Università di Pisa

DIPARTIMENTO DI ECONOMIA E MANAGEMENT
Corso di dottorato in Economia Politica

Essays on Labour Market Inequalities in the United Kingdom

PhD Thesis in Economics (SECS-P/01)

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Submitted
March 2014

Acknowledgments

Foremost, I would like to express my gratitude to Dr. Nicola Meccheri for his guidance and constant support during my Ph.D study, and to the University of Pisa for financial support.

I am also very grateful to Prof. Arrigo Opocher for his expert advice and for guiding me through difficult times. It was a pleasure to work together for the PRIN 2009 research project on "Structural change and growth".

My sincere thanks also go to Prof. Paul Gregg and Prof. Paul Clarke for their insightful comments and encouragement. Our stimulating discussions and their hard questions helped me to substantially improve my research skills. It was an honour for me to carry out collaborative research with them. I would like to thank the Centre for Market and Public Organisation (CMPO) at the University of Bristol for giving me such opportunity, hosting me for more than one year as a visiting Ph.D student.

A particular acknowledgment to Dr. Andrea Salvatori for his supervision and motivation while I was visiting the Institute for Social and Economic Research (ISER). His valuable suggestions contributed to improve my work.

I thank for their comments all the participants to the 25th SASE conference (Milan, June 2013), the 25th EALE conference (Turin, September 2013), and seminars and workshops held at CMPO and ISER.

A special thank to my family for having always supported my choices.

Finally, I also thank the UK Data Archive for making the data available. The usual disclaimer applies.

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Introduction

In this work, we aim at investigating recent trends and developments in the British labour market. This dissertation is composed of three research papers that present and discuss different aspects of labour market inequalities in the United Kingdom. The first and the second chapters are solo papers, while the third one is co-authored with Prof. Paul Gregg and Prof. Paul Clarke.

In the first chapter, we analyze recent changes in the labour market structure at the occupational level in Britain. Using data from the UK Skills Surveys between 1997 and 2006, we present evidence of job polarisation, that is a shift from a monotonic to a U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. The economic literature highlights the role of technological change as the driving force behind these changes. Autor, Levy and Murnane (2003) (hereafter ALM) provided the so called "routinisation" hypothesis, showing that technological progress can lead to a reduction of routine tasks - easily replicated by machines - which are usually performed by middle-skilled workers. On the contrary, non-manual non-routine tasks carried out mainly within high-paying occupations, are productive complements to technology. Finally, despite manual non-routine tasks that comprise many of the unskilled low-paid jobs are not directly influenced by technological progress, its impact in other parts of the economy is likely to lead to a rise in employment in these kind of works because of shift of employment from technologically progressive industries (e.g. manufacturing) to non-progressive industries (e.g. services). In this chapter we analyze in detail the task content of the occupations which display the most significant employment changes between 1997 and 2006 in light of ALM (2003) "routinisation hypothesis". We show that changes in employment shares are negatively related to the initial level of routine intensity. Unlike previous studies using the same data, we explore the impact of computerisation on routine task inputs excluding low-paying occupations that are not supposed to be directly affected by technological change. We show that our routine measure, which is negatively related to computerisation, is likely to capture both the manual and the cognitive routine dimension. Finally, by using retrospective questions on past jobs, we provide evidence of occupational mobility of middle-paid workers, showing that they did not predominantly reallocate their labour supply to low-paying occupations. Our interpretation is that explanations of the significant job expansion at the lower tail of the distribution entirely based on the displacement of national middle-skilled workers are not fully satisfactory. The role of increasing immigration inflows of low-skilled workers should also be taken into account.

The second chapter investigates recent changes in the occupational distribution of immigrants in the United Kingdom and it deals with the effects of immigration on local labour markets. From the mid-1990s, there was an increasing tendency for immigrants to be present at the lower end of the occupational classification (particularly in operatives, service and sale workers and elementary occupations) and not only in very high-skilled jobs. One major concern for immigrant-receiving countries are of course the effects that foreign-born supply has on local labour market. Previous literature considers traditional labour market outcomes such as wages, employment, unemployment and participation rate. Here we adopt a different perspective introduced by Peri and Sparber (2009) who investigate the effect of immigration on the task specialisation of natives. This paper aims at evaluating whether natives, who are assumed to have a comparative advantage relative to immigrants in communication as opposed to manual tasks, are induced to specialise in communication-intensive jobs in response to immigration inflows. We focus on the bottom end of the occupational distribution by looking at the impact of less-skilled foreign-born on similarly educated native workers. Our main data source is the UK Labour Force Survey (LFS) for the years 1997-2006 and we derive our task intensity measures at the occupational level from an additional source, the UK Skills Surveys. In this paper not only do we contribute to the literature on migration in the United Kingdom by applying a novel task-based approach, but we also make a methodological progress with respect to previous studies on immigration and task-specialisation in European countries by measuring the task content of occupations from national survey data, instead of relying on US sources (O*Net). Our main empirical findings show that in the UK natives respond to increasing immigration by shifting their task supply and providing more communication relative to manual tasks. By instrumenting the share of foreign-born workers, we show that the positive effect on the relative task supply is plausibly causal.

Finally, the third chapter considers an additional source of inequality in the labour market due to earnings disparities between men and women within households. Over the last 40 years or so the labour market has seen a gender revolution in labour market participation and wages. The traditional male breadwinner model, with the male earning in the labour market and women engaged in child bearing and home production, steadily declined. In this paper we explore the implications of these huge changes for the evolution of the spousal wage gap, alternatively called spousal pay gap or gender pay gap within couples, and its relationship with the overall pay gap, changes in labour force participation and the level of assortative mating between partners. Gender wage differentials have been extensively studied by labour economists and the literature is very broad and well-established. Yet, empirical research has traditionally focused on overall differences between men's and women's wages and there are few studies on earning disparities within couples. The specific interest on spousal wage gap can show how the shift towards greater gender equality plays out within families. But also because of the potential to change investment decisions within couples and by employers which affect in the long-run future earnings growth and labour market outcomes and for future economic modeling of gender wage differentials based on the household. The paper starts with a statistical model which shows how the probability of a positive spousal wage gap (male wage greater than partners) depends on the average gender wage gap, the variance of the male and female wage distributions and on the level of sorting or assortative mating, based on wages, there is among couples. The model shows how men can still earn more than their partners even with a low overall pay gap when assortative mating is high or the variance in earnings is low. We show how the model fits the data well and use it to explore what lies behind the observed decline in men earning more than their partners in terms of hourly wages. Among dual earner couples 79% of men earn more than their partners in 1991 and this falls to just above 72% by 2008. This is being driven by falls in the within couple gender pay gap from nearly 45% to 32% over the period. We then turn to changing participation patterns of men and women and how this affects our story. We employ the estimation method developed by Wooldridge (1995) to correct for sample selection in panel data models where we can observe wages in other periods for individuals. We show that women who are excluded from labour market participation are increasingly those with the lowest potential wage.

Chapter 1

Job Polarisation in Britain from a Task-Based Perspective. Evidence from the UK Skills Surveys

1.1 Introduction

From the 1990s onwards, radical changes in the employment structure at the occupational level occurred in several industrialised countries, notably the United States and the United Kingdom. Together with the employment growth in high-paying managerial and professional occupations and the fall in the share of middle-income jobs, low-paying service occupations started to grow. These changes led to a shift from a monotonic to a U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. This phenomenon has been defined as "job polarisation".

The economic literature highlights the role of demand shocks - particularly the technology-based ones - as the driving force behind these changes. Autor, Levy and Murnane (2003) (hereafter ALM) explain job polarisation in light of the impact of technological change on the categories of workplace tasks. Substitution or complementarity opportunities between computer use and the activities performed by workers led to a polarised labour market. Middle-income workers performing routine activities, replaced by machines, were induced to reallocate their labour supply in non-routine intense occupations and to perform tasks with a higher marginal productivity.

We contribute to the literature on employment polarisation in the United Kingdom at the occupational level using data from the UK Skills Surveys, which allow a detailed analysis of activities performed in British workplaces and the use of computers. Differently from Goos and Manning (2003 and 2007), we do not rely on task measures for the United States[1] to quantify the task intensities associated to each occupation. No assumption on the same task composition of occupations and the same impact of technology in the two countries is therefore needed.

We first provide preliminary evidence of job polarisation in our sample, confirming that between 1997 and 2006 employment shares increased at the two extremes of the occupation wage distribution, while they decreased in the middle. There is no evidence instead that wages followed the same pattern. We classify occupations in manual/non-manual and routine/non-routine according to the ALM theoretical framework. We analyze in detail the task content of those occupations which display the most significant employment changes during the period under consideration.

Next, we explore the relationship between computer use and routine task inputs, which we define on the basis of the frequency of repetitive activities that workers are asked to perform on the job. Unlike previous studies using the same data at the occupational level (e.g. Green, 2009 and 2012)[2], we exclude from the analysis low-paying occupations that are not supposed to be directly affected by technological change and for which there are no clear predictions from a theoretical standpoint. We deem that this exclusion is also appropriate in light of the findings on the routine dimension in these occupations, which could be a source of bias. The negative impact of computerisation that we find is therefore clearly associated with routine middling-paying jobs.

Claiming that the *a priori* identification of routine tasks is problematic, Green

[1] The US Department of Labor's Dictionary of Occupational Titles (DOT) and the subsequent online database Occupational Information Network (O*NET) are used to impute to workers the task measures associated with their occupations. ALM provide details on how the DOT/O*NET task measures are constructed.

[2] Lindley (2012) explores the gender dimension of technological change but at the industry level and not considering the routineness of tasks.

(2012) considers as such only repetitive manual activities. We show that our repetitive task index is equally correlated both with the O*Net manual and cognitive routine measures, once low-paying occupations are excluded. Although we cannot disentangle the negative effect of computerisation on routine tasks into a cognitive and a manual component (typical of clerical and production work, respectively), we deem that both aspects are embedded in our index.

Finally, we exploit retrospective questions on past jobs, relating the phenomenon of employment polarisation to the displacement of middle-paid workers. We find evidence of an increasing tendency over time of middle-paid workers to change occupation. The fact that these workers did not predominantly shift towards low-paying occupations is consistent with the argument that also low-skilled immigrants played a major role in the expansion of low-paid jobs.

The paper is organised as follows. Section 2 provides a review of the literature. In Section 3 we describe the data used. Section 4 provides preliminary evidence on labour market polarisation. Section 5 examines the association between employment changes and the task content of occupations. Section 6 focuses on the impact of computer adoption on routine tasks, considering only high and middling-paying occupations for which there are clear predictions of substitution or complementarity effects. Section 7 analyses the occupational mobility of middle-paid workers. Section 8 concludes.

1.2 Literature Review on Job Polarisation

Evidence of employment polarisation, that is a relative employment increase of low and high-paid (skilled)[3] jobs with respect to the middle-paid (skilled) ones, have been found for the United States (Wright and Dwyer, 2003; Autor and Dorn, 2009; Acemoglu and Autor, 2011), the United Kingdom (Goos and Manning, 2003 and 2007), Germany (Spitz-Oener, 2006; Dustmann et al. 2009; Kampelmann and Rycx, 2011) and Japan (Ikenaga and Kambayashi, 2010). With regards to Europe,

[3]The term *skilled* is here used as a synonym for *educated*. Formal education is a traditional skill measure widely used in the skill-biased technological change (SBTC) literature. Being education positively related to wages at the occupational level, we consider high, middle and low-skilled workers to be on average also high, middle and low-paid.

results are more mixed. Goos et al. (2010) conclude that on average the employment structure in Western European countries has been polarising between 1993 and 2006. Conversely, Fernández-Macías (2012) and Nellas and Olivieri (2012), show very heterogenous results among European countries and do not provide evidence of a pervasive polarisation[4].

Whereas in the United States there was a clear correspondence between employment (quantity) and wage (price) movements, the polarisation of wages does not seem to be common to other countries. Dustmann et al. (2009) show that Germany and the United States experienced similar changes at the top of the wage distribution from the 1980s and 1990s, but the pattern of lower-tail movements was distinct. Similarly, Antonczyk et al. (2010) find little evidence of wage polarisation in Germany. Concerning more specifically the United Kingdom, the well-documented increase in overall wage inequality since the early 1980s (e.g. Machin, 1996 and 2008) began to slow in the mid-1990s. Trends in inequality then split into two, with the ratio of middle to bottom earnings flattening out and the ratio of top to middle continuing to grow (Stewart, 2012). However, there is no evidence that low wages grew faster than the middle ones leading to a polarised trend (Holmes and Mayhew, 2010)[5]. More generally, Massari et al. (2013) conclude that there are no wage polarisation trends in Europe, neither at the industry nor at the individual level.

The positive and monotonic relationship between wage and employment growth characterising the 1980s is well explained by the skill-biased technological change (SBTC) hypothesis[6] (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman

[4] It should be noted, however, that the methodology used in these analyses is not exactly the same. Differently from Goos et al. (2010), Nellas and Olivieri (2012) rank occupations according to the average educational attainments and not the average wage. Fernández-Macías (2012) classify occupations in three equally-sized groups in terms of employment shares instead of using the uneven grouping followed by Goos et al. (2010).

[5] Oesch and Rodríguez Menés (2011) provide evidence of a positive correlation coefficient between changes in wages and employment across quintiles in Britain from 1993 to 2008. However, the authors claim that their findings should be treated with caution given that the analysis is not based on high quality data for wages (ie. the Labour Force Survey).

[6] Other explanations are considered, but the technology-based one is the most prominent. Several studies focus on the role of expanding international trade and offshoring, which involves the relocation to lower wage countries of only certain parts of the production process and therefore specific occupations (Feenstra and Hanson, 2005, Blinder, 2007; Grossman and Rossi-Hansberg, 2008; Acemoglu and Autor, 2011). Other studies investigate the role of labour market institutions,

et al., 1998; Machin and Van Reenen, 1998). The SBTC hypothesis relates the job expansion at the top quintiles of the wage distribution and the increase in college wage to technological progress favoring high-skilled workers at the expense of the others. However, it is not able to explain an increase of employment shares in low-skilled jobs and it therefore does not provide a wholly satisfactory framework for interpreting recent key trends in labour markets[7].

In light of the above remarks, a more nuanced and refined version of SBTC was put forward to explain the phenomenon of job polarisation, focusing on the impact of computerisation on the different categories of workplace tasks. ALM provided the so called "routinisation" hypothesis which is consistent with a "task-biased" version of technological change. In the ALM model, technological progress takes the form of an exogenous drop in the price of computers which leads to a reduction of both non-manual and manual routine tasks.

Non-manual routine tasks are characteristic of clerical and administrative occupations while manual routine tasks are typical of production and operative occupations. Given a strong substitution with technology, these tasks can be easily replicated by machines and automated. On the contrary, non-manual non-routine tasks carried out mainly within managerial, professional and creative occupations and usually performed by high-skilled workers, are productive complements to computers. Finally, concerning manual non-routine tasks, the ALM framework does not explicitly predict neither strong substitution nor strong complementarity with computers because this category is not supposed to be directly affected by technological change. Indeed, manual non-routine tasks which are typical of service occupations are difficult to automate as they require direct physical proximity or flexible interpersonal communication, and they rely on dexterity. At the same time, they do not need problem solving or managerial skills to be carried out, hence there are limited opportunities for complementarity.

Despite manual non-routine tasks that comprise many of the unskilled jobs are not directly influenced by technological progress, its impact in other parts of the economy is likely to lead to a rise in employment in these kind of works.

wage-setting in particular, which can affect employment opportunities of different kind of workers (DiNardo, Fortin and Lemieux, 1996; Acemoglu et al., 2001; Card, 2001; Lemieux, 2007).

[7] See Acemoglu and Autor (2011) for an extensive analysis of the limits of the SBTC hypothesis (the "canonical model") in this context.

Goos et al. (2007) apply Baumol's (1967) predictions - a shift of employment from technologically progressive industries (e.g. manufacturing) to non-progressive industries (e.g. services) in order to keep the balance of output in different products - to explain the increase in low-paid service jobs and employment falls in routine middling jobs. Productivity growth favours the increase in output of goods which, under imperfect substitution between goods and services, ultimately leads to an increase in the demand for service outputs and employment (Autor and Dorn, 2009). In a closed economy, this can lead to the displacement of middle-skilled workers towards service occupations as a side effect. Because routine and non-routine tasks are q-complements in production, the net increase of routine tasks input, due to an inflow of computer capital, raises the marginal productivity of non-routine tasks. According to the ALM theoretical framework, marginal middle-skilled workers who mainly perform routine tasks are induced to supply non-routine tasks with a higher marginal productivity. Under the assumption that the relative comparative advantage of middle-skilled workers is greater in low than high-skilled tasks, Autor et al. (2011) interpret employment growth in low-paid services as an implication of the substitution of skills across tasks (i.e. shifts of middle-paid workers towards low-paying occupations).

1.3 Data

The data that we use come from three UK Skills Surveys of 1997, 2001 and 2006. The main aim of these surveys is to provide an analysis of the level and distribution of skills being used in British workplaces. At each wave, information on job characteristics and working conditions are collected: these include details on the intensity of the tasks being performed, the degree of repetition of the activities carried out and the use of computers or computerised equipment in the workplace. Additional information on wages, educational qualification levels and past jobs are available, as well as other demographic variables.

The three repeated cross-sections cover altogether 14,717 workers (men and women), respectively 2,467 in 1997, 4,470 in 2001 and 7,780 in 2006. Sampling weights adjusted for response rate are used throughout the analysis[8]. We restrict

[8] See Felstead et al. (2007) for further details.

our analysis to individuals aged 20 to 60 and we drop from the third wave Northern Ireland and Highlands and Islands respondents due to their exclusion in 1997 and 2001, reducing the observations in 2006 to 6,704. We classify occupations according to the ISCO-88 nomenclature at the three-digit level. We retain only those occupations which appear in all the three years with at least 5 observations, reducing the total number from 104 to 67. At this point the average number of individual observations in each occupation was around 34 in 1997, 63 in 2001 and 88 in 2006.

Differently from the US O*NET database, whose original purpose was an administrative evaluation by Employment Services offices of the fit between workers and occupations, the UK Skills Surveys were conducted exclusively for research[9]. In the O*NET, analysts at the Department of Labor assign scores to each task according to standardised guidelines to describe their importance within each occupation. Spitz-Oener (2006) claims that this process encourages experts to underestimate true changes on job content. Although the UK Skills Surveys present a higher level of subjectivity, this feature has the advantage of giving a more precise idea of the tasks performed within each occupation. Autor and Handel (2009), who use a similar type of survey to derive individual task measures (the Princeton Data Improvement Initiative survey, PDII), prove that their data have a greater explanatory power for wages than those derived from the O*NET.

We derive three tasks measures using 35 questions on job content. At each wave, every respondent is asked how much a particular activity is important for his/her job on a 5-point scale ranging from 1 ("not at all/does not apply) to 5 ("essential"). All these variables in Likert scale are converted into increasing cardinal scale from 0 ("not at all/does not apply) to 4 ("essential"). We manually assign the different activities performed by workers to three broad categories: the first two, analytical and interpersonal, represent non-manual tasks (including respectively 25 and 6 activities); the third comprises manual tasks (4 activities) (see Appendix A.1 for a complete list). The Cronbach's scale reliability coefficient for the internal consistency of the three groups is respectively 0.93, 0.72 and 0.79. Examples of analytical tasks are: problem solving, analysing complex problems in depth and doing calculations using advanced mathematical or statistical pro-

[9]The study was directed by the following researchers: Francis Green, Alan Felstead, Duncan Gallie and Ying Zhou.

cedures. Among interpersonal tasks we include persuading or influencing others, selling a product or service and counseling, advising or caring for customers or clients. Finally, we consider as manual those tasks such as working for long periods on physical activities or carrying, pushing and pulling heavy objects. For each one of the three categories above mentioned (analytical, interpersonal and manual) a principal component analysis is performed[10]. Further details on how the principal component analysis was conducted can be found in Appendix AA, together with the derivation of all the other variables used in the empirical analysis.

