in manufacturing and business services are relocated to another country. It could imply outsourcing to an external firm which is located within the same developed country.

5.2.2 Offshoring, Blinder's (2007) Occupation Tradability Index & TBTC

Section 4.2.2 to 4.2.4 from chapter 4 provided a detailed synopsis of how each of these variables: offshoring (materials and services), the most tradable jobs defined by Blinder's (2007) occupation tradability index and the four job task variables from the routinization hypothesis (Autor *et al.,* 2003) are measured and the sources of data that are used to measure them. Rather than to repeat this process again, please refer to sections 4.2.2, 4.2.3 and 4.2.4 which provides the details of how each of the variables are measured. All of these variables are measured and incorporated into the data in the same way; the only difference is the analysis period. This chapter examines the changes to job security (the probability of becoming unemployed) from 1992 to 2005; chapter 4 examined how these variables affected wage levels (job stability) over the 1992 to 2007 time frame.

It is predicted that if job security has fallen over the last two decades, then one should find that offshoring (material and services) and the advancements in technology should make many more jobs potentially more tradable and jobs that are routine intensive are more likely to have a higher probability of a job-to-unemployment transition over time.

5.3 Data & Estimation Strategy

5.3.1 Data

To explore the impact of offshoring (measured at the industry level), the impact from Blinder's (2007) occupation tradability index and the impact from the TBTC hypothesis on job security, I use the British Household Panel Survey (BHPS). The BHPS is a nationally representative annual survey, carried out by the Institute for Social and Economic Research at the University of Essex, of each adult member of a nationally representative sample of more than 5,000 private households (with a total of approximately 10,000 individual interviews) randomly selected south of the Caledonian Canal. The first wave of the BHPS was conducted during the autumn of 1991, and annually thereafter (Taylor *et al.*, 2006). Although the BHPS first commenced in 1991, the availability of data used from Input-Output Supply & Use tables to measure industry level service and material offshoring intensity is only available from 1992 onwards. Therefore, the availability of this data has a bearing on the sample that is used for analysis by this chapter.

For this chapter, I use data covering the period 1992-2005[2], whereas chapter 4 used data covering the period 1992-2007. An additional difference to the data sample used by this chapter and the previous chapter relates to its composition: the previous chapter only considered workers in employment to examine how offshoring, potential occupation tradability and the TBTC hypothesis could affect wage levels. This chapter consists of all workers aged 16 to 65 years, who are in employment, who are unemployed, who are self-employed and not in the labour force. This sample is bigger because I focus on three types of job transitions over time. I explore whether the probability of job-to-unemployment transitions have increased over the last two decades or whether the probability of new job transitions which can result in new employment have also increased over time and whether the probability of job spells with the same employers has declined over time. But the job-to-self employment transitions and job-to-non activity transitions are also important because they are competing risks to the event of becoming unemployed or remaining in employment in year j.

Each of these job transitions are identified as the fraction of workers making a given transition in year j, given that the sample of individuals survive in employment up until year $j-1$. That is they transition to: (a) employment (continued employment with current employer or new

[2] The use of the BHPS data in this chapter differs with respect to chapter 4 as I have excluded data for years 2006 and 2007. For years 2006 and 2007 there is a key variable: -wcjsten- which is a derived variable that had quite a lot of missing values. This is a variable that is required to accurately measure job tenure in present employment at the time of writing this chapter. With a large number of missing values, I am unable to accurately measure job tenure with the present employer for years 2006 and 2007. A notice announced in May 2009 from ISER, noted that the latest wave of BHPS data released in March 2009 were found to contain corrupted data for some variables. The advice was to download data from the UKDA for corrected data deposited from ISER. This newly deposited data makes no difference to the results I obtain for job tenure at the time of writing this chapter. As job tenure is a key variable that is required in the estimation process, I exclude these two years of data.

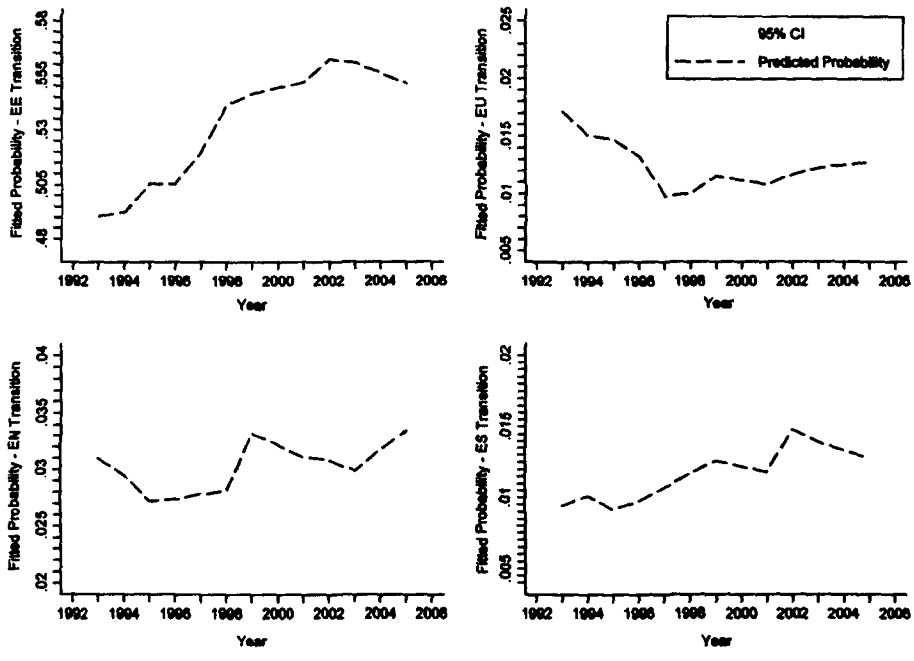
jobs from one year to the next); (b) unemployment through job loss (although non-voluntary job separations that can occur through redundancies and firm closures cannot be identified with this data set directly); (c) non-activity, where workers leave the labour market due to ill health or to start a family among other reasons for not participating in the labour market and (d) self-employment, where workers may leave employment as an employee and start to work for themselves by starting their own business in time period j. Each of these job transitions are annual job transitions.

This chapter measures job security by exploring the probability of experiencing job-to-unemployment transitions over time. If the probability of job-to-unemployment transitions is rising over time, this reflects a fall in job security as more workers have a higher probability of becoming unemployed. However, the other job transition states are also important as lower job security may also reflect a rise in the probability of new job transitions as well as not participating in the labour force or to start to work as a self-employed worker in time period j.

Figure 5.1 presents four graphs which depict the change in probability for the four job transition states over time; these are job-to-job transitions, job-to-unemployment transitions, job-to-non activity transitions and job-to-self employment transitions. Each graph plots the fitted job transition probability relative to the base year of 1992 with a 95 percent confidence interval. These graphs were obtained by simply estimating probit models with year dummy variables representing each year of data minus year 1992; no other explanatory variables were included in the estimation. The marginal effects from these estimated regressions were then evaluated at zero to obtain the change in the probability. These estimates were then plotted to examine the trend changes over time.

From figure 5.1, the top left graph shows the change in the job-to-job transition probability relative to year 1992. Over time, this job transition probability has risen, implying that most individuals in the sample have been in paid employment with very little evidence to show there has been fall. The top right graph plots the change in the job-to-unemployment transition probability relative to year 1992. This graph shows a downward trend in this probability over time, though from 1997 there has been a rise in this job transition probability which is very small. From the bottom row of graphs, the job-to-non activity transitions and job-to-self employment transition probabilities show they have risen over the time frame, although these job transition probabilities are still relatively small in comparison to the number of individuals who are in employment.

Figure 5.1: Job Transitions over Time

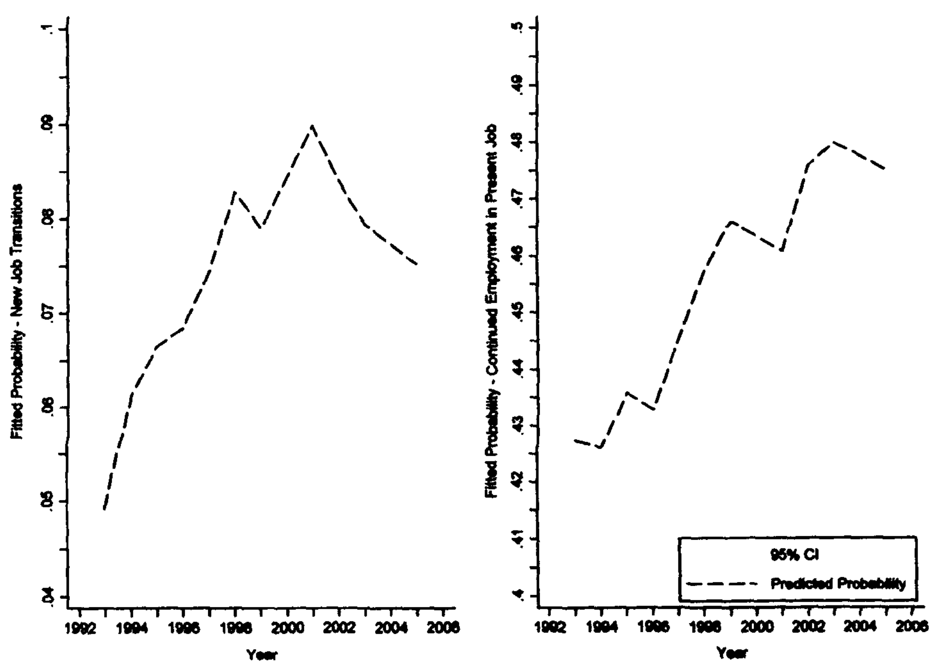


Source: Compiled by the author.

Figure 5.2 further examines the changes to the job-to-job transition probability. It is further split into new job transitions for individuals who are in employment as employee but change employers from time period $j-1$ to time period j; these job transitions are identified by individuals having less than one year of job tenure. The second category of job-to-job transitions relates to workers who are in employment and continue to work for their current employer from time period $j-1$ to time period j; these workers are identified with having more than one of job tenure.

The first graph on the left hand side shows the change in the job-to-job transition probability for workers who change employers and transition into new jobs in time period j. This graph shows there has been a rise for this probability relative to the base year of 1992, although after 2001 this probability has continued to fall. The second graph on the right hand side from figure 5.2 shows the probability of workers who continue to work for their current employers from time period $j-1$ to time period j to be rising over time relative to the base year. These graphs indicate that workers in this sample of data have a higher probability to remain in employment over time.

Figure 5.2: Job to Job Transitions over Time



Source: Compiled by the author.

Table 5.1 presents the summary statistics and a list of the variables that will be used in estimation; many of the explanatory variables will be discussed in further detail in the next section. From table 5.1, the average age of individuals in this sample is 38 years where roughly 53 percent of the sample is female. Roughly 42 percent of individuals have dependent children in their households, where 23 percent of females have dependent children. Turning to employment duration or job tenure, approximately 22 percent of workers have job tenure of less than one year and greater than nine years. Far more workers – roughly 26 percent have job tenure of between one to three years, whilst fewer workers have job tenure of 7 to 9 years. From the job transition states, roughly 53 percent of the sample is in employment; this can be with the same employer or by remaining in employment but changing employers from one time period to next period. Roughly 1.2 percent of the sample have experienced job to unemployment transitions over the sample time frame and three percent of the sample have transitioned into non-activity from employment. By far the lowest job transition state is job-to-self employment transitions which only accounts for roughly one percent of the sample over time. Approximately 55 percent of the sample has A-level qualifications and a university degree (a medium level education level) if not higher. And other variables show, the average unemployment rate over the sample is 7 percent and roughly 15 percent of the sample are members of a trade union. The average service offshoring intensity is lower than the average material offshoring intensity and roughly 18 percent of the individuals in this sample are employed in potentially the most tradable jobs as defined by Blinder's (2007) occupation tradability index.

Table 5.1: Summary Statistics

	Mean	Std. Dev.
Transition: Job-to-Job (E-E)	0.5285	0.4992
Transition: Job-to-Unemployment (E-U)	0.0127	0.1120
Transition: Job-to-Non-Activity (E-N)	0.0305	0.1720
Transition: Job-to Self-Employment (E-S)	0.0116	0.1071
Transition: New Job Transition	0.0683	0.2522
Transition :Continued Employment with current Employer	0.4198	0.4935
Age	38.7511	13.4708
Age Squared	1683.1090	1084.2950
Dummy: Female	0.5322	0.4990
Employment Duration: < 1 Year	0.2175	0.4126
Employment Duration: 1-3 Years	0.2610	0.4392
Employment Duration: 4-6 Years	0.1180	0.3226
Employment Duration: 7-9 Years	0.0607	0.2387
Employment Duration: > 9 Years	0.2184	0.4132
Dependent Children in HH	0.4193	0.4934
Dummy: Married	0.6848	0.4646
Dummy: Females with dependent Children	0.2337	0.4232
Dummy: Married Females	0.3648	0.4814
Dummy: Firm Size < 25	0.2240	0.4169
Dummy: Firm Size 25-99	0.1687	0.3745
Dummy: Firm Size 100-999	0.1892	0.3917
Dummy: Firm Size >= 1000	0.0643	0.2452
Dummy: Firm in Public Sector	0.1642	0.3704
Dummy: White	0.9608	0.1940
Occupation: Legislators, Senior Officials, Managers	0.1128	0.3163

Occupation: Professionals	0.0946	0.2926
Occupation: Technicians & Associate Professionals	0.0926	0.2899
Occupation: Clerks	0.1207	0.3257
Occupation: Shop Worker & Shop/Market Sales	0.1194	0.3243
Occupation: Skilled Agricultural & Fishery	0.0077	0.0875
Occupation: Craft & Related Trades	0.0776	0.2675
Occupation: Plant, Machine Operators, Assemblers	0.0581	0.2339
Occupation: Elementary Occupations	0.0506	0.2192
Education: High	0.0244	0.1542
Education: Medium	0.5300	0.4991
Education: Low	0.4456	0.4970
National Unemployment Rate - %	6.9754	1.9650
Dummy: Member of Union	0.1538	0.3607
Research & Development Intensity	0.3506	0.6812
Net Exports/1000	-2.5123	12.6875
Industry Level Output/1000	142.3049	124.0568
Service Offshoring Intensity - OSS	1.7590	2.3828
Material Offshoring Intensity - OSM	1.9538	4.8479
Dummy: Most Tradable Jobs from Blinder Index >= 65	0.1750	0.3800
Routine Job Tasks	0.1132	3.0008
Non-Routine Abstract Job Tasks	0.8206	3.9193
Non-Routine Manual Job Tasks	0.0859	3.7910
Service Job Tasks	-0.0332	3.5784
Year Dummy: 1992	0.0782	0.2686
Year Dummy: 1993	0.0752	0.2637
Year Dummy: 1994	0.0752	0.2638
Year Dummy: 1995	0.0731	0.2604
Year Dummy: 1996	0.0761	0.2652
Year Dummy: 1997	0.0758	0.2648
Year Dummy: 1998	0.0734	0.2608
Year Dummy: 1999	0.0724	0.2591
Year Dummy: 2000	0.0710	0.2568
Year Dummy: 2001	0.0695	0.2544
Year Dummy: 2002	0.0669	0.2499
Year Dummy: 2003	0.0653	0.2471
Year Dummy: 2004	0.0633	0.2436
Year Dummy: 2005	0.0644	0.2454
Region: NW & NE	0.1689	0.3747
Region: Yorks & Humber	0.0955	0.2939
Region: EM & WM	0.1742	0.3793
Region: East	0.0415	0.1995
Region: London	0.0959	0.2945
Region: SE	0.1947	0.3959
Region: SW	0.0911	0.2878
Region: Wales	0.0520	0.2221
Region: Scotland	0.0862	0.2806
Industry: Agriculture, Forestry & Fishing	0.0112	0.1051
Industry: Mining & Quarrying	0.0029	0.0535
Industry: Manufacturing	0.1350	0.3417
Industry: Electricity, Gas & Water Supply	0.0060	0.0770
Industry: Construction	0.0410	0.1983
Industry: Distribution & Hotels	0.1514	0.3584
Industry: Transport & Communications	0.0448	0.2069
Industry: Finance & Business Services	0.1083	0.3108
Industry: Public Admin & Defence	0.4095	0.4917
Industry: Education, Health & Social Care	0.1397	0.3466
Industry: Other Services	0.0483	0.2144
Observations:	99,967	

Source: *Author's own calculations from the BHPS.*

5.3.2 Estimation Strategy

To model the affects offshoring, the potential tradability of jobs and the TBTC hypothesis might have on job security, I follow the contributions of Munch (2009), Geichecker (2008) and Egger *et al.*, (2007) and use yearly job spell data from the BHPS to analyse individual level job transitions via discrete time survival analysis. The analysis from this chapter departs from these papers on a number of fronts. First, Geishecker (2008) and Munch (2009) explore the impact of material offshoring intensity on individual level job transitions. My analysis explores the impact of material and services offshoring intensity, which has so far not been examined by this literature. It is interesting to examine the impact that service offshoring intensity might have on job security because the current wave of globalisation has been aided by the advancements of ICT. This has made many more service related jobs at risk of job loss which may lower job security by raising the probability of job-to-unemployment and job-to-new employment transitions over time. This could also affect those workers who have continued to work with their present employers over time.

Second, I also examine the impact of the routinization hypothesis on job security; this application has so far not been examined in this context, but there is research that has explored this hypothesis's impact on employment (see Goos *et al.*, 2009a,b) and wages (see chapter 4 from this thesis). Third, Geishecker (2008) examines a single job transition state, which is monthly work-to-non-employment transitions. This job transition is identified if the respondent ceases to work and reports having become unemployed or engages in house work. His paper is unable to identify monthly job-to-job transitions due to lack of information on these spells. Munch (2009) concentrates on two job spell states: job-to-job spells and job-to-out of employment spells. For this chapter, I examine three yearly job transition states: job transitions into new employment, job-to-unemployment transitions and the annual job-transitions that show the continuous employed with present employers.

5.3.2.1 Modelling the Duration out of Employment

To model the duration out of employment to other destination states, this chapter specifies a discrete time hazard model which accounts for duration dependence and unobserved heterogeneity. Accounting for unobserved heterogeneity (or 'frailty' as it is referred to in the bio-medical sciences) is important as this accounts for omitted variables that may not be observable (e.g. innate ability is a trait that cannot be observed by data or be measured) and because of measurement error in the regressors (Jenkins, 2005). These omitted variables only matter if they are correlated with the offshoring intensity variables measured at the industry level, the potential tradability of occupations according to Blinder's (2007) index and in particular from the four job task intensity variables which examine the impact of the routinization hypothesis.

Jenkins (2005) suggests that a model which does not take account for frailty can over (under) estimate the degree of negative (positive) duration dependence in the hazard. And one can get an under-estimate of the true response of the hazard to a change in a regressor X_k from a non-frailty model (Jenkins, 2005). To account for frailty in discrete time models, there are two types of approaches that can be taken: (1) a parametric approach or (2) a non-parametric approach.

For a model with no frailty, the hazard function can be of the following form, assuming it has a complementary log-log specification:

$$\lambda_{i,j} = 1 - \exp\left[-\exp\left(e_i + \beta_0 + \beta' X_{i,j}\right)\right] \qquad (1)$$

where β_0 is an intercept, e_i is an error term and $\beta' X_{i,j}$ is a linear function of covariates, where i denotes each individual and j denotes the time. With a parametric approach to model the frailty distribution, the error term can be modelled by assuming a Normal (Gaussian) distribution with a zero mean. The hazard function takes the following form:

$$\lambda_{i,j} = 1 - \exp\left[-\exp\left(u_i + \beta_0 + \beta' X_{i,j}\right)\right] \qquad (2)$$

Where frailty is assumed to be distributed by: $u_i \backsim N(0, \sigma_u^2)$. With this assumption, Jenkins (2005) notes there to be no closed form expression for the survivor function because the survivor function is a product of the complements of the period-specific hazards. And with frailty, these hazard rates also depend on the unobserved error term. With the error term following a Normal distribution, numerical quadrature techniques are used to 'integrate out'. The most common empirical approach to this problem in practice has been to calculate survivor functions conditioning on a particular error term value, by using the estimates of covariate coefficients from the frailty model but setting the error term equal to its mean[3].

For the non-parametric approach to characterise the frailty distribution was developed by Heckman & Singer (1984). Instead of assuming a parametric form for the frailty distribution, this approach fits an arbitrary distribution using a set of parameters representing a set of 'mass points' for a number of different types, z and the probabilities, P_z that a person is located at each of the mass points[4]. The hazard function for an individual belonging to type z is given by:

$$\lambda_{i,j} = 1 - \exp\left[-\exp\left(m_z + \beta_0 + \beta' X_{i,j}\right)\right] \qquad (3)$$

Where m = the number of mass points and $z = 1, \ldots, Z$ is the number of types. This is a random intercept model where the randomness is characterised by using a discrete distribution[5]. In practise these models are difficult to estimate using large data sets as these models can be slow to converge because the programs use numerical derivatives. Additionally

[3] For this first approach, built in programs in STATA can be used to estimate these models depending on the form of the hazard function. If the error term has a gamma distribution, one can estimate this model using the '*pgmhaz8*' program written by Jenkins (2005). For models which assume the error term is distributed by following a Normal distribution, the '*xtlogit*' model can be estimated or an '*xtcloglog*' model can be estimated for logit and cloglog models where the data must be organised in person-period form – this concept will be discussed shortly.

[4] Note that the number of mass points to be estimated is unobserved; Jenkins (2005) suggests that the number of mass points that are estimated is decided by the researcher. Usually the standard procedure is to estimate two. But Geishecker (2008) and Munch (2009) estimated four mass points. Geishecker (2008) estimates two mass points and then subsequently adds additional mass points holding all parameters constant at their previous maximum level until the log-likelihood fails to increase significantly.

[5] Heckman & Singer type models can be estimated in STATA by using the '*hshaz*' program written by Jenkins (2005) or by using the '*gllamm*' program written by Sophia Rabe-Hesketh. For other types of models see Jenkins (2005).

these models may not converge if the likelihood surface is not globally concave or in some cases the maximisation process may get stuck on a flat surface (Jenkins, 2005).

I estimate a discrete time hazard model with a parametric form for the frailty distribution as a starting point. These models will provide a starting point to obtain estimates that will provide an indication of whether frailty matters in the sample of data or not. If it does not matter, then the non-parametric models may be very difficult to estimate with a large data set (Jenkins, 2005).

To estimate a discrete time single risk model of leaving employment with right censoring, I follow the methodology outlined by Jenkins (2005): First it is assumed that each interval is a year long. We observe person $i's$ spell from year $k = 1$ through to the end of the j^{th} year, where at this point, person $i's$ spell is either complete ($c_i = 1$: meaning this person experiences the event of transitioning out of employment and into unemployment) or the spell is right censored. Right censoring can occur when the event at risk (in this chapter, this is the event of becoming unemployed) is not observed. This can occur when workers experience other competing events during each interval. For example, instead of becoming unemployed, workers may find another job without an intervening spell of unemployment; or they may become self-employed by starting their own business or they leave the labour force altogether.

The discrete time hazard is defined by the following equation:

$$\lambda_{i,j}(X_{i,j}, \gamma_{i,j}, u_i) = \Pr(T_i = j | T_i \geq j, X_{i,j}, \gamma_{i,j}, u_i) \qquad (4)$$

$$= \Pr(T_i = j | T_i > j - 1, X_{i,j}, \gamma_{i,j}, u_i) \qquad (5)$$

From equation (5), the discrete time hazard is defined as the conditional probability that the event of unemployment occurs at time j, given there is survival up to time $j - 1$. From equation (5), $X_{i,j}$ is a vector of individual, job and industry level characteristics; this vector also includes time dummy variables as well as the variables that measure offshoring intensity, the potential tradability of jobs and the job task intensity variables and $\gamma_{i,j}$ represents the set of interval dummy variables for employment duration. And finally, $u_i$represents a time-invariant error component. A parametric form for the random error component is assumed to account for the frailty distribution, where $u_i \sim N(0, \sigma_u^2)$.

The likelihood contribution for a censored spell is given by the following discrete time survivor function:

$$\mathcal{L}_i = \Pr\left(T_i > j, X_{i.j}, \gamma_{i,j}, u_i\right) = S_i(j) \tag{6}$$

$$= \prod_{k=1}^{j}(1 - \lambda_{i,k}) \tag{7}$$

And the likelihood contribution for each completed spell is given by the following discrete time density function:

$$\mathcal{L}_i = \Pr\left(T_i = j, X_{i.j}, \gamma_{i,j}, u_i\right) = f_i(j) \tag{8}$$

$$= \lambda_{i,j} \times S_i(j-1)$$

$$= \frac{\lambda_{i,j}}{1-\lambda_{i,j}} \prod_{k=1}^{j}(1 - \lambda_{i,k}) \tag{9}$$

The likelihood function for the whole sample is given by:

$$\mathcal{L}_i = \prod_{i=1}^{n}[\Pr(T_i = j)]^{c_i} \times [\Pr(T_i > j)]^{1-c_i} \tag{10}$$

Substituting (7) and (9) into (10):

$$\mathcal{L}_i = \prod_{i=1}^{n}\left[\left(\frac{\lambda_{i,j}}{1-\lambda_{i,j}}\right)\prod_{k=1}^{j}(1 - \lambda_{i,k})\right]^{c_i} \times \left[\prod_{k=1}^{j}(1 - \lambda_{i,k})\right]^{1-c_i} \tag{11}$$

$$\mathcal{L}_i = \prod_{i=1}^{n}\left[\left(\frac{\lambda_{i,j}}{1-\lambda_{i,j}}\right)\prod_{k=1}^{j}(1-\lambda_{i,k})\right]^{c_i} \tag{12}$$

From equation (12), c_i is the censoring indicator, where $c_i = 1$ if the spell is completed (that is the event at risk is becoming unemployed) and $c_i = 0$ if the spell is right censored (that is the transition into unemployment does not happen in the j^{th} interval or following the completion of the j^{th} cycle). From equation (12), the log likelihood function can be given by the following expression:

$$log\mathcal{L} = \sum_{i=1}^{n} c_i \, log\left[\frac{\lambda_{i,j}}{1-\lambda_{i,j}}\right] + \sum_{i=1}^{n}\sum_{k=1}^{j}\log\,(1-\lambda_{i,j}) \tag{13}$$

Next, defining $y_{i,k}$ to be a binary indicator variable, which takes a value of $y_{i,k} = 1$ if person i makes a transition into unemployment in year k and $y_{i,k} = 0$ otherwise. That is:

$$c_i = \begin{cases} 1 \;\Rightarrow y_{i,k} = 1 \, for\ k = T_i;\;\; y_{i,k} = 0 \; otherwise \\ 0 \;\Rightarrow y_{i,k} = 0 \, for\ all\ k \end{cases} \tag{14}$$

Following equation (14), equation (13) can be re-written as follows:

$$log\mathcal{L} = \sum_{i=1}^{n}\sum_{k=1}^{j} y_{i,k} \, log\left[\frac{\lambda_{i,k}}{1-\lambda_{i,k}}\right] + \sum_{i=1}^{n}\sum_{k=1}^{j}\log\,(1-\lambda_{i,k}) \tag{15}$$

Choosing a complementary log-log (cloglog) specification for the hazard function[6]:

$$\lambda_{i,j}(X_{i,k}, \gamma_{i,k}, u_i) = 1 - \exp\,(-\exp(\beta' X_{i,k} + \gamma_{i,k} + u_i)) \tag{16}$$

Substituting (16) into (15):

$$log\mathcal{L} = \sum_{i=1}^{n}\sum_{k=1}^{j} y_{i,k} \, log\left[\frac{1-\exp(-\exp(\beta' X_{i,k}+\gamma_{i,k}+u_i))}{\exp(-\exp(\beta' X_{i,k}+\gamma_{i,k}+u_i))}\right] +$$

$$\sum_{i=1}^{n}\sum_{k=1}^{j}\log\,(\exp\,(-\exp(\beta' X_{i,k} + \gamma_{i,k} + u_i))) \tag{17}$$

[6] Clog-log models represent a third alternative model specification after logistic and probit analysis for binary response variables. The complementary log-log models are frequently used when the probability of an event is very small or very large.

To estimate equation (17), the data must first be organised into person-year form before proceeding to estimation (Jenkins, 2005). What this means is there is one observation for each year each person is at risk from becoming unemployed in the data[7]. If the interval was defined to be a month, then the data would have to be expanded to be in person-month form; this would mean each person would have an observation for each month of data they are at risk of becoming unemployed.

5.3.2.2 Competing Risks Model

The discrete time hazard model has so far assumed there is a single state process, where a rise in the offshoring intensity, or the advancements in technology can potentially raise the tradability of an occupation or TBTC can only lead workers to experience the risk of one event at anytime – namely a job-to-unemployment spell. But, workers may experience the risk of multiple states of labour market activity. For example, workers may experience a job transition to a new job or become self employed in addition to experiencing unemployment, or workers could leave the labour market altogether and transition into non-activity. All of these transitions can happen at time j are competing risks to the event of becoming unemployed assuming workers remain in employment up until year $j-1$. Thus, a competing risks model is a model for multiple destinations states. Multiple destinations can be observed from being in a state of employment at time $j-1$ to: (a) new employment, (b) self employment, (c) unemployment or even (d) non-activity at time j.

Formally, the individual sample likelihoods contribute to an independent competing risk model with two destination states, where there are three types. We have the following multiple destination states:

[7] This can be difficult in practice as individuals may not take part in each survey if they are not available. For example, if respondents' die or they leave the country to take a job overseas.

$\mathcal{L}_A$: **Destination A** - Individual transitions to new employment;

$\mathcal{L}_B$: **Destination B** - Individual exits to unemployment;

$\mathcal{L}_C$: **Destination C** - The spell is right censored – meaning workers do not transition to a new job or unemployment but may continue to remain in employment and work for their current employers; they may start their own business and work for themselves; or they simply leave the labour market and transition into non-activity.

Following the methodology set out by Jenkins (2005), the discrete hazard rate for exit at time j to any destination is the sum of the destination specific discrete hazards:

$$\lambda(j) = \lambda_A(j) + \lambda_B(j) \tag{18}$$

As survival times are discrete, if there is an exit to one of the destinations at a given survival time, then there cannot be an exit to other destinations at the same time. The overall likelihood contribution for an individual with an observed spell into one of two destinations with an observed spell length of j cycles (the cycle refers to the time frame) is:

$$\mathcal{L} = (\mathcal{L}^A)^{\delta^A}(\mathcal{L}^B)^{\delta^B}(\mathcal{L}^C)^{1-\delta^A-\delta^B}$$

$$\mathcal{L} = \left[\frac{\lambda_A(j)}{1-\lambda_A(j)-\lambda_B(j)}\right]^{\delta^A} + \left[\frac{\lambda_B(j)}{1-\lambda_A(j)-\lambda_B(j)}\right]^{\delta^B} \times \prod_{k=1}^{j}[1-\lambda_A(k)-\lambda_B(k)] \tag{19}$$

Where destination specific censoring indicators are defined as:

$$\delta^A = \begin{cases} 1 \text{ if person } i \text{ exits to A} \\ 0 \text{ otherwise (exit to B or censored)} \end{cases} \tag{20}$$

$$\delta^B = \begin{cases} 1 \text{ if person } i \text{ exits to B} \\ 0 \text{ otherwise (exit to A or censored)} \end{cases} \tag{21}$$

Jenkins (2005) notes there are no neat separability results in the discrete case; but it is still straight forward to estimate an independent competing risks model. Allison (1982) demonstrates that the trick is to assume a particular form for the destination-specific hazards:

$$\lambda_A(k) = \left[\frac{\exp(\beta_A' X + \gamma)}{1+\exp(\beta_A' X + \gamma) + \exp(\beta_B' X + \gamma)}\right] \tag{22}$$

$$\lambda_B(k) = \left[\frac{\exp(\beta_B' X + \gamma)}{1+\exp(\beta_A' X + \gamma) + \exp(\beta_B' X + \gamma)}\right] \tag{23}$$

$$1 - \lambda_A(k) - \lambda_B(k) = \left[\frac{1}{1+\exp(\beta_A' X + \gamma) + \exp(\beta_B' X + \gamma)}\right] \tag{24}$$

With destination-specific censoring indicators δ^A and δ^B, the likelihood contributions for each person with spell length j is written as:

$$\mathcal{L} = \left[\frac{\exp(\beta_A' X + \gamma)}{1+\exp(\beta_A' X + \gamma)+\exp(\beta_B' X + \gamma)}\right]^{\delta^A} \left[\frac{\exp(\beta_B' X + \gamma)}{1+\exp(\beta_A' X + \gamma)+\exp(\beta_B' X + \gamma)}\right]^{\delta^B}$$

$$\times \left[\frac{1}{1+\exp(\beta_A' X + \gamma) + \exp(\beta_B' X + \gamma)}\right]^{1-\delta^A-\delta^B} \times \prod_{k=1}^{j-1} \left[\frac{1}{1+\exp(\beta_A' X + \gamma) + \exp(\beta_B' X + \gamma)}\right] \tag{25}$$

As Allison (1982) notes, the likelihood of equation (25) has the same form for a multinomial logit model, which can be estimated in four steps: The first step is to expand the data into person-period form; for this chapter the data must be in person-year form as I am examining annual job transitions in the time interval $[j-1, j]$. The second step is to construct a dependent variable for the data, which takes a value of 0 for all censored observations. For persons exiting to destinations state A, the dependent variable is equal to 1 and for those in destination state B, the dependent variable is equal to 2. The third step is to create other additional variables that are required for analysis. The final step is to estimate the model with a multinomial logit program, where the base group category is set equal to 0.

5.3.3 Control Variables & Estimation Issues

For each estimation strategy outlined above, the following control variables are included. First, it is important to account for duration dependence ($\gamma_{i,j}$), as this might have important implications for the probability of exit out of employment and into unemployment in year j. I choose to include a number of discrete job tenure dummy variables defined as: DD1: less than one year; DD2: 1-3 years; DD3: 4-6 years; DD4: 7-9 years and DD5: > 9 years. These dummy variables capture the potential length of employment spells. They capture the potential cost of firing workers, which can increase with workers' skill levels (e.g. Mortensen & Pissarides, 1999); the probability of ending an employment spell will decline with job duration if workers accumulate general and specific human capital (Ritter, 2009); see chapters 2 and 3, for a review of the literature on job security. Little is known *a priori*, regarding the exact form that duration dependence takes; but, I take a non-parametric form for duration dependence, where for each respondent, the hazard rate is freely determined in a specified time interval, but there are no further constraints that are applied to the functional form. Job transitions occur in continuous time, but the precise date of the transition is not observed in the data (e.g. the date or the month when workers transition out of employment). Instead, these events occur at some point in time between the annual interview dates. Job transition data of this nature are grouped or interval censored. For the competing risks model, I exclude these discrete bands and include a variable that measures job tenure. This is because modelling the risk of new job transitions in year j causes the job tenure dummy variables for one to nine plus years to drop out of estimation.

Each model also includes a range of individual and work related characteristics which capture a range of time-varying and non-varying level characteristics which are accounted for by the vector $X_{i,j}$. These variables include controls for age, dependent children, gender, union membership, education level, firm size, the unemployment rate, industry and regional dummy variables to control for unobserved industry and region heterogeneity and year dummy variables. Accordingly, I follow Geishecker (2008) and Munch's (2009) analysis, where I do not control for the frequency and duration of past employment spells. Geishecker (2008) argues that the inclusion of these variables in addition to the set of individual level variables may give rise to multi-collinearity and this may not improve the fit of the model as other explanatory variables such as education, occupation and industry may determine them.

Additionally, I do not include the real hourly wage rate as an explanatory variable. Royalty (1998) and Geishecker (2008) are two paper which have included this variable. But Zavodny (2003) and Bernhardt *et al.*, (1999) exclude this variable as there is the potential that the real hourly wage could be endogenous. That is, the explanatory variables that are used to explore individual job separations are also variables that were used to determine the hourly wage (see chapter 4 for the model used to estimate Mincerian wage regressions).

To examine the impact of offshoring intensity (material and services) on job security, I merge in data from the annual input-output supply and use tables from the Office for National Statistics (ONS) in the U.K. Additionally, to examine the TBTC hypothesis on job security, I create four job task variables measuring service, routine, non-routine manual and non-routine abstract tasks using data from O*NET to estimate a single principal component across each SOC in O*NET, which has been collapsed to the ISCO-88 level; see section 4.2.2, 4.2.3 and 4.2.4 from chapter 4 for a reminder of the details.

Additional control variables are also included in estimation (many of these variables are the same control variables that were included in the Mincerian wage regressions); the following paragraphs provide a recap: Research and development intensity and net exports are included in estimation. Research and development intensity is measured by: $\frac{R\&D}{Y}$, where R&D is industry expenditure on research and development and Y is the output level from each industry. Data for R&D was obtained from the U.K. Business Enterprise Research and Development (BERD) publication available from ONS. Missing data from BERD was supplemented by data from the OECD ANBERD. This data is available by product groups. To obtain R&D expenditure by industry groups, I used an unpublished concordance provided by ONS to allocate the R&D expenditure by product groups into industry groups. Data for industry output is available from Input-Output tables available from ONS. Net exports are measured by subtracting imports from exports: (exports – imports). This data relates to the export and import of goods and services which is available from ONS. The inclusion of research and development intensity accounts for technological progress and along with industry dummy variables and net exports account for the potential job creation and job destruction effects that may have important affects on raising or lowering job security (Kletzer, 2000, 2004; Klein *et al.*, 2004 and Davidson & Matusz (2005) highlight the importance of export orientation and international competition as being important determinants).

The inclusion of micro-level individual data combined with industry level aggregate data could give rise to contemporaneous correlations in the error term which can result with biased estimates for the standard errors (Geishecker, 2008). This issue has been stressed by Moulton (1986, 1990); he suggests remedying this issue by multiplying the standard errors with a common factor that reflects the average intra-cluster residual correlation. But, Angrist & Lavy (2002) note that this method imposes an equi-correlated error structure on the standard errors which is inappropriate in the context of models with binary outcomes. They suggest instead applying the Generalised Estimation Equation Method (GEE)[8], which multiplies the standard errors by a factor reflecting the intra-cluster residual correlation, which varies between clusters. However, Geishecker (2008) notes that whilst clustering the standard errors has become a standard in the literature, the problem with this approach is that the number of clusters needs to be large relative to the number of within cluster observations (Wooldridge,

[8] This was a framework that was devised and developed by Liang & Zeger (1986). This is basically the cluster option in STATA.

2002). Thus, I follow Geishecker (2008) and Munch (2009), who do not cluster the standard errors in their combined micro- and macro-level data within their models. But they reduce this contemporaneous error with the inclusion of industry and region variables to account for the correlation within the clusters due to time constant unobserved heterogeneity. This should estimate a within industry (fixed effects) model.

5.4 Results

The estimated results are presented in two parts. Section 5.4.1 presents the estimated results from the discrete time hazard model where the frailty distribution is assumed to follow a Normal distribution. And, section 5.4.2 presents the results from the competing risks model.

5.4.1 Single Risk Model Results

This section provides the estimated results from the single risk model where the frailty distribution is assumed to be normally distributed. Ten versions of this single risk model have been estimated and the results are presented within tables 5.2a to 5.4a accompanied by tables 5.2b to 5.4b which provide likelihood ratio tests for frailty. Each of these tables presents the impact of offshoring (services and materials), the potential tradability of jobs (Blinder's (2007) index) and the impact from the job task variables from routinization hypothesis have had on the probability of transitioning into unemployment in year *j* over time.

First, from eight of the ten estimated versions of the single risk model (with frailty) which looks at the impact of offshoring and the potential tradability of occupations from Blinder's (2007) occupation tradability index on job security (or the risk of becoming unemployed), the likelihood ratio tests for frailty presented in tables 5.2b to 5.4b are not statistically significant. What this means is that frailty is not important in these models. A second way to check whether frailty is not important in these models is to compare the estimated coefficients in models where frailty is accounted for in estimation with models that do not account for frailty. If the estimated coefficients between the two types of models are the same, then frailty is not important; but if the estimated coefficients differ, then frailty does matter. The estimated results presented in tables 5.1A to 5.3A located in appendix 1 show that when frailty is not taken into account, the estimated coefficients from these single risk models are the same as the estimated coefficients from the single risk models that account for frailty in most cases. The only differences between the results from models that account of frailty (tables 5.2a to 5.4a) to those that do not (tables 5.1A to 5.3A in appendix 1) are the estimated standard errors. But frailty is important in two versions of the single risk models; these models relate to the impact from the four job task variables from the routinization hypothesis (located in column (4) in table 5.2a and column (2) in table 5.4a). Second, from all ten versions of the single risk model, the estimated baseline parameters show the probability of becoming unemployed is most likely to occur during the first year of employment. This probability declines with job tenure; these results are also shown by the single risk models that do not account for individual heterogeneity (see tables 5.1A to 5.3A in appendix 1).

Table 5.2a provides the estimated coefficients from the affects of offshoring (material and services) on the probability of transitioning into unemployment in year j. The estimated coefficients from these four versions of the model show the probability of becoming unemployed increases non-linearly with age. Being married, having dependent children and female workers who are married are less likely to become unemployed, though many of these estimated coefficients are not significant. Females who have dependent children are also less likely to become unemployed. These findings contrast with findings reported by Geishecker (2008) and Royalty (1998). Geishecker (2008) finds married females and females who have dependent children have a higher probability of leaving employment; but the dependent variable in his paper incorporates individuals who leave the labour force altogether in addition to those workers who lose their jobs and become unemployed. This could account for the significant coefficients for females who have dependent children. Additionally, the results from this chapter show females and females who are also married do not have a higher probability of becoming unemployed compared to male workers who are also not married.

Being a member of a trade union reduces the probability of becoming unemployed and in contrast to the expected results, a rise in the national unemployment rate does not raise the probability of becoming unemployed. This result is surprising because one would expect the probability of becoming unemployed to rise as the national unemployment rate increases. But if one takes another look at the probability of becoming unemployed from figure 5.1, one can see that over the period 1992-2005, this probability has declined over this time frame and additionally, if one recalls the national unemployment rate trends from figure 3.2 from chapter 3 showed a falling unemployment rate over this very period. This could explain the positive relationship.

There is a positive relationship between firm size and the probability of becoming unemployed. The estimated results show workers employed by smaller firms have a lower probability of becoming unemployed compared to being employed by larger firms with over a thousand employees. Other results show workers are less likely to become unemployed when employed by the public sector and coefficients from education which proxy for workers' skill intensities show that workers who have a medium-level of education (workers who have completed their A-levels or equivalent qualifications with a first university degree) are approximately 18% less likely to become unemployed. A rise in the research and development intensity raises the probability of becoming unemployed and net exports and industry level output lowers the probability of becoming unemployed, though these variables do not have a statistically significant impact.

Moving onto the variables of interest, the results from column (1) show a one percent rise in service offshoring intensity lowers the probability of becoming unemployed by approximately 22% [exp(-0.2435)-1]. Similarly, the estimated results from column (3) shows a one percent rise in material offshoring intensity lowers the probability of becoming unemployed by 21% [exp(-0.2377)-1]. These results seem quite surprising as they disagree with the reported findings from Geishecker (2008) and Munch (2009); both of these papers find material offshoring intensity at the industry level raises the probability of a job separation in Germany and Denmark. However, these results reflect the fall in the job-to-unemployment transition probability shown by figure 5.1; from this graph and the results, they suggest that a rise in material and service offshoring intensity has not raised the risk of becoming unemployed but it appears to lower this risk and it thereby suggest there is no higher risk to become unemployed.

The estimated coefficients from columns (2) and (4) present the interaction of service and material offshoring intensity with the high and medium education dummy variables. These estimated coefficients show service offshoring has not had a statistically significant impact. But medium skilled workers employed within industries that engage in material offshoring are less likely to become unemployed compared to less skilled workers.

