ESSAYS ON LABOUR MARKET DYNAMICS

Michael Stewart Simmons

Submitted for the degree of Doctor of Philosophy

Royal Holloway, University of London
September 2020

This is for Barry, Cefa, Chaddie, Tim, Angela and Kat

Contents

Abstract

This thesis presents three essays that address two of the most basic features of labour markets: job loss and job finding. Chapter 1 introduces the topic. Chapter 2, the first essay, presents considerable evidence that workers in the UK labour market can foresee job loss and respond by starting to search for new employment. The chapter then builds and estimates a model of the labour market in order to estimate how far in advance and how many workers change their search behaviour prior to job loss; and to study the welfare implications of job loss anticipation, and how the associated welfare gains interact with policy. Chapter 3 seeks to understand why the unemployment rate rises during recessions in the UK and US using the flows based approach. The chapter argues that one will overstate the contribution of layoffs to the rise in unemployment during recessions, if one ignores the large number of workers switching jobs. The final essay, Chapter 4, studies why variations in unemployment rates differ so markedly between genders for eighteen OECD countries, using a similar approach to chapter two. The results indicate that unemployment inflows explain the majority of the dynamics of the gender unemployment gap for all eighteen countries. The chapter also demonstrates that a candidate explanation across all countries for this result is the differing gender composition by sector. The thesis is concluded in Chapter 5.

Chapter 2: Pre-layoff search

Note: This paper won the Sir Alec Cairncross Prize at the Scottish Economic Society Conference in 2021, and The Best Paper by a Finalist at Royal Holloway in 2020.

How do workers mitigate unemployment risk? Can they foresee job loss? If so, how many and how far in advance? In this paper, I provide evidence that workers can foresee impending layoff by tracking changes in their search behaviour prior to job loss. Equipped with this information, I build a search model of the labour market with stochastic human capital, where workers may receive information of job insecurity, and are able to respond by picking their search effort and savings. I show that the dynamics of "pre-layoff search" pins down key parameters governing the changes in the average worker's information set prior to job loss. The model estimates reveal that, two-fifths and three-fifths of low and high skill workers, respectively, know of impending job loss on average about three months before becoming unemployed. As well as fitting the dynamics of pre-layoff

search, the model is also able to replicate the level of involuntary job switching, and the costs of job loss for workers who immediately find new employment and for workers who do not, ascribing an integral role for the job ladder and human capital dynamics. Counterfactual analysis shows that the associate welfare gains from anticipating job loss are large: 1.6% in consumption equivalent variation, or an extra at least £600 million in unemployment benefit expenditure. Endogenous changes in search, as opposed to endogenous changes in savings, drives almost all these gains.

Chapter 3: Job-to-job transitions, job finding and the ins of unemployment

Increases in the ins of unemployment during recessions are the result of two major forces: increased layoffs, or a fall in job finding of potential job-to-job transitions. This paper quantifies the contribution of these two channels using the flows approach to the labour market in the UK and US over a period of two decades. The results show that fluctuations in job finding of potential job-to-job transitions are at least as important as layoffs, where procyclical quits play a moderating role in recessions. I show that these results are not driven by compositional changes in observable characteristics, and are robust to an adjustment for time-aggregation.

Chapter 4: The ins and outs of the gender unemployment gap

Note: This paper is joint work with Reamonn Lydon. He has agreed that this paper represents a significant contribution on my part and can appear in this thesis. This paper is a working paper at the Central Bank of Ireland. The views expressed in this paper are those of the authors only and do not necessarily reflect the views of the Central Bank of Ireland or the ESCB.

Variations in the unemployment rates of men and women often differ markedly. To understand the dynamics of the gender unemployment gap, this paper estimates the inflows to, and outflows from, unemployment by gender for 18 OECD countries over the last four decades. Whilst there are cross-country differences in the relative contribution of inflows and outflows by gender, there is a clear common pattern: differences in the variations of the inflow of unemployment explain the majority of the dynamics of the gender unemployment gap for all countries under study. Specifically, in the recessions covered by our data, the change in the flow of males into unemployment

is typically larger than the change in the flow of females into unemployment. Using data on output by sector, we show that a candidate explanation for these results for each country is the differing gender composition by sector. Over the four decades of data we analyse, and across all countries, females were more likely to work in sectors less exposed to economic downturns.

Acknowledgements

Thanks very much to my supervisors, Jonathan Wadsworth and Ija Trapeznikova. Manolis Galenianos, Carl Singleton and Jesper Bagger have also provided considerable help with different chapters of this thesis. I also thank Reamonn Lydon for working alongside me to produce the final essay of this thesis.

Finally, I would also like to thank my friends and family. Especially my dogs, cats, Father, Mother and fiancé who have all provided, in their own way, so much support over the last four years.

Chapter 1

Introduction to the thesis

Labour markets are dynamic. They are categorised by large flows into and out of employment and from one job to another - approximately one million workers flow into and out of employment and 800,000 workers switch employers each quarter in the UK. These flows change considerably during times when the economy is booming to when the economy is in recession (see Figure 1.1).
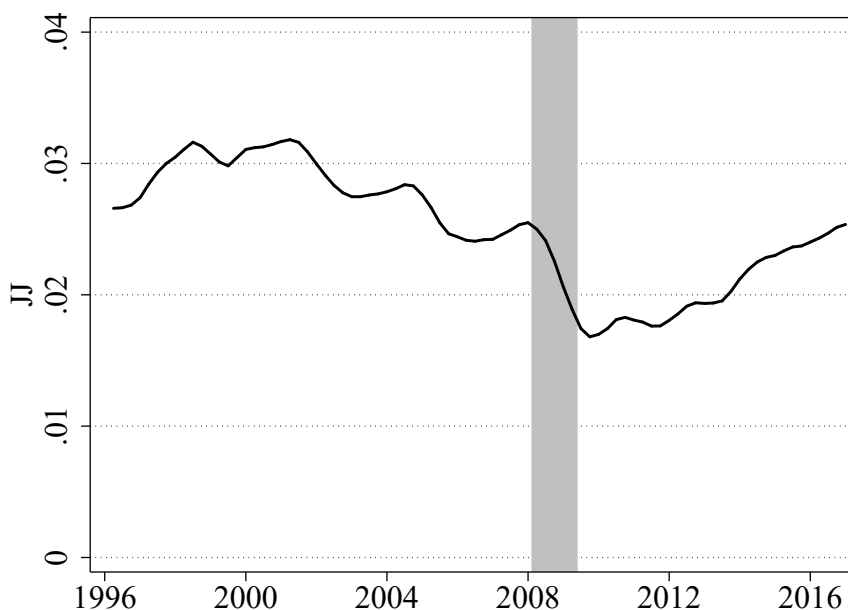
FIGURE 1.1: The UK quarterly job-to-job transition probability. The vertical axis represents the proportion of the employed who switch jobs each quarter. A job switch is defined as any worker who reports to be employed in quarter t and quarter $t+1$, and has less than three months tenure in quarter $t+1$. The shaded region represents the Great Recession period.

An immense literature has studied these flows to understand how labour markets function, and to understand how and when policy makers should intervene to improve welfare. Of particular interest in this thesis is the study of workers moving from one job to another, or job-to-job transitions, and captures the attention of the first two chapters.

1

One would suspect that job-to-job transitions represent quits by workers, but this is not always the case. Around a quarter of all job-to-job transitions actually proceed a layoff in the UK. The abundance of "involuntary job-to-job transitions" suggests that many workers know of impending job loss, be it through formal advance notice of informally catching wind, and respond by increasing search to avoid a spell of unemployment. Is there evidence of increased search prior to layoff? How many workers have knowledge of impending job loss? How valuable is knowledge of future job loss to the worker? What is the most important mechanism that workers use prior to losing their job? How do policy instruments impact job loss anticipation? It is these questions that are the focus of Chapter 2.

Using microdata from the UK Labour Force Survey and UK Household Longitudinal Panel, I provide an array of evidence that workers have knowledge of impending job loss. Most notably, I show that the proportion of workers who report to be searching increases significantly during the quarters that precede job loss. And that the prevalence of "pre-layoff search" is stronger for high skill relative to low skill workers. Using this information, I build and estimate a job ladder model of the labour market where workers may receive information of impending job loss and can respond by choosing their search effort and consumption. The model is able to jointly replicate the reality of pre-layoff search and involuntary job-to-job switching, as well as the large earnings losses associated with job loss for those who transition into unemployment, and much smaller losses for those who manage to switch employers.

The model estimates reveal that two-fifths and three-fifths of low and high-skill workers have knowledge of impending job loss, approximately three months prior to being pushed into unemployment. This anticipatory behaviour has sizeable welfare gains for workers, increasing consumption by about 1.3% and 1.9% for the low and high-skill workers, respectively. These welfare gains can be split into those attributed to increased search, and increased saving whilst employed. The welfare gains are almost entirely due to increased search. I further show the unemployment rate is reduced by around 20% as a result of the endogenous decisions taken by individuals to mitigate the costs of job loss.

A basic question that has acquired a lot of attention from macro economists is, why does the unemployment rate rise in recessions and fall in expansions? This question can be answered in different ways, through either structural or purely empirical methods. The approach I adopt in Chapter 3 of this thesis is purely empirical, through the use of worker flows: does the unemployment rate rise in recessions because more workers are let go, or because fewer workers can find employment. Using data from the UK Labour Force Survey for the UK, and the Current Population Survey and Survey of Income and Program Participation for the US, the chapter shows that ignoring

job-to-job transitions and the relationship between the ins of unemployment and job finding can result in significantly understating the contribution of job finding to unemployment dynamics, and overstating the contribution of layoffs.

In Chapter 4, again using worker flows, we study why the unemployment varies so differently for males and females for 18 OECD countries over the last four decades. We decompose the changes in the gender unemployment gap into those attributable to differences in the rate at which males and females flow into unemployment, the inflow gap, and differences in the rate at which males and females flow of unemployment, the outflow gap. For all 18 countries, variations in the inflow gap explain the majority of the dynamics of the gender unemployment gap. Using data on output by sector, we show that a candidate explanation for this result is the gender composition by sector: males tend to be in sectors that are more susceptible to economic swings than females, which in turn increases the average precarity of a job held by males more than for females in recessions.

Chapter 2

Pre-layoff search

Note: This paper won the Sir Alec Cairncross Prize at the Scottish Economic Society Conference in 2021, and the prize for The Best Paper by a Finalist at Royal Holloway in 2020.

2.1 Introduction

Job loss is a fundamental and pervasive aspect of labour markets. In the UK, on average around a million workers are laid off from their jobs every year. A vast literature has studied how workers fare post displacement, finding that earnings are significantly depressed in the short and long-run.[1] *How do workers mitigate this unemployment risk?*

Interestingly, job loss does not always result in unemployment. Around a quarter of all layoffs in the UK result in a worker transitioning directly to a new employer without an intervening spell of non-employment, and these workers experience much smaller earnings losses post job loss.[2] Figure 2.1 shows the pre and post layoff earnings dynamics for all job losers and for only those who immediately find new employment in the UK.

The fact that a large number of workers manage to switch jobs immediately post layoff, suggests that many workers have received information of impending job loss, be it through formal advance notice or informally catching wind.[3] Using data from the UK, I find clear evidence that some workers have knowledge of impending job loss by tracking the changes in the proportion of workers who report to be searching during the four quarters prior to layoff, a stylised fact I refer to as "pre-layoff search". I study this pre-layoff behaviour in a model of on-the-job search, savings and stochastic human capital, and find that the model is able to replicate salient features

---

[1]See Jacobson et al. (1993), Stevens (1997), Couch and Placzek (2010) and Davis and Von Wachter (2011) to name just a few. The costs of job loss shown in Figure 2.1, are estimated using a framework shown in Section 2.5.

[2]These types of transitions are not unique to the UK. A similar magnitude is present in the US, see Carrillo-Tudela and Smith (2017). Schwerdt (2011) finds that some workers leave quarters before mass layoffs in Austria, and experience significantly smaller earnings declines than those who remain until the end.

[3]In the UK firms are required to provide advance notice to workers, or if written in the contract, instead provide the worker payment in lieu. See UKGov (2020) for further information regarding mandatory advanced notice in the UK, and I discuss the institutional setting further in Section 2.2.
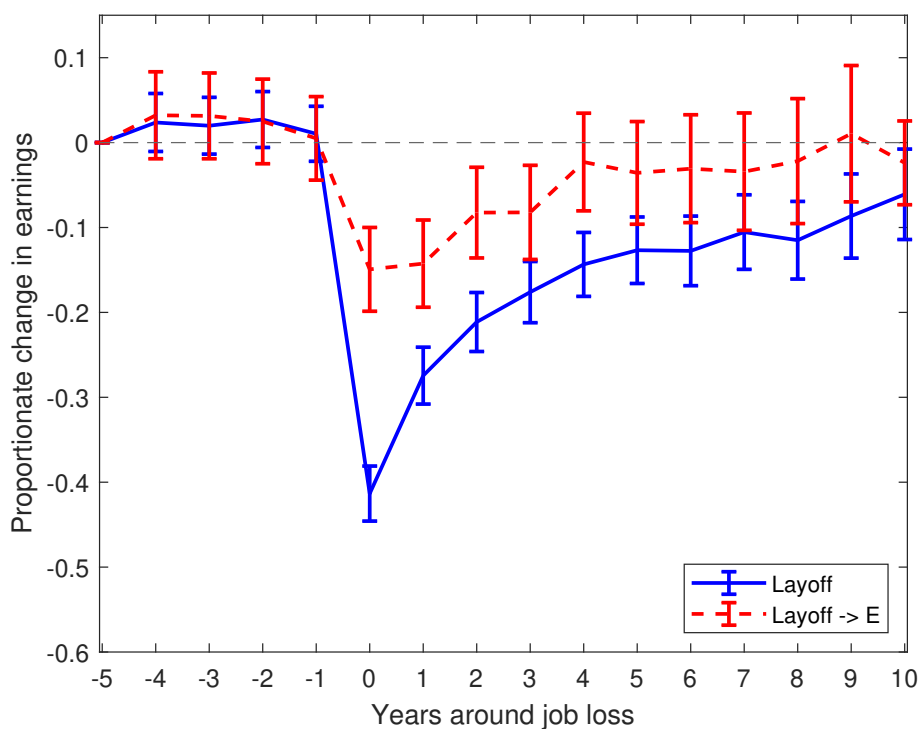
FIGURE 2.1: The estimated costs of job loss in the UK

Note: The bold line shows the estimated costs of job loss for all workers who lose their job. The dashed line shows the estimated costs of job loss for all workers who immediately find new employment following job loss. Workers report their yearly labour market histories throughout the year, allowing me to categorise direct job-to-job transitions that proceed a layoff (without a non-employment spell in between). The costs are estimated using (2.29). Bars represent 95% confidence intervals. 1991-2018.

Source: Data from the British Household Panel Survey and the UK Household Longitudinal Study.

of search, job switching and earnings dynamics associated with job loss. The estimated model provides new insights into, how many workers receive information of impending job loss, how far in advance they change their behaviour, the driving forces behind the smaller costs of job loss for those switching employers relative to those transitioning into unemployment, the size of the welfare gains pre-layoff information provides to workers, and how these changes in behaviour impact policy analysis.

To study how workers' search changes before job loss, I use data from the UK Labour Force Survey (LFS). The LFS has unusually rich on-the-job search information for large representative data sets. Workers are asked, whether they are searching, the reasons for searching, and how many methods used. This, coupled with a longitudinal component, makes the LFS a particular good data set to study search dynamics before job loss. In Section 2.2, using data over the past two decades, I document three novel facts from the LFS. First, search incidence increases by approximately 20 percentage points (pp) during the quarter that precedes job loss, and this "pre-layoff search" is predominantly due to workers "thinking their job may end". Second, the increase in search incidence is much stronger for high-skill (32pp) relative to low-skill (17pp) workers.[4] Finally, the average wage change for a job-to-job transition following a layoff is negative.[5] These results build a clear picture of search and involuntary job switching in the labour market. Workers somehow, formally or informally, realise that their job is less stable than before, and respond by increasing search effort and reducing their current reservation wage.

With these empirical observations in mind, I build a job ladder model, split into two skill levels, where workers may receive information that their job is less secure. The model also incorporates savings and stochastic human capital. The model captures the essence of "pre-layoff" search: workers respond to information that their job is more likely to end by increasing search and reducing the reservation productivity to regain a more stable employment relationship. Intuitively, following the displacement information, the model also predicts that workers reduce consumption in order to save for the increased possibility of unemployment. These mechanisms are endogenous decisions taken by the worker in order to mitigate the costs associated with job loss.

I perform a full estimation of the model and show that the estimated levels of increased search at different quarters before job loss, identify key parameters regarding job loss anticipation in

---

[4]I study further heterogeneity by observable characteristics, and find that pre-layoff search does not vary significantly by gender, age, firm size and even by firm tenure. This final observable is particularly interesting given the fact that government mandated advance notice is increasing in firm tenure.

[5]I consolidate these results with evidence from the British Household Panel Survey (BHPS) on subjective job insecurity elicitations. I find that workers who report that their job is very likely to end have a large increased likelihood of moving into unemployment, but also switching jobs following a layoff.

the model. Whilst fitting the levels of pre-layoff search, the model also replicates other salient features in the labour market, namely the reality of job-to-job transitions following layoff, and post displacement earnings losses for those workers who transition into unemployment and for those who switch jobs involuntarily. The model estimates reveal that approximately 42% and 62% of low and high skill workers, respectively, know that job insecurity has increased on average three months prior to becoming unemployed.