We take into account an additional dimension related to the possibility of tasks being easily replicated by machines and readily subject to automation. Individuals in the UK Skills Surveys were asked the following question about the frequency of routine activities they performed within their job: "How often does your job involve carrying out short, repetitive tasks?". To this item they could respond on a 5-point scale ranging from "never" to "always" (intermediate answers were "rarely", "sometime" and "often"). Arguing that the *a priori* identification of routine activities is difficult, Green (2012) considers as such only repetitive manual activities. The author obtains a repetitive physical skill index by combining the physical skill measure (derived exactly from the same items of our manual dimension) with the question on task repetition.

1.4 Job Polarisation: Preliminary Evidence

In this section we investigate the phenomenon of employment polarisation as a preliminary step for the subsequent analysis. We compute, on the basis of the number of workers, employment shares for each occupation and their changes over time. We then rank occupations according to their initial median hourly wage. Finally we plot the percentage point change in employment share against the (log) median wage. Figure 1.1 shows that, between 1997 and 2006, employment in low and high-paying occupations increased while it decreased in the middle of the distribution. We can clearly detect a U-shaped curve in the evolution of employment shares when occupations are ranked according to their average wage.

[10] Previous studies use 32 items to generate eight skill indexes, identified by an exploratory factor analysis, as average scores from the responses.

Figure 1.1
Employment shares growth in Britain (1997-2006) by median hourly wage

Notes: Scatter plot and quadratic prediction curve. The dimension of each circle corresponds to the number of observations within each ISCO-88 three-digit occupation in 1997; the gray area shows 95% confidence interval. Employment shares are measured in terms of workers. *Source*: UK Skill Surveys.

To test in a more rigorous way employment polarisation we follow Goos and Manning (2007) estimating models of the quadratic form:

$$\Delta E_k = \alpha_0 + \alpha_1 \log(w_{k,0}) + \alpha_2 \log(w_{k,0})^2 + \varepsilon_k \tag{1.1}$$

where ΔE_k is the change in employment shares of occupation k between the initial and the final year considered and $\log(w_{k,0})$ is the initial log median wage of occupation k. A U-shaped relationship between employment growth and the initial level of wages corresponds to a negative linear term and a positive quadratic term. Table 1.1 shows the results of OLS regressions using initial number of observations in each occupation as weights to ensure that results are not biased by compositional changes in small occupations. Coefficients have the expected signs and are all statistically significant at the 1% level. Coefficients are also increasing in absolute value the longer the period considered, as well as the adjusted R-square. Because employment growth at the lower tail of the distribution could be linked to part-

Table 1.1
OLS regressions for employment polarisation analysis

	Dependent variable	
	Change in employment share	
	1997-2001	1997-2006
	(1)	(2)
(log) median hourly wage 1997	-6.820***	-9.402***
	(2.363)	(3.389)
sq. (log) median hourly wage 1997	1.773***	2.406***
	(0.597)	(0.854)
constant	6.185***	8.738**
	(2.299)	(3.314)
N	67	67
Adj. R-square	0.161	0.156
F	4.545	3.994

Notes: Each occupation is weighted by the initial number of observations. Robust standard errors in parentheses, significance levels *** p< 0.01, ** p< 0.05,*p< 0.10. *Source*: UK Skills Surveys.

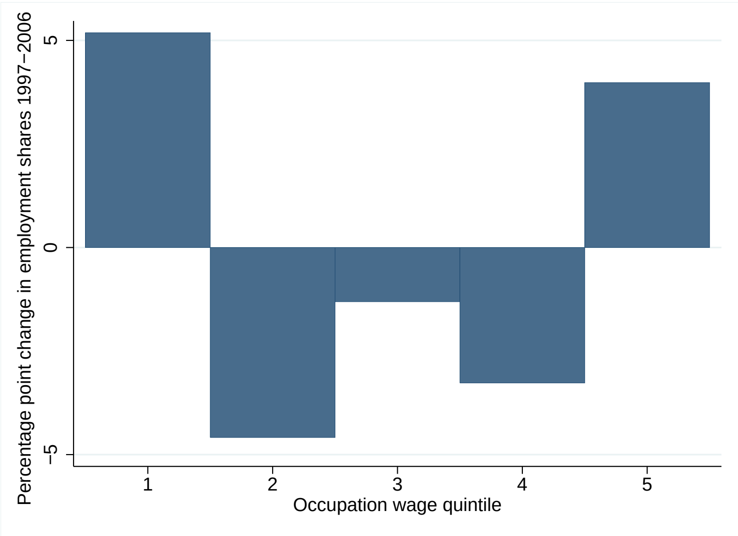
time rather than full time jobs, we further test the same model using weekly hours worked[11] as a measure for employment shares rather than expressing them in terms of bodies. Results are robust to this alternative specification. The phenomenon of employment polarisation is also robust to the use of the mean instead of the median.

We also analyze polarisation by defining occupation wage quintiles. Quintiles are created ranking occupations by their initial median wage and then aggregating them into five equally-sized groups. Each group contains almost the same percentage of employment in the initial year[12]. We plot in Figure 1.2 the change in the employment share from 1997 to 2006 by occupation wage quintiles. The period from 1997 to 2006 is characterised by a marked polarisation in employment growth: there is a rapid employment growth at the first quintile, a decline in the employment shares of middle-skilled jobs and increasing employment shares at the

[11]We decided to drop those individuals reporting negative values, zero or more than 80 hours per week.

[12]This methodology has been first applied by Wrigth and Dwyer (2003). It is not possible to create groups which contain exactly the same percentage of employment since occupations are defined as inseparable units.

Figure 1.2
Evolution of employment changes between 1997 and 2006 by occupation wage quintiles



Notes: Occupation wage quintiles are based on three-digit ISCO-88 median wages in 1997. *Source*: Uk Skill Surveys.

top of the wage distribution (fifth quintile).

Next, we examine whether changes in the labour market's quantity side find their natural counterpart in changes in the price side, as the United States. We test with OLS regression the correspondence between changes in occupational employment shares and changes in occupational wages between 1997-2006. We find that the link between changes in employment shares and changes in (log) median wages is not statistically significant: we estimate β=0.012 (t-value: 1.50)[13]. These findings suggest that in Britain, between 1997 and 2006, wages did not experience the same polarised pattern of employment shares. As a robustness check for our findings on the absence of wage polarisation, we follow Kampelmann and Rycx (2011) estimating the following model:

$$\Delta log(w_k) = \alpha_0 + \alpha_1 \log(w_{k,0}) + \alpha_2 \log(w_{k,0})^2 + \varepsilon_k \tag{1.2}$$

[13]Our regression includes a constant and is weighted by the number of individuals within an occupational group in 1997.

Table 1.2
OLS REGRESSIONS FOR WAGE POLARISATION ANALYSIS, ASHE DATA

	Change in (log) median wage, 1997-2006
(log) median hourly wage 1997	0.009
	(0.256)
sq. (log) median hourly wage 1997	-0.016
	(0.059)
constant	0.303
	(0.260)
N	67
Adj. R-square	0.021
F	1.190

Notes: Results are based on the same 67 occupations selected for the UK Skills Survey analysis. *Source*: Annual Survey of Hours and Earnings (ASHE), 1997 and 2006.

Because of possible wage measurement error in our main source which would cause attenuation bias in the estimates, we prefer to use data from the Annual Survey of Hours and Earnings[14]. The ASHE provides information about earnings and hours worked for employees by sex and full-time/part-time workers in all industries and occupations. Given that the ASHE is based on a one per cent sample of employees taken from payroll records collected by the HM Revenue & Customs, we consider it to be a more reliable and accurate source to analyze the evolution of gross hourly pay at the occupation level. Table 1.2 reports estimates only for the same 67 occupations that are considered in the UK Skill Surveys. Results obtained from this additional dataset confirm that there is no evidence of wage polarisation at the occupational level for the period 1997-2006.

1.5 Employment Changes and Task Intensities

To interpret previous findings on the phenomenon of job polarisation in Britain, we follow a task-based approach exploiting information on the activities carried

[14] Available at: http://data.gov.uk/dataset/annual_survey_of_hours_and_earnings. We manually map the SOC nomenclature into the ISCO-88 three-digit classification to allow comparability between results.

Table 1.3
CORRELATIONS AMONG TASK MEASURES AND THE EDUCATION VARIABLE

	Analytical	Interpersonal	Manual	Routine	Education
Analytical	1				
Interpersonal	0.664	1			
Manual	-0.501	-0.531	1		
Routine	-0.675	-0.578	0.497	1	
Education	0.736	0.528	-0.571	-0.705	1

Notes: Correlations are computed at the 3-digit occupational level. *Source*: UK Skills Surveys.

out on workplaces. All workers perform a wide range of tasks but they do it with different intensities. This means that occupations are not uniquely associated with one single type of task; still, they can be classified as predominantly non-manual or manual according to the intensity of analytical, interpersonal and manual activities. Likewise, occupations can be categorised as routine or non-routine depending on how much the required activities are repetitive.

Table 1.3 presents the correlation among the task and routine measures and the education variable at the occupation level. The manual dimension is negatively correlated with the analytical and interpersonal measures and the education variable. Education is instead positively correlated with the two non-manual dimensions. The routine measure is negatively correlated with the analytical and interpersonal dimension and with the level of educational attainment and positively with the manual measure[15].

We proceed with our analysis aggregating the 67 occupations so far considered at the ISCO-88 two-digit level. This aggregation offers a clear interpretation of the tasks content of the occupations that mainly contributed to the polarisation of the employment structure. Table 1.4 presents the 24 two-digit occupations ranked in ascending order by their median wage in 1997[16], which is reported in column

[15] Results are similar to those reported in Green (2012) who explores at the individual level the correlation of nine job skill indexes with the education variable, but using the required education level of the job and not worker's actual highest qualification. We additionally provide an estimate of the correlation between the routine and the manual measures.

[16] The high value of the Spearman rank correlation coefficient (0.93) suggests that the wage ranking was fairly stable over time.

1, and the percentage point change in their employment share during the period 1997-2006. Table 1.3 also shows the mean of the educational attainment in 1997, computed from a three-level education variable ranging from 1 (low-skilled) to 3 (high-skilled).

We draw on the work of Goos et al. (2009) to classify these occupations into three major groups which we label as low, middling and high-paying[17]. This grouping reflects the theoretical classification of the ALM model with service and elementary occupations being the low-paying, productive and administrative occupations the middling-paying, professional and managerial the high-paying. Column 1 to 4 of Table 1.5 report the average values of the task measures for each occupation. Matching these figures with the statistics on changes in employment shares, we have a clear picture of the task content of the occupations which determined employment polarisation between 1997 and 2006.

1.5.1 Non-manual and Manual Dimensions

Among the group of high-paying occupations, “Corporate Managers” (ISCO 12), “Life science and health associate professionals” (ISCO 32) and “Other Professionals” (ISCO 24) are those that experienced the most significant employment growth. All these three major occupations score higher on the non-manual dimension, an average of analytical and interpersonal measures, than on the manual one.

Within middling-paying occupations, those losing more employment share between 1997 and 2006 were “Office clerks” (ISCO 41), scoring on average higher on the non-manual dimension; “Metal, machinery and trade workers” (ISCO 72) and “Machine operators and assemblers” (ISCO 82), scoring respectively 0.78 and 0.66 in the manual measure.

[17] Our groups include respectively 6, 10 and 8 occupations. Fernández-Macías (2012) criticises the methodological strategy developed by Goos et al. (2009), claiming that a division in even groups would not lead to conclude that there was a pervasive polarisation in Europe. Our findings for Britain are instead robust to an alternative classification in three even groups, with the middle group still declining in terms of employment shares and the two extreme groups increasing.

Table 1.4

Occupations, median wages and education

Occupations	ISCO-88 code	Median wage in 1997 (1)	Mean level of education in 1997 (2)	Total change in employment share 1997-2006 (3)
Sales and services elementary occupations	91	3.90	1.13	1.61
Salespersons, models and demonstrators	52	4.26	1.17	0.23
Personal and protective services workers	51	4.68	1.34	1.69
Market-oriented skilled agricultural and fishery workers	61	4.85	1.41	-0.48
Agricultural, fishery etc. labourers	92	4.87	1.79	-0.11
Labourers in mining, construction, manufacturing and transport	93	4.96	1.03	1.66
Other craft and trades workers	74	5.02	1.11	-0.77
Customer services clerks	42	5.31	1.41	-0.25
Drivers and mobile-plant operators	83	5.41	1.14	-0.26
Machine operators and assemblers	82	5.68	1.34	-2.72
Extraction and building trades workers	71	6.42	1.33	1.45
Stationary-plant operators	81	6.58	1.07	-0.22
Office clerks	41	6.69	1.50	-5.01
Managers of small enterprises	13	6.69	1.38	-0.29
Metal, machinery and trades workers	72	7.61	1.49	-2.72
Precision, handicraft, printing and trades workers	73	7.78	1.37	-0.52
Physical and engineering science associate professionals	31	8.93	2.15	0.02
Other associate professionals	34	9.00	1.74	0.80
Life science and health associate professionals	32	9.27	1.95	3.26
Corporate managers	12	10.72	1.95	2.06
Other professionals	24	10.72	2.45	0.98
Physical, mathematical and engineering science professionals	21	11.40	2.39	-1.43
Teaching professionals	23	11.47	2.76	0.49
Life science and health professionals	22	15.64	2.72	0.52

Notes: Occupations ranked in ascending order by the median hourly wage in 1997; column 2 reports the mean of the educational attainment in 1997, based on a three-values variable (”low”=1, ”medium”=2 and ”high”=3); column 3 shows the percentage point change in employment share over the period 1997-2006. *Source*: UK Skills Surveys.

Table 1.5

Task measures by occupation

Occupations	ISCO-88 code	Analytical (1)	Interpersonal (2)	Manual (3)	Routine (4)
Sales and services elementary occupations	91	0.41	0.45	0.48	0.61
Salespersons, models and demonstrators	52	0.54	0.77	0.45	0.63
Personal and protective services workers	51	0.60	0.68	0.53	0.63
Market-oriented skilled agricultural and fishery workers	61	0.48	0.60	0.75	0.63
Agricultural, fishery etc. labourers	92	0.49	0.37	0.71	0.68
Labourers in mining, construction, manufacturing and transport	93	0.48	0.46	0.71	0.65
Other craft and trades workers	74	0.52	0.44	0.67	0.75
Customer services clerks	42	0.59	0.73	0.37	0.74
Drivers and mobile-plant operators	83	0.46	0.54	0.62	0.60
Machine operators and assemblers	82	0.60	0.51	0.66	0.66
Extraction and building trades workers	71	0.60	0.63	0.83	0.60
Stationary-plant operators	81	0.59	0.44	0.72	0.65
Office clerks	41	0.61	0.61	0.34	0.64
Managers of small enterprises	13	0.69	0.80	0.60	0.56
Metal, machinery and trades workers	72	0.65	0.59	0.78	0.54
Precision, handicraft, printing and trades workers	73	0.62	0.55	0.70	0.64
Physical and engineering science associate professionals	31	0.67	0.68	0.50	0.53
Other associate professionals	34	0.71	0.79	0.28	0.45
Life science and health associate professionals	32	0.65	0.75	0.57	0.49
Corporate managers	12	0.75	0.79	0.34	0.46
Other professionals	24	0.78	0.73	0.30	0.43
Physical, mathematical and engineering science professionals	21	0.76	0.70	0.33	0.39
Teaching professionals	23	0.79	0.76	0.37	0.39
Life science and health professionals	22	0.76	0.74	0.53	0.50

Notes: Occupations are ranked in ascending order by the median hourly wage in 1997. Column 1 to 4 report normalised task measures in 1997, ranging [0,1].*Source*: UK Skills Surveys.

Concerning the group of the lowest paying occupations, four out of six have growing employment shares. Those occupations with a positive percentage point change over 1997-2006 are low-paying services, such as “Personal and protective service workers” (ISCO 51) and “Salespersons, models and demonstrators” (ISCO 52) and low-paying elementary occupations, such as “Sales and services elementary occupations” (ISCO 91) and “Labourers in mining, construction, manufacturing and transport” (ISCO 93). Within the elementary occupations (ISCO 91 and 93) the categories growing more were “Messengers, porters, doorkeepers” (ISCO 915, +2.19 percentage points change) which can be classified as private consumer services, and “Transport labourers and freight handlers” (ISCO 933, +1.27 percentage points change) which are instead considered business services. Our findings confirm that the increase of employment at the lower tail of the wage distribution is mainly driven by a job expansion in the service sector. The task content of these jobs is mixed, with elementary occupations being predominantly manual and service occupations scoring higher in the interpersonal dimension. This is in line with the fact that low-paid service jobs rely both on physical proximity and interpersonal communication, therefore are not directly affected by technological progress.

1.5.2 Routine Intensity

After having classified the occupations in manual and non-manual, we take into account an additional dimension related to the extent to which the involved activities are repetitive. The ALM theoretical framework split the routine dimension into two components: routine cognitive tasks (for example documenting or processing information) and routine manual (for instance the importance of repetitive motions and physical activities). However, the single question on repetitiveness in the UK Skills Survey does not allow this decomposition. Using O*Net data on task measures at the occupational level[18], we find that that the correlation between the UK Skills Survey routine measure and the O*Net routine manual and cognitive scales is respectively 0.62 and 0.33 (see Table 1.6). One can see that, despite our routine measure is more strongly related to the manual rather than

[18] U.S. Census 2000 codes in the O*net data are matched to the International Standard Classification of Occupations (ISCO-88). We thank David Autor for making the data publicly available at: http://economics.mit.edu/faculty/dautor/data.

Table 1.6
Correlation between UK Skills Surveys routine measure and O*Net routine-cognitive and routine-manual indexes

	Skill Surveys routine	O*Net routine-cognitive	O*Net routine-manual
Skill Surveys routine	1		
O*Net routine-cognitive	0.325	1	
O*Net routine-manual	0.617	0.339	1

Notes: Correlations are computed at the 3-digit occupation level. *Source*: UK Skills Surveys and O*Net data.

the cognitive O*Net routine dimension, we still observe a positive correlation also for this second case. Using data from the Princeton Data Improvement Initiative survey (PDII), Autor and Handel (2009, p. 20) find instead that their measure of routine activity correlates positively with the O*Net routine manual scale (0.36) and negatively with the O*Net routine cognitive scale (-0.22), concluding that it placed far greater weight on the manual rather than cognitive dimension of repetitiveness. The question on repetitiveness in the UK Skill Survey is almost identical to that included in the Princeton Data Improvement Initiative survey (PDII).

In light of the above findings, we analyze the routine measure among the occupations previously considered. As expected, high-paying managerial and professional occupations (ISCO 12, 24, 32) are predominantly characterised by non-routine activities; on the contrary, declining middling-paying occupations such as ISCO 41 or 82 mainly involve routine tasks. These results are compatible with the ALM routinisation hypothesis which clearly predicts that the impact of computerisation caused a substantial substitution with routine tasks typical of middling-paying occupations and strong complementarity with non-routine tasks performed high-paying occupations.

Surprisingly, low-paying occupations are mostly routine. However, one caveat must be expressed. The repetitiveness dimension could have been interpreted by respondents as mundane and tedious rather than mechanistic and readily subject to automation. This is the reason why also Autor and Handel (2009), who evaluate this dimension using a similar question on repetitiveness, find that service

Table 1.7
OLS regression of changes in employment share and the initial level of routine intensity

	Dependent variable	
	Change in employment share 1997-2006	
	(1)	(2)
Routine intensity 1997	-1.716	-3.076**
	(1.421)	(1.441)
N	67	52
Adj. R-square	0.028	0.128
F	1.459	4.557

Notes: All regressions include a constant. Column 1 shows results for all occupations; column 2 reports estimates excluding the low-paying ones. Robust standard errors between brackets.*Source*: UK Skills Surveys.

occupations score really high in the routine measure. Similarly, Kampelmann and Rycz (2011) suggest that in Germany gains in employment shares at the low-wage occupations are linked to low-skilled services both routine and non-routine. Their definition of routine tasks is also based on whether a job is characterised by monotony of procedures. These findings should therefore be interpreted carefully in light of the above reasoning and not considered in contrast to the ALM theoretical framework.