Table 5.2a: Single Risk Model Results: OSS, OSM & Education

Pr(Job to Unemployment)	(1)	(2)	(3)	(4)
Age	0.2375	0.2364	0.2348	0.2342
	(0.0256)***	(0.0256)***	(0.0256)***	(0.0256)***
Age Squared	-0.0032	-0.0032	-0.0031	-0.0031
	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***
Dummy: Married	-0.0493	-0.0554	-0.0541	-0.0603
	(0.1625)	(0.1626)	(0.1627)	(0.1628)
Dummy: Female	-0.0161	-0.0147	-0.0322	-0.0346
	(0.1700)	(0.1700)	(0.1702)	(0.1701)
Dummy: Married Females	-0.1536	-0.1502	-0.1480	-0.1397
	(0.2140)	(0.2140)	(0.2138)	(0.2139)
Dependent Children in HH	-0.0329	-0.0320	-0.0308	-0.0278
	(0.1501)	(0.1501)	(0.1499)	(0.1500)
Dummy: Females with dependent Children	-1.1167	-1.1223	-1.1074	-1.1114
	(0.2197)***	(0.2198)***	(0.2195)***	(0.2196)***
Employment Duration: < 1 Year	2.9999	2.9906	3.0030	2.9918
	(0.2170)***	(0.2171)***	(0.2170)***	(0.2171)***
Employment Duration: 1-3 Years	0.9902	0.9843	0.9938	0.9902
	(0.2599)***	(0.2599)***	(0.2598)***	(0.2598)***
Employment Duration: 4-6 Years	0.2757	0.2716	0.2760	0.2714
	(0.3915)	(0.3915)	(0.3915)	(0.3914)
Employment Duration: 7-9 Years	-0.6836	-0.6868	-0.6714	-0.6771
	(0.7362)	(0.7362)	(0.7362)	(0.7362)
Dummy: Member of Union	-0.6596	-0.6738	-0.6510	-0.6849
	(0.3856)*	(0.3861)*	(0.3850)	(0.3852)*
National Unemployment Rate	-0.2968	-0.2978	-0.4463	-0.4464
	(0.1341)**	(0.1341)**	(0.1292)***	(0.1295)***
Education: High	0.0940	0.3717	0.1194	0.3285
	(0.3533)	(0.3691)	(0.3536)	(0.3593)
Education: Medium	-0.1999	-0.1422	-0.1888	-0.1230
	(0.1086)*	(0.1218)	(0.1086)	(0.1130)
Dummy: Firm Size < 25	-0.3441	-0.3498	-0.5112	-0.5145
	(0.2127)	(0.2127)	(0.2003)**	(0.2007)**
Dummy: Firm Size 25-99	-0.5382	-0.5397	-0.6803	-0.6814
	(0.2405)**	(0.2403)**	(0.2317)***	(0.2321)***
Dummy: Firm Size 100-999	-0.8651	-0.8681	-0.9808	-0.9792
	(0.2710)***	(0.2708)***	(0.2650)***	(0.2650)***
Dummy: Firm in Public Sector	-0.7262	-0.7424	-0.6459	-0.6698
	(0.3085)**	(0.3089)**	(0.3049)**	(0.3049)**
Research & Development Intensity	0.3720	0.3818	0.4588	0.4707
	(0.3973)	(0.3976)	(0.3946)	(0.3947)
Industry Level Output/1000	-0.0005	-0.0003	-0.0018	-0.0019
	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Net Exports/1000	-0.0126	-0.0138	-0.0189	-0.0205
	(0.0159)	(0.0159)	(0.0177)	(0.0177)
Race: White	-0.0208	-0.0192	-0.0280	-0.0211
	(0.2278)	(0.2279)	(0.2279)	(0.2281)
Service Offshoring Intensity: OSS	-0.2435	-0.2043	-	-
	(0.0683)***	(0.0738)***	-	-
Material Offshoring Intensity: OSM	-	-	-0.2377	-0.2061
	-	-	(0.1125)**	(0.1138)*
Education: High*OSS	-	-0.8299	-	-
	-	(0.8334)	-	-
Education: High*OSS	-	-0.0722	-	-
	-	(0.0644)	-	-
Education: High*OSM	-	-	-	-23.0553
	-	-	-	(42.3017)
Education: Medium*OSM	-	-	-	-0.0694
	-	-	-	(0.0315)**
Constant	-5.2394	-5.2769	-4.5240	-4.5351
	(1.4217)***	(1.4235)***	(1.3627)***	(1.3693)***
Observations	77545	77545	77545	77545
Log Likelihood	-1612.0573	-1610.0874	-1618.2433	-1614.3052

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10*. Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Table 5.2b: Likelihood Ratio Test for Frailty for Table 5.2a

Likelihood Ratio Test	*(1)*	*(2)*	*(3)*	*(4)*
σ_u^2	0.0066	0.0066	0.0065	0.0065
	(0.0370)	*(0.0367)*	*(0.0370)*	*(0.0364)*
Rho	0.0000	0.0000	0.0000	0.0000
	(0.0003)	*(0.0003)*	*(0.0003)*	*(0.0003)*
χ^2	0.00045	0.00045	0.00044	0.00046
	(0.492)	*(0.492)*	*(0.492)*	*(0.491)*
Evidence	Not Significant	Not Significant	Not Significant	Not Significant
H_0: *Frailty is equal to zero*	Accepted	Accepted	Accepted	Accepted

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* σ_u^2 is the standard deviation of the heterogeneity variance. Rho is the ratio of the heterogeneity variance to one plus the heterogeneity variance. Standard errors are presented within the parentheses.

Table 5.3a presents the estimated coefficients which examine the impact from being employed in a job that is highly tradable (defined by Blinder's (2007) occupation tradability index) and the impact from the routinization hypothesis (Autor *et al.*, 2003). The estimated results from column (1) show being employed within the most tradable occupations (defined by jobs having an index value of 65 or more from Blinder's (2007) index) does not have a statistically significant positive impact on the probability of becoming unemployed. The estimated coefficient is negative which implies a fall in the probability of becoming unemployed. Similarly, the estimated coefficients from columns (2) and (3) shows being employed within highly tradable jobs within industries that engage in material and service offshoring does not have a statistically significant impact on the probability of becoming unemployed, although both of the estimated coefficients are positive. Finally, the estimated coefficients from column (4) show none of the job task variables have a statistically significant impact on the probability of becoming unemployed. These estimated coefficients show being employed in jobs that have a high importance for completing routine intensive job tasks lowers the probability of becoming unemployed as does being employed in jobs that have a high importance for non-routine abstract job tasks. But being employed in jobs that have a high importance for non-routine manual jobs tasks and service job tasks does have a positive impact on the probability of transitioning into unemployment in year *j*.

Table 5.3a: Single Risk Model: OSS, OSM, Blinder's (2007) Job Tradability Index & TBTC

Pr(Job to Unemployment)	*(1)*	*(2)*	*(3)*	*(4)*
Service Offshoring Intensity: OSS	-	-0.2570	-	-
	-	*(0.0706)****	-	-
Material Offshoring Intensity: OSM	-	-	-0.2469	-
	-	-	*(0.1138)***	-
Blinder Index: Most Offshorable Jobs	-0.1487	-0.3626	-0.2606	-
	(0.2103)	*(0.3355)*	*(0.2590)*	-
Blinder Index * OSS	-	0.1074	-	-
	-	*(0.1023)*	-	-
Blinder Index * OSM	-	-	0.0282	-
	-	-	*(0.0333)*	-
Routine Intensive Job Tasks	-	-	-	-0.1315
	-	-	-	*(0.1108)*
Non-Routine Abstract Job Tasks	-	-	-	-0.0512
	-	-	-	*(0.0473)*
Non-Routine Manual Job Tasks	-	-	-	0.1177
	-	-	-	*(0.0733)*
Service Job Tasks	-	-	-	0.0237
	-	-	-	*(0.0532)*
Constant	-4.6344	-5.2234	-4.5468	-5.3890
	*(1.3627)****	*(1.4223)****	*(1.3653)****	*(2.0816)***
Observations	77545	77545	77545	64544
Log Likelihood	-1619.12	-1611.39	-1617.6535	-794.1267

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* Each model includes industry, occupation, regional level control variables and time dummy variables. The full list of estimated coefficients can be found in appendix 2, table 5.4A. Robust standard errors are presented within the parentheses.

Table 5.3b: Likelihood Ratio Test for Frailty for Table 5.3a

Likelihood Ratio Test	*(1)*	*(2)*	*(3)*	*(4)*
σ_u^2	0.0065	0.0066	0.0065	1.0174
	(0.0371)	*(0.0367)*	*(0.0370)*	*(0.3026)*
Rho	0.0000	0.0000	0.0000	0.3862
	(0.0003)	*(0.0003)*	*(0.0003)*	*(0.1410)*
χ^2	0.00044	0.00046	0.00044	2.75
	(0.492)	*(0.491)*	*(0.492)*	*(0.049)***
Evidence	Not Significant	Not Significant	Not Significant	Significant
H_0: Frailty is equal to zero	Accepted	Accepted	Accepted	Rejected

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* σ_u^2 is the standard deviation of the heterogeneity variance. Rho is the ratio of the heterogeneity variance to one plus the heterogeneity variance. Standard errors are presented within the parentheses.

Table 5.4a examines the interaction between a number of dummy variables taking specific values from Blinder's (2007) job tradability Index and the routine intensive job task variable on the probability of becoming unemployed. The idea here is to examine if workers who are employed in the most tradable jobs, which are additionally jobs that are intensive in routine job tasks are more likely to face job loss because they are the most offshorable jobs – there should be a positive impact on the probability of becoming unemployed. The results from column (1) show no statistically significant coefficients from a series of dummy variables that have specific values from Blinder's (2007) job tradability index. These results also reaffirm the results from table 5.3a - column (1), where the most tradable jobs (occupations which have an index value of 65+) does not have a significant impact on the probability of becoming unemployed. However, the results from column (2) show that when these dummy variables are interacted with the routine job task variable, there are two statistically significant coefficients. They show that workers who are employed in tradable jobs that have a Blinder (2007) index value of 36-45 and 76-85, that are also jobs that are routine job tasks intensive have a positive impact on the probability of becoming unemployed over time.

Table 5.4a: Single Risk Model: Blinder (2007) Index & TBTC Variables

Pr(Job to Unemployment)	*(1)*	*(2)*
Blinder Index Value: 25	-0.9274	-0.9535
	(1.1309)	*(1.8001)*
Blinder Index Value: 26-35	-0.2892	-0.5052
	(0.5120)	*(0.6806)*
Blinder Index Value: 36-45	0.1607	-0.1105
	(0.4206)	*(0.4758)*
Blinder Index Value: 46-55	-0.4859	-1.0668
	(0.5062)	*(0.7692)*
Blinder Index Value: 56-65	-0.5156	-0.6829
	(0.4236)	*(0.4783)*
Blinder Index Value: 66-75	-0.1599	-0.1847
	(0.2704)	*(0.3546)*
Blinder Index Value: 76-85	-0.1266	0.5648
	(0.4505)	*(0.5305)*
Blinder Index Value: 86+	-0.8578	-0.9024
	(0.5285)	*(0.5771)*
Routine Intensive Job Tasks	-	-0.0487
	-	*(0.0761)*
Blinder Index Value: 25*Routine Job Tasks	-	0.8305
	-	*(6.2744)*
Blinder Index Value: 26-35*Routine Job Tasks	-	0.2390
	-	*(0.2552)*
Blinder Index Value: 36-45*Routine Job Tasks	-	0.2316
	-	*(0.1286)**
Blinder Index Value: 46-55*Routine Job Tasks	-	-0.2523
	-	*(0.2540)*
Blinder Index Value: 56-65*Routine Jobs Tasks	-	0.0438
	-	*(0.1268)*
Blinder Index Value: 66-75*Routine Job Tasks	-	0.0741
	-	*(0.0934)*
Blinder Index Value: 76-85*Routine Job Tasks	-	0.3770
	-	*(0.1633)***
Blinder Index Value: 86+*Routine Job Tasks	-	0.1059
	-	*(0.2520)*
Constant	-4.6341	-5.0964
	*(1.3663)****	*(2.0828)***
Observations	77545	64544
Log Likelihood	-1615.9648	-788.4486

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* Each model includes industry, occupation, regional level control variables and time dummy variables. The full list of estimated coefficients can be found in appendix 3, table 5.5A. Robust standard errors are presented within the parentheses.

Table 5.4b: Likelihood Ratio Test for Table 5.4a

Likelihood Ratio Test	*(1)*	*(2)*
σ_u^2	*0.0065*	*0.9827*
	(0.0377)	*(0.3092)*
Rho	*0.0000*	*0.3699*
	(0.0003)	*(0.1467)*
χ^2	*0.00042*	*2.43*
	(0.492)	*(0.060)**
Evidence	Not Significant	Significant
H_0: *Frailty is equal to zero*	Accepted	Rejected

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* σ_u^2 is the standard deviation of the heterogeneity variance. Rho is the ratio of the heterogeneity variance to one plus the heterogeneity variance. Standard errors are presented within the parentheses.

5.4.2 Competing Risks Model Results

The last section provided little evidence showing the impact from offshoring (material and services), the potential tradability of jobs and the routine intensive nature of job tasks did not have a significant impact on raising the probability of becoming unemployed over time; but there was evidence which showed that workers employed in the most tradable jobs which were also routine job task intensive did raise their probability of becoming unemployed. One of the potential downsides to estimating a single risk model is that it potentially overlooks the impact that these variables may have on other competing labour market states. For example, if globalisation and technological innovations have potentially enabled many more jobs to be offshored to firms located in developing countries that are able to provide goods and services at lower cost, domestic workers should lose their jobs and become unemployed or transition to a new job with low pay that may be a temporary job in the short-term. Or workers could negotiate with their employers to lower their wage levels. This would lower the cost of production for firms which would enable firms to keep their current labour force and production processes in the developed country. This would also enable workers to remain with their current employers rather than to lose their jobs and become unemployed or to transition to temporary jobs which may only have a fixed-term contract with low pay in the short-run. Additionally, many workers could decide to leave the labour force altogether or start up their own business if they did not want to accept the lower wage levels. The empirical evidence from the previous chapter found that service offshoring, the potential tradability of jobs and the jobs that are intensive in routine job task had a negative impact on the wage levels of workers, but does this mean that workers remain in employment with their current employers rather than finding new jobs or becoming unemployed?

To explore the impact from offshoring, the potential tradability of jobs and the routinization hypothesis on competing labour market states, this section estimates a series of competing risks models with a distinction between (a) a job transition to a new job (these are job transitions with job tenure under one year), (b) a job transition to unemployment and (c) the base category which represents right censored observations, consisting of workers who remain in employment with their current employers in the time interval $[j-1, j]$. This base category also accounts for workers who transition out of the labour force or start up their own businesses and work for themselves. The estimated results are presented in tables 5.5 to 5.9, where the estimated coefficients are relative risk ratios.

First, tables 5.5 and 5.6 present the estimated coefficients from the impact of service and material offshoring. From both of these tables, the estimated results show the relative risk of becoming unemployed or transitioning to a new job falls with job tenure; more tenured workers are less likely to transition to a new job or to become unemployed. The relative risk of becoming unemployed or obtaining a new job is non-linear with increasing age and married workers are roughly 30% more likely to transition to new jobs relative to non-married workers; but they are also less likely to become unemployed.

Other results show workers who have dependent children in their households are less likely to transition to a new job relative to workers who do not have dependent children in their households. Female workers with dependent children are less likely to become unemployed or transition to a new job relative to other workers. Workers who are members of a trade union are more likely to transition to new jobs relative to workers who are not members of a trade union. A rise in the national unemployment rate does not raise the likelihood of transitioning to a new job or to become unemployed; these results disagree with Munch (2009) as one would expect the transition to unemployment or to a new job to rise with a rise in the unemployment rate. But on the other hand, these results could suggest that workers may be prepared to remain in employment with their current employers and possibly take a pay cut (see the empirical evidence from chapter 4) than to become unemployed or transition to a new job that may be temporary. Workers with a medium-level of education are less likely to transition to new jobs or become unemployed compared to less skilled workers. And workers employed by firms that employ less than a thousand employees are three times more likely to transition to new jobs than to become unemployed over time.

Turning to the variables of interest: from table 5.5, column (1), a one percent rise in service offshoring intensity lowers the risk of becoming unemployed by roughly 22 percent; there is no significant coefficient for new job transitions. Similarly, from table 5.6 column (1), a one percent rise in material offshoring also lowers the risk of becoming unemployed by roughly 20 percent; there is once again a non significant coefficient for new job transitions. Column (2) from tables 5.5 and 5.6 both examine the impact offshoring has on workers who have different skill levels. The estimated coefficients from table 5.5 show high-skilled workers employed in industries that engage in service offshoring are less likely to transition into unemployment relative to less skilled workers. But medium-skilled workers employed in industries that engage in material offshoring (table 5.6) are less likely to become unemployed relative to less skilled workers.

Table 5.7 examines whether workers employed in the most tradable jobs (these are occupations which have a Blinder (2007) index value of 65 and over) are more likely to become unemployed or transition to new jobs over time. The estimated coefficient from column (1) shows that workers are 15 percent more likely to make new job transitions over time relative to workers who are not employed in the most tradable jobs. They are not more likely to become unemployed. These results appear to rest with the view that many workers who are employed in the most tradable jobs have specific skills to those jobs. And with job loss, many of these workers do not have general human capital skills that can be transferred to new employment (Ritter, 2009). Hence, workers may be employed in temporary jobs in the short-term so that employers can view whether workers have the necessary skills to perform the jobs. If workers do not have the necessary skills they lose their jobs and they once again find new jobs. In some cases, these new jobs that may be temporary may be stepping stones towards permanent jobs.

Columns (2) and (3) from table 5.7 find no significant evidence showing workers employed in the most tradable jobs and employed within industries that engage in service and material offshoring are more likely to become unemployed or transition into new employment over time.

Table 5.8a presents the estimated coefficients from the four job task variables. One would expect workers employed in jobs that are intensive in routine job tasks to face a higher risk of job loss because these job tasks can potentially be replaced by computer capital and these are jobs that are most likely to be offshored aboard. The estimated coefficients show workers employed in jobs that have a one standard deviation more importance to their jobs for the completion of routine job tasks are 4.5 percent less likely to transition to new jobs and are less likely to become unemployed, although this latter coefficient is not significant. Similarly, workers employed in jobs that have a one standard deviation more importance in service job tasks are roughly 6 percent less likely to transition to new jobs; this result is line with the empirical evidence which shows jobs that have a high importance for service tasks has had a positive impact on the demand for labour (Goos *et al.,* 2009b). But workers who are employed in jobs that have a high importance for non-routine abstract job tasks are more likely to make new job transitions over time.

This result could relate to the fact that many high-skilled workers may make new job transitions, if these workers remain on fixed-term or temporary employment contracts over time. This conclusion is supported by empirical findings from the literature. Gash (2008) finds that high-skilled workers in the U.K. employed in temporary employment contracts (in academia, consulting or research contracts, etc.) are less likely to make transitions to permanent employment compared to the reference group of manual workers. This would imply that they have a higher probability of making new job transitions. And previous research on temporary workers' transitions in the U.K. by Booth *et al.,* (2002) also find higher grades of workers are less likely to transition to permanent jobs. These empirical findings support this latter result, but it is counter intuitive to what the ALM hypothesis predicts.

Table 5.8b shows the interaction of the routine task variable with the skill intensity variables: high/medium/low education variables proxy for skill. The results from this table try to further understand the counter intuitive results from table 5.8a. This is because in relation to the results from table 5.8a, one would expect high-skilled workers to have a lower probability of becoming unemployed or to make new job transitions because the TBTC hypothesis suggests that computer capital complements non-routine abstract job tasks; however the results shown are not in favour of this view. And also this hypothesis suggests that routine jobs tasks are more likely to be replaced by computer capital; thus, workers employed in jobs that have a high importance for these job tasks should have a higher probability of becoming unemployed and to make new job transitions. But again the results from the competing risks model does not find in favour of this view.

The results from table 5.8b show that skilled workers with routine intensive job tasks are less likely to make new job transitions but are more likely to be displaced, although the estimated coefficients for both transitions are not significant. The empirical evidence suggests that medium-skilled workers are more likely to be employed in jobs that are intensive in routine tasks (Acemoglu & Autor, 2010 & forthcoming). The estimated coefficients show these workers are more likely to transition to new jobs and become unemployed, although the estimated coefficient for the latter transition is not significant.

Lastly, low skilled workers employed in jobs that are routine job task intensive are significantly less likely to make new job transitions. This result makes sense because low skilled workers are more likely to be employed in non-routine manual intensive jobs situated at the bottom end of the skill distribution. Thus, the results from tables 5.8a and 5.8b show that the skill intensity of workers that are interacted with the job task variables are important to the analysis to generate intuitive results[9].

[9] Similar conclusions are reached and are consistent with the job polarization and TBTC hypothesis when the other remaining job task variables are interacted with the skill variables; although some of the results are counter intuitive (the full list of results are not presented in this thesis due to reasons for brevity). Consider table FN2 below which presents the estimated coefficients:

Skill Intensity	High Skill		Medium Skill		Low Skill	
	New Job	Unemployment	New Job	Unemployment	New Job	Unemployment
Routine Tasks	0.9533 *(0.0514)*	1.1085 *(0.2252)*	1.0308$^{\Omega}$ *(0.0134)***	1.0278$^{\Omega}$ *(0.0650)*	0.9724 *(0.0127)***	0.9662 *(0.0608)*
Service Tasks	1.0151 *(0.3448)*	0.9716 *(0.1507)*	0.9733$^{\Omega}$ *(0.0105)***	1.0219$^{\Omega}$ *(0.0538)*	1.0269 *(0.0113)***	0.9812 *(0.0567)*
Non-Routine Abstract Tasks	1.0348$^{\alpha}$ *(0.0336)*	1.0458$^{\alpha}$ *(0.1933)*	1.0195 *(0.0106)**	0.9689 *(0.0479)*	0.9770 *(0.0104)***	1.0292 *(0.0526)*
Non-Routine Manual Tasks	0.9645 *(0.0406)*	1.1000 *(0.0794)*	1.0266 *(0.0105)***	1.0227 *(0.0503)*	0.9756$^{\Omega}$ *(0.0101)***	0.9721$^{\Omega}$ *(0.0477)*

The estimated coefficients with 'Ω' appear to be consistent with the job polarization (Goss & Manning, 2003, 2007) and TBTC (Autor *et al.*, 2003) hypotheses. Estimated coefficients with 'α' appear to be inconsistent. For example, the estimated coefficients for high-skilled workers interacted with the non-routine abstract task variable show estimated relative risk ratios that are greater than one implying these workers are more likely to transition to new jobs and they are more likely to be displaced. This appears counter intuitive to the TBTC and job polarization hypotheses because one would expect lower probabilities for transitioning to each of the destination states in year *j*. This is because high-skilled workers are more likely to have jobs that have more importance for non-routine abstract job tasks, where technology complements these skills and this should therefore have a positive impact on staying in employment. Consistent estimates are shown for non-routine manual tasks interacted with low skill intensity. These coefficients are less than one and imply these workers have a lower probability of transitioning to new jobs and to become unemployed. This may be because many of these jobs are more likely to be in non-tradable sectors where technology cannot substitute for the job tasks in hairdressing, waiting staff in bars and restaurants and cleaners, etc. For service job tasks interacted with the skill intensity variables, the estimated coefficients appear to be consistent with the hypotheses. Similar conclusions are obtained when the competing risks model distinguishes between (1) new job transitions; (2) remaining in employment with present employer and (3) unemployment in time period *j*. Note that these latter results are not presented in the thesis.

Finally, table 5.9 presents the estimated coefficients from the interaction of dummy variables that take specific values from Blinder's (2007) occupation tradability index with the routine job task variable. The estimated coefficients from column (1) show jobs with specific values from the job tradability index are more likely to transition to new jobs than to become unemployed over time. But the estimated coefficients from column (2) shows that workers employed in jobs that are also routine job task intensive are more likely to become unemployed than transition to new jobs over time. The estimated results from this column show that jobs with a Blinder (2007) index value of 25, 36-45 and 76-85 (see figure 4.1 from chapter 4 for a reminder of Blinder's (2007) occupation tradability index) and which have a high importance for routine job tasks are more likely to become unemployed over time relative to other workers. These findings complement the empirical results from chapter 4. The results from chapter 4 found workers who are employed in the most tradable jobs that are also routines job task intensive can potentially face large losses in their income levels over time. The results from this chapter suggest that these workers are more likely to become unemployed where the potential earnings losses from being unemployed can be large over time for these workers (see empirical evidence from chapter 3).

5.4.2.1 Robustness Checks

The results from the competing risks model (from tables 5.5 and 5.6) both showed offshoring (services and material intensity) lowers the risk of becoming unemployed in year j, but the question is whether workers continue to remain in employment with their current employers rather than to lose their jobs or transition to new jobs. As a robustness check, this section explores a competing risks model which examines three destination states. These are: (1) to remain in employment, but transition to new employment at time j; (2) to remain in employment with current employers at time j; (3) to become unemployed at time j and (4) the observations are right censored at time j, - this accounts for individuals who leave employment and transition into self-employment or leave the labour market altogether. The estimated coefficients from this model are presented in appendix 7 in tables 5.9A to 5.18A.

The estimated coefficients from this model show workers are more likely to remain in employment with their current employers from a rise in offshoring (materials and services) – see table 5.9A and table 5.11A. The results also show high and medium-skilled workers employed within industries that engage in offshoring (materials and services) are also more likely to remain in employment with their current employers relative to less-skilled workers (see tables 5.10A and 5.12A). And workers employed in potentially the most tradable jobs are more likely to remain in employment – this can be with their current employers or in new jobs rather than to become unemployed (see tables 5.13A and 5.16A).

Additionally, workers employed in the most tradable jobs and employed within industries that engage in service offshoring are less likely to remain in employment with their current employers (see table 5.14A); there are no significant coefficients from material offshoring (table 5.15A). From the TBTC hypothesis (table 5.16A) – workers employed in jobs that have a high importance for the completion of routine intensive job tasks are more likely to remain in employment with their current employers (column (2)) – although this estimated coefficient is not significant. But workers employed in jobs that have a high importance for non-routine abstract job tasks are more likely to transition to new jobs and remain with their current employers. This result is consistent with the evidence presented by Gash (2008) in the last section. And finally, table 5.18A shows workers employed in tradable jobs which have an index value of 25, 66-75 and 76-85 are less likely to remain in employment (transition to a new job or remain with their current employers) but they are more likely to be become unemployed over time.

Table 5.5: Competing Risks Model – OSS & Education

Competing Risks Model	(1)		(2)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Age	1.3204	1.3013	1.3206	1.2999
	*(0.0142)****	*(0.0343)****	*(0.0142)****	*(0.0343)****
Age Squared	0.9966	0.9965	0.9966	0.9965
	*(0.0001)****	*(0.0003)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3026	0.9853	1.3033	0.9809
	*(0.0784)****	*(0.1708)*	*(0.0785)****	*(0.1699)*
Dummy: Female	0.9306	0.9665	0.9306	0.9714
	(0.0592)	*(0.1685)*	*(0.0592)*	*(0.1693)*
Dummy: Married Females	1.0952	0.8553	1.0948	0.8567
	(0.0823)	*(0.1920)*	*(0.0823)*	*(0.1922)*
Dependent Children in HH	0.7863	0.9682	0.7861	0.9710
	*(0.0410)****	*(0.1442)*	*(0.0410)****	*(0.1446)*
Dummy: Females with dependent Children	0.6509	0.2981	0.6510	0.2952
	*(0.0469)****	*(0.0690)****	*(0.0469)****	*(0.0684)****
Job Tenure	0.0634	0.5865	0.0634	0.5873
	*(0.0020)****	*(0.0481)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	1.2728	0.4245	1.2714	0.4175
	*(0.0738)****	*(0.1552)***	*(0.0738)****	*(0.1530)***
National Unemployment Rate	0.0121	0.6886	0.0121	0.6897
	*(0.0003)****	*(0.0828)****	*(0.0003)****	*(0.0829)****
Education: High	0.9688	1.0637	1.0808	1.4863
	(0.1085)	*(0.3856)*	*(0.1623)*	*(0.5601)*
Education: Medium	0.9603	0.8085	0.9558	0.8649
	*(0.0377)****	*(0.0910)**	*(0.0517)*	*(0.1087)*
Dummy: Firm Size < 25	4.3801	0.8914	4.3809	0.8830
	*(0.2760)****	*(0.1596)*	*(0.2761)****	*(0.1589)*
Dummy: Firm Size 25-99	4.4052	0.7153	4.4077	0.7122
	*(0.2927)****	*(0.1574)*	*(0.2930)****	*(0.1565)*
Dummy: Firm Size 100-999	4.6823	0.4790	4.6815	0.4763
	*(0.3150)****	*(0.1128)****	*(0.3150)****	*(0.1122)****
Dummy: Firm in Public Sector	1.2291	0.4351	1.2267	0.4289
	*(0.0833)****	*(0.1183)****	*(0.0832)****	*(0.1171)****
Research & Development Intensity	1.0191	1.4059	1.0197	1.4285
	(0.0757)	*(0.5940)*	*(0.0757)*	*(0.6058)*
Industry Level Output/1000	1.0004	0.9996	1.0004	0.9998
	(0.0004)	*(0.0024)*	*(0.0004)*	*(0.0024)*
Net Exports/1000	0.9988	0.9878	0.9987	0.9861
	(0.0029)	*(0.0143)*	*(0.0029)*	*(0.0141)*

Race: White	1.2963	0.9600	1.2971	0.9564
	*(0.1232)****	*(0.2362)*	*(0.1233)****	*(0.2366)*
Service Offshoring Intensity: OSS	1.0040	0.7847	1.0042	0.8184
	(0.0149)	*(0.0465)****	*(0.0173)*	*(0.0558)****
Education: High*OSS	-	-	0.9441	0.4367
	-	-	*(0.0468)*	*(0.2115)**
Education: Medium*OSS	-	-	1.0017	0.9240
	-	-	*(0.0146)*	*(0.0615)*
Observations	77545		77545	
Log Likelihood	-12663.854		-12660.953	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios.

Table 5.6: Competing Risks Model – OSM & Education

Competing Risks Model	(1)		(2)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Age	1.3206	1.2977	1.3207	1.2970
	*(0.0142)****	*(0.0342)****	*(0.0142)****	*(0.0341)****
Age Squared	0.9966	0.9965	0.9966	0.9965
	*(0.0001)****	*(0.0003)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3022	0.9777	1.3042	0.9719
	*(0.0784)****	*(0.1694)*	*(0.0785)****	*(0.1687)*
Dummy: Female	0.9308	0.9544	0.9308	0.9549
	(0.05920	*(0.1659)*	*(0.0592)*	*(0.1659)*
Dummy: Married Females	1.0951	0.8623	1.0931	0.8674
	(0.0823)	*(0.1929)*	*(0.0821)*	*(0.1942)*
Dependent Children in HH	0.7863	0.9683	0.7855	0.9729
	*(0.0410)****	*(0.1439)*	*(0.0410)****	*(0.1448)*
Dummy: Females with dependent Children	0.6509	0.3008	0.6518	0.2987
	*(0.0469)****	*(0.0694)****	*(0.0469)****	*(0.0691)****
Job Tenure	0.0634	0.5861	0.0634	0.5875
	*(0.0020)****	*(0.0481)****	*(0.0020)****	*(0.0480)****
Dummy: Member of Union	1.2726	0.4227	1.2709	0.4104
	*(0.0738)****	*(0.1544)***	*(0.0738)****	*(0.1504)***
National Unemployment Rate	0.0120	0.5978	0.0120	0.5979
	*(0.0003)****	*(0.0699)****	*(0.0003)****	*(0.0701)****
Education: High	0.9689	1.0805	1.0243	1.4190
	(0.1085)	*(0.3918)*	*(0.1217)*	*(0.5268)*
Education: Medium	0.9600	0.8180	0.9604	0.8826
	(0.0377)	*(0.0920)**	*(0.0416)*	*(0.1039)*
Dummy: Firm Size < 25	4.3932	0.7563	4.3906	0.7490
	*(0.2757)****	*(0.1288)*	*(0.2755)****	*(0.1274)**
Dummy: Firm Size 25-99	4.4167	0.6244	4.4166	0.6189
	*(0.2927)****	*(0.1318)***	*(0.2927)****	*(0.1311)***
Dummy: Firm Size 100-999	4.6951	0.4326	4.6919	0.4292
	*(0.3158)****	*(0.1003)****	*(0.3155)****	*(0.1000)****
Dummy: Firm in Public Sector	1.2254	0.4837	1.2247	0.4722
	*(0.0829)****	*(0.1279)****	*(0.0828)****	*(0.1251)****
Research & Development Intensity	1.0220	1.5398	1.0245	1.5723
	(0.0761)	*(0.6456)*	*(0.0763)*	*(0.6595)*
Industry Level Output/1000	1.0004	0.9983	1.0004	0.9982
	(0.0004)	*(0.0023)*	*(0.0004)*	*(0.0023)*
Net Exports/1000	0.9978	0.9813	0.9977	0.9787
	(0.0032)	*(0.0147)*	*(0.0032)*	*(0.0146)*

Race: White	1.2973	0.9528	1.2959	0.9530
	*(0.1232)****	*(0.2341)*	*(0.1232)****	*(0.2349)*
Material Offshoring Intensity: OSM	0.9827	0.7943	0.9835	0.8246
	(0.0257)	*(0.0438)****	*(0.0261)*	*(0.0472)****
Education: High*OSM	-	-	0.9626	0.0000
	-	-	*(0.0241)*	*(0.0000)*
Education: Medium*OSM	-	-	0.9998	0.9275
	-	-	*(0.0066)*	*(0.0302)***
Observations	77545		77545	
Log Likelihood	-12669.835		-12664.075	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios.

Table 5.7: Competing Risks Model – OSS, OSM & Blinder Index of Occupation Tradability

Competing Risks Model	(1)		(2)		(3)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Service Offshoring Intensity: OSS	-	-	1.0026	0.7746	-	-
	-	-	*(0.0152)*	*(0.0488)****	-	-
Material Offshoring Intensity: OSM	-	-	-	-	0.9777	0.7860
	-	-	-	-	*(0.0257)*	*(0.0462)****
Blinder Index: Most Offshorable Jobs	1.1453	0.8986	1.1285	0.7339	1.1106	0.8008
	*(0.0514)****	*(0.1898)*	*(0.0718)**	*(0.2337)*	*(0.0584)****	*(0.2051)*
Blinder Index * OSS	-	-	1.0056	1.1075	-	-
	-	-	*(0.0170)*	*(0.1069)*	-	-
Blinder Index * OSM	-	-	-	-	1.0082	1.0292
	-	-	-	-	*(0.0070)*	*(0.0342)*
Observations	77545		77545		77545	
Log Likelihood	-12666.081		-12658.464		-12663.8	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios. The full set of estimated coefficients are presented in appendix 4, table 5.6A.

Table 5.8a: Competing Risks Model –TBTC Hypothesis

Competing Risks Model		
	New Job Transition	Unemployment Transition
Routine Intensive Job Tasks	0.9550	0.8781
	*(0.0205)***	*(0.1056)*
Non-Routine Abstract Job Tasks	1.0588	0.9546
	*(0.0103)****	*(0.0508)*
Non-Routine Manual Job Tasks	0.9918	1.1245
	(0.0147)	*(0.0848)*
Service Job Tasks	0.9398	1.0228
	*(0.0098)****	*(0.0555)*
Observations	64544	
Log Likelihood	-10605.02	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios. The full set of estimated coefficients are presented in appendix 5, table 5.7_1A.

Table 5.8b: Competing Risks Model –TBTC Hypothesis and Skill Interactions

Competing Risks Model	*(1)*		*(2)*		*(3)*	
	New Job Transition	**Unemployment Transition**	**New Job Transition**	**Unemployment Transition**	**New Job Transition**	**Unemployment Transition**
Routine Intensive Job Tasks	0.9434	1.0165	0.9251	1.0066	0.9519	1.0375
	*(0.0111)****	*(0.0594)*	*(0.0129)****	*(0.0632)*	*(0.0120)****	*(0.0713)*
High Skill * Routine Job Task	0.9533	1.1085	-	-	-	-
	(0.0514)	*(0.2252)*	-	-	-	-
Medium Skill * Routine Job Task	-	-	1.0308	1.0278	-	-
	-	-	*(0.0134)***	*(0.0650)*	-	-
Low Skill * Routine Job Task	-	-	-	-	0.9724	0.9662
	-	-	-	-	*(0.0127)***	*(0.0608)*
Observation	64544		64544		64544	
Log Likelihood	-10630.685		-10628.276		-10628.7	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios. The full set of estimated coefficients are presented in appendix 5, table 5.7_2A.

Table 5.9: Competing Risks Model – Blinder's (2007) Offshorability Index and TBTC

Pr(Job to Unemployment)	(1)		(2)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Blinder Index Value: 25	0.8280	0.4093	0.7515	0.3999
	(0.1615)	*(0.4595)*	*(0.1527)*	*(0.4732)*
Blinder Index Value: 26-35	1.2721	0.8127	1.3604	0.6009
	*(0.1449)***	*(0.4359)*	*(0.1820)***	*(0.3972)*
Blinder Index Value: 36-45	1.1960	1.1504	1.0804	0.8380
	*(0.1039)***	*(0.5107)*	*(0.1039)*	*(0.3832)*
Blinder Index Value: 46-55	1.1533	0.6289	1.0844	0.3423
	*(0.0922)**	*(0.2862)*	*(0.1140)*	*(0.2700)*
Blinder Index Value: 56-65	1.1394	0.5896	1.0662	0.4929
	*(0.0883)**	*(0.2447)*	*(0.0935)*	*(0.2215)*
Blinder Index Value: 66-75	1.2663	0.9070	1.1111	0.8378
	*(0.0806)****	*(0.2396)*	*(0.0792)*	*(0.2794)*
Blinder Index Value: 76-85	1.4108	0.9502	1.2025	2.0059
	*(0.1325)****	*(0.4534)*	*(0.2057)*	*(1.0728)*
Blinder Index Value: 86+	1.0752	0.4384	0.9696	0.3993
	(0.1012)	*(0.2329)*	*(0.1010)*	*(0.2395)*
Routine Intensive Job Tasks	-	-	0.9597	0.9482
	-	-	*(0.0159)***	*(0.0781)*
Blinder Index Value: 25*Routine Job Tasks	-	-	0.9083	2.4494
	-	-	*(0.2645)*	*(0.8513)***
Blinder Index Value: 26-35*Routine Job Tasks	-	-	0.9091	1.2575
	-	-	*(0.0543)*	*(0.3222)*
Blinder Index Value: 36-45*Routine Job Tasks	-	-	0.9480	1.2593
	-	-	*(0.0283)**	*(0.1444)***
Blinder Index Value: 46-55*Routine Job Tasks	-	-	0.9990	0.7673
	-	-	*(0.0347)*	*(0.1903)*
Blinder Index Value: 56-65*Routine Jobs Tasks	-	-	1.0020	1.0460
	-	-	*(0.0236)*	*(0.1156)*
Blinder Index Value: 66-75*Routine Job Tasks	-	-	0.9467	1.0686
	-	-	*(0.0180)*	*(0.0967)*
Blinder Index Value: 76-85*Routine Job Tasks	-	-	0.9306	1.5053
	-	-	*(0.0497)*	*(0.2521)***
Blinder Index Value: 86+*Routine Job Tasks	-	-	0.9833	1.1288
	-	-	*(0.0456)*	*(0.2596)*
Observations	77545		64544	
Log Likelihood	-12655.873		-10608.437	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported within the parentheses. Estimated coefficients are relative risk ratios. The full set of estimated coefficients are presented in appendix 6, table 5.8A.

5.5 Conclusion

This chapter has examined whether offshoring intensity (measured at the industry level), the advancements in technology that can make many more jobs potentially tradable (according to Blinder's (2007) occupation tradability index), and jobs that are more intensive in routine tasks which can according to the ALM hypothesis (Autor *et al.,* 2003) be replaced by computer capital but are also job tasks that are most likely to be traded internationally (Acemoglu & Autor, 2010 & forthcoming) can cause job insecurity to rise over time.

The results from the competing risks models (from section 5.4.2) show that a rise in service and material offshoring intensity does not increase job insecurity. Workers are more likely to remain in employment rather than to become unemployed over time. Offshoring is also found to lower the risk of becoming unemployed for highly-skilled and medium-skilled workers which results that are in line with the findings from the empirical literature (Munch, 2009). The most tradable jobs (defined as having a Blinder (2007) index value of 65+) have a higher probability of making new job transitions over time but these jobs do not have a significant or positive impact on the risk of becoming unemployed. And the evidence from the job task variables exploring the impact from the ALM hypothesis (Autor *et al.,* 2003) show workers employed in jobs that are intensive in routine job task are more likely to make new job transitions over time rather than to raise the risk of the job-to-unemployment hazard. These results continue to hold for medium-skilled workers employed in jobs that are more intensive in routine job tasks as this group of workers are more likely to be employed in occupations that have a high importance for routine intensive job tasks. The estimated results show that medium-skilled workers employed in jobs that are intensive in routine job tasks have a higher probability of making new job transitions. Additionally, workers who are employed within the more potentially tradable jobs that also have a high importance for routine job tasks face a higher risk of becoming unemployed over time. Other results suggest that high-skilled workers employed in jobs that have a high importance for non-routine abstract tasks are more likely to make new job transitions over time. The evidence from Gash (2008) and Booth *et al.,* (2002) support this result as they find high-skilled workers are less likely to make transitions to permanent jobs as these workers may be employed in fixed-term jobs over time.

The estimated results from this chapter show job security has not fallen because of an increasing likelihood to become unemployed over time that may result from offshoring or related to technology substituting domestic labour for computer capital that may deliver job tasks from foreign labour markets. Workers are more likely to remain in employment with their current employers. This could mean that workers employed by industries that engage in offshoring have secure jobs that might not otherwise exist if firms did not engage in offshoring or invest in technology. These results contrast with the findings from the literature which show material offshoring lowers job and economic security for workers in Germany and Denmark.

The results from this chapter and chapter 4 suggest that workers are more likely to remain in employment with their current employers as workers are more likely to have lower real wage levels over time rather than to become unemployed. The empirical results from chapter 4 showed offshoring intensity, the most tradable jobs (defined by Blinder's (2007) occupation tradability index) and routine intensive job tasks exert a negative and significant impact on wage levels over time. However, the empirical results from this chapter show workers are less likely to become unemployed or seek new employment from one year to the next – job security is maintained with lower pay rather than to risk becoming unemployed. One possible reason for this result is that employers may wish to maintain their workforces during bad times and therefore workers may accept shorter work hours and a fall in real pay (this lowers job stability) in order to have a job (this raises the probability of job security). The next empirical chapter investigates whether job security has changed over time. The results from this chapter show workers are more likely to remain in employment with little impact on job security; this would suggest that job security trends should have changed very little over the last two decades.