I first use the estimated model to understand the driving forces behind the differences in earnings losses post job loss for those who manage to switch jobs compared to those who transition into unemployment. The losses can be decomposed into three contributing components: an employment effect, a job ladder effect, and a human capital effect. In the model, the employment effect quickly dissipates and the job ladder effect is very small, and the human capital effect drives all the long-run differences. When workers manage to switch employers and avoid unemployment following layoff, they do not lose out on foregone human capital accumulation. This human capital effect drives significant long-run differences in the costs of job loss between the two destinations.

Next, I study to what extent the endogenous decisions taken by workers, prior to layoff, to mitigate the costs of job loss, increase aggregate welfare. The model shows large welfare benefits, equal to approximately 1.31% and 1.89% of consumption equivalent variation for the low and high skill workers, respectively. This is equivalent to increasing unemployment benefits by 48% and 60% for the low and high skill workers, respectively, which would cost the government at least £600 million.[6] These welfare gains are due to workers increasing their search effort and increasing their savings following the increase in job insecurity. The welfare gains can be decomposed into those attributable to each mechanism. I find that the gains are almost entirely due to endogenous search: increased saving following the anticipation shock provides negligible benefits to workers. The dominant force that workers use to mitigate the increased unemployment risk is to change their search effort.

I finally use the model to understand the implications for policy. I first study whether the employed would be willing to forego earnings in order to finance a scheme that provides them with further time to find new employment - are workers willing to pay for information of impending job loss? The model shows that such a scheme is only beneficial to workers once endogenous changes in search behaviour are allowed. If workers do not increase search on this scheme, workers remain in the scheme for much longer, resulting in the costs of implementing the scheme outweighing the benefits. When I allow for endogenous changes in search, workers experience significant welfare gains - they are willing to forego earnings in return for more advance knowledge of job loss.

---

[6]Calculated using 2020 information from Statista (2018).

Next, I study how the welfare gains from anticipating job loss are dependent on the level of unemployment benefits in the economy. I model an unemployment benefit scheme, again financed by taxing labour income. An intuitive result is that, increasing unemployment benefits reduces the gains from anticipating job loss - the pre-layoff warning becomes less valuable when unemployment becomes more enjoyable. I show that this distortion does not, however, impact the optimal unemployment benefits level in the economy, which is close to the current level in the UK labour market.

Related literature

There are only a small number of studies analysing pre-layoff behaviour. These include Stephens Jr (2001, 2002, 2004), Benito (2006), Gong (2011), Basten et al. (2016), Hendren (2017) and Bryan and Longhi (2018) who study how workers' consumption, asset holdings or spousal labour supply, change before job loss. Bryan and Longhi (2018) find no significant increase in spousal labour supply in the quarter prior to layoff in the UK, suggesting that "unemployment is a surprise". Using search information, this paper presents clear evidence that unemployment is not a surprise to a large proportion of workers in the UK.

To the best of my knowledge, the only paper that studies search prior to job loss is found in Burgess and Low (1992).[7] Using recall information of the currently unemployed, Burgess and Low (1992) show that a significant proportion of workers report that they were searching before losing their job and moving into unemployment. In this paper, I do not rely on recall. Instead I follow workers up until they lose their job, allowing me to track the changes in search incidence before layoff. Tracking how search incidence changes before layoff is necessary for pinning down important parameters that describe how many workers receive information of impending job loss, and how far in advance they change their behaviour. Another distinction is that I do not only look at those who are laid off and move into unemployment, but also those who switch jobs and describe the reason for separation as involuntary.

A central feature of the model in this paper is to incorporate involuntary job-to-job transitions, which in turn results in an economy where some job switching results in wage falls.[8] To match these features, many papers including, but not limited to, Jolivet et al. (2006), Bagger et al. (2014), Tjaden and Wellschmeid (2014) and Bagger and Lentz (2019) invoke the so called "godfather shock", in environments in the spirit of Burdett and Mortensen (1998). The godfather shock

---

[7]There is also a related literature on advanced notice that studies to what extent longer notice periods impact labour market outcomes post job loss. See Swaim and Podgursky (1990), Nord and Ting (1991) for two examples.

[8]See Jolivet et al. (2006) for evidence of a significant number of job switching with wage falls in Europe and the US.

forces the worker into a take-it-or-leave-it job offer, where the workers' reservation wage is equal to that of unemployment, resulting in job switching with wage cuts. In this paper I estimate that the job ladder effect plays only a negligible role in explaining the differing paths between those who lose their job and move to unemployment compared with those who lose their job and move directly to a new job. This implies that workers behave similarly to the unemployed when they are in layoff employment, and so invoking the godfather shock in these models is appropriate.

A paper with an explicit focus on developing a mechanism for involuntary job switching is shown in Carrillo-Tudela and Smith (2017).[9] They build a model that incorporates return employment. When workers are subject to job destruction shocks, they are able to re-sample from declined firm contacts to see if the job still exists. The more contacts the worker has, the less likely they are to experience unemployment. This is described as search capital, an insurance mechanism for the worker. The model is used to study the implications of search capital for the unemployment rate and productivity. In this paper, I show that the size and shape of pre-layoff search is able to replicate the level of involuntary job switching in the UK.

The seminal paper of Davis and Von Wachter (2011), showed that off the shelf job search models find difficulty in replicating the average workers earnings decline following layoff. A significant literature has been dedicated to augmenting search models to replicate and understand the scarring affects of layoff, and to understand the policy implications of fitting this feature of labour markets. Jarosch (2021) and Krolikowski (2017) aid the job ladder model by, in different ways, including a distribution of unemployment risk. Separations, therefore, are more likely to precede further separations and increase the costs of initial job loss. Burdett et al. (2020) build a model with skill loss in unemployment (Jarosch (2021) also incorporates skill loss in unemployment). They are able to replicate the cost of job loss, arguing that, human capital loss is the main long run cost of job loss.

Following on from Jacobson et al. (1993), research has shown that the welfare costs of these displacement events are large (see Daniel (1987), Hansen and Imrohoroglu (1990), Rogerson and Schindler (2002) and Low et al. (2010)). It is not surprising, therefore, that allowing search models to replicate the earnings decline post job loss is important for policy and welfare analysis, as is shown in Jarosch (2021) and Cozzi and Fella (2016). Cozzi and Fella (2016) show that positive severance pay provides welfare gains for workers, a result in contrast to the preceding literature (see Alvarez and Veracierto (2001)). They show that the reason for this difference in result is because their model can replicate the costs of job loss. In order to estimate the gains associated

---

[9]Garibaldi (2004) studies the Diamond-Mortensen-Pissarides model (Pissarides (2000)) with advance notice, allowing for transitions that are analogous to involuntary job switches.

with the pre-layoff warning and understand how these gains interact with policy, it is important, therefore, that the model is able to replicate the large earnings falls post layoff. In this paper I follow the theme of skill loss in unemployment and a job ladder, which allows the model to replicate the differing costs of job loss by destination.

The remainder of the paper is structured as follows. Section 2.2 presents considerable evidence that workers can foresee job loss in the UK labour market, and most notably tracks changes in the incidence of search before job loss. Section 2.3 describes the model and presents the key endogenous features. Section 2.4 derives the model counterpart of pre-layoff search, and shows that two key parameters govern the dynamics of pre-layoff search. Section 2.5 outlines the estimation strategy and presents the model fit. Section 2.6 studies the model implications for the costs of job loss. I pay close attention to understanding the economic forces that drive the observed difference in the costs of job loss for those transitioning to unemployment relative to those who switch employers. Section 2.7 presents counterfactual analysis where I study the impact of switching off the pre-layoff warning on consumption and unemployment. In Section 2.8 I model salient policies financed by taxing labour income. Finally, Section 2.9 concludes.

2.2 Pre-layoff search in the UK

In this section, I document three novel results for the UK labour market. (1) The proportion of workers who report to be searching increases by 20pp during the quarter that precedes job loss, and this increased incidence is solely due to workers "thinking their job may end". (2) The prevalence of pre-layoff search is stronger for high-skill relative to low-skill workers. (3) The average involuntary job switch results in a 10% wage cut.[10] Before I present these results, I will briefly describe the institutional setting and the data.

2.2.1 Fixing ideas: why might workers be able to foresee job loss?

Here I outline some possible reasons as to why workers may be able to foresee unemployment approaching. I draw the reader to three likely causes

1. The institutional setting.

2. Privately bargained notice periods.

---

[10]In Appendix A.1 I also show that subjective job insecurity elicitations provide significant explanatory power in predicting whether a worker will make an employment to unemployment transition or an involuntary job switch.

3. Informally catching wind of job loss.

The institutional setting: In the UK workers must either receive a mandatory notice period that is increasing in tenure, or can instead be paid in lieu of the stipulated notice period length. For workers with less than two years tenure, the worker is required to receive at least one week of advance notice. The length of notice increases by one week for every extra year that the worker is employed, up to a maximum of three months. **Privately bargained notice periods**: Firms may provide longer notice periods than those mandated by the government, or provide notice periods in institutional settings that do not mandate them. We can think of many reasons for why longer notice periods may be written into contracts. The notice period length is a salient feature of the contract for the worker, and the worker may bargain for it to be increased in length. Notice periods may also be thought to increase the productivity of the worker, as they are not worrying about the possibility of unemployment the following day. Since workers can be paid in lieu of contract, however, the institutional setting or contractual notice periods do not guarantee that workers are able to foresee unemployment. Paying the worker in lieu of contract may well be optimal for the firm, if the current productive capacity of the worker has suddenly reduced or is expected to reduce significantly. I do not have information on how many workers work their notice or receive payments in lieu.

Informally catching wind of job loss: Workers may also receive private information about the insecurity of the job, that is unrelated to more formal firing procedures. I show in Appendix A.1 that workers subjective elicitations of their own job insecurity has significant explanatory power - if workers report that their job is "very likely to end in the next 12 months", they are around 30 percentage points more likely to lose their job than those who report that their job is "very unlikely to end in the next 12 months". This is an order of magnitude greater than the baseline. Of course, the fact that workers have explanatory power could be due to presence of mandatory notice periods in the economy. This private information of job insecurity is, however, also found in the US in Stephens Jr (2001, 2002, 2004) and Hendren (2017), a country with very short mandatory notice periods. *In this work, I will not take a stance on which of these contributing factors is of most importance, but it is possible that all three play a role.*

2.2.2 Data

The UK Labour Force Survey

The LFS is a household-based survey that is used as the backbone for UK government labour force statistics. While the survey was originally used for cross-sectional analysis, in 1992 the

survey introduced a longitudinal component. Following this reform, survey participants are sampled for five consecutive quarters, allowing for the construction of a five quarter panel of workers from 1992 to the present. As well as having a longitudinal component, the LFS has unusually high quality on the job search information for large representative data sets.[11] Workers are asked three main questions: whether they are searching for a different job, the reasons for searching for a different job, and the number of methods used for searching.[12] A longitudinal component coupled with quality on the job search information allows for a comprehensive study of changing search behaviour prior to job loss.

The British Household Panel Survey

The BHPS is a household longitudinal study. It followed individuals from 1991 to 2009, and began with 10,000 households. As well as the LFS, the BHPS is used for official statistics. The BHPS is required firstly to estimate the costs of job loss as seen in Figure 2.1. To do so, we need to be determine whether a worker made an involuntary job-to-job transition. In the BHPS, workers provide a full labour market history of the preceding year, including all changes in spells and employers, the start and end date of each job, and the reason a job ended. We can, therefore, identify job-to-job transitions without an intervening spell of non-employment, and subsequently determine whether the job ended due to the job being lost or due to a quit. Second, the survey provides information on subjective job security elicitations as well as reasons for separation, allowing me to consolidate findings from the LFS. Finally, the survey contains information on wealth and consumption that I will use in the estimation and evaluation of the results.

2.2.3 Raw measures

I begin by providing a brief overview of on the job search in the UK. In the LFS, employed workers are asked whether they are searching for a different job. There are two clear possible questions that a sceptic would ask of one who is using such information: (1) Are some people searching but just not answering the question? (2) Is job search a good indicator for whether someone subsequently switches jobs and, therefore, a good indicator for whether they are practically

---

[11]Because of this, other researchers have used the LFS to understand search patterns on the job, see Pissarides and Wadsworth (1994), Longhi and Taylor (2010) and Fujita (2012).

[12]The exact questions are: "Were you looking for a different or additional paid job or business in the week ending Sunday the [date]?", "Why were you looking for another job?", and "In the four weeks ending Sunday the [date], did you do any of these things...". The third question refers to methods of search.

searching? In Table 2.1, I show that, by these accounts, on the job search is a credible measure in the LFS.

The top panel of Table 2.1 shows the answers to the question and percentages. The vast majority of respondents answer either yes (6.04%) or no (93.43%) to the question, a negligible amount do not answer, and a small but non negligible amount respond by saying it does not apply. It is not true that a large proportion of workers do not report whether they are searching or not in the LFS. For the remainder of the paper, I continue assuming that both of the final categorisations are not searching.

The lower panel shows the percentage of the employed who report to be searching prior to either remaining at their employment, switching jobs, or being laid off. I assign a job switch as when a worker is employed in period t and, given that the data has a quarterly frequency, also employed in period $t + 1$ with less than three months tenure.[13] A layoff is defined as any transition out of a job that remains in the labour force and is described as involuntary.[14] 5.19% of the stayers are searching. This increases by about 6 fold for those who subsequently switch jobs to 30.7%.[15] These statistics are reassuring and suggest that reporting to be searching on the job is a good indicator for whether a worker is practically searching. Table 2.1, therefore, shows that the on the job search indicator in the LFS is a useful measure to study the search patterns of the employed.

The final column shows the proportion of workers who report to be searching when they lose their job in the next period. 24.8% of workers report to be searching before a layoff. Layoffs proceed a much higher incidence of on the job search relative to staying at your employer. The final two rows split the statistics by low and high skill workers.[16] The conclusions are broadly similar for both of these worker types, but search incidence is larger prior to layoff for high skill relative to low skill workers. These results suggest that some workers have knowledge that their job is soon to end, and are responding by changing their search effort in order to avoid unemployment.

---

[13]There may be non-employment spells in between in the LFS data. This is not, however, important for the determination of pre-layoff search dynamics, all we care about is whether they lost their job. We can, however, look at "true" job-to-job transitions with the BHPS data since workers give a full labour market history of the preceding year.

[14]See Appendix A.2 for the categorisation of involuntary separations.

[15]This is likely understated due to time aggregation: since workers are only surveyed ever quarter, they may begin searching in between surveys.

[16]High skill is defined as those who have more than A levels.

	Yes	No	No answer	Does not apply
All	6.04	93.43	0.01	0.53
Low skill	5.69	93.73	0.01	0.57
High skill	6.97	92.69	0.02	0.32

	All	Stayer at $t+1$	JJ at $t+1$	LO at $t+1$
All	6.04	5.19	30.7	24.8
Low skill	5.69	4.86	29.8	22.8
High skill	6.97	6.09	33.2	32.9

TABLE 2.1: Answers by percentages to the job search question.

Note: Question - were you looking for a different or additional paid job or business in the week ending Sunday the [date]? *LO* refers to layoff, where I assign layoffs using the categorisations shown in Section A.2. N = 2,219,645 (1,663,565, 556,080). 1995Q1 - 2016Q1.
Source: Data from the UK Labour Force Survey.

2.2.4 Pre-layoff search

The above results suggest that the possibility of layoff induces on the job search. One may argue, however, that perhaps individuals who search hard before layoff are always searching hard. It is not, therefore, the resulting layoff that is inducing a high incidence of search by the workers, but instead it reflects worker heterogeneity. Next I formally assess whether the proportion of workers who report to be searching changes as they approach layoff using the longitudinal nature of the LFS. If search incidence increases as workers approach layoff, this is strong evidence that they have correctly anticipated layoff and are responding with search.

To estimate how workers search incidence changes before layoff, I follow a similar technique in the job loss literature and compare workers who are laid off to a control group (See Jacobson et al. (1993)). The control group consists of workers who never separate from their job during the entire five quarters. Between 1995 and 2016, this leaves me with 291,502 individuals in the control group. It is important to note that some of the control group may experience layoff in quarter six. The treatment group consists of workers who remain at their job from quarter one to quarter four, and are laid off during the final quarter. This leaves me with 1,073 separation events

that satisfy the above. Using these restrictions I estimate the following distributed lag model

$$s_{it} = a_i + \gamma_t + X_{it}\beta + \sum_{k=1}^{3} \delta^{-k} D_{it}^{-k} + \varepsilon_{it}. \tag{2.1}$$

s_{it} is an indicator variable taking the value 1 if the individual reports to be searching and 0 if not. α_i and γ_t are individual and time fixed effects, respectively. X_{it} contains observables - a quartic in age. D^{-k} takes the value of 1 if the individual is laid off in k quarters and 0 otherwise. The stream of δ^{-k} gives the percentage change in search incidence k quarters before the layoff event relative to their search incidence four quarters before layoff and that of the control group. As previously mentioned the LFS also asks participants the reason that they are searching.[17] I concentrate on one answer: "I think my current job may end". To assess whether the changes in search are primarily driven by this factor, I also run (2.1) with the dependent variable being an indicator taking a value of 1 if the worker reports to be searching because they think their job may end and 0 otherwise. I will call this insecure search. Figure 2.2 shows the results for both searching and insecure search.

There is a significant and strong rise in search incidence prior to job loss. During the period before workers lose their jobs, the percentage of workers who report to be searching increases by around 20pp relative to four quarters before layoff. As we can see from the dotted line, this increased search incidence is predominantly due to workers thinking their job may end. This is clear evidence that workers are able to foresee job loss, and respond by searching harder to avoid unemployment spells.