Table 1.7 present results of OLS regressions of changes in employment shares between 1997-2006 and the initial level of routine intensity for each occupation. Panel (a) show estimates using all the 67 three-digit occupations, while panel (b) considers only middling and high-paying occupations. As expected, in both cases there is a negative relationship between the two variables. However, the coefficient is statistically significant only in the second case, possibly because of a misguided interpretation of the routine question by low-paid workers.

1.6 Technological Change and Routine Tasks

Similarly to Green (2012), we analyze the relationship between computerisation and routine task inputs at the occupational level creating a pseudo-panel. Unlike previous studies using the same data, we exclude from the analysis workers in low-paid service and elementary occupations for which the ALM theoretical framework predicts limited opportunities for substitution or complementarity. We deem that this exclusion is not only relevant from a theoretical standpoint but also from an empirical one, given our findings on the repetitiveness dimension in these occupations.

Furthermore, we decide to evaluate the routine index by itself and not combined with the manual one as in Green (2012). In the previous section we showed that the routine measure in the UK Skill Surveys is more strongly related to the manual rather than the cognitive measures available in the O*Net data. However, after dropping low-paying occupations, the correlation coefficient between our routine measure and the routine cognitive O*Net variable increases substantially from 0.33 to 0.57, while the other essentially stays constant (from 0.61 to 0.65). It is therefore reasonable to assume that, when testing the ALM model on those occupations for which there are clear theoretical predictions, the basic routine measure available in our data well captures both the manual and the cognitive dimension of repetitive tasks, despite we are treating two factors as one.

We collapse the variables of interest at the 3-digit ISCO-88 occupation level, specifying the following model:

$$\bar{T}_{jt} = \beta \bar{C}_{jt} + \sum_{t=1}^{T-1} \theta_t + \delta_j + \bar{\varepsilon}_{jt} \tag{1.3}$$

where $\bar{T}_{jt}$ is the routine task measure at the occupation level at time t, $\bar{C}_{jt}$ is the variable capturing computer intensity (see Appendix AB for further details on how it is derived) in occupation j at time t, θ_t is a set of year effects and δ_j is a set of occupation effects. Time fixed effects control for omitted variables which are constant across occupations but evolve over time; occupation fixed effects are included to control for omitted variables that vary across occupations but not over time.

Table 1.8 reports the estimates using fixed effects with occupation cell size as weights. We find that technology is significantly negatively related with routine task inputs. Since low-paying occupations were excluded from the analysis, the negative impact of computerisation is only associated with routine middle-paid

Table 1.8
IMPACT OF COMPUTER ADOPTION ON TASK MEASURES

	Dependent variable			
	Routine	Repetitive physical	Analytical	Interpersonal
Computer use	-0.151*	-0.170***	0.225***	0.193***
	(0.076)	(0.063)	(0.050)	(0.061)
N	156	156	156	156
R-squared	0.860	0.955	0.932	0.948
F(Year dummies)	2.83	1.51	6.81	0.06

Notes: Fixed-effects estimates at the 3-digit occupation level are weighted by cell size. Robust standard errors in parenthesis. *Source*: UK Skills Surveys.

jobs. As Column 2 shows, interacting the repetitive and the manual indexes improves the estimate significantly. However, this would imply to classify as routine only repetitive physical activities as in Green (2012) and we are not imposing this restriction. Although one important limitation is that we cannot disentangle the effect of computerisation on the routine cognitive and manual components (typical of clerical and production work, respectively), it is reasonable to think that both aspects are embedded in the basic measure.

For the sake of completeness, we estimate equation (3) also for analytical and interpersonal tasks. This is done to investigate whether non-manual tasks, which mainly refer to those individuals working in professional, managerial and creative non-routine occupations, are complements with computer use. Our findings are in line with the positive effect of computer technologies on the use of greater generic skills (such as literacy, numeracy, influencing and self-planning) found in Green (2009 and 2012). This is not surprising since the exclusion of low-paying occupations is not suppose to affect results for the high-paying ones.

1.7 The Displacement of Middle-paid Workers

In this section we explore the occupational mobility of middle-paid (skilled) workers[19]. Increasing demand for low-paid services can be considered as a side-effect

[19] The terms *paid* and *skilled* are interchangeable in our context.

Table 1.9
Occupational mobility by educational group

	Occupational change	
	1992-1997	1996-2001
Education	(1)	(2)
Low	64.57	71.21
Medium	58.39	70.88
High	57.01	54.21
N	727	1,776

Notes: The table shows the percentages of workers who changed occupation among those with the same educational attainment. *Source*: UK Skills Surveys.

of the impact of technological change on other parts of the economy. In a closed economy context, this demand is compensated by labour supply shifts of middle-skilled workers performing routine activities, easily substituted by machines, which ultimately lead to employment growth in low-paid jobs. ALM model predicts that marginal routine workers are induced to reallocate their labour supply to non-routine intense occupations.

We use information on past jobs for 2,503 national workers[20]. In 1997 and 2001 respondents were asked whether their historical job (5 years before) was the same as the current job (same employer). Workers also declared whether the job was in the same occupation or not. We compute the percentages of high, middle and low-skilled workers who changed occupation, given the total number of high, middle and low-skilled individuals in the sample indicating an historical occupational code. Looking at Table 1.9, we observe that middle-skilled workers became increasingly more mobile over time (+12.49 percentage points, against -2.8 of high-skilled and +6.64 of low-skilled).

Next, we want to establish where the displaced middle-paid workers moved by looking at the direction of their shifts, either towards low or high-paying occupations. Given that each survey covers exclusively workers, we can analyze only

[20]The UK Skills Surveys contain information on ethnicity which we use as a proxy to distinguish natives from foreign-born, given the absence of a variable on nationality. This restriction is minimal as a low number of observations is dropped.

downward and upward mobility and not flows into unemployment or inactivity. Our inquiry builds on the analysis of transition probability matrices[21]. According to the economic theory, we should see over time an increasing probability of middle-income workers to move towards low-paid services. In 2006 the employment history question was related to the past industry and not occupation, hence it is not comparable to the other waves. We decide to integrate our main source with an additional dataset to extend the period of analysis. Using the BHPS (British Household Panel Survey), we investigate occupational mobility from 2001 to 2006 after having applied to the data all the necessary restrictions to obtain a comparable sample. From Table 1.10 one can see that the probability that workers in middling-paying occupations did not change group decreased (from 0.69 to 0.58), while it increased for those in low and high-paying occupations (respectively from 0.58 to 0.69, and from 0.73 to 0.81).

We further check whether these shifts were due to a self-selection process rather than a forced displacement. According to the Roy (1951) model of wage determination and self-selection, workers chose occupations endogenously moving into those with the highest average reward to their bundle of tasks. If this were the case we would expect that middle-paid displaced workers earn more that the average wage of the selected low or high-paying occupation. Among those workers who moved out middling-paying occupations (i.e. 1,030, of which 654 from BHPS), we find that 74.57% of those moving upwards and 57.81% of those moving downwards earn an hourly wage lower than the average. While the former figure could simply reflect differences in returns from educational attainments, the latter seems to indicate that displaced middle-paid workers are not well rewarded despite a reasonable comparative advantage.

Our findings suggest that there was a forced reallocation of middle-paid workers' labour supply. However, these workers did not predominantly move towards low-paid services. The probability of moving towards high-paying occupations increased too. Our interpretation is that explanations of the significant job expansion

[21]In a transition probability matrix each cell corresponds to the transition probability from one state to another given by: $p_{ij} = \Pr(X_t = j|X_t = i)$. This is computed as: $p_{ij} = N_{ij}/\sum_{j=1}^{n} N_{ij}$, where N_{ij} is the number of workers changing from state i to j (the cell count) and $\sum_{j=1}^{n} N_{ij}$ the total number of workers in a certain occupation group (the row count).

Table 1.10
Transition probability matrix

		Occupation in 1997			
		Low	Middling	High	Total
Occupation in 1992	Low	0.58	0.26	0.17	1
	Middling	0.14	0.69	0.17	1
	High	0.08	0.19	0.73	1
		Occupation in 2001			
		Low	Middling	High	Total
Occupation in 1996	Low	0.56	0.29	0.14	1
	Middling	0.19	0.60	0.21	1
	High	0.07	0.17	0.75	1
		Occupation in 2006			
		Low	Middling	High	Total
Occupation in 2001	Low	0.69	0.14	0.17	1
	Middling	0.17	0.58	0.25	1
	High	0.06	0.12	0.81	1

Notes: Each cell corresponds to the transition probability form one state to another. Occupations are grouped into low, middling and high-paying. N=739 in 1997, 1,785 in 2001 and 3,645 in 2006. *Source*: UK Skills Surveys and BHPS.

at the lower tail of the distribution entirely based on the displacement of national middle-skilled workers are not fully satisfactory.

One has to consider that since the mid-1990s immigration flows increased sharply in the United Kingdom[22]. Apart from the concentration in very high-skilled jobs, notably health professionals, there has been an increasing tendency over time for immigrants to be predominant also in jobs at the bottom end of the occupational classification. Nickell and Saleheen (2009) show that the ratio between recent immigrants and natives has increased by proportionately more in low skilled elementary and operative occupations over the last two decades. Oesch and

[22]Statistics on international migration flows for the UK are available at:http://www.statistics.gov.uk/hub/population/migration/international-migration.

Rodríguez Menés (2011), by resorting to an exercise in counterfactuals, find that between 1991 and 2008 the expansion in the low-paid occupations of the lowest quintile in Britain was mainly determined by job growth among foreign-born and not national workers.

1.8 Summary and Conclusions

In this paper we contribute to the debate on labour market polarisation in Britain using UK task data to measure the job content of occupations. We confirm that employment in Britain experienced a polarising trend at the occupational level between 1997 and 2006 but there is no evidence of a similar course in wages. Our sample suggests that jobs in high and low-paying occupations increased, while employment shares decreased in the middle of the distribution.

We interpret the evolution of occupational employment from a task-based perspective exploring ALM model's predictions. We find that high-paying occupations which increased the most can be safely classified as non-manual non-routine, while middling-paying occupations which have lost significant employment shares are predominantly routine (both manual and non-manual). The task content of low-paying occupations is more mixed, with elementary occupations being predominantly manual and service occupations scoring higher in the interpersonal dimension, and the routine dimension appears more difficult to evaluate. Still, we find that changes in employment shares are negatively related to the initial level of routine intensity.

Similarly to Green (2012), we formally test the association between routine task inputs and technology in workplaces, but we decide to exclude from the analysis low-paying occupations for which the ALM model predicts limited opportunities for substitution or complementarity. Moreover, we do not constrain our routine measure to represent only repetitive physical activities. From a comparison with O*Net data, we show that the routine measure in the UK Skills Surveys well captures both the manual and the cognitive routine dimension once low-paying occupations are dropped. The negative impact of computerisation that we find is therefore likely to be associated both with manual and cognitive routine middling-paying jobs, although we are not able to disentangle the effect.

Finally, we exploit retrospective questions on past jobs to evaluate the extent to which the displacement of middle-paid workers, caused by an adverse impact of technological advances, contributed to the employment growth at the lower tail of the distribution. We find that workers in middling-paying occupations became more mobile over time. However, they did not predominantly move towards low-paying occupations. This is consistent with the argument that the surge of low-skilled immigrants in Britain from 1997 onwards played a major role in the expansion of low-paid jobs.

Chapter 2

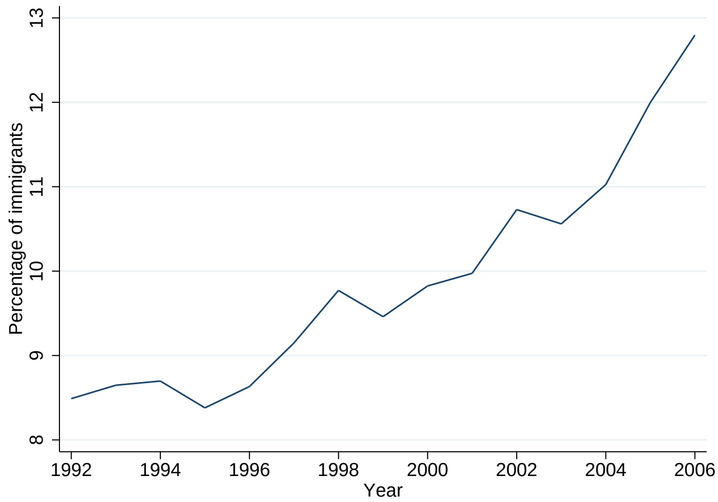
How does immigration affect natives' task-specialisation? Evidence from the United Kingdom.*

2.1 Introduction

Net immigration inflows into the UK have increased sharply since 1997, reaching their maximum in 2005 with the EU enlargement to Central and Eastern European Countries and falling afterwards (Dustmann et al., 2008; Wadsworth, 2012). Figure 2.1 shows that since the mid-1990s the percentage of immigrants in the UK working age population has been rising from around 8.5 to almost 13 percent in 2006. Unlike the US or some continental European countries (e.g. Italy or Spain), immigration to Britain in the past has not been predominantly concentrated at the bottom of the skill distribution. Many immigrants are indeed highly-qualified and find a job in high-paying occupations, as it is the case for health professionals. Yet, major changes in the distribution of immigrants from the mid-1990s happened at the lower end of the occupational classification (Nickell and Saleheen, 2009).

*I thank the Institute for Social and Economic Research (ISER) for hosting me during my research. I am also deeply grateful to Dr Joanne Lindley for her valuable comments and suggestions on earlier drafts.

Figure 2.1
PERCENTAGE OF IMMIGRANTS IN UK'S WORKING AGE POPULATION



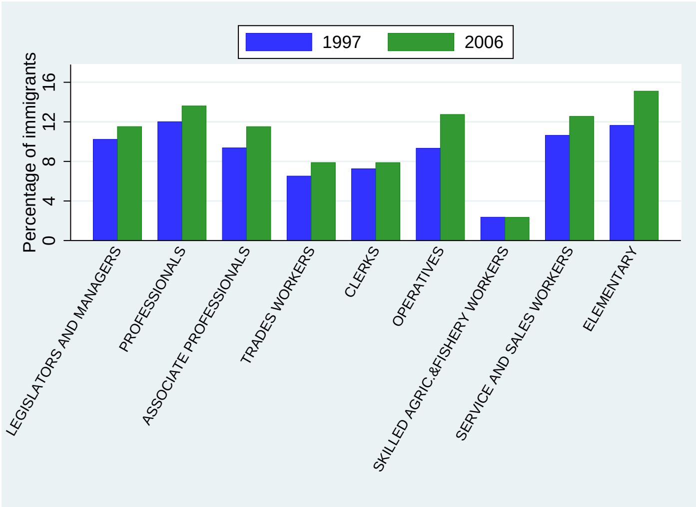
Notes: Percentage of foreign-born in working age population 16-65. *Source*: Labour Force Survey (LFS) and author's calculations.

Today immigrants are indeed over-represented both in the very high-skilled and very low-skilled occupations (Wadsworth, 2012). This is shown by Figure 2.2 which compares the occupational distribution of immigrants between 1997 and 2006. As one would note, there was a relatively more marked increase in the presence of immigrants at the bottom of the occupational classification, particularly in operatives, service and sale workers and elementary occupations[1]. The increasing presence of immigrants in low-paying occupations is even more marked when considering only recent immigrants (i.e. those with at most five years of residence in the UK) (see Figure 2.3)[2].

[1]For the sake of completeness, Figure 2.2 includes also the ISCO-88 category "Skilled agricultural and fishery workers", although employment in this occupation occurs only in small numbers compared to the yearly average across all occupations.

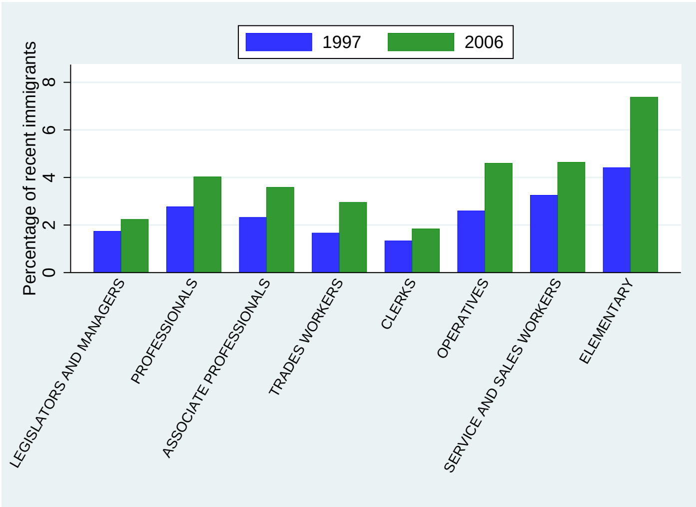
[2]Our analysis follows Nickell and Saleheen (2009) who look at immigration across occupations distinguishing between all and new immigrants.

Figure 2.2
Percentage of immigrants by occupation



Notes: ISCO-88 occupations are ranked according to their initial 1997 mean hourly wage, from the highest (left) to the lowest (right). *Source*: Labour Force Survey (LFS) and author's calculations.

Figure 2.3
Percentage of recent immigrants by occupation



Notes: ISCO-88 occupations are ranked according to their initial 1997 mean hourly wage, from the highest (left) to the lowest (right). Recent immigrants are defined as those with at most five years of residence in the UK. *Source*: Labour Force Survey (LFS) and author's calculations.

By resorting to a counterfactual exercise, Oesch and Rodríguez Menés (2011) confirm that the job expansion in low-paid jobs that Britain experienced from the late 1990s was mainly determined by surges of immigration. These changes could be reasonably explained both by downgrading of immigrants upon arrival, who end up competing with lower educated native workers because of language or cultural barriers (Dustmann et al., 2008), and recent high inflows of low skilled immigrants due to the EU enlargement in 2004 (Nickell and Saleheen, 2009).

One major concern for immigrant-receiving countries are the effects that foreign-born supply has on local labour market. Previous literature considers traditional labour market outcomes such as wages, employment, unemployment and participation rate. Here we adopt a different perspective introduced by Peri and Sparber (2009) who investigate the effect of immigration on the task specialisation of natives. This paper aims at evaluating whether natives, who are assumed to have a comparative advantage relative to immigrants in communication as opposed to manual tasks, are induced to specialise in communication-intensive jobs in response to immigration inflows. In light of the above described recent developments of immigration patterns in Britain, we focus on the bottom end of the occupational skill distribution by looking at the impact of less-skilled foreign-born on similarly educated native workers. In this paper not only do we contribute to the literature on migration in the UK by applying a novel task-based approach, but we also make a methodological progress with respect to previous studies on immigration and task-specialisation in European countries by measuring the task content of occupations from national survey data, instead of relying on US sources. Our main empirical findings show that in the UK natives respond to increasing immigration by shifting their task supply and providing more communication relative to manual tasks. By instrumenting the share of foreign-born workers, we show that the positive effect on the relative task supply is plausibly causal. Results obtained for the UK are consistent with previous literature for the US, Spain and Europe.

The rest of the paper is organised as follows. Section 2 presents an overview of the relevant literature. Section 3 outlines the theoretical model of comparative advantages in task performance developed by Peri and Sparber (2009), on which we draw heavily. Section 4 discusses the empirical specification and the identification strategy. Section 5 describes the data used and the construction of our main variables. Section 6 reports results from the empirical analysis. Finally, in Section 7 we assess how the effects of immigration on natives' task specialisation vary across demographic groups and we perform a sensitivity analysis by utilising alternative task variables. Section 8 concludes.

2.2 Related Literature

There is a recent but growing literature on the benefits and costs of immigration inflows in the UK. Some papers use a spatial correlation, or inter-area, approach which consists in slicing the labour market by area within a country and then relying on regional variations to identify the effects of immigration on labour market outcomes (e.g Dustmann et al., 2005); others follow the so-called national approach which implies that the national labour market is divided by skill group (education-age cells) (e.g Manacorda et al., 2012). This second strategy was proposed to overcome the problem that labour markets are not closed economies and natives are free to move in or out. However, this approach depends on the assumption that immigrants and natives are perfect substitutes within pre-defined skill categories, which does not hold if immigrants considerably downgrade after arrival, as shown by Dustmann et al. (2013) in their analysis for Britain[3].