5.6 Appendices

Appendix 1

Table 5.1A: Single Risk Model with No Frailty – OSS, OSM & Education

Pr(Job to Unemployment)	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.2375	0.2364	0.2348	0.2342
	*(0.0238)****	*(0.0239)****	*(0.0239)****	*(0.0239)****
Age Squared	-0.0032	-0.0032	-0.0031	-0.0031
	*(0.0003)****	*(0.0003)****	*(0.0003)****	*0.0003)****
Dummy: Married	-0.0493	-0.0554	-0.0541	-0.0603
	(0.1647)	*(0.1647)*	*(0.1650)*	*(0.1652)*
Dummy: Female	-0.0161	-0.0147	-0.0322	-0.0346
	(0.1681)	*(0.1680)*	*(0.1680)*	*(0.1679)*
Dummy: Married Females	-0.1536	-0.1502	-0.1480	-0.1397
	(0.2155)	*(0.2155)*	*(0.2150)*	*(0.2153)*
Dependent Children in HH	-0.0329	-0.0320	-0.0308	-0.0278
	(0.1446)	*(0.1446)*	*(0.1443)*	*(0.1444)*
Dummy: Females with dependent Children	-1.1167	-1.1223	-1.1074	-1.1114
	*(0.2241)****	*(0.2240)****	*(0.2234)****	*(0.2237)****
Employment Duration: < 1 Year	2.9999	2.9906	3.0030	2.9918
	*(0.2202)****	*(0.2204)****	*(0.2204)****	*(0.2209)****
Employment Duration: 1-3 Years	0.9902	0.9843	0.9938	0.9902
	*(0.2613)****	*(0.2618)****	*(0.2612)****	*(0.2614)****
Employment Duration: 4-6 Years	0.2757	0.2716	0.2760	0.2714
	(0.3919)	*(0.3917)*	*(0.3920)*	*(0.3920)*
Employment Duration: 7-9 Years	-0.6836	-0.6868	-0.6714	-0.6771
	(0.7392)	*(0.7389)*	*(0.7389)*	*(0.7391)*
Dummy: Member of Union	-0.6596	-0.6738	-0.6510	-0.6849
	*(0.3718)**	*(0.3726)**	*(0.3708)**	*(0.3720)**
National Unemployment Rate	-0.2968	-0.2978	-0.4463	-0.4464
	*(0.1213)***	*(0.1215)***	*(0.1168)****	*(0.1172)****
Education: High	0.0940	0.3717	0.1194	0.3285
	(0.3554)	*(0.3611)*	*(0.3564)*	*(0.3573)*
Education: Medium	-0.1999	-0.1422	-0.1888	-0.1230
	*(0.1094)**	*(0.1217)*	*(0.1094)**	*(0.1146)*
Dummy: Firm Size < 25	-0.3441	-0.3498	-0.5112	-0.5145
	*(0.1788)**	*(0.1794)**	*(0.1694)****	*(0.1692)****
Dummy: Firm Size 25-99	-0.5382	-0.5397	-0.6803	-0.6814
	*(0.2191)***	*(0.2189)***	*(0.2099)****	*(0.2104)****
Dummy: Firm Size 100-999	-0.8651	-0.8680	-0.9808	-0.9792
	*(0.2367)****	*(0.2366)****	*(0.2333)****	*(0.2333)****
Dummy: Firm in Public Sector	-0.7262	-0.7424	-0.6459	-0.6697
	*(0.2748)****	*(0.2762)***	*(0.2693)***	*(0.2697)***
Research & Development Intensity	0.3720	0.3818	0.4588	0.4707
	(0.4224)	*(0.4238)*	*(0.4201)*	*(0.4199)*
Industry Level Output/1000	-0.0005	-0.0003	-0.0018	-0.0019
	(0.0024)	*(0.0025)*	*(0.0023)*	*(0.0024)*
Net Exports/1000	-0.0126	-0.0138	-0.0189	-0.0205
	(0.0145)	*(0.0144)*	*(0.0147)*	*(0.0147)*
Race: White	-0.0208	-0.0192	-0.0280	-0.0211
	(0.2346)	*(0.2355)*	*(0.2345)*	*(0.2351)*
Service Offshoring Intensity: OSS	-0.2435	-0.2043	-	-
	*(0.0593)****	*(0.0687)****	-	-
Material Offshoring Intensity: OSM	-	-	-0.2377	-0.2061
	-	-	*(0.0540)****	*(0.0553)****
Education: High*OSS	-	-0.8299	-	-
	-	*(0.5595)*	-	-
Education: High*OSS	-	-0.0722	-	-
	-	*(0.0656)*	-	-
Education: High*OSM	-	-	-	-23.0552
	-	-	-	*(23.5340)*
Education: Medium*OSM	-	-	-	-0.0694
	-	-	-	*(0.0323)***
Constant	-5.2394	-5.2769	-4.5240	-4.5351
	*(1.3103)****	*(1.3166)****	*(1.2533)****	*(1.2614)****
Observations	76663	76663	76663	76663

Log Likelihood	-1612.0570	-1610.0871	-1618.2430	-1614.3049

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10*. Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Table 5.2A: Single Risk Model with No Frailty – OSS, OSM, Blinder (2007) Index & TBTC

Pr(Job to Unemployment)	*(1)*	*(2)*	*(3)*	*(4)*
Age	0.2342	0.2375	0.2350	0.0617
	*(0.0239)****	*(0.0238)****	*(0.0239)****	*(0.0508)*
Age Squared	-0.0031	-0.0032	-0.0031	-0.0008
	*(0.0003)****	*(0.0003)****	*(0.0003)****	*(0.0007)*
Dummy: Married	-0.0534	-0.0508	-0.0541	-0.6000
	(0.1649)	*(0.1647)*	*(0.1649)*	*(0.3257)**
Dummy: Female	-0.0326	-0.0201	-0.0340	0.2874
	(0.1681)	*(0.1682)*	*(0.1679)*	*(0.3455)*
Dummy: Married Females	-0.1473	-0.1510	-0.1477	0.5638
	(0.2151)	*(0.2155)*	*(0.2150)*	*(0.3907)*
Dependent Children in HH	-0.0322	-0.0342	-0.0326	0.4562
	(0.1443)	*(0.1446)*	*(0.1443)*	*(0.2589)**
Dummy: Females with dependent Children	-1.1058	-1.1143	-1.1054	-1.2077
	*(0.2234)****	*(0.2242)****	*(0.2234)****	*(0.3966)****
Employment Duration: < 1 Year	3.0030	3.0014	3.0033	1.3615
	*(0.2204)****	*(0.2202)****	*(0.2203)****	*(0.2986)****
Employment Duration: 1-3 Years	0.9946	0.9903	0.9940	0.3562
	*(0.2612)****	*(0.2614)****	*(0.2613)****	*(0.3187)*
Employment Duration: 4-6 Years	0.2769	0.2758	0.2773	0.1111
	(0.3919)	*(0.3918)*	*(0.3920)*	*(0.4233)*
Employment Duration: 7-9 Years	-0.6721	-0.6833	-0.6716	-0.5884
	(0.7388)	*(0.7392)*	*(0.7388)*	*(0.7473)*
Dummy: Member of Union	-0.6547	-0.6648	-0.6618	-0.9831
	*(0.3705)**	*(0.3726)**	*(0.3731)*	*(0.3944)***
National Unemployment Rate	-0.4229	-0.2980	-0.4438	-0.2062
	*(0.1151)****	*(0.1216)***	*(0.1171)****	*(0.1458)*
Education: High	0.1200	0.0886	0.1194	-0.0020
	(0.3565)	*(0.3555)*	*(0.3562)*	*(0.6912)*
Education: Medium	-0.1858	-0.2007	-0.1892	-0.4236
	*(0.1095)**	*(0.1094)**	*(0.1095)**	*(0.2141)***
Dummy: Firm Size < 25	-0.5259	-0.3287	-0.5045	0.2260
	*(0.1674)****	*(0.1806)**	*(0.1698)****	*(0.2708)*
Dummy: Firm Size 25-99	-0.6868	-0.5200	-0.6720	0.1197
	*(0.2081)****	*(0.2209)***	*(0.2105)****	*(0.3027)*
Dummy: Firm Size 100-999	-0.9788	-0.8417	-0.9676	-0.3381
	*(0.2368)****	*(0.2427)****	*(0.2385)****	*(0.3284)*
Dummy: Firm in Public Sector	-0.6414	-0.7230	-0.6506	-0.0900
	*(0.2696)***	*(0.2757)****	*(0.2704)***	*(0.3611)*
Research & Development Intensity	0.4174	0.3349	0.4582	0.3322
	(0.4126)	*(0.4213)*	*(0.4206)*	*(0.4122)*
Industry Level Output/1000	-0.0016	-0.0007	-0.0018	-0.0016
	(0.0024)	*(0.0024)*	*(0.0023)*	*(0.0024)*
Net Exports/1000	-0.0032	-0.0108	-0.0188	0.0014
	(0.0143)	*(0.0145)*	*(0.0148)*	*(0.0149)*
Race: White	-0.0329	-0.0204	-0.0269	-0.4768
	(0.2345)	*(0.2346)*	*(0.2343)*	*(0.4463)*
Service Offshoring Intensity: OSS	-	-0.2570	-	-
	-	*(0.0633)****	-	-
Material Offshoring Intensity: OSM	-	-	-0.2469	-
	-	-	*(0.0576)****	-
Blinder Index: Most Offshorable Jobs	-0.1487	-0.3626	-0.2606	-
	(0.2083)	*(0.3122*	*(0.2530)*	-
Blinder Index * OSS	-	0.1074	-	-
	-	*(0.0950)*	-	-
Blinder Index * OSM	-	-	0.0282	-
	-	-	*(0.0329)*	-
Routine Intensive Job Tasks	-	-	-	-0.1322
	-	-	-	*(0.1188)*
Non-Routine Abstract Job Tasks	-	-	-	-0.0485
	-	-	-	*(0.0533)*
Non-Routine Manual Job Tasks	-	-	-	0.1199
	-	-	-	*(0.0753)*
Service Job Tasks	-	-	-	0.0215
	-	-	-	*(0.0550)*
Constant	-4.6344	-5.2233	-4.5467	-4.8986
	*(1.2603)****	*(1.3088)*	*(1.2588)****	*(1.9654)***
Observations	76663	76663	76663	63687

Log Likelihood	-1619.12	-1611.3862	-1617.6533	-795.4995

Source: Own estimates from the BHPS. Significance Level: ******p<0.01, **p<0.05 and *p<0.10***. Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Table 5.3A: Single Risk Model with No Frailty –Blinder (2007) Index & TBTC

Pr(Job to Unemployment)	*(1)*	*(2)*
Age	0.2349	0.0608
	*(0.0239)****	*(0.0513)*
Age Squared	-0.0031	-0.0008
	*(0.0003)****	*(0.0007)*
Dummy: Married	-0.0509	-0.5694
	(0.1645)	*(0.3202)**
Dummy: Female	-0.0395	0.2474
	(0.1689)	*(0.3445)*
Dummy: Married Females	-0.1514	0.5165
	(0.2150)	*(0.3863)*
Dependent Children in HH	-0.0328	0.4661
	(0.1445)	*(0.2637)*
Dummy: Females with dependent Children	-1.1019	-1.2127
	*(0.2237)****	*(0.4022)****
Employment Duration: < 1 Year	3.0009	1.3554
	*(0.2202)****	*(0.2992)****
Employment Duration: 1-3 Years	0.9905	0.3530
	*(0.2612)****	*(0.3183)*
Employment Duration: 4-6 Years	0.2744	0.1124
	*(0.3920)****	*(0.4223)*
Employment Duration: 7-9 Years	-0.6771	-0.5974
	(0.7389)	*(0.7468)*
Dummy: Member of Union	-0.6935	-0.9765
	*(0.3777)**	*(0.3960)***
National Unemployment Rate	-0.4235	-0.1999
	*(0.1155)****	*(0.1448)*
Education: High	0.1084	-0.0677
	(0.3552)	*(0.6987)*
Education: Medium	-0.1886	-0.4221
	*(0.1097)**	*(0.2160)**
Dummy: Firm Size < 25	-0.5256	0.2242
	*(0.1687)****	*(0.2737)*
Dummy: Firm Size 25-99	-0.6759	0.1248
	*(0.2096)****	*(0.3082)*
Dummy: Firm Size 100-999	-0.9771	-0.3515
	*(0.2390)****	*(0.3316)*
Dummy: Firm in Public Sector	-0.6356	-0.0387
	*(0.2779)***	*(0.3601)*
Research & Development Intensity	0.4253	0.3204
	(0.4127)	*(0.4080)*
Industry Level Output/1000	-0.0016	-0.0015
	(0.0024)	*(0.0024)*
Net Exports/1000	-0.0031	0.0018
	(0.0144)	*(0.0150)*
Race: White	-0.0378	-0.4864
	(0.2347)	*(0.4405)*
Blinder Index Value: 25	-0.9274	-0.9459
	(1.1192)	*(1.1818)*
Blinder Index Value: 26-35	-0.2892	-0.4984
	(0.5320)	*(0.6655)*
Blinder Index Value: 36-45	0.1607	-0.1224
	(0.4450)	*(0.4620)*
Blinder Index Value: 46-55	-0.4859	-1.0628
	(0.4608)	*(0.7946)*
Blinder Index Value: 56-65	-0.5156	-0.6888
	(0.4157)	*(0.4503)*
Blinder Index Value: 66-75	-0.1599	-0.1879
	(0.2590)	*(0.3353)*
Blinder Index Value: 76-85	-0.1266	0.5783
	(0.4739)	*(0.5274)*
Blinder Index Value: 86+	-0.8578	-0.9041
	(0.5285)	*(0.5987)*
Routine Intensive Job Tasks	-	-0.0460
	-	*(0.0811)*
Blinder Index Value: 25*Routine Job Tasks	-	0.8343
	-	*(0.3445)***
Blinder Index Value: 26-35*Routine Job Tasks	-	0.2333

	-	*(0.2577)*
Blinder Index Value: 36-45*Routine Job Tasks	-	0.2333
	-	*(0.1139)***
Blinder Index Value: 46-55*Routine Job Tasks	-	-0.2504
	-	*(0.2404)*
Blinder Index Value: 56-65*Routine Jobs Tasks	-	0.0409
	-	*(0.1105)*
Blinder Index Value: 66-75*Routine Job Tasks	-	0.0734
	-	*(0.0899)*
Blinder Index Value: 76-85*Routine Job Tasks	-	0.3753
	-	*(0.1647)***
Blinder Index Value: 86+*Routine Job Tasks	-	0.1012
	-	*(0.2312)*
Constant	-4.6341	-4.6546
	*(1.2675)****	*(1.9586)****
Observations	76663	63687
Log Likelihood	-1615.9646	-789.6618

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10*. Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Appendix 2

Table 5.4A: Single Risk Model with Frailty: OSS, OSM, Blinder (2007) Index & TBTC

Pr(Job to Unemployment)	(1)	(2)	(3)	(4)
Age	0.2342	0.2375	0.2350	0.0633
	*(0.0256)****	*(0.0256)****	*(0.0256)****	*(0.0531)*
Age Squared	-0.0031	-0.0032	-0.0031	-0.0008
	*(0.0003)****	*(0.0003)****	*(0.0003)****	*(0.0007)*
Dummy: Married	-0.0534	-0.0508	-0.0541	-0.5864
	(0.1627)	*(0.1625)*	*(0.1627)*	*(0.3197)**
Dummy: Female	*-0.0326*	*-0.0201*	*-0.0340*	*0.2888*
	(0.1703)	*(0.1701)*	*(0.1702)*	*(0.3339)*
Dummy: Married Females	-0.1473	-0.1510	-0.1477	0.5520
	(0.2138)	*(0.2140)*	*(0.2138)*	*(0.3959)*
Dependent Children in HH	-0.0322	-0.0342	-0.0326	0.4338
	(0.1499)	*(0.1501)*	*(0.1499)*	*(0.2794)*
Dummy: Females with dependent Children	-1.1058	-1.1143	-1.1054	-1.1949
	*(0.2195)****	*(0.2197)****	*(0.2195)****	*(0.4023)****
Employment Duration: < 1 Year	3.0030	3.0014	3.0033	1.3336
	*(0.2170)****	*(0.2170)****	*(0.2170)****	*(0.2835)****
Employment Duration: 1-3 Years	*0.9946*	*0.9903*	*0.9940*	*0.3413*
	*(0.2598)****	*(0.2599)****	*(0.2598)****	*(0.3138)*
Employment Duration: 4-6 Years	0.2769	0.2758	0.2773	0.0994
	(0.3915)	*(0.3915)*	*(0.3914)*	*(0.4229)*
Employment Duration: 7-9 Years	-0.6721	-0.6833	-0.6716	-0.5913
	(0.7362)	*(0.7362)*	*(0.7362)*	*(0.7435)*
Dummy: Member of Union	-0.6547	-0.6648	-0.6618	-0.9809
	*(0.3852)**	*(0.3864)**	*(0.3856)**	*(0.4037)***
National Unemployment Rate	-0.4229	-0.2980	-0.4438	-0.2049
	*(0.1275)****	*(0.1343)***	*(0.1293)****	*(0.1591)*
Education: High	0.1200	0.0886	0.1194	-0.0050
	(0.3537)	*(0.3534)*	*(0.3536)*	*(0.6465)*
Education: Medium	-0.1858	-0.2007	-0.1892	-0.4362
	*(0.1086)**	*(0.1086)**	*(0.1086)**	*(0.2086)***
Dummy: Firm Size < 25	-0.5259	-0.3288	-0.5045	0.2114
	*(0.1995)****	*(0.2139)*	*(0.2012)***	*(0.2774)*
Dummy: Firm Size 25-99	-0.6868	-0.5200	-0.6720	0.1014
	*(0.2313)****	*(0.2420)***	*(0.2327)****	*(0.2998)*
Dummy: Firm Size 100-999	-0.9788	-0.8417	-0.9676	-0.3641
	*(0.2656)****	*(0.2732)****	*(0.2670)****	*(0.3350)*
Dummy: Firm in Public Sector	-0.6414	-0.7230	-0.6506	-0.1035
	*(0.3052)***	*(0.3096)***	*(0.3057)***	*(0.3765)*
Research & Development Intensity	0.4174	0.3349	0.4582	0.3258
	(0.3922)	*(0.3977)*	*(0.3947)*	*(0.4006)*
Industry Level Output/1000	-0.0016	-0.0007	-0.0018	-0.0017
	(0.0024)	*(0.0025)*	*(0.0024)*	*(0.0025)*
Net Exports/1000	-0.0032	-0.0108	-0.0188	0.0016
	(0.0157)	*(0.0160)*	*(0.0177)*	*(0.0164)*
Race: White	-0.0329	-0.0204	-0.0269	-0.4938
	(0.2279)	*(0.2278)*	*(0.2279)*	*(0.4424)*
Service Offshoring Intensity: OSS	-	-0.2570	-	-
	-	*(0.0706)****	-	-
Material Offshoring Intensity: OSM	-	-	-0.2469	-
	-	-	*(0.1138)***	-
Blinder Index: Most Offshorable Jobs	-0.1487	-0.3626	-0.2606	-
	(0.2103)	*(0.3355)*	*(0.2590)*	-
Blinder Index * OSS	-	0.1074	-	-
	-	*(0.1023)*	-	-
Blinder Index * OSM	-	-	0.0282	-
	-	-	*(0.0333)*	-
Routine Intensive Job Tasks	-	-	-	-0.1315
	-	-	-	*(0.1108)*
Non-Routine Abstract Job Tasks	-	-	-	-0.0512
	-	-	-	*(0.0473)*
Non-Routine Manual Job Tasks	-	-	-	0.1177
	-	-	-	*(0.0733)*
Service Job Tasks	-	-	-	0.0237

	-	-	-	*(0.0532)*
Constant	-4.6344	-5.2234	-4.5468	-5.3890
	*(1.3627)****	*(1.4223)****	*(1.3653)****	*(2.0816)***
Observations	77545	77545	77545	64544
Log Likelihood	-1619.12	-1611.39	-1617.6535	-794.1267

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Appendix 3

Table 5.5A: Single Risk Model with Frailty: Blinder (2007) Index & TBTC Variables

Pr(Job to Unemployment)	*(1)*	*(2)*
Age	0.2349	0.0621
	*(0.0256)****	*(0.0530)*
Age Squared	-0.0031	-0.0008
	*(0.0003)****	*(0.0007)*
Dummy: Married	-0.0509	-0.5572
	(0.1625)	*(0.3189)**
Dummy: Female	-0.0395	0.2449
	(0.1706)	*(0.3331)*
Dummy: Married Females	-0.1514	0.5011
	(0.2138)	*(0.3956)*
Dependent Children in HH	-0.0328	0.4438
	(0.1499)	*(0.2787)*
Dummy: Females with dependent Children	-1.1019	-1.1954
	*(0.2194)****	*(0.4017)****
Employment Duration: < 1 Year	3.0009	1.3276
	*(0.2170)****	*(0.2839)****
Employment Duration: 1-3 Years	0.9905	0.3375
	*(0.2598)****	*(0.3140)*
Employment Duration: 4-6 Years	0.2744	0.1016
	(0.3915)	*(0.4229)*
Employment Duration: 7-9 Years	-0.6771	-0.6009
	(0.7362)	*(0.7436)*
Dummy: Member of Union	-0.6935	-0.9735
	*(0.3876)**	*(0.4037)***
National Unemployment Rate	-0.4235	-0.1982
	*(0.1276)****	*(0.1589)*
Education: High	0.1084	-0.0641
	(0.3538)	*(0.6528)*
Education: Medium	-0.1886	-0.4364
	*(0.1087)**	*(0.2098)***
Dummy: Firm Size < 25	-0.5256	0.2105
	*(0.2011)****	*(0.2793)*
Dummy: Firm Size 25-99	-0.6759	0.1064
	*(0.2325)****	*(0.3017)*
Dummy: Firm Size 100-999	-0.9771	-0.3776
	*(0.2675)****	*(0.3369)*
Dummy: Firm in Public Sector	-0.6356	-0.0567
	*(0.3086)***	*(0.3758)*
Research & Development Intensity	0.4253	0.3158
	(0.3918)	*(0.3995)*
Industry Level Output/1000	-0.0016	-0.0016
	(0.0024)	*(0.0025)*
Net Exports/1000	-0.0031	0.0020
	(0.0157)	*(0.0164)*
Race: White	-0.0378	-0.5032
	(0.2280)	*(0.4419)*
Blinder Index Value: 25	-0.9274	-0.9535
	(1.1309)	*(1.8001)*
Blinder Index Value: 26-35	-0.2892	-0.5052
	(0.5120)	*(0.6806)*
Blinder Index Value: 36-45	0.1607	-0.1105
	(0.4206)	*(0.4758)*
Blinder Index Value: 46-55	-0.4859	-1.0668
	(0.5062)	*(0.7692)*
Blinder Index Value: 56-65	-0.5156	-0.6829
	(0.4236)	*(0.4783)*
Blinder Index Value: 66-75	-0.1599	-0.1847
	(0.2704)	*(0.3546)*
Blinder Index Value: 76-85	-0.1266	0.5648
	(0.4505)	*(0.5305)*
Blinder Index Value: 86+	-0.8578	-0.9024
	(0.5285)	*(0.5771)*
Routine Intensive Job Tasks	-	-0.0487

	-	*(0.0761)*
Blinder Index Value: 25*Routine Job Tasks	-	0.8305
	-	*(6.2744)*
Blinder Index Value: 26-35*Routine Job Tasks	-	0.2390
	-	*(0.2552)*
Blinder Index Value: 36-45*Routine Job Tasks	-	0.2316
	-	*(0.1286)**
Blinder Index Value: 46-55*Routine Job Tasks	-	-0.2523
	-	*(0.2540)*
Blinder Index Value: 56-65*Routine Jobs Tasks	-	0.0438
	-	*(0.1268)*
Blinder Index Value: 66-75*Routine Job Tasks	-	0.0741
	-	*(0.0934)*
Blinder Index Value: 76-85*Routine Job Tasks	-	0.3770
	-	*(0.1633)***
Blinder Index Value: 86+*Routine Job Tasks	-	0.1059
	-	*(0.2520)*
Constant	-4.6341	-5.0964
	*(1.3663)****	*(2.0828)***
Observations	77545	64544
Log Likelihood	-1615.9648	-788.4486

Source: Own estimates from the BHPS. Significance Level: ****p<0.01, **p<0.05 and *p<0.10*. Each model includes industry, occupation, regional level control variables and time dummy variables. Robust standard errors are presented within the parentheses.

Appendix 4

Table 5.6A: Competing Risks Model – OSS, OSM & Blinder Index of Occupation Tradability

Competing Risks Model	(1)		(2)		(3)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Age	1.3211	1.2966	1.3211	1.3011	1.3213	1.2975
	*(0.0142)****	*(0.0341)****	*(0.0142)****	*(0.0342)****	*(0.0142)****	*(0.0342)****
Age Squared	0.9966	0.9965	0.9966	0.9965	0.9966	0.9965
	*(0.0001)****	*(0.0003)****	*(0.0001)****	*(0.0003)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3040	0.9772	1.3042	0.9844	1.3052	0.9791
	*(0.0785)****	*(0.1693)*	*(0.0786)****	*(0.1706)*	*(0.0786)****	*(0.1695)*
Dummy: Female	0.9258	0.9545	0.9253	0.9638	0.9254	0.9537
	(0.0590)	*(0.1659)*	*(0.0590)*	*(0.1681)*	*(0.0590)*	*(0.1656)*
Dummy: Married Females	1.0908	0.8628	1.0906	0.8564	1.0896	0.8613
	(0.0820)	*(0.1930)*	*(0.0820)*	*(0.1923)*	*(0.0820)*	*(0.1927)*
Dependent Children in HH	0.7872	0.9674	0.7870	0.9682	0.7878	0.9680
	*(0.0410)****	*(0.1437)*	*(0.0410)****	*(0.1442)*	*(0.0410)****	*(0.1439)*
Dummy: Females with dependent Children	0.6489	0.3014	0.6491	0.2987	0.6486	0.3011
	*(0.0467)****	*(0.0696)****	*(0.0467)****	*(0.0692)****	*(0.0467)****	*(0.0695)****
Job Tenure	0.0633	0.5865	0.0633	0.5865	0.0633	0.5864
	*(0.0020)****	*(0.0481)****	*(0.0020)****	*(0.0481)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	1.2829	0.4221	1.2829	0.4233	1.2799	0.4196
	*(0.0743)****	*(0.1542)***	*(0.0743)****	*(0.1549)***	*(0.0741)****	*(0.1543)***
National Unemployment Rate	0.0121	0.6113	0.0121	0.6872	0.0120	0.5988
	*(0.0003)****	*(0.0706)****	*(0.0003)****	*(0.0827)****	*(0.0003)****	*(0.0701)****
Education: High	0.9730	1.0796	0.9729	1.0591	0.9746	1.0813
	(0.1090)	*(0.3912)*	*(0.1090)*	*(0.3839)*	*(0.1092)*	*(0.3919)*
Education: Medium	0.9618	0.8198	0.9616	0.8081	0.9613	0.8177
	(0.0378)	*(0.0922)**	*(0.0378)*	*(0.0910)**	*(0.0378)*	*(0.0920)**
Dummy: Firm Size < 25	4.3569	0.7439	4.3525	0.9031	4.3685	0.7604
	*(0.2731)****	*(0.1254)**	*(0.2745)****	*(0.1635)*	*(0.2741)****	*(0.1298)*
Dummy: Firm Size 25-99	4.3626	0.6185	4.3590	0.7259	4.3696	0.6278
	*(0.2891)****	*(0.1294)***	*(0.2901)****	*(0.1608)*	*(0.2898)****	*(0.1327)***
Dummy: Firm Size 100-999	4.6213	0.4317	4.6186	0.4875	4.6284	0.4380
	*(0.3112)****	*(0.1013)****	*(0.3117)****	*(0.1174)****	*(0.3120)****	*(0.1033)****
Dummy: Firm in Public Sector	1.2426	0.4870	1.2440	0.4369	1.2380	0.4813
	*(0.0841)****	*(0.1288)****	*(0.0844)****	*(0.1191)****	*(0.0839)****	*(0.1275)****
Research & Development Intensity	1.0171	1.4788	1.0173	1.3586	1.0223	1.5404
	(0.0753)	*(0.6112)*	*(0.0758)*	*(0.5732)*	*(0.0761)*	*(0.6467)*
Industry Level Output/1000	1.0004	0.9985	1.0004	0.9994	1.0004	0.9983

	(0.0004)	*(0.0023)*	*(0.0004)*	*(0.0024)*	*(0.0004)*	*(0.0023)*
Net Exports/1000	0.9987	0.9965	0.9988	0.9894	0.9976	0.9813
	(0.0029)	*(0.0143)*	*(0.0029)*	*(0.0143)*	*(0.0032)*	*(0.0147)*
Race: White	1.3069	0.9494	1.3069	0.9598	1.3096	0.9540
	*(0.1245)****	*(0.2333)*	*(0.1245)****	*(0.2362)*	*(0.1248)*	*(0.2342)*
Service Offshoring Intensity: OSS	-	-	1.0026	0.7746	-	-
	-	-	*(0.0152)*	*(0.0488)****	-	-
Material Offshoring Intensity: OSM	-	-	-	-	0.9777	0.7860
	-	-	-	-	*(0.0257)*	*(0.0462)****
Blinder Index: Most Offshorable Jobs	1.1453	0.8986	1.1285	0.7339	1.1106	0.8008
	*(0.0514)****	*(0.1898)*	*(0.0718)**	*(0.2337)*	*(0.0584)****	*(0.2051)*
Blinder Index * OSS	-	-	1.0056	1.1075	-	-
	-	-	*(0.0170)*	*(0.1069)*	-	-
Blinder Index * OSM	-	-	-	-	1.0082	1.0292
	-	-	-	-	*(0.0070)*	*(0.0342)*
Observations	77545		77545		77545	
Log Likelihood	-12666.081		-12658.464		-12663.8	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Appendix 5

Table 5.7_1A: Competing Risks Model –TBTC

Competing Risks Model	New Job Transition	Unemployment Transition
Age	1.3111	1.0639
	*(0.0152)****	*(0.0564)*
Age Squared	0.9967	0.9992
	*(0.0002)****	*(0.0007)*
Dummy: Married	1.3243	0.5436
	*(0.0839)****	*(0.1744)**
Dummy: Female	1.0004	1.2875
	(0.0676)	*(0.4481)*
Dummy: Married Females	1.0778	1.7876
	(0.0855)	*(0.6956)*
Dependent Children in HH	0.7821	1.5532
	(0.0425)	*(0.4019)*
Dummy: Females with dependent Children	0.6645	0.2837
	*(0.0506)****	*(0.1136)****
Job Tenure	0.0615	0.8364
	*(0.0020)****	*(0.0426)****
Dummy: Member of Union	1.3352	0.3420
	*(0.0801)****	*(0.1325)****
National Unemployment Rate	0.0107	0.7676
	*(0.0003)****	*(0.1120)**
Education: High	0.9248	0.9784
	(0.1124)	*(0.6772)*
Education: Medium	0.9634	0.6339
	(0.0400)	*(0.1366)**
Dummy: Firm Size < 25	3.2862	1.3656
	*(0.2135)****	*(0.3656)*
Dummy: Firm Size 25-99	3.2926	1.1958
	*(0.2239)****	*(0.3563)*
Dummy: Firm Size 100-999	3.4233	0.7180
	*(0.2353)****	*(0.2326)*
Dummy: Firm in Public Sector	1.0440	0.9021
	(0.0738)	*(0.3270)*
Research & Development Intensity	0.9989	1.4147
	(0.0762)	*(0.5864)*
Industry Level Output/1000	1.0003	0.9983
	(0.0004)	*(0.0024)*
Net Exports/1000	0.9993	1.0017
	(0.0030)	*(0.0151)*
Race: White	1.3210	0.6054
	*(0.1337)****	*(0.2693)*
Routine Intensive Job Tasks	0.9550	0.8781
	*(0.0205)***	*(0.1056)*
Non-Routine Abstract Job Tasks	1.0588	0.9546
	*(0.0103)****	*(0.0508)*
Non-Routine Manual Job Tasks	0.9918	1.1245
	(0.0147)	*(0.0848)*
Service Job Tasks	0.9398	1.0228
	*(0.0098)****	*(0.0555)*
Observations	64544	
Log Likelihood	-10605.02	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.7_2A: Competing Risks Model –TBTC and Skill Interactions

Competing Risks Model	(1)		(2)		(3)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Age	1.3161	1.0568	1.3148	1.0568	1.3147	1.0565
	*(0.0152)****	*(0.0552)*	*(0.0152)****	*(0.0554)*	*(0.0152)****	*(0.0554)*
Age Squared	0.9966	0.9993	0.9967	0.9993	0.9967	0.9993
	*(0.0002)****	*(0.0007)*	*(0.0002)****	*(0.0007)*	*(0.0002)****	*(0.0007)*
Dummy: Married	1.3291	0.5431	1.3310	0.5433	1.3306	0.5435
	*(0.0843)****	*(0.1737)**	*(0.0844)****	*(0.1740)**	*(0.0843)****	*(0.1740)**
Dummy: Female	0.9624	1.2796	0.9643	1.2835	0.9643	1.2834
	(0.0645)	*(0.4447)*	*(0.0646)*	*(0.4457)*	*(0.0646)*	*(0.4453)*
Dummy: Married Females	1.0765	1.7932	1.0739	1.7914	1.0746	1.7915
	(0.0853)	*(0.6955)*	*(0.0850)*	*(0.6946)*	*(0.0851)*	*(0.6946)*
Dependent Children in HH	0.7800	1.5633	0.7815	1.5670	0.7821	1.5683
	*(0.0424)****	*(0.4057)**	*(0.0425)****	*(0.4067)**	*(0.0425)****	*(0.4070)**
Dummy: Females with dependent Children	0.6670	0.2826	0.6635	0.2814	0.6631	0.2811
	*(0.0507)****	*(0.1130)****	*(0.0504)****	*(0.1126)****	*(0.0504)****	*(0.1124)****
Job Tenure	0.0625	0.8360	0.0624	0.8359	0.0624	0.8358
	*(0.0020)****	*(0.0427)****	*(0.0020)****	*(0.0428)****	*(0.0020)****	*(0.0428)*
Dummy: Member of Union	1.2823	0.3609	1.2797	0.3601	1.2795	0.3601
	*(0.0765)****	*(0.1374)****	*(0.0763)****	*(0.1372)****	*(0.0763)****	*(0.1372)****
National Unemployment Rate	0.0107	0.7689	0.0107	0.7687	0.0107	0.7682
	*(0.0003)****	*(0.1125)**	*(0.0003)****	*(0.1119)**	*(0.0003)****	*(0.1119)**
Education: High	0.8653	1.0664	0.8864	0.9146	0.9795	1.5398
	(0.1269)	*(0.7399)*	*(0.1093)*	*(0.6526)*	*(0.1142)*	*(1.0238)*
Education: Medium	0.9626	0.6322	0.9497	0.6182	-	-
	(0.0399)	*(0.1358)***	*(0.0396)*	*(0.1383)***	-	-
Education: Low	-	-	-	-	1.0520	1.6292
	-	-	-	-	*(0.0438)*	*(0.3640)***
Dummy: Firm Size < 25	3.2458	1.3719	3.2480	1.3728	3.2467	1.3746
	*(0.2106)****	*(0.3676)*	*(0.2109)****	*(0.3701)*	*(0.2108)****	*(0.3705)*
Dummy: Firm Size 25-99	3.2809	1.2008	3.2858	1.2013	3.2851	1.2026
	*(0.2233)****	*(0.3576)*	*(0.2237)****	*(0.3599)*	*(0.2237)****	*(0.3602)*
Dummy: Firm Size 100-999	3.4528	0.7173	3.4614	0.7172	3.4597	0.7182
	*(0.2375)****	*(0.2322)*	*(0.2382)****	*(0.2333)*	*(0.2381)****	*(0.2337)*
Dummy: Firm in Public Sector	1.0415	0.9450	1.0421	0.9443	1.0417	0.9454
	(0.0733)	*(0.3346)*	*(0.0733)*	*(0.3338)*	*(0.0732)*	*(0.3340)*
Research & Development Intensity	0.9963	1.4215	0.9974	1.4201	0.9977	1.4202
	(0.0758)	*(0.5877)*	*(0.0759)*	*(0.5871)*	*(0.0759)*	*(0.5872)*
Industry Level Output/1000	1.0004	0.9983	1.0003	0.9983	1.0003	0.9983
	(0.0004)	*(0.0024)*	*(0.0004)*	*(0.0024)*	*(0.0004)*	*(0.0024)*

Net Exports/1000	0.9992	1.0016	0.9994	1.0018	0.9994	1.0018
	(0.0030)	*(0.0151)*	*(0.0030)*	*(0.0151)*	*(0.0030)*	*(0.0151)*
Race: White	1.3084	0.6237	1.3019	0.6148	1.3045	0.6153
	*(0.1321)****	*(0.2791)*	*(0.1315)****	*(0.2732)*	*(0.1317)****	*(0.2737)*
Routine Intensive Job Tasks	0.9434	1.0165	0.9251	1.0066	0.9519	1.0375
	*(0.0111)****	*(0.0594)*	*(0.0129)****	*(0.0632)*	*(0.0120)****	*(0.0713)*
High Skill * Routine Job Task	0.9533	1.1085	-	-	-	-
	(0.0514)	*(0.2252)*	-	-	-	-
Medium Skill * Routine Job Task	-	-	1.0308	1.0278	-	-
	-	-	*(0.0134)***	*(0.0650)*	-	-
Low Skill * Routine Job Task	-	-	-	-	0.9724	0.9662
	-	-	-	-	*(0.0127)***	*(0.0608)*
Observation	64544		64544		64544	
Log Likelihood	-10630.685		-10628.276		-10628.7	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Appendix 6

Table 5.8A: Competing Risks Model – Blinder's (2007) Offshorability Index and TBTC

Pr(Job to Unemployment)	(1)		(2)	
	New Job Transition	Unemployment Transition	New Job Transition	Unemployment Transition
Age	1.3200	1.2972	1.3149	1.0634
	*(0.0142)****	*(0.0342)****	*(0.0152)****	*(0.0568)*
Age Squared	0.9966	0.9965	0.9967	0.9993
	*(0.0001)****	*(0.0003)****	*(0.0002)****	*(0.0007)*
Dummy: Married	1.3080	0.9804	1.3297	0.5597
	*(0.0788)****	*(0.1694)*	*(0.0845)****	*(0.1769)**
Dummy: Female	0.9314	0.9497	0.9789	1.2268
	(0.0595)	*(0.1658)*	*(0.0660)*	*(0.4248)*
Dummy: Married Females	1.0874	0.8563	1.0750	1.7178
	(0.0819)	*(0.1914)*	*(0.0854)*	*(0.6621)*
Dependent Children in HH	0.7857	0.9652	0.7771	1.5652
	*(0.0410)****	*(0.1436)*	*(0.0424)****	*(0.4124)**
Dummy: Females with dependent Children	0.6534	0.3033	0.6712	0.2836
	*(0.0471)****	*(0.0701)****	*(0.0512)****	*(0.1147)****
Job Tenure	0.0631	0.5866	0.0621	0.8370
	*(0.0020)****	*(0.0481)****	*(0.0020)****	*(0.0426)****
Dummy: Member of Union	1.3063	0.4106	1.3042	0.3447
	*(0.0762)****	*(0.1523)***	*(0.0791)****	*(0.1342)****
National Unemployment Rate	0.0121	0.6112	0.0107	0.7700
	*(0.0003)****	*(0.0707)****	*(0.0003)****	*(0.1117)**
Education: High	0.9728	1.0731	0.9407	0.9597
	(0.1092)	*(0.3877)*	*(0.1146)*	*(0.6720)*
Education: Medium	0.9640	0.8181	0.9604	0.6365
	(0.0380)	*(0.0921)**	*(0.0400)*	*(0.1387)**
Dummy: Firm Size < 25	4.3876	0.7460	3.2650	1.3686
	*(0.2756)****	*(0.1264)**	*(0.2127)****	*(0.3697)*
Dummy: Firm Size 25-99	4.3733	0.6233	3.2887	1.2078
	*(0.2905)****	*(0.1308)***	*(0.2249)****	*(0.3655)*
Dummy: Firm Size 100-999	4.6135	0.4321	3.4525	0.7142
	*(0.3111)****	*(0.1021)****	*(0.2392)****	*(0.2335)*
Dummy: Firm in Public Sector	1.2343	0.4873	1.0468	0.9427
	*(0.0837)****	*(0.1323)****	*(0.0742)*	*(0.3422)*
Research & Development Intensity	1.0156	1.4904	0.9999	1.4210
	(0.0753)	*(0.6151)*	*(0.0762)*	*(0.5852)*
Industry Level Output/1000	1.0004	0.9986	1.0003	0.9984
	(0.0004)	*(0.0023)*	*(0.0004)*	*(0.0024)*

Net Exports/1000	0.9988 *(0.0029)*	0.9962 *(0.0144)*	0.9992 *(0.0030)*	1.0020 *(0.0151)*
Race: White	1.3044 *(0.1243)****	0.9448 *(0.2322)*	1.3054 *(0.1321)****	0.6002 *(0.2634)*
Blinder Index Value: 25	0.8280 *(0.1615)*	0.4093 *(0.4595)*	0.7515 *(0.1527)*	0.3999 *(0.4732)*
Blinder Index Value: 26-35	1.2721 *(0.1449)***	0.8127 *(0.4359)*	1.3604 *(0.1820)***	0.6009 *(0.3972)*
Blinder Index Value: 36-45	1.1960 *(0.1039)***	1.1504 *(0.5107)*	1.0804 *(0.1039)*	0.8380 *(0.3832)*
Blinder Index Value: 46-55	1.1533 *(0.0922)**	0.6289 *(0.2862)*	1.0844 *(0.1140)*	0.3423 *(0.2700)*
Blinder Index Value: 56-65	1.1394 *(0.0883)**	0.5896 *(0.2447)*	1.0662 *(0.0935)*	0.4929 *(0.2215)*
Blinder Index Value: 66-75	1.2663 *(0.0806)****	0.9070 *(0.2396)*	1.1111 *(0.0792)*	0.8378 *(0.2794)*
Blinder Index Value: 76-85	1.4108 *(0.1325)****	0.9502 *(0.4534)*	1.2025 *(0.2057)*	2.0059 *(1.0728)*
Blinder Index Value: 86+	1.0752 *(0.1012)*	0.4384 *(0.2329)*	0.9696 *(0.1010)*	0.3993 *(0.2395)*
Routine Intensive Job Tasks	- -	- -	0.9597 *(0.0159)***	0.9482 *(0.0781)*
Blinder Index Value: 25*Routine Job Tasks	- -	- -	0.9083 *(0.2645)*	2.4494 *(0.8513)***
Blinder Index Value: 26-35*Routine Job Tasks	- -	- -	0.9091 *(0.0543)*	1.2575 *(0.3222)*
Blinder Index Value: 36-45*Routine Job Tasks	- -	- -	0.9480 *(0.0283)**	1.2593 *(0.1444)***
Blinder Index Value: 46-55*Routine Job Tasks	- -	- -	0.9990 *(0.0347)*	0.7673 *(0.1903)*
Blinder Index Value: 56-65*Routine Jobs Tasks	- -	- -	1.0020 *(0.0236)*	1.0460 *(0.1156)*
Blinder Index Value: 66-75*Routine Job Tasks	- -	- -	0.9467 *(0.0180)*	1.0686 *(0.0967)*
Blinder Index Value: 76-85*Routine Job Tasks	- -	- -	0.9306 *(0.0497)*	1.5053 *(0.2521)***
Blinder Index Value: 86+*Routine Job Tasks	- -	- -	0.9833 *(0.0456)*	1.1288 *(0.2596)*
Observations	77545		64544	
Log Likelihood	-12655.873		-10608.437	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Appendix 7

This section of the appendix provides estimates from the estimation of various competing risks models as a robustness check. These models estimate the impact of offshoring (materials and services), Blinder's (2007) job tradability Index and the routinization hypothesis can have on the probability of making a job transition from employment in time period $j-1$ to: (a) new employment, (b) remain in employment with current employer and (c) become unemployment in time period j.