Next I assess whether the prevalence of pre-layoff search is stronger for high-skill relative to low-skill workers as suggested in Table 2.1. I run the same as in (2.1), but split by skill types. Figure 2.3 shows the results. Pre-layoff search is stronger for high relative to low skill workers. The percentage of high skill (low skill) workers who report to be searching increases by around 32pp (17pp) relative to four quarters before layoff.

Finally, I assess four further possible factors that may result in different levels of pre-layoff search: tenure, firm size, age and sex. As already discussed, in the UK, firms must give mandatory advanced notice of layoff, or pay the staff in lieu but this must be written in the contract, and the length of mandatory advanced notice is increasing in tenure. One would expect, that when we compare workers who lose their job with less than three years tenure to workers who lose their job with more than three years tenure, the high tenure group would show stronger levels of pre-layoff search. Figure 2.4 shows that, surprisingly, the level of tenure does not seem to play a particularly important role. While this suggests that government mandated notice periods are not necessarily

---

[17]See Appendix A.2 for the possible reasons workers give.

FIGURE 2.2: Pre-layoff search

Note: The vertical axis gives the change in the proportion of workers who report to be searching on the job or insecure searching, relative to the percentage searching 4 quarters before job loss, and the changing proportion of search for workers who do not lose their job. -1 refers to the quarter before job loss. Bars represent 95% confidence intervals. Source: Data from the UK Labour Force Survey.
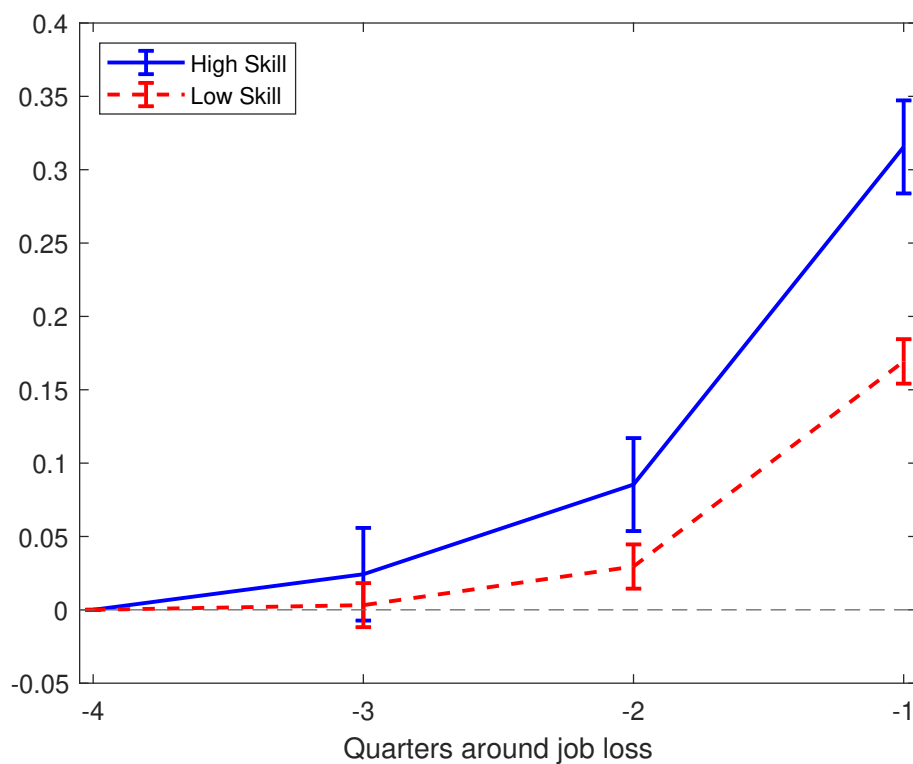
FIGURE 2.3: Pre-layoff search by skill level

Note: The vertical axis gives the change the proportion of workers who report to be searching on the job, relative to the percentage searching 4 quarters before job loss, and the changing proportion of search for workers who do not lose their job. High skill workers are those with qualifications greater than A levels.
Source: Data from the UK Labour Force Survey.
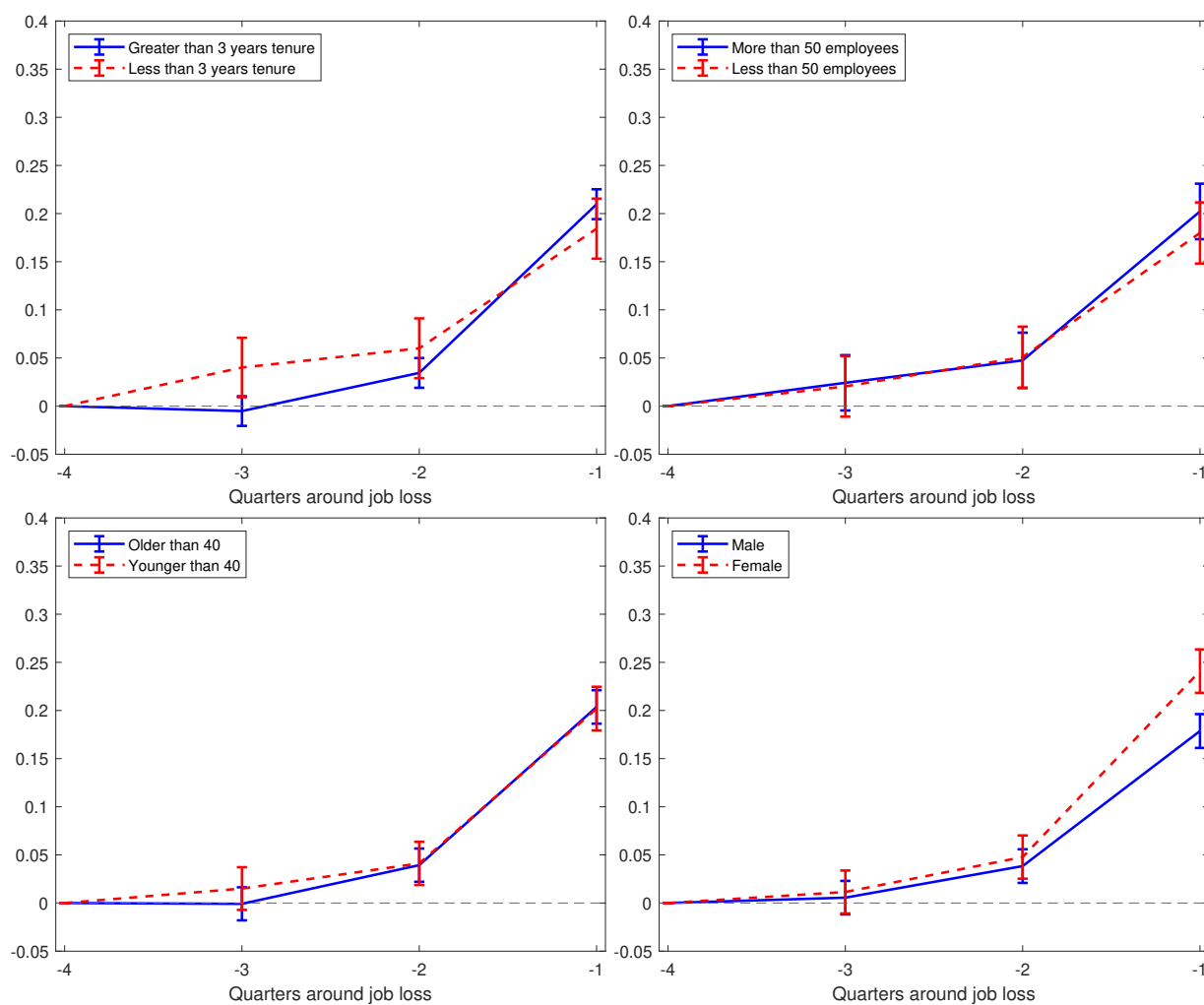
FIGURE 2.4: Pre-layoff search by tenure, firm size, age and sex
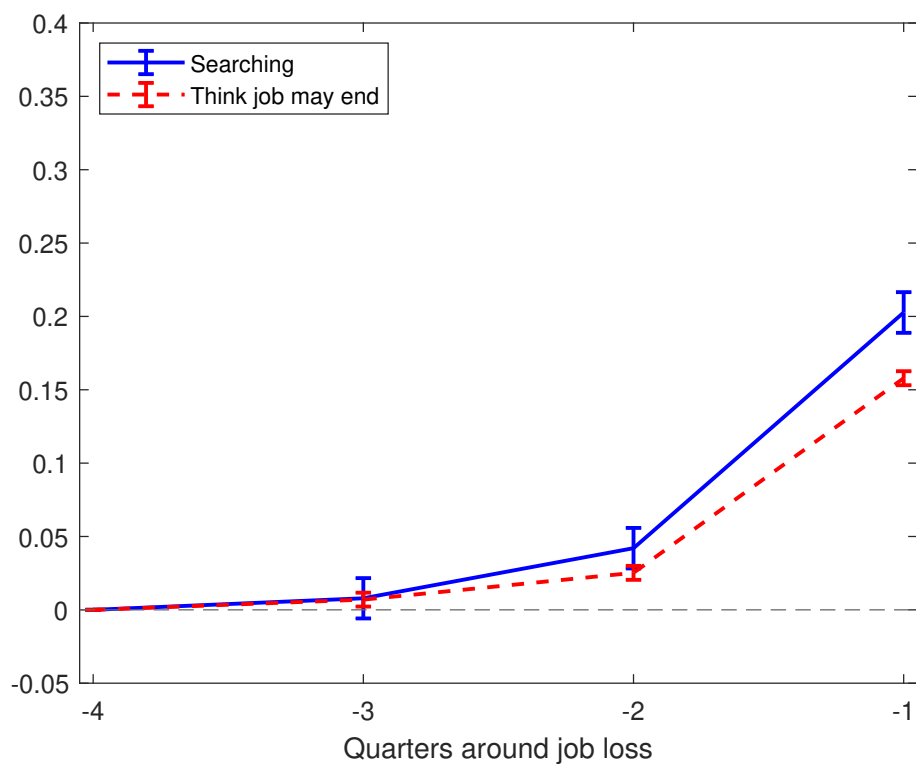
Note: The vertical axis gives the change the proportion of workers who report to be searching on the job relative to the percentage searching 4 quarters before job loss, and the changing proportion of search for workers who do not lose their job. -1 refers to the quarter before job loss.
Source: Data from the UK Labour Force Survey.

the main explanation, those who have differing levels of tenure are likely to have differing gains from search due to factors unrelated to tenure, such as their current level of savings or human capital level. As previously stated, I will not take a stance on why we observe pre-layoff search in the data. Figure 2.4 also shows that the size of the firm, and the age and sex of the individual does not seem to play particularly important role in determining workers search before job loss.

2.2.5 Wage changes

The previous subsections have demonstrated a clear rationale for involuntary job switching - job-to-job transitions following layoff occur because workers catch wind of job loss, and respond by changing search behaviour. One would expect that involuntary job switching is more likely to result in wage cuts because workers are willing to forgo some of their wages for job security. Jolivet et al. (2006) documents that downward wage change for job switchers is a common aspect of many economies across Europe and the US. Here I provide evidence that, indeed, involuntary job switching on average results in wage cuts, whereas voluntary job switching on average results in wage increases.

A subset of participants of the LFS provide wage information during the first and fifth quarters. I analyse workers who provide wage information in both quarters, were employed during the first and fifth quarters, and made exactly one job-to-job transition between the first and fifth quarters or made no transition during the five quarters. I also remove the top and bottom five percent of wages in each period. The regression I run takes the following form

$$\log(w_{it+1}) - \log(w_{it}) = \alpha + \gamma_t + X_{it}\beta + \delta^i JJi_{it} + \delta^v JJv_{it} + \varepsilon_{it}, \tag{2.2}$$

where X_{it} contains controls (sex, age, education and job tenure), JJi is an indicator variable taking a value of one if the worker made a job-to-job transition and described it as involuntary and zero otherwise, and JJv is an indicator variable taking a value of one if the worker made a job-to-job transition and described it as voluntary and zero otherwise. Table 2.2 shows the results.

The results clearly show that, relative to remaining at the same employer, voluntary job switching on average results in wage gains (3.2%) and involuntary job switching results in wage cuts (-10.3%). This result holds true when analysing high and low skill workers separately.

The basic story that underlies the results in this section is simple and intuitive. Using pre-layoff search and job security elicitations, I have provided strong evidence that workers can correctly anticipate job loss, and respond by increasing search to avoid unemployment. This naturally results in involuntary job-to-job transitions. These transitions are more likely to result in wage

	All $\Delta \log(w_{it})$	Low skill $\Delta \log(w_{it})$	High skill $\Delta \log(w_{it})$
δ^i	-.103**	-.096**	-.126**
	(.008)	(.009)	(.003)
δ^v	.032**	.032**	.034**
	(.003)	(.004)	(.006)
N	146,053	102,709	43,344

TABLE 2.2: Wage change following involuntary and voluntary job-to-job transitions

Note: The top left coefficient reads, those making involuntary job-to-job transitions on average experience a 10.3% wage fall relative to those who remain at their employer. Standard errors in parentheses. The top and bottom 5 percent of wages were removed in quarter one and quarter five. All regressions include sex, age, tenure, and time dummies as controls, and the first also includes education. 1995Q1 - 2016Q1.*, ** indicate statistical significance at 5% and 1% levels, respectively.
Source: Data from the UK Labour Force Survey.

falls, plausibly because workers forgo wages for job security. In Section 2.3 I build a model of the labour market that incorporates these features.

2.3 A job ladder model with a job insecurity shock

I embed pre-layoff search into an incomplete markets model with endogenous search, human capital accumulation, risk aversion, and an exogenous distribution of firm productivity. The model is set in partial equilibrium - firms are fictitious. I choose to leave firm behaviour for future work. While this is a simplification, in this work I am interested in the behaviour of workers before and after job loss and the importance of the acquisition of information regarding job insecurity for the worker, and, while this is also very interesting, not about why this transmission of information necessarily occurs.

2.3.1 Environment

Time is at a weekly frequency and workers live forever, discounting the future with a common discount factor β. There are three labour market states: secure employment (S), layoff employment (L), and unemployment (U). I next describe all features of the model split into the following sections: preferences and decision making, wages, human capital, changes in job security, and timing of events and transitions.

Preferences and decision making. Workers are ex-ante homogeneous within two skill groups, and risk averse with preferences given by

$$\psi(c,s) = u(c) - \kappa(s), \tag{2.3}$$

where c is consumption, s is search effort, $u(c)$ is the utility from consumption, and $\kappa(s)$ is the cost of search effort. $u(c)$ and $\kappa(s)$ have the following standard properties $u'(c) > 0$ and $u''(c) < 0$, and $\kappa'(s) > 0$ and $\kappa''(s) > 0$. The individual chooses to invest in a single risk free asset with rate of return equal to r. The consumption of the worker, c, in any period is $c = a(1+r)+i-a'$, where a and a' are current and future asset holdings, and i is the wage or unemployment benefit. The objective of the worker is to pick their search effort s and future asset holdings a' to maximise the expected present discounted value of the match or unemployment.

Wages. All the unemployed receive a flat rate b in line with the UK labour market. The wage of the worker is equal to the product of the productivity of the fictitious firm, $p \in [0,1]$, and the human capital level of the worker, z

$$w(p,z) = pz. \tag{2.4}$$

This implies that the wage only changes throughout the match following changes in human capital. Other more sophisticated and common wage setting protocols with on-the-job search include Nash bargaining as in the Diamond-Mortensen-Pissarides model, see Pissarides (1994), or the sequential auctioning model shown in Postel-Vinay and Robin (2002) and Cahuc et al. (2006), where incumbent and poaching firms bid for workers where the incumbent firm is able to raise the wage of the worker in order to try and retain them, which in turn results in increased wages with job tenure.[18] These protocols require modelling the firm which I abstract from in this work. While the wage function I adopt in this paper is simplistic, Hubmer (2018) shows that a similar model with the same wage function is able to closely replicate new estimates on higher order moments of the wage distribution documented by Guvenen et al. (2015).

Human capital. I model human capital accumulation following Ljungqvist and Sargent (1998). Workers have some initial level of human capital $z \in \{\underline{z},...,\overline{z}\}$. When employed, the workers' human capital increases from z to $min\{z+\Delta z, \overline{z}\}$ with probability ω_E, and when unemployed falls from z to $max\{z-\Delta z, \underline{z}\}$ with probability ω_U. I will clearly explain the associated grid and value

---

[18]Shimer (2006) discusses why the standard Nash bargaining solution is not applicable in the Diamond-Mortensen-Pissarides model with on-the-job search. Gottfries (2021), however, shows that Nash bargaining is applicable when wages can be renegotiated.

Δz in Section 2.5.

Changes in job security. Motivated by the results in Section 2.2, prior to a worker being fired, the worker may catch wind of impending layoff. With probability $\delta(1-\phi)$ a match in secure employment is destroyed and the worker becomes unemployed. With probability $\delta\phi$ the worker receives some information that the job will end. The information provided to the worker is that the job destruction rate has increased to a new level δ_L, where $\delta_L > \delta$. I do not take a stance on why the worker receives this information. This may be due to mandatory advance notice, negotiated contractual advance notice, simply catching wind of job loss, or, perhaps most likely, some combination of the three.

Timing of events and transitions. At the start of the period in each of the states, the human capital level is revealed and the individual decides how much to search and consume. In secure employment, after making these decisions, the worker either: finds and moves to new secure employment with probability $s_S\lambda[1-F(p)]$ (where s_S is the optimal search effort in secure employment), receives a shock and moves to layoff employment with probability $\delta\phi$, receives a shock and moves straight into unemployment with probability $\delta(1-\phi)$, or nothing happens with probability $1-s_S\lambda[1-F(p)]-\delta$. The wage does not change following a transition to layoff employment.