Overall, this literature finds that immigration had no appreciable effect on the average wages and employment of native-born workers (see Wadsworth, 2012, for a review)[4]. Dustmann et al. (2005) find no strong evidence that immigration has overall effects on aggregate employment, participation, unemployment and wages at the regional level. Lemos and Portes (2008) contribute to the UK migration literature by looking at the effects of the 2004 EU enlargement. They find modest effects of migration from Central and Eastern European Countries on regional labour markets, with no significant fall in wages nor rise in claimant unemployment. Nickell and Saleheen (2009) refine previous studies incorporating the occupational dimension into a regional analysis of immigration in Britain. They find a small neg-

[3]Dustmann et al. (2013) introduce a novel approach analysing the impact of immigration along the distribution of native wages, rather than on wages of different skill groups, without imposing any ex-ante restriction on where immigrants compete with natives.

[4]This evidence is consistent with findings for the US (see Borjas, 2003; Borjas and Katz, 2007; Card, 2001, 2005; Card and Lewis, 2007).

ative impact of immigration on average occupational wages in the semi/unskilled services sector.

As emphasised by Ottaviano and Peri (2006, 2008), the effects of immigration significantly depend on the degree of substitution between natives and foreign-born workers with similar observable characteristics. If immigrants and natives within the same educational group do not possess the same skills, they specialise in different tasks and therefore different occupations. Ottaviano and Peri (2006, 2008) explain the minimal impact of immigration on local labour markets in light of the fact that natives and immigrants do not compete for the same job. Peri and Sparber (2009) advance this literature by focusing on workers with little educational attainment (i.e. those without a college education) in the US. Less-educated immigrants and natives are imperfect substitutes in production: the former have a comparative advantage in occupations requiring simple physical ("manual") tasks, mainly because of limited language proficiency, lack of specific human capital skills and imperfect knowledge of the local labour markets; the latter have an advantage in occupations which require the use of interactive and communication ("complex") tasks. The authors provide empirical evidence that less educated immigrants tend to specialise in physical demanding jobs and at the same time that natives respond to immigration by increasing their supply of complex tasks.

To the best of our knowledge, there are only two studies which explore these findings outside the US. Amuedo-Dorantes and de la Rica (2011), by looking at Spanish data and adding in the gender dimension to the empirical specification of Peri and Sparber (2009), show that both native men (women) relocate to jobs with a higher interactive or communication content in response to an increase in male (female) immigration. D'Amuri and Peri (2012) analyze the impact of immigration on 15 European countries and explore its variation in light of the differences in labour markets' institutional characteristics. Again, they establish that higher immigration pushes natives to occupations with higher skill contents, and that this process is stronger in countries with low levels of employment protection legislation. The purpose of this article is to fill the gap in evidence for Britain.

2.3 Theoretical Model

In this section we outline the Peri and Sparber (2009) model of comparative advantages in task performance. In our analysis we entirely follow its predictions and empirical specification.

Assume that an open economy produces a final good Y using intermediate inputs Y_L and Y_H, which are produced by less and high-educated workers respectively. Given that the focus is on workers with little educational attainment, Peri and Sparber (2009) simply assume that Y_H is produced according to a linear technology equal to the total supply of highly-educated workers, that is $Y_H = H$. On the contrary, Y_L requires the combination of two different type of tasks, manual (M) and communication (C), according to the following CES function:

$$Y_L = \left[\beta_L M^{\frac{\theta_L - 1}{\theta_L}} + (1 - \beta_L) C^{\frac{\theta_L - 1}{\theta_L}}\right]^{\frac{\theta_L}{\theta_L - 1}} \tag{2.1}$$

where $\beta_L \in (0, 1)$ captures the relative productivity of manual skills and $\theta_L \in (0, \infty)$ measures the elasticity of substitution between M and C.

Manual tasks, such as carrying heavy objects, or using hands/tools on the workplace, are those requiring physical skills. Communication tasks (for instance making speeches or presentations, and writing documents) require instead good language skills. Under the assumption of perfect competition, profit maximisation yields to the following relative demand function for communication versus manual tasks:

$$\frac{C}{M} = \left(\frac{1 - \beta_L}{\beta_L}\right)^{\theta_L} \left(\frac{w_C}{w_M}\right)^{-\theta_L} \tag{2.2}$$

The relative task demand in equation (2.2) is directly related to the worker's relative efficiency in performing different tasks and the relative task compensation.

"Domestic" native-born workers (D) and "foreign-born" immigrant workers (F) differ from each other in terms of relative task productivity. Each less-educated worker allocate one unit of time to perform μ_j units of manual tasks, ζ_j units of communication tasks, or some partition of the two. The assumption that natives have a comparative advantage in communication tasks implies that $(\zeta_D/\mu_D) > (\zeta_F/\mu_F)$.

The equilibrium relative supply of communication versus manual tasks for natives and immigrants is derived from labour income maximisation of a representative individual who allocate her/his time between the two types of tasks[5]:

$$\frac{c_j}{m_j} = \left(\frac{w_C}{w_M}\right)^{\frac{\delta}{1-\delta}} \left(\frac{\zeta_j}{\mu_j}\right)^{\frac{1}{1-\delta}} \tag{2.3}$$

where $\delta \in (0,1)$ captures the decreasing returns from performing a single task. Equation (2.3) describes the individual relative task supply of communication versus manual tasks for natives (j=D) and immigrants (j=F)[6]. The relative supply depends positively on relative task compensation, (w_C/w_M), and on worker's relative efficiency in performing tasks, (ζ_j/μ_j). The relative task supply C/M in the whole economy, obtained by aggregating individual task supply in (2.3), is a weighted average of the relative supply by natives and immigrants of both tasks:

$$\frac{C}{M} = \frac{C_F + C_D}{M_F + M_D} = \varphi(f)\frac{C_F}{M_F} + (1-\varphi(f))\frac{C_D}{M_D} \tag{2.4}$$

The weight $\varphi(f)$ represents the share of manual tasks provided by immigrants, which is simply a monotonic transformation of the foreign-born share of less-educated workers $f = L_F/(L_F + L_D)$. This weighting procedure allows to account for different optimal task provisions between immigrants and natives. The equilibrium relative compensation of tasks w_C^*/w_M^* is then easily obtained by substituting (2.3) for natives and immigrants in (2.4) and then by equating the relative supply to the relative demand in (2.2):

$$\frac{w_C^*}{w_M^*} = \left(\frac{1-\beta_L}{\beta_L}\right)^{\frac{(1-\delta)\theta_L}{(1-\delta)\theta_L+\delta}} \left[\frac{\zeta}{\mu}\left(\underset{-}{f}, \underset{+}{\frac{\zeta_F}{\mu_F}}\right)\right]^{\frac{-1}{(1-\delta)\theta_L+\delta}} \tag{2.5}$$

where the function $\frac{\zeta}{\mu}\left(f, \frac{\zeta_F}{\mu_F}\right)$ is the average relative communication ability. More precisely, $\frac{\zeta}{\mu}\left(f, \frac{\zeta_F}{\mu_F}\right) = \left[\varphi(f)(\zeta_F/\mu_F)^{\frac{1}{(1-\delta)}} + (1-\varphi(f))(\zeta_D/\mu_D)^{\frac{1}{(1-\delta)}}\right]^{(1-\delta)}$.

The expression for the optimal provision of communication to manual tasks by natives is derived by substituting the equilibrium wage into the aggregate task

[5] We skip some derivations for simplicity. A more detailed exposition can be found in the original paper.

[6] In the original notation, j represents not only the type of worker (native or immigrant) but also her/his occupation. Indeed, it is on the basis of their relative effectiveness in performing different tasks that workers select the occupation.

supply for natives:

$$\frac{C_D^*}{M_D^*} = \left(\frac{1-\beta_L}{\beta_L}\right)^{\frac{\delta\theta_L}{(1-\delta)\theta_L+\delta}} \left(\frac{\zeta_D}{\mu_D}\right)^{\frac{1}{(1-\delta)}} \left[\frac{\zeta}{\mu}\left(\underset{-}{f}, \underset{+}{\frac{\zeta_F}{\mu_F}}\right)\right]^{\frac{-1}{(1-\delta)\theta_L+\delta}\frac{\delta}{1-\delta}} \tag{2.6}$$

From equation (2.5) one can see how an increase in the share of immigrants (f) has a negative effect on the average relative communication ability $\frac{\zeta}{\mu}\left(f, \frac{\zeta_F}{\mu_F}\right)$. This, in turn, implies an increase in the return to communication relative to manual tasks and, ultimately, a rise in the relative supply of communication tasks by natives. Hence, the hypothesis that we empirically test is that less-educated natives respond to immigration inflows of similarly educated workers by increasing their provision of communication tasks.

2.4 Empirical implementation

By taking the logarithmic derivative of the optimal provision of communication to manual tasks in equation (2.6), one can derive an empirically implementable specification:

$$\ln\left(\frac{C_D}{M_D}\right)_{rt} = \alpha_r + \tau_t + \gamma f_{rt} + \varepsilon_{rt} \tag{2.7}$$

where $\ln(C_D/M_D)_{rt}$ is the (log) average ratio of communication versus manual task supply at the region(r)-year(t) level, our spatial unit of analysis[7]. Region fixed-effects α_r, which account for region-specific unobserved characteristics of the population, capture the term $(1/(1-\delta))$ x $\ln(\zeta_D/\mu_D)$ from (2.6). Time fixed-effects τ_t account for common time-varying technological parameters (i.e. nation-wide shocks) and capture the term $(\delta\theta_L/((1-\delta)\theta_L+\delta))$ x $\ln((1-\beta_L)/\beta_L)$ from (2.6). The term $(f)_{rt}$ represents the share of low-educated foreign-born workers at the region-year cell. Its coefficient $\gamma \equiv -(1/((1-\delta)\theta_L+\delta))(\delta/(1-\delta))$ x $(\partial \ln(\zeta/\mu)/\partial f)$ is our main parameter of interest. Following the predictions of the theoretical model presented in Section 2.3, we will empirically test the hypothesis that $\gamma > 0$, i.e. that less-educated native workers increase their relative supply of communication versus manual tasks

[7]In this paper we follow the so-called spatial correlation approach, as opposed to the national approach (see Section 2.2 for details).

in response to inflows of similarly skilled immigrants.

The measurement of the effect of immigration on local labour markets requires some identification assumptions which are widely discussed in the literature. The first one is that natives should not out-migrate from their region as a consequence of immigration flows, since this would disperse the effect of immigration across the national economy and undermine the ability to identify it. The second assumption in the OLS estimates is that, after controlling for the fixed effects and demographic characteristics, the variation of the share of less-educated foreign-born is exogenous and is not driven by unobserved employment opportunities. An additional related issue is potential measurement error in the share of low-educated foreign born workers at the regional level which could cause attenuation bias in OLS estimates. In what follows we discuss all these problems.

2.4.1 Natives' inter-regional mobility

Whether the out-migration of natives affects the measurement of immigration's impact on local labour markets outcomes remains still disputed and previous studies for the US present conflicting results. While Wright et al. (1997), Card and DiNardo (2000) and Card (2001) find little or no evidence of an adverse effect of immigration on native internal mobility, Frey (1995) and Borjas (2003) consider out-migration a relevant issue.

As far as Britain is concerned, Hatton and Tani (2005) recently examined the relationship between immigration and interregional mobility. Their analysis, which covers the period from 1982 to 2000, shows that there is a negative correlation between net migration rate from abroad and inter-regional net migration rates. This relationship is however significant only for the southern regions. Moreover, their study is based on population and not labour force flows and it does not investigate the differential impact by education levels. Using Labor Force Survey data, Gregg et al. (2004) show little evidence of any significant trend in regional mobility during the period 1979 to 2000. They also find that mobility is more limited amongst low educated people. Additionally, Wadsworth (2012) find a very week correlation between UK-born mobility and immigrant inflows at the level of local areas between 2004 and 2008. We can therefore argue that the assumption that labour markets are regional in scope is a reasonable one.

2.4.2 Endogenous allocation of immigrants and measurement error

A more relevant identification issue is the potential endogeneity of the share of foreign-born workers. There are a number of possible omitted variables that influence the allocation of immigrants across the regions of the receiving country. Indeed, it is likely that immigrants are not randomly allocated across local labour markets and might be attracted to areas with a particular occupation according to expected employment opportunities. Our concern is that unobserved labour demand conditions at the regional level could have simultaneously affected immigrant choices and the relative supply of communication tasks by less-educated natives. Moreover, potential measurement error of the share of low-educated foreign born workers at the region-year level could lead to attenuation bias in OLS estimates.

In order to address both endogeneity and measurement error, we construct an instrumental variable for the share of low-educated foreign-born workers. We follow a traditional approach in the literature, based on the Card (2001) shift-share instrument, which consists of exploiting past immigrant concentrations to remove the effect of unobserved demand shocks that might affect location choices[8]. Past concentrations are indeed an important determinant of immigrants' location decisions, especially for low educated workers. Because of information networks and other personal preferences, immigrants are attracted in those areas where groups with the same cultural and linguistic background are located. Under the assumption that historical settlements are uncorrelated with current economic shocks within each cell, we can obtain an exogenous measure for the share of immigrants.

Similarly to D'Amuri and Peri (2012) we combine Labour Force Survey data, the main dataset used in this paper and described in Section 2.5, with two external sources. From the 1991 national Census[9], we calculate the population levels of immigrants by region and continent of origin (a) (Asia, Africa, North America, South

[8]Alternative identification strategies take advantage of natural experiments or government policies (see Dustmann et al., 2008, for a short review).

[9]We downloaded Individual SARs (Sample of Anonymized Records) for Great Britain and Northern Ireland. Further information can be found at: http://www.ccsr.ac.uk/sars.

America, Europe, and Oceania). We then multiply these initial (1991) values for the national growth rates of each area of origin immigrant group, constructed from yearly immigration flows available in the Ortega-Peri database[10]. These imputed number of less-educated immigrants for each area of origin are then aggregated at the region-year level. Our instrument is then obtained dividing the total number of imputed immigrants by the total population in the cell (total natives plus total imputed immigrants). More formally we have that:

$$f\_imputed_{rt} = \frac{\sum_{a=1}^{6}(imm_{ar,1991}) * (1 + g_{a,1991-t})}{natives_{r,t} + \sum_{a=1}^{6}(imm_{ar,1991}) * (1 + g_{a,1991-t})} \tag{2.8}$$

where $(1+g_{a,1991-t})$ is the overall growth rate of immigrants by area of origin between 1991 and year t. This instrumental variable not only has the advantage of exploiting the area of origin of immigrants, but it also uses a larger Census sample to address potential measurement error.

2.5 Data and descriptive statistics

Our main data source is the UK Labour Force Survey (LFS) for the years 1997-2006[11]. We exclude the years of the Great Recession due to data limitation in the construction of our instrument. The LFS is a continuous household survey of the employment circumstances of the UK population. It contains hundreds of variables which cover many features of the UK labour market and related topics. The LFS has been running on a biannual basis from 1973 and 1983; it then became annual in 1984. Data were made available quarterly from Spring 1992, increasing almost fourfold the sample size. Each LFS' quarter about 60,000 households are interviewed. We append the four quarterly datasets in a given year into one, retaining only respondents who were interviewed for the first time at each quarter[12].

We restrict our analysis to native and immigrant workers (i.e. employees and self-employed), aged between 16 and 65. While the LFS does not collect data on

[10]We thank Francesc Ortega and Giovanni Peri for making the data publicly available at http://economics.ucdavis.edu/people/gperi/site/papers/copy_of_ortega_peri_bilateral_migration_2012.zip.

[11]Neither the New Annual Survey Panel Dataset (NESPD) nor the Annual Survey of Hours and Earnings (ASHE) contain information on the place of birth. So we deem that the LFS is the best available source at present.

[12]We use the variable *thiswv* to ensure that each household is only included once each year.

immigration status, it does include questions on country of birth and nationality. We define immigrants those individuals who are foreign-born. Because we want to focus primarily on the impact that less-educated immigrants have on natives' task-specialisation, we exclude from our analysis highly educated workers. We exploit information on the age at which respondents left full-time education to define educational achievements. It is indeed well known that the measure based on the highest qualification achieved classifies foreign qualifications into the general category of "other qualification", irrespective of the level of the qualification held (see Manacorda et al., 2012, for more details). Individuals who left-full time education at age 21 or later are classified as highly educated. Among less educated workers, we distinguish individuals with a secondary education (left full-time education at ages 17-20) from those without it (never had full-time education or left it before 17). Individuals still in education are entirely excluded from the sample.

Area studies by Peri and Sparber (2009) and Amuedo-Dorantes and de la Rica (2011) interpret as labour markets US states and Spanish provinces respectively. For the UK, we chose 13 regions as our econometric unit of analysis. The LFS codes 20 regions[13] but we reduce the number to 13 by aggregating some of them in order to reflect the Census 1991 classification: North, Yorks and Humber, East Midlands, East Anglia, Inner London, Outer London, Rest of South East, South West, West Midlands, North West, Wales, Scotland and Northern Ireland.

Table 2.1 presents some descriptive statistics of the sample. Natives and immigrants with little educational attainments are quite similar in terms of human capital characteristics. The most significant difference is in terms of educational attainments, with a higher percentage of immigrants having a secondary education compared to natives, as similarly found by Amuedo-Dorantes and de la Rica (2011) for Spain. As far as the regional distribution is concerned, Figure 2.4 shows that in 2006 Inner and Outer London were the areas with the highest concentration of foreign-born workers, followed by the Rest of South East and East Anglia.

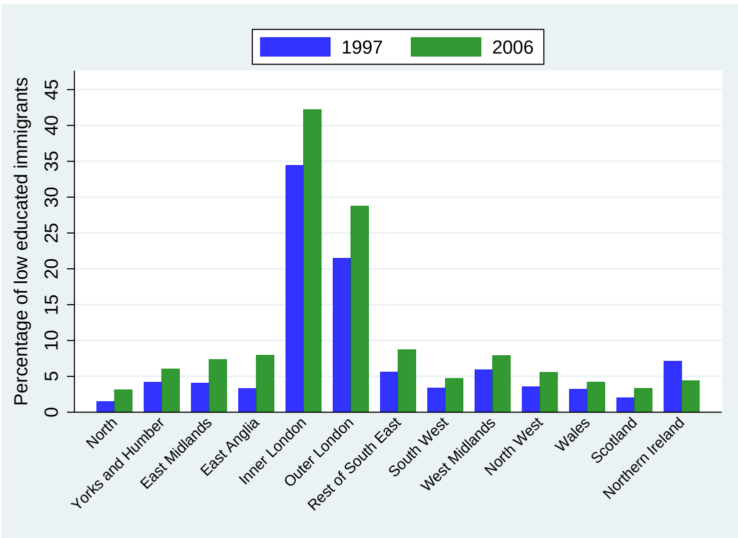
[13]Tyne and Wear, Rest of Northern Region, South Yorkshire, West Yorkshire, Rest of Yorkshire and Humberside, East Midlands, East Anglia, Inner London, Outer London, Rest of the South East, South West, West Midlands, Rest of West Midlands, Greater Manchester, Merseyside, Rest of North West, Wales, Central Clydeside, Scotland and Northern Ireland.

Table 2.1
DESCRIPTIVE STATISTICS, LESS-EDUCATED WORKERS (1997-2006)

Variables	Natives	Immigrants
Human capital characteristics		
Average age	40.3	40.1
Average years of education	16.4	17.6
Female (%)	46.2	46.0
Younger than 40 (%)	51.1	51.3
Secondary education (%)	30.9	55.2
Primary education (or less) (%)	69.1	44.8
Tot. obs.	350,409	24,655
Average obs. per region-year cell	2,695.45	189.65

Notes: Workers (employees and self-employed) aged 16-65. Secondary education: left full-time education between the ages of 17 and 20; primary education (or less): left full-time education before 16 years old (included) or never had full- time education. Full-time students are excluded. *Source*: Labour Force Survey (LFS).