Table 5.9A: Competing Risks Model - OSS

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5993	1.4155	1.3867
	*(0.0197)****	*(0.0086)****	*(0.0369)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3736	1.1134	1.0190
	*(0.0961)****	*(0.0417)****	*(0.1746)*
Dummy: Female	1.0522	1.1595	1.0211
	(0.0786)	*(0.0482)****	*(0.1785)*
Dummy: Married Females	1.0441	0.9713	0.8222
	(0.0916)	*(0.0462)*	*(0.1854)*
Dependent Children in HH	0.7798	0.9011	0.9860
	*(0.0472)****	*(0.0290)****	*(0.1477)*
Dummy: Females with dependent Children	0.4176	0.5072	0.2623
	*(0.0352)****	*(0.0224)****	*(0.0614)****
Job Tenure	0.0670	1.0448	0.5990
	*(0.0020)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	3.1841	3.1856	0.9386
	*(0.2353)****	*(0.1381)****	*(0.3424)*
National Unemployment Rate	0.0081	0.0077	0.5506
	*(0.0002)****	*(0.0001)****	*(0.0689)****
Education: High	1.0093	1.0776	1.0483
	(0.1404)	*(0.0862)*	*(0.3829)*
Education: Medium	0.9203	0.9688	0.7914
	*(0.0420)**	*(0.0230)*	*(0.0902)***
Dummy: Firm Size < 25	16.8671	15.9919	2.4217
	*(1.1728)****	*(0.5176)****	*(0.4208)****
Dummy: Firm Size 25-99	16.8864	15.4363	1.9721
	*(1.2334)****	*(0.5361)****	*(0.4236)****
Dummy: Firm Size 100-999	19.1100	16.6688	1.4301
	*(1.4079)****	*(0.5776)****	*(0.3303)*
Dummy: Firm in Public Sector	2.6925	3.4508	0.6699
	*(0.2225)****	*(0.1552)****	*(0.1776)*
Research & Development Intensity	1.0854	1.1217	1.4407
	(0.1006)	*(0.0601)***	*(0.6156)*
Industry Level Output/1000	1.0005	1.0003	1.0000
	(0.0005)	*(0.0003)*	*(0.0024)*
Net Exports/1000	0.9963	0.9970	0.9811
	(0.0036)	*(0.0021)*	*(0.0142)*
Race: White	1.5771	1.4160	0.9830
	*(0.1760)****	*(0.0840)****	*(0.2404)*
Service Offshoring Intensity: OSS	0.9953	1.0129	0.7487
	(0.0171)	*(0.0090)*	*(0.0437)****
Observations		77545	

Log Likelihood	-38519.533

Source: Author's own calculations from the BHPS. Significance Level Key: *** $p<0.01$; ** $p<0.05$; * $p<0.10$. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.10A: Competing Risks Model – OSS & Education

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5992	1.4151	1.3861
	*(0.0197)****	*(0.0086)****	*(0.0368)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3738	1.1137	1.0148
	*(0.0961)****	*(0.0417)****	*(0.1739)*
Dummy: Female	1.0535	1.1617	1.0283
	(0.0787)	*(0.0483)****	*(0.1798)*
Dummy: Married Females	1.0437	0.9703	0.8231
	(0.0916)	*(0.0462)*	*(0.1856)*
Dependent Children in HH	0.7797	0.9011	0.9873
	*(0.0472)****	*(0.0290)****	*(0.1479)*
Dummy: Females with dependent Children	0.4171	0.5066	0.2592
	*(0.0352)****	*(0.0224)****	*(0.0607)****
Job Tenure	0.0670	1.0449	0.6001
	*(0.0020)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	3.1809	3.1800	0.9257
	*(0.2352)****	*(0.1379)****	*(0.3382)*
National Unemployment Rate	0.0081	0.0077	0.5512
	*(0.0002)****	*(0.0001)****	*(0.0689)****
Education: High	1.1084	1.0857	1.4187
	(0.2074)	*(0.1188)*	*(0.5372)*
Education: Medium	0.9589	1.0464	0.8577
	(0.0602)	*(0.0334)*	*(0.1092)*
Dummy: Firm Size < 25	16.8729	15.9875	2.3983
	*(1.1734)****	*(0.5175)****	*(0.4181)****
Dummy: Firm Size 25-99	16.9060	15.4348	1.9620
	*(1.2354)****	*(0.5363)****	*(0.4209)****
Dummy: Firm Size 100-999	19.1295	16.6886	1.4257
	*(1.4100)****	*(0.5784)****	*(0.3293)*
Dummy: Firm in Public Sector	2.6797	3.4368	0.6602
	*(0.2217)****	*(0.1549)****	*(0.1759)*
Research & Development Intensity	1.0869	1.1216	1.4643
	(0.1008)	*(0.0602)***	*(0.6278)*
Industry Level Output/1000	1.0005	1.0003	1.0002
	(0.0005)	*(0.0003)*	*(0.0025)*
Net Exports/1000	0.9960	0.9967	0.9795
	(0.0036)	*(0.0021)*	*(0.0140)*
Race: White	1.5789	1.4155	0.9796
	*(0.1762)****	*(0.0840)****	*(0.2406)*
Service Offshoring Intensity: OSS	1.0046	1.0291	0.7852
	(0.0200)	*(0.0103)****	*(0.0537)****
Education: High*OSS	0.9533	1.0006	0.4584
	(0.0571)	*(0.0336)*	*(0.2129)**
Education: Medium*OSS	0.9834	0.9699	0.9156
	(0.0168)	*(0.0085)****	*(0.0617)*
Observations		77545	
Log Likelihood		-38511.126	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.11A: Competing Risks Model – OSM

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5989	1.4151	1.3819
	*(0.0197)****	*(0.0086)****	*(0.0368)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3740	1.1135	1.0078
	*(0.0962)****	*(0.0417)****	*(0.1730)*
Dummy: Female	1.0518	1.1620	1.0033
	(0.0786)	*(0.0483)****	*(0.1748)*
Dummy: Married Females	1.0443	0.9707	0.8352
	(0.0917)	*(0.0462)*	*(0.1876)*
Dependent Children in HH	0.7792	0.9013	0.9826
	*(0.0471)****	*(0.0290)****	*(0.1468)*
Dummy: Females with dependent Children	0.4180	0.5068	0.2654
	*(0.0353)****	*(0.0224)****	*(0.0620)****
Job Tenure	0.0670	1.0448	0.5984
	*(0.0020)****	*(0.0020)****	*(0.0482)****
Dummy: Member of Union	3.1834	3.1829	0.9096
	*(0.2353)****	*(0.1379)****	*(0.3328)*
National Unemployment Rate	0.0081	0.0078	0.4734
	*(0.0002)****	*(0.0001)****	*(0.0579)****
Education: High	1.0087	1.0766	1.0627
	(0.1403)	*(0.0861)*	*(0.3881)*
Education: Medium	0.9207	0.9694	0.8023
	*(0.0420)**	*(0.0230)*	*(0.0912)**
Dummy: Firm Size < 25	16.8458	16.0010	1.9151
	*(1.1653)****	*(0.5157)****	*(0.3179)****
Dummy: Firm Size 25-99	16.8604	15.4203	1.6196
	*(1.2277)****	*(0.5349)****	*(0.3363)***
Dummy: Firm Size 100-999	19.1076	16.6367	1.2286
	*(1.4066)****	*(0.5763)****	*(0.2831)*
Dummy: Firm in Public Sector	2.6896	3.4424	0.7560
	*(0.2214)****	*(0.1537)****	*(0.1956)*
Research & Development Intensity	1.0914	1.1035	1.5833
	(0.1012)	*(0.0591)**	*(0.6693)*
Industry Level Output/1000	1.0005	1.0004	0.9987
	(0.0005)	*(0.0003)*	*(0.0023)*
Net Exports/1000	0.9978	1.0014	0.9773
	(0.0040)	*(0.0024)*	*(0.0148)*
Race: White	1.5791	1.4169	0.9719
	*(0.1762)****	*(0.0841)****	*(0.2373)*
Material Offshoring Intensity: OSM	1.0271	1.0853	0.8173
	(0.0323)	*(0.0230)****	*(0.0449)****
Observations		77545	
Log Likelihood		-38523.033	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.12A: Competing Risks Model – OSM & Education

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5987	1.4148	1.3822
	*(0.0197)****	*(0.0085)****	*(0.0368)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3736	1.1114	1.0013
	*(0.0961)****	*(0.0416)****	*(0.1722)*
Dummy: Female	1.0547	1.1662	1.0054
	(0.0788)	*(0.0485)****	*(0.1750)*
Dummy: Married Females	1.0427	0.9706	0.8398
	(0.0915)	*(0.0462)*	*(0.1888)*
Dependent Children in HH	0.7784	0.9004	0.9838
	*(0.0471)****	*(0.0290)****	*(0.1471)*
Dummy: Females with dependent Children	0.4183	0.5072	0.2640
	*(0.0353)****	*(0.0224)****	*(0.0617)****
Job Tenure	0.0670	1.0449	0.5999
	*(0.0020)****	*(0.0020)****	*(0.0480)****
Dummy: Member of Union	3.1948	3.2020	0.8887
	*(0.2362)****	*(0.1389)****	*(0.3260)*
National Unemployment Rate	0.0081	0.0078	0.4747
	*(0.0002)****	*(0.0001)****	*(0.0582)****
Education: High	0.9611	0.9435	1.3483
	(0.1407)	*(0.0798)*	*(0.5035)*
Education: Medium	0.8845	0.9190	0.8533
	*(0.0439)***	*(0.0232)****	*(0.1016)*
Dummy: Firm Size < 25	16.8785	16.1054	1.8910
	*(1.1676)****	*(0.5201)****	*(0.3127)****
Dummy: Firm Size 25-99	16.9409	15.5602	1.5952
	*(1.2342)****	*(0.5414)****	*(0.3328)***
Dummy: Firm Size 100-999	19.1546	16.7590	1.2125
	*(1.4099)****	*(0.5816)****	*(0.2808)*
Dummy: Firm in Public Sector	2.6990	3.4584	0.7372
	*(0.2223)****	*(0.1548)****	*(0.1915)*
Research & Development Intensity	1.0946	1.1017	1.6137
	(0.1014)	*(0.0588)**	*(0.6827)*
Industry Level Output/1000	1.0005	1.0005	0.9986
	(0.0005)	*(0.0003)*	*(0.0023)*
Net Exports/1000	0.9983	1.0021	0.9756
	(0.0040)	*(0.0024)*	*(0.0148)*
Race: White	1.5751	1.4168	0.9738
	*(0.1757)****	*(0.0840)****	*(0.2384)*
Material Offshoring Intensity: OSM	1.0131	1.0663	0.8390
	(0.0326)	*(0.0231)****	*(0.0477)****
Education: High*OSM	1.0253	1.0708	0.0000
	(0.0342)	*(0.0209)****	*(0.0000)*
Education: Medium*OSM	1.0198	1.0231	0.9416
	*(0.0084)***	*(0.0048)****	*(0.0310)**
Observations		77545	
Log Likelihood		-38498.592	

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.13A: Competing Risks Model – Blinder's (2007) Occupation Tradability Index

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.6005	1.4158	1.3807
	*(0.0198)****	*(0.0086)****	*(0.0367)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3750	1.1134	1.0072
	*(0.0963)****	*(0.0416)****	*(0.1729)*
Dummy: Female	1.0407	1.1500	1.0020
	(0.0779)	*(0.0479)****	*(0.1745)*
Dummy: Married Females	1.0401	0.9698	0.8351
	(0.0914)	*(0.0462)*	*(0.1877)*
Dependent Children in HH	0.7796	0.9016	0.9818
	*(0.0471)****	*(0.0290)****	*(0.1467)*
Dummy: Females with dependent Children	0.4161	0.5053	0.2660
	*(0.0351)****	*(0.0224)****	*(0.0621)****
Job Tenure	0.0669	1.0447	0.5988
	*(0.0020)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	3.2111	3.2026	0.9106
	*(0.2369)****	*(0.1385)****	*(0.3336)*
National Unemployment Rate	0.0081	0.0077	0.4849
	*(0.0002)****	*(0.0001)****	*(0.0582)****
Education: High	1.0241	1.0971	1.0634
	(0.1425)	*(0.0877)*	*(0.3882)*
Education: Medium	0.9214	0.9703	0.8041
	*(0.0421)**	*(0.0230)*	*(0.0914)**
Dummy: Firm Size < 25	16.7400	16.0249	1.8858
	*(1.1565)****	*(0.5168)****	*(0.3108)****
Dummy: Firm Size 25-99	16.6072	15.3223	1.6039
	*(1.2089)****	*(0.5317)****	*(0.3313)***
Dummy: Firm Size 100-999	18.6831	16.4378	1.2301
	*(1.3760)****	*(0.5697)****	*(0.2878)*
Dummy: Firm in Public Sector	2.7321	3.4622	0.7585
	(0.2251)	*(0.1546)****	*(0.1965)*
Research & Development Intensity	1.0880	1.1137	1.5152
	(0.1004)	*(0.0594)***	*(0.6311)*
Industry Level Output/1000	1.0004	1.0003	0.9988
	(0.0005)	*(0.0003)*	*(0.0023)*
Net Exports/1000	0.9962	0.9967	0.9914
	(0.0036)	*(0.0020)*	*(0.0142)*
Race: White	1.5989	1.4332	0.9682
	*(0.1789)****	*(0.0852)****	*(0.2364)*
Blinder Index: Most Offshorable Jobs	1.2971	1.2556	0.9466
	*(0.0709)****	*(0.0380)****	*(0.1993)*
Observations		77545	
Log Likelihood		-38499.056	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.14A: Competing Risks Model – Blinder's (2007) Occupation Tradability Index & OSS

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.6005	1.4154	1.3860
	*(0.0198)****	*(0.0086)****	*(0.0368)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3746	1.1142	1.0177
	*(0.0963)****	*(0.0417)****	*(0.1744)*
Dummy: Female	1.0418	1.1500	1.0168
	(0.0780)	*(0.0479)****	*(0.1779)*
Dummy: Married Females	1.0397	0.9699	0.8230
	(0.0914)	*(0.0462)*	*(0.1857)*
Dependent Children in HH	0.7798	0.9014	0.9866
	*(0.0472)****	*(0.0290)****	*(0.1479)*
Dummy: Females with dependent Children	0.4157	0.5054	0.2633
	*(0.0351)****	*(0.0224)****	*(0.0617)****
Job Tenure	0.0669	1.0448	0.5992
	*(0.0020)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	3.2072	3.2018	0.9390
	*(0.2366)****	*(0.1385)****	*(0.3431)*
National Unemployment Rate	0.0081	0.0077	0.5492
	*(0.0002)****	*(0.0001)****	*(0.0688)****
Education: High	1.0242	1.0969	1.0460
	(0.1426)	*(0.0878)*	*(0.3821)*
Education: Medium	0.9214	0.9711	0.7916
	*(0.0421)**	*(0.0231)*	*(0.0902)***
Dummy: Firm Size < 25	16.7585	15.9564	2.4620
	*(1.1647)****	*(0.5168)****	*(0.4333)****
Dummy: Firm Size 25-99	16.6365	15.2995	2.0055
	*(1.2156)****	*(0.5315)****	*(0.4342)****
Dummy: Firm Size 100-999	18.7015	16.4239	1.4586
	*(1.3797)****	*(0.5693)****	*(0.3455)*
Dummy: Firm in Public Sector	2.7300	3.4848	0.6703
	*(0.2259)****	*(0.1569)****	*(0.1783)*
Research & Development Intensity	1.0884	1.1274	1.3877
	(0.1011)	*(0.0605)***	*(0.5920)*
Industry Level Output/1000	1.0004	1.0003	0.9998
	(0.0005)	*(0.0003)*	*(0.0024)*
Net Exports/1000	0.9959	0.9965	0.9828
	(0.0036)	*(0.0021)*	*(0.01420)*
Race: White	1.5982	1.4325	0.9829
	*(0.1788)****	*(0.0852)****	*(0.2403)*
Service Offshoring Intensity: OSS	0.9953	1.0162	0.7376
	(0.0175)	*(0.0092)**	*(0.0461)****
Blinder Index: Most Offshorable Jobs	1.3258	1.3350	0.7742
	*(0.1034)****	*(0.0584)****	*(0.2472)*
Blinder Index * OSS	0.9920	0.9772	1.1123
	(0.0205)	*(0.0114)***	*(0.1087)*
Observations		77545	
Log Likelihood		-38484.077	

Source: Author's own calculations from the BHPS. Significance Level Key: ***$p<0.01$; **$p<0.05$; *$p<0.10$. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.15A: Competing Risks Model – Blinder's (2007) Occupation Tradability Index & OSM

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.6003	1.4156	1.3814
	*(0.0198)****	*(0.0086)****	*(0.0368)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3752	1.1125	1.0093
	*(0.0963)****	*(0.0416)****	*(0.1731)*
Dummy: Female	1.0402	1.1511	1.0017
	(0.0778)	*(0.0479)****	*(0.1744)*
Dummy: Married Females	1.0400	0.9704	0.8336
	(0.0914)	*(0.0462)*	*(0.1873)*
Dependent Children in HH	0.7802	0.9014	0.9829
	*(0.0472)****	*(0.0290)****	*(0.1468)*
Dummy: Females with dependent Children	0.4158	0.5051	0.2659
	*(0.0351)****	*(0.0224)****	*(0.0621)****
Job Tenure	0.0669	1.0448	0.5987
	*(0.0020)****	*(0.0020)****	*(0.0481)****
Dummy: Member of Union	3.2007	3.2016	0.9092
	*(0.2362)****	*(0.1384)****	*(0.3346)*
National Unemployment Rate	0.0081	0.0078	0.4739
	*(0.0002)****	*(0.0001)****	*(0.0580)****
Education: High	1.0232	1.0928	1.0645
	(0.1423)	*(0.0874)*	*(0.3885)*
Education: Medium	0.9215	0.9711	0.8022
	*(0.0421)**	*(0.0231)*	*(0.0912)**
Dummy: Firm Size < 25	16.7523	15.9676	1.9260
	*(1.1581)****	*(0.5151)****	*(0.3206)****
Dummy: Firm Size 25-99	16.6050	15.2766	1.6263
	*(1.2091)****	*(0.5302)****	*(0.3382)***
Dummy: Firm Size 100-999	18.6902	16.3915	1.2456
	*(1.3775)****	*(0.5682)****	*(0.2926)*
Dummy: Firm in Public Sector	2.7258	3.4827	0.7503
	*(0.2247)****	*(0.1556)****	*(0.1948)*
Research & Development Intensity	1.0913	1.1024	1.5807
	(0.1011)	*(0.0589)**	*(0.6690)*
Industry Level Output/1000	1.0005	1.0004	0.9987
	(0.0005)	*(0.0003)*	*(0.0023)*
Net Exports/1000	0.9974	1.0012	0.9773
	(0.0040)	*(0.0023)*	*(0.0149)*
Race: White	1.6013	1.4315	0.9726
	*(0.1792)****	*(0.0851)****	*(0.2373)*
Material Offshoring Intensity: OSM	1.0222	1.0855	0.8084
	(0.0320)	*(0.0226)****	*(0.0474)****
Blinder Index: Most Offshorable Jobs	1.2737	1.2853	0.8445
	*(0.0802)****	*(0.0440)****	*(0.2157)*
Blinder Index * OSM	1.0042	0.9935	1.0281
	(0.0088)	*(0.0049)*	*(0.0346)*
Observations		77545	
Log Likelihood		-38488.222	

Source: Author's own calculations from the BHPS. Significance Level Key: ***$p<0.01$; **$p<0.05$; *$p<0.10$. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.16A: Competing Risks Model – Blinder's (2007) Occupation Tradability Index

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5989	1.4151	1.3813
	*(0.0198)****	*(0.0086)****	*(0.0369)****
Age Squared	0.9944	0.9960	0.9958
	*(0.0002)****	*(0.0001)****	*(0.0003)****
Dummy: Married	1.3778	1.1106	1.0088
	*(0.0967)****	*(0.0417)****	*(0.1729)*
Dummy: Female	1.0461	1.1494	0.9970
	(0.0785)	*(0.0480)****	*(0.1747)*
Dummy: Married Females	1.0357	0.9697	0.8305
	(0.0912)	*(0.0463)*	*(0.1866)*
Dependent Children in HH	0.7786	0.9031	0.9793
	*(0.0472)****	*(0.0291)****	*(0.1464)*
Dummy: Females with dependent Children	0.4212	0.5090	0.2679
	*(0.0356)****	*(0.0226)****	*(0.0626)****
Job Tenure	0.0669	1.0455	0.5989
	*(0.0020)****	*(0.0020)****	*(0.0482)****
Dummy: Member of Union	3.2565	3.2120	0.8874
	*(0.2411)****	*(0.1390)****	*(0.3298)*
National Unemployment Rate	0.0081	0.0077	0.4835
	*(0.0002)****	*(0.0001)****	*(0.0581)****
Education: High	1.0157	1.0902	1.0518
	(0.1414)	*(0.0871)*	*(0.3828)*
Education: Medium	0.9219	0.9696	0.8025
	*(0.0422)**	*(0.0231)*	*(0.0913)**
Dummy: Firm Size < 25	16.7585	15.9581	1.8888
	*(1.1605)****	*(0.5163)****	*(0.3127)****
Dummy: Firm Size 25-99	16.5418	15.2089	1.6169
	*(1.2075)****	*(0.5301)****	*(0.3352)***
Dummy: Firm Size 100-999	18.6112	16.3721	1.2418
	*(1.3744)****	*(0.5706)****	*(0.2934)*
Dummy: Firm in Public Sector	2.6752	3.3837	0.7581
	*(0.2207)****	*(0.1512)****	*(0.2015)*
Research & Development Intensity	1.0811	1.1068	1.5171
	(0.0998)	*(0.0590)**	*(0.6298)*
Industry Level Output/1000	1.0004	1.0003	0.9989
	(0.0005)	*(0.0003)*	*(0.0023)*
Net Exports/1000	0.9963	0.9968	0.9913
	(0.0036)	*(0.0020)*	*(0.0142)*
Race: White	1.5951	1.4324	0.9620
	*(0.1786)****	*(0.0855)****	*(0.2350)*
Blinder Index Value: 25	0.5786	0.5582	0.3679
	*(0.1346)***	*(0.0669)****	*(0.4134)*
Blinder Index Value: 26-35	1.4662	1.3195	0.8859
	*(0.2029)****	*(0.0997)****	*(0.4646)*
Blinder Index Value: 36-45	1.4180	1.3449	1.2870
	*(0.1490)****	*(0.0782)****	*(0.5645)*
Blinder Index Value: 46-55	0.9398	0.8114	0.5388
	(0.0860)	*(0.0377)****	*(0.2475)*
Blinder Index Value: 56-65	1.3435	1.3533	0.6446
	*(0.1267)****	*(0.0702)****	*(0.2678)*
Blinder Index Value: 66-75	1.4783	1.3874	0.9657
	*(0.1125)****	*(0.0572)****	*(0.2512)*
Blinder Index Value: 76-85	1.7818	1.5084	1.0964
	*(0.2050)****	*(0.0978)****	*(0.5153)*
Blinder Index Value: 86+	1.0346	0.9918	0.4167
	(0.1146)	*(0.0590)*	*(0.2220)*
Observations		77545	
Log Likelihood		-38420.453	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.17A: Competing Risks Model – TBTC

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.5937	1.4113	1.2731
	*(0.0212)****	*(0.0092)****	*(0.0673)****
Age Squared	0.9945	0.9960	0.9972
	*(0.0002)****	*(0.0001)****	*(0.0007)****
Dummy: Married	1.3565	1.0679	0.5392
	*(0.1004)****	*(0.0418)**	*(0.1718)**
Dummy: Female	1.1601	1.2271	1.4517
	*(0.0923)**	*(0.0543)****	*(0.5002)*
Dummy: Married Females	1.0637	1.0235	1.8557
	(0.0992)	*(0.0517)*	*(0.7322)*
Dependent Children in HH	0.7713	0.9030	1.5627
	*(0.0490)****	*(0.0302)****	*(0.4066)**
Dummy: Females with dependent Children	0.4219	0.5014	0.1842
	*(0.0380)****	*(0.0237)****	*(0.0745)****
Job Tenure	0.0649	1.0459	0.8611
	*(0.0021)****	*(0.0024)****	*(0.0436)*
Dummy: Member of Union	3.2518	3.1857	0.7982
	*(0.2490)****	*(0.1414)****	*(0.3122)*
National Unemployment Rate	0.0075	0.0072	0.5630
	*(0.0002)****	*(0.0001)****	*(0.0838)****
Education: High	0.9156	1.0140	0.9502
	(0.1363)	*(0.0841)*	*(0.6661)*
Education: Medium	0.9139	0.9679	0.6036
	*(0.0445)**	*(0.0246)*	*(0.1306)***
Dummy: Firm Size < 25	13.0024	13.3294	4.9627
	*(0.9583)****	*(0.4613)****	*(1.3695)****
Dummy: Firm Size 25-99	12.8498	12.7131	4.3519
	*(0.9869)****	*(0.4657)****	*(1.3075)****
Dummy: Firm Size 100-999	14.2091	13.6316	2.7808
	*(1.0994)****	*(0.4982)****	*(0.9237)****
Dummy: Firm in Public Sector	1.9983	2.5664	1.6309
	*(0.1772)****	*(0.1240)****	*(0.5925)*
Research & Development Intensity	1.0433	1.0704	1.4625
	(0.0981)	*(0.0568)*	*(0.6086)*
Industry Level Output/1000	1.0003	1.0001	0.9984
	(0.0005)	*(0.0003)*	*(0.0024)*
Net Exports/1000	0.9971	0.9975	0.9976
	(0.0037)	*(0.0021)*	*(0.0149)*
Race: White	1.5803	1.3753	0.7113
	*(0.1885)****	*(0.0863)*	*(0.3177)*
Routine Intensive Job Tasks	0.9665	1.0073	0.8830
	(0.0245)	*(0.0133)*	*(0.1070)*
Non-Routine Abstract Job Tasks	1.0991	1.0709	0.9900
	*(0.0125)****	*(0.0065)****	*(0.0529)*
Non-Routine Manual Job Tasks	0.9636	0.9616	1.0987
	*(0.0170)***	*(0.0090)****	*(0.0838)*
Service Job Tasks	0.9002	0.9260	0.9811
	*(0.0110)****	*(0.0058)****	*(0.0536)*
Observations		64544	
Log Likelihood		-33414.61	

Source: Author's own calculations from the BHPS. Significance Level Key: ****p*<0.01; ***p*<0.05; **p*<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

Table 5.18A: Competing Risks Model – Blinder (2007) Occupation Tradability Index & TBTC

Competing Risks Model	New Job Transition	Current Employer	Unemployment Transition
Age	1.6017	1.4181	1.2778
	*(0.0213)****	*(0.0092)****	*(0.0685)****
Age Squared	0.9944	0.9960	0.9972
	*(0.0002)****	*(0.0001)****	*(0.0007)****
Dummy: Married	1.3540	1.0601	0.5513
	*(0.1005)****	*(0.0417)*	*(0.1731)**
Dummy: Female	1.1044	1.1681	1.3501
	(0.0876)	*(0.0516)****	*(0.4635)*
Dummy: Married Females	1.0650	1.0262	1.7947
	(0.0994)	*(0.0519)*	*(0.7008)*
Dependent Children in HH	0.7637	0.8970	1.5677
	*(0.0486)****	*(0.0302)****	*(0.4154)**
Dummy: Females with dependent Children	0.4296	0.5061	0.1846
	*(0.0387)****	*(0.0239)****	*(0.0755)****
Job Tenure	0.0654	1.0474	0.8624
	*(0.0021)****	*(0.0024)****	*(0.0436)****
Dummy: Member of Union	3.1036	3.0439	0.7900
	*(0.2391)****	*(0.1353)****	*(0.3093)*
National Unemployment Rate	0.0074	0.0071	0.5626
	*(0.0002)****	*(0.0001)****	*(0.0835)****
Education: High	0.9412	1.0530	0.9610
	(0.1403)	*(0.0877)*	*(0.6801)*
Education: Medium	0.9059	0.9637	0.6035
	*(0.0442)***	*(0.0246)*	*(0.1319)***
Dummy: Firm Size < 25	12.7221	12.9896	4.9395
	*(0.9385)****	*(0.4522)****	*(1.3764)****
Dummy: Firm Size 25-99	12.6411	12.3964	4.3580
	*(0.9745)****	*(0.4576)****	*(1.3287)****
Dummy: Firm Size 100-999	14.2828	13.5257	2.7822
	*(1.1120)****	*(0.4982)****	*(0.9332)****
Dummy: Firm in Public Sector	1.9804	2.5243	1.6842
	*(0.1752)****	*(0.1212)****	*(0.6118)*
Research & Development Intensity	1.0423	1.0659	1.4654
	(0.0979)	*(0.0565)*	*(0.6066)*
Industry Level Output/1000	1.0003	1.0001	0.9985
	(0.0005)	*(0.0003)*	*(0.0024)*
Net Exports/1000	0.9971	0.9977	0.9980
	(0.0037)	*(0.0021)*	*(0.0150)*
Race: White	1.5645	1.3669	0.7071
	*(0.1856)****	*(0.0855)****	*(0.3119)*
Blinder Index Value: 25	0.4960	0.5223	0.2672
	*(0.1216)****	*(0.0670)****	*(0.3179)*
Blinder Index Value: 26-35	1.6064	1.3023	0.7225
	*(0.2666)****	*(0.1199)****	*(0.4809)*
Blinder Index Value: 36-45	1.2395	1.2071	0.9494
	*(0.1419)**	*(0.0734)****	*(0.4352)*
Blinder Index Value: 46-55	0.8629	0.7255	0.2793
	(0.1040)	*(0.0421)****	*(0.2206)*
Blinder Index Value: 56-65	1.2030	1.2018	0.5662
	*(0.1272)**	*(0.0671)****	*(0.2557)*
Blinder Index Value: 66-75	1.2399	1.1916	0.9506
	*(0.1067)****	*(0.0548)*	*(0.3198)*
Blinder Index Value: 76-85	1.3338	1.1528	2.2627
	(0.2620)	*(0.1078)**	*(1.2185)*
Blinder Index Value: 86+	0.9148	0.8878	0.3897
	(0.1118)	*(0.0559)**	*(0.2337)*
Routine Intensive Job Tasks	0.9542	0.9840	0.9454
	*(0.0182)***	*(0.0096)**	*(0.0776)*
Blinder Index Value: 25*Routine Job Tasks	1.1393	1.3400	3.5281
	(0.3657)	*(0.1636)***	*(1.2512)****
Blinder Index Value: 26-35*Routine Job Tasks	0.8690	0.9442	1.1979
	*(0.0617)***	*(0.0352)*	*(0.3079)*
Blinder Index Value: 36-45*Routine Job Tasks	0.9236	0.9710	1.2222
	*(0.0323)***	*(0.0179)*	*(0.1405)**
Blinder Index Value: 46-55*Routine Job Tasks	1.0052	1.0148	0.7734
	(0.0390)	*(0.0173)*	*(0.1923)*
Blinder Index Value: 56-65*Routine Jobs Tasks	0.9900	0.9859	1.0293

	(0.0281)	*(0.0147)*	*(0.1145)*
Blinder Index Value: 66-75*Routine Job Tasks	0.9220	0.9645	1.0374
	*(0.0212)****	*(0.0117)****	*(0.0952)*
Blinder Index Value: 76-85*Routine Job Tasks	0.8574	0.8882	1.3987
	*(0.0525)***	*(0.0258)****	*(0.2365)*
Blinder Index Value: 86+*Routine Job Tasks	0.9735	0.9950	1.1075
	(0.0532)	*(0.0281)*	*(0.2557)*
Observations	64544		
Log Likelihood	-33407.523		

Source: Author's own calculations from the BHPS. Significance Level Key: ***p<0.01; **p<0.05; *p<0.10. Base group relates to the censored spells. Each regression model includes industry, regional and calendar year variables. Robust standard errors are reported in the parentheses. Estimated coefficients are relative risk ratios.

6

Job Security Trends in Britain: 1991-2007

6.1 Introduction

The last two decades has seen vast research on the subject of job security and job stability with one primary goal: to see whether there is evidence of a secular decline in the security and the stability of jobs over time. Research has in part been promoted by media[1] reports posting the following headlines: 'end of a job for life', 'job hopping is now the norm', 'contracts are becoming more common than staff jobs', 'the number of part-time jobs has soared' and 'job flexibility is key to maintaining employment'. One interesting point made by Green (2003) is that concerns about job security were less of a focus during the 1980s. Figure 1, page 4 from Green's (2003) paper [see figure 1.3A from appendix 3, chapter 1 from this thesis for visual details] presents press references to job security and insecurity from 1980-2002 for the U.K. and U.S. From this graph, press references to job security and insecurity during the 1980s amounted to approximately 50-200 references per year for the U.K. However, post 1980, press references to these terms rose from the onset of the early 1990s recession. They reached a peak of approximately 900-1000 press references by 1996. These trends seem puzzling since the unemployment rate reached a peak of approximately 12% by 1984[2], which

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[1] Media references were taken from a news paper article printed by The Guardian Newspaper on August 14th, 1999. This article was written by Patrick Collinson; title of article: "Now and then: Jobs for life still not dead and buried; Anti-union reaction prompted by old-style hard-liners like Red Robbo seemed to signal a thumbs down for security at work as employers gained the upper hand. But, youngsters entering the labour market will find that the myths don't always match the reality". This article was obtained from Nexis UK. This article talks about the myths and realities relating to job stability and job security.

[2] Series MGSX LFS Unemployment rate for U.K. for all aged 16 and over, seasonally adjusted; from the National Statistics Online.

should have heightened workers' concerns about the security of their employment. After 2000, press references stayed close to around 400 references per year with an unemployment rate that had fluctuated between 5-5½% prior to onset of the most recent recession[3].

Concerns about declining job security may relate to a change in the rate of job creation and job destruction over time. Job turnover is a necessary part of innovation and growth if the jobs which are created are more productive than those which are destroyed. This process of creative destruction is necessary for economic prosperity, but unfortunately this process can lead to job reallocations which can lower labour market security for some workers. Labour market security is defined by a trio of measures: (a) job security; (b) the volatility of income within jobs (job stability) and (c) the earnings losses following job displacement between jobs. Labour market security can fall if the rate of job destruction rises over time. The forces that can lead to changes to the job creation and destruction rates over time can be caused by structural shifts in labour demand between firms, industries, occupations and regions.

There is a large empirical literature on job security. Chapter 2 explored the theoretical explanations that could cause job security and labour market security to change over time. This chapter explained that changes in the rates of job creation and destruction could be caused by structural shifts in tastes and technology that could be linked to globalisation. Forces such as offshoring, outward FDI, product market competition, a fall in transportation costs, improvements in telecommunication and technology, the dynamic nature of comparative advantage and reforms to labour market institutions encourage labour market flexibility and raise job turnover rates. From the empirical evidence accompanying this review, I found limited empirical evidence showing these forces have not lowered labour market

[3] Press references have continued to remain high over the last decade. This chapter carried out a simple search on one of the U.K.'s leading broadsheet newspaper's websites – the timesonline.com, looking for the search term 'job cuts' over the period 2000-2010. Results from this search can be viewed from figure 6.3A (appendix 10) shows for the first quarter of 2010 press references from the times-online web search yielded 257 references. For the period 2003-2009 press references averaged approximately 911 references to the search term 'job cuts' per year. The number of references peaked to a high of nearly 900 references in 2004 prior to the onset of the most recent recession.

security in the U.K. The evidence shows these forces have had a small negative impact on the employment and wages levels of workers where this impact has been limited to low-skilled labour. See chapter 2 for further details.

Chapter 3 reviewed the empirical evidence to substantiate if job and labour market security had fallen over the 1970s to the 1990s. Evidence *à la* Gregg & Wadsworth (1995 & 2002) and Gregg *et al.*, (2000) found small declines in elapsed job tenure: they found median elapsed job tenure fell by 10 percent from the late 1970s to the late 1990s. They also found elapsed job tenure shares greater than or equal to 5 years and greater than or equal to 10 years fell by 4-8 percent for men and for women with no dependent children. But these medium and long term job tenure shares for women with dependent children rose from the mid 1980s to the 1990s. These trends have continued from recently published trends by Faggio *et al.*, (2011) for the period 1985 to 2009. Similarly, Burgess & Rees (1996) reported average elapsed job tenure fell for men and for women between 1975 and 1992. And Booth *et al.*, (1999) found job separation hazard rates were higher for recent cohorts of workers than for earlier cohorts over the period 1915 to 1990. But Burgess & Rees (1997 & 1998) found men and women continued to largely have stable and secure employment from the 1970s to the early 1990s. This review concluded there was little evidence showing job security had declined from the 1970s to the 1990s for the U.K.

From the U.S. literature, there is no evidence to support claims for *'the end of life-time jobs'* (Jaeger & Huff Stevens, 1999). There is evidence of stable jobs for workers employed by large corporations and for older and experienced workers over the 1980s and 1990s (Hall, 1982; Farber, 1995; Diebold *et al.*, 1997; Allen *et al.*, 1999; Neumark *et al.*, 1999; and Huff Stevens, 2005). Additionally, evidence *à la* Davis (2008) and by Farber (2009) show job loss rates have not increased from the 1970s to the post 2000 time frame. Other sources of empirical evidence show a decline in the inflow rate into unemployment over the last three decades

(See Elsby *et al.*, 2007 and Fujita & Ramey, 2006 for the evidence). And, the empirical evidence for the other components of labour market security, namely income volatility within jobs and the earnings losses following job displacement between jobs, show they have not increased over the last three decades to substantiate claims that workers have become worse off.

This chapter contributes to the empirical literature on three fronts. The first contribution clearly defines what is meant by 'job stability' and 'job security'. The empirical literature refers to these terms quite interchangeably without defining precisely what their relation is to the employment relationship. Although the concepts are related to each other, they refer to very different aspects of an employment relationship. This chapter defines job stability and job security as follows: Job stability refers to 'how stable are continuing jobs'. Job stability is likely to depend on wage movements, changes to the number of hours worked, job re-assignments within employment which may or may not result in demotion and affect how stable jobs may be over time. Job security refers to, 'how long do jobs last' and it reflects the probability of a job ending. The security of an employment spell is dependent upon the exit-type from the employer, where the exit can be voluntary (worker initiated job separation or quit) or non-voluntary (firm initiated job separation, where the exit type may be due to plant-closure or redundancies from mass-layoffs). The changes to job security can also vary with the business cycle – the general well-being of the economy as well as business conditions. There is a sense of job security during good times, where voluntary quits dominate layoffs than during bad times where firm-initiated job separations dominate quits.

To assess if there has been any change to job security over time, the empirical literature has typically looked at the length of elapsed job tenure and job retention probabilities at similar points along the business cycle at different points in time. For the second contribution, I measure elapsed job tenure by utilising the methodology employed by Gregg & Wadsworth

(2002). Their analysis assessed job security from 1975 to 2000 by measuring the duration of uncompleted employment spells based on two measures: (1) median elapsed job tenure and (2) the proportion of job tenure shares in three specific job tenure bands: these are short, medium and long-term job tenure shares over time. This chapter uses these measures of elapsed job tenure to extend their analysis period by using the Quarterly Labour Force Survey (QLFS) and the British Household Panel Survey (BHPS) for the period 1991-2006.

For the third contribution, I explore the trends from three job transition states. These job transition states are (a) job-to-job transitions, (b) job-to-unemployment transitions and (c) job-to-inactivity transitions. These are annual job transitions from year $t-1$ to year t. This third contribution has two aims. First, they are an alternative measure for job security as they explore the types of job transitions workers can make over time in comparison to elapsed job tenure. Changes to elapsed job tenure simply tells us whether it is increasing or falling over time only; it does not tell us why job tenure has increased or fallen over time. This alternative measure is able to examine if job security is changing over time because more workers are making new job transitions to new employers, becoming unemployed, starting up their own business or leaving the labour force altogether in time period t. Secondly, by exploring job-to-unemployment 'EU' transitions, it enables one to establish whether the probability of becoming unemployed is rising over time. The British empirical literature has so far measured job security by exploring the changes from various job tenure shares. There are no papers to my knowledge that have explored the changes from job transitions as an alternative measure for job security. Although this chapter is not able to distinguish between voluntary and non-voluntary forms of job separations directly, there are questions within the BHPS and the QLFS surveys that allow one to distinguish whether job separations are due to firm closure or through layoffs.

Thus, the aim of this chapter is threefold. The first step has established definitions for job stability and job security. The second step is to try and obtain consistent estimates for median elapsed job tenure and the share of job tenure proportions in specific job tenure bands that are consistent for comparable periods of analysis using the methodology employed by Gregg & Wadsworth (2002) (methodology outline is in section 6.2). This chapter will provide own estimates of elapsed job tenure (presented in section 6.3), to analyse evidence for the post 1990 period and to establish whether there have been continued changes to job security and whether this may constitute a change over time in relation to the results from Gregg & Wadsworth's (2002) paper. The third contribution examines the trends from three job transitions states (section 6.4). Section 6.5 provides a brief discussion of the findings, and section 6.6 provides the concluding comments.

6.2 Data & Methodology

This chapter uses the Quarterly Labour Force Survey (QLFS) and the British Household Panel Survey (BHPS) to explore job security trends in Britain. The QLFS was first carried out from the spring quarter of 1992 onwards. This survey consists of a rolling panel of 60,000 households, where respondents are observed over five consecutive quarters[4]. The BHPS is a nationally representative annual survey, carried out by the Institute for Social and Economic Research (ISER) at the University of Essex. The survey interviews each adult member of a nationally representative sample of more than 5,000 private households (with a total of approximately 10,000 individual interviews) randomly selected south of the Caledonian Canal. The first wave of the BHPS was conducted during the autumn of 1991, and annually thereafter (Taylor, 2007)[5].

[4] Further details relating to the background and information about the QLFS can be found on the ONS website at the following link: http://www.statistics.gov.uk/statbase/Product.asp?vlnk=1537 .

[5] There have been three additional sub-samples added to the BHPS. The first was from wave 7, where the BHPS began providing data for the United Kingdom European Community Household Panel (ECHP). The ECHP ceased at the end of 2001 (or wave 11 of

Authors Burgess & Rees (1996, 1997 & 1998) have used the General Household Survey (GHS) to measure elapsed job tenure trends and Gregg & Wadsworth (1995, 2000 & 2002) have used the British Labour Force Survey (LFS), the QLFS and the GHS to reconcile the estimates for elapsed job tenure over time. Both of these data sets provide data from the late 1970s to the early 1990s. Yet, the literature has failed to reconcile job tenure estimates from the BHPS. Primarily this may be because the BHPS commenced in 1991 and thus this survey does not provide sufficient data of comparable length to compare estimates with the LFS or with the GHS. As my research explores the changes to elapsed job tenure post 1990 and not from the 1970s, I am able to utilise the BHPS for this task. I make use of the QLFS data in addition to the BHPS for two reasons. First, as I am replicating Gregg & Wadsworth's (2002) paper by using their methodology; I want to compare my estimates of elapsed job tenure with their estimates over comparable periods. And, secondly, I want to reconcile the estimates from the BHPS with the QLFS over the post 1990 period.

Gregg & Wadsworth's (2002) sample is based on employees and the continuously self-employed. Their sample is restricted to men aged 16-64 years and females aged 16-59 years. Their analysis uses questions from the annual Labour Force Survey (LFS) and the QLFS. Following Gregg & Wadsworth's (2002) estimation strategy, the first step is to identify the questions used from the QLFS, to construct this chapter's measure for elapsed job tenure. The question utilised by Gregg & Wadsworth (2002) to carry out much of their analysis from the LFS involves the variable named: *'EMPLEN'*. This variable is defined as the, "length of time with current employer or continuously self employed[6]". The coverage of this variable has varied throughout the 1980s, where in 1984 this variable asked for the length of time spent

the BHPS) due to lack of funding. Wave 9 saw the introduction of two additional samples to the BHPS in Scotland and Wales. All members of households recruited at the first wave of the extension samples are treated as original sample members. Finally, at wave 11 a new sample of Northern Ireland, known as the Northern Ireland Household Panel Survey (NIHPS) was added. This chapter's analysis will focus solely on the sample of respondents who first took part in the BHPS from wave 1 onwards; this excludes the sample extensions of the ECHP, Scotland, Wales and Northern Ireland.

6 Regression analysis estimating time trend coefficients based on a sample of 'employees' only as opposed to a sample consisting of 'employees' and the 'continuously self-employed' does not alter the estimated time trend coefficients; there are very minor differences between the estimated time trend coefficients between the two samples. These comment based on QLFS data analysis only.

with current employer only. From 1985-1988 this variable consisted of employees and self-employed individuals' reporting the time spent with current employer or continuously self-employed. Finally, from 1989-1991 this variable accounted for all in employment, but no details are provided by the LFS as to what is meant by 'all in employment'.

From the spring quarter of 1992 onwards, the QLFS asks all respondents three questions that can be viewed from appendix 1. These questions relate to the year the individual first started to work continuously for their present employer [question 101]; the year they first started to continuously work as self-employed [question 102] and the month they first started to work in their respective states of employment [question 103]. The first of these two questions lie in a similar vein to the question mentioned by Gregg & Wadsworth (2002), but there is no mention of the third question from appendix 1. This chapter utilises all three questions displayed in appendix 1 to calculate more accurately the number of months respondents have been employed by their current employer/have been continuously self-employed. However, an answer to question 103 [the month when employment with current employer/continuous self employment commenced] is only reported if answers to questions 101 [the year the individual first started working for their employer] or 102 [the year the individual started working continuously as self-employed] are reported within an eight year window of the current survey year for respondents' current job/continuous self-employment. For example, if a respondent was to answer these questions during the spring quarter of 1992, an answer to question 103 is only reported if the year reported for questions 101 or 102 is stated to be after 1984 onwards. An answer for the month [question 103] is coded to not apply to respondents if during the 1992 questionnaire, they report starting work with their current employer or working as continuously self-employed before 1984. Therefore, to estimate precisely the number months respondents' have worked for their current employer/continuously self-employed requires identifying those respondents who lie within and up to the 8 year reporting period for an answer to question 103 to be identified and used.

In addition to the first method, a second method is employed to calculate the number months worked by those individuals who have worked for their current employer/worked continuously self-employed before 1984 in the example. I assume the current month of employment/self-employment is January rather than assigning any arbitrary value from one to twelve. Therefore, this second method of identification is a little inaccurate due to rounding of reported months and years worked by respondents.

There are differences between the QLFS and the BHPS surveys in relation to the questions that are asked to respondents eliciting information about time spent in present employment. The QLFS questions ask respondents when they first started to work for their *current employer/working as continuously self-employed*. The BHPS[7] asks respondents how long they have been working in their *present position* of employment. To obtain consistent data for spells of employment experienced by the respondents in present employment with their current employer, I make use of job history data to identify these spells. A similar procedure to calculate accurate job tenure data is reported by Dustmann & Pereira (2008)[8].

6.2.1 Calculation of Elapsed Job Tenure: Median & Sample Proportions

The first step is to calculate median elapsed job tenure. Gregg & Wadsworth (2002) estimate median job tenure rather than mean job tenure because the raw data on job tenure from the GHS and LFS is reported in discrete bands. The authors' report these discrete job tenure bands are not consistent over time and therefore this influences much of their work. Thus, due to the discrete nature of the data, they do not calculate mean elapsed job tenure because

[7] Appendix 2 provides details of the questions that are asked by the BHPS survey relating to time spent in present position of employment.