In layoff employment, the worker either: moves into unemployment with probability δ_L, moves into secure employment with probability $s_L\lambda[1-F(p_L)]$ (where s_L is the optimal search effort in layoff employment, and p_L is reservation productivity that I define in the next subsection), or nothing happens with probability $1-s_L\lambda[1-F(p_L)]-\delta_L$. *I define all transitions into unemployment or out of layoff employment as a layoff, whether they are subsequently employed or unemployed.* Those in unemployment either transition to secure employment with probability $s_U\lambda[1-F(p_U)]$ (where s_U is the optimal search effort in unemployment, and p_U is reservation productivity that I define in the next subsection) or remain in unemployment with probability $1-s_U\lambda[1-F(p_U)]$.

2.3.2 Value functions

We can conveniently describe the above environment in recursive form, of which I outline next. Let the present discounted value of unemployment, secure employment and layoff employment be, respectively, given as $V_U(z,a)$, $V_S(p,z,a)$ and $V_L(p,z,a)$. Where again p, z, and a are the productivity of the firm, the worker's general human capital level, and the worker's asset level, respectively. The reservation productivities for workers in unemployment, $p_U(z,a)$, and layoff

employment, $p_L(p,z,a)$, respectively solve

$$V_S(p_U(z,a),z,a) = V_U(z,a) \text{ and } V_S(p_L(p,z,a),z,a) = V_L(p,z,a). \qquad (2.5)$$

Let z' and a' denote the following periods human capital and optimally chosen future asset level. The present discounted value of unemployment, secure employment and layoff employment are, respectively, given as

$$V_U(z,a) = \max_{s_U,a_U'} \left\{ u(a(1+r)+b-a_U') - \kappa(s_U) + \mathbb{E}_{z'|z}\left[\beta\left(V_U(z',a_U')\right.\right.\right.$$
$$\left.\left.\left. + s_U\lambda \int_{p_U(z',a_U')} \left(V_S(x,z',a_U') - V_U(z',a_U'))dF(x)\right)\right]\right\}, \quad (2.6)$$

$$V_S(p,z,a) = \max_{s_S,a_S'} \left\{ u(a(1+r)+w(p,z)-a_S') - \kappa(s_S) + \beta\,\mathbb{E}_{z'|z}\left[V_S(p,z',a_S')\right.\right.$$
$$+ s_S\lambda \int_p \left(V_S(x,z',a_S') - V_S(p,z',a_S'))dF(x) + \delta\left(\phi V_L(p,z',a_S') + (1-\phi)V_u(z',a_S') - V_S(p,z',a_S'))\right]\right\},$$
$$(2.7)$$

and

$$V_L(p,z,a) = \max_{s_L,a_L'} \left\{ u(a(1+r)+w(p,z)-a_L') - \kappa(s_L) + \beta\,\mathbb{E}_{z'|z}\left[V_L(p,z',a_L')\right.\right.$$
$$+ s_L\lambda \int_{p_L(p,z',a_L')} \left(V_S(x,z',a_L') - V_L(p,z',a_L'))dF(x) + \delta_L\left(V_U(z',a_L') - V_L(p,z',a_L'))\right]\right\}. \quad (2.8)$$

The values are equal to the net flow utility, plus the discounted continuation value, plus the discounted net returns from making job switches and, when in employment, the discounted net returns from being forced to layoff employment or unemployment following an exogenous shock. Notice that in secure employment, the final term includes a linear combination of the value of moving to layoff employment and unemployment. This is the key feature in the model that, as I will discuss later, allows the model to replicate pre-layoff search documented in Section 2.2.

Optimal search and asset accumulation. The first order conditions for optimal search gained from equations (2.6), (2.7) and (2.8) equate the marginal benefit from search with the marginal

cost of search for each state - the gains from an increase in search are equal to the increased cost, where the convexity of the cost function ensures that a solution exists. The optimal levels of search in unemployment, secure employment and layoff employment are, respectively, given as

$$s_U(z,a) = \gamma \left(\beta \, \mathbb{E}_{z'|z} \left[\lambda \int_{p_U(z',a')} V_S(x,z',a_U') - V_U(z',a_U') dF(x) \right] \right), \tag{2.9}$$

$$s_S(p,z,a) = \gamma \left(\beta \, \mathbb{E}_{z'|z} \left[\lambda \int_p V_S(x,z',a_S') - V_S(p,z',a_S') dF(x) \right] \right), \tag{2.10}$$

and

$$s_L(p,z,a) = \gamma \left(\beta \, \mathbb{E}_{z'|z} \left[\lambda \int_{p_L(p,z',a')} V_S(x,z',a_L') - V_L(p,z',a_L') dF(x) \right] \right), \tag{2.11}$$

where γ is the inverse function of the marginal cost of search.

Like search effort, a' is chosen by matching marginal costs with marginal benefits. The following Euler equations describe this for unemployment, secure employment and layoff employment

$$u'(c) = (1+r)\beta \, \mathbb{E}_{z'|z} \left[u'(c_U) + s_U(z,a)\lambda \int u'(c_S(x)) - u'(c_U) dF(x) \right], \tag{2.12}$$

$$u'(c) = (1+r)\beta \, \mathbb{E}_{z'|z} \left[u'(c_S)(1-\delta) + \delta \big((1-\phi)u'(c_U) + \phi u'(c_L) \big) \right.$$
$$\left. + s_S(p,z,a)\lambda \int u'(c_S(x)) - u'(c_S) dF(x) \right], \tag{2.13}$$

and

$$u'(c) = (1+r)\beta \, \mathbb{E}_{z'|z} \left[u'(c_L)(1-\delta_L) + \delta_L u'(c_U) + s_L(p,z,a)\lambda \int u'(c_S(x)) - u'(c_L) dF(x) \right]. \tag{2.14}$$

c_U, c_S and c_L represent next period's optimally chosen level of consumption in unemployment, secure employment, and layoff employment, respectively. The decision is intertemporal. The conditions state that the utility foregone in sacrificing a unit of consumption now (LHS), should be equivalent to the expected marginal benefit of additional consumption in the future (RHS). The third terms in (2.13) and (2.14) on the right hand side, describe the marginal gains of a unit increase in assets associated with switching employers. The first and seconds terms in (2.13) and (2.14)

on the right hand side describe the marginal gains of a unit increase in assets associated with not receiving a shock and receiving a shock, respectively. As the precarity of the job increases ($\delta_L > \delta$), a higher weight is placed on the marginal returns of consumption in future unemployment. Next I discuss three fundamental properties of acceptance, search and savings in the economy.

2.3.3 Inspecting the search and savings mechanisms

Motivated by the evidence in Section 2.2, workers are fed with information regarding impending job loss. Here I discuss how the realisation that a workers job insecurity has increased impacts optimal behaviour. Proposition 1 describes the optimal behaviour of the worker in layoff employment relative to an identical worker in secure employment.

Proposition 1 *(i) $p_L(p,z,a) \leq p$, (ii) $s_L(p,z,a) \geq s_S(p,z,a)$ and (iii) without stochastic human capital $a'_L(p,z,a) \geq a'_S(p,z,a)$ in all acceptable matches.*
Proof See Appendix A.3.

Proposition 1 describes three inequalities that are all natural and intuitive. In any worker-firm match, the value of layoff employment to the worker is lower than secure employment because of the increased risk of unemployment. The worker in layoff employment is, therefore, willing to forego wages for job security. And since the returns from searching are larger in the layoff employment state - the worker is not just searching with the possibility of increased wages, but also to regain job security - the optimal intensity of search is weakly greater than search in the secure state. Also, the marginal returns from asset accumulation in unemployment are larger than that for employment. Workers in layoff employment, weight this possibility greater than those in secure employment. The optimal behaviour of the worker is to, therefore, increase assets (weakly) more in layoff employment relative to secure employment, but only when workers are not subject to human capital losses in unemployment.[19]

The level of search and level of assets taken by the worker are decided on jointly. Interesting is the interaction between these two functions. (2.13) and (2.14) reveal an intuitive insight first described by Lise (2013). Notice that the last terms in both (2.13) and (2.14) are negative because of the concavity of the utility function. The implication being, that when the incentive to search is large ($s_S\lambda$ is large), this reduces the incentive to save, alternatively, when the incentive to search is low ($s_S\lambda$ is low), this increases the incentive to save.

---

[19]Because of human capital depreciation in unemployment, the unemployed are willing to accept lower wages than in a model without human capital. The result here is that the marginal utility of consumption is higher in these low wage jobs than unemployment. I find this quantitatively to be second order though.
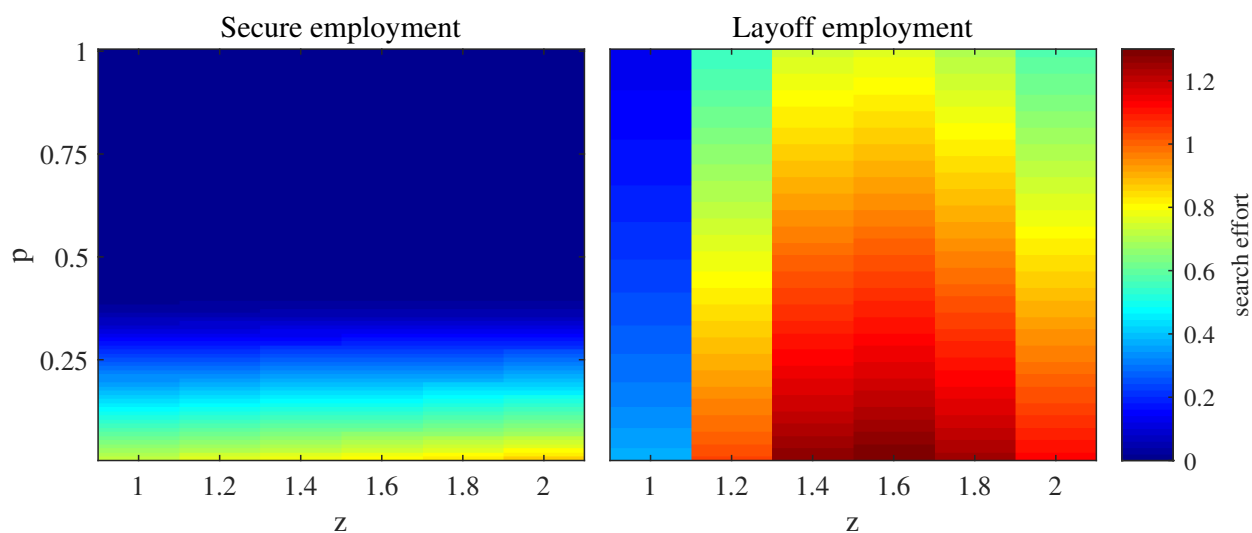
FIGURE 2.5: Optimal search in the secure employment (left) and layoff employment states (right)

Note: search effort is $s(p,z,a=50)$. p is the firm productivity. z is human capital level. The worker has an asset level with approximately two lots of the average annual income, $a=50$. Search effort calculated using the estimated parameters in Section 2.5. Note that search effort is higher for the secure employed at the bottom left. These jobs are not accepted by anyone in the model.
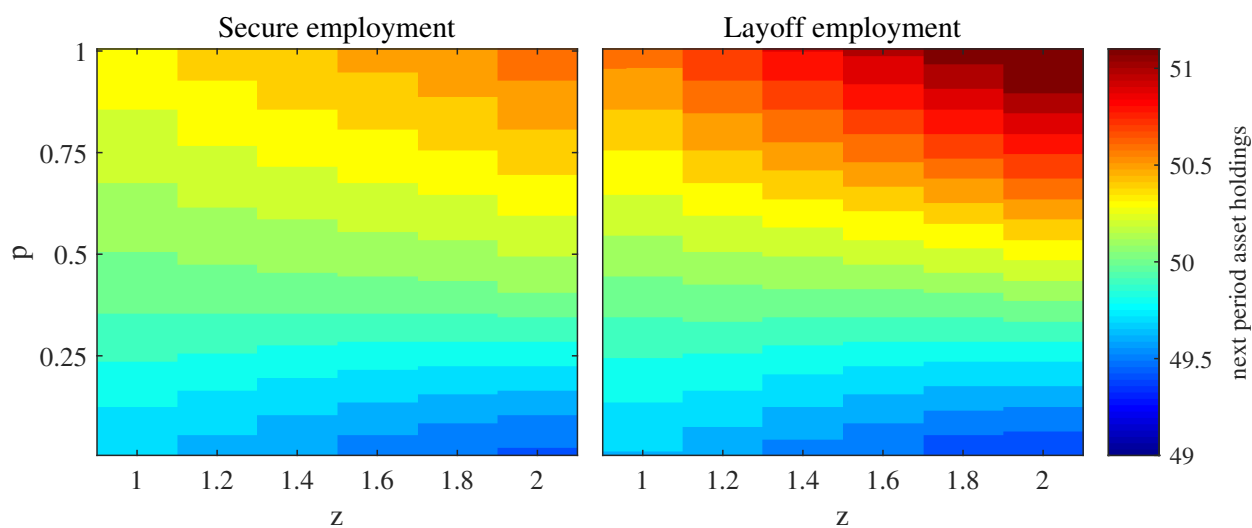
FIGURE 2.6: Optimal asset levels in the secure employment (left) and layoff employment states (right)

Note: next period asset holdings is $a^{'}(p,z,a=50)$. p is the firm productivity. z is human capital level. The worker has an asset level with approximately two lots of the average annual income, $a=50$. Asset levels calculated using the estimated parameters in Section 2.5.

More relevant to this study is the interaction between search and asset accumulation in layoff employment. In the model, workers save because of the possibility of unemployment spells in the future - the motive to save is precautionary. When a worker transitions into layoff employment, search is now also precautionary - search effort can increase job security. When the worker transitions into layoff employment, they choose a combination of these two precautionary mechanisms optimally to mitigate the increased probability of unemployment. Which of these mechanisms is most important will be quantified in Section 2.7.

Figures 2.5 and 2.6 show graphically how workers change their search effort and asset holdings, respectively, when they are in secure employment (left) and when they are in the layoff employment (right). In the Figures, we can see that workers increase search effort and asset accumulation in layoff employment.[20] Following the realisation of increased job insecurity, there are clear changes in the workers behaviour. These changes are optimal intuitive decisions taken by the worker in order to mitigate, as much as possible, the costs associated with job loss.

2.4 Dynamics of pre-layoff search in the model

Before we move on to the estimation of the model, it is important to discuss the dynamics of pre-layoff search through the lens of the model, and assess why a model with a jump in job insecurity is able to replicate the changing search behaviour documented in Section 2.2.

Before I do so, I first outline how I will relate information on search at the extensive margin from the data, to the continuous measure of search in the model. I use the following straight forward procedure to map search in the model to the data. I determine a threshold search intensity where those searching with greater intensity will be deemed as searching, and those below will be deemed as not searching. The threshold will be set such that the proportions who are "searching" and "not-searching" match those seen in Table 2.1. See Appendix A.4 for a graphical explanation of this.

Instead of using this threshold method with continuous search, we could have specified a model with binary on the job search. In a model with binary search, we would estimate a scalar cost of search such that the proportion that are searching in the model is equal to the same proportion in the data. Implicitly a threshold method is used such that those who have the greatest

---

[20]There is a slight difference at lower wages with regards to saving. Workers are willing to accept lower wages than unemployment benefits in the model. The marginal utility of consumption is higher in these low wage jobs than in unemployment. This results in workers reducing savings more when in layoff employment compared to secure employment. The reason for these jobs being accepted by workers is due to the incorporation of differing human capital dynamics in employment and unemployment.

returns from searching begin to search. The model of continuous search with the threshold method I use will result in the same individuals being deemed as searching as those searching in a binary model, ignoring any differences in the population distributions in these two environments. The continuous search approach is attractive as it allows for workers to receive job offers without "reporting to be searching" - a reality in the data. I will assess whether the model is able replicate the proportion of job-to-job transitions that proceed an incidence of search, and, therefore, whether this is an adequate method in Section 2.5.

We can write down pre-layoff search in period $t - j$, given a layoff in period t, relative to the baseline period $t - T$ (where $T > j$) as

$$PLS_{t-j,T} = \underbrace{P(Search_{t-j}|LO_t)}_{\text{proportion searching j periods before layoff}} - \underbrace{P(Search_{t-T}|LO_t)}_{\text{proportion searching in the baseline period}}, \tag{2.15}$$

where LO_t refers to layoff in period t, and throughout I am conditioning on workers not being unemployed, inline with how I estimate pre-layoff search in the data.[21] Pre-layoff search in period $t - j$, is equal to the probability of searching in period $t - j$ conditional on being laid off in period t, relative to the same probability in the baseline period $t - T$. Using the different employment states in the model, coupled with the threshold method described above, $P(Search_{t-j}|LO_t)$ can be written as

$$P(Search_{t-j}|LO_t) = \underbrace{P(Search_{t-j}|LOEmp_{t-j})P(LOEmp_{t-j}|LO_t)}_{\text{proportion of those who are in layoff employment and searching } j \text{ periods before layoff}}$$
$$+ \underbrace{P(Search_{t-j}|SecEmp_{t-j})P(SecEmp_{t-j}|LO_t)}_{\text{proportion of those who are in secure employment and searching } j \text{ periods before layoff}}, \tag{2.16}$$

where $LOEmp_{t-j}$ refers to layoff employment, and $SecEmp_{t-j}$ refers to secure employment, both in period $t - j$. The probability of searching in period $t - j$ given a layoff occurs in period t, is equal to the probability of searching conditional on being in layoff employment in period $t - j$, multiplied by the probability of being in layoff employment given that a layoff will occur in period t, plus the same for secure employment. As said previously, any transition into unemployment or out of layoff employment is described as a layoff.