Figure 2.4
PERCENTAGE OF LOW EDUCATED IMMIGRANTS BY REGION, 1997 AND 2006



Source: Labour Force Survey (LFS) and author's calculations.

2.5.1 Task-intensity variables

In order to investigate the effects of immigrants on natives' task specialisation, we need information on the activities performed by workers on the job. We derive our task intensity measures at the occupational level from an additional source, the UK Skills Surveys. Unlike previous studies on immigration and task-specialisation in European countries (see Amuedo-Dorantes and de la Rica, 2011; D'Amuri and Peri, 2012) we do not rely on the U.S. Department of Labor's O*Net abilities survey to derive data on job task requirements. Hence, we do not need to assume that the task composition of occupations is the same in the two countries.

The aim of the UK Skills Surveys is to provide an analysis of the level and distribution of skills being used in British workplaces. They are not carried out continuously each year and data are available only for 1997, 2001 and 2006. At each wave, information on job characteristics and working conditions are collected, including details on the tasks performed. The three cross-sections cover altogether 14,717 workers (2,467 in 1997, 4,470 in 2001 and 7,780 in 2006).

We convert occupational codes from the Standard Occupation Classification (SOC90 and SOC2000) into the International Standard Classification of Occupations (ISCO-88) using crosswalks made available by the CAMSIS project[14]. This classification makes our results easily comparable with previous studies for European countries. We retain only those occupations at the 2-digit level which appear in all three waves and exclude those for which the data appeared unreliable: army (ISCO 1), legislators and senior officials (ISCO 11) and agricultural, fishery and related labourers (ISCO 92). Employment in these occupations occurred only in a very small number.

At each wave respondents are asked how much a particular activity is important for his/her job on a 5-point scale ranging from 1 ("not at all/does not apply) to 5 ("essential"). These variables in Likert scale are converted into increasing cardinal scale from 0 ("not at all/does not apply) to 4 ("essential") and then normalised in order to range between 0 and 1. Among all the available ability scores, we only select those relevant for our analysis, which are used to derive measures of the

[14]Available at: http://www.camsis.stir.ac.uk/occunits/uksoc90toisco88v1.sps and http://www.camsis.stir.ac.uk/occunits/uksoc00toisco88v1.sps

"manual" and "communication" skills. We follow the existing literature as close as possible by selecting abilities from the UK Skills Surveys which resemble to those available in the O*Net dataset. We retain responses on "Skill or accuracy in using hands/fingers"(e.g. to assemble or repair), "Physical stamina"(e.g. to work on physical activities) and "Physical strength"(e.g. to carry, push or pull heavy objects) for the manual aspect, and on "Making speeches and presentations"and "Writing long documents with correct spelling and grammar"for the communication (oral and written) dimension[15]. Task measures are then collapsed at the ISCO-88 2-digit level for the pooled dataset, weighting each observation for the individual sampling weight. The final dataset is then merged with LFS data by occupation[16]. Finally, the manual and communication indicators are both derived as an average of the selected elements above mentioned. Table 2.2 reports their values, together with their ratio, in each occupation. As one would expect, the values of C/M are lowest among craft and trade workers, and in operative and elementary occupations. Managers and professionals score instead among the highest.

2.6 The effects of immigrants on natives' relative task performance

In this section we test whether less-skilled natives increase their relative supply of communication tasks as a response to immigration by estimating equation 2.7. However, we must first take into account the fact that there are personal characteristics which affect task supply at the individual (and regional) level and may be also correlated with immigration stock. Peri and Sparber (2009) avoid this potential spurious correlation by constructing manual and communication task supply which are "cleaned" of demographic effects. We apply their methodology by regressing natives' task supply at the individual level on gender (a female indicator), age, and education (a secondary education dummy)[17]. Next, we use the "cleaned"

[15]Using O*Net data, (Peri and Sparber, 2009) consider the following skill sub-types: "Limb, hand, and finger dexterity", "Body coordination and flexibility" and "Strength" for the manual category, and "Oral" and "Written" skills for the communication index.

[16]SOC90 and SOC2000 codes in the LFS were also mapped into the ISCO-88 classification.

[17]Results would be qualitatively the same if we controlled for demographic characteristics at the region-year cell level in the final regression (see Amuedo-Dorantes and de la Rica, 2011).

Table 2.2
Task intensities by occupation

Occupations (ISCO-88 code)	M	C	C/M
12. Corporate managers	0.29	0.59	2.05
13. General managers	0.54	0.39	0.72
21. Physical, mathematical and engineering science professionals	0.27	0.54	2.00
22. Life science and health professionals	0.45	0.56	1.23
23. Teaching professionals	0.38	0.75	1.96
24. Other professionals	0.23	0.62	2.73
31. Physical and engineering science associate professionals	0.39	0.42	1.08
32. Life science and health associate professionals	0.62	0.50	0.81
33. Teaching associate professionals	0.34	0.60	1.79
34. Other associate professionals	0.30	0.54	1.84
41. Office clerks	0.28	0.36	1.26
42. Customer services clerks	0.31	0.29	0.92
51. Personal and protective services workers	0.56	0.33	0.59
52. Salespersons, models and demonstrators	0.53	0.21	0.40
61. Market-oriented skilled agricultural and fishery workers	0.81	0.25	0.31
71. Extraction and building trades workers	0.81	0.23	0.29
72. Metal, machinery etc trades workers	0.73	0.28	0.39
73. Precision, handicraft, printing etc trades workers	0.68	0.22	0.32
74. Other craft etc trades workers	0.71	0.20	0.28
81. Stationary-plant etc operators	0.70	0.21	0.30
82. Machine operators and assemblers	0.66	0.24	0.36
83. Drivers and mobile-plant operators	0.59	0.18	0.30
91. Sales and services elementary occupations	0.55	0.20	0.36
93. Labourers in mining, construction manufacturing and transport	0.70	0.21	0.30

Notes: Authors' calculations based on UK Skills Surveys 1997, 2001 and 2006, and LFS 1997-2009. Only working individuals between 16 and 65 with little educational attainment (secondary and primary or less education) are considered. The manual (M) and communication (C) indexes are derived averaging task measures which capture respectively the intensity of physical activities and language (oral and written) skills.

Table 2.3
Task supplies "cleaned" of demographic effects

Variable	$\boldsymbol{M}$	$\boldsymbol{C}$
Female	-0.095***	0.015***
	(0.001)	(0.000)
Age	-0.001***	0.001***
	(0.000)	(0.000)
Primary educ.	0.097***	-0.093***
	(0.001)	(0.001)
Constant	0.509***	0.359***
	(0.001)	(0.001)
N	350,409	350,409

Notes: We use the "cleaned" residuals from the above regressions to compute the manual and communication task supply measures used in the empirical specification. *Source*: Labour Force Survey (LFS) and UK Skills Surveys.

residuals to compute the manual and communication task supply measures used in equation 2.7. Table 2.3 reports results from these first-stage cleaning procedure. As it would be expected, the coefficient for the female indicator and age are negative for manual tasks and positive for communication tasks. Conversely, there is a positive effect of primary education (with respect to the base category, that is secondary education) on the supply of manual tasks.

We first estimate equation 2.7 by ordinary least squares (OLS), clustering standard errors by region. Column 1 of Table 2.4 presents the estimate of γ, which provides a direct test of the Peri and Sparber (2009) theoretical model. We find that an increase in the share of foreign-born workers has a positive and significant impact on natives' relative supply of communication and manual tasks. Results suggest that a one percentage-point increase in the foreign-born share of less-educated workers increases the relative supply of communication versus manual tasks among natives by 0.55 percent.

We also test whether this positive effect is mostly related to an increase in the supply of communication skills (oral and written) or a decrease in natives supply

Table 2.4
THE IMPACT OF FOREIGN-BORN WORKERS ON LESS-EDUCATED NATIVES' RELATIVE TASK PERFORMANCE, OLS AND WLS.

Explanatory variable: share of low-educated foreign-born workers				
Dependent variables	OLS (1)	WLS (2)	OLS w/o London (3)	WLS w/o London (4)
$\ln(C_D/M_D)$	0.55***	0.47**	0.60***	0.49
	(0.11)	(0.18)	(0.18)	(0.33)
$\ln(C_D)$	0.35***	0.33***	0.36***	0.34*
	(0.05)	(0.09)	(0.10)	(0.17)
$\ln(M_D)$	-0.15*	-0.08	-0.23**	-0.14
	(0.08)	(0.11)	(0.08)	(0.15)
Region and year fixed effects	✓	✓	✓	✓
Observations	130	130	110	110

Notes: Standard errors robust to serial correlation and heteroskedasticity are reported in parentheses. Specifications (3) and (4) do not include Inner and Outer London. Significance levels * p< 0.1, ** p< 0.05, *** p< 0.001.

of physical tasks. This is done by separately estimating equations 2.9 and 2.10:

$$\ln(C_D)_{rt} = \alpha_r + \tau_t + \gamma_c f_{rt} + \varepsilon_{rt} \tag{2.9}$$

$$\ln(M_D)_{rt} = \alpha_r + \tau_t + \gamma_m f_{rt} + \varepsilon_{rt} \tag{2.10}$$

The estimates of γ_c and γ_m in column 1 of Table 2.4 suggest that one percentage-point increase in the foreign-born share is associated with a significant 0.35 rise in natives' supply of communication tasks, but only a small decline of 0.15 in the manual task supply. As column 2 shows, taking into account variation in the employed population across regions by using weighted least squares (WLS) does not significantly alter our findings. The magnitude of our coefficients is consistent with the findings for the US. The estimates of γ, γ_c and γ_m reported in Peri and Sparber (2009) are respectively 0.34, 0.31 an -0.03.

We also run the same regressions excluding Inner and Outer London where

Table 2.5
THE IMPACT OF FOREIGN-BORN WORKERS ON LESS-EDUCATED NATIVES' RELATIVE TASK PERFORMANCE, OLS AND IV.

Explanatory variable: share of low-educated foreign-born workers		
Dependent variables	OLS (1)	IV (2)
$\ln(C_D/M_D)$	0.55***	0.79***
	(0.11)	(0.13)
$\ln(C_D)$	0.35***	0.56***
	(0.05)	(0.08)
$\ln(M_D)$	-0.15*	-0.07
	(0.08)	(0.13)
Region and year fixed effects	✓	✓
First stage F-test (p-value)	.	35.2
		(0.00)
Observations	130	130

Notes: Standard errors robust to serial correlation and heteroskedasticity are reported in parentheses. The first stage F-test refers to the specification where $\ln(C_D/M_D)$ is used as a dependent variable. Significance levels * $p< 0.1$, ** $p< 0.05$, *** $p< 0.001$.

immigrants concentrations are substantially higher than the average. Columns 3 and 4 of Table 2.4 report OLS and WLS results. As one would note, our results are not driven by the exclusion of these outliers in the data. The OLS estimate of γ increases only to 0.60 from 0.55.

Table 2.5 reports instead results from IV estimates. As column 2 shows, the estimated IV impact is higher that OLS effects, suggesting a downward bias in the first specification. Indeed, the estimate of γ increases to 0.79, γ_c to 0.55 and γ_m to -0.07. Results obtained instrumenting the share of foreign-born workers suggest that the impact of immigration on natives' task-specialisation is plausibly causal. 2SLS estimates of γ in Peri and Sparber (2009) range from 0.37 to 0.51, making our coefficient from 1.5 to 2 times larger than the one estimated in the US. The first stage F-test shows that our instrument is highly correlated with the endogenous regressor f_{rt}. Amuedo-Dorantes and de la Rica (2011) also find a similar effect for all natives, although estimates diverge when men and women are separately considered (a point we return to in Section 2.7).

Table 2.6
Average relative task supply across group of less-educated workers.

Variable	Natives	All immigrants	Long-term immigrants	Recent immigrants
C/M	0.943	0.918	0.943	0.809
	(0.680)	(0.672)	(0.628)	(0.679)
N	350,409	24,655	20,066	4,166

Notes: Authors' calculations based on UK Skills Surveys 1997, 2001 and 2006, and LFS 1997-2009. Only working individuals between 16 and 65 with little educational attainment (secondary and primary or less education) are considered. Recent immigrants are those with at most 5 years of residence in the UK. Standard deviations in parenthesis.

2.6.1 Recent and long-term immigrants

In the model by Peri and Sparber (2009), immigrants have a comparative advantage in performing manual, as oppose to communication, tasks because of language and cultural barriers. Among all foreign-born workers, we would therefore expect recent immigrants (defined as those with at most five years of residence in the UK) to have an even greater comparative advantage with respect to long-term immigrants. We would like to test in two separate regressions whether the effects of the share of recent immigrants on natives' specialisation are greater than those induced by long-term immigrants. However, similarly to Amuedo-Dorantes and de la Rica (2011), we find that the correlation between the share of recent and long-term immigrants is very high (i.e. 0.9). Therefore, high collinearity does not allow us to directly compare the effect of recent as opposed to long-term immigrants. Still, we can assess whether language and cultural barriers play a crucial role in our framework by testing if there are statistically significant differences in the ratio of communication to manual tasks across these two groups.

Table 2.6 displays the average relative supply of communication tasks for recent and long-term immigrants, and for natives and all immigrants as well. Natives and long-term immigrants score higher than all immigrants and recent-immigrants. We performed two-sample t test for every pair of groups. The corresponding two-tailed p-values are always lower than 0.01. We therefore conclude that the difference of means in the ratio of communication and manual tasks between natives and all immigrants, and recent and long-term immigrants is significantly different from 0. These results confirm the intuition that language and cultural barriers are an important driver of task-specialisation, as found by Amuedo-Dorantes and de la Rica (2011) for Spain.

2.7 Extensions and Sensitivity analysis

2.7.1 Findings across demographic groups

We now take a closer look at the effects of an increase in foreign-born share on natives' relative task supplies by separately focusing on different demographic groups. We replicate our analysis by gender, age and educational attainment to assess whether there are significant differences in natives' response to immigration. Table 2.7 displays the estimates from separate regressions for each specific group, using OLS, WLS and IV as methods of estimation.

IV estimates suggest that men respond to a percentage point increase in the foreign-born share by increasing their relative supply of communication vs manual tasks by 1.13 percent. Conversely, the effect on women's task specialisation is substantially lower and not statistically significant. The impact of foreign-born workers on natives' relative task performance varies also by age, being higher among young workers (i.e. those aged less than 40, the sample average) relatively to old workers (the estimated γ being 1.03 and 0.45 respectively). Finally, differences arise also when natives are grouped by educational level. Indeed, workers with primary education (or less) shift their relative task supply more than workers with secondary education, but differences between coefficients are smaller. In line with Peri and Sparber (2009), these findings confirm the intuition that the impact of immigration is slightly higher among young natives because of greater occupational mobility, and among very low educated natives because they are more vulnerable to job competition.

Table 2.7
THE IMPACT OF FOREIGN-BORN WORKERS ON LESS-EDUCATED NATIVES' RELATIVE TASK PERFORMANCE FOR SPECIFIC DEMOGRAPHIC GROUPS.

Explanatory variable: share of low-educated foreign-born workers			
Dependent variables	OLS (1)	WLS (2)	IV (3)
$\ln(C_{men}/M_{men})$	0.75***	0.61**	1.13***
	(0.15)	(0.25)	(0.12)
$\ln(C_{women}/M_{women})$	0.24*	0.22	0.18
	(0.12)	(0.13)	(0.12)
$\ln(C_{young}/M_{young})$	0.60***	0.46**	1.03***
	(0.13)	(0.20)	(0.17)
$\ln(C_{old}/M_{old})$	0.49***	0.44*	0.45***
	(0.13)	(0.22)	(0.17)
$\ln(C_{primary}/M_{primary})$	0.74***	0.58**	0.96***
	(0.18)	(0.26)	(0.13)
$\ln(C_{secondary}/M_{secondary})$	0.40*	0.51**	0.89***
	(0.20)	(0.17)	(0.19)

Notes: Each cell contains estimates from separate regressions and $\ln(C/M)$ is calculated for each specific demographic group of natives. The total number of observations for each regression is 130 (10 years x 13 regions). We define individuals with primary education (or less) those who left full-time education before 16 years old (included) or never had full-time education. Region and year dummies are included but not reported. Standard errors robust to serial correlation and heteroskedasticity are reported in parentheses. Significance levels * $p< 0.1$, ** $p< 0.05$, *** $p< 0.001$.

2.7.2 O*Net task variables

Thus far we have shown that in the UK natives respond to increasing immigration by shifting their task supply and providing more communication relative to manual tasks. We rely on the UK Skills Surveys to measure the task content of occupations, instead of exploiting the more common O*Net dataset used in the literature. However, as we are aware that a perfect correspondence between task variables in the two datasets does not exist and that we only selected the measures of interest which resemble each other the most, we perform the same analysis using the O*Net data with the aim of comparing results.

Table 2.8
THE IMPACT OF FOREIGN-BORN WORKERS ON LESS-EDUCATED NATIVES' SPECIALISATION, USING *O*Net task intensities.*

Explanatory variable: share of low-educated foreign-born workers			
Dependent variables	OLS (1)	WLS (2)	IV (3)
$\ln(C_D/M_D)$	0.48**	0.38	0.46**
	(0.16)	(0.22)	(0.15)
$\ln(C_D)$	0.30*	0.24	0.26**
	(0.11)	(0.13)	(0.09)
$\ln(M_D)$	-0.12*	-0.08	-0.05
	(0.06)	(0.08)	(0.08)
Region and year fixed effects	✓	✓	✓
First stage F-test (p-value)	.	.	35.2
			(0.00)
Observations	130	130	130

Notes: Standard errors robust to serial correlation and heteroskedasticity are reported in parentheses. Task intensities at the occupational level are derived from the O*Net dataset. The first stage F-test refers to the specification where $\ln(C_D/M_D)$ is used as a dependent variable.

Table 2.8 reports the estimates obtained by deriving the manual and communication indexes from exactly the same ability scores used in Peri and Sparber (2009), after a suitable conversion of occupational codes[18]. We note that all coefficients have the expected sign, confirming the findings presented in the previous section. OLS estimates of γ, γ_c and γ_m are almost identical to those obtained measuring the task content of occupations from the UK Skills Surveys. Some differences arise when instrumenting the share of foreign born workers. However, although the magnitude is 1.7 times lower, γ is still positive and statistically significant. These findings suggest that the arbitrary choice of variables to measure the task content of occupations, driven by the absence of a perfect matching between UK Skills

[18]US SOC1990 occupational codes in O*Net were matched to the ISCO-88 classification using the crosswalk available at: http://www.cf.ac.uk/socsi/CAMSIS/occunits/us90toisco88v2.sps. We thank Giovanni Peri and Chad Sparber for making the data available.

Surveys and O*Net questionnaires, does not substantially alter our conclusions.

2.8 Summary and Conclusions

In this paper we assess the impact of immigration on local labour markets in the UK from a task-based perspective. We empirically test the predictions of Peri and Sparber (2009) model of comparative advantage in tasks performance to evaluate whether less-skilled natives responded to increasing immigration inflows of similarly educated workers by shifting their provision of task supplies. Using Labour Force Survey (LFS) and UK Skills Survey data from 1997 through 2006, we find that an increase in the foreign-born share has a significant positive effect on natives' relative communication task supply. In order to cope with potential endogeneity of the share of immigrants, we construct a suitable instrumental variable based on past immigration concentrations. IV estimates suggest that natives increased their relative task supply by 0.79 percent for every percentage point increase in the foreign-born share. We also show that this effect vary across demographic groups, being higher among men, young people and workers with primary education (or less) relatively to women, old people and workers with secondary education respectively. We conclude that also in the UK, similarly to the US and Spain, less-educated native workers responded to immigration inflows of similarly educated workers by increasing their relative supply of communication tasks.