[8] Dustmann & Pereira (2008) calculate job tenure as an explanatory variable to explore wage growth trends using the BHPS.

this would require making an assumption about the form for the maximum value for the open upper band of the job tenure groups. Instead they choose to estimate median job tenure and the share of elapsed job tenure specific to one of three bands. Although there are continuous job tenure data available from the QLFS and the BHPS from 1991 to 2006, I choose to estimate median elapsed job tenure and the share of job tenure in specific bands for two reasons. First, I want to reconcile my calculations of median job tenure with Gregg & Wadsworth's (2002) estimates over comparable periods. And second, I do not calculate average job tenure because there are potential problems with the accuracy of the reported job tenure data noted in the last section[9].

To estimate median elapsed job tenure, the first step is to assume there are three job tenure bands[10]: These are (1) less than five years, (2) five to ten years and (3) ten years or more. The five to ten year job tenure band is used to calculate the median job tenure if the median should lie in this band. If the median lies within this band, a uniform distribution is assumed in that band to calculate the value for each percentile. For example, if 30 percent of the data occupy the job tenure band of five to ten years, then each percentile occupies 2 months (60[11]/30 = 2); if 47 per cent of the sample have job tenure of less than five years, then the median job tenure is 66 months (60 + 3(2) = 66) (Gregg & Wadsworth, 2002).

Much of Gregg & Wadsworth's (2002) assessment of job security are based on analysing the changes to the share of elapsed job tenure from three specific job tenure bands via regression analysis. These three bands are (1) job tenure under one year; (2) job tenure greater than or equal to five years and (3) job tenure greater than or equal to ten years. They use these bands

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[9] For the QLFS data, there is the problem of identifying as accurately as possible the number of years and months workers has continuously worked with their employer. Information on the month respondents started working for present employers is missing if workers have worked for the same employer for more than 8 years. For the BHPS data, there is the issue of identifying job tenure from present employer rather than from the present job position with their current employer. This requires using the job history data.

[10] Note that these job tenure bands differ with respect to bands that are used to examine the changes to the short, medium and long term job tenure shares over time.

[11] Sixty months here refers to 5 years – the lowest number of years of job tenure possible for this job tenure band.

because they do not require any distribution assumptions to be made about each job tenure band unlike to calculate the median. The proportion of workers with job tenure under one year is taken to be a measure of the share of new jobs. This represents the sum of new hires from the creation of new vacancies and from firm relocations and worker replacements. They also examine the proportion of job tenure shares of five years and ten years or more because average job tenure depends on the share of new jobs and the stability of existing jobs. These job tenure bands allow one to explore secular changes in job security with the aim of looking at the changes in these three conditional job tenure shares over time (Farber, 1995; Burgess & Rees, 1998). These categories enable one to examine whether job turnover has grown over time with a rise in the share of job tenure less than one year or whether the fraction of workers with job tenure of five or ten years or more has fallen over time.

6.2.2 The Exploration of Job Tenure via Regressions Analysis

Job tenure shares from three specific bands are explored via regression analysis to explore the secular changes in more detail. The regression analysis is carried out in two stages:

First Stage

$$\Pr(Tenure = 1 | X, Y, Z, Year)_{i,j,t} = \beta_1 X_{i,j,t} + \beta_2 Y_{i,j,t} + \beta_3 Z_{i,j,t} + \beta_4 Year + \varepsilon_{i,j,t} \qquad (1)$$

Equation (1) is estimated at the first stage for individual i, employed within industry j at time t. This stage requires each cross section of each data set to be pooled together to estimate the probability of belonging to the three job tenure bands, conditional upon a set of year dummy variables and a set of control variables. From equation (1), Tenure is a dummy variable equal to one if elapsed job tenure is (a) less than one year; (b) greater than or equal to five years and (c) greater than or equal to 10 years. For each of the job tenure bands, probit regression models are estimated.

Each regression includes control variables for the composition of the workforce and other socio-economic variables that could influence the job tenure shares over time. These control variables are: **Individual Controls** ($X_{i,j,t}$) consisting of age, educational attainment, children, marital status and regional dummy variables; **Job Control I** ($Y_{i,j,t}$) consists of variables measuring part-time jobs, self-employment and five broad industry groupings. **Job Control II** ($Z_{i,j,t}$)[12] examine the effects on short-term job tenure shares (job tenure <1 year); these variables are temporary working and government schemes. These variables are used to capture the possible differential ability of firms to release workers across time. **Year** represents a series of calendar year dummy variables for each cross section of data used for estimation. Finally, ε is the error term.

For the first stage regressions, the probability of having a job for five years or more is estimated on a sample aged 25 years and over and the probability of having a job for ten years or more is estimated from a sample aged 30 years and over. These restrictions are placed on these job tenure shares because it is not feasible for an individual who is aged 18 years to have had job tenure for five or even ten years. These age restrictions will prevent these individuals from entering these regressions[13].

Second Stage

$$\widehat{me} = \beta_0 + \beta_1 Cycle_t + \beta_2 Time_t + \varepsilon_t \qquad (2)$$

For the second stage of the estimation strategy, equation (2) is estimated where the cycle accounts for the economic environment and Time represents a linear time-trend. The aim from this second stage of estimation is to obtain estimates from the *'Time'* coefficient. This

[12] This paper excludes individuals on government schemes; Job Control II is therefore defined by this paper as temporary working only.

[13] Initial first stage regressions were estimated without any age restrictions placed on job tenure shares >=5 years and tenure shares >=10 years. The results obtained from this first stage were then utilised in the second stage regression analysis which yielded strange results in comparison to the Gregg & Wadsworth's (2002) results if these restrictions are not placed. These results are not presented.

coefficient will provide the per-year trend changes for each of the job tenure shares from the specific bands over the sample period. This is achieved through following a similar estimation strategy pursued by Jaeger & Huff Stevens (1999)[14] for the U.S. This estimation strategy takes the marginal effects ($\widehat{me}$) which are evaluated around the sample mean of the dependent variable[15] for each of the calendar year dummy variables from the first stage. They are then regressed onto a linear time-trend and a cyclical control variable from the second stage (estimation is via OLS). Gregg & Wadsworth (2002) use the vacancy-employment rate as their cyclical measure for the share of short-term job share (tenure < 1 year)[16], the employment-population rate as their cyclical measure for medium term job share (tenure shares >= 5 years) and the unemployment rate as their cyclical measure for long-term job share (tenure shares >= 10 years) regressions[17,18]. I make use of the same cyclical control variables for this chapter. The year estimates effectively measure sample year average proportions and they may be subject to heteroskedasticity when pooled. In accordance with the estimation strategy pursued by Gregg & Wadsworth (2002), the standard errors from the second stage regressions are bootstrapped and the standard errors from these estimates are reported from these repetitions. Maddala (1999) recommends this strategy when faced with heteroskedasticity in small samples. The reported standard errors come from 500 repetitions.

[14] For the first stage regressions, they estimate logit models for the probability of having employer tenure of less than 1 year and having employer tenure less than 10 years with control variables: age, age squared, race, education and calendar year variables. The calendar year coefficients are used to calculate year-specific probabilities. From the second stage of their regression analysis, the year probabilities are regressed on a linear time-trend using ordinary least squares; but no attempt is made to control for cyclical fluctuation. Due to the error term being heteroskedastic in the second stage regression, they estimate via jacknife heteroskedasticity-consistent standard errors in their results tables.

[15] Jaeger & Huff Stevens (1999) evaluate the logit function at the observed mean of the other covariates; this paper evaluates the marginal effects at the mean of the independent variables.

[16] Please refer to Appendix 3 for a note on these second stage regressions for short term job tenure shares.

[17] Alternative specifications were estimated for second stage regressions. It was further investigated whether the use of the same cyclical control variables for the different job tenure shares at the second stage had a similar impact on the estimated time-trend coefficients compared to using three different cyclical control variables. Appendix 4 provides the details for this robustness check.

[18] Appendix 9 provides the details for the data sources that are used to construct these cyclical control variables.

6.3 Results: Job Tenure

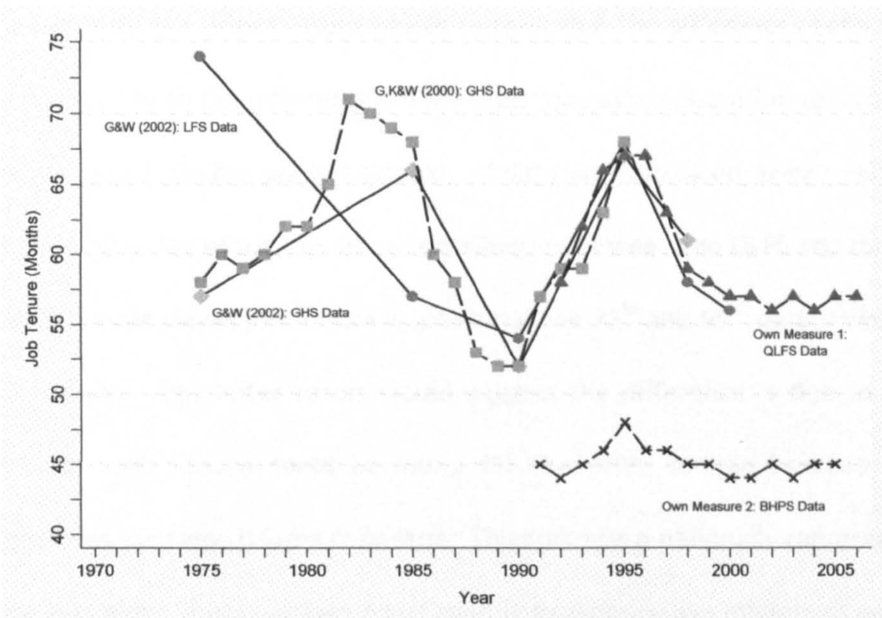
This section presents various results from the analysis of job tenure for job security. Section 6.3.1 examines trends from median job tenure and the shares of tenure proportions from three bands at the aggregate level and at the disaggregate level by gender and by presence of children. Section 6.3.2 will present results from the multivariate regression analysis where the estimated time-trend coefficients try to establish whether there has been a secular decline in job security over the period 1991 to 2006.

6.3.1 The Analysis of Job Tenure Trends

Tables 6.1A to 6.5A present the calculations of median job tenure and sample proportion from the QLFS and BHPS; these tables can be viewed in appendix 5 from this chapter. The results from these calculations have been plotted by figures 6.1 to 6.6. These graphs have two purposes: the first is to compare my calculations with that of Gregg & Wadsworth's (2002) measures and the second is to view the trends for job tenure beyond the sample of Gregg & Wadsworth's (2002) analysis period.

Figure 6.1 presents comparisons of median job tenure trends for the aggregate sample. This figure presents the published trends from Gregg & Wadsworth (2002) and from an earlier study by Gregg *et al.,* (2000). This chapter's calculations of median job tenure are presented by Own Measure 1 (QLFS data) and Own Measure 2 (BHPS data). Figure 6.1 shows own measure 1 (QLFS data) has similar cyclical variations and movements to the findings from the empirical literature. However, calculations from own measure 2 (BHPS data) shows a large difference between the results. Comparing own measure 2 with own measure 1, the gap is almost 15 months at 1995 between the two trends.

Figure 6.1: Comparison of Median Job Tenure



Note: Figure compiled by the author.

The differences between these results could be due to two reasons: (1) the two surveys use different questions to obtain information on job tenure. The QLFS asks respondents the period of time they have worked for their <u>*current employer*</u>. The BHPS on the other hand asks respondents the time they have spent in their <u>*current position*</u> regardless of whether this time has been spent with a current or new employer. And (2), the difference could be due to the samples of data: the BHPS aims to follow the same respondents over time, whilst the QLFS only follows respondents for five consecutive quarters.

To explore whether these explanations account for the differences, figure 6.2A (Appendix 8) plots the imputed median job tenure for workers and the continuously self-employed from both data sets. This graph shows the trends for median elapsed job tenure are quite similar over the time frame and the big gap observed in figure 6.1 is not as big but at most 4 months from figure 6.2A. Table 6.16A in appendix 8 further examines whether the differences is related to the questions or with the pooled samples of data. The results from table 6.16A presents job tenure in months for the 25th, the 50th, the 75th and the 99th percentiles from cross sections of data for years 1992, 1996, 2002 and 2005. The results from this table show from each of the percentiles over each year of data, there is little difference in job tenure between the two surveys. These results would suggest that the differences between the two samples are not related to the differences in the questions asked about job tenure. However, when the percentiles from the pooled samples of data are calculated, they reveal a greater difference in the upper tail of the job tenure distribution between the QLFS and the BHPS data sets. The QLFS sample shows job tenure is greater at the 75th and 99th percentiles compared to the BHPS sample. This latter result would suggest the difference is due to the pooled samples of data. Job tenure could be lower for the BHPS sample because this survey essentially observes the same people over time. This survey is a nationally representative, and as the sample gets older, these workers consequently experience less job moves and approach retirement from the labour market, which would mean they are no long observed in the labour market.

Returning back to figure 6.1, the U.K. experienced a recession over the early 1990s, where median job tenure was at most 53 months (4 years and 5 months) in 1990. After the early 1990s recession, all median job tenure measures from the literature and from own measure 1 peaked at 68 months in 1995. Post 1995, median job tenure declined, where there has been no apparent trend after year 2000. These trends indicate median job tenure has remained stable over the post 2000 time frame. For the period 1992-2006, calculations from own measure 1 (based upon calculations displayed within table 6.1A – Appendix 5) show median job tenure fell by 1 month or 1.72%. In 1992 median job tenure was 58 months (4 years, 10 months), this rose to a peak of 5 years, 7 months in 1996 (this represents a rise in median job tenure of 15.5%). From 1996 to 2006, median job tenure steadily declined by approximately 15%. From the BHPS data, own measure 2 shows for the period 1991-2005, there was no change to median job tenure; it has remained at 3 years and 9 months in 1991 and in 2005. Median job tenure reached a peak of 4 years by 1995 (a rise of 3 months from 1991) but median job tenure gradually declined back to 3 years and 9 months by 2005. Overall, the median job tenure trends from the aggregate sample analysis reveals that they are counter cyclical to the business cycle, which makes it difficult to judge whether secular changes have taken place over time. But figure 6.1 does illustrate the median job tenure trends have remained stable post year 2000 where economic conditions have been favourable.

If job security has remained stable since year 2000, why is it that press references have remained high since 1995 and have continued to grow after year 2000? To answer this question, the first point to note is whether there is evidence that workers have felt insecure about their jobs over the last decade – the answer is in some respects yes. A publication from a survey conducted by Right Management Consultants, reported on by the BBC[19] back in 2005 reported U.K. employees topped a job insecurity table. Workers from the U.K. reported the lowest sense of job security out of employees from eighteen of the world's leading economies that were surveyed as part of the research. Thus, workers feel insecure even though the unemployment rate and job security as measured by median job tenure has remained stable. Part of this reason could relate to the high rates of job creation and destruction which can lead to high job turnover rates. Recent job creation and destruction estimates from Hijzen *et al.*, (2007) show roughly 15 percent of jobs are destroyed annually and roughly 15 percent of newly created jobs come into being. Figure 6.8A in appendix 13 plots the rates of job creation and destruction from Hijzen *et al.*, (2007) for the U.K. This graph shows job creation rates were higher than the rate of job destruction from 1998 to 2002. But post 2002, the job destruction rates have been higher than the job creation rates. This can lead to higher job turnover rates and this could be one of the reasons why workers continue to feel insecure about their jobs.

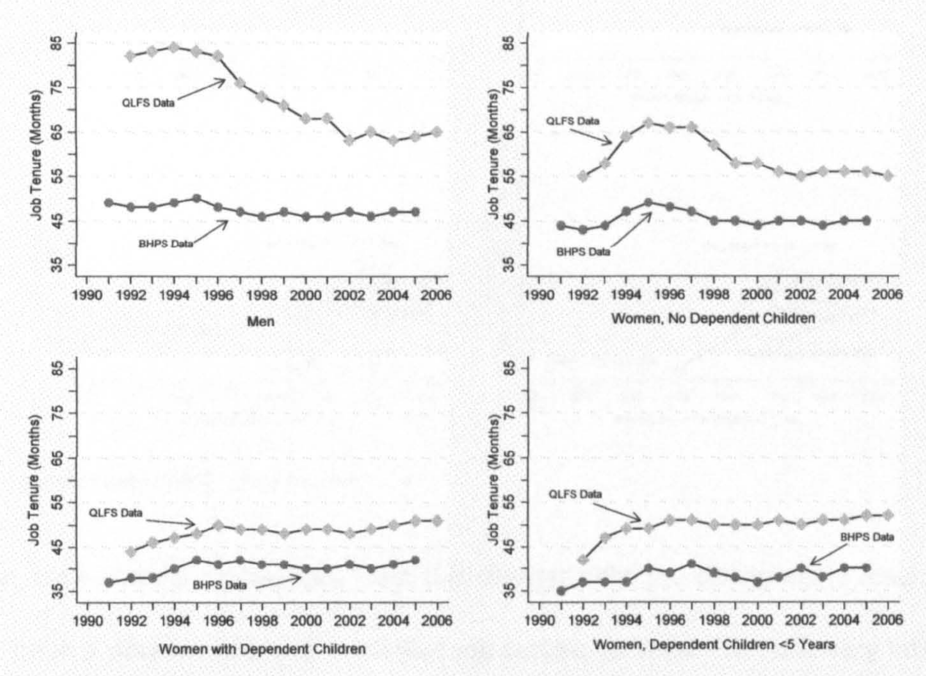
[19] Press reference to this article can be obtained from the following link: http://news.bbc.co.uk/1/hi/business/4443406.stm.

Figure 6.2 presents the median job tenure trends by gender and by presence of children (the calculation for each graph can be viewed from tables 6.2A – 6.5A for the QLFS and BHPS data respectively in Appendix 5). The first point to note is that the median job tenure trends from the QLFS are much higher compared to the BHPS. For men, there has been a gradual decline in median job tenure from the QLFS data; median job tenure was at most 85 months in 1995 and after 2001 median job tenure remained stable at 65 months. From the BHPS data, there has been a very modest decline for men. Median job tenure fluctuated between 45-50 months over the sample with there being an overall decline of only 2 months over the 15 year sample period.

For women with no children, median job tenure rose during the early half of the 1990s to approximately 66 months, but declined to around 55 months by 2000. This is where median job tenure has remained stable over the latter half of the sample for the QLFS data. For women with no children, the results from the BHPS data show less of a trend, but they follow the same overall trend depicted by the QLFS data. These trends show median job tenure rose slightly during the mid 1990s to approximately 47 months. From 1998 onwards, median job tenure remained steady at approximately 45 months. Over the sample, median job tenure rose by one month.

For women with dependent children and women with children under the age of 5 years, median job tenure trends from both data sets have increased over time. For women with children, median job tenure rose by seven months from the QLFS data and by five months from BHPS data. For women with children under the age of five years, estimates show a rise of ten months and five months from the QLFS and BHPS data sets. One interesting observation from these plots is that for all women, whether they have or do not have children, the median job tenure trends from both data sets are closer to each other. For men, these very same trends differ greatly, where this difference between the two data sets is greater during the early 1990s. This gap between each data set narrows over time, but the gap between each data set remains at most 10 months over the 2000 periods for women with no children and for women who have dependent children.

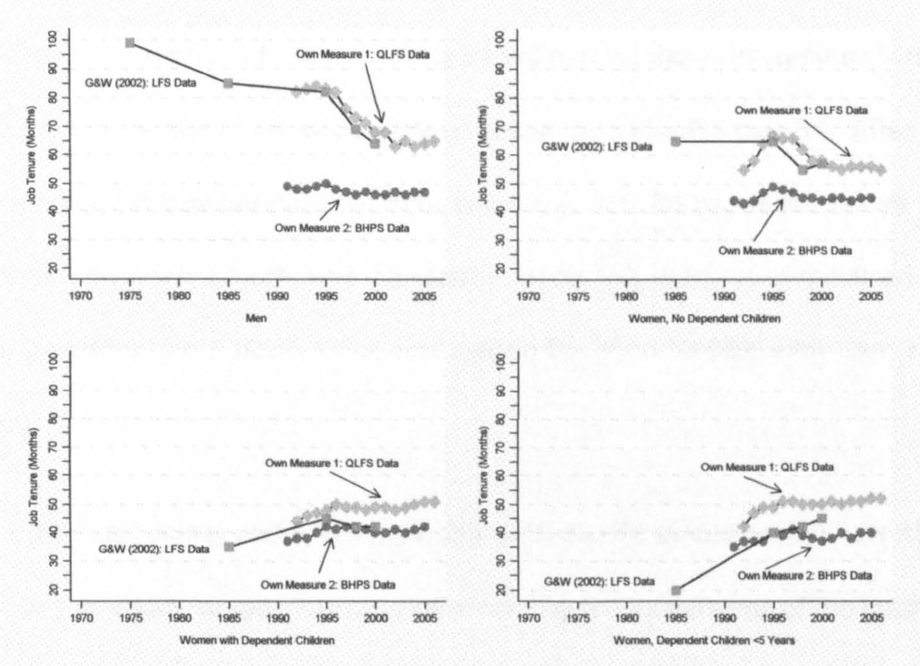
Figure 6.2: Comparison of Median Job Tenure by Gender & Presence of Children



Source: Figure compiled by the author.

Figure 6.3 compares the median job tenure trends from this chapter with those from Gregg & Wadsworth's (2002) paper. For men and for women with no dependent children, the trends published by Gregg & Wadsworth (2002) follow similar trends to the calculations from own measure 1. For women with children and for women with children under the age of five years, differences exist between the QLFS calculations. This chapter's calculations are bigger, whereas the calculations from Gregg & Wadsworth (2002) lie in closer proximity with the BHPS calculations (own measure 2). These graphs illustrate a downward trend in median job tenure for men from Gregg & Wadsworth's (2002) calculations and from own measure 1. These graphs also show: a downward trend in median job tenure for women with no dependent children and an upward trend in median job tenure for women with dependent children and with children under the age of five years.

Figure 6.3: Comparison of Median Job Tenure by Gender & Presence of Children with G & W (2002)



Source: Figure compiled by the author.

To sum up, based on the calculations from this chapter only, the disaggregate results suggest there has been a downward trend in median job tenure for men. There is very little change for women with no children and rising median job tenure for women with dependent children and for women with children under the age of five years. After year 2000, there has been very little change to median job tenure for all groups. These plots confirm the aggregate trends from figure 6.1.

6.3.2 Job Tenure Proportions in Specific Tenure Bands

Figure 6.4 presents aggregate sample plots for job tenure shares <1 year and >=5 years. These plots compare this chapter's calculations to those presented by Gregg & Wadsworth (2002)[20]. These estimates relate to the calculations from the raw data.

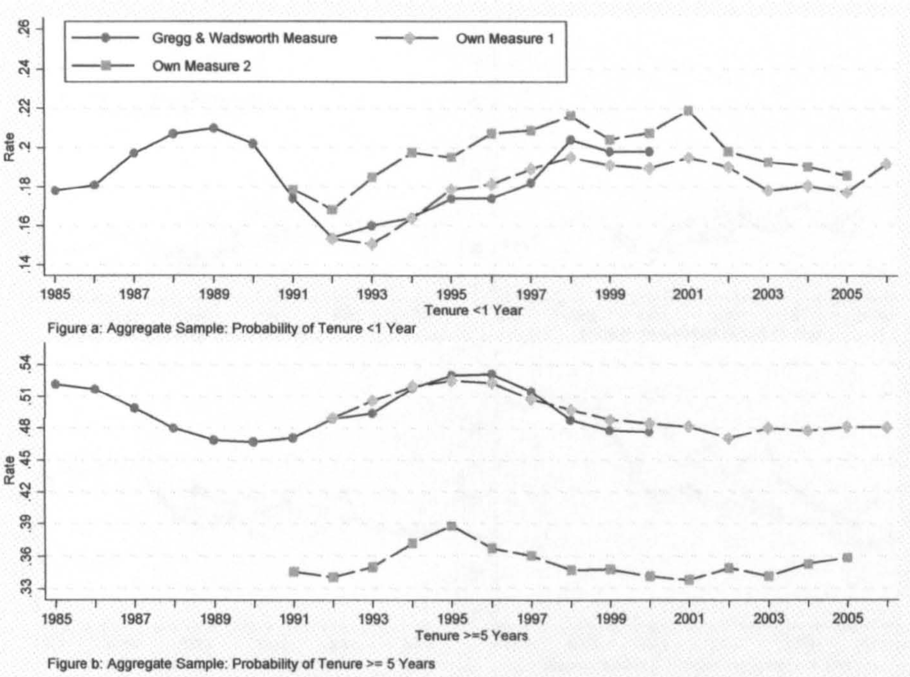
[20] There are plots for job tenure shares <1 year and >=5 years but there is no plot comparing the trends from job tenure shares >=10 years. This is because Gregg & Wadsworth (2002) do not provide a graph or sufficient data for a comparison to be made with data from this chapter. Therefore, I have chosen not to plot this data.

The trends from Gregg & Wadsworth's (2002) paper show during the latter part of the 1980s, job tenure shares under one year were rising and job tenure shares >=5 years were declining. Post 1990 the U.K. experienced a recession, figure 6.4 part (a) shows job tenure shares <1 year falling and job tenure shares >=5 years rising as shown by figure 6.4 part (b). After 1995, the U.K. experienced a steady period of growth, figure 6.4, part (a) shows job tenure shares <1 year fluctuated between 18-22% and job tenure shares >=5 years have remained steady at 48% from Own Measure 1 (QLFS Data) and ranged between 33-36% with Own Measure 2 (BHPS Data).

Figures 6.2 (median tenure) and 6.4 (sample shares in specific tenure bands) have shown that job tenure as a measure for job security is influenced by the movements of the business cycle. During an economic downturn, the number of individuals quitting their positions of employment is far less then firm-initiated job separations (either through redundancies or plant closure). Therefore, job tenure rises as there are fewer workers with job tenure under one year. However, the converse in true during an economic upturn, where voluntary quits dominates firm initiated layoffs as workers seek better opportunities. Thus on average, job tenure falls as there are a greater proportion of workers with job tenure under one year.

What these graphs demonstrate is median job tenure and job tenure shares in specific tenure bands are not very good measures for job security because their movements are countercyclical to the movements of the business cycle. These trends do not provide a clear picture as to whether there has been a secular rise (decline) for tenure shares <1 year (>=5 years) which would provide some evidence of a decline (rise) in job security (job insecurity) for the U.K. over the post 1990 period.

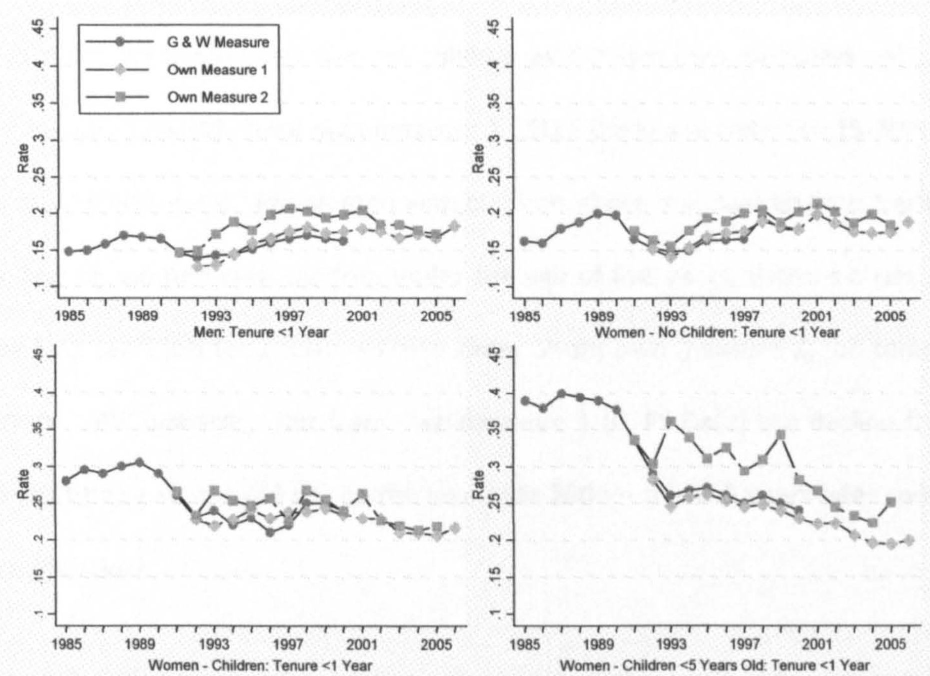
Figure 6.4: Aggregate Sample: Probability of Tenure <1 Year & >=5 Years



Source: Figure compiled by the author. Figures for these graphs are available from appendix 5. These plots relate to the raw data.

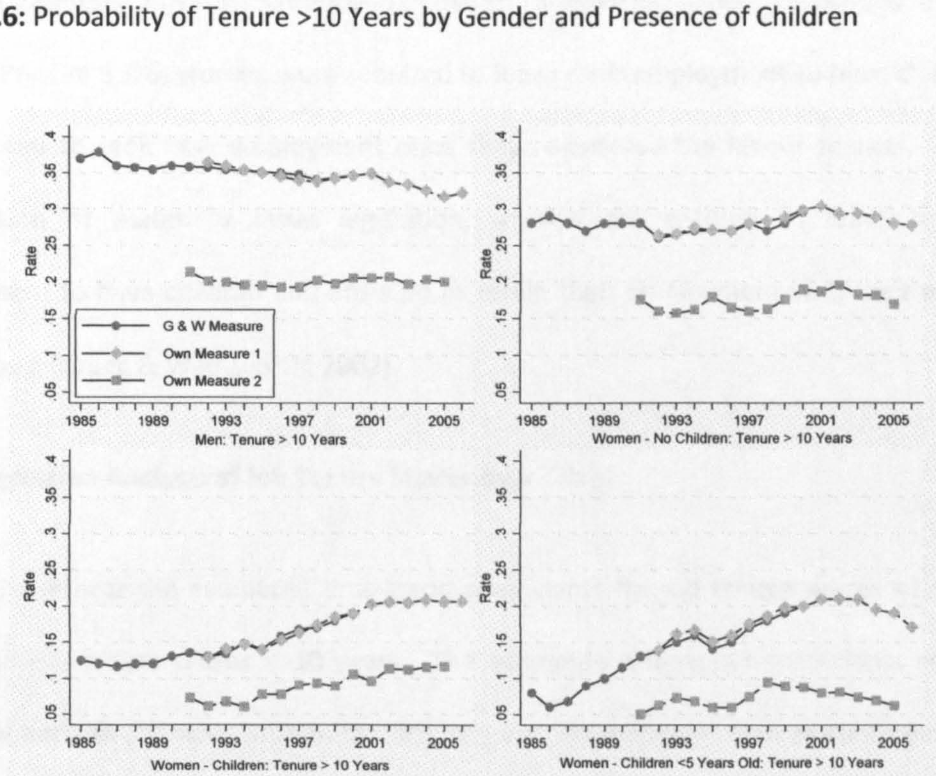
The aggregate job tenure shares may mask different trends across different types of workers, therefore figures 6.5 and 6.6 present job tenure plots for job tenure shares <1 year and >=10 years by gender and by presence of dependent children. Figure 6.5 presents various plots for job tenure shares <1 year. This graph shows there has been a decline in job tenure shares <1 year for women with children and for women with children under the age of five years but there has also been a slight upward trend from these job tenure shares for men and for women with no children.

Figure 6.5: Probability of Tenure <1 Year by Gender and Presence of Children



Source: Figure compiled by the author. These plots relate to the raw data.

Figure 6.6: Probability of Tenure >10 Years by Gender and Presence of Children



Source: Figure compiled by the author. These plots relate to the raw data.

Figure 6.6 shows a gradual decline in job tenure shares >=10 years for men from own measure 1 (QLFS data); but there is very little variation from own measure 2 (BHPS data). There is no evidence of a decline for women with no children as the two own measures appear stable, fluctuating between 25-30% from own measure 1 (QLFS Data) and between 15-20% from the own measure 2 (BHPS data). For women with children, there is a clear upward trend from all measures, but for women with children under the age of five years, there is a rise and a fall from these long-term job tenure shares over time. From own measure 2, job tenure shares declined from 1998 onwards. But from own measure 1 (QLFS Data) the decline from these long-term job tenure shares did not commence until 2004 – this is 6 years later compared to the BHPS calculations.

Part of the explanation for the rise in job tenure shares >=10 years (and 5 years not displayed) and the decline in job tenure shares under one year for women who have dependent children can be accounted for by the introduction of maternity leave legislation, introduced in Britain in 1976[21]. Prior to 1976, women were required to leave their employment to have children and were forced to seek new employment once they re-entered the labour market. With the introduction of maternity leave legislation, women are entitled to leave from their employment to have children and are able to retain their employment with their employers upon return (Gregg & Wadsworth, 2002).

6.3.3 Regression Analysis of Job Tenure Shares over Time

Table 6.1 presents the estimated time-trend coefficients for job tenure shares <1 year, >=5 years and job tenure shares >=10 years. The estimated time-trend coefficients control for individual and job characteristics in the first stage of estimation as well as controlling for the

[21] For details of maternity leave legislation in Britain, Waldfogel (1998) provides details of maternity legislation entitlements in Appendix A, part B of her paper.

business cycle from the second stage of estimation[22]. All estimated coefficients (and robust standard errors) have been multiplied by 100 so that the time-trend coefficients can be interpreted as yearly percentage point changes.

For job tenure shares under one year, the estimated time-trend coefficients from both data sets (from column 1-4) are not significant for the aggregate and disaggregate samples. These results therefore suggest little change over time.

For job tenure shares >=5 years, column (1) provides the results from the QLFS which show significant and negative time-trend coefficients for the total sample, for men and for women with no children. Women with no children have a greater yearly percentage point decline at 0.58% per year (this is an 8.7% decline over the sample period). For men the figure is -0.53% per year (this represents a 7.95% decline over the sample). For the aggregate sample the estimated time-trend coefficient for job tenure shares >=5 years suggest there has been a 0.36 yearly percentage point decline (this is a 5.4% decline over the sample). Results from the BHPS (column 3) show a 0.15 per year percentage point rise for women with children (this amounts to a 2.25% rise over the sample period); whilst medium job tenure shares rose by 0.28 percentage points per year (a 4.2% rise over the sample period) for women with children under the age of five years.

These estimated time trend coefficients indicate that on average for the aggregate sample, the number of workers who have at least five years of job tenure has gradually declined over the period 1992 to 2006. At the disaggregate level, there has been a gradual decline in the

[22] There were a number of regression specifications which explored estimates of time-trend coefficients which controlled for/did not control for the business cycle and for individual and job characteristics at each of the first and second stages of the estimation procedure outlined in section 6.2.2. The previous two sections from this chapter have shown median job tenure and job tenure shares in specific bands are counter-cyclical to the movements of the business cycle; but these trends are also likely to vary with individual and job characteristics. Battu *et al.*, (2002) found certain personal characteristics may allow workers to obtain greater job security through favourable contractual lock-in effects. They report married males are offered favourable contractual arrangements whilst the presences of children or career interruptions offer fewer contractual safeguards. Whilst the type of contract workers are offered is important, this chapter wishes to explore whether jobs have become shorter and hence may not last a life-time without being influenced in anyway by personal characteristics. Appendices 6 and 7 provide the full list of tables and the estimated coefficients for the various regression specifications that were run from the BHPS and QLFS data sets. The estimated coefficients presented in tables 6.1 to 6.4 only report estimated time-trend coefficients which account for individual, jobs and cycle controls.

number men and women with no dependent children who have at least five years job tenure. The estimated time-trend coefficients are small and they suggest a small change to medium term job tenure shares over time. For example, if average job tenure is at most 60 months, then roughly speaking these estimated time-trend coefficients suggest these job tenure shares have declined by approximately 5-10%. This roughly translates to a 3 to 6 month fall in medium job tenure over the period 1992 to 2006.

For job tenure shares >=10 years, estimated time-trend coefficients from the QLFS show a significant decline for the aggregate sample, for men and for women with no children. The estimated coefficients show men experienced a 0.59 per year percentage point decline in long term job tenure shares (this is an 8.85% fall over the sample period). Women with no children experienced a 0.53 yearly percentage point decline (this equates to a 7.95% over the sample period). For the sample as a whole there has been a 0.42 yearly percentage point fall (this a 6.9% decline over the fifteen year sample period). The estimated results from the BHPS (results from column 3) show only women with children have seen a 0.06 yearly percentage point rise in job tenure shares >=10 years. This is a 0.9% rise in their long term job tenure shares over the sample. There are no other significant time-trend coefficients for any other group presented within this table.

These estimated time-trend coefficients suggest that the number of men and women with no dependent children who have job tenure shares greater than or equal to ten years has declined over the sample time frame. For example, if average job tenure is roughly 120 months and these long term job tenure shares have roughly declined by 10% over the period 1992 to 2006, this figure suggests long term job tenure shares have declined by roughly 12 months. For men and for women with no children, these long term job tenure shares have declined by less than 10%, thus they indicate long term job tenure shares have declined by at most 10 months over fifteen years. This is a very small fall in the long term job tenure shares. These results re-affirm the results from figure 6.6.

Table 6.1: Estimated Time Trend Coefficients for Short, Medium & Long Term Tenure Trends

	QLFS Data: 1992-2006		BHPS 1991-2005	
	Individual + Job I + cycle (1)	*Individual + Job II + cycle (2)*	*Individual + Job I + cycle (3)*	*Individual + Job II + cycle (4)*
Tenure <1 Year				
Total	0.14	0.17	0.08	0.17
	(0.25)	*(0.20)*	*(0.28)*	*(0.22)*
Men	0.21	0.22	0.23	0.26
	(0.24)	*(0.19)*	*(0.46)*	*(0.33)*
Women No	0.16	0.20	-0.04	0.03
Children	*(0.25)*	*(0.22)*	*(0.23)*	*(0.23)*
Women with	-0.16	-0.06	-0.09	0.10
Children	*(0.37)*	*(0.34)*	*(0.57)*	*(0.59)*
Women with	-0.45	-0.34	-0.09	0.03
Children <5yrs	*(0.29)*	*(0.30)*	*(1.29)*	*(1.25)*
Tenure >=5 Years				
Total	-0.36	n/a	0.08	n/a
	*(0.14)***	n/a	*(0.10)*	n/a
Men	-0.53	n/a	-0.02	n/a
	*(0.09)****	n/a	*(0.07)*	n/a
Women No	-0.58	n/a	0.12	n/a
Children	*(0.23)***	n/a	*(0.31)*	n/a
Women with	0.19	n/a	0.15	n/a
Children	*(0.16)*	n/a	*(0.08)**	n/a
Women with	0.18	n/a	0.28	n/a
Children <5yrs	*(0.20)*	n/a	*(0.13)***	n/a
Tenure >=10 Years				
Total	-0.42	n/a	0.01	n/a
	*(0.08)****	n/a	*(0.02)*	n/a
Men	-0.59	n/a	-0.05	n/a
	*(0.11)****	n/a	*(0.03)*	n/a
Women No	-0.53	n/a	-0.10	n/a
Children	*(0.07)****	n/a	*(0.10)*	n/a
Women with	0.002	n/a	0.06	n/a
Children	*(0.05)*	n/a	*(0.01)****	n/a
Women with	-0.15	n/a	-0.09	n/a
Children <5yrs	*(0.11)*	n/a	*(0.16)*	n/a

Source: Author's own calculations from the BHPS and QLFS. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Time-trend coefficients and standard errors are multiplied by 100 so the trend can be read as a yearly percentage point change. Bootstrapped standard errors are presented in the parentheses. Please refer to appendices 6 (BHPS estimates – table 6.64A) and 7 (QLFS estimates – table 6.11A) for the full set of estimated coefficients.

6.3.3.1 Education Specific Regressions

Job Tenure Shares <1 Year

The top half of table 6.2 presents the estimated time-trend coefficients from the education specific regressions for the disaggregate sample. The estimated results from the BHPS reveals there are no significant time-trend coefficients for men (column 5) or for women with no children (referred to as WNC from the table - column 6) across all education groups. For women with dependent children, the estimated results show a rise for some education groups; those who have graduate level education (column 7) have seen their job tenure shares <1 year rise by 0.31 yearly percentage points (this represents 4.65% rise over the total sample). Whilst for women with children under the age five years, their estimated time-trend coefficients suggest a 2.32 yearly percentage point decline for graduates (this represents a 34.8% fall for the sample) and a rise of 12.71 percentage points for non-educated women over the period 1993-2005.

The results for men and for women with no children from the QLFS provide no evidence of any change across all education groups. There is also no significant evidence of any change for women with dependent children and for women with children under the age of five years. These estimated results are in line with the trends shown by figure 6.5.

Job Tenure Shares >= 5 Years

The top half of table 6.3 presents the estimated time-trend coefficients from the education specific regressions for job tenure shares >=5 years for men and for women with and without dependent children. The QLFS results show significant and negative time-trend coefficients for men and for women with no children across all education categories. The magnitude of the fall is greater for those with a lower intermediate level of education: There is a 0.71 yearly percentage point decline for men (this is a 10.65% fall over the sample). For women with no children the time-trend coefficient is slightly bigger at 0.78 yearly percentage point decline (this is an 11.7% fall over the sample). For women with children (column 3) there is a significant rise for the no qualification group, accounting for a 0.29 yearly percentage point rise (this is a 4.35% rise over the sample). And for women with children aged under the age of five years (column 4), the estimated coefficient suggests a 0.76 yearly percentage rise for the no education group (this is an 11.4% rise over the sample period).

In contrast to the QLFS results, the estimated coefficients from the BHPS show no clear pattern across the education groups. The results show a 0.41 yearly percentage point decline for men with graduate level education; this is a 6.15% fall over the sample. This estimated time-trend coefficient for men is twice as big as the QLFS result (column 1). From other results, there is a 0.75 (column 5) yearly percentage point rise for men with no education (the QLFS data presents a negative coefficient). There are no significant time-trend coefficients for women with no children. For women with children and for women with children under the age of five years, there have been significant declines for women with graduate level education: a 1.09 yearly percentage point decline for women with children (this is a 16.35% decline over the sample span) whilst for women with children under the age of five years experienced a slightly bigger decline at 1.36 yearly percentage points per year (this is 20.4% fall for the sample span). Women with dependent children (column 7) but with no educational qualifications experienced a 0.76 yearly percentage point rise in job tenure shares >=5 years (or 11.4% rise over the fifteen year period).

Job Tenure Shares >= 10 Years

Finally the top half of table 6.4 presents the estimated time-trend coefficients from the education specific regressions for job tenure shares >=10 years for the sample of men and for women with and without dependent children. For men and for women with no children, the QLFS presents significant and negative time-trend coefficients across all education groups, where the yearly percentage point decline increases in magnitude for those workers with lower education levels. But the results also show a rise for women with children who have lower intermediate or no educational qualifications.

Lower intermediate educated males and females with no children experienced a 0.63 and 0.76 yearly percentage point decline respectively in their long-term job tenure shares (this is a 9.45% and 11.4% fall over the sample). For women who have children with graduate level education and with a lower intermediate level of education, they experienced a 0.25 yearly percentage points fall (this is a 3.75% fall over the sample) and a 0.13 yearly percentage point rise (this is a 1.95% rise over the sample) in their long-term job tenure shares.

Women with children under the age of five years experienced a 0.31 yearly percentage point fall (this is a 4.65% fall over the sample) and a 0.42 yearly percentage point rise (a 6.3% rise over the sample) in their long-term job tenure shares with graduate level and no educational qualifications respectively. It is unclear why women with children who have fewer educational qualifications should have higher long term job tenure shares compared to educated women. One possible explanation could be that women with education may feel they have better prospects of obtaining another job compared to women with fewer qualifications where their chances of obtaining another job will be lower; thus they continue with their existing employment relationships. This explanation may explain the rise in their long-term and medium-term job tenure shares from the QLFS.

The estimated results from the BHPS tell a similar story. For men and women with no children and with graduate level education experienced a 0.27 and 0.12 yearly percentage point declines in their long-term job tenure shares over the sample; these magnitudes are significantly smaller compared to the QLFS results. For women with children, who have graduate level education, they experienced a 0.68 yearly percentage point decline in their long-term job tenure shares; whereas women who have no educational qualifications experienced a 1.39 yearly percentage point rise in their long-term job tenure shares over the sample.

6.3.3.2 Age Specific Regressions

Job Tenure Shares <1 Year

For job tenure shares <1 year, the bottom half of table 6.2 presents no significant time-trend coefficients from the BHPS data for men or for women with no children across all age groups. For women with dependent children (column 7), the 16-24 age group experienced a 2.14 yearly percentage point rise (this represents a 32.1% rise over the sample). For women with dependent children under the age of five years, (column 8), the estimated coefficient is a 5.14 yearly percentage point decline for the 40+ age group (this is a 56.54% fall over the period 1993 to 2003).