Next, make the following assumption, $P(LOEmp_{t-T}|LO_t) = 0$. We will soon see that this is true as long as T is sufficiently large - the further back before t we go, the less likely that a worker

---

[21]Here I am ignoring the control group of workers who do not lose their job. This is not an issue in the model as workers are hit with shocks at an exogenous rate, so the control group and treatment group would have behaved the same, if we were not conditioning on the treatment group losing their job at time t.

in layoff employment will survive until period t. Note also that whether a worker is searching in a state is independent of time. Using the fact that $1 - P(LOEmp_{t-j}|LO_t) = P(SecEmp_{t-j}|LO_t)$, we can finally write $PLS_{t-j,T}$ as

$$PLS_{t-j,T} = \underbrace{\left(P(Search|LOEmp) - P(Search|SecEmp)\right)}_{\text{difference in search propensity between layoff employment and the baseline}} \times$$

$$\underbrace{P(LOEmp_{t-j}|LO_t)}_{\text{probability of being in layoff employment before layoff}}. \qquad (2.17)$$

Pre-layoff search in period $t - j$ is equal to the difference in the probability of searching between those in layoff employment in period $t - j$ and those in the baseline period $t - T$, multiplied by the probability of being in layoff employment in period $t - j$ conditional on being laid off in period t. The difference within the brackets, $P(Search|LOEmp) - P(Search|SecEmp)$, is positive (following from Proposition 1) and is independent of j. It should be made clear that this difference is determined by the model and, therefore, dependent on the parameterisations I use. What will drive the dynamics of pre-layoff search is solely due to how $P(LOEmp_{t-j}|LO_t)$ changes with j. I show in Appendix A.3 that there is a neat categorisation for this probability, and is given as

$$P(LOEmp_{t-j}|LO_t) = \phi\left(1 - \delta_L - \bar{s}_L\lambda\overline{F}(\overline{p}_L)\right)^{j-1}, \qquad (2.18)$$

where $\bar{s}_L$ is the average search effort, and $\overline{F}(\overline{p}_L) = 1 - F(\overline{p}_L)$ is the average acceptance probability, both in layoff employment. $P(LOEmp_{t-j}|LO_t)$ is equal to the product of, the proportion moving into layoff employment following the shock with probability δ, ϕ, and the probability of remaining in layoff employment for $j - 1$ periods, $\left(1 - \delta_L - \bar{s}_L\lambda\overline{F}(\overline{p}_L)\right)^{j-1}$. There are some important properties. Firstly, PLS, is dependent on ϕ and δ_L, and the average probability of moving from layoff employment to secure employment. Next, notice that

$$\frac{\partial PLS_{t-j,T}}{\partial j} < 0, \quad \frac{\partial^2 PLS_{t-j,T}}{\partial j^2} > 0 \quad \text{and} \quad \lim_{j\to\infty} PLS_{t-j,T} = 0$$

$$\text{when } \phi > 0 \text{ and } \delta_L > 0 \text{ or } \bar{s}_L\lambda\overline{F}(\overline{p}_L) > 0. \quad (2.19)$$

As we move further away from the layoff event, the proportion of workers who are in layoff employment decreases, and tends towards zero as j tends to infinity. Another way of describing this, as I have previously said, is a worker who is in layoff employment one year prior to the layoff at time t is unlikely to last in layoff employment until time t. This justifies the assumption made previously that $P(LOEmp_{t-T}|LO_t) = 0$ as long as T is sufficiently large.

The categorisation of $P(LOEmp_{t-j}|LO_t)$ allows us to make important identification arguments for ϕ and δ_L, of which I will outline now and further discuss in Section 2.5. First, notice that

$$\frac{PLS_{t-(j-1)}}{PLS_{t-j}} = \frac{P(LOEmp_{t-(j-1)}|LO_t)}{P(LOEmp_{t-j}|LO_t)} = 1 - \delta_L - \bar{s}_L \lambda \overline{F}(\overline{p}_L). \tag{2.20}$$

Given the probability of making an involuntary job-to-job transition each period $(\bar{s}_L \lambda \overline{F}(\overline{p}_L))$, which I measure in the data, the ratio of pre-layoff search at consecutive periods pins down δ_L. There are two important points here: i) the ratio of pre-layoff search at consecutive periods is constant, and any deviation from this in the data will be evidence that the model is not correctly specified; ii) this identification argument relies on information on PLS_{t-j} at different values of j, and that both of these values do not equal zero.[22] Second, notice that

$$P(LOEmp_{t-1}|LO_t) = \phi. \tag{2.21}$$

As we approach a specified layoff event, the probability that a worker is in the layoff employment state increases up to ϕ. The parameter ϕ, therefore, plays an important role in allowing the model to replicate the changing proportion of workers who are searching in the periods that immediately precede job loss.

Putting all these points together, the one off rise in unemployment risk that workers face in the model is able to generate the gradual increase in the incidence of search prior to layoff, where ϕ and δ_L pin down the observed levels and shape of the schedule.

2.5 Estimation

I now proceed to estimate the model by skill level, making the assumption that low and high skill workers partake in different labour markets. Before I do, I make some simplifying parametric assumptions. I assume that firm level heterogeneity, p, follows a beta distribution, $p \sim \beta(\sigma_a, \sigma_b)$. I assume that the returns from consumption, $u(c)$, and the cost of search function, $\kappa(s)$, take the following forms

$$u(c) = \frac{c^{1-\alpha} - 1}{1 - \alpha} \quad \text{and} \quad \kappa(s) = \kappa_0 \frac{s^{1+\frac{1}{\kappa_1}}}{1 + \frac{1}{\kappa_1}}, \tag{2.22}$$

---

[22]Suppose that the measured level of pre-layoff search 2 quarters before job loss was zero. The ratio would, therefore, not pin down δ_L, and would instead only provide a lower bound on the estimate. One requires a panel with a short enough frequency in the data to pin down δ_L, under the model environment.

where α, κ_0, $\kappa_1 > 0$. I model human capital accumulation following Ljungqvist and Sargent (1998). Workers have some initial level of human capital on the following grid $z \in \{\underline{z},...,\overline{z}\}$ that, along with the productivity of the firm, determines the wage that the worker receives. When employed, the workers' human capital increases from z to $min\{z + \Delta z, \overline{z}\}$ with probability ω_E, and when unemployed falls from z to $max\{z - \Delta z, \underline{z}\}$ with probability ω_U. I choose $\underline{z} = 1$, $\overline{z} = 2$, and $\Delta z = 0.2$, resulting in six unique points on the human capital grid. To ensure that a worker's human capital moves up as fast as it moves down, I estimate ω_U and set ω_E such that it solves, $\omega_E(1 - u) = \omega_U u$.

I can now proceed to estimate the model. I predefine $\beta = 1/1.05^{1/48}$ to be equivalent with an annual 5% social discount rate. I let $b = 0.25$, which corresponds to a replacement rate of approximately 0.5 in the estimated model. This is inline with the UK replacement rate estimated by the Organisation for Economic Cooperation and Development (see OECD (2018a)). The job finding probability with intensity equal to 1 is normalised to $\lambda = 0.05$. Finally, I set $\alpha = 1$ which implies logarithmic utility at the limit. This leaves the following vector containing the remaining nine structural parameters to estimate $\theta = \{\kappa_0, \kappa_1, \sigma_a, \sigma_b, \delta, \phi, \delta_L, \omega_U, r\}$. I estimate the model by indirect inference. That is, I numerically solve for the model policy functions, simulate a panel of data and generate moments, $m^s(\theta)$, from the simulated data to fit moments from "true" data described in Section 2.2, m. The indirect inference estimator is given in (2.23). See Appendix A.5 for detailed information regarding the solution and estimation procedure.

$$\hat{\theta} = argmin_\theta \left\{ [m - m^s(\theta)]W[m - m^s(\theta)] \right\}.^{23} \tag{2.23}$$

2.5.1 Moments and identification

The model is highly non-linear and moments from the data are impacted by more than just one parameter. Here I provide arguments for why specific moments provide information for parameters in θ.

Identification of δ_L and ϕ. Two of the key parameters in the model are δ_L and ϕ. Following from the previous section, I identify the reciprocal of the average length of layoff employment, δ_L, and the proportion who move into layoff employment, ϕ, using the levels and shape of pre-layoff search documented in Figure 2.3 - δ_L and ϕ determine the ratio of pre-layoff search between two consecutive periods, and pre-layoff search just before job loss. Figure 2.7 shows this graphically

---

[23]The optimal weighting matrix, W, is equal to the inverse of the covariance matrix of the data moments. In practice I use the identity matrix multiplied by the vector of the reciprocals of the empirical moments. This re-weights smaller moments to be as important as larger moments when minimising the criterion function.

- how does the pre-layoff search schedule change as ϕ (left) and δ_L (right) are increased and decreased? A change in ϕ and δ_L change the shape of the schedule differently.
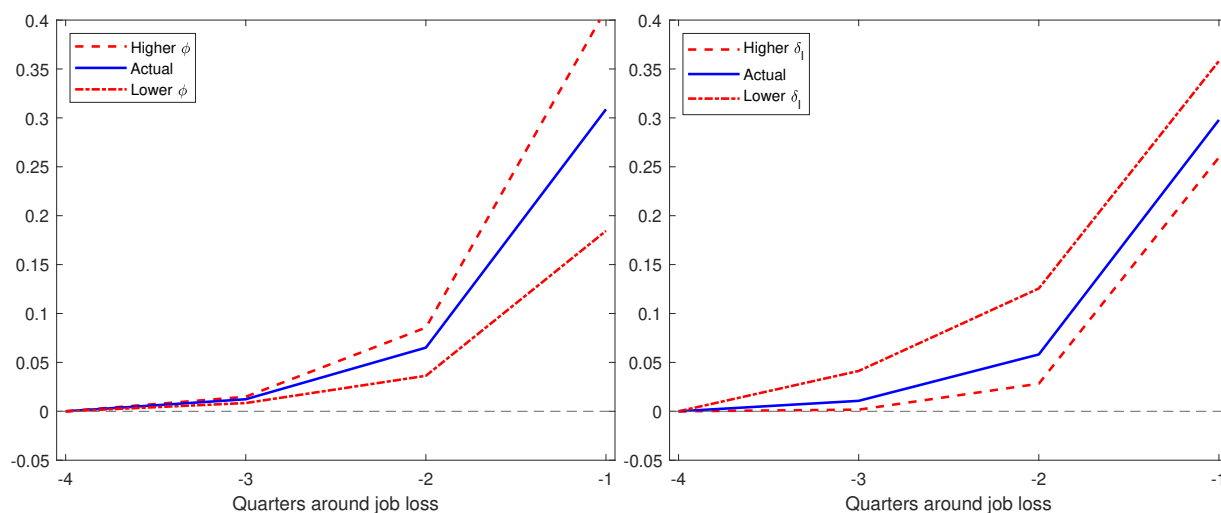
FIGURE 2.7: Identification of ϕ and δ_L

Note: Pre-layoff search for high skill workers. The bold line shows the actual pre-layoff search and the dotted lines show how pre-layoff search changes in response to 20% increase and decrease in the parameters as described by the legend.

As well as fitting the shape and levels of pre-layoff search, I also ask if the model can jointly replicate the proportion of job-to-job transitions that proceed layoff. I define an involuntary job-to-job transition in the model as a job-to-job transition that occurs in layoff employment. This is an important objective of the estimation process to see whether the model can map changes in the behaviour in search before job loss with outcomes after.

Finally, to assess whether the outcomes of workers who are deemed searching in the model match the same outcomes in the data, using the described threshold effort that determines "search" and "no-search", I also ask the model to fit the proportion of all job-to-job transitions that proceed a reported incidence of on-the-job search. This is important as we may be concerned that the method to assign whether a worker is searching in the model, which is used to calculate pre-layoff search in the model, does not translate into overall search and job-to-job transitions as seen in the data.

Identification of the scale parameter of the cost of search, κ_0, and the curvature parameter of the cost of search, κ_1. In Appendix A.3, I show that search effort in secure employment can

be written as

$$s_S(p,z,a) = \left(\beta \, \mathbb{E}_{z'|z} \left[\frac{\lambda}{\kappa_0} \int_p \frac{\frac{\partial u}{\partial c}\frac{dc}{dp} + \frac{\beta\delta\phi\frac{\partial u}{\partial c}\frac{dc}{dp}}{(1-\beta[1-\delta_L-\lambda s_L(x,z',a')\overline{F}(x)])}}{(1-\beta[1-\delta-\lambda s_S(x,z',a')\overline{F}(x)])} \overline{F}(x)dx \right] \right)^{\kappa_1}. \tag{2.24}$$

Search effort in layoff employment and unemployment are categorised in a similar manner to search in secure employment, as seen in (2.24), but where the lower bound of the integral is from $p_L(p,z,a)$ and $p_U(z,a)$, respectively. Holding the other parameters constant, κ_0 is identified by the level of unemployment duration, given as

$$ulength = \left(\int \int \lambda s_U(z,a)\overline{F}(p_U(z,a))g(z,a)dzda \right)^{-1}. \tag{2.25}$$

We can see that unemployment duration is increasing in κ_0.[24] Intuitively, unemployment duration pins down κ_0 since, an increase (reduction) in κ_0 increases (reduces) the cost of search for each intensity and so increases (reduces) unemployment duration.

The curvature of the cost of search, κ_1, is a key parameter in the model. As we can see from (2.24), κ_1 largely determines the curvature of search function along the productivity distribution. Notice that search effort in secure employment is also a function of search in layoff employment. I inform the parameter of the curvature of the cost of search with information on the voluntary job-to-job and involuntary job-to-job transition rates conditional on wages, as they tell us about how search effort changes in response to a change in productivity,

$$\frac{\partial \lambda s_S(p,z,a)\overline{F}(p)}{\partial p} \quad \text{and} \quad \frac{\partial \lambda s_L(p,z,a)\overline{F}(p_L(p,z,a))}{\partial p}.^{25} \tag{2.26}$$

The job-to-job transition probabilities for a worker in state (p,z,a) is equal to the product of the job contact rate, $s(p,z,a)\lambda$, and the job acceptance rate, $\overline{F}$. I estimate the following models using the BHPS

$$JJv_{it} = \alpha_i^v + \gamma_t^v + X_{it}\beta + \tau^v w_{it} + \varepsilon_{it}^v \quad \text{and} \quad JJi_{it} = \alpha_i^v + \gamma_t^j + X_{it}\beta + \tau^i w_{it} + \varepsilon_{it}^i. \tag{2.27}$$

JJv_{it} and JJi_{it} represent indicator variables, taking the value of 1 if the worker switches jobs and describes the switch as voluntary and involuntary and 0 if they remain at their employer,

---

[24]To see this more clearly, we can write $ulength = \frac{\kappa_0^{\kappa_1}}{\lambda^{1+\kappa_1}} \left(\int \int \lambda \tilde{s}_U(z,a)\overline{F}(p_U(z,a))g(z,a)dzda \right)^{-1}$, where $\tilde{s}_U(z,a)\left(\frac{\lambda}{\kappa_0}\right)^{\kappa_1} = s_U(z,a)$. Given a value for λ and κ_1, $ulength$ pins down κ_0.

[25]Lise (2013) uses a very similar method to identify the curvature of the cost of search.

for individual i at time t. Only transitions that are reported to be direct to a new employer are counted as from job-to-job. w_{it} is the log of the wage for individual i at time t. τ^v and τ^i provide information on how search effort changes along the wage distribution, and so is used to pin down κ_1.[26] The point estimates for the high skill workers are $\hat{\tau}^v = -.055$ and $\hat{\tau}^i = .002$. There is a much stronger response for voluntary transitions than for involuntary transitions. The model is able to replicate this difference because a worker's search effort is less responsive to productivity when they are in layoff employment compared to secure employment as seen in Figure 2.5.

Identification of the human capital depreciation parameter, ω_U. I inform the human capital depreciation parameter, which in turn determines the human capital appreciation parameter, with information regarding the relationship between workers' hiring wage and the preceding unemployment spell length. Following Jarosch (2021) and Burdett et al. (2020), I estimate the following model on data from the BHPS by skill level

$$w_{it} = \gamma_t^{dur} + X_{it}\beta + \tau^{dur}udur_{it} + \beta_{\overline{w}}\overline{w}_i + \varepsilon_{it}^{dur}. \tag{2.28}$$

The model contains time fixed effects and the logarithm of the workers average wage to address issues surrounding selection - those who experience longer unemployment durations may also have lower wages on average. $udur$ is the length of the unemployment spell that preceded the job with logarithmic hiring wage, w_{it}. Through the context of the model, τ^{dur} is directly related to the speed of skill loss in unemployment, and so used to pin down ω_U.

Identification of the risk free interest rate, r. Given a fixed value for β, r is pinned down by the wealth to annual income ratio, which I estimate using data from the BHPS. In the data, an individual's wealth is determined by their liquid and illiquid assets. This includes their savings, investments and home value, minus outstanding debt including the mortgage. This is inline with wealth measures used in Low et al. (2010), and I use the same procedure to estimate wealth from the BHPS as in Crossley and O'Dea (2010).