Chapter 3

Spousal Wage Gap and Assortative Mating*

3.1 Introduction

Post-war Britain, and other developed countries, saw the high point of the male breadwinner model. Strong gender division of labour, with the male earning in the labour market and women engaged in child bearing and home production, meant that most men worked but few women did. Theoretical models have demonstrated that, even in absence of gender based pay discrimination, expectations of lower engagement in the labour market can create gender pay gaps as firms and individuals invest in the careers of men and women differentially and within couples the spouses invest more in maximising the wage of the primary earner (François and Van Ours, 2000). So as Winkler (1998) suggests, given that the primary earner is more likely to have the chance to improve his or her career and to raise his or her wage, the distribution of earnings within couples will ultimately affect the size and the evolution of the overall gender wage gap. In the face of even minor initial pay differences across genders or just occupational segregation with women being in lower paid positions, a self-reinforcing cycle of lower participation among the

*This chapter is the result of a research conducted with Prof. Paul Gregg (Centre for Market and Public Organisation, University of Bristol) and Prof. Paul Clarke (Institute for Social and Economic Research, University of Essex). I thank the Centre for Market and Public Organisation (CMPO) for hosting me.

lower earning spouse (the woman in the male breadwinner model) and investment within a couple on the career of the spouse with the higher potential wage will emerge.

Over the last 40 years or so the labour market has seen a gender revolution in women's participation and wages. Some 9% fewer working age women than men work now (67% women to 76% men) compared to a 40% gap in the 1970s. Likewise the gender pay gap has steadily fallen. Between the mid-1970s and the early 1990s, the ratio of full-time female average earnings to average male earnings rose from 59 to 77% (Harkness, 1996) and now stands at 85% (Office for National Statistics, 2013) and the median full-time pay gap is now under 10% (Office for National Statistics, 2013). Although including part-time workers which are generally lower paid and more often women the pay gap remains around 20%. In this paper we explore the implications of these huge changes for the evolution of the spousal wage gap, alternatively called spousal pay gap or gender pay gap within couples, and its relationship with the overall pay gap, changes in labour force participation and the level of assortative mating between partners. Gender wage differentials have been extensively studied by labour economists and the literature is very broad and well-established. Yet, empirical research has traditionally focused on overall differences between men's and women's wages and there are few studies on earning disparities within couples. The specific interest on spousal wage gap can show how the shift towards greater gender equality plays out within families. But also because of the potential to change investment decisions within couples and by employers which affect in the long-run future earnings growth and labour market outcomes and for future economic modeling of gender wage differentials based on the household.

The paper starts with a statistical model which shows how the probability of a positive spousal wage gap (male wage greater than partners) depends on the average gender wage gap, the variance of the male and female wage distributions and on the level of sorting or assortative mating, based on wages, there is among couples. The model shows how men can still earn more than their partners even with a low overall pay gap when assortative mating is high or the variance in earnings is low. We show how the model fits the data well and use it to explore what lies behind the observed decline in men earning more than their partners in terms of hourly wages. Among dual earner couples 79% of men earn more than their partners in 1991 and this falls to just above 70% by 2008. This is being driven by falls in the within couple gender pay gap from nearly 45% to 30% over the period. We then turn to changing participation patterns of men and women and how this affects our story. We employ the estimation method developed by Wooldridge (1995) to correct for sample selection in panel data models where we can observe wages in other periods for individuals. We show that women who are excluded from labour market participation are increasingly those with the lowest potential wage.

The remainder of the paper is organised as follows. Section II presents an overview of the relevant literature. Section III provides a statistical framework to assess the impact of matching between partners on the probability that men earn more than women. Section IV provides a counterfactual exercise. Section V presents the data used in the empirical analysis. Section VI reviews recent changes in the spousal wage gap and couples' earnings arrangements in the UK. Section VII then goes on to assess quantitatively how well the statistical framework match empirical developments. Finally, in Section VII we correct for sample selection in a panel data context and we analyze the evolution of the spousal wage gap using potential wages for non-working spouses when we observe a wage for their partner. Section IX concludes.

3.2 Literature Review

As in many other industrialised countries, in the United Kingdom the overall gender pay gap has significantly fallen over the last 30 years (Anderson et al., 2001; Joshi and Paci, 1996, 1998; Manning and Robinson, 2004). Between the mid-1970s and the early 1990s, the ratio of full-time female average earnings to average male earnings rose from 59 to 77% (Harkness, 1996) and now stands at 85% (Office for National Statistics, 2013) and the median full-time pay gap is now under 10% (Office for National Statistics, 2013). Although including part-time workers which are generally lower paid and more often women the pay gap remains around 20%. Relative to other European countries, the United Kingdom ranks very high in terms of gender wage differentials (Beblo et al., 2003; Blau and Kahn, 1996). While there are many papers concerning the evolution of the overall gender pay gap over time, the analysis of income disparities within families and couples in Britain is extremely scarce. Nicodemo (2009) investigates the recent evolution of the gender gap within married couples in European countries. However, given that the study is focused on Mediterranean countries, the empirical evidence for the United Kingdom that is presented is very limited.

In recent years there has been growing sociological research on couples' earnings patterns in the United States. Several studies (e.g. Raley et al., 2006; Winkler, 1998; Winslow-Bowe, 2009a) document the decline in pure gender-based specialisation among American couples, the increase in the proportion of co-providing dual-earner couples and the rise of "non-traditional" couples (i.e. those in which the woman is the primary earner). Other papers explore the effect of changes in gender differentials within households on the division of labour at home and on marital disruption (e.g. Bittman et al., 2003; Brines, 1994, Heckert et al., 1998; Sayer and Bianchi, 2000 as cited in Winslow-Bowe 2009b). As far as assortative mating[1] patterns are concerned, during the recent decades educational homogamy has increased in the United States (Kalmijn, 1991; Mare, 1991; Schwartz and Mare, 2005) and in many European countries (Blossfeld and Timm, 2003). Trends in assortative mating were mainly determined by increasing positive mate selection rather than increasing similarity in men and women's educational attainments which changed marital opportunities (Hou and Myles, 2008). Spouses' similarity has also been measured in terms of income. Burtless (1999), Sweeney and Cancian (2004) and Schwartz (2010) show growing correlation between husband's and wife's earnings in the United States from the 1970s onwards. Bredemeier and Juessen (2013) find a very similar pattern of the correlation coefficient between spousal wage decile positions, showing however that the increase was particularly marked between the 1980s and the 1990s while the last decade was characterised by a much slower trend. Esping-Andersen (2007) estimates the couple correlation of earnings for some European countries, among which the United Kingdom, in two points in time (1993 and 2001), he however includes those with zero earnings. In recent years, the relationship between assortative mating and labour market outcomes has

[1]The term was coined by Becker (1973) who suggested that 'likes' marry 'likes', referring to a positive relationship between partners' characteristics. Partners do not randomly pair, but they rather tend to match in terms of assortative traits, such as education or income.

been increasingly investigated. Bredemeier and Juessen (2013) show that trends in assortative mating affect the patterns of wives' hours worked. Other studies analyse the impact of assortative mating on inequality throughout the earnings distribution (Burtless, 1999; Fernández et al., 2005; Hyslop, 2001; Kremer, 1996; Schwartz, 2010; Worner, 2006).

3.3 Statistical Framework

We start by presenting a very simple statistical framework to understand the impact of assortative mating, defined in terms of partners' wage correlation, on the spousal pay gap.

Let X_1 be a random variable for male wage, and X_0 for female wage, and assume that both wage distributions are normally distributed:

$$X_g \sim N(\mu_g, \sigma_g^2),$$

where $(g = 1)$ for men and $(g = 0)$ for women. In this case the spousal wage gap (WG) is simply the difference of the expected values:

$$WG = E[X_1] - E[X_0] = \mu_1 - \mu_0 > 0,$$

which we take to be positive.

If we relax the random pairing of men and women in couples with respect to wage, so that there is some positive assortative mating, the couple-wise income distribution is therefore:

$$\begin{pmatrix} X_1 \\ X_0 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_1 \\ \mu_0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_0 \\ & \sigma_0^2 \end{pmatrix}\right),$$

where $\rho = \sigma_{10}/\sigma_1\sigma_0$ is the correlation coefficient and σ_{10} is the covariance between X_1 and X_0. Random mating and perfect sorting correspond to the extreme cases where $\rho = 0$ and $\rho = 1$, respectively.

The probability that a randomly sampled man's wage exceeds that of his female partner is:

$$q \equiv \Pr(X_1 > X_0).$$

Because we are assuming that both distributions are normal and $X_1 > X_0$ is equivalent to $X_1 - X_0 > 0$,

$$X_1 - X_0 \sim N(WG, \sigma_1^2 + \sigma_0^2 - 2\rho\sigma_1\sigma_0),$$

recalling that WG is the positive wage gap. It follows that:

$$q = 1 - \Phi\left(-\frac{WG}{\sqrt{\nu}}\right) = \Phi(WG/\sqrt{\nu}) \tag{3.1}$$

where $\Phi(WG/\sqrt{\nu})$ is the complement of the standard normal cumulative density function (CDF), and $\nu = \sigma_1^2 + \sigma_0^2 - 2\rho\sigma_1\sigma_0$. The probability that the gender pay gap within a couple is positive not only depends on the expected value and the standard deviations of the two distributions but also on their correlation.

If the variance of the two wage distributions is equal, so that $\sigma_1 = \sigma_0 = \sigma$, then $\nu = 2\sigma^2(1-\rho)$ and one can see that:

$$\Phi\left(\frac{WG}{\sqrt{2\sigma^2}}\right) < \Phi\left(\frac{WG}{\sqrt{2\sigma^2(1-\rho)}}\right) < 1,$$

if $WG > 0$ and there is a positive correlation. In other words, for two populations with the same average gap and the same standard deviations, non-random mixing increases the probability of the man's wage exceeding his partner's. The lower bound is the probability under random mixing, and the upper bound is relevant because $\Phi(WG/\sqrt{2\sigma^2}) \to 1$ as $\rho \to 1$, that is, if there is a perfect correlation then it is certain that the man's wage is higher.

More realistically, we can assume that both income distributions follow a log-normal distribution, that is,

$$X_g \sim \log N(\mu_g, \sigma_g^2),$$

for men ($g = 1$) and for women ($g = 0$), where the parameters are those for the normally distributed (natural) logarithm of X_g: the mean and the variance of

$\log(X_g) \equiv Y_g$ (assuming there are no zero wages) for $g = 0, 1$[2].

The spousal pay gap is just:

$$WG = E[X_1] - E[X_0] = \exp(\mu_1 + \sigma_1/2) - \exp(\mu_0 + \sigma_0/2),$$

which depends on the means and standard deviations of the two log-wage distributions. To calculate the man's-income-exceeds-the-woman's probability, we might consider working with $X_1 - X_0$ which can be closely approximated by a log-normal distribution (Lo, 2012), but all subsequent calculations would involve inequalities about zero and so cannot be solved.

Instead, we note that:

$$\Pr(X_1 > X_0) = \Pr(X_1/X_0 > 1) = \Pr[\log(X_1/X_0) > 0] = \Pr(Y_1 > Y_0),$$

provided that $X_1,\ X_0 > 0$. Using the final equality, we show that the man's-wage-exceeds-the-woman's probability is:

$$q = \Phi\left(-\frac{\hat{\mu}_1 - \hat{\mu}_0}{\sqrt{\nu}}\right) = \Phi\left(\frac{\widehat{WG}}{\sqrt{\nu}}\right), \tag{3.2}$$

which is identical to (3.1) except for the means, standard deviations and correlations being based on (normally distributed) log-wage Y_g rather than wage X_g.

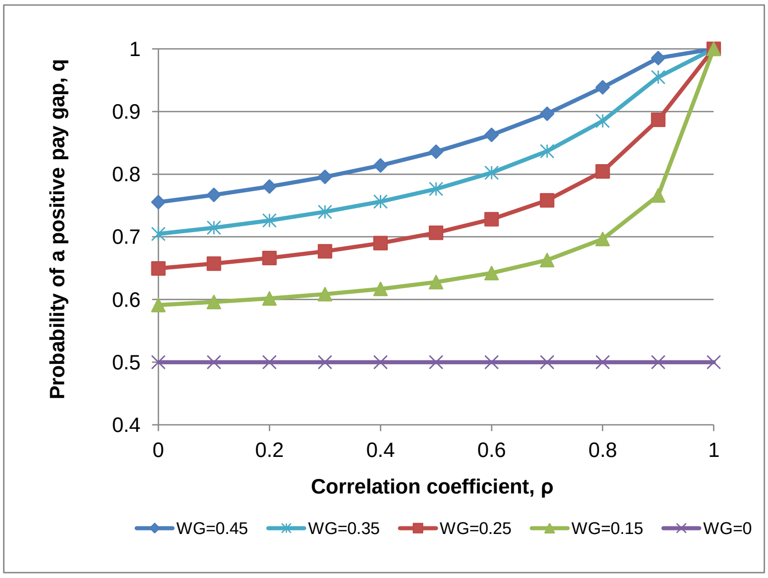
3.4 Counterfactual Analysis

Equation (3.2) can be manipulated to answer counterfactual questions. For instance, suppose that the gender pay gap in the population under study is $\widehat{WG}$ and the estimated man's-wage-exceeds-the-woman's probability is $\hat{q}$ then, if the spread of the two wage distributions is fixed but the pay gap is reduced to $WG = \widehat{WG} - \delta$

[2]The relationship between the normal and the lognormal distributions is indeed:

$$X_g \sim \log N(\mu_g, \sigma_g^2),\ \log X_g \sim N(\mu_g, \sigma_g^2).$$

Figure 3.1
PROBABILITY OF A POSITIVE SPOUSAL WAGE GAP (q) AT DIFFERENT LEVELS OF ASSORTATIVE MATING (ρ) AND MEAN GAP (WG), HOLDING CONSTANT THE STANDARD DEVIATIONS OF WAGE DISTRIBUTIONS (σ_0 AND σ_1)



(for some decrement $\delta > 0$), the within-couple correlation required to preserve $\hat{q}$:

$$\rho(\delta) = \frac{1}{2\hat{\sigma}_0\hat{\sigma}_1}\left\{\hat{\sigma}_1^2 + \hat{\sigma}_0^2 - (\hat{\sigma}_1^2 + \hat{\sigma}_0^2 - 2\hat{\rho}\hat{\sigma}_1\hat{\sigma}_0)\left(\frac{\widehat{WG} - \delta}{\widehat{WG}}\right)^2\right\}, \tag{3.3}$$

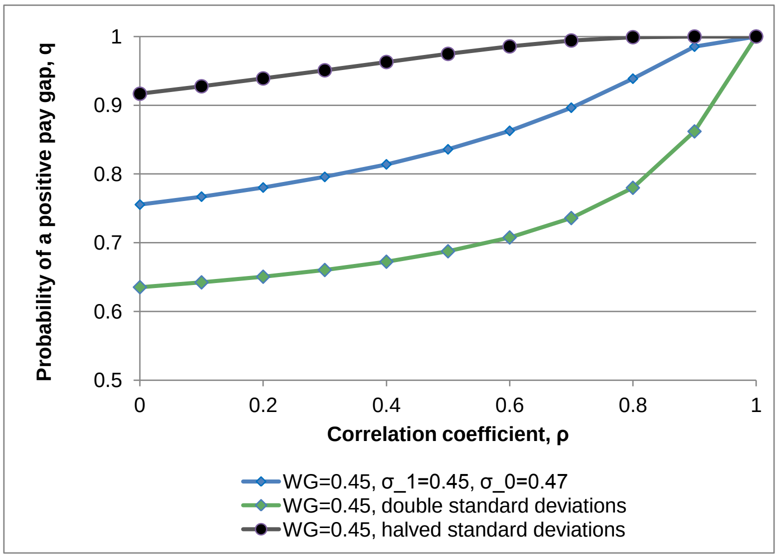
where $\hat{\sigma}_0$ and $\hat{\sigma}_1$ are estimates of wage distributions' standard deviations, and $\hat{\rho}$ is the observed correlation[3].

Figure 3.1 presents a counterfactual exercise that explores the impact of an increasing assortative mating on the probability that the pay gap (male wage greater than that of female partner) is positive at different levels of the mean gap, holding constant only the standard deviations of the male and female wage distributions. It shows the results from simulating a drop in the mean pay gap from 0.45, the starting value in the data we analyze later, to 0. Different levels of positive sorting within couples give rise to non-linearities in the probability that the pay

[3]Equation 3.3 is derived equating $\Phi\left(\frac{\widehat{WG}}{\sqrt{\nu}}\right)$ to $\left(\frac{\widehat{WG}-\delta}{\sqrt{\nu_\delta}}\right)$, where $\sqrt{\nu}_\delta = \hat{\sigma}_1^2 + \hat{\sigma}_0^2 - 2\rho(\delta)\hat{\sigma}_1\hat{\sigma}_0$.

Figure 3.2

PROBABILITY OF A POSITIVE SPOUSAL WAGE GAP (q) AT DIFFERENT LEVELS OF THE CORRELATION COEFFICIENT (ρ) AND STANDARD DEVIATIONS OF THE WAGE DISTRIBUTIONS (σ_0 AND σ_1), HOLDING CONSTANT THE MEAN GAP (WG)



gap is positive: the lower the positive mean pay gap, the less the relationship is linear until the case of a zero mean pay gap which implies equal probabilities that either men's or women's wage is the highest within couples, no matter the value of the correlation coefficient.

Figure 3.2 shows simulation results which shifts the standard deviation of the two distributions, as well as levels of assortative mating, given the observed level of average pay gap at the beginning of our data period. This is done to assess the effect of either a decrease or an increase of wage inequality in both male and female wage distributions on the probability of a positive pay gap. In one case the standard deviations of men's and women's wage distribution were halved, while in the second one they were both doubled. For a given observed value of the average pay gap and correlation coefficient, an increase in wage inequality implies a decrease in the probability that the male wage is greater than a partners. This also has implications for measurement error in the data as it shows how such errors will lead to underestimation of the primacy of the male wage within couples. A point we return to below. The simulations results thus show that the male wage can be higher within couples even with very small gender pay gaps when assortative mating is high and increasing inequality in wages will result in more women earning more than their partner if the overall pay gap and levels of assortative mating remain the same.

3.5 Data and Imputation Strategy

The data set used in our empirical analysis come from the British Household Panel Survey (BHPS), a survey of private households in Britain which was carried out annually from 1991 to 2008, when it was rolled into the larger Understanding Society panel. The new data saw some changes to earnings reporting and hence we stop our analysis in 2008. The survey initially consisted of around 5,500 households and 10,000 individual interviews drawn from 250 different areas of Great Britain, and then all residents of these households were traced and re-interviewed in successive waves and new partners of initial sample members joined the survey. In each wave there are flows in and out of the survey, therefore the panel is highly unbalanced.

We consider all 18 available waves that cover the period 1991-2008. The sample is then constrained to men and women aged between 20 and 60, as the state pension for women was 60 over this period and very few people are co-residing as couple before the age of 20. We exclude couples containing individuals who are self-employed and those still in full-time education. Real hourly wages are derived as nominal monthly gross earnings divided by the number of hours worked per month and deflated by the 2005 Consumer Price Index. The wage distribution is trimmed such that those earning less than £1 and more than £200 per hour are excluded from the sample. It is well known that derived hourly wage measures in household surveys are subject to severe measurement error which would clearly cause bias in the estimates, as discussed in the previous section (see Dickens and Manning, 2004). However, as compared to, say, the LFS, the BHPS has a much longer panel dimension that we can exploit to reduce the downward bias. Our approach to reduce measurement error in wages is to compute, whenever possible, a three-period window moving average for individuals.

In order to analyze the gender pay gap within couples we only keep people declaring to be married or living as a couple, whose spouse/partner is also interviewed. When the same individual change partner over time, we follow the couple observation with the longest panel dimension. Couples where none of the partners ever worked are excluded from the sample (582 observations). Observations where members of a couple are observed in work but do not report a wage are also dropped[4].

The final sample consists of 46,556 individuals or 23,278 couple observations based on 3,207 distinct couples. Couples are classified as: 1) “dual-earners”, where both partners are in paid employment and they report a wage in the relevant year (16,650 observations); 2) “man sole earner”, where we observe a positive wage for the man and non participation in the labour market for the woman (4,243 observations); 3) “woman sole earner”, where the woman is working and she reports a wage while the male partner is not (1,238 observations); 4) “no earner”, where no one in the couple is working in a particular year (1,147 observations), who are excluded from the analysis of earnings gap.