The QLFS results show a 0.12 yearly percentage point rise for men aged 25-39 years (this is a 1.8% rise over the sample). There are no other significant time-trend coefficients for women with dependent children. These estimated results provide some evidence for rising job tenure shares under one year for prime aged men and for women with children for the 16 to 24 age group, but a decline for older women with dependent children under the age of five years.

Job Tenure Shares >= 5 Years

For job tenure shares >=5 years, the estimated time-trend coefficients from the bottom half of table 6.3 (column 1) show these job tenure shares have declined over time for men from the QLFS, where the estimated magnitude from the time-trend coefficients is greatest for prime-aged workers. The magnitude decreases for each subsequent age group. For example, men aged 25-39 years experienced a 0.47 yearly percentage point decline (this is 7.05% decline over the sample); men aged 40-49 experienced a 0.40 yearly percentage point decline (this is a 6% fall over the sample) and men aged 50+ years experienced a 0.12 yearly percentage point decline (this is a 1.8% fall over the sample). For women with no children the opposite trend is observed from the results, where the magnitude of the decline from the estimated time-trend coefficients increases with age. The 25-39 age group experienced a 0.61 yearly percentage point decline (this is a 9.15% fall over the sample), whilst the 40-49 age group experienced a 0.72 yearly percentage point decline (this is a 10.8% fall over the sample). For women with children under the age of five years and are aged between 40-49 years, there is evidence of a 0.70 yearly percentage point rise for these medium-term job tenure shares (this is a 10.5% rise over the sample). These results suggest women who have dependent children as they get older are more likely to retain their jobs as they start their families to maintain job security rather than to have lengthy spells out of employment with small children. Whereas men tend to spend more time in employment as they get older and in most cases, men who have dependent children tend to be the bread winners in their families.

From the BHPS results, there are fewer significant coefficients in contrast to the QLFS results. The BHPS results show men aged 40-49 years experienced a 0.36 yearly percentage point rise in job tenure shares >=5 years (this is a 5.4% rise over the sample). Whilst the 50+ age group experienced a 0.27 yearly percentage point decline in their medium-term job tenure shares (this is a 4.05% fall over the sample). For women with no children there are no significant time trend coefficients. For women with children and for women with children under the age of five years, there has been a rise for the 25-39 age group. The estimated time-trend coefficients show a 0.56 and 0.85 yearly percentage rises over the main child-bearing age. This is an 8.4% and 12.75% rise over the sample.

The evidence from the medium job tenure shares show there have been secular declines for men and for women under the age of 50 years, whilst prime-aged and older women with dependent children have experienced a rise over this time frame.

Job Tenure Shares >= 10 Years

The bottom half of table 6.4 presents the estimated results for job tenure shares >=10 years. From the QLFS results, the estimated time-trend coefficients for men are negative and they show the decline in long-term job tenure shares increase with age: The 30-39 age group experienced a 0.84 yearly percentage point decline (this is a 12.6% fall over the sample). For the 40-49 age group, the yearly percentage point decline rises to 0.99 (this is a 14.85% fall over the sample). For women with no children, the estimated time-trend coefficients show job tenure shares have declined over time, where the magnitude of the fall decreases with increasing age. The 30-39 age group experienced a 1.13 yearly percentage point decline (this is a 16.95% fall over the sample). The 40-49 age group experienced a 0.99 yearly percentage point decline (this is a 14.85% fall over the sample) and the 50+ age group experiencing a 0.42 yearly percentage point decline (this is a 6.3% fall over the sample span). For women with dependent children there is a significant rise in long-term job tenure shares for the 50+ age group; there is a half a percentage point rise per year or a 7.05% rise over the sample. There are no significant time-trend coefficients for women with children aged under five years.

From the BHPS data, there is no evidence of any change across the age groups for men or for women with no dependent children. For women with children aged less than 40 years (column 7) there is a very small rise amounting to a 0.08 yearly percentage points (this is a 1.2% rise over the sample). But there is no evidence of significant changes for other groups of workers by age or by presence of dependent children.

The estimated coefficients for job tenure shares >=10 years show men and women with no dependent children experienced a fall in their long-term job tenure shares over the period 1991 to 2006 for workers under the age of 50. Additionally, these long-term job tenure shares have continued to rise for women who have dependent children and for women with children under the age of five years. But these latter results show the estimated time-trend coefficients are smaller in magnitude for the 1991 to 2006 period in comparison to the reported results from Gregg & Wadsworth's (2002) analysis from the mid 1970s to 1998.

Gregg & Wadsworth (2002) conclude from their results that the changing nature of jobs that are offered to workers and changes in the structure of industry may have lead to the decline in the medium and long-term job tenure shares. This may be true if the nature of job contracts offered to new workers entering the workforce has changed over time. For example, if staff contacts were phased out and replaced with flexible job contracts – this could explain the decline in the medium and long-term job tenure shares and a rise in short-term job tenure shares over the mid 1970s to the 1990s. This may also explain why women with dependent children have experienced a smaller rise in their long-term job tenure shares over the post 1990 period. But these explanations are just suppositions as the observed changes to short, medium and long-term job tenure shares have increased and declined over time but they do not provide an explanation as to why these trends have been observed over time. The exploration of job transitions trends from time period $t-1$ to t may provide the answer to this question.

These results may be linked to a rise in job-to-job transitions – that is workers who remain continuously in employment but transition to new employment from one year to the next. Or it could also be the result of a rise in job-to-unemployment transitions over time. These explanations may account for the fall in these medium and longer job tenure shares over time. I would argue that there is more impetus for these explanations for the last two decades as the advancements in technology have enabled many forces associated with globalisation, such offshoring, outward FDI and the dynamic nature of comparative advantage to affect the job creation and destruction rates over time. The reported changes that have been observed to the short, medium and long-term job tenure shares as measures of job security are not able to provide these explanations. Job tenure as a measure for job security simply just tells one that it has increased or declined over time but it does not provide an explanation as to why these changes may have occurred over time. This is one potential sort coming for job tenure as a measure for job security.

The next section examines whether the secular decline in these long and medium job tenure shares and a rise in short term job tenure shares can be explained by a rise in job-to-job or job-to-unemployment transitions as well as other job transition states over time.

Table 6.2: Estimated Time Trend Coefficients from Education & Age Specific Regression for Job Tenure under 1 Year

	QLFS 1992-2006				BHPS 1991-2005			
	Men	WNC	WC	WC5	Men	WNC	WC	WC5
	Individual + Job I + cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job I + cycle (3)*	*Individual + Job I + cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job I + cycle (6)*	*Individual + Job I + cycle (7)*	*Individual + Job I + cycle (8)*
Education								
Graduate	0.22	-0.02	-0.25	-0.25	0.13	0.06	0.31	-2.32$^{\sigma}$
	(0.30)	*(0.60)*	*(0.36)*	*(0.36)*	*(0.90)*	*(0.62)*	*(0.13)***	*(0.92)***
High Intermediate	0.10	-0.18	-0.09	-0.42	0.20	-0.10	0.24	0.47
	(0.22)	*(0.24)*	*(0.27)*	*(0.27)*	*(0.46)*	*(0.33)*	*(0.61)*	*(1.43)*
Low Intermediate	0.26	0.48	-0.09	-0.56	-0.10	-0.09	0.02	0.53
	(0.34)	*(0.33)*	*(0.47)*	*(0.43)*	*(0.70)*	*(0.71)*	*(1.06)*	*(2.16)*
None	0.37	0.52	-0.30	-0.46	0.54	-0.05	-0.90	12.71$^{\beta}$
	(0.32)	*(0.51)*	*(0.79)*	*(1.85)*	*(0.60)*	*(0.36)*	*(3.10)*	*(7.58)**
Age								
Age 16-24	0.40	-0.04	0.10	-0.78	0.40	0.69	2.14	-0.02
	(0.56)	*(0.49)*	*(1.06)*	*(1.05)*	*(0.90)*	*(0.79)*	*(1.06)***	*(1.07)*
Age 25-39	0.12	0.12	-0.07	-0.19	0.11	-0.02	-0.07	0.10
	*(0.05)***	*(0.09)*	*(0.11)*	*(0.16)*	*(0.27)*	*(0.31)*	*(0.23)*	*(0.44)*
Age 40-49	0.08	0.03	-0006	-0.11	0.003	-0.14	-0.09	-5.14$^{\Omega}$
	(0.05)	*(0.04)*	*(0.08)*	*(0.46)*	*(0.09)*	*(0.18)*	*(0.19)*	*(3.02)**
Age 50+	0.009	0.03	n/a	n/a	0.04	-0.01	n/a	n/a
	(0.03)	*(0.03)*	n/a	n/a	*(0.09)*	*(0.07)*	n/a	n/a

Source: Estimates compiled by the author. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Time-trend coefficients and standard errors are multiplied by 100 so the trend can be read as a yearly percentage point change. Bootstrapped standard errors presented in the parentheses. Identification Key: WNC = women with no dependent children; WC = women with dependent children and WC5 = women with dependent children under the age of 5 years. Symbol Key: Ω – regression run for the period 1993-2005; β – regression run for period 1991-2005; σ – regression run for the period 1991-2002; α – Age dummy groups 46-50, 51-55 and 56-59 dropped; the latter two groups dropped out due to collinearity, the former due to year dummy 1992 being dropped. See appendices 6 (BHPS data estimates – tables 6.7A - 6.8A) and 7 (QLFS estimates – tables 6.12A – 6.13A) for the full set of estimated coefficients with different sets of control variables used at the first and second stage of estimation.

Table 6.3: Estimated Time Trend Coefficients from Education & Age Specific Regression for Job Tenure greater than or equal to 5 Years

	QLFS 1992-2006				BHPS 1991-2005			
	Men	WNC	WC	WC5	Men	WNC	WC	WC5
	Individual + Job I + cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job I + cycle (3)*	*Individual + Job I + cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job I + cycle (6)*	*Individual + Job I + cycle (7)*	*Individual + Job I + cycle (8)*
Education								
Graduate	-0.19	-0.28	-0.17	-0.23	-0.41	0.05	-1.09	-1.36
	*(0.05)****	*(0.06)****	*(0.09)**	*(0.20)*	*(0.08)****	*(0.09)*	*(0.22)****	*(0.33)****
High Intermediate	-0.49	-0.72	0.27	0.30	-0.02	0.03	-0.05	0.22
	*(0.10)****	*(0.24)****	*(0.23)*	*(0.30)*	*(0.07)*	*(0.20)*	*(0.04)*	*(0.17)*
Low Intermediate	-0.71	-0.78	0.28	0.39	-0.19	-0.03	0.27	0.43
	*(0.08)****	*(0.32)***	*(0.20)*	*(0.22)**	*(0.14)*	*(0.85)*	*(0.17)*	*(0.35)*
None	-0.43	-0.64	0.29	0.76	0.75	-0.19	0.76	1.07^{σ}
	*(0.15)****	*(0.29)***	*(0.12)***	*(0.15)****	*(0.23)****	*(0.52)*	*(0.17)****	*(3.53)*
Age								
Age 25-39	-0.47	-0.61	0.29	0.30	-0.08	0.22	0.56	0.85
	*(0.19)***	*(0.31)***	*(0.20)*	*(0.29)*	*(0.18)*	*(0.40)*	*(0.18)****	*(0.33)***
Age 40-49	-0.40	-0.72	0.24	0.70	0.36	0.42	0.03	-0.15
	*(0.05)****	*(0.27)****	*(0.23)*	*(0.33)***	*(0.15)***	*(0.43)*	*(0.36)*	*(1.21)*
Age 50+	-0.12	-0.15	0.41	n/a	-0.27	-0.08	0.80	n/a
	*(0.06)**	*(0.10)*	*(0.29)*	n/a	*(0.10)***	*(0.30)*	*(0.87)*	n/a

Source: Estimates compiled by the author. Significance Level: ****p<0.01, **p<0.05* and **p<0.10.* Time-trend coefficients and standard errors are multiplied by 100 so the trend can be read as a yearly percentage point change. Bootstrapped standard errors presented in the parentheses. Identification Key: WNC = women with no dependent children; WC = women with dependent children and WC5 = women with dependent children under the age of 5 years. Symbol Key: Ω – regression run for the period 1993-2003; β– regression run for period 1991-2005; σ– regression run for the period 1991-2002; α– Age dummy groups 46-50, 51-55 and 56-59 dropped; the latter two groups dropped out due to collinearity, the former due to year dummy 1992 being dropped. See appendices 6 (BHPS data estimates – tables 6.9A – 6.10A) and 7 (QLFS estimates – tables 6.14A – 6.15A) for the full set of estimated coefficients with different sets of control variables used at the first and second stage of estimation.

Table 6.4: Estimated Time Trend Coefficients for Education & Age Specific Regression for Job Tenure greater than or equal to 10 Years

	QLFS 1992-2006				BHPS 1991-2005			
	Men	**WNC**	**WC**	**WC5**	**Men**	**WNC**	**WC**	**WC5**
	Individual + Job I + cycle (1)	***Individual + Job I + cycle (2)***	***Individual + Job I + cycle (3)***	***Individual + Job I + cycle (4)***	***Individual + Job I + cycle (5)***	***Individual + Job I + cycle (6)***	***Individual + Job I + cycle (7)***	***Individual + Job I + cycle (8)***
Education								
Graduate	-0.37	-0.36	-0.25	-0.31	-0.27	-0.12	-0.68	-
	*(0.06)****	*(0.06)****	*(0.06)****	*(0.13)***	*(0.04)****	*(0.05)***	*(0.18)****	-
High Intermediate	-0.47	-0.68	-0.13	-0.24	-0.07	-0.10	-0.03	-0.08
	*(0.13)****	*(0.20)****	*(0.13)*	*(0.25)*	*(0.03)***	*(0.16)*	*(0.04)*	*(0.15)*
Low Intermediate	-0.63	-0.76	0.13	-0.13	0.03	-0.11	0.15	0.37
	*(0.12)****	*(0.11)****	*(0.06)***	*(0.15)*	*(0.11)*	*(0.29)*	*(0.08)**	*(0.66)*
None	-0.53	-0.68	0.07	0.42	0.36	-0.52	1.39	-
	*(0.11)****	*(0.17)****	*(0.07)*	*(0.23)**	*(0.25)*	*(0.52)*	*(0.57)***	-
Age								
Age 30-39	-0.84	-1.13	-0.03	-0.20	-0.13	-0.03	0.08	-0.01
	*(0.17)****	*(0.25)****	*(0.04)*	*(0.15)*	*(0.09)*	*(0.06)*	*(0.02)****	*(0.09)*
Age 40-49	-0.99	-0.99	0.11	-0.19	-0.20	0.01	-0.001	-0.78
	*(0.15)****	*(0.13)****	*(0.14)*	*(0.53)*	*(0.13)*	*(0.26)*	*(0.05)*	*(0.69)*
Age 50+	-0.17	-0.42	0.47	n/a	-0.19	-0.25	0.33	n/a
	(0.17)	*(0.16)****	*(0.28)**	n/a	*(0.37)*	*(0.27)*	*(0.27)*	n/a

Source: Estimates compiled by the author. Significance Level: ****p<0.01, **p<0.05* and **p<0.10*. Time-trend coefficients and standard errors are multiplied by 100 so the trend can be read as a yearly percentage point change. Bootstrapped standard errors presented in the parentheses. Identification Key: WNC = women with no dependent children; WC = women with dependent children and WC5 = women with dependent children under the age of 5 years. See appendices 6 (BHPS data estimates – tables 6.9A – 6.10A) and 7 (QLFS estimates – tables 6.14A – 6.15A) for the full set of estimated coefficients with different sets of control variables used at the first and second stage of estimation.

6.4 Job Transition Trends: An Alternative Measure for Job Security

This section of the chapter explores whether the fall in medium and long-term job tenure shares and the rise in short-term job tenure shares noted in the last section can be explained by the type of job transitions that can occur over time. There are four types of job transitions that can be made from year $t-1$ to year t, these are: (1) job-to-job transitions; (2) job-to-unemployment transitions; (3) job-to-non-activity transitions and (4) job-to-self-employment transitions.

This section of analysis has two purposes: First, the type of job transitions made over time is used as an alternative measure for job security in comparison to job tenure. Job tenure as a measure for job security only tells one that it is rising over time – indicating jobs are stable and secure. Or they are falling over time – because workers quit their jobs or because workers were made redundant through mass layoffs/plant closures. These changes to job tenure tell us nothing about why it is rising or falling over time. Second, the job transition analysis examines whether the rise in short-term job tenure and the fall in medium and long-term job tenure shares can be explained by a rise in job-to-job transitions or whether this can be due to a rise in the probability of becoming unemployed (a job-to-unemployment transition) or because of a higher proportion of workers becoming inactive from the labour market.

This chapter explores the changes from three types of job transition states from time period $t-1$ to t; these are: (a) job-to-job (EE) transitions, (b) job-to-unemployment (EU) transitions and (c) job-to-non-activity (EN) transitions. The job-to-job transition (EE) state is further split into two additional groups: the first is *measure (1)*, which explores the proportion of EE transitions that accounts for workers who may be described as job-stayer. These workers continue to remain in employment with their current employer from one year to the next. Job transitions for these workers are identified as having 12 months of job tenure or more and are differentiated from EE transitions as EE1 transitions[23]. *Measure (2)* explores job-to-job transitions for workers who remain in employment but transition to new jobs from one year to the next. These individuals are identified with having less than 12 months of job tenure and are distinguished from EE transitions as EE2 transitions. This further classification of job transition measure 'EE' is important as these measures enable the exploration of whether job-to-job transitions are driven by measure (1) or by measure (2). These measures also enable one to explore whether jobs are continuing to last with current employers (one expects an upward trend for job stayers) but also whether jobs are becoming shorter because there is an upward trend towards remaining in employment but frequently transitioning to new jobs. A point of note here is that these measures are imperfect but they are used to assess job security trends along with job-to-unemployment (EU) transition trends as there is no direct way to identify voluntary or involuntary job separations from the BHPS and QLFS.

6.4.1 Estimation Strategy

To explore the changes to these job transitions states over time, I follow the two step estimation strategy outlined in section 6.2 but with a few minor changes to the first and second stages of the estimation procedure.

First Stage

$$\Pr(ET = 1 \mid X, Y, Year)_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 Y_{i,t} + \beta_3 Year + \varepsilon_{i,t} \qquad (3)$$

For the first stage, equation (3) is estimated for individual i at time t. The data for each year of the sample (that is 1992-2007 for the QLFS and 1991-2005 for the BHPS) are pooled together to identify the changes to each of the job transition states, conditional upon a set of calendar year dummy variables and a set of control variables. Variable ET identifies the job

[23] Exploring job-to-job trends for workers who may be classed as job stayers are not strictly job transitions per se as workers are not moving to other jobs. Hence these trends cannot be strictly described as transitions but rather job stayer trends.

transition state (T) made in period t from period $t-1$ where the individual is in a state of employment (E). The other transition states are: T = E, E1, E2, or U, which were defined above.

Equation (3) includes control variables for the composition of the workforce and other socio-economic factors that could influence the job transitions over time. These control variables are: **Individual Controls** ($X_{i,t}$) consisting of age, educational attainment, children, marital status and regional dummy variables. **Job Controls** ($Y_{i,t}$) consists of 5 broad industry dummy variables only. No attempt is made to control for the occupations that workers are employed by in period t or whether a job is temporary or part-time. This is because job security can change due to task biased technological change. Autor, Levy and Murnane (2003) argue that computer capital may be able to substitute for human labour in job tasks that are routine and repetitive in nature; see the empirical evidence from chapters 2 and 5. Temporary and part-time job characteristics are also factors that may affect job security over time. Therefore, using occupation dummies as controls could inhibit the full extent of the changes made from one job transition state to another. Finally, variable **Year** represents a series of calendar year dummy variables for each cross section of data that is used in estimation.

Equation (3) is estimated via probit specification using the QLFS for the period 1994-2007 and for the BHPS data sample covering 1993-2005. The marginal effects from the calendar year dummy variables are evaluated at the mean of the independent variables.

Second Stage

$$\widehat{me} = \beta_0 + \beta_1 Unemployment_t + \beta_2 Time_t + \varepsilon_t \qquad (4)$$

For the second stage of estimation, equation (4) is estimated. The estimated marginal effects ($\widehat{me}$) from the calendar year dummy variables from equation (3) are regressed (via OLS) onto a linear time-trend (this is variable Time) and the unemployment rate is used to control for the economic environment. Controlling for the cycle is important as this chapter seeks to establish whether there is evidence of a secular rise in job insecurity emanating from changing job transition states over time. The analysis from section 6.3 noted voluntary job separations can be pro-cyclical and involuntary job separations can be counter-cyclical to the movements of the business cycle which could affect the type of job transition that is made over time. Not accounting for the cycle or not utilising control variables may lead to wrong conclusions.

As with the job tenure analysis, the year estimates are effectively sample year average transition estimates and therefore may be subject to heteroskedasticity when pooled. The standard errors from the second stage regression analysis are bootstrapped with robust standard errors reported from these repetitions. The reported standard errors come from 500 repetitions.

6.4.2 Regression Analysis of Job Transition Shares over Time

Tables 6.5a and 6.5b present the estimated time-trend coefficients from the two-stage regression analysis. All estimated coefficients account for individual and job controls from the first stage of estimation and the cycle in the second stage[24]. All estimated coefficients have been multiplied by 100 so that the time-trend coefficients can be interpreted as yearly percentage point changes. They reflect the sample average job transition change per year – this means that if the estimated time-trend coefficient is positive for EU transitions, this implies on average EU transitions have risen by 'X'% per year. Specific job transition regressions are estimated for the aggregate sample, men, and women with and without dependent children, by education and age specific regressions along with specific regression for public and private sector workers.

[24] Due to reasons for brevity, I have not provided a copy of all the estimated time-trend coefficients for each of the job transitions states with the inclusions of different combinations of individual, job and cycle control variables that were estimated with the QLFS and BHPS data sets in this thesis. They can be obtained by requesting a copy from the author. The results from these regressions show the cyclical control variable within the second stage of estimation is important because otherwise the estimated time-trend coefficient would be under-estimated. The inclusion of the control variables in the first stage appears to have negligible effects upon the overall estimated time-trend coefficients.

For the aggregate sample, columns (1) to (3) from table 6.5a presents the time-trend coefficients for three types of job-to-job transitions; these are EE, EE1 and EE2 transitions. They capture the differing degree of employer attachment from period $t-1$ to period t. From column (1), job-to-job transitions declined by 2 percent over the sample time frame (this is a 0.132 per year percentage point fall). Accounting for these trends lies with EE2 transitions (new employment transitions), which declined by 1.206 percentage points per year (this is a 17 percent fall over the period 1994-2007). From EE1 - job stayer transitions show there has been a 0.033 per year percentage point decline (this is a half a percent decline over the sample). These latter time-trend coefficients signify strong worker attachments to current employers and this could explain why job tenure shares of less than one year have not significantly increased over the period 1991 to 2006 – see table 6.1. From column (4), the estimated results for the aggregate sample indicate a 0.060 per year percentage point rise for EU transitions; this is a one percent rise over the sample. There are no significant EN transition trends (column 5).

Overall, these results indicate a negligible decline in job security, but this secular fall is very small over the sample period as a large number of workers have continued to remain with their current employers. The estimated time-trend coefficients also show a decline in the number of workers making new job transitions (EE2) over the time frame. But more importantly these results indicate a very small rise in job-to-unemployment transitions.

At the disaggregate level, the estimated time-trend coefficients for men are similar to the aggregate sample results – which show a decline in job-to-job transitions and a very small rise in EU transitions over time. For women, their estimated EU time-trend coefficient signifies a 0.714% rise over the sample. Additionally, the estimated magnitudes of the EU time-trend coefficients for women with and without dependent children are very similar per year. But, these time-trend coefficients are very small and they imply there is no increasing tendency for women with and without children to become unemployed over time.

Workers employed in highly skilled occupations experienced a 1.72% fall in EE transitions over the sample. Part of this fall is attributed to a half a percentage point fall in job stayer trends with present employers and a one percent point rise in EU and EN transitions over the sample. Low skilled workers are least likely to make new job transitions over time; their estimated time-trend coefficient shows a 17.6% fall in new job transitions (EE2); they are more likely to become unemployed with a 0.84% rise in EU transitions over the sample. This evidence shows that although EU transitions have increased by a percentage point or less over the sample for high and low skilled workers, these time-trend coefficients are very small and they imply that the risk of becoming unemployed has been very small over the period 1994 to 2007. Finally, estimated time-trend coefficients for private sector workers are very small. These workers are less likely to make new job transitions, where the estimated coefficient signifies a 6.23% fall in their job changing (EE2) transitions. This group of workers are also less likely to become unemployed as the estimated EU transition coefficient is close to zero but also insignificant.

The results from the BHPS data show there are no significant coefficients for the aggregate sample. For men and for women with no children and women with children, skill groups, and private sector workers, the estimated time trend-coefficients from columns (1) to (5) also provide few significant coefficients. The lack of significant time-trend coefficients suggests there is no evidence that job security has changed over the period 1991 to 2007.

To sum up, the estimated results from table 6.5a, panel (A) reveal very little evidence to suggest there has been a secular rise in job insecurity over time. There is no evidence to show EE2 transition trends have increased over time and there is also no great tendency for workers to become unemployed over time. But the estimated results do suggest that workers are more likely to remain in employment with their current employers.

From table 6.5b, panel (B) presents the estimated coefficients from the education specific regressions. From the QLFS data, individuals with graduate level education experienced a 2 percent fall (a 0.153 per year percentage point fall) from EE transitions. Workers with lower intermediate level education and workers with no formal qualifications also have negative EE time-trend coefficients, but workers with no qualifications are more likely to transition to unemployment. Their estimated time-trend coefficient is positive and it implies a 0.134 per year percentage point rise – or a 2 per cent rise in EU transitions over the sample. The BHPS estimates from panel (B) provide only two significant coefficients which are different to the QLFS results. These two coefficients show workers with graduate level education are more likely to remain in employment and workers with no educational qualifications are less likely to transition to unemployment.

Finally from table 6.5b, panel (C) presents age specific regressions. The results from the QLFS data show young workers aged 16-24 years are less likely to make new job transitions (EE2); the estimated coefficient implies a decline of 30% over the sample. This group of workers are more likely to experience EU transitions; the estimated coefficient indicates a 4% rise on average over the sample. These results imply that this age group are most likely to experience unemployment as they are new entrants to the labour market where they will not have accumulated the general human capital experiences compared to the other age groups. They are more likely to experience employment changes early on within their careers as these workers try to find a good employer – employee job match. The BHPS results show prime-aged workers (25-39) are less likely to make new job transitions (column (8); the estimated time-trend coefficient implies a 14 per cent decline over the sample). And workers aged 40-49 years are more likely to be in employment, the estimated time-trend coefficient suggests a 0.250 per year percentage point rise in EE transitions or a 3.25% rise over time.

In summary, the results from tables 6.5a and 6.5b yield few significant coefficients. There are few EU time-trend coefficients that are significant and positive; the magnitude from these estimated coefficients are small and they imply a small secular rise in the probability of becoming unemployed. But there is no clear pattern across the education and age groups. If anything, job security appears to have changed very little over time as there is no increasing tendency to become unemployed or to change employers.

Table 6.5a: Estimated Time Trend Coefficients for various Job Transitions States

Sample Category	QLFS Data					BHPS Data				
	EE (1)	EE1 (2)	EE2 (3)	EU (4)	EN (5)	EE (6)	EE1 (7)	EE2 (8)	EU (9)	EN (10)
	Panel (A): Sample Specific Trends									
Aggregate Sample	-0.132	-0.033	-1.206	0.060	0.022	0.098	0.033	-0.506	-0.003	-0.029
	*(0.053)***	*(0.015)***	*(0.509)***	(0.017)***	*(0.027)*	*(0.093)*	*(0.066)*	*(0.615)*	*(0.013)*	*(0.041)*
Men	-0.156	-0.042	-1.440	0.064	-0.007	0.103	0.044	-0.727	-0.009	-0.037
	*(0.039)****	*(0.043)*	*(0.478)****	*(0.034)**	*(0.023)*	*(0.108)*	*(0.062)*	*(0.707)*	*(0.014)*	*(0.030)*
WNC	-0.136	-0.010	-1.061	0.051	0.053	0.126	0.085	-0.497	0.002	-0.050
	(0.094)	*(0.010)*	*(1.087)*	*(0.024)***	*(0.056)*	*(0.138)*	*(0.088)*	*(0.834)*	*(0.021)*	*(0.068)*
Women	-0.112	-0.022	-0.992	0.052	0.013	0.069	0.018	-0.281	-0.008	0.053
	(0.076)	*(0.010)***	*(0.679)*	*(0.011)****	*(0.056)*	*(0.098)*	*(0.089)*	*(0.591)*	*(0.014)*	*(0.083)*
WC	-0.086	-0.035	-0.991	0.052	-0.042	-0.074	-0.115	0.047	-0.027	0.269
	(0.094)	*(0.009)****	*(0.608)*	*(0.030)**	*(0.087)*	*(0.276)*	*(0.230)*	*(1.263)*	*(0.012)***	*(0.202)*
High Skill	-0.123	-0.036	-1.355	0.070	0.070	-0.172	-0.098	-1.033	-0.012	0.039
	*(0.069)**	*(0.016)***	*(0.978)*	(0.025)***	*(0.025)****	*(0.0156)*	*(0.141)*	*(0.607)**	*(0.010)*	*(0.091)*
Medium Skill	-0.156	-0.028	-1.232	0.045	0.055	-0.200	-0.128	-0.781	-0.030	0.158
	(0.100)	*(0.016)**	*(0.691)**	(0.046)	*(0.037)*	*(0.103)**	*(0.130)*	*(0.307)***	*(0.028)*	*(0.087)**
Low Skill	-0.194	-0.018	-1.258	0.061	0.083	0.065	0.043	0.052	-0.038	0.183
	*(0.054)****	*(0.030)*	*(0.515)***	(0.034)*	*(0.060)*	*(0.372)*	*(0.282)*	*(1.084)*	*(0.081)*	*(0.201)*
Public Sector Workers	-	-	-	-	-	-0.058	-0.075	-0.004	-0.013	0.073
	-	-	-	-	-	*(0.122)*	*(0.092)*	*(0.657)*	*(0.019)*	*(0.092)*
Private Sector Workers	-0.072	-0.039	-0.445	-0.003	0.075	-0.144	-0.112	-0.347	-0.033	0.137
	*(0.025)****	*(0.021)**	*(0.232)**	*(0.004)*	*(0.029)****	*(0.060)***	*(0.057)***	*(0.150)***	(0.024)	*(0.047)****

Source: Results compiled by the author. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Identification Key: WNC = Women with no dependent children; WC = Women with dependent children; Women – women with and without children. Time-trend coefficients and standard errors (in parentheses) are multiplied by 100 so the time-trend coefficients can be read as yearly percentage point changes. Bootstrapped standard errors are presented in the parentheses. Reported coefficients account for individual and job characteristics and for the cycle. High Skilled Occupations: legislators, senior officials and managers; professionals; technicians and associate professionals. Medium Skilled Occupations: clerks; services workers and shop and market sales workers; craft and related trades workers. Low Skilled Occupations: skilled agricultural and fishery workers; plant and machine operators and assemblers and elementary occupations.

Table 6.5b: Estimated Time Trend Coefficients for various Job Transitions States

Sample Category	QLFS Data					BHPS Data				
	EE *(1)*	EE1 *(2)*	EE2 *(3)*	EU *(4)*	EN *(5)*	EE *(6)*	EE1 *(7)*	EE2 *(8)*	EU *(9)*	EN *(10)*
Panel (B): Education Specific Regressions										
Graduate Level	-0.153	-0.074	-0.714	0.038	0.002	0.293	0.196	0.415	-0.011	-0.152
	*(0.057)****	*(0.051)*	*(0.866)*	*(0.022)**	*(0.025)*	*(0.172)**	*(0.156)*	*(1.234)*	*(0.017)*	*(0.097)*
Higher Intermediate	-0.062	0.007	-1.193	0.030	0.002	-0.098	-0.080	-0.949	0.025	-0.020
	(0.089)	*(0.020)*	*(0.519)***	(0.034)	*(0.044)*	*(0.124)*	*(0.092)*	*(0.746)*	*(0.017)*	*(0.041)*
Lower Intermediate	-0.124	-0.042	-1.368	0.077	-0.032	0.164	-0.003	0.301	-0.006	0.026
	*(0.070)**	*(0.022)**	*(0.471)****	*(0.046)**	*(0.053)*	*(0.188)*	*(0.149)*	*(1.271)*	*(0.025)*	*(0.094)*
No Education	-0.267	-0.033	-1.607	0.134	0.056	0.619	0.264	*-0.401*	-0.085	0.151
	*(0.139)**	*(0.037)*	*(0.901)**	(0.029)***	*(0.142)*	*(0.455)*	*(0.225)*	(2.382)	*(0.029)****	*(0.162)*
Panel (C): Age Specific Regressions										
16-24	-0.698	-0.032	-2.144	0.279	0.188	-0.343	-0.323	-0.559	-0.051	0.344
	*(0.166)****	*(0.035)*	*(0.382)****	(0.110)**	*(0.132)*	*(0.476)*	*(0.212)*	*(1.362)*	*(0.128)*	*(0.284)*
25-39	-0.130	-0.042	-1.075	0.036	-0.008	0.106	0.097	-1.087	-0.007	-0.050
	(0.100)	*(0.027)*	*(0.893)*	*(0.044)*	*(0.060)*	*(0.099)*	*(0.081)*	*(0.618)**	*(0.009)*	*(0.051)*
40-49	-0.027	-0.051	-0.546	0.011	-0.032	0.250	0.100	0.852	0.004	-0.071
	(0.063)	*(0.033)*	*(0.411)*	*(0.021)*	*(0.030)*	*(0.115)***	*(0.076)*	*(1.272)*	*(0.018)*	*(0.054)*
50+	-0.097	-0.031	-0.518	0.064	-0.015	-0.104	-0.115	-0.991	-0.004	0.078
	(0.063)	*(0.016)***	*(0.595)*	*(0.027)***	*(0.052)*	*(0.264)*	*(0.129)*	*(2.652)*	*(0.032)*	*(0.157)*

Source: Results compiled by the author. Significance Level: ****p<0.01*, ***p<0.05* and **p<0.10*. Identification Key: WNC = Women with no dependent children; WC = Women with dependent children; Women – women with and without children. Time-trend coefficients and standard errors (in parentheses) are multiplied by 100 so the time-trend coefficients can be read as yearly percentage point changes. Bootstrapped standard errors are presented in the parentheses. Reported coefficients account for individual and job characteristics and for the cycle. Graduate Level Education = Degree or higher level; Higher Intermediate Level = A-level or equivalent level qualifications; Lower Intermediate Level = completion of secondary level education or equivalent and No Qualifications = no qualifications. Full specifications of results comparing time-trend coefficients where different control variables are employed can be obtained from the author by request.

6.4.3 EU and EN Transitions: The Identification of Non-Voluntary Job Separations

The estimated time-trend coefficients from the last section showed there is some evidence that EU transitions have slightly increased over time, although they only indicate a very small rise over time. This section tries to determine whether this rise in EU transitions is due non-voluntary job separations through redundancies or plant closures. If job insecurity has increased over time, it is likely to stem from job separations that may be non-voluntary. Although there are no direct questions in the BHPS and QLFS surveys that allow one to identify voluntary and non-voluntary job separations directly, there are potential questions within the two surveys that can be used to identify potential job separations that could be considered to be voluntary or non-voluntary.

Appendices 11 and 12 provide details of the survey questions that were used from both data sets to try to identify non-voluntary job separations. It must be noted here that the BHPS does not provide a comprehensive set of questions that allow for a further examination of the reasons for the job separations that can take place compared to the QLFS; therefore there are fewer results from this data set. Table 6.6 provides the estimated time-trend coefficients which specifically look at EU and EN transition changes over time for individuals who may have become redundant by using these questions.

There are no questions within the surveys which allow one to identify non-voluntary job separations directly. However there are questions within the surveys that try to articulate the reasons for job separations which could be deemed to be non-voluntary. For example, a job may terminate for a variety of reasons, for instance: (I) dismissal, (II) temporary job finishing, (III) staff-cut backs, (IV) firm closure, etc. Firm closure can be thought of as a form of non-voluntary job separation as workers choose not to vacate their jobs but are forced to do so because of firm closure. Other reasons such as temporary job ending or staff-cut backs are reasons that cannot be identified outwardly as non-voluntary job separations. This is because there are no additional questions or information that may allow one to identify those individuals who may have known their jobs were temporary, but may not have wanted the job to end. And the second point in relation to this first point is that staff-cut backs may be associated with workers who may or may not have been encouraged to take redundancies by their employers. This would insinuate that some of the redundancies may be voluntary job separations, when in fact some of the separations may be non-voluntary. Additionally, EN job transitions are also explored over time to assess whether there is a rising tendency for workers who may become redundant, these workers may choose to not participate within the labour market, if they choose to take a break.

The estimated time-trend coefficients from table 6.6 were obtained by applying the same two step procedure outlined in section 6.4.1, but the sample of EU and EN transitions have been further filtered by the reasons for the job separation that occur during period t.

From table 6.6, question M1 explores whether workers may have experienced a redundancy within the last three months from the interview date. From this question, the estimated time-trend coefficient from column (1) suggests there has been a 3.963 per year percentage point rise in EU transitions. For the sample period 1994-2007, this figure implies there has been a 55 percent rise in EU transitions. The estimated coefficient from column (2) suggests there has been no significant tendency for EN transitions ensuing from redundancies within the last three months. From the BHPS data, column (3) shows there is no significant coefficient; whereas column (4) suggests there has been a 0.795 per year percentage point decline in EN transitions resulting from redundancies.

Question M2 explores whether redundancies within the last three months were due to: (I) dismissal, (II) workers being made redundant/took voluntary redundancy and (III) temporary job finishing. Column (1) reports a 4.452 per year percentage point rise in EU transitions resulting from the three listed reasons for job separations (this is a 58 percent rise over the sample period). EN transitions that may emanate from these reasons show there has been a 2.281 per year percentage point fall (this is a 30 percent fall for the sample period).

Question M3 explores EU and EN transitions resulting from leaving last job due to: (I) dismissal, (II) being made redundant/took voluntary redundancy and (III) temporary job finishing, whilst relaxing the redundancy criterion in the last three months. The estimated coefficients from the application of question M3 suggest that EU transitions rose by 2.107 percentage points per year (this is a 27 percent rise over the sample period). EN transitions declined by 0.883 percentage points per year (this is an 11 percent drop over the sample).

Question M4 tries to further refine Question M3 by exploring the reasons for leaving last job which may constitute a non-voluntary job separation. From the various reasons that are listed as part of question M3, dismissal and temporary job ending may constitute non-voluntary job separations. From columns (1) and (2), EU and EN time-trend coefficients are not significant. Additionally, the estimated coefficients from the BHPS data also provide no significant results to similarly worded questions to the QLFS survey. These results provide no evidence to show there has been a rise in the number of workers experiencing non-voluntary job separations that result in becoming unemployed over time.

Questions M5 to M8 explore job terminations that may represent voluntary and non-voluntary job terminations. Jobs that are terminated due to firm closure may be classed as a non-voluntary job separation. And jobs which may end due to staff-cut backs can be a result of voluntary job separations, although they can also be non-voluntary job separations if employers seek to terminate the employment positions of workers who have low ability and low productivity (Gibbons & Katz, 1991). From question M5, the estimated time-trend coefficient is positive and significant and it implies an 8.327 per year percentage point rise for EU transitions (this is a 108 percent rise for the sample period). There are no significant time-trends coefficients for EN job transitions culminating from redundancies resulting from firm closure in the last three months. Similarly, question M6 explores redundancies resulting from firm closure (differing from question M5 by relaxing the 'redundancy' made in last three months refinement) suggests there has been a 7.427 per year percentage point rise in EU transitions (this is a 96.5 percent rise over the sample period). Again there is no evidence for a rise in EN job transitions resulting from firm closure.

Questions M7 and M8 explore the redundancies that may be the result from staff-cut backs. From these two questions, there are no significant time-trend coefficients for EU and EN transitions. Questions M9 and M10 explore EU and EN transitions that may result from firm closure or staff-cutbacks. Question M9 suggests that redundancies within the last 3 months resulting from firm closure/staff-cut backs have seen EU transitions rise by 5.090 percentage points per year (this is a 66 percent rise over the sample period); whilst EN transitions have fallen by approximately 2 percentage points per year. The estimated coefficients from question M10 indicate there have been similar changes to EU and EN transitions over time as shown from question M9. Thus, the estimated time-trend coefficients from questions M5-M10 suggest there is evidence showing there has been a secular rise in job insecurity where the reasons for job separations reflect rising EU transitions being driven by redundancies that are the result from firm closure and not staff cut backs. Questions M11 and M12 seem to conclude similar findings to the above array of question filters which is: rising job insecurity resulting from firm closure.

However, the estimated time-trend coefficients from this analysis are very large in magnitude and they signify very large increases in EU transitions over time which is at odds with the results from the previous section and from the job tenure analysis. One reason that could explain these inflated coefficients could be because this analysis is based on a very small sub-sample of individuals who may have experienced a redundancy. Kennedy (2010) notes that probit estimation is asymptotically unbiased, but it is biased in small samples. This could mean that the filtration of the questions that were used to analyse EU and EN job transitions that can be result from voluntary and non-voluntary job separation could result with the estimated time-trend coefficients that were based on a sample of less than one hundred observations covering almost 14 years of data as part of the first stage estimations. This small sample may exaggerate the estimated time-trend coefficients based upon the reasons for job dislocation. Thus, to sum up, based on this information, I would say that these time-trend coefficients exaggerate the rise in job insecurity over the period 1991 to 2007. The post 1990 and post 2000 time frame explored by this chapter, is a period that has experienced continuous growth in GDP since 1992 and a falling unemployment rate since the early 1990s[25]. These estimated time-trend coefficients seem to be at odds with these facts.

[25] See figure 3.2 from chapter 3 for further details.

Table 6.6: Estimated Time Trend Coefficients for EU and EN Job Transition Trends by Reason for Job Separations

Reasons For Job Separations	QLFS Data		BHPS Data	
	EU	EN	EU	EN
	(1)	*(2)*	*(3)*	*(4)*
M1: Redundancy in the last three months (QLFS Data: 1994-2007)	3.963	-1.678	0.613	-0.795
	*(1.811)***	*(0.993)*	*(0.572)*	*(0.371)***
M2: Redundancy in the last three months due to: (I) dismissed, (II) made redundant/took voluntary redundancy and (III) temporary job finished (QLFS Data: 1995-2007)	4.452	-2.281	-	-
	*(2.002)***	*(1.103)***	-	-
M3: Reasons for leaving last job due to: (I) dismissed, (II) made redundant/ took voluntary redundancy and (III) temporary job finished (QLFS Data: 1995-2007)	2.107	-0.883	-	-
	*(0.723)****	*(0.458)**	-	-
M4: Reasons for leaving last job due to: (I) dismissed, and (III) temporary job finished (QLFS Data: 1995-2007)	1.504	-0.971	0.213	-0.236
	(1.028)	*(0.998)*	*(0.582)*	*(0.225)*
M5: Redundancy in the last three months as a result from firm closure (QLFS Data: 1995-2007)	8.327	-1.000	-	-
	*(4.974)**	*(2.595)*	-	-
M6: Redundancy as a result from firm closure (QLFS Data: 1995-2007)	7.427	-2.074	-	-
	*(2.139)****	*(2.176)*	-	-
M7: Redundancy in the last three months emanating from staff cut-backs (QLFS Data: 1995-2007)	2.512	-1.431	-	-
	(3.034)	*(1.334)*	-	-
M8: Redundancy emanating from staff cut-backs (QLFS Data: 1995-2007)	1.919	-1.636	-	-
	(2.560)	*(1.342)*	-	-
M9: Redundancy in the last three months resulting from firm closure or staff cut-backs (QLFS Data: 1995-2007)	5.090	-2.018	-	-
	*(2.816)**	*(1.200)**	-	-
M10: Redundancy resulting from firm closure or staff cut-backs (QLFS Data: 1995-2007)	4.581	-2.089	-	-
	*(2.256)***	*(1.241)**	-	-
M11: Redundancy in the last three months resulting from being made redundant/ taken voluntary redundancy resulting from firm closure (QLFS Data: 1995-2007)	8.830	-1.093	-	-
	*(5.331)**	*(2.696)*	-	-
M12: Redundancy resulting from being made redundant/taken voluntary redundancy resulting from firm closure (QLFS Data: 1995-2007)	7.881	-2.053	-	-
	*(2.374)****	*(2.143)*	-	-

Source: Author's own calculations from the BHPS and QLFS. Note: Significance Level: ****p<0.01, **p<0.05 and *p<0.10.* Time-trend coefficients and standard errors (in parentheses) are multiplied by 100 so the time-trend coefficients can be read as yearly percentage point changes. The bootstrapped standard errors are presented in the parentheses. Appendices 11 and 12 provide details of questions that are used to generate questions M1-M12. The BHPS data questions (appendix 12) are not the same as the QLFS data (appendix 11). For question M4, the BHPS estimates account for reasons for job separations in last job as being made redundant, dismissed or sacked and temporary job ended. For question M1, the BHPS data explored job separations in last the job that is the result from being made redundant. Reported coefficients account for individual and job characteristics and for the cycle.