Remaining parameters. Since ϕ and δ_L are separately identified, δ is identified with the level of employment tenure. Finally I inform the distribution parameters, σ_a and σ_b, with the variance and skewness of the wage distribution estimated from the BHPS, where I strip out individual, time and age effects.[27]

---

[26]Ideally, I would also use information on how job-to-job transitions change along the asset distribution since $\frac{\partial s(p,z,a)}{\partial a} \neq 0$. Quantitatively, I find that the response of search along the productivity distribution is far stronger compared to along the asset distribution. I currently do not incorporate information on assets.

[27]The variance and skewness are functions of the two parameters, $var(x) = \frac{\sigma_a \sigma_b}{(\sigma_a+\sigma_b)^2(\sigma_a+\sigma_b+1)}$, $skew(x) = \frac{2(\sigma_b-\sigma_a)\sqrt{\sigma_a+\sigma_b+1}}{(\sigma_a+\sigma_b+2)\sqrt{\sigma_a\sigma_b}}$. Without on the job search, the variance and skewness of the offer distribution would be the same

2.5.2 Model fit

Tables 2.3 and 2.4 show the moments and estimated parameters for the model. In general the model fits the data well.

Firstly, the model importantly does a good job at hitting pre-layoff search documented in the data (see Figure 2.8), whilst simultaneously matching the reality of involuntary job switching. This suggests that the changes in behaviour before job loss as measured by pre-layoff search reflect well the actual changes in search behaviour before job loss. The change in search prior to layoff identify ϕ and δ_L. The results reveal that 62% of high skilled workers receive a warning to job loss, compared with just 42% for low skilled workers. When workers are provided with a warning, the average amount of time that a worker has to increase search and increase saving prior to losing their job, $\frac{1}{\delta_L}$, is on average slightly longer for the high skilled workers relative to the low skilled, but both approximately equal to three months. If a worker is lucky enough to be warned about an upcoming layoff as opposed to being dismissed right away, the amount of time they have to change their behaviour is large, and can help the worker prepare for and mitigate the costs of job loss.

Moving to the spell length moments, the spell length of unemployment is longer for the low skill workers. This should correspond to a higher scale parameter for the cost of search for the low skilled. The cost of search lower for the low skilled. Why is the model able to generate differences in the length of the average unemployment spell between skill groups? The reason is because of the difference in the expected offer from the productivity distribution - high skilled workers will receive more productive job offers on average than low skill workers. The incentives to search are, therefore, lower for low skilled workers and so results in longer unemployment spells. Employment tenure is longer for high skilled workers relative to low skilled workers. Initially one may think that this is all reflected in higher job security for high skill workers. The ratio of employment tenure between skills in the model is approximately 1.35. To fit the difference between employment tenures, without pre-layoff search, the ratio of δ would also be 1.35. However, the ratio is approximately 1.25. The reason for this is that high skill workers are more likely to make an involuntary job-to-job transitions as opposed to a transition into unemployment than low skill workers, because of the magnitude and length of pre-layoff search. The differences in pre-layoff search between high skill workers can, therefore, partially explain differences in employment outflows between skill levels.

---

as the sampling distribution. Wage change information for job-to-job transitions, and experience, provides further information for how job-to-job transitions impact the underlying offer distribution.

	Low skill		High skill	
	Data	Model	Data	Model
Transition moments				
u length (*months*)	7.466	7.779	5.950	6.749
job tenure (*years*)	7.283	6.921	7.049	7.688
e tenure (*years*)	11.95	11.13	15.41	15.00
inv JJ/JJ	.2528	.2597	.1964	.2205
ojs JJ/JJ	.3015	.4362	.3154	.4296
Wage moments				
τ^v	-.0466	-.0492	-.0548	-.0581
τ^i	.0001	.0018	.0018	.0044
τ^{udur}	-.0031	-.0051	-.0051	-.0084
$\Delta \log(w)^{JJ}$	.0670	.2130	.0782	.1512
$\Delta \log(w)^{JJi}$	-.0460	-.0663	-.0425	-.1129
$\Delta \log(w)$	.0141	.0158	.0198	.0131
$var(\log(w))$	.0563	.0785	.0706	.0729
$skew(\log(w))$	.1618	-.0785	-.0455	-.2047
wealth/anninc	1.644	1.415	1.826	1.581
Pre-layoff search				
δ^{-1}	.1693	.1766	.3155	.3191
δ^{-2}	.0295	.0304	.0854	.0857
δ^{-3}	.0032	.0037	.0243	.0213

TABLE 2.3: Model fit

Note: Transition moments and pre-layoff search moments are estimated from the LFS. Wage moments are estimated from the BHPS where I strip out age effects, individual fixed effects and time fixed effects. Wealth includes an individual's savings, investments and home value, minus outstanding debt including the mortgage.
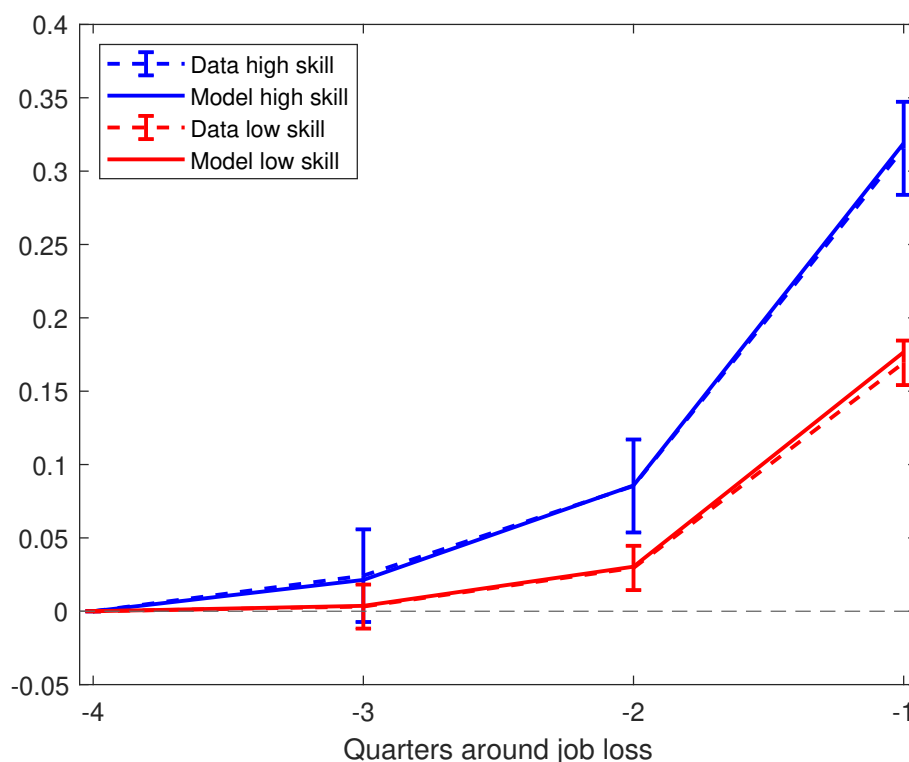
FIGURE 2.8: Pre-layoff search: data vs model

The model does a good job at fitting τ^v and τ^i, which are measures for how prevalent voluntary and involuntary job-to-job transition are along the wage distribution. The related parameter κ_1 - the curvature of the cost of search - is 4.0595 and 2.7048 for the low and high skill workers, respectively. A typical value found in the literature is between 1.5 and 3, and so the estimated levels of the curvature of the cost of search are not unreasonable.[28]

The log wage distribution is more negatively skewed for high skill workers which is relatively well fit by the distribution parameters, where the growth in wages following a job-to-job transition is currently overstated in the model. With regards to human capital depreciation, the rate at which workers lose human capital in unemployment is 0.0212 and 0.0272 for low and high skilled workers, respectively. This means that it takes on average about a year and three-quarter of a year for a low and high skilled worker, respectively, to fall down one rung in the human capital distribution. Finally, turning to wealth, in the data, workers have between 1.5 and 2 times their annual income in wealth on average (this includes household wealth). Where the ratio is slightly larger for high relative to low skill workers. The model is able to replicate this magnitude and difference in magnitude in wealth, and is reflected in a slightly higher estimated real interest rate for the high skilled.

---

[28]Lise (2013), Bagger and Lentz (2019), Liu (2019) and Faberman et al. (2020).

Parameters	Description	Low skill Values	High skill Values
	Predefined parameters		
α	relative risk aversion	1	1
β	discount factor	$1/1.05^{1/48}$	$1/1.05^{1/48}$
λ	job offer arrival rate per unit of search	0.05	0.05
b	unemployment benefits	0.25	0.25
	Estimated parameters		
δ	shock rate	.00212 (.0000)	.00169 (.0000)
κ_0	scale parameter	4.2447 (.0794)	4.7622 (.0263)
κ_1	curvature parameter	4.0595 (.1285)	2.7048 (.2680)
σ_a	productivity distribution	8.2978 (.1252)	7.8850 (.3274)
σ_b	productivity distribution	19.4773 (.2501)	13.7122 (.4474)
δ_L	search period length	.0882 (.0013)	.0772 (.0023)
ϕ	percent warned	.4209 (.0069)	.6248 (.0190)
r	interest rate	.00106 (.0004)	.00109 (.0006)
ω_U	human capital depreciation	.0212 (.0000)	.0272 (.0000)
ω_E	human capital appreciation	.0011	.0009

TABLE 2.4: Estimated parameters

Note: Asymptotic standard errors in parentheses. Time period is one week. $\alpha = 1$ implies log utility at the limit. For the low skill $\frac{1}{\delta_L} \approx 11.33$ weeks, and for the high skill $\frac{1}{\delta_L} \approx 12.95$ weeks.

2.5.3 Consumption changes in the model and data

As well as increasing search, workers may also increase their savings to mitigate unemployment spells. Is this change in behaviour economically important? There is mixed evidence regarding changes in consumption before job loss. Benito (2006) finds evidence that consumption is related to job insecurity in the UK. Stephens Jr (2004) and Hendren (2017) both find that workers have private information regarding their own job insecurity in the US, yet find conflicting evidence on whether this results in reduced consumption before job loss.

I assess how consumption changes before job loss in the UK using the available consumption information in the BHPS. Individuals are asked how much they spent on food inside and outside of the home in the last week. This is a common consumption measure used in other studies, see Gruber (1997) for a prominent example. Using this information, I estimate average consumption changes in the year before and after job loss, and the average change over an employment spell. Table 2.5 shows the results. We find that the model overstates the consumption declines after job loss. The changes in consumption before, however, are small in the data and model. Despite workers realising their job insecurity has increased, their change in consumption is very small. This suggests that the dominant force that workers use to mitigate the costs of job loss is to increase their search effort.

	Over employment spell	Year before job loss	Year after job loss
	Low skill		
Model	1.4%	1.3%	-12.5%
Data	3.0%	1.3%	-6.9%
	High skill		
Model	1.1%	.7%	-16.7%
Data	2.0%	4.7%	-5.7%

TABLE 2.5: Consumption changes in the model and data

2.6 The cost of job loss

I now move to testing a key aspect of the model - can the model fit the large losses associated with job loss, and is it able to replicate the earnings losses for those workers who lose their job but do not experience unemployment? This is an important piece of the data to replicate if one aims to conduct appropriate welfare analysis (Jarosch (2021) and Cozzi and Fella (2016)), and in particular, put a value on the pre-layoff information workers receive.

I study the consequences of job loss in the data using the BHPS in line with Upward and Wright (2017). As already described, the BHPS follows individuals from 1991 to 2009, and ask detailed information regarding their employment, including the reason for separation. For period $t \in \{1992,...,2008\}$ I assign a job loss if workers separated from their job into unemployment or described the transition, perhaps to another job, as involuntary.[29] As the control group, I pick workers who remain at their employer in the same period. To conform to the literature, the treatment and control groups both must have at least 3 years of consecutive tenure at the firm they are in at time t and must be between 25 and 55 years of age. The tenure restriction, joint with fixed effects, addresses issues of selection on unobservables into the control group.

For both the separators and the control group, I drop observations after $t + 10$ and before $t - 5$. This leaves me with a specific cohort of separators and controls at time t. I replicate this for all $t \in \{1992,...,2008\}$ leaving me with 17 cohorts. I then stack the cohorts together which gives me my sample dataset. It is possible that workers are in a treatment cohort and several control cohorts.

Using this dataset I run the standard distributed lag model found in the literature, see Jacobson et al. (1993). It takes the following form

$$y_{it} = a_i + \gamma_t + X_{it}\beta + \sum_{k=-4}^{10} \delta_k D_{it}^k + u_{it}, \tag{2.29}$$

where y_{it} is the earnings for individual i at time t, a_i and γ_t are person and time fixed effects, respectively, and X_{it} is a set of controls (a quartic in age). Like in (2.1), D_{it}^k are dummy variables taking the value of one if the individual will separate from their job in k periods, and zero otherwise. δ_k, therefore, gives the earnings change relative to 5 years before job loss and of that of the control group.

---

[29]See appendix A.2 for how I categorise separations as involuntary.

To compare the model earnings losses with the data, I turn the weekly simulated dataset into an annual dataset by taking the earnings of the worker during the final week of the year. I stack cohorts in the exact same way in the simulated data as I do in the empirical data, and perform the same regression. Figure 2.9 shows how the model earnings losses compare to those estimated from the BHPS, where I compare all layoff events and only those who transition directly to a new job. In general, the model does a relatively good job at fitting the earnings decline from job loss, on average, and also for only those who manage to switch employers.
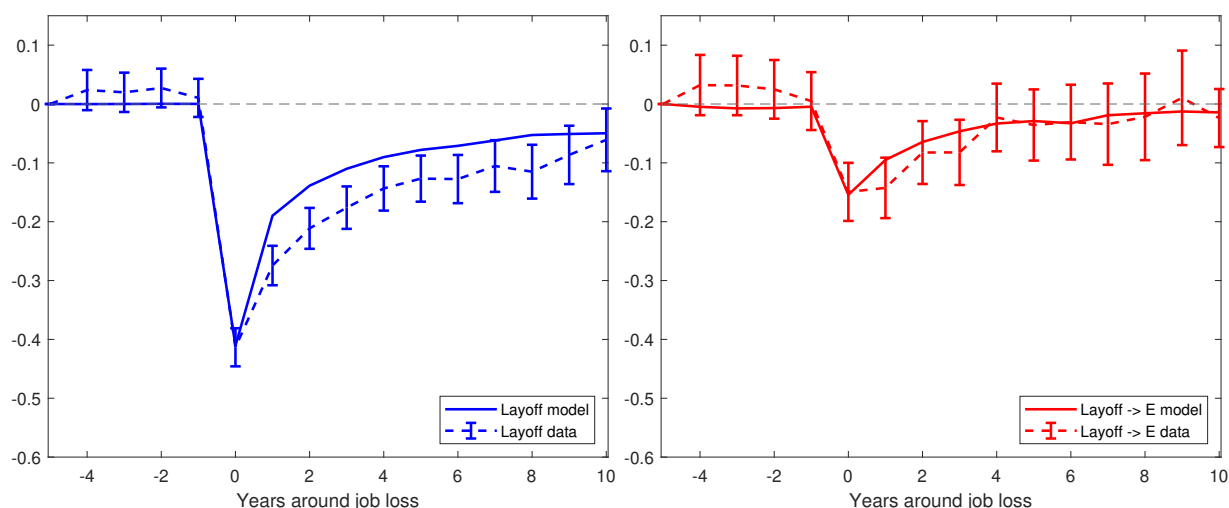
FIGURE 2.9: Earnings losses: data vs model

Davis and Von Wachter (2011) show that many of the off the shelf job search models find difficulty in reproducing these earnings losses. Following from this, a significant amount of recent work has been dedicated to augmenting job search models in order to explain the short and long-run losses. Krolikowski (2017) and Jarosch (2021) aid the job ladder model by, in different ways, incorporating slippery bottom rungs. This results in separations more likely preceding further separations, therefore, increasing the cost of the initial job loss. Jung and Kuhn (2018) argue that the loss of a particularly good job at the top of the wage distribution is the main explanation for the large losses. Burdett et al. (2020) build a model with a job ladder and skill loss in unemployment (Jarosch (2021) also incorporates skill loss in unemployment). They are able to replicate the cost of job loss, arguing that, human capital loss is the main long run cost of job loss. The present model follows this theme with skill loss in unemployment.

One may worry that comparing workers who manage to find new employment and those who do not may be invalid because of selection. Those who immediately find new employment following the layoff may be systematically different to those who do not. While this is likely to be true, the mechanisms in the model that result in persistent costs of job loss on average, are

able to also replicate the differences in the losses for each destination. In other words, while systematic differences likely exist, the economic forces in the model alone are able to fit the differing schedules.

2.6.1 Decomposing the differences in the losses

The previous subsection showed that the model can replicate the costs of job loss for those transitioning to unemployment and employment. We can decompose these costs of job loss in to the model contributing factors. First, the job ladder effect (JL), the worker loses the high productive firm and must spend time climbing the job ladder. Second, the employment effect (Emp), the worker loses out on earnings due to experiencing unemployment. Finally, the human capital effect (HC), the worker loses out on foregone human capital increases in employment, and experiences falls in human capital in unemployment. To fix ideas, I begin by writing down the $COJL$ as a function of these contributions at time t, where t represents the number of years after job loss.

$$COJL_t^x = C_{JLt}^x + C_{Empt}^x + C_{HCt}^x \quad \text{where} \quad x \in \{lo, eu, jji\}. \tag{2.30}$$

lo, eu and jji represent overall job loss, job loss into unemployment, and job loss to another job, respectively. I estimate the three components numerically by switching off the underlying factors one by one. First, I estimate the employment effect by only considering those who are in employment. Second, I estimate the job ladder effect by estimating the change in the productivity of the firm for those who find employment. Finally, the human capital effect is the residual.