3.5.1 Wooldridge’s Estimator

When estimating the spousal pay gap and the level of assortative mating, we face the problem that wages can only be measured when individuals participate in the labour market. In this section, we describe the method used to predict potential wages for non-working men and women. Given that participation decision is likely to be non-random, we need to correct for sample selection. Heckman (1979) developed an estimator to deal with this source of bias for cross-sectional data. For panel data, the fixed effects estimator solves the problem when the selection process is either randomly determined or time constant, which is implausible. Several methods which allow for additive individual specific effects both in the binary selection equation and the wage equation have been suggested to deal with the problem (see e.g. Kyriazidou, 1997; Rochina-Barrachina, 1999; Vella and Verbeek, 1999; Wooldridge, 1995).

Here we apply the estimation method developed by Wooldridge (1995), which

[4]Differences in the means of key explanatory variables - such as age and education - among labour market participants which are due to this restriction are very small and negligible.

relies on level equations to correct for sample selectivity. To the best of our knowledge, there are few empirical applications which estimate wage equations correcting for selection into the work force in a panel data context (see e.g. D'Addio et al., 2002; Dustmann and Rochina-Barrachina, 2007; Jäckle and Himmler, 2010; Semykina and Woodridge, 2008).

Let us consider the following model:

$$w_{it} = x_{it}\beta_1 + \alpha_i + \varepsilon_{it}; \quad t = 1, ..., T \tag{3.4}$$

$$s_{it}^* = z_{it}\gamma_1 + k_i + u_{it}; \quad s_{it} = 1[s_{it}^* > 0], \tag{3.5}$$

where 1[.] is an indicator function that equals one if the argument is true (i.e. if the individual participates in the labour market) and zero otherwise. Wages w_{it} are observable only if s_{it}=1. The vector of exogenous explanatory variables x_{it} is a subset of z_{it} which contains in addition some elements that drive selection but are not included in the wage equation[5]. Although the model is identified even if z_{it}=x_{it}, a more convincing identification scheme is to have exclusion restrictions.

Both k_i and α_i are individual-specific unobserved effects, while u_{it} and ε_{it} are unobserved disturbances. Following Mundlak (1978) and Wooldridge (1995), we assume that k_i can be written as a linear projection onto the time averages of z_{it}, denoted by $\bar{z}_i$, and an orthogonal residual:

$$k_i = \bar{z}_i + a_{it}, \tag{3.6}$$

Equation (3.5) can be therefore written as:

$$s_{it}^* = z_{it}\gamma_1 + \bar{z}_i + v_{it}, \tag{3.7}$$

where the composite error term v_{it}=u_{it} + a_{it} is independent of z_{it} and normally distributed with zero mean and σ^2 variance.

Concerning the wage equation, Wooldridge (1995) assumes that the unobserved

[5]Semykina and Woodridge (2008, 2010) show the procedure to correct for sample selection with panel data in the presence of endogenous explanatory variables in the primary equation.

effect α_i is a linear projection onto $\bar{x}_i$ and b_{it}. Moreover, ε_{it} is assumed to be mean independent of z_{it} conditional on v_{it} and its conditional mean is linear in v_{it}. Under these assumptions, we can write equation (3.4) as:

$$w_{it} = \bar{x}_i\psi_1 + x_{it}\psi_2 + \lambda_{it}\xi_t + e_{it}; \quad t = 1, ..., T \tag{3.8}$$

where e_{it} is an orthogonal residual, and λ_{it}=$\lambda(\bar{z}_i\gamma_1)$ is the Inverse Mills Ratio.

Wooldridge (1995) suggests a procedure to correct for selection bias. This is done by first running a probit of s^*_{it} on z_i and $\bar{z}_i$ for each t and saving $\hat{\lambda}_{it}$, the Inverse Mills Ratio (IMR). Next, for the selected sample, equation (3.8) is consistently estimated by pooled OLS. Note that we assume different coefficients for λ_{it} in each time period which Wooldridge (1995) suggests to implement by adding interaction terms of the IMR and time dummies. Standard errors corrected for first stage probit estimates and robust to heteroskedasticity and serial correlation should be computed. This can be done with panel bootstrap, using the cross section units for the resampling (Wooldridge, 2010).

3.5.2 Empirical Model and Estimation Results

We write our logwage equation as follow:

$$log(w_{it}) = \beta_0 + age_{it}\beta_1 + age^2_{it}\beta_2 + educ_{it}\beta_3 + \sum_{t=1}^{17}\tau_t + \alpha_i + \varepsilon_{it} \tag{3.9}$$

We let wages for each individual i at each time period t depend on age and its square, years of education and time dummies. Next, we write the participation equation as:

$$\begin{aligned} s^*_{it} = \gamma_0 + x_{it}\gamma_1 + nch_{it}\gamma_2 + health_{it}\gamma_3 + pwork_{it}\gamma_4 \\ +nonlabincome_{it}\gamma_5 + k_i + u_{it}, \end{aligned} \tag{3.10}$$

where x_{it} is the $1xK$ vector of all exogenous variables included in wage equation (3.9). In equation (3.10), $s_{it} = 1[s^*_{it} > 0]$. We recall that participation in the labour market is defined as being in paid employment the week before the interview. We allow the participation decision to depend, in addition to years of education, age and its square, also on: the number of children, a dummy variable for the presence of health problems, an indicator variable for the partner's labour market participation, and household non labour income (net of the benefit component, i.e. pension, transfer and investment income only). All regressors in the participation equations are assumed to be exogenous. Table B.1 provides a detailed description of all the variables.

We use both participants and nonparticipants with valid information on the explanatory variables to estimate the participation equation (3.10) separately for men and women. For the estimation of the wage equation and for the purpose of carrying out a preliminary test for selection bias, we only use all individuals that work in at least two waves.

In the spirit of Wooldridge (1995), we carry out a preliminary test for the presence of selection bias. This is done using "a variable addition" test which consists in including in the wage equation the estimates of the IMR obtained from the sample selection probit at each time period, λ_{it}, as well as their interactions with time dummies. We then perform a Wald test on the joint significance of the selection effects in the wage equation estimated by fixed-effects on the selected sample. The value of the test statistic is $\chi^2_{18} = 51.22$ for women and $\chi^2_{18} = 28.39$ for men. Thus, the null hypothesis that the eighteen selection effects are equal to zero is not accepted.

Columns 5 of Tables B.2 and B.3 report the estimates for the wage equation for women and men, obtained by following Wooldridge (1995)'s procedure for sample selection correction described in Subsection 3.5.1. Columns 1 to 4 display pooled ordinary least squares (OLS), random effects (RE), fixed-effects (FE) and Heckman (two-steps) estimates. Tables B.4 and B.5 show results of first stage probit from the Heckman estimator and Mundlak probit.

3.6 Empirical Evidence

3.6.1 Recent trends in the raw gender pay gap

Figure 3.3 presents the evolution over time of the raw gender pay gap at three different level of analysis: the overall gender pay gap between all employed men and women, the gender pay gap over couples (i.e. between men and women declar-

Figure 3.3
GENDER LOG WAGE DIFFERENTIALS OVER YEARS

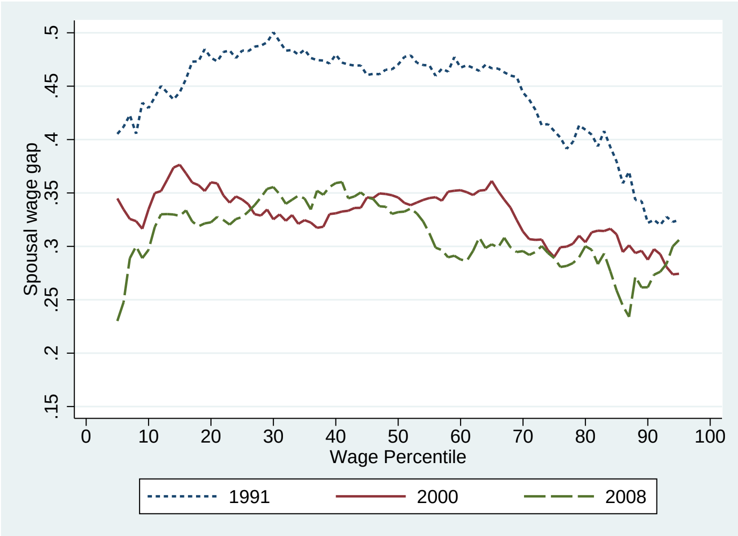
Notes: BHPS, 1991-2008. 73,515 observations for the overall pay gap; 55,168 for the gender pay gap over couples; 16,650 for the spousal wage gap.

ing to be married, living as a couple or in civil partnership) and the spousal pay gap (i.e. within couples). The second measure includes those with non-working partners whilst the third measure excludes them.

Earning disparities are more significant within dual-earner couples, compared to overall gender wage differentials by around 5 log points. The gender pay gap over couples is higher than the spousal pay gap at almost every year. This is down to the fact that it also includes working men with non-working partners who are excluded in the within couple difference for dual-earner couples only.

Figure 3.4 displays gender differential within couples across the pay distribution, showing the wage gap of the separate male and female log wage distributions for earners in couples. The figure shows that there have been larger changes in the tails of the distributions. At the very bottom of the distribution the gap closed faster than the middle, while at the highest percentiles there was little wage convergence for a lower starting base.

Figure 3.4
Spousal wage gap by percentile, selected years



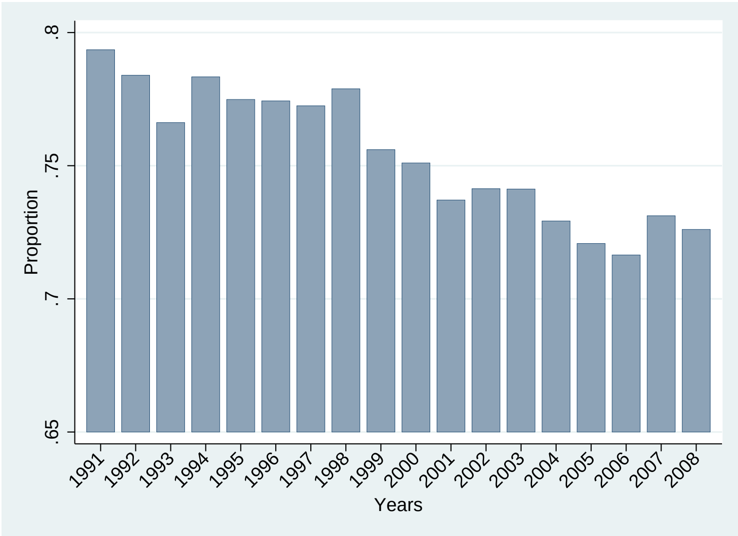
Notes: BHPS, 1991-2008. 1,051 observations in 1991, 970 in 2000 and 752 in 2008. The spousal wage gap is computed as a difference between the percentiles of the male and female wage distributions among dual-earners.

3.6.2 Changes in couples' earnings patterns

Figure 3.5 and Table 3.1 show how these changes in gender pay gaps play out in terms of which partner has the highest earnings. Figure 3.5 shows that among dual-earner couples the proportion where the man had a higher hourly rate of pay fell from almost 80% to just 73% over the 18 years period[6]. These findings are in line with U.S. data which indicate that the percentage of wives who earn more than their husbands increased from 18% to 29% from 1987 to 2009 (Bureau of Labor Statistics, 2011). Table 3.1 gives more detail on the "non-traditional"couples in the sample (4,068 observations). It shows the female wage premium, computed as a percent of men's wage. As one might expect, more than one third of the observations fall in the first category, which is the one where women earn only up

[6]We do not find remarkable differences between old and young couples, defined as those where the average between the age of the two partners is lower than 40. Still, as one would expect, the percentage of women earning more than men is slightly higher for the youngest generations

Figure 3.5
PROPORTION OF MEN EARNING MORE THAN THEIR PARTNERS IN DUAL-EARNER COUPLES



Notes: BHPS, 1991-2008. The total number of dual-earner couples is 16,650.

to 25 percent more than their partner. By utilising panel data, recent research in the U.S. found that, although women are increasingly likely to earn more than their partners, the income advantage is often temporary and do not persist for many years (Winkler et al., 2005; Winslow-Bowe, 2006). The BHPS does not allow to explore this aspect given that non-traditional dual-earner couples continuously followed for at least three years are only 533 (3,303 observations).

3.6.3 Assortative Mating

The statistical framework presented in Section 3.3 can now be used to explore what lies behind this decline in share of couples where men have the higher hourly wage. The approach relies on the Pearson correlation coefficient between spouses' wage levels to assess the degree of sorting between partners. One potential limitation of this measure is that it is unable to disentangle changes in the gender-specific marginal distributions from changes in the association between partners' once marginal distributions are held constant (see Halpin and Chan, 2003; Hou and Myles, 2008; Liu and Lu, 2006; Mare, 1991). Changes in the absolute or overall

Table 3.1
PERCENTAGE OF WOMEN EARNING MORE THAN MEN AND FEMALE WAGE PREMIUM IN NON-TRADITIONAL DUAL-EARNER COUPLES.

Year	Women earning more than men	Women earning up to 25% more	Women earning more than 25%
1991	20.65	77.42	22.58
1992	21.60	80.95	19.05
1993	23.38	82.63	17.37
1994	21.66	78.33	21.67
1995	22.51	77.67	22.33
1996	22.57	80.28	19.72
1997	22.75	82.86	17.14
1998	22.11	80.53	19.47
1999	24.40	84.77	15.23
2000	24.90	82.23	17.77
2001	26.29	81.96	18.04
2002	25.86	82.59	17.41
2003	25.88	82.20	17.80
2004	27.08	81.51	18.49
2005	27.92	79.08	20.92
2006	28.35	80.50	19.50
2007	26.88	80.28	19.72
2008	27.39	76.21	23.79

Notes: BHPS, 1991-2008. Column 1 shows the percentage of women earning more than their male partner in dual-earner couples; Columns 2 and 3 display women's income advantage, defined as a percent of men's wage, for two different ranges of values. The total number of non-traditional dual-earner couples in the sample is 4,068, with an average of 226 observations per year.

rate of assortative mating may reflect both changes in the male-female wage distributions, and changes in the mate selection process of individuals once marginal changes have been taken into account. In order to overcome this problem and provide a robustness test for our measure, we follow Bredemeier and Juessen (2013) who suggest measuring the strength of the relationship between spouses wages in terms of deciles instead of levels. Given that the distribution of deciles is constant over time by construction, they argue that an increase in the correlation between wage relative positions implies an underlying increase in positive assortative mat-

Table 3.2
CORRELATION BETWEEN SPOUSAL WAGE LEVELS AND DECILE POSITIONS

Years	**Correlation wage levels**	**Correlation wage deciles**
1991-1996	0.29	0.28
1997-2002	0.32	0.31
2003-2008	0.30	0.30

Notes: BHPS, 1991-2008. The total number of dual-earner couples is 16,650.

ing. Table 3.2 presents the correlation coefficient between spousal wages computed both in terms of wage levels and deciles. We provide estimates for three different subperiods. The correlation coefficient increased from 0.29 in 1991-1996 to 0.32 in 1997-2002, after which it slightly decreased to 0.30. The fact that we obtain very similar results with this alternative measure suggests that the movements in the correlation of wages in terms of levels well reflect changes in the process of sorting within couples[7].

The BHPS perhaps covers a too recent period to reveal a significant increase in the association between spousal wages over time, which would likely be detected by looking at the same values in the early 1970s. Bredemeier and Juessen (2013) find that in the United States the correlation coefficient between spousal wage decile positions increased substantially over time and almost doubled from the 1970s to the 2000s. Our estimates for the 1990s and 2000s are consistent with their results.

Given the decline in the spousal wage gap and little change in inequality and assortative mating it is perhaps no surprise that our statistical framework predicts it is the former which drives the fall in the fraction of couples where the male wage is higher. The model shows that the probability that women's wage exceeds men's is driven by four parameters: the difference of the wage distributions' means (WG), the wage distributions' standard deviations (σ_1 and σ_0) and the correlation coefficient between wage levels (ρ). The last three terms are used to compute the difference of the wage distributions' variances, denoted by ν in the final formula

[7]We also estimate the correlation of partners' educational attainments in terms of years of schooling and we find that this is decreasing over time, from 0.41 in 1991 to 0.34 in 1999 and 0.29 in 2008.

Figure 3.6

Real proportions and predicted probabilities that men outearn their partners

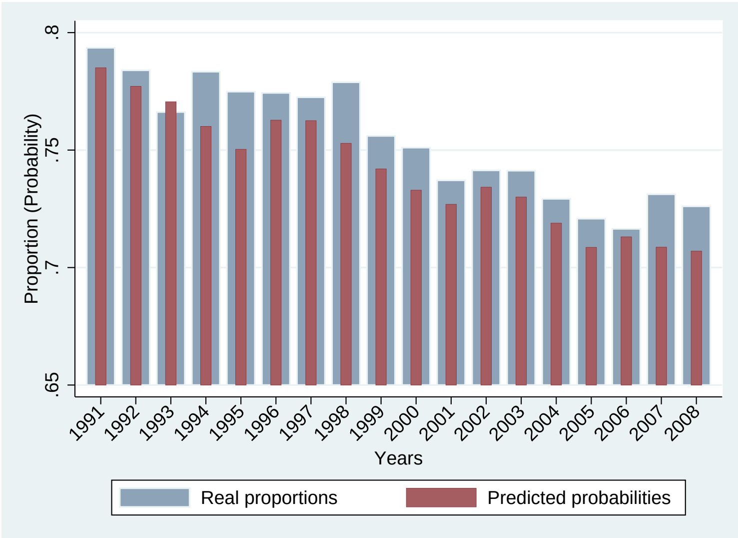


Figure 3.6 compares actual proportions of men earning more than their partners in the sample with predicted probabilities based on the statistical framework. The predicted probabilities are well matched at the empirical level. The average absolute difference between the predicted probabilities and empirical proportions is only 1%.

Of the four parameters of the model, the mean spousal pay gap is the one which accounts for most of the variability in the predicted probabilities. If the mean wage gap in the final year were the same of 1991, the predicted probability that men outearn women would be 0.780 instead of 0.726, given the values of the other parameters in 2008. We would instead obverse a counterfactual probability of 0.699 if the correlation coefficient between wage levels in 2008 were the same of 1991, or 0.719 if the standard deviations of the wage distributions did not change over time. Because both the correlation coefficient between wage levels and the standard deviations of the wage distributions do not exhibit significant changes over the period under consideration, their contribution to the evolution of predicted probabilities is negligible.

Table 3.3
PERCENTAGE OF COUPLES BY YEAR AND CATEGORY

Year	Dual earners	Man sole-earner	Female sole-earner	No earners	Tot. obs.
1991	68.56	22.50	5.22	3.72	1,533
1992	66.58	21.71	6.10	5.62	1,460
1993	67.23	19.56	6.86	6.35	1,355
1994	67.41	18.63	7.63	6.33	1,390
1995	67.98	18.72	6.91	6.39	1,346
1996	68.80	18.09	6.77	6.34	1,404
1997	70.73	18.70	5.82	4.75	1,305
1998	72.02	17.90	5.00	5.07	1,419
1999	71.91	17.98	5.42	4.69	1,385
2000	71.16	19.40	4.76	4.69	1,366
2001	73.76	17.79	3.95	4.49	1,315
2002	74.78	16.44	4.39	4.39	1,277
2003	74.51	16.75	4.74	4.00	1,224
2004	74.49	17.03	4.07	4.41	1,180
2005	74.63	16.48	4.27	4.62	1,147
2006	75.62	16.55	4.00	3.83	1,124
2007	76.29	15.43	3.86	4.42	1,063
2008	76.35	15.23	4.67	3.76	985

Notes: BHPS 1991-2008, own calculations. The total number of couples in the sample is 23,278, of which 16,650 dual-earners, 4,243 man sole-earner, 1,238 woman sole-earner and 1,147 no earners.