6.5 Discussion

This chapter has explored two different measures for job security. These are: (a) median job tenure and job tenure shares from three specific bands measuring short, medium and long-term job tenure shares and (b) five different job transition states. This section discusses a summary of the findings.

Using job tenure as a measure for job security, this chapter first provided calculations for median job tenure. They were found to be close to the reported findings from the empirical literature using the QLFS data (figure 6.1). The estimated calculations showed median job tenure was stable post year 2000, at approximately 57 months according to the QLFS estimates and at around 45 months from the BHPS estimates. Over the sample, my results showed median job tenure at most fell by one month, although median job tenure movements are counter cyclical to the movements of the business cycle and thus this measure of job security does not definitively show the secular changes that might occur and affect job security over time.

The second part of the analysis explored job tenure shares from three specific bands. The main results are summarised by table 6.7 which compares this chapter's estimates of time-trend coefficients to that of Gregg & Wadsworth's (2002) paper. This chapter finds no evidence of a decline in job tenure shares of less than one year for women with children and for women with children under the age of five years, unlike Gregg & Wadsworth (2002). From job tenure specific regressions greater than or equal to 5 years, both papers find significant declines for men. My estimates show medium job tenure shares declined by 7.95% for the period 1992-2006, whereas Gregg & Wadsworth (2002) find a 6.96% fall for the period 1975-1998. These estimates show the decline in medium job tenure shares for men were greater over the post 1990 period than over a twenty four year time span explored by Gregg &

Wadsworth (2002). Additionally, this chapter finds modest declines for all workers and for women with no children.

The evidence from long-term job tenure shares show a continued fall for all workers, men and for women with no children. For the aggregate sample, job tenure shares greater than or equal to 10 years fell by 6.3%; for men there was an 8.85% fall and for women with no dependent children, there was a 7.95% fall. These estimates again suggest the decline in long-term job tenure shares has been greater over the 1992 to 2006 period compared to the 1975 to 1998 period analysed by Gregg & Wadsworth (2002). I find no evidence for continued rising long-term job tenure shares for women with dependent children and for women with children under the age of five years compared to the reported results from Gregg & Wadsworth (2002). A possible reason for the secular decline in these long-term job tenure shares could be attributed to a decline in staff contracts and with the rise in flexible job contracts. The Unfair Dismissal and Statement of Reasons for Dismissal (Variation of Qualifying Period) Order was introduced in 1999 by the Labour Government; this policy reduced the qualifying period to claim unfair dismissal from employment from 24 months to 12 months. Thus, firms have two options: (1) to employ better monitoring procedures to make sure workers with the right skill intensities are hired and (2) to specifically state when advertising vacancies that jobs are attached with a short term contract. Although, these explanations are only speculation, which have not formally been examined by this thesis.

From the education and age specific regressions (results not reported here), I find no evidence of there being a rise in job tenure shares of less than one year for men or for women without children. But Gregg & Wadsworth (2002) report a rise for men across all education groups (higher rises were for those with graduate level education) with significant time-trend coefficients observed for women with no children. From the age specific regressions, Gregg & Wadsworth (2002) find the 16-24 age groups for men and women with no children experienced a rise in their short-term job tenure shares over time. For women with children and for women with children under the age of five years, Gregg & Wadsworth (2002) find declines across most age and education groups, with the greater magnitude of the decline for the most educated workers and those aged less than 40 years.

From job tenure shares greater than or equal to 5 years and greater than or equal to 10 years, I find significant declines across most age and all education groups for men and for women with no children. My results also show these medium and long-term job tenure shares have continued to rise for women with children and for women with children under the age of five years in accordance with the results from Gregg & Wadsworth's (2002) paper. But my results present fewer significant coefficients that are smaller in magnitude. Gregg & Wadsworth (2002) find significant declines from long-term job tenure shares for men and for women with no children, but rises across most age and education groups for women with children and for women with children under the age of five years in age.

With job security assessed from a variety of short, medium and long-term job tenure shares over time, my results show there is evidence of a secular decline in job security, but they are small. The evidence shows medium and longer-term job tenure shares declined for men and for women with no children. For women with children and for women with children under the age of five years, this chapter finds little change in their job security. Although short-term job tenure shares declined for women who have dependent children, their medium and long-term job tenure shares have not risen as much over the post 1990 period analysed by this chapter compared to Gregg & Wadsworth (2002). This could be because the three job tenure classifications used to examine these trends do not pick up those with job tenure between one and five years.

The next stage of analysis tried to understand whether the fall in medium and long-term job tenure shares were the result of a rise in job-to-job transitions or job-to-unemployment transitions or both. If globalisation has increasingly integrated world markets, ideas through trade and advancements in information technology, jobs could increasingly become less secure if competition puts pressure on production costs. This could in turn affect the demand for labour. Job creation and destruction rates could rise as the nature of comparative advantage becomes more kaleidoscopic. This would mean workers would continually be forced to search for new jobs if their jobs are not permanent and/or secure or they may become unemployed if they are unable to find another job. Thus, this next stage of analysis tried to determine whether job-to-job (EE) transitions or job-to-unemployment (EU) transitions had increased over time.

Taking EU transitions as a measure for job security, my results show there has been a small rise in EU transitions – insinuating a small rise in job insecurity over time. This evidence shows there has been a slight decline in job security for the aggregate sample, for men and for various sub-samples for women. By age and education specific regressions, there is very little evidence of declines in job security from the results.

Finally, the last part of this chapter explored EU and EN transitions resulting from the reasons that lead to job separations. The aim of this analysis was to gage whether EU and EN transitions had increased over time because of non-voluntary job separations emanating from firm closure and layoffs. This analysis showed the estimated time-trend coefficients were large and positive for EU and EN transitions. However, the estimated time-trend coefficients were brought into doubt because the analysis was based on a small sample of observations which focused on workers who had become redundant over a period of ten years or more. This chapter concludes there is no evidence of rising job insecurity emanating from job dislocations that may be non-voluntary.

Table 6.7: Comparison of Findings from Time Trend Coefficients

	Gregg & Wadsworth (2002)		
	LFS Data: 1985-2000	GHS Data: 1975-1998	LFS Data: 1985-2000
	Tenure <1 yr	Tenure >=5 yrs	Tenure >=10 yrs
All Workers	-0.10 *(0.17)*	-0.14 *(0.06)*	-0.20 *(0.03)***
Men	0.09 *(0.15)*	-0.29 *(0.06)***	-0.36 *(0.04)***
WNC	0.11 *(0.20)*	-0.24 *(0.07)*	-0.26 *(0.05)***
WC	-0.76 *(0.14)***	0.40 *(0.09)***	0.42 *(0.06)***
WC5	-1.32 *(0.12)***	0.58 *(0.10)***[26]	0.47 *(0.06)***
	Calculations from Prajapati (2011)[27]		
	QLFS Data: 1992-2006		
	Tenure <1 yr	Tenure >=5 yrs	Tenure >=10 yrs
All Workers	0.14 *(0.25)*	-0.36 *(0.14)***	-0.42 *(0.08)****
Men	0.21 *(0.24)*	-0.53 *(0.09)****	-0.59 *(0.11)****
WNC	0.16 *(0.25)*	-0.58 *(0.23)***	-0.53 *(0.07)****
WC	-0.16 *(0.37)*	0.19 *(0.16)*	0.002 *(0.05)*
WC5	-0.45 *(0.29)*	0.18 *(0.20)*	-0.15 *(0.11)*

Source: Table compiled by the author. Significance Level Key: ***$p<0.01$, **$p<0.05$ and *$p<0.10$. Specifically referring to Gregg & Wadsworth (2002) estimates, asterisks indicate significant time-trend coefficients only; they do not signify the level of significance. Identification Key: WNC = women with no dependent children; WC = women with dependent children and WC5 = women with dependent children under the age of 5 years. Time-trend coefficients and standard errors are multiplied by 100 so the trend can be read as a yearly percentage point change. Bootstrapped standard errors presented in the parentheses. Reported coefficients include controls for individual and job characteristics and for the cycle.

Each of the measures of job security utilised by this chapter does not provide a complete picture as to 'how long jobs do last' and they do not satisfactorily measure job security on their own. Each of these measures and a number of labour market indicators such as the employment level, the unemployment inflow rate, the uptake of job seekers allowance figures have to be viewed to assess job security trends in Britain. Davis (2008) presents evidence from a variety of indicators that tell a similar story for the U.S.

6.6 Conclusion

This chapter set out to address whether there has been a decline in job security over the last two decades. The changes from two measures of job security were explored to answer this

[26] For women with children under 5 years, analysis commences from 1979-1998 for the GHS.
[27] This citation is made in reference to this chapter.

question. The first measure of job security was based on exploring the changes to median job tenure and job tenure shares from three specific bands over the period 1991 to 2006. The second measure explored the changes to yearly job transitions to different states of employment from year $t-1$ to year t over the period 1991 to 2007.

From these two measures of job security, there is evidence which shows over the period 1991-2006, there was a secular decline in job security for men and for women with no children. These declines have been greater over the most recent two decades compared with the results from Gregg & Wadsworth (2002). However the overall declines cannot be described as substantial but small. My results show medium job tenure shares (job tenure greater than or equal to five years) declined by 7.95% and 8.70% for men and for women with no children. Additionally, my results also show the long-term job tenure shares declined by 8.85% and 7.95% for men and for women with no children. Roughly speaking, these medium and long-term job tenure share have declined by approximately 10% over fifteen years, meaning if average job tenure was roughly 60 (120) months, medium (long) job tenure shares would have declined by roughly 5 (10) months over fifteen years. These declines in these medium and long-term job tenure shares are concentrated among men and women with no dependent children under the age of 50 years.

My results also show short-term job tenure (job tenure under one year) has not increased over time for men and for women with no children as found by Gregg & Wadsworth (2002). There is also no evidence of rising medium and long-term job tenure shares for women with children and for women who have children under the age of five years over the last two decades. These results may reflect the changing nature of the industrial structure, the retirement of the baby boom generation born post 1940s, the changes in the composition of jobs that are offered to workers and because of the forces associated with globalisation. Or lack of significance could be due to the job tenure shares between 1 and 5 years are not accounted for within the results. A combination of these reasons could explain the lack of significant changes to these job tenure shares over time.

Statistics from the ONS relating to the uptake of claimant benefits (see figure 3.5 from chapter 3) have not increased over this period and nor has the inflow rate into unemployment (Petrongolo & Pissarides, 2008), which would suggest there is no evidence of large scale job destruction rates over the last two decades. Part of Gregg & Wadsworth (2002) explanation for their results relating to the rise in short-term job tenure shares and the subsequent decline in the medium and longer-term job tenure shares they conclude could relate to a rise in job-to-job transitions. The results from section 6.4 dispel this explanation as there is no evidence showing new job transitions or job stayer transitions have increased over the period 1991 to 2007. The fall in new job transitions could explain the lack of evidence showing any significant time-trend coefficients for short-term job tenure shares (table 6.1). But there is evidence showing job-to-unemployment and job-to-non-employment transitions have risen over this time frame, which may explain the fall in the medium and long-term job tenure shares from this chapter. Further evidence shows that these job transitions have not arisen because of involuntary job separations resulting from redundancies or from firm closures.

Thus, a possible explanation for the rise in job-to-unemployment transitions could be linked to the type of job contracts workers have been offered over the period 1991 to 2007. If there has been a decline in staff contracts, then workers who come to the end of their jobs may become unemployed in the short-term whilst they find new jobs. This could explain the fall in new job transitions and the fall in job stayer transitions over this period and why there has been a rise in job-to-unemployment transitions. Thus, this chapter concludes there is little evidence showing there has been a substantial decline in job security as insinuated by press references from Green (2003) and from newspaper headlines that note the death nail to jobs for life.

6.7 Appendices

Appendix 1

The QLFS questions below identify the start dates for respondents' from the survey, working with present employer/continuously self-employed.

[Q101]: In which year did you start working (continuously) for your current employer? [Variable Name: CONMPY]

[Q102]: In which year did you start working continuously as a self-employed person? [Variable Name: CONSEY]

[Q103]: And which month was that? [Variable Name: CONMON]

Appendix 2

The BHPS questions relate to dates spent by respondents' in their present position of employment. These questions do not relate to the year or month the respondents' first started working for their present employer.

Q AE25M: What was the date you started working in your position, by that I mean the beginning of your current spell of the job you are doing now for your present employer? Month. [Variable Name: wJBBGM]

Q AE25Y: What was the date you started working in your position, by that I mean the beginning of your current spell of the job you are doing now for your present employer? Year. [Variable Name: wJBBGY]

Q AE43M: On what date did you start doing your present job, by that I mean the beginning of your current spell of doing the work you are doing now on a self-employed basis? Month [Variable Name: wJSBGM]

Q AE43Y: On what date did you start doing your present job, by that I mean the beginning of your current spell of doing the work you are doing now on a self-employed basis? Year [Variable Name: wJSBGY]

Appendix 3

Second Stage Regressions:

Gregg & Wadsworth (2002) estimate the following second stage OLS regression for their job tenure analysis in three specific bands:

$$\widehat{me} = \beta_0 + \beta_1 Cycle_t + \beta_2 Time_t + \varepsilon_t \qquad \text{(A1)}$$

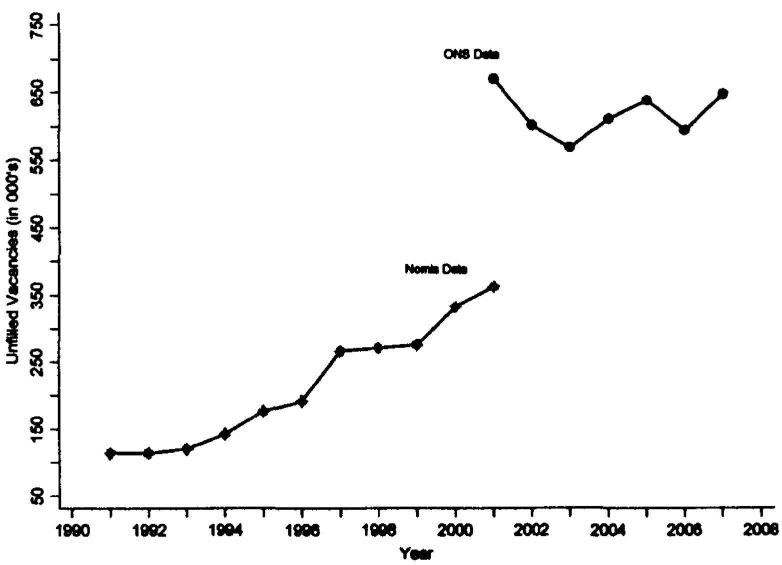
Where Time = linear time trend; cycle = cyclical component dependent upon short, medium and long-term job tenure shares and $\widehat{me}$ = estimated marginal effects evaluated at the mean of the independent variables obtained from the first stage regressions.

For the short-term job tenure share regressions, this chapter uses the vacancy-employment ratio constructed by using data on unfilled vacancies at Job Centres divided by work force jobs. The vacancy data utilised by Gregg & Wadsworth (2002) uses data series name BCOM (from Economic Trends - data from the ONS website). This data series runs from the 1950s to 1999Q1, upon which this data series is discontinued due to the following reasons. A technical report published by Labour Market Trends in July 2003[28] provides details of the deferred publication of Job Centre vacancy statistics since May 2001 was due to distortions in the reported data. Up until March 2001, employers would notify the Employment Service about a vacancy by contacting their local Job Centre. The Job Centres would try to fill the vacancies that were notified to them by the employers. However it was common practice amongst some Job Centres to only record as many vacancies that were filled, even if the employers may have notified more. From March 2001, the method for reporting vacancies changed as Employer Direct was introduced. Under Employer Direct, centre staff record the number of vacancies notified to them by the employers. This lead to a 20% increase in the level of

[28] This report is available at: http://www.statistics.gov.uk/articles/labour_market_trends/JobCentrePlus_LMT0703.pdf. The report is written by Jessica Arrowsmith for the DWP.

recorded notifications. This can be seen from figure 6.1A below, which plots the unfilled vacancy data. From this graph, Nomis data for unfilled vacancies show an upward trend. The ONS data for notified vacancies under the new system of reporting show the vacancy data trends are substantially higher compared to the Nomis data which was collected under the old system. ONS data shows no trend after the new system of reporting vacancies was implemented.

Figure 6.1A: Vacancy Data Trends



Note: Figure compiled by the author. Unfilled vacancy data from Nomis presents figures for Great Britain. Appendix 9 provides details for the data source.

Therefore, the data for vacancies from July 2002 onwards are not comparable with the original data series. Hence, with two differing sources of vacancy data, the second stage regressions for short-term job tenure shares needed to take this discrepancy into account. Thus, this chapter ran the following regression shown by equation (A2):

$$\widehat{mte} = \beta_0 + \beta_1(Cycle) * D_1 + \beta_2(Cycle) * (1 - D_1) + \beta_3 Time_t + \varepsilon_t \qquad \text{(A2)}$$

From equation (A2), the cycle variable is interacted with the dummy variable D_1; this variable accounts for vacancy data for the period 1991-2000. This procedure should account for the distortion associated with the notified vacancy data. Variable *(cycle)*D_1* from equation (A2), accounts for the vacancy data for the period 1992-2000 (this is for the QLFS data; for the BHPS the period is 1991-2000). The second term *(cycle)*(1-D_1)* accounts for vacancy data for the period 2001-2006 (this is for the QLFS data; for the BHPS the period of analysis is 2001-2005).

There were concerns that from estimating equation (A2), the specification for this equation's use of the vacancy data to measure the vacancy-employment ratio may have had some impact on the estimation of the linear time-trend coefficients due to the change in measurement for the vacancy data. To check this concern and to gather whether equation (A2) was correctly specified, the following analysis was carried out. Equation (A2) was re-estimated with the inclusion of a dummy variable D_1 equal to 1 for the period 1992-2000 (this is for the QLFS data; for the BHPS the period is 1991-2000) and zero otherwise. The new equation specified for re-estimation was equation (A3). This re-estimation helped to determine whether $\beta_1 = \beta_2$.

$$\widehat{me} = \beta_0 + \beta_1(Cycle) * D_1 + \beta_2(Cycle) * (1 - D_1) + \beta_3 Time_t + \beta_4 D_1 + \varepsilon_t \qquad \text{(A3)}$$

The test command in STATA was used after two sets of estimations:

1. The test command was used after estimating equation (A3) without bootstrapped corrected standard errors in the second stage of the estimation procedure.
2. The test command was used after estimating equation (A3) with the additional step of estimating bootstrapped standard errors in the second stage of the estimation procedure.

From results (not presented) for job tenure shares less than one year reveal that with the test command carried out after estimating models with bootstrapped standard errors, the null hypothesis of $\beta_1 = \beta_2$ was accepted from all estimated models. However, when the test command was employed after estimating the OLS regression models without bootstrapped standard errors, there were a few results where the null hypothesis was rejected. Thus, with the first method, this robustness check provides evidence that changes in the vacancy data and the subsequent estimation of equation (A2) has had no influence on the estimated linear time-trend coefficients for the short-term job tenure shares from this chapter's analysis.

Appendix 4

Gregg & Wadsworth (2002) use different cyclical control variables in the second stage of estimation for the three job tenure share bands of <1year, >=5 years and >=10 years. An alternative specification was explored whereby for each of the three job tenure share bands for the second stage regressions were estimated with the use of only two cyclical variables. The two cyclical control variables that were used were the vacancy-employment ratio and the unemployment rate. The equation that was estimated is specified by equation (A4) below:

$$\widehat{me} = \beta_0 + \beta_1(Vacancy) * D_1 + \beta_2(Vacancy) * (1 - D_1) +$$

$$\beta_3 Time_t + \beta_4 D_1 + \beta_5 Unemployment + \varepsilon_t \qquad \text{(A4)}$$

The aim of estimating this equation was twofold: The first was to see whether the estimated results were sensible and the second reason was to determine whether the inclusion of the unemployment rate reveals whether β_1 and β_2 are positive. From the results (not presented), the estimation of equation (A4) for the three job tenure shares reveals estimated coefficients β_1 and β_2 are not always positive; on some occasions, either one of the two estimated beta coefficients were negative. The estimated time-trend coefficients from equation (A4) were different to the results provided from the estimation of equation (1) [see section 6.2] for job tenure shares >=5 and >=10 years and equation (A1) for job tenure shares <1 year. In some instances, the estimated time-trend coefficients were quite similar to the estimated time-trend coefficients from the regressions which used the three different cyclical control variables in the three job tenure share regressions. And in other cases where equation (A4) was used to estimate the linear time-trend coefficients, there were differences between the two sets of results (this refers to estimated results from equation [A1] and [A2] compared to [A4]) and changes to the signs for some of the estimated coefficients. The most important observation from these regressions (from estimating equation [A4]) was the estimated time-trend coefficients were not significant. And in the majority of cases the estimated bootstrapped standard errors were very big, indicating the possibility of collinearity between the two cyclical control variables resulting with the insignificance for the estimated time-trend coefficients. Therefore these second stage regressions are quite sensitive to the choice of the cyclical variables employed in estimation for the different job tenure shares.

Appendix 5

Table 6.1A: Median Job Tenure and Sample Proportions for the Aggregate Sample

Aggregate Sample								
	QLFS Data				*BHPS Data*			
Year	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*
1991	-	-	-	-	3,9	17.85	39.63	24.00
	-	-	-	-		*(0.5)*	*(0.7)*	*(0.7)*
1992	4,10	15.31	56.38	39.83	3,8	16.82	38.62	22.18
		(0.1)	*(0.2)*	*(0.2)*		*(0.5)*	*(0.7)*	*(0.7)*
1993	5,2	15.03	57.36	39.19	3,9	18.49	39.58	21.92
		(0.1)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
1994	5,6	16.38	58.62	38.90	3,10	19.76	41.93	21.56
		(0.1)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
1995	5,7	17.89	59.19	38.02	4,0	19.51	43.91	22.53
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
1996	5,7	18.12	59.22	37.77	3,10	20.73	41.55	21.90
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
1997	5,3	18.90	57.62	37.67	3,10	20.88	40.91	21.97
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
1998	4,11	19.52	56.66	37.58	3,9	21.62	39.71	22.84
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
1999	4,10	19.08	55.42	37.95	3,9	20.41	39.30	22.59
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
2000	4,9	18.94	55.00	38.58	3,8	20.74	38.65	23.96
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
2001	4,9	19.48	57.68	38.96	3,8	21.89	38.06	23.11
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.7)*	*(0.7)*
2002	4,8	19.00	53.56	38.19	3,9	19.81	39.04	23.76
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
2003	4,9	17.80	54.33	37.79	3,8	19.25	38.13	22.22
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
2004	4,8	18.03	54.16	37.08	3,9	19.03	39.23	22.84
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
2005	4,9	17.71	54.31	36.15	3,9	18.55	39.99	22.42
		(0.2)	*(0.2)*	*(0.2)*		*(0.6)*	*(0.8)*	*(0.7)*
2006	4,9	19.17	54.28	36.46	-	-	-	-
		(0.2)	*(0.2)*	*(0.2)*	-	-	-	-

Source: Author's own calculations from the BHPS and QLFS data sets. Median job tenure is presented in years and months; standard errors of the sample proportions are in the parentheses.

Table 6.2A: Median Job Tenure and Sample Proportions for Men

Men								
	QLFS Data				*BHPS Data*			
Year	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*
1991	-	-	-	-	4,1	14.70	45.69	28.87
	-	-	-	-		*(0.6)*	*(1.0)*	*(1.0)*
1992	6,10	12.72	63.65	48.65	4,0	14.87	44.03	26.76
		(0.2)	*(0.3)*	*(0.3)*		*(0.7)*	*(1.0)*	*(1.0)*
1993	6,11	12.93	63.93	47.62	4,0	17.15	45.06	26.89
		(0.2)	*(0.3)*	*(0.3)*		*(0.7)*	*(1.1)*	*(1.0)*
1994	7,0	14.4	64.32	46.6	4,1	18.86	45.36	26.18
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
1995	6,11	15.92	64.49	45.58	4,2	17.68	46.48	26.23
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
1996	6,10	16.55	63.71	44.99	4,0	19.79	43.75	26.07
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
1997	6,4	17.55	61.38	44.05	3,11	20.69	42.40	25.99
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
1998	6,1	18.07	60.26	43.17	3,10	20.30	41.90	27.18
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
1999	5,11	17.28	59.4	43.54	3,11	19.37	41.85	26.03
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
2000	5,8	17.58	58.57	43.96	3,10	19.76	41.05	26.78
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
2001	5,8	17.88	58.42	43.98	3,10	20.45	40.84	26.66
		(0.3)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.0)*	*(1.0)*
2002	5,3	17.52	57.27	42.75	3,11	18.47	41.61	26.36
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
2003	5,5	16.63	57.69	42.18	3,10	18.48	40.88	24.79
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
2004	5,3	17.12	57.34	40.97	3,11	17.67	42.12	25.59
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
2005	5,4	16.59	57.14	39.92	3,11	17.26	42.60	25.22
		(0.2)	*(0.3)*	*(0.3)*		*(0.8)*	*(1.1)*	*(1.0)*
2006	5,5	18.29	57.22	40.50	-	-	-	-
		(0.2)	*(0.3)*	*(0.3)*	-	-	-	-

Source: Author's own calculations from the BHPS and QLFS data sets. Median job tenure is presented in years and months; standard errors of the sample proportions are in the parentheses.

Table 6.3A: Median Job Tenure and Sample Proportions for Women with No Dependent Children

Women, No Dependent Children								
	QLFS Data				*BHPS Data*			
Year	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*
1991	-	-	-	-	3,8	17.68	40.66	26.81
	-	-	-	-		*(1.0)*	*(1.4)*	*(1.4)*
1992	4,7	15.14	55.47	39.36	3,7	16.36	38.33	24.36
		(0.3)	*(0.4)*	*(0.5)*		*(1.0)*	*(1.4)*	*(1.4)*
1993	4,10	14.04	57.42	39.26	3,8	15.50	40.02	23.58
		(0.3)	*(0.4)*	*(0.5)*		*(1.0)*	*(1.5)*	*(1.4)*
1994	5,4	15.37	59.29	39.91	3,11	17.68	45.20	24.50
		(0.3)	*(0.4)*	*(0.5)*		*(1.0)*	*(1.5)*	*(1.4)*
1995	5,7	16.86	60.7	39.15	4,1	19.41	48.07	26.25
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
1996	5,6	17.41	60.29	38.54	4,0	18.96	45.69	24.47
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.4)*
1997	5,6	17.59	59.99	39.27	3,11	20.06	44.46	23.70
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.4)*
1998	5,2	18.91	58.43	39.46	3,9	20.48	41.69	24.19
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.4)*	*(1.4)*
1999	4,10	18.34	56.21	39.51	3,9	18.78	40.86	25.24
		(0.3)	*(0.4)*	*(0.5)*		*(1.0)*	*(1.4)*	*(1.4)*
2000	4,10	17.88	56.06	40.70	3,8	20.28	41.01	27.80
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
2001	4,8	19.85	54.69	41.02	3,9	21.34	40.71	26.76
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
2002	4,7	18.73	53.18	39.86	3,9	20.27	40.80	27.77
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
2003	4,8	17.51	54.30	39.72	3,8	18.74	39.53	25.11
		(0.3)	*(0.4)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.4)*
2004	4,8	17.41	53.90	38.83	3,9	19.85	39.92	25.41
		(0.3)	*(0.5)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
2005	4,8	17.48	54.17	37.77	3,9	18.47	40.42	24.53
		(0.3)	*(0.5)*	*(0.5)*		*(1.1)*	*(1.5)*	*(1.5)*
2006	4,7	18.86	53.43	37.68	-	-	-	-
		(0.3)	*(0.5)*	*(0.5)*	-	-	-	-

Source: Author's own calculations from the BHPS and QLFS data sets. Median job tenure is presented in years and months; standard errors of the sample proportions are in the parentheses.

Table 6.4A: Median Job Tenure and Sample Proportions for Women with Dependent Children

Women with Children								
	QLFS Data				*BHPS Data*			
Year	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*
1991	-	-	-	-	3,1	26.50	23.22	8.79
	-	-	-	-		*(1.3)*	*(1.3)*	*(1.0)*
1992	3,8	22.68	37.28	16.37	3,2	23.29	24.26	7.05
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(0.9)*
1993	3,10	21.85	40.1	17.57	3,2	26.65	25.09	7.72
		(0.4)	*(0.4)*	*(0.4)*		*(1.5)*	*(1.5)*	*(1.0)*
1994	3,11	22.76	43.02	18.23	3,4	25.32	28.91	6.84
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(0.9)*
1995	4,0	24.16	43.87	17.71	3,6	24.65	32.04	9.16
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.6)*	*(1.0)*
1996	4,2	22.92	46.57	19.03	3,5	25.60	30.95	9.42
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.0)*
1997	4,1	23.78	45.53	20.39	3,6	22.58	32.64	10.43
		(0.4)	*(0.5)*	*(0.4)*		*(1.3)*	*(1.5)*	*(1.1)*
1998	4,1	23.85	45.60	21.83	3,5	26.73	31.39	11.01
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.1)*
1999	4,0	24.30	44.74	22.93	3,5	25.51	30.74	10.90
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.1)*
2000	4,1	23.46	45.01	23.45	3,4	23.90	29.75	12.89
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.2)*
2001	4,1	22.94	45.52	24.88	3,4	26.28	28.19	10.95
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.1)*
2002	4,0	22.90	44.83	25.53	3,5	22.62	30.61	13.25
		(0.4)	*(0.5)*	*(0.4)*		*(1.4)*	*(1.5)*	*(1.2)*
2003	4,1	21.00	46.10	25.22	3,4	21.87	29.79	13.05
		(0.4)	*(0.5)*	*(0.4)*		*(1.3)*	*(1.5)*	*(1.2)*
2004	4,2	20.91	46.70	25.93	3,5	21.29	31.58	13.70
		(0.4)	*(0.5)*	*(0.4)*		*(1.3)*	*(1.6)*	*(1.2)*
2005	4,3	20.59	47.65	25.66	3,6	21.86	33.18	13.59
		(0.4)	*(0.5)*	*(0.4)*		*(1.3)*	*(1.6)*	*(1.2)*
2006	4,3	21.62	48.10	25.64	-	-	-	-
		(0.4)	*(0.5)*	*(0.5)*	-	-	-	-

Source: Author's own calculations from the BHPS and QLFS data sets. Median job tenure presented in years and months; standard errors of the sample proportions are in the parentheses.

Table 6.5A: Median Job Tenure and Sample Proportions for Women with Dependent Children under the age of 5 Years

Women with Children aged <5 years								
	QLFS Data				*BHPS Data*			
Year	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*	*Median*	*<1 yr*	*>5 yrs*	*>10 yrs*
1991	-	-	-	-	2,11	33.57	19.26	7.09
	-	-	-	-		*(2.8)*	*(2.5)*	*(2.2)*
1992	3,6	28.13	34.93	20.34	3,1	30.36	22.06	7.94
		(0.7)	(0.8)	(0.9)		*(3.1)*	*(2.9)*	*(2.4)*
1993	3,11	24.58	39.44	23.2	3,1	36.17	22.38	9.29
		(0.7)	(0.8)	(0.9)		*(3.1)*	*(2.9)*	*(2.5)*
1994	4,1	25.82	42.74	23.24	3,1	33.86	23.68	8.23
		(0.7)	(0.8)	(0.9)		*(3.0)*	*(2.8)*	*(2.2)*
1995	4,1	26.21	42.36	22.32	3,4	31.10	28.82	8.14
		(0.7)	(0.8)	(0.9)		*(2.9)*	*(3.0)*	*(2.1)*
1996	4,3	25.32	44.91	22.08	3,3	32.59	29.49	8.47
		(0.7)	(0.8)	(0.8)		*(2.8)*	*(3.0)*	*(2.1)*
1997	4,3	24.44	44.76	23.63	3,5	29.37	31.17	10.12
		(0.7)	(0.8)	(0.8)		*(2.8)*	*(3.0)*	*(2.3)*
1998	4,2	24.77	43.93	24.77	3,3	30.94	29.82	13.66
		(0.7)	(0.8)	(0.8)		*(2.8)*	*(3.0)*	*(2.7)*
1999	4,2	24.01	44.5	25.87	3,2	34.29	27.50	13.61
		(0.7)	(0.8)	(0.8)		*(2.8)*	*(2.9)*	*(2.6)*
2000	4,2	22.92	44.65	26.00	3,1	28.10	23.83	14.12
		(0.7)	(0.8)	(0.8)		*(2.7)*	*(2.8)*	*(2.8)*
2001	4,3	22.14	45.77	26.40	3,2	26.62	25.62	10.27
		(0.7)	(0.9)	(0.9)		*(2.7)*	*(2.8)*	*(2.2)*
2002	4,2	22.22	45.76	27.63	3,4	24.50	30.22	10.86
		(0.7)	(0.9)	(0.9)		*(2.7)*	*(3.1)*	*(2.3)*
2003	4,3	20.58	46.27	27.54	3,2	23.27	26.24	9.25
		(0.7)	(0.9)	(0.9)		*(2.7)*	*(3.0)*	*(2.2)*
2004	4,3	19.58	46.51	26.06	3,4	22.32	29.58	9.70
		(0.7)	(0.9)	(0.9)		*(2.7)*	*(3.1)*	*(2.3)*
2005	4,4	19.41	46.6	25.50	3,4	25.10	30.84	7.60
		(0.7)	(0.9)	(0.9)		*(2.8)*	*(3.2)*	*(2.0)*
2006	4,4	19.88	45.81	22.58	-	-	-	-
		(0.7)	(0.9)	(0.9)	-	-	-	-

Source: Author's own calculations from the BHPS and QLFS data sets. Median job tenure is presented in years and months; standard errors of the sample proportions are in the parentheses.

Appendix 6

Table 6.6A: Estimated Yearly Percentage Point Time Trend Coefficients for Short, Medium and Long-Term Job Tenure Shares, 1991-2005

BHPS 1991-2005	*No Controls (1)*	*No Controls + cycle (2)*	*Individual + cycle (3)*	*Individual + Job I + cycle (4)*	*Individual + Job II + cycle (5)*
Tenure <1 Year					
Total	0.05	0.02	0.12	0.08	0.17
	(0.04)	*(0.11)*	*(0.29)*	*(0.28)*	*(0.22)*
Men	0.07	0.07	0.26	0.23	0.26
	(0.05)	*(0.18)*	*(0.48)*	*(0.46)*	*(0.33)*
Women No	0.10	-0.04	-0.04	-0.04	0.03
Children	*(0.03)****	*(0.09)*	*(0.21)*	*(0.23)*	*(0.23)*
Women with	-0.14	-0.06	-0.06	-0.09	0.10
Children	*(0.05)****	*(0.25)*	*(0.58)*	*(0.57)*	*(0.59)*
Women with	-0.56	-0.01	0.08	-0.09	0.03
Children <5yrs	*(0.10)****	*(0.67)*	*(1.33)*	*(1.29)*	*(1.25)*
Tenure >=5 Years					
Total	-0.12	0.05	0.04	0.08	n/a
	(0.09)	*(0.11)*	*(0.09)*	*(0.10)*	n/a
Men	-0.31	-0.12	-0.09	-0.02	n/a
	*(0.07)****	*(0.13)*	*(0.07)*	*(0.07)*	n/a
Women No	-0.16	0.05	0.11	0.12	n/a
Children	*(0.17)*	*(0.25)*	*(0.29)*	*(0.31)*	n/a
Women with	0.31	0.40	0.13	0.15	n/a
Children	*(0.10)****	*(0.19)***	*(0.07)**	*(0.08)**	n/a
Women with	0.32	0.48	0.16	0.28	n/a
Children <5yrs	*(0.10)****	*(0.22)***	*(0.08)***	*(0.13)***	n/a
Tenure >=10 Years					
Total	0.02	-0.12	0.01	0.01	n/a
	(0.02)	*(0.05)***	*(0.02)*	*(0.02)*	n/a
Men	-0.08	-0.24	-0.07	-0.05	n/a
	*(0.03)****	*(0.06)****	*(0.03)****	*(0.03)*	n/a
Women No	0.05	-0.16	-0.12	-0.10	n/a
Children	*(0.04)*	*(0.13)*	*(0.11)*	*(0.10)*	n/a
Women with	0.08	0.06	0.06	0.06	n/a
Children	*(0.01)****	*(0.02)****	*(0.01)****	*(0.01)****	n/a
Women with	0.001	-0.08	-0.05	-0.09	n/a
Children <5yrs	*(0.02)*	*(0.08)*	*(0.05)*	*(0.16)*	n/a

Source: Author's own calculations from the BHPS. Individual controls consist of 9 age dummies for men, 8 for women, 3 dummies for education, gender dummy, child indicator dummy, 9 regional dummies. Job Controls I comprise of part-time job dummy, self-employment dummy and 5 broad industry dummy variables; Job Controls II comprise in addition to job control I variables a temporary job dummy variable. Bootstrapped standard errors are reported in the parentheses. The estimated coefficients and standard errors multiplied by 100 so the time-trend can be read as a yearly percentage point change. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.*

Table 6.7A: Estimated Time Trend Coefficients for Job Tenure Shares under One Year, 1991-2005 - Men & Women with No Dependent Children

BHPS 1991-2005	Men			Women, No Dependent Children		
	Cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job II (3)*	*Cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job II(6)*
Education						
Graduate	0.001	0.13	0.78	-0.11	0.06	0.07
	(0.24)	*(0.90)*	*(0.14)****	*(0.57)*	*(0.62)*	*(0.12)*
High Intermediate	0.04	0.20	0.32	-0.10	-0.10	0.11
	(0.20)	*(0.46)*	*(0.08)****	*(0.16)*	*(0.33)*	*(0.07)*
Low Intermediate	0.02	-0.10	0.34	-0.03	-0.09	0.70
	(0.25)	*(0.70)*	*(0.14)***	*(0.21)*	*(0.71)*	*(0.13)****
None	0.26	0.54	0.22	0.11	-0.05	0.26
	(0.22)	*(0.60)*	*(0.19)*	*(0.15)*	*(0.36)*	*(0.07)****
Age						
Age 16-24	0.50	0.40	0.49	0.96	0.69	0.78
	(0.69)	*(0.90)*	*(0.26)**	*(0.75)*	*(0.79)*	*(0.11)****
Age 25-39	0.11	0.11	0.23	0.03	-0.02	0.10
	(0.22)	*(0.27)*	*(0.06)****	*(0.32)*	*(0.31)*	*(0.06)**
Age 40-49	0.02	0.003	0.04	-0.07	-0.14	0.10
	(0.08)	*(0.09)*	*(0.02)*	*(0.13)*	*(0.18)*	*(0.03)****
Age 50+	0.05	0.04	0.02	-0.02	-0.01	0.01
	(0.10)	*(0.09)*	*(0.01)***	*(0.07)*	*(0.07)*	*(0.01)*

Source: Author's own calculations from the BHPS. Refer to notes from Table 6.6A

Table 6.8A: Estimated Time Trend Coefficients for Job Tenure Shares under One Year, 1991-2005 – Women with Dependent Children

BHPS 1991-2005	Women with dependent children			Women with dependent Child < 5yrs Old		
	Cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job II + cycle (3)*	*Cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job II + cycle (6)*
Education						
Graduate	-0.65	0.31	0.28	-1.92	-2.32^{α}	-2.28^{α}
	(0.62)	*(0.13)***	*(0.12)***	*(1.97)*	*(0.92)***	*(0.92)***
High Intermediate	0.12	0.24	0.27	0.51	0.47	0.29
	(0.26)	*(0.61)*	*(0.59)*	*(0.86)*	*(1.43)*	*(1.23)*
Low Intermediate	0.13	0.02	0.31	0.69	0.53	0.68
	(0.57)	*(1.06)*	*(1.12)*	*(1.57)*	*(2.16)*	*(2.31)*
None	-0.16	-0.90	-0.98	8.40^{β}	12.71^{β}	13.15^{β}
	(1.07)	*(3.10)*	*(3.14)*	*(4.42)**	*(7.58)**	*(7.83*)*
Age						
Age 16-24	2.42	2.14	2.26	1.81	-0.02	-0.03
	*(1.01)***	*(1.06)***	*(1.16)**	*(1.77)*	*(1.07)*	*(1.10)*
Age 25-39	-0.11	-0.07	0.04	0.22	0.10	0.14
	(0.27)	*(0.23)*	*(0.24)*	*(0.65)*	*(0.44)*	*(0.39)*
Age 40-49	-0.13	-0.09	-0.08	-1.91^{Ω}	-5.14^{Ω}	-5.28^{Ω}
	(0.26)	*(0.19)*	*(0.18)*	*(1.02)**	*(3.02)**	*(2.85)**

Source: Author's own calculations from the BHPS. Refer to notes from Table 6.6A. Symbol Key: Ω – regression run for the period 1993-2003; β – regression run for period 1991-2005; σ – regression run for the period 1991-2002; α – Age dummy groups 46-50, 51-55 and 56-59 dropped; the latter two groups dropped out due to collinearity, the former due to year dummy 1992 being dropped.

Table 6.9A: Estimated Time Trend Coefficients for Shares of Medium and Long-Term Job Tenure, 1991-2005 - Men & Women No Dependent Children

	Men		Women, No Dependent Children			Men		Women, No Dependent Children	
BHPS 1991-2005									
Medium Term					**Long Term**				
	Cycle (1)	*Individual + Job I + cycle (2)*	*Cycle (3)*	*Individual + Job I + cycle (4)*		*Cycle (5)*	*Individual + Job I + cycle (6)*	*Cycle (7)*	*Individual + Job I + cycle (8)*
Education					**Education**				
Graduate	-0.09	-0.41	0.49	0.05	Graduate	-0.01	-0.27	-0.09	-0.12
	(0.20)	*(0.08)****	*(0.25)**	*(0.09)*		*(0.08)*	*(0.04)****	*(0.13)*	*(0.05)***
High Intermediate	0.06	-0.02	0.23	0.03	High Intermediate	-0.27	-0.07	-0.07	-0.10
	(0.17)	*(0.07)*	*(0.17)*	*(0.20)*		*(0.09)****	*(0.03)***	*(0.28)*	*(0.16)*
Low Intermediate	-0.06	-0.19	0.51	-0.03	Low Intermediate	-0.06	0.03	-0.09	-0.11
	(0.14)	*(0.14)*	*(0.80)*	*(0.85)*		*(0.21)*	*(0.11)*	*(0.46)*	*(0.29)*
None	1.00	0.75	0.09	-0.19	None	0.66	0.36	-0.12	-0.52
	*(0.26)****	*(0.23)****	*(0.47)*	*(0.52)*		*(0.39)**	*(0.25)*	*(0.36)*	*(0.52)*
Age					**Age**				
Age 25-39	-0.26	-0.08	-0.04	0.22	Age 30-39	-0.10	-0.13	-0.03	-0.03
	*(0.13)***	*(0.18)*	*(0.17)*	*(0.40)*		*(0.05)***	*(0.09)*	*(0.07)*	*(0.06)*
Age 40-49	0.11	0.36	0.19	0.42	Age 40-49	-0.30	-0.20	-0.08	0.01
	(0.15)	*(0.15)***	*(0.40)*	*(0.43)*		*(0.07)****	*(0.13)*	*(0.19)*	*(0.26)*
Age 50+	-0.51	-0.27	-0.15	-0.08	Age 50+	-0.43	-0.19	-0.37	-0.25
	*(0.12)****	*(0.10)***	*(0.29)*	*(0.30)*		*(0.32)*	*(0.37)*	*(0.29)*	*(0.27)*

Source: Author's own calculations from the BHPS. Refer to notes from Table 6.6A.