Figure 2.10 shows the costs of overall job loss (lo) decomposed into the constituent components over the 10 years post job loss for low (left) and high (right) skill workers. There are a three main points. First, for both the high and low skilled, the employment effect quickly dissipates. Second, the job ladder effect is stronger for the high skilled, which is reflected in the higher efficiency of search effort. Finally, the costs ten years post job loss, are almost completely due to losses in foregone human capital. This picture is qualitatively similar to that shown in Burdett et al. (2020).

We can also decompose the differences in the cost of job loss between destinations. For example, the contribution of job the ladder to the difference in earnings losses for those transitioning into unemployment relative to those who avoid unemployment is given as

$$C_{JLt}^{eu} - C_{JLt}^{jji}. \tag{2.31}$$

Figure 2.11 shows the contributions to the differences in the costs of the losses. We can see the job ladder effect contributes very little to the differences in losses. In the short run, the
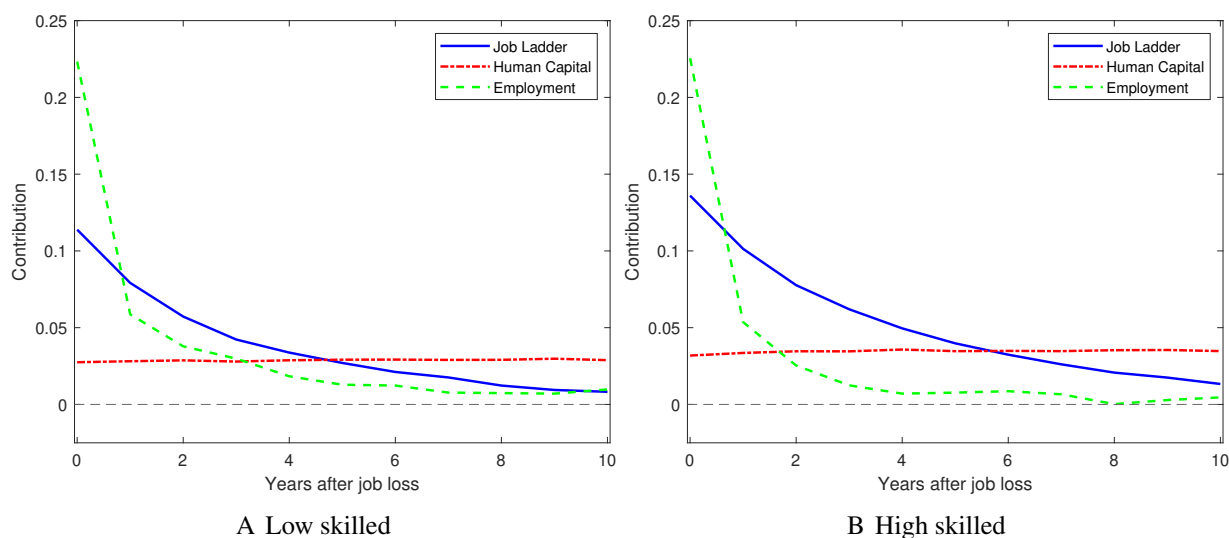
FIGURE 2.10: The decomposed costs of job loss

Note: Here, I include all those who lose their job, $COJL_t^{lo}$. The contributions are estimated using the following method. First, I estimate the employment effect by switching off any period of unemployment. Second, I estimate the job ladder effect by estimating the change in productivity for all those who are employed. Finally, the human capital effect is the residual. One can switch the second and third step in this procedure, but the results are quantitatively similar.

differences in employment rates and human capital dynamics, explains the differences in earnings losses. In the long run, the differences in earnings losses are all due to foregone human capital accumulation for those who experienced unemployment. The main benefits for a worker to search and find new employment before becoming unemployed are to avoid the possibility of skill loss in unemployment.

It is important to briefly discuss why the job ladder is not important in explaining the differences in the losses between the destinations in the model. When workers enter layoff employment from secure employment, they reduce their reservation productivity, as seen in Proposition 1. The size of this change determines the contribution of the job ladder to the differences between the destinations. If workers reduce their reservation productivity only slightly, the average accepted job out of layoff employment will be more productive than those accepted out of unemployment. If workers reduce their reservation productivity significantly, the average accepted job out of layoff employment will be closer to those accepted out of unemployment. The fact that job ladder effect is negligible, shows that workers in the layoff employment state behave almost as though they are unemployed. Notice that an implication of this is that, a simple way of incorporating these types of transitions into a model to understand wage dynamics, that is consistent with this picture, is to invoke reallocation or "godfather" shocks, as is traditionally done in the literature.

A Low skilled

B High skilled
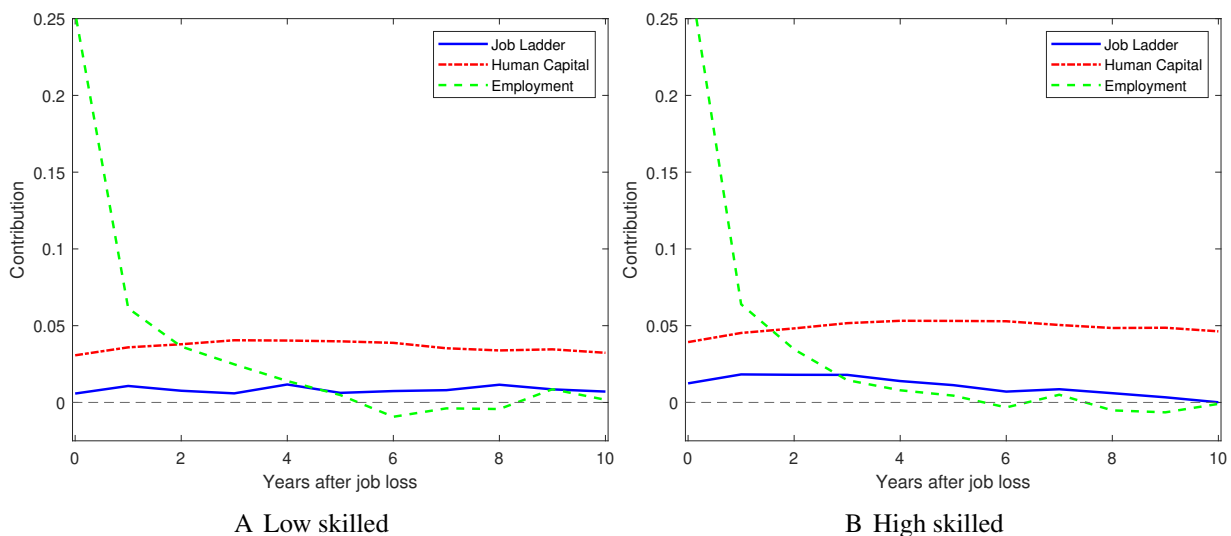
FIGURE 2.11: The decomposed difference in the costs of job loss for those transitioning into unemployment relative to those managing to switch jobs

Note: Here I compare between those who transition to new employment relative to unemployment, $COJL_t^{eu} - COJL_t^{jji}$. The contributions are estimated using the following method. First, I estimate the employment effect by switching off any period of unemployment. Second, I estimate the job ladder effect by estimating the change in productivity for all those who are employed. Finally, the human capital effect is the residual. One can switch the second and third step in this procedure, but the results are quantitatively similar.

2.7 Implications of anticipating job loss for the aggregate economy: putting a value on advanced knowledge

I now ask how do welfare and other labour market aggregates change when workers are unable to anticipate job loss?

2.7.1 Labour market quantities and welfare

To understand how the ability to anticipate job loss impacts welfare, I force employed individuals, who are in the layoff employment state, to search and consume as though they are in secure employment, and compare overall welfare to workers in the baseline model. Welfare in the economy is the expected present discounted value of utility net of search costs. The welfare measure, ψ, that I use follows Krusell et al. (2010). It solves

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t\left(\log(c_t(1+\psi)) - \kappa(s_t)\right)\right] = \mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t\left(\log(\tilde{c}_t) - \kappa(\tilde{s}_t)\right)\right], \qquad (2.32)$$

where $\tilde{c}$ and $\tilde{s}$ are consumption and search in the economy without job loss anticipation. ψ describes how much consumption would have to change in order for individuals in the economy with job loss anticipation to be as happy as those without job loss anticipation. This is traditionally described as consumption equivalent variation (*CEV*).[30]

Table 2.6 shows the impacts on welfare and other labour market aggregates for the economy as a whole and split by high and low skill workers. Column one shows ψ for all workers and split by education group. If workers are unable to anticipate job loss, *CEV* is -1.60% for all workers, -1.89% for high skill workers, and -1.31% for low skill workers.

As described in the model in Section 2.3, workers have two mechanisms that they can use to mitigate the costs of job loss when job insecurity has increased. The worker can either increase their search effort, or increase savings. Which of these endogenous responses is most important for worker welfare? In column two, I report the proportion of consumption losses from not being able to anticipate job loss into those attributable to the increased search channel. The gains from increased search far outweigh those from the increased savings channel. For the low skill, the ability to smooth consumption prior to job loss provides virtually no benefits, and the benefits are slightly larger but still very small for the high skill. Through the context of the model, changes in savings behaviour following an increase in job insecurity is second order in importance with regards to welfare, with the most important behavioural change that the worker makes being to increase search.

To put these welfare measures into a different context, in column three I report how much unemployment benefits would have to increase if workers cannot anticipate job loss, at no cost to the workers, for welfare to be equivalent to the world with job loss anticipation. For the low skill, unemployment benefits would have to increase from 0.25 to 0.37, or 48%, and from 0.25 to 0.4, or 60%, for the high skilled. If the government were to increase unemployment benefits by this much, it would cost at least £600 million.[31]

The final five columns show the impact on unemployment, employment tenure, and the wage distribution. Endogenous decisions taken by the workers to find new employment in response to the increased unemployment risk has significant impacts on the aggregate unemployment rate, and the length of an employment spell. Overall the unemployment rate is reduced by 16%, and an

---

[30]It is straight forward to show that

$$\psi = exp\left[\left(1-\beta\right)\left(\mathbb{E}_0\left(\sum_{t=0}^{\infty}\beta^t\left(\log(\tilde{c}_t)-\kappa(\tilde{s})\right)\right)-\mathbb{E}_0\left(\sum_{t=0}^{\infty}\beta^t\left(\log(c_t)-\kappa(s)\right)\right)\right)\right]-1.$$

[31]See Statista (2018) for information on spending on unemployment benefits in the UK in 2020.

employment spell is increased by 2.2 years. The impact is unsurprisingly stronger for high skill workers (19% reduction in unemployment and 3.0 year increase in the length of an employment spell) relative to low skill workers (13% reduction in unemployment and a 1.5 year increase in the length of an employment spell).

	Welfare				Aggregates			
	$\psi\%$ (*CEV*)	*b*	% due to *PLS*	*u*	*eten*	$\overline{w}$	*var*	*skew*
All								
Anticipation	0	.25		4.67	13.07	.536	.0781	-.1831
No Anticipation	-1.60	.39	97.9	5.52	10.83	.529	.0790	-.1612
Low skill								
Anticipation	0	.25		5.63	11.13	.486	.0785	-.0732
No anticipation	-1.31	.37	98.7	6.45	9.66	.482	.0793	-.0511
High skill								
Anticipation	0	.25		3.71	15.00	.585	.0729	-.2047
No anticipation	-1.89	.40	96.8	4.58	12.00	.576	.0743	-.1818

TABLE 2.6: The impact of anticipating job loss

Note: ψ is calculated using (2.32), and describes how much consumption would have to change in order for workers in the baseline model with anticipation to have the same present discounted utility as those without job loss anticipation. *PLS* refers to pre-layoff search. *b* does not represent the unemployment replacement rate. The replacement rate at a value of $b = 0.25$ is approximately 0.5. Column (1) shows how much lifetime consumption would have to change for workers who can anticipate job loss to be as happy as workers who cannot anticipate job loss. Column (2) asks what he unemployment benefit level would have to be in order for workers in an economy without job loss anticipation to be as happy as those with job loss anticipation. Column (3) shows the percentage of welfare gains that are due to pre-layoff search. Columns (4)-(8) describe the changes in the relevant variables.

Switching off job loss anticipation has interesting effects on the wage distribution. Workers in layoff employment have greater reservation wages than workers in unemployment, implying that the average accepted wage for a worker in layoff employment is greater than for a worker in unemployment. Switching off anticipatory behaviour implies more workers experience unemployment, which in turn reduces the mean accepted wage out of these two states, which reduces wages. On the other hand, those in layoff employment are willing to accept wage falls, and, if workers in

unemployment do not find jobs, switching off anticipatory behaviour can reduce the average wage. Overall, I find that the average wage falls, the wage skewness falls and variance of wages increase, when workers cannot anticipate job loss.[32]

2.8 Lessons for policy

I use the model to study the implications of job loss anticipation for two policies: advance notice and unemployment benefits. It should be made clear that the model is in partial equilibrium, and so any conclusions should be made with this in mind. The importance of incorporating firm entry into a model to study optimal unemployment benefits, for example, was shown in Krusell et al. (2010) - higher unemployment benefits raise the reservation wage of workers, forcing firms to increase wages, disincentivising vacancy creation.

2.8.1 Notice

As has been shown in the previous sections, the main long run benefit of switching employers without a spell of unemployment following job loss, is to avoid human capital depreciation. It is natural, therefore, to ask, what are the implications for welfare if workers were given more time to find a new job whilst still employed.

Here I ask the following question. Are workers willing to pay the wages of those workers who would have otherwise become unemployed for a certain number of weeks. I formulate this experiment by allowing the government to move money from those in employment, to the employed who have received a job destruction shock, and would otherwise be unemployed. I model this in a straight forward way. Those who are in secure employment now move into notice employment with probability $(1 - \phi)\delta$, as opposed to unemployment. Those who are in layoff employment, now move into notice employment with probability δ_L, as opposed to unemployment. The only way a worker can enter unemployment is following the culmination of notice. I show the changes to the value functions from introducing notice into the economy in Appendix A.3.

Of importance is the job destruction rate in notice, δ_N. This tells us the average length of notice schemes currently in place in the economy, $\frac{1}{\delta_N}$. The government can increase and reduce

---

[32]The fact that incorporating involuntary job-to-job transitions into a job ladder model reduces the variance of wages is inline with work by Tjaden and Wellschmeid (2014). They show that incorporating exogenous job-to-job transitions where the reservation wage is unemployment, the godfather shock, results in reducing the contribution of frictional wage dispersion to the variance of wages.

the average length financed by taxing labour income. The government budget constraint is

$$e_N(1-\tau)\int\int w(p,z)g_N(p,z)dpdz = (1-u-e_N)\tau\int\int w(p,z)g(p,z)dpdz, \qquad (2.33)$$

where e_N is the proportion of the population in notice, τ is the tax rate, $g_N(p,z)$ is the proportion of workers in a firm with productivity p and human capital z where the worker is on notice, and $g(p,z)$ is the proportion of workers in a firm not on notice with productivity p and human capital z. Instead of worrying about transitional dynamics, I focus on comparing steady states.

I plot ψ relative to no changes in the notice length, and compare three scenarios. First the baseline economy where workers are able to change their behaviour prior to notice and prior to job loss. Second, where workers cannot anticipate job loss prior to notice but are able to change their search behaviour in notice. Finally, where workers do not change search effort when transitioning into layoff employment or notice employment. In all these experiments, workers human capital in notice employment evolves as though they are employed. Figure 2.12 plots the schedules.

When workers can can choose their search effort on notice, extending the length up to approximately four months provides welfare gains to workers, with the benefits plateauing after. Interestingly, when workers are unable to change their search effort during notice, extending the length of the scheme only damages workers. Providing workers with longer time to search prior to job loss is only beneficial when workers choose search endogenously. Figure A.16 explains why. The Figure shows the notice employment rate e_N, and the tax rate that is required to finance the scheme under the assumption that the government balances the budget constraint. If workers do not use the notice period to increase search, the employment rate in notice and, therefore, the tax rate increases very quickly. The costs of financing such a scheme then increase very quickly, which creates a gulf in the schedules as the length of the scheme approaches a year, as is seen in Figure 2.12.

This experiment is clearly stylised, and there would plausibly be a host of obstacles that would impede such a policy. The main aim here is not to highlight the best policy to implement in the economy, but instead to highlight the gains from advance knowledge to workers. Workers are more than willing to reduce wages in order to be provided with more information of impending job loss. This is because it allows workers a better chance at mitigating the costs of job loss, which are mostly due to losses in human capital.
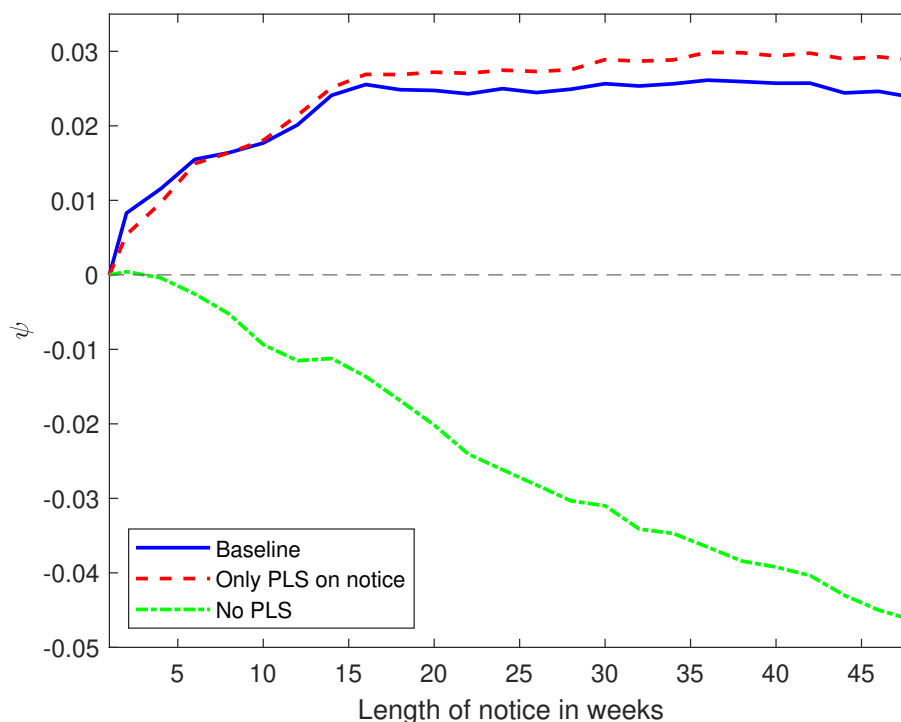
FIGURE 2.12: The value of knowledge of job loss and the importance of endogenous search

Note: ψ is calculated using (2.32). The horizontal axis shows $\frac{1}{\delta_N}$.