3.6.4 Sample Selection Correction

To date we have only considered dual-earner couples but we know that labour force participation have radically changed over this period. The percentage of British couples which fit the traditional pattern in which the man is the sole earner decreased from 23% to 15% between 1991 and 2008, with a corresponding increase in dual-earner couples (as shown in Table 3.3). These changes are consistent with findings for the United States. Using Current Population Survey data, Raley et al. (2006) show that in 1970 the husband was the sole provider in 56% of couples; by 2001 this percentage decreased to 25%. They also show that the proportion of co-providing dual-earner couples nearly tripled during the same period.

Figure 3.7

Spousal wage gap: setting zero wages for non-workers

Notes: BHPS, 1991-2008. The figure shows the spousal wage gap when man and female sole earner couples are included in the analysis and the wage for the non-working spouse is set to zero.

Figure 3.7 shows the implication of including couples where one spouse is not working but the other is to the earnings gap where the hourly wage for the non-worker is set at zero[8]. As would be expected, imputing zero wages for non-working women increases substantially the spousal wage gap but the decline over the full period is similar. The additional inclusion of female sole earner couples contributes to lower the earnings gap within couples. The slightly more marked decline of the early 1990s is likely to be determined by lower participation rates among men during the economic recession. The disproportionate fall in male employment creating more female sole-earner couples (see Table 3.3) which reduces the spousal wage gap with zero wages for non-earners.

Colums 2 to 5 of Table 3.4 show how this naïve imputation affects the estimates of the proportion of men earning more than their partners and the correlation coefficient between wage levels. Including male sole earner couples in the assessment of which spouse earns the higher wage, with the non-earner given a zero hourly

[8] At this stage, no earner couples are excluded from our analysis.

wage, sees the male primary wage rising from 79% to 84% at the beginning of the period and from 69% to 75% at the end. Compared to its original values based on observable wages, the correlation coefficient decreases substantially and the additional inclusion of female sole earner couples originates even negative estimates. So a natural next step is to deal with the selection process behind non-participation more formally. We exploit the panel nature of our data where we can observe wages for currently non-working spouses in other data periods to improve the efficiency of the selection equation estimation. Here we use the estimator set out in Wooldridge (1995).

3.6.5 Wage Imputation

Next, we use Wooldridge's hourly wage predictions to impute values for non-working individuals and to investigate how the spousal wage gap changes accordingly. Figures 3.8 show the implication to the earnings gap of imputing wages for non-workers in couples where we observe the real wage for one spouse and we can observe the wages of the non-earning spouse in other periods. So we are exploiting the panel element of the data. As one would expect, the imputation of potential wages for non-working women (2,296 imputed observations) increases the spousal wage gap compared to dual-earning couples, which means that the fall in the spousal wage gap is less than that observed in dual earner couples. The effect is particularly marked from the late 1990s onwards. This means that the women who are excluded from labour market participation are increasingly those with the lowest potential wage and the narrowing of the spousal wage gap is slightly exaggerated by this increasingly negative selection of which women do not work. The additional inclusion of couples where the man is not working but the woman is (723 imputed observations) does not substantially alter the evolution of the spousal wage gap over time.

Table 3.4

THE EFFECT OF DIFFERENT WAGE IMPUTATION METHODS FOR NON-WORKING INDIVIDUALS

	Zero wages women		**Zero wages women and men**		**Potential wages women**		**Potential wages women and men**	
Year	**Prop.**	**Corr.**	**Prop.**	**Corr.**	**Prop.**	**Corr.**	**Prop.**	**Corr.**
1991	0.84	0.06	0.80	-0.06	0.80	0.24	0.80	0.24
1992	0.84	0.11	0.78	-0.01	0.79	0.28	0.79	0.28
1993	0.82	0.12	0.76	0.00	0.77	0.29	0.77	0.29
1994	0.83	0.10	0.76	-0.03	0.79	0.30	0.79	0.29
1995	0.82	0.07	0.76	-0.02	0.78	0.28	0.78	0.27
1996	0.82	0.06	0.76	-0.03	0.79	0.30	0.78	0.29
1997	0.82	0.14	0.77	0.02	0.78	0.32	0.78	0.31
1998	0.82	0.12	0.78	0.02	0.79	0.34	0.79	0.34
1999	0.80	0.09	0.76	0.00	0.77	0.31	0.77	0.31
2000	0.80	0.06	0.76	-0.03	0.76	0.26	0.76	0.26
2001	0.79	0.05	0.76	-0.02	0.75	0.26	0.75	0.26
2002	0.79	0.06	0.75	0.00	0.76	0.32	0.76	0.31
2003	0.79	0.05	0.75	-0.02	0.76	0.28	0.76	0.28
2004	0.78	0.07	0.75	-0.02	0.75	0.31	0.74	0.31
2005	0.77	0.08	0.74	0.00	0.73	0.29	0.74	0.28
2006	0.77	0.07	0.74	0.00	0.73	0.28	0.74	0.27
2007	0.78	0.07	0.75	0.00	0.74	0.26	0.75	0.26
2008	0.77	0.13	0.73	0.04	0.73	0.29	0.74	0.29
Tot. obs.	20,893	20,893	22,131	22,131	18,946	18,946	19,669	19,669

Notes: Columns 2 to 5 show the implication of including couples where one spouse is not working but the other is to the proportion of men earning more than their partner and to the correlation coefficient between wage levels, where the hourly wage for the non-worker is set at zero. Columns 6 to 9 show the effect of the alternative imputation of potential wages based on Wooldridge's (1995) estimator.

Figure 3.8

Spousal wage gap: stepwise imputation of potential wages for non-working women and men with more than two wage observations.

Notes: BHPS, 1991-2008. Predicted hourly wages for non-working women and men, in man and woman-sole earner couples respectively, are computed from Wooldridge estimates.

Colums 6 to 9 of Table 3.4 present the effect that the stepwise imputation of potential wages has on the proportion of men earning more than their partner and on the correlation coefficient between wages. Figure 3.8 and the last two columns of Table 3.4 suggest that changing selection of who is in work is exaggerating the convergence in wages within couples. The raw decline in the spousal wage gap, the extent men earn more than their partners, fell from 45% to 32% accounting for the fact that is increasingly women with very low potential earnings who are left not working. Likewise the proportion of men earning more than their partner falls a little less rapidly.

When interpreting these results, one *caveat* should be expressed. Taking into account the panel dimension comes at the additional cost of excluding from the sample those couples where partners do not participate in the labour market for at least two years. When it comes to wage imputation for non-working people, one should consider that excluded individuals are likely to have a potential wage lower than the average. Table B.6 presents sample statistics by gender for non-working people, divided into those who do not participated in the labour market for at least two waves and those having instead two wage observations or more. The figures suggest that individuals with less than two wage observations are on average older, lower educated, with more health problems and their partner earn a lower wage compared to those who are employed for at least two waves. Figure B.1 shows the evolution of the spousal wage gap under the wage imputation based on the Heckman estimator, including also individuals with less than two wage observation.

3.7 Conclusions

This paper analyses the evolution of the spousal wage gap (i.e. gender pay gap within couples) and its relationship with the overall pay gap, changes in labour force participation and the level of assortative mating between partners. We present a statistical model which shows how the probability of a positive spousal wage gap depends on the average gender wage gap, the variance of the male and female wage distributions and the correlation between partner's wages. The model shows how men can still earn more than their partners even with a low overall pay gap when assortative mating is high or the variance in earnings is low. We show how the model fits the data well and use it to explore what lies behind the observed decline in men earning more than their female partners. We then take into account changes in labour force participation patterns. We employ the estimation method developed by Wooldridge (1995) to correct for sample selection in panel data models where we can observe wages in other periods for individuals. We show how increasing participation of women has drawn in those with higher potential pay leaving those with lowest potential earnings still out of the labour market. Overall the picture is that men have around 32% higher hourly wages than their partners when both work. This is down from 45% in 1991. It is now the case that a little over one in four women have higher hourly pay than their partner. If we take into account that it is women with very low potential wages who remain out of work the pay gap remains at 35%.

Appendix A

Description of variables (Chapter 1)

A.1 List of tasks

Analytical

Paying close attention to detail
Teaching people (individuals or groups)
Making speeches/ presentations
Working with a team of people
Specialist knowledge or understanding
Knowledge of how organisation works
Spotting problems or faults
Working out cause of problems/faults
Thinking of solutions to problems
Analysing complex problems in depth
Checking things to ensure no errors
Noticing when there is a mistake
Planning own activities
Planning the activities of others
Organising own time
Thinking ahead

Reading written information (e.g. forms, notices and signs)
Reading short documents (e.g. reports, letters or memos)
Reading long documents (e.g. manuals, articles or books)
Writing materials (e.g. forms, notices and signs)
Writing short documents (e.g. reports, letters or memos)
Writing long documents with correct spelling and grammar
Adding, subtracting, multiplying and dividing numbers
Calculations using decimals, percentages or fractions
Calculations using advanced statistical procedures

Interpersonal
Dealing with people
Persuading or influencing others
Selling a product or service
Counselling, advising or caring for customers or clients
Listening carefully to colleagues
Knowledge of particular products or services

Manual
Physical strength (e.g. to carry, push or pull heavy objects)
Physical stamina (e.g. to work on physical activities)
Skill or accuracy in using hands/fingers (e.g. to assemble)
Knowledge of use or operation of tools/equipment machinery

A.2 Variables construction

Wages. Our wage variable is the gross hourly pay (gpayp). This derived variable is available for all the three waves of the UK Skill Survey. For most cases gpayp was computed as gross usual weekly pay divided by usual hours worked per week (including usual overtime). In 1997 respondents quoted an hourly rate directly: these values, when available, were used to replace gpayp (727 cases). Nominal gross hourly wages are deflated by the Consumer Price Index, with 2005 as the base year. Wages are measured in British Pounds. We trim our data such that hourly wages lower than 1 and higher than 100 are excluded.

Occupations. We classify occupations according to the International Standard Classification of Occupations (ISCO−88) (see ILO, 1990). Occupations were originally classified according to the Standard Occupation Classification (SOC 90 in 1997, SOC 2000 in 2001 and 2006). Codes are manually matched on the basis of the guidelines distributed by the Occupational Information Unit of the Office for National Statistics, correcting both for employment status and the size of the organisation/establishment (number of people working) when available. The same procedure is applied to the variables indicating the past occupation. Crosswalks are made available by the CAMSIS project at: http://www.camsis.stir.ac.uk/occunits. This harmonisation allows to compare occupations over time and to make our results strictly comparable to other papers. ISCO-88 defines four levels of aggregation, consisting of 10 major groups (one-digit), 28 sub-major groups (two-digits), 116 minor groups (three-digits) and 390 unit groups (4-digits).

Education. Our education variable distinguishes three groups of workers: high, medium and low educated (skilled). For all the three waves we exploit the variable dquals1 which indicates the highest qualification held by the interviewee. Both educational and vocational qualification levels are available in the list provided to respondents. In 2001 and 2006 one more options, "Masters or PhD degree", was added whereas earlier respondents were not allowed to differentiate the type of degree. We follow Schneider (2008) to convert the UK's educational and vocational qualifications to International Standard Classification of Education (ISCED-97) levels. The usual ISCED division into low, medium and high is then adopted where low is equivalent to ISCED 0-2 (i.e. primary and lower secondary education), medium is given by ISCED 3-4 (i.e. upper secondary and post-secondary non-tertiary education) and high is ISCED 5-7 (i.e. tertiary education). The derived categorical variable for education takes value of 1 for low educated, 2 for medium and 3 for high.

Task measures. We create task content measures which capture the intensity of the different activities carried out by each worker. This is done by performing a principal component analysis (PCA) for each of the three groups into which we categorise the 35 tasks (analytical, interpersonal and manual). The PCA is a statistical technique which aims at reducing correlated variables into a smaller number of principal components. It is a common procedure in the existing literature on job content analysis (see Autor et al., 2003; Autor and Handel, 2009; Goos et al. 2010). A detailed description of the PCA technique can be found in Jolliffe (2002). The routine measure is derived from a question related to the frequency of routine activities performed by workers on the job (b13 in 1997, brepeat in 2001 and 2006). All task measures above described are rescaled to range between 0 and 1.

Computer use. We create a measure which captures the intensity of computer adoption, interacting the scores of two questions: one related to the importance of computer use (from "essential" to "not at all/does not apply"); the other to its complexity (from "simple" to "advance"). The variables used are ja17 and m1 for the 1997 survey, cusepc and dusepc for 2001 and 2006. This variable is normalised to [0-1].

Appendix B

Extra Figures and Tables (Chapter 3)

Figure B.1
Potential wages for non-working women and men.

Notes: BHPS, 1991-2008. Potential wages for non-working women and men, in man and woman-sole earner couples respectively, are computed from Heckman estimates. Individual with less than two wage observations are also included in the sample.

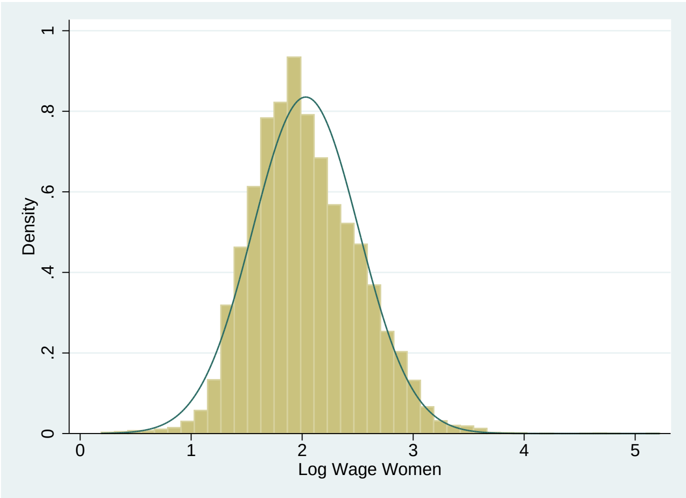
Figure B.2

Density of the male log wage distribution in dual-earner couples

Source: BHPS, 1991-2008.

Figure B.3

Density of the female log wage distribution in dual-earner couples



Source: BHPS, 1991-2008.

Table B.1

Description of the main variables in the wage and selection equations

Log. Hourly wage	Log wage per hour (deflated by the 2005 Consumer Price Index)
Age	Age in years
Age squared	Age in years squared (divided by 10)
Education	Years of education
Work	Dummy variable; 1 if the individual works
Number of children	Number of children in the household
Health problems	Dummy variable; 1 if the individual has some health problems
Partner works	Dummy variable; 1 if the partner/spouse works
Non labour income	Household non labour income (excluding benefits) in thousands (divided by 1000)

Table B.2
WAGE EQUATION WOMEN, 1991-2008

Variable	(1) **Pooled OLS**[(a)]	(2) **Random effects**[(a)]	(3) **Fixed effects**[(a)]	(4) **Heckman 2-steps**[(b)]	(5) **Wooldridge (1995)**[(b)]
Age	0.025***	0.027***	0.024**	0.013***	0.005
	(0.005)	(0.004)	(0.009)	(0.003)	(0.013)
Age sq.	-0.003***	-0.003***	-0.003***	-0.001***	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Education	0.080***	0.080***		0.074***	0.076***
	(0.004)	(0.004)		(0.001)	(0.004)
Lambda (Heckman)				-0.366***	
				(0.020)	
N	15,859	15,859	15,859	15,859	15,859
Wald test					
Unobs.(c)					χ^2_{19}=25.71

Notes: BHPS 1991-2008. Constant and year dummies are included but not reported. Standard errors in parenthesis. (a) Standard errors robust to serial correlation and heteroskedasticity; (b) boostrapped standard errors (1,000 replications); (c) χ_{19} test statistics for the joint significance of the variables in the vector $\bar{x}_{it}$. Significance levels *** p< 0.01, ** p< 0.05,*p< 0.10.

Table B.3
WAGE EQUATION MEN, 1991-2008

Variable	(1) **Pooled OLS**(a)	(2) **Random effects**(a)	(3) **Fixed effects**(a)	(4) **Heckman 2-steps**(b)	(5) **Wooldridge (1995)**(b)
Age	0.077***	0.079***	0.072***	0.079***	0.070***
	(0.005)	(0.005)	(0.009)	(0.003)	(0.011)
Age sq.	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Education	0.062***	0.063***		0.062***	0.061***
	(0.004)	(0.003)		(0.001)	(0.004)
Lambda (Heckman)				0.055	
				(0.039)	
N	19,211	19,211	19,211	19,211	19,211
Wald test Unobs.(c)					χ^2_{19}=31.73

Notes: BHPS 1991-2008. Constant and year dummies are included but not reported. Standard errors in parenthesis. (a) Standard errors robust to serial correlation and heteroskedasticity; (b) boostrapped standard errors (1,000 replications); (c) χ_{19} test statistics for the joint significance of the variables in the vector $\bar{x}_{it}$. Significance levels *** p< 0.01, ** p< 0.05,*p< 0.10.

Table B.4
Selection equation women, 1991-2008

Variable	(1) Probit[(a)]	(2) Mundlak Probit[(a,b)]
Age	0.183***	0.209***
	(0.016)	(0.048)
Age sq.	-0.025***	-0.020***
	(0.002)	(0.002)
Education	0.045***	0.045***
	(0.010)	(0.010)
N. children	-0.372***	-0.239***
	(0.020)	(0.021)
Health	-0.218***	-0.067*
	(0.039)	(0.028)
Partner works	0.567***	0.365***
	(0.062)	(0.052)
Non labour income	-0.168***	-0.108***
	(0.041)	(0.031)
N	21,167	21,167

Notes: BHPS 1991-2008. Year dummies are included but not reported. Standard errors in parenthesis. (a) Standard errors robust to serial correlation and heteroskedasticity; (b) unobserved individual effects are modeled as a linear projection onto the within means of the regressors. The constant is included but not reported. Significance levels *** $p < 0.01$, ** $p < 0.05$,*$p < 0.10$.

Table B.5
Selection equation men, 1991-2008

Variable	(1) **Probit**[(a)]	(2) **Mundlak Probit**[(a,b)]
Age	0.143***	0.300***
	(0.020)	(0.064)
Age sq.	-0.020***	-0.026***
	(0.002)	(0.003)
Education	0.066***	0.066***
	(0.011)	(0.011)
N. children	-0.120***	-0.054*
	(0.030)	(0.027)
Health	-0.485***	-0.038
	(0.048)	(0.037)
Partner works	0.556***	0.343***
	(0.055)	(0.050)
Non labour income	-0.361***	-0.386***
	(0.082)	(0.096)
N	21,846	21,846

Notes: BHPS 1991-2008. Year dummies are included but not reported. Standard errors in parenthesis. (a) Standard errors robust to serial correlation and heteroskedasticity; (b) unobserved individual effects are modeled as a linear projection onto the within means of the regressors. The constant is included but not reported. Significance levels *** $p < 0.01$, ** $p < 0.05$, *$p < 0.10$.

Table B.6
Sample statistics for non-working women and men.

Variable	Less than two wage observations		More than two wage observations	
	Women	Men	Women	Men
Age	42.232	49.072	37.908	46.025
	(11.226)	(9.457)	(9.454)	(10.36)
Age squared	190.949	249.729	152.637	222.547
	(91.931)	(83.675)	(77.011)	(89.951)
Education	11.743	11.229	12.341	12.368
	(2.26)	(2.106)	(2.408)	(2.722)
N. children	1.064	0.564	1.314	0.729
	(1.151)	(0.907)	(1.04)	(1.003)
Health	0.642	0.861	0.577	0.654
	(0.48)	(0.439)	(0.494)	(0.476)
Non labour income	0.174	0.213	0.151	0.46
	(0.658)	(0.383)	(0.421)	(0.794)
Log. wage partner	2.314	1.75	2.465	1.983
	(0.537)	(0.468)	(0.545)	(0.55)
N	1,581	445	2,296	723

Notes: Columns 2 and 3 report descriptive statistics for non-working women and men with valid information on all the variables in the wage and participation equations, who participate in the labour market in less than two waves. Columns 4 and 5 display the same figures for women and men with two or more wage observations. Standard deviations in parenthesis. No earners couples are excluded.

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