Table 6.10A: Estimated Time Trend Coefficients for Shares of Medium and Long-Term Job Tenure, 1991-2005 - Women with Dependent Children

	Women, Dependent Children		Women, Dependent Children <5yrs			Women, Dependent Children		Women, Dependent Children <5yrs	
BHPS 1991-2005									
Medium Term					**Long Term**				
	Cycle (1)	*Individual + Job I + cycle (2)*	*Cycle (3)*	*Individual + Job I + cycle (4)*		*Cycle (5)*	*Individual + Job I + cycle (6)*	*Cycle (7)*	*Individual + Job I + cycle (8)*
Education					**Education**				
Graduate	0.50	-1.09	1.01	-1.36	Graduate	0.07	-0.68	-	-
	*(0.25)***	*(0.22)****	*(0.51)***	*(0.33)****		*(0.10)*	*(0.18)****	-	-
High Intermediate	0.08	-0.05	0.25	0.22	High Intermediate	-0.02	-0.03	-0.02	-0.08
	(0.13)	*(0.04)*	*(0.24)*	*(0.17)*		*(0.05)*	*(0.04)*	*(0.08)*	*(0.15)*
Low Intermediate	0.47	0.27	0.54	0.43	Low Intermediate	0.17	0.15	-0.14	0.37
	(0.44)	*(0.17)*	*(0.36)*	*(0.35)*		*(0.10)**	*(0.08)**	*(0.25)*	*(0.66)*
None	1.32	0.76	1.39$^{\sigma}$	1.07$^{\sigma}$	None	0.12	1.39	-	-
	*(0.43)****	*(0.17)****	*(1.99)*	*(3.53)*		*(0.10)*	*(0.57)***	-	-
Age					**Age**				
Age 25-39	0.44	0.56	0.43	0.85	Age 30-39	0.07	0.08	-0.06	-0.01
	*(0.15)****	*(0.18)****	*(0.21)***	*(0.33)***		*(0.02)****	*(0.02)****	*(0.07)*	*(0.09)*
Age 40-49	-0.08	0.03	0.12	-0.15	Age 40-49	-0.02	-0.001	-0.16	-0.78
	(0.33)	*(0.36)*	*(0.95)*	*(1.21)*		*(0.04)*	*(0.05)*	*(0.23)*	*(0.69)*
Age 50+	0.67	0.80	n/a	n/a	Age 50+	0.62	0.33	n/a	n/a
	(0.72)	*(0.87)*	n/a	n/a		*(0.43)*	*(0.27)*	n/a	n/a

Source: Author's own calculations from the BHPS. Refer to notes from Table 6.6A. Symbol Key: Ω – regression run for the period 1993-2003; β – regression run for period 1991-2005; σ – regression run for the period 1991-2002; α – Age dummy groups 46-50, 51-55 and 56-59 dropped; the latter two groups dropped out due to collinearity, the former due to year dummy 1992 being dropped.

Appendix 7

Table 6.11A: Estimated Yearly Percentage Point Time Trend Coefficients for Short, Medium and Long-Term Job Tenure Shares, 1992-2006

QLFS 1992-2006	*No Controls (1)*	*No Controls + cycle (2)*	*Individual + cycle (3)*	*Individual + Job I + cycle (4)*	*Individual + Job II + cycle (5)*
Tenure <1 Year					
Total	0.09	0.04	0.18	0.14	0.17
	*(0.030)****	*(0.09)*	*(0.28)*	*(0.25)*	*(0.20)*
Men	0.12	0.08	0.30	0.21	0.22
	*(0.03)****	*(0.09)*	*(0.31)*	*(0.24)*	*(0.19)*
Women No	0.10	0.05	0.18	0.16	0.20
Children	*(0.03)****	*(0.08)*	*(0.26)*	*(0.25)*	*(0.22)*
Women with	-0.06	-0.13	-0.20	-0.16	-0.06
Children	*(0.03)**	*(0.14)*	*(0.40)*	*(0.37)*	*(0.34)*
Women with	-0.28	-0.33	-0.61	-0.45	-0.34
Children <5yrs	*(0.03)****	*(0.15)***	*(0.31)***	*(0.29)*	*(0.30)*
Tenure >=5 Years					
Total	-0.34	-0.23	-0.34	-0.36	n/a
	*(0.07)****	*(0.11)***	*(0.13)***	*(0.14)***	n/a
Men	-0.57	-0.37	-0.55	-0.53	n/a
	*(0.05)****	*(0.06)****	*(0.09)****	*(0.09)****	n/a
Women No	-0.42	-0.43	-0.50	-0.58	n/a
Children	*(0.13)****	*(0.21)***	*(0.22)***	*(0.23)***	n/a
Women with	0.50	0.49	0.17	0.19	n/a
Children	*(0.12)****	*(0.20)***	*(0.13)*	*(0.16)*	n/a
Women with	0.55	0.48	0.13	0.18	n/a
Children <5yrs	*(0.15)****	*(0.26)**	*(0.15)*	*(0.20)*	n/a
Tenure >=10 Years					
Total	-0.18	-0.43	-0.34	-0.42	n/a
	*(0.03)****	*(0.10)****	*(0.06)****	*(0.08)****	n/a
Men	-0.56	-0.63	-0.54	-0.59	n/a
	*(0.03)****	*(0.13)****	*(0.09)****	*(0.11)****	n/a
Women No	-0.09	-0.61	-0.42	-0.53	n/a
Children	*(0.07)*	*(0.12)****	*(0.07)****	*(0.07)****	n/a
Women with	0.44	0.13	0.02	0.002	n/a
Children	*(0.04)****	*(0.06)**	*(0.03)*	*(0.05)*	n/a
Women with	0.26	-0.19	-0.08	-0.15	n/a
Children <5yrs	*(0.08)****	*(0.19)*	*(0.07)*	*(0.11)*	n/a

Source: Author's own calculations from the QLFS. Individual controls consist of 9 age dummies for men, 8 for women, 3 dummies for education, gender dummy, child indicator dummy, 9 regional dummies. Job Controls I comprise of part-time job dummy, self-employment dummy and 5 broad industry dummy variables; Job Controls II comprise in addition to job control I variables a temporary job dummy variable. Bootstrapped standard errors are reported in the parentheses. The estimated coefficients and standard errors are multiplied by 100 so the time-trend can be read as a yearly percentage point change. Significance Level: ****p<0.01, **p<0.05 and *p<0.10.*

Table 6.12A: Estimated Time Trend coefficients for Job Tenure Shares under One Year 1992-2006 - Men & Women with No Dependent Children

QLFS 1992-2006	Men			Women, No Dependent Children		
	Cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job II (3)*	*Cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job II(6)*
Education						
Graduate	0.04	0.22	0.18	-0.15	-0.02	0.25
	(0.03)	*(0.30)*	*(0.05)****	*(0.27)*	*(0.60)*	*(0.08)****
High Intermediate	0.08	0.10	0.17	-0.12	-0.18	0.19
	(0.07)	*(0.22)*	*(0.04)****	*(0.12)*	*(0.24)*	*(0.07)****
Low Intermediate	0.03	0.26	0.39	0.10	0.48	0.44
	(0.11)	*(0.34)*	*(0.08)****	*(0.09)*	*(0.33)*	*(0.05)****
None	0.18	0.37	0.28	0.16	0.52	0.38
	(0.13)	*(0.32)*	*(0.06)****	*(0.08)***	*(0.51)*	*(0.07)****
Age						
Age 16-24	0.64	0.40	0.56	0.35	-0.04	0.41
	(0.76)	*(0.56)*	*(0.17)****	*(0.68)*	*(0.49)*	*(0.13)****
Age 25-39	0.13	0.12	0.12	0.16	0.12	0.12
	(0.09)	*(0.05)***	*(0.02)****	*(0.13)*	*(0.09)*	*(0.01)****
Age 40-49	0.08	0.08	0.07	0.02	0.03	0.09
	(0.05)	*(0.05)*	*(0.009)****	*(0.04)*	*(0.04)*	*(0.01)****
Age 50+	0.01	0.009	0.009	0.03	0.03	0.007
	(0.03)	*(0.03)*	*(0.005)***	*(0.03)*	*(0.03)*	*(0.005)*

Source: Author's own calculations from the QLFS. Refer to notes from Table 6.11A.

Table 6.13A: Estimated Time Trend Coefficients for Job Tenure Shares under One Year, 1992-2006 – Women with Dependent Children

QLFS 1992-2006	Women with dependent children			Women with dependent Child < 5yrs Old		
	Cycle (1)	*Individual + Job I + cycle (2)*	*Individual + Job II + cycle (3)*	*Cycle (4)*	*Individual + Job I + cycle (5)*	*Individual + Job II + cycle (6)*
Education						
Graduate	-0.16	-0.25	-0.14	-0.07	-0.25	0.25
	(0.15)	*(0.36)*	*(0.33)*	*(0.16)*	*(0.36)*	*(0.12)***
High Intermediate	-0.04	-0.09	0.01	-0.17	-0.42	-0.25
	(0.15)	*(0.27)*	*(0.27)*	*(0.19)*	*(0.27)*	*(0.24)*
Low Intermediate	-0.13	-0.09	-0.02	-0.41	-0.56	-0.48
	(0.22)	*(0.47)*	*(0.39)*	*(0.27)*	*(0.43)*	*(0.43)*
None	0.06	-0.30	-0.33	-0.50	-0.46	-0.42
	(0.37)	*(0.79)*	*(0.76)*	*(1.36)*	*(1.85)*	*(1.85)*
Age						
Age 16-24	0.19	0.10	0.15	-0.69	-0.78	-0.68
	(1.02)	*(1.06)*	*(0.99)*	*(1.13)*	*(1.05)*	*(0.99)*
Age 25-39	-0.09	-0.07	-0.02	-0.24	-0.19	-0.14
	(0.12)	*(0.11)*	*(0.11)*	*(0.17)*	*(0.16)*	*(0.16)*
Age 40-49	-0.05	-0006	-0.03	-0.15	-0.11	-0.07
	(0.07)	*(0.08)*	*(0.08)*	*(0.49)*	*(0.46)*	*(0.38)*

Source: Author's own calculations from the QLFS. Refer to notes from Table 6.11A.

Table 6.14A: Estimated Time Trend Coefficients for Shares of Medium and Long-Term Job Tenure, 1992-2006 - Men & Women with No Dependent Children

	Men		Women, No Dependent Children			Men		Women, No Dependent Children	
QLFS 1992-2006									
Medium Term					Long Term				
	Cycle (1)	*Individual + Job I + cycle (2)*	*Cycle (3)*	*Individual + Job I + cycle (4)*		*Cycle (5)*	*Individual + Job I + cycle (6)*	*Cycle (7)*	*Individual + Job I + cycle (8)*
Education					**Education**				
Graduate	-0.28	-0.19	0.13	-0.28	Graduate	-0.87	-0.37	-0.16	-0.36
	*(0.11)****	*(0.05)****	*(0.18)*	*(0.06)****		*(0.20)****	*(0.06)****	*(0.22)*	*(0.06)****
High Intermediate	-0.27	-0.49	-0.22	-0.72	High Intermediate	-0.43	-0.47	-0.44	-0.68
	*(0.07)****	*(0.10)****	*(0.19)*	*(0.24)****		*(0.06)****	*(0.13)****	*(0.28)*	*(0.20)****
Low Intermediate	-0.44	-0.71	-0.30	-0.78	Low Intermediate	-0.54	-0.63	-0.67	-0.76
	*(0.06)****	*(0.08)****	*(0.27)*	*(0.32)***		*(0.14)****	*(0.12)****	*(0.12)****	*(0.11)****
None	-0.27	-0.43	-0.32	-0.64	None	-0.57	-0.53	-0.76	-0.68
	*(0.10)****	*(0.15)****	*(0.26)*	*(0.29)***		*(0.12)****	*(0.11)****	*(0.29)****	*(0.17)****
Age					**Age**				
Age 25-39	-0.73	-0.47	-0.87	-0.61	Age 30-39	-0.89	-0.84	-0.92	-1.13
	*(0.17)****	*(0.19)***	*(0.29)****	*(0.31)***		*(0.14)****	*(0.17)****	*(0.21)****	*(0.25)****
Age 40-49	-0.48	-0.40	-0.59	-0.72	Age 40-49	-1.01	-0.99	-0.75	-0.99
	*(0.04)****	*(0.05)****	*(0.25)***	*(0.27)****		*(0.13)****	*(0.15)****	*(0.13)****	*(0.13)****
Age 50+	-0.21	-0.12	-0.12	-0.15	Age 50+	-0.24	-0.17	-0.26	-0.42
	*(0.08)****	*(0.06)**	*(0.10)*	*(0.10)*		*(0.17)*	*(0.17)*	*(0.14)**	*(0.16)****

Source: Author's own calculations from the QLFS. Refer to notes from Table 6.11A.

Table 6.15A: Estimated Time Trend Coefficients for Shares of Medium and Long-Term Job Tenure, 1992-2006 - Women with Dependent Children

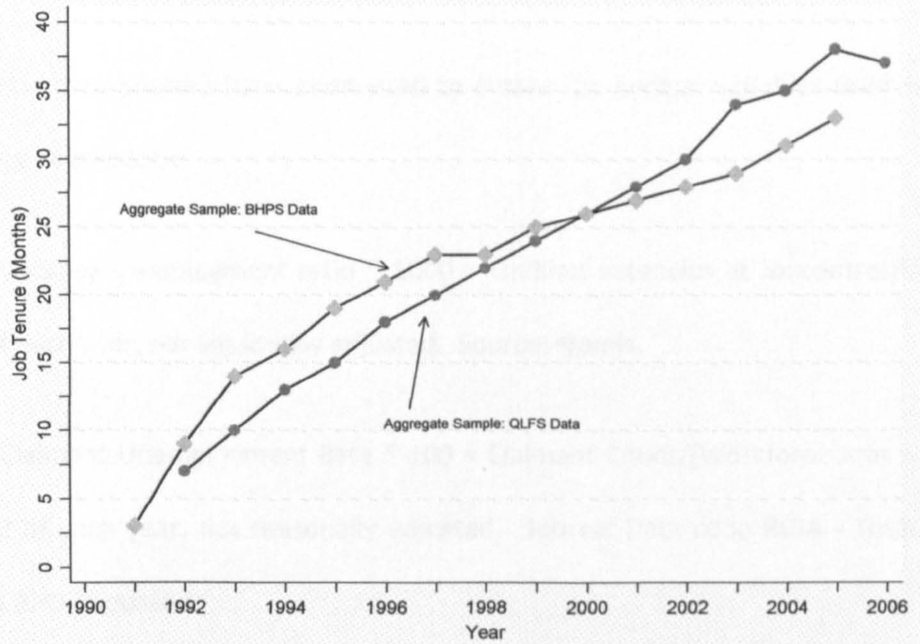
QLFS 1992-2006	Women, Dependent Children		Women, Dependent Children <5yrs	
Medium Term				
	Cycle (1)	Individual + Job I + cycle (2)	Cycle (3)	Individual + Job I + cycle (4)
Education				
Graduate	0.003	-0.17	-0.27	-0.23
	(0.29)	(0.09)*	(0.40)	(0.20)
High Intermediate	0.32	0.27	0.24	0.30
	(0.26)	(0.23)	(0.37)	(0.30)
Low Intermediate	0.53	0.28	0.52	0.39
	(0.22)**	(0.20)	(0.23)**	(0.22)*
None	0.44	0.29	1.03	0.76
	(0.18)**	(0.12)**	(0.24)***	(0.15)***
Age				
Age 25-39	0.32	0.29	0.36	0.30
	(0.20)	(0.20)	(0.28)	(0.29)
Age 40-49	0.25	0.24	0.77	0.70
	(0.24)	(0.23)	(0.33)**	(0.33)**
Age 50+	0.51	0.41	n/a	n/a
	(0.28)*	(0.29)	n/a	n/a

	Women, Dependent Children		Women, Dependent Children <5yrs	
Long Term				
	Cycle (5)	Individual + Job I + cycle (6)	Cycle (7)	Individual + Job I + cycle (8)
Education				
Graduate	-0.23	-0.25	-0.53	-0.31
	(0.20)	(0.06)***	(0.28)*	(0.13)**
High Intermediate	-0.10	-0.13	-0.23	-0.24
	(0.12)	(0.13)	(0.27)	(0.25)
Low Intermediate	0.20	0.13	-0.10	-0.13
	(0.06)***	(0.06)**	(0.18)	(0.15)
None	0.13	0.07	1.00	0.42
	(0.10)	(0.07)	(0.43)**	(0.23)*
Age				
Age 30-39	-0.30	-0.03	-0.25	-0.20
	(0.07)	(0.04)	(0.18)	(0.15)
Age 40-49	0.12	0.11	-0.22	-0.19
	(0.13)	(0.14)	(0.46)	(0.53)
Age 50+	0.63	0.47	n/a	n/a
	(0.27)**	(0.28)*	n/a	n/a

Source: Author's own calculations from the QLFS. Refer to notes from Table 6.11A.

Appendix 8

Figure 6.2A: Comparison of Imputed Median Job Tenure



Source: Figure compiled by the author.

Table 6.16A: Comparison of Job Tenure in Months

Year	Percentiles	QLFS Data	BHPS Data
		Job Tenure (Months)	
1992	25	3	1.68
	50	7	3.8
	75	10	6.48
	99	16	10.06
1996	25	7	8.28
	50	18	21.3
	75	36	37.74
	99	62	68.02
2002	25	11	12.88
	50	30	28.81
	75	64	56.27
	99	132	135
2005	25	13	14.1
	50	38	33.43
	75	77	65.88
	99	168	168
Total Sample	25	8	9
	50	23	23
	75	51	44
	99	156	135

Source: Table compiled by the author. The sample span for the BHPS data is 1991-2005. The sample span for the QLFS is 1992-2006.

Appendix 9

Data sources used for Cyclical Measures in Second Stage Regressions:

The following data sources have been used to create the cyclical variables used within the second stage regressions:

Vacant – Vacancy - employment ratio * 1000 = Unfilled vacancies at Jobcentres/Workforce Jobs, Q2 of each year, not seasonally adjusted. Source: **Nomis.**

Unemp – Claimant Unemployment Rate * 100 = Claimant Count/(Workforce Jobs + Claimant Count), Q2 of each year, not seasonally adjusted. Source: Data code **BCJA** - Total Claimant Count NSA (UK) Thousand.

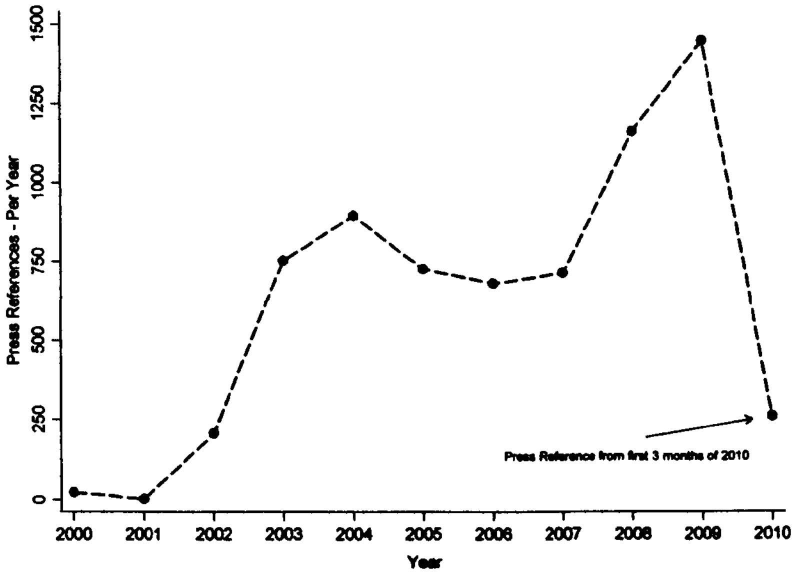
Upop – Unemployment population ratio * 100 = Claimant Count/Population Working Age, Q2 of each year, not seasonally adjusted. Source: Data code **BCJA** - Total Claimant Count NSA (UK) Thousand.

Epop – Employment population ratio * 100 = Workforce Jobs/Population Working Age, Q2 of each year, not seasonally adjusted. Source: **DYDA** UK Workforce Jobs NSA.

Population of Working Age numbers were derived from published Tables from the Annual Abstract of Statistics.

Appendix 10

Figure 6.3A: Press References per Year to the search term 'Job Cuts'



Source: Figure compiled by the author.

Source of Information:

Press references to the search term 'job cuts' have come from the times-online web site only.

Appendix 11

QLFS Questions:

Three redundancy data variables were utilised from the QLFS data and the estimated results from the use of these questions are presented in table 6.6 in section 6.4. The variables that were used are: (1) **'REDUND'** measures whether a redundancy occurred in the last three months; (2) **'REDYLFT'** measures the reasons for leaving last job and (3) **'REDCLOS'**, which captures the reason for leaving last job in last three months. This variable follows on to some extent from variable **'REDYLFT'** and **'REDUND'**. The definitions for all variables (taken from the code book) are given by figures 6.4A, 6.5A and 6.6A.

Figure 6.4A: Definition of variable 'REDUND'

REDUNDANCY WITHIN LAST 3 MONTHS

REDUND - Whether made redundant in last three months

(1) **Made redundant**
(2) **Not made redundant**

FREQUENCY: Each quarter from Spring 92

COVERAGE: Applies to all respondents aged 16+.

NOTES: This variable combines all the questionnaire variables and should be used in all analysis of redundancies.

This variable is derived from AGE, EVERWK, REFWKY, LEFTYR, REFWKM, LEFTM, REDYLFT, REDANY, CONMPY, CONMON, CONSEY & REDPAID

Changes have made to the derivation of REDUND in the LFS. It now covers the number of people who were not in employment during the reference week and who reported that they had been made redundant in the month of the reference week or in the two calendar months prior to this; plus the number of people who were in employment during the reference week who started their job in the same calendar month as, or the two calendar months prior to, the reference week, and who reported that they had been made redundant in the past three months.

See article on p225-226 of the May 2000 *Labour Market Trends* for further details.

Figure 6.5A: Definition of variable 'REDYLFT'

REDYLFT - Reason left last job

(1) **Dismissed**
(2) **Made redundant/took voluntary redundancy**
(3) **Temporary job finished**
(4) **Resigned**
(5) **Gave up work for health reasons**
(6) **Took early retirement**
(7) **Retired (at or after state pension age)**
(8) **Gave up for family or personal reasons**
(9) **Other reason**

FREQUENCY: Each quarter from Spring 95

COVERAGE: Applies to all respondents who left paid job in last 3 months or not working and left job in 8 years before reference week (REDPAID = 1 OR YLESS <=8).

NOTES: If analysing data on redundancies made in the last three months, you should also filter on the variable REDUND = 1 (made redundant).

Figure 6.6A: Definition of variable 'REDCLOS'

REDCLOS - Reason for leaving job left in last three months

(1) Closing down
(2) Cutting back on staff
(3) Other reason

FREQUENCY: Each quarter from Spring 95

COVERAGE: Applies to all respondents who were made redundant from last job (REDYLFT = 2 AND REDPAID = 1) OR REDANY = 1)).

NOTES: If analysing data or redundancies made in the last three months, you should also filter on the variable REDUND = 1 (made redundant).

These three variables are used to construct the twelve different measures for exploring EU and EN job transitions over time. Questions **M1-M4** are constructed from variables **'REDUND'** and **'REDYLFT'**. Questions **M5-M12** makes use of some or all of these variables. The definitions of the twelve new measures are defined as follows for the aggregate sample measures only:

Question (M1): Uses derived variable REDUND only to capture EU and en transitions emanating from a redundancy in the last three months. The period of coverage for this variable is 1993-2007.

Question (M2): Uses derived variable REDUND as well as variable REDYLFT to capture EU and en transitions emanating from a redundancy in the last three months based on reasons for leaving last job. The reasons for leaving last job which are part of this measure are: (I) dismissed, (II) made redundant/took voluntary redundancy and (III) temporary job finished. The period of coverage for this variable is 1995-2007.

Question (M3): Uses variable REDYLFT to capture EU and en transitions emanating from reasons for leaving last job. The reasons for leaving last job which are part of this measure are: (I) dismissed, (II) made redundant/took voluntary redundancy and (III) temporary job finished. The period of coverage for this variable is 1995-2007.

Question (M4): Uses variable REDYLFT to capture EU and EN transitions emanating from reasons for leaving last job. This fourth measure is an attempt to obtain a measure for involuntary job separations. The reasons for leaving last job which are part of this measure are: (I) dismissed and (III) temporary job finished. It could be the case that being dismissed or a temp job ending may be a non-voluntary job separation if the worker may have wanted to continue to work at a particular firm but are unable to do so. The second category is omitted from this measure because there is not an additional variable within the data set that can separate the distinction between voluntary and non-voluntary job separations. The period of coverage for this variable is 1995-2007.

Question (M5): Uses derived variable **REDUND** and **REDCLOS** to capture EU and EN transitions emanating from a redundancy in the last three months as a result from firm closure. That is [**REDUND==1 & REDCLOS==1**]. The period of coverage for this variable is 1995-2007.

Question (M6): Uses variable **REDCLOS** only to capture EU and EN transitions emanating from a redundancy as a result of firm closure. That is **[REDCLOS==1]**. The period of coverage for this variable is 1995-2007.

Question (M7): Uses derived variable **REDUND** and **REDCLOS** to capture EU and EN transitions emanating from a redundancy in the last three months emanating from staff cut-backs. That is [**REDUND==1 & REDCLOS==2**]. The period of coverage for this variable is 1995-2007.

Question (M8): Uses variable **REDCLOS** only to capture EU and EN transitions emanating from a redundancy as a result staff cut-backs. That is **[REDCLOS==2]**. The period of coverage for this variable is 1995-2007.

Question (M9): Uses derived variable **REDUND** and **REDCLOS** to capture EU and EN transitions emanating from a redundancy in the last three months resulting from firm closure or staff cut-backs. That is **[REDUND==1 & (REDCLOS==1 | REDCLOS==2)]**. The period of coverage for this variable is 1995-2007.

Question (M10): Uses variable **REDCLOS** only to capture EU and EN transitions emanating from a redundancy as a result firm closure or staff cut-backs. That is **[REDCLOS==1 |REDCLOS==2]**. The period of coverage for this variable is 1995-2007.

Question (M11): Uses derived variable **REDUND, REDYLFT** and **REDCLOS** to capture EU and EN transitions emanating from a redundancy in the last three months resulting from being made redundant/taken voluntary redundancy resulting from firm closure. That is **[REDUND==1 & REDYLFT==2 & REDCLOS==1]**. The period of coverage for this variable is 1995-2007.

Question (M12): Uses variables **REDYLFT** and **REDCLOS** to capture EU and EN transitions emanating from a redundancy, resulting from being made redundant/taken voluntary redundancy resulting from firm closure. That is **[REDYLFT==2 & REDCLOS==1]**. The period of coverage for this variable is 1995-2007.

From all of these definitions, I believe that questions M5, M6, M11 and M12 may capture involuntary job separations because the reason for the redundancy is due to plant closure.

Appendix 12

BHPS Questions:

With the BHPS data, only two measures are created using variable 'wJHSTPY'; this variable consists of the reasons for ending last job and this is shown by figure 6.7A below.

Figure 6.7A: Definition of variable 'wJHSTPY'[29]

NJHSTPY — **Reason for stopping previous job** — Individual (81)

Question Number and Text: NJ27 : Would you look at this card (J4) please and tell me which of the statements on the card best describes why you stopped doing that job?

Value Label	Value	Frequency	%	Valid %
Promoted	1	449	10.2	15.5
Left for better job	2	791	17.9	27.3
Made redundant	3	232	5.3	8.0
Dismissed or sacked	4	48	1.1	1.7
Temporary job ended	5	240	5.4	8.3
Took retirement	6	100	2.3	3.5
Stopped health reas	7	104	2.4	3.6
Left to have baby	8	50	1.1	1.7
Children/home care	9	50	1.1	1.7
Care of other person	10	7	.2	.2
Moved area	11	90	2.0	3.1
Started college/univ	12	95	2.2	3.3
Other reason	13	640	14.5	22.1
Missing or wild	-9	34	.8	Missing
Inapplicable	-8	1487	33.7	Missing
Refused	-2	1	.0	Missing

Using this variable, two measures that are generated are as follows to explore EU and EN job transitions:

Question (M1): explores EU and EN job transitions based on the reasons for leaving last job as being made redundant only.

Question (M4): explores EU and EN job transitions based on the reasons for leaving last job as being made redundant, dismissed or sacked and temporary job ended.

Both of these questions should capture elements of involuntary job separations; but there are reasons that may constitute voluntary job separations as well. For instance, having left for a better job may be considered to be a voluntary job separation.

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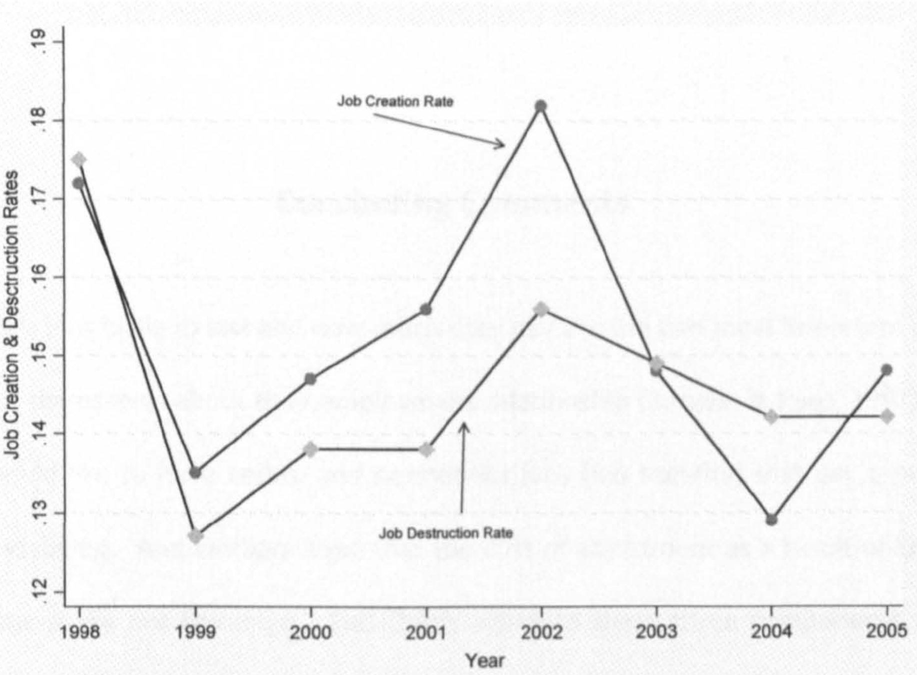
[29] For reasons of brevity, the definition for variable wJHSTPY has been taken from wave N or year 2004 survey. This variable has on the whole remained the same throughout the survey. Although there were a few additional categories that were added to this variable, they relate to reasons why students may have left their job. Please refer to the BHPS codebook for further details.

Appendix 13

Figure 6.8A: Rates of Job Creation & Job Destruction



Source: Data taken from Hijzen *et al.*, (2007) – Table 2.

7

Concluding Comments

How long are jobs likely to last and how much they pay are the two most important questions workers ask themselves about their employment relationship (Burgess & Rees, 1997). Ideally, workers would like to have secure and permanent jobs (job security) that pay a predictable wage (job stability). And workers hope that the cost of adjustment as a result of layoffs and re-employment are not too large. This thesis refers to these three components as labour market security.

However, many workers believe 'jobs are not for life' and this is in part attributed towards globalisation – increased trade and advancements in technology, the fall in transportation costs, exchange rate volatility and offshoring are all potential factors that have contributed towards greater competition in world markets for goods and services over the last thirty years. Workers believe this has caused jobs to be less secure and has contributed towards changing the structure of employment. The forgoing chapters have shown there is some evidence of downward pressure on wage levels but there is no evidence that job insecurity has increased as a result of offshoring and ICT substituting for routine intensive job tasks, although workers who are employed in the most tradable jobs that are also intensive in routine job tasks have a higher probability of becoming unemployed. But there is no evidence to suggest there has been a secular decline in job security over the last two decades. Further details are provided below.

This thesis began by asking if potential forces associated with globalisations such as trade, technology and policy reforms to labour market institutions could change the three components of labour market security over time. The answer is that these forces can affect the rate of job creation and destruction, which underlies the life and death of all jobs and thus can affect job turnover rates over time. They have also contributed towards raising the elasticity of labour demand for less skilled workers. Yet the empirical evidence shows job creation and destruction rates for the U.K. have not changed much over time; if anything they have declined over time (Hijzen *et al.,* 2007). The empirical evidence presented by Davis *et al.*, (1997) shows job creation and destruction rates on average observe the 15 percent rule: approximately 15 percent of all jobs are destroyed each year and roughly 15 percent of new jobs come into being as a share of jobs. This percentage is roughly observed by all national economies, where job creation and destruction rates are higher in the services sector than in the manufacturing sector. This reflects the growing decline of the manufacturing sector as fewer jobs are created and destroyed and the growing presence of the services sector as technology and innovation create new jobs that embody the latest technology and replace old jobs. Although this empirical evidence suggests these rates have not changed much over time, the 15 percent rule does imply the possibility that job turnover rates can lead to changes in labour market security.

The empirical evidence also shows offshoring (material & services), exchange rate volatility, ICT innovations and reforms to labour market institutions have affected the employment and wage levels but so far the empirical research has only found material offshoring to have increased the elasticity of labour demand for less skilled workers over the last 20 years. MNEs are footloose with higher exit rates (Görg & Strobl, 2003; Bernard & Sjöholm, 2003 & Bernard & Jensen, 2007), yet they are able to provide secure jobs which would otherwise not exist (Becker & Muendler, 2008) and the empirical evidence reviewed by Crinò (2009a) shows that whilst domestic and foreign workers are substitutes in the MNEs technology, the strength of the relationship is weak. The substitutability between domestic and foreign labour is found to be driven by affiliate firms to MNEs in high-income countries, which results from horizontal FDI. The substitutability between domestic and foreign workers is found to be much weaker with respect to employment in affiliate firms in low income countries, which is the result from vertical FDI. Although, at present the impact from offshoring and the substitutability between domestic and foreign labour is small, this could change in the future.

The next question that this thesis asked was whether empirical evidence exists to substantiate claims of a fall in labour market security. Chapter 3 examined the empirical evidence for the three components of labour market security, which is composed of (a) job security; (b) income volatility within jobs (job stability) and (c) the loss of earnings between jobs. This chapter assessed whether these three components changed over time to make workers worse off. The short answer is that they have not changed significantly over time though this could change in the future.

The U.K. empirical evidence for job security showed there is evidence of a small decline in long and medium term job tenure shares (job tenure greater than or equal to five and ten years) for male and female workers who have no dependent children. But the change in these job tenure shares has been very small (they have fallen by less than 10 percent from 1975 to 1998). Faggio *et al.*, (2011) find long term job tenure for men has continued to fall, especially for young men but has rose for women with young children over the period 1985-2009. And the evidence from the U.S. literature showed job loss rates have not increased over time and job retention rates have not declined over time. The additional empirical evidence from papers that have explored the unemployment inflow rates also adds weight to there being secure jobs over time as does a decline in the uptake of the Federal State Unemployment Insurance benefits for involuntarily displaced workers (Davis, 2008).

For the second component of labour market security, the empirical evidence from the income volatility and mobility literature based on U.S. evidence showed the permanent and transitory components of income volatility rose from the 1970s to 1980s. There was little change over the 1990s, but a rise once again after 1998 and over the most recent decade. However, average income volatility has not increased for all individuals over time. Income volatility did rise for those individuals who have high tolerances for risk with income levels in the 90th plus percentile of the income distribution. But generally, the vast majority of individuals who have income below the 75th percentile have not had as volatile income levels over the last thirty years (Jensen & Shore, 2008). Additionally, the research from the income mobility and income dispersion literature is not conclusive, that is the literature fails to signify whether individuals have become better off or have become worse off over time (Winship, 2009).

The final component of labour market security reviewed the evidence from the earnings losses from job displacement between jobs. The empirical evidence shows the size of the earnings losses depend on two potential factors: (1) the nature of job displacement – whether job displacement is the result from mass layoffs or through plant closures and (2) the economic environment. Bearing these two factors in mind, the literature shows the earnings losses following job displacement can be large during unfavourable economic conditions compared to favourable economic conditions. These earnings losses are also larger for workers displaced from mass layoffs than from plant closures. But the question is whether these earnings losses have become larger over time to leave workers worse off. This literature review reconciled the findings from administrative and survey data sets to find the magnitude of the earnings losses have not increased over time. They show the earnings losses lay in the region of 7-16 percent per year, five years after job displacement based on the U.S. findings. The literature from the U.K. shows earnings losses are larger from plant closures than from mass layoffs where the subsequent earnings losses are lower. But it is harder to reconcile the findings from the British literature because there are few papers to compare the estimates for the earnings losses over time to determine whether workers have had to accept worse jobs following job loss. Overall, this literature review shows labour market insecurity has not increased over time.

Following these literature reviews, this thesis examined the following questions: (I) can offshoring and the advancements in ICT lead to a rise in wage instability (job stability)? (II) Can a rise in offshoring and related activities associated with globalisation raise job insecurity? And (III) have job security trends declined over the last two decades?

To explore these questions, this thesis has made a number of significant contributions to the empirical literature: From chapter 4, this thesis explored the impact from service and material offshoring intensity, job tradability from the creation of a British version of Blinder's (2007) job offshorability index, and the impact from technology analysing the implications from the TBTC hypothesis (Autor *et al.*, (2003) on wage levels (at the individual level) rather than on relative wages (that has used industry level data) to gage the monetary impact from these factors at the individual level. These factors had not been explored on wage levels using British data. Two further contributions from this chapter relate to the creation of data that can be made available to other researchers: First, the creation of a British version of Blinder's (2007) job tradability index is a potentially useful resource that can be made available and be used by other researchers. Secondly, the application of the O*NET data and the details of the variables that were used from O*NET and applied to British data to measure the TBTC via principal component analysis can also be made available. Chapter 5 examined the impact from the same variables used in chapter 4 to explore their impact on job security, which was measured by different job transitions flows. These factors had not been examined on job security for the U.K.

And chapter 6 examined whether there had been a secular decline in job security over the post 1990 time frame. This chapter used two measures of job security: the first was job tenure (a stock measure), where I replicated the empirical paper by Gregg & Wadsworth (2002). And the second measure was employment transition (a flow measure) data that was used to look at flows into and out of employment. This second measure had not been used to explore job security by the British empirical literature. This thesis finds the following evidence.

Chapter 4 addresses the first of these three questions. This chapter examined the effects of industry level offshoring intensity (services and materials), the potential impact from job tradability (Blinder, 2007) and the implications of the ALM hypothesis (Autor *et al.*, 2003) on the wage levels for individual workers. Using the BHPS from 1992 to 2007 by estimating Mincerian wage regressions, this chapter found the impact of service offshoring (measured at the industry level), the potential threat from the advancements of technology that increasingly pose a threat to many more potentially tradable occupations (job tradability measured from the creation and application of a British version of Blinder's (2007) occupation tradability index) and the threat of TBTC – particularly from the importance of completing routine intensive job tasks, have all had a negative and significant impact on the wage levels of workers. But material offshoring intensity did not have a significant impact on wage levels. Material offshoring intensity was found to benefit skilled workers at the expense of lesser skilled workers. These findings are consistent with the reported results from the empirical literature: Feenstra & Hanson (1995, 1996 & 1999) and Crinò (2009c) from the U.S. and Geishecker & Görg (2008a, b), Hummels *et al.*, (2009) and Munch & Skaksen (2009) from the European countries.

Additionally, the potential wage losses associated with offshoring and technology can be significantly higher for workers employed in the most tradable jobs and for those workers that are employed in jobs that have a high importance for routine intensive job tasks. These latter results imply there is considerable scope to suggest that offshoring and the advancements in technology can lower wage levels within industries. Yet, do these forces raise job insecurity? This is the question that was posed by chapter 5.

Chapter 5 examined whether a rise in offshoring intensity and the advancements in technological innovations had increasingly made many more jobs at risk of being offshored abroad or replaced by computer capital which could lead to a rise in job insecurity by increasing the probability of becoming unemployed. This chapter used BHPS data for the period 1992 to 2005 to explore the impact these factors have had on the probability of experiencing job-to-unemployment transitions during the annual time intervals $[j-1, j]$. The results from the estimation of single risk models via discrete time hazard analysis showed a rise in offshoring (materials and services) did not lower job security. Further examination of these results from the estimation of competing risk models showed that a rise in offshoring raised the probability of workers remaining in employment with their current employers over time. This result may seem surprising, however the U.K. unemployment rate (see figure 3.2 in chapter 3) has declined over the time frame of data. And these results also suggest that these factors appear to aid job security. What the findings from chapters 4 and 5 collectively suggest together is that workers are more likely to remain in employment with their current employers by potentially having lower real wage levels rather than to lose their jobs and become unemployed. This should imply secure jobs. This is because real wages could fall as workers may be prepared to take a nominal pay freeze in return for firms to retain or hoard labour during unfavourable trading conditions by reducing the number of hours and days worked. This process can serve two purposes: First, by retaining labour, firms are able to have the capacity to expand production when trading conditions improve. This allows firms to not have to go through the process of hiring labour during favourable trading conditions as this process can be costly. Second, workers have job security in the sense that they do not incur the costs associated with job loss from becoming unemployed.

The final chapter addressed the third question: whether there has been a secular decline in job security over the last two decades. This chapter explored two measures of job security using data from the QLFS and the BHPS for the period 1991 to 2007. The first measure of job security examined the changes to the shares of job tenure from three job tenure groups: short, medium and long-term job tenure shares over time. For the second measure, the trends from three different job transitions: job-to-job, job-to-unemployment and job-to-inactivity were examined over time. The results from the changes to job tenure showed medium [longer-term] job tenure shares (job tenure greater than or equal to five [ten)] years) declined by 7.95% [8.85%] and 8.70% [7.95%] for men and for women with no children. These percentage changes represent very small changes to these job tenure shares from 1992 to 2006. Roughly speaking, these medium and long term job tenure share have declined by approximately 10% over fifteen years, meaning if average job tenure was roughly 60 (120) months, medium (long) job tenure shares would have declined by roughly 5 (10) months over fifteen years. This fall in long and medium term job tenure shares is found not to be indicative of a rise in job-to-job transitions, but from a slender rise in job-to-unemployment and job-to-non-employment transitions over the time frame. Further analysis also shows there is no evidence that these latter job transition results have increased over time because of a rise in involuntary job separations resulting from redundancies or firm closures.

In summary, this thesis posed three questions: (I) Can offshoring and the advancements in technology raise wage instability? The answer to this question is unclear as these factors can lower wage levels, but their monetary impact has so far been small.

(II) Can a rise in offshoring and related activities associated with globalisation raise job insecurity? The answer to this question is no. The evidence from this thesis suggests that it does not have a significant impact. The evidence from chapters 4 and 5 suggest that it may be preferable to experience job instability than to suffer job loss and become unemployed. Thus to have job security, workers may accept lower wage levels to remain in employment rather than suffer the costs associated with unemployment scarring on wage levels and future employment prospects and spend considerable time and effort searching for new jobs. This could explain the lack of evidence.

And (III) have job security trends declined over the last two decades? This thesis has found no evidence of a secular decline in job security over the last two decades. There is evidence of a negligible fall in job tenure from medium and long term job tenure shares over time for men and women with no children, but this does not indicate a rise in job insecurity.

Future avenues of research that could build upon this this thesis may want to examine the magnitude of income losses from unemployment scarring for the U.K. over the most recent time frame. At present there is no clear consensus as to whether they have increased over time. Additionally, further innovations in ICT may shift the composition of employment; at present, the empirical evidence currently suggests that ICT innovations and offshoring have benefited high skilled workers in line with a developed countries' comparative advantage. However, this could change in the future. With further innovations in technology, many more workers, especially skilled workers in high skilled white collar jobs may potentially face the risk of job loss because of structural changes in tastes and technology in the future, though this thesis does not find evidence of this fact at present, this could change in the future.

Another area of research may look to explore the impact of job polarization over a longer time horizon for the U.K. For instance do new workers enter the labour market and into jobs that are non-routine intensive and what happens to workers to older workers who have jobs that are routine intensive? How does technology affect relatively skilled and non-skilled workers who work for the same employer over time? Do these relatively skilled workers upgrade their job tasks from routine to non-routine job tasks within a firm? And, is it more likely that less skilled routine worker are more likely to lose their jobs but end up in other low paid non-routine jobs. And finally, to build upon the analysis from chapter 6, there would be scope to follow the work of Elsby *et al.*, (2007, 2009) to construct a steady state/equilibrium unemployment rate model based on the flows into and out of unemployment. This research could be further used to assess job security in the U.K.

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