2.8.2 Unemployment benefits

Finally, I study the implications for unemployment benefits, where I revert back to the baseline model without advance notice. Again, the government wants to maximise welfare. To do so they are able to move money from one agent in employment to another agent in unemployment through unemployment benefits. Again, the government must balance their budget when doing so given as the following

$$ub = (1-u)\tau \int \int w(p,z)g(p,z)dpdz. \qquad (2.34)$$

Again, instead of worrying about transitional dynamics, I focus on comparing steady states.

Figure 2.13 presents how the welfare gains associated with anticipatory behaviour are impacted by the level of unemployment benefits in the economy. As unemployment benefits increase, anticipating job loss becomes less valuable to the worker but this impact is only slight. This is intuitive; when unemployment becomes better (worse), the gains from avoiding it decrease (increase).
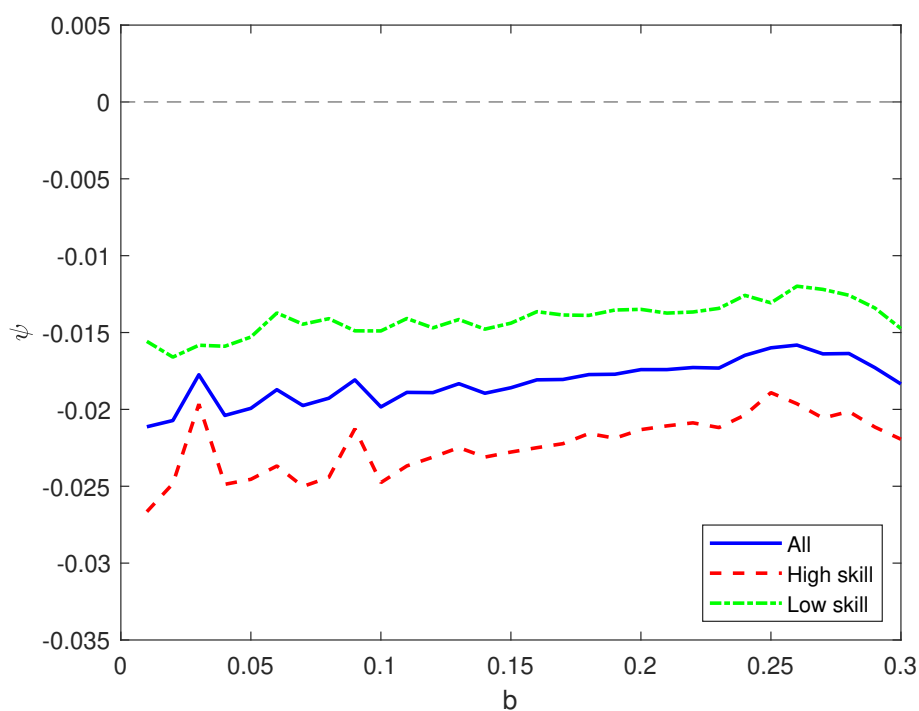
FIGURE 2.13: The welfare losses from not anticipating job loss at different unemployment benefits.

Note: ψ is calculated using (2.32). b does not represent the unemployment replacement rate. The replacement rate at a value of $b = 0.25$ is approximately 0.5.

2.9 Conclusion

Understanding the entirety of the impacts to workers when they lose their jobs is undoubtedly an important task. Despite the immense literature studying workers actions and outcomes post job loss, comparatively little work has studied how workers react and change their behaviour before job loss. This paper takes an in depth look at how workers change their search behaviour before job loss in the UK labour market.

I show that search incidence increases significantly during the quarter before job loss for low and high skill workers, respectively, but that the increase is stronger for high skill workers. This information provides clear evidence that workers are able to correctly anticipate job loss. Motivated by this empirical finding, I build a job search model in which workers receive information of increased job insecurity before job loss, and identify key parameters that govern the changes in average workers information set regarding their own job security. The model estimates reveal that around two-fifths and three-fifths of low and high skill workers know of impending job loss, on average three months before becoming unemployed. Using the estimated model, I show that the ability to anticipate job loss provides large welfare benefits for workers, with the most important behavioural change being to increase search.

I use the model to study the implications for the costs of job loss. There has been a significant effort to augment search models in order to replicate the earnings declines following job loss. I show that the proposed model in this paper is able to replicate the average costs of job loss, but also the differences in earnings losses for those workers who manage to immediately switch jobs following layoff, and those who take the plunge into unemployment. I decompose the differences in earnings losses and show that the main benefits of switching employers following job loss is to avoid skill loss in unemployment.

There are important implications of these results for the coronavirus crisis in 2020. Many countries have adopted furlough schemes in order to mitigate the individual costs to workers. As the furlough schemes unwind, however, there is real concern over the possibility of a large number of workers experiencing job loss. Workers have clear knowledge regarding the end of the furlough scheme, and, therefore, possible unemployment. As shown in this paper, workers do not sit idly by, waiting to fall off the edge into the abyss. They take action, most importantly by increasing their search for new employment prior to job loss, and so reducing the number of workers who experience a period of unemployment. Future work that seeks to appropriately appraise these schemes should take the changing search for new employment into account, which seems like a promising route for future work.

Chapter 3

Job-to-job transitions, job finding and the ins of unemployment

3.1 Introduction

Why does the unemployment rate rise during recessions? A large body of literature has decomposed unemployment variations into components attributed to the inflows into and outflows from unemployment. The main conclusions being that the ins and outs of unemployment are both important to varying degrees.[1] Analysing the ins and outs of unemployment is, however, not necessarily informative with regards to the contribution of layoffs and job finding. In particular, there are two main channels by which employment to unemployment transitions rise: first, an increase in layoffs; and second, a fall in job finding of potential job-to-job transitions.[2] This presents an issue when attempting to understand the importance of layoffs and job finding using an inflow outflow analysis - attributing the contribution of the ins of unemployment to layoffs may be inaccurate. In this paper, I estimate which of these two channels is most important in driving changes in employment to unemployment transitions, and the unemployment rate, over the business cycle.

Previous work that has addressed this issue has studied the problem in steady-state, assumed a two-state economy and, most importantly, has not split separations into layoffs and quits.[3] As is well known, layoffs and quits behave very differently over the business cycle, and so grouping these fundamentally different reasons for separation together will mask important features of

---

[1]The influential work of Shimer (2012) and Hall (2005) conclude that outflows are far more important than inflows. This result was contrary to conventional wisdom (Darby et al. (1985), Darby et al. (1986) and Davis and Haltiwanger (1992)) and was challenged by Fujita and Ramey (2009) and Elsby et al. (2009) who conclude that the role of inflows was understated by Shimer and Hall.

[2]This point was originally made by Perry (1972b) and reemphasized by Hall (2005), Bachmann (2005) and Nagypal (2008). Perry (1972b) discussing the inflows: *It consists of persons about to enter the labour force, and of workers about to leave one job to look for another, either at their own initiative (quitting) or at their employer's (layoff or firing). These additional job seekers can be conceived of as holding lottery tickets just as the unemployed do. These tickets define the probability that, when they make the transition into the labour force or out of their present jobs, their numbers come up and they have new jobs. If their numbers do not come up, they become this week's newly unemployed.*

[3]See Bachmann (2005) and Nagypal (2008).

recessions.[4] Using data from the US and UK over a period of two decades, I find that fluctuations in job finding of potential job-to-job transitions are at least as important as layoffs, in explaining the contribution of fluctuations in employment to unemployment transitions to the dynamics of unemployment. I show that these results are not driven by changes in observable characteristics over the business cycle, and robust to an adjustment for time aggregation.

In order to estimate which of these two forces is most important in driving changes in the ins of unemployment over the business cycle, I begin by decomposing the ins of unemployment into distinct components, following Nagypal (2008). In particular, the employment to unemployment transition is decomposed into a job separation component - whether a worker separates from their job - and a job finding component - whether the worker has a job lined up following the separation. Using information on the reason for separation, I split separations into layoffs and quits to assess their dynamics separately. In line with the literature, I find that layoffs rise and quits fall in recessions. This increase in layoffs gives rise to increased employment to unemployment transitions. As well as the increase in layoffs, workers who separate from their jobs, whether it be due to a quit or a layoff, are less likely to have a job lined up in recessions. This in turn results in greater increases in employment to unemployment transitions in recessions.

I build the decomposition of the ins of unemployment into a three state framework of worker flows, and assess the contribution of changes in the flow probabilities to the dynamics of unemployment out of steady state.[5] I find that, inline with recent literature, employment to unemployment transitions are important in both the UK and US, contributing to around a third of unemployment dynamics. I find, however, that fluctuations in job finding of potential job-to-job transitions are at least as important as fluctuations in layoffs, at explaining this contribution. An interesting feature of business cycles is also the role of procyclical quits, which play a moderating role in recessions as fewer workers voluntarily leave their jobs.

The main reason for these results is the prevalence of quits into unemployment, and layoffs directly to another job. When some workers quit their jobs, they don't always move to new employment, and many workers manage to line up jobs to transition straight into following the layoff. Chapter 2 shows that workers increase search prior to layoff in the UK, with the predominant rationale being that workers "think their job may end". This suggests that workers are able to foresee job loss approaching. When job finding falls in recessions, less of this precautionary job search will be matched with an employer, increasing employment to unemployment transitions.

---

[4]See Slichter (1919), Akerlof et al. (1988), Anderson and Meyer (1994) and Davis et al. (2012), who show that layoffs are countercyclical and quits are procyclical

[5]I do this using a non-steady state variance decomposition as in Elsby et al. (2015).

In this paper, I show that, in the UK, workers also significantly increase search incidence prior to a quit to new employment, but also a quit to unemployment. And that the rationale for this increased search is solely due to worker dissatisfaction with their current job, for both voluntary job-to-job and employment to unemployment transitions. When recessions hit, less job search is matched with new employment, increasing the probability that a worker will take the plunge into unemployment.

This observation that search incidence increases before workers separate from their jobs for any reason and remain in the labour force, suggests that employment to unemployment and job-to-job transitions are inherently interrelated through the ability to find jobs. Some employment to unemployment transitions would have instead resulted in a switch to a new job if the worker was lucky enough to line up a new job prior to the dissolution of the match.

The remainder of this paper proceeds as follows. Section 3.2 discusses the conceptual framework, and outlines the decomposition of the ins of unemployment. Section 3.3 discusses the data and presents important time series. Section 3.4 shows how it is possible to assess the fluctuations of the decomposed ins of unemployment in a three-state system, presents the results and spells out the results from the heterogeneity analysis. Section 3.5 provides further discussion and evidence for the relationship between employment to unemployment and job to job transitions using on the job search. Section 3.6 concludes.

3.2 Conceptual framework

Workers leave their jobs for many different reasons, but these reasons can be broadly narrowed down to two distinct categories: because of layoff, or because of a quit. The first reason, a layoff or involuntary separation, is naturally thought of as synonymous with an employment to unemployment transition. However, many workers in the US and UK are fired from their jobs but also move directly to new employment without an intervening spell of unemployment. This suggests that workers are able to foresee that job loss is approaching, and respond by changing their search behaviour to avoid unemployment. Chapter 2 shows clear evidence of this in the UK, and that incorporating this into a job ladder model can replicate the level of involuntary job switching in the labour market. It follows that, when job finding falls in a recession, those who have information of impending job loss are less likely to have a suitable replacement job lined up, which in turn increases the likelihood that a layoff will result in unemployment.

The second reason, a quit or voluntary separation, is often described as synonymous with a job-to-job transition. However, many workers in the US and UK quit their jobs and move into unemployment to continue the search for another job. Workers who quit their jobs to move to unemployment, know that they are about to leave and so likely start searching for new jobs before the job has ended. When job finding falls in a recession, those who are about to quit their job are less likely to have a replacement job lined up, which in turn increases the likelihood that a quit will result in unemployment. The reality of both involuntary job switching and voluntary employment to unemployment transitions suggests that the fall in job finding during a recession contributes to the increase in employment to unemployment transitions.

The above story suggests that the level of employment to unemployment transitions in an economy is, in part, impacted by the job finding rate. We can see this by decomposing the employment to unemployment transition probability using the accounting identity following Nagypal (2008),

$$p^{eu} = p_t^{sep} p_t^{lf|sep} (1 - p_t^{jj|lf\&sep}).[6] \tag{3.1}$$

The employment to unemployment transition probability is split into three components, (i) the probability of separating from ones job (ii) the probability of remaining in the labour force upon separation, and (iii) the probability of not having a replacement job lined up. I will refer to component (iii) as the job finding component.[7] Under this setting changes in the job finding rate can result in changes in the job finding component, and changes in the employment to unemployment probability.

Is this the correct way to think about transitions from a job to unemployment? The common feature of the story in this section is on the job search. Increased on the job search precedes separations into unemployment and to a new job, be it due to a quit or layoff. When job finding falls, it is less likely that search is matched with a firm, and so the worker is more likely to experience unemployment. Chapter 2 shows a significant increase in the incidence of search prior to layoff, where the main rationale for this search is that the worker "thinks their job may end". In Section 3.5, I present evidence that, not only does increased on the job search occur prior to voluntary separations into unemployment and a new job, but the magnitude and the rationale for the increased search are very similar.

---

[6]The components of equation (3.1) are calculated by: $p_t^{sep} = \frac{Sep_t}{E_{t-1}}$, $p_t^{lf|sep} = \frac{LFSep_t}{Sep_t}$ and $p_t^{jj|lfsep} = \frac{JJLFSep_t}{LFSep_t}$. Sep_t constitutes the stock of all those who separate from their employer between $t-1$ and t. $LFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t and are in the labour force at t. $JJLFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t and are in employment at t.

[7]See a flow diagram of the decomposition in Appendix B.4.

3.3 Empirical evidence on labour market flows

In this section I will present the main evidence regarding the relationship between the ins of unemployment and the job finding rate. Before I do so, I will briefly describe the data, and paint the basic picture of worker flows in the US and UK.

3.3.1 Data

Current Population Survey

The Current Population Survey (CPS) is household-based survey used for US government labour force statistics. Entrants are surveyed consecutively for four months, dropped for eight months, and then surveyed again for a further four months. The longitudinal nature of the CPS allows for estimation of monthly labour force flows. I use the period between 1978m1 and 2016m12. I use the available weights provided by the US Census Bureau to bring the estimates to a population level.[8]

While flows between the three labour market states can be estimated from the CPS going as far back as 1978, job-to-job transitions cannot. However, in 1994 the CPS underwent a redesign. A particular new question asked survey participants whether they were still working for the same employer they had last month. This allows for the estimation of monthly job-to-job transitions.

While the CPS is a comprehensive survey, it does not provide users with the reason that survey participants switched employers. I use the next data set to overcome this issue.

The Survey of Income and Program Participation

The Survey of Income and Program Participation (SIPP) is a longitudinal survey of US households. The survey is split into panels. Each panel features a nationally representative sample interviewed over a multi-year period lasting approximately four years. I analyse the 1996, 2001, 2003 and the most recently completed panel in 2008. During the first month of a panel, a quarter of the entire sample, described as a rotation group, give detailed information regarding their exploits in the last four months. This is the beginning of the first wave. A month later the second rotation group give detailed information regarding their exploits in the last four months. This then continues for a further two rotation groups. In the fifth month, the second wave begins and rotation group one

---

[8]Further details of the weights can be found by looking at the corresponding guides that accompany the CPS, SIPP and LFS.

is interviewed again, and so on. The rolling nature of the survey allows for the calculation of monthly labour market transitions in the US, which I again weight using the longitudinal calendar year weights provided by the US Census Bureau.

During each interview, individuals give information on as many as two jobs and as many as two businesses they have held during the preceding four months. Each job or business is given a unique identifier that remains the same for the entire panel. Attached to each job or business is information on when the individual started working for the employer or started the business, and, if the relationship ended during the preceding four months, information on when the individual ended working for the employer or ended the business. Using this information it is possible to construct monthly job-to-job transitions using the SIPP.[9]

The SIPP provides the reason for separation from a workers previous employer. I categorise the reason for separating, r, in the following way.

Involuntary (I) - On layoff, discharged/fired, employer bankrupt, employer sold business, job was temporary and ended.

$$
\textbf{Voluntary (V)} \begin{cases} \textbf{Quit (Q)} \text{ - Quit to take another job, slack work or business} \\ \text{conditions, unsatisfactory work conditions.} \\ \textbf{Personal (P)} \text{ - Retirement or old age, childcare problems,} \\ \text{other family/personal obligations, own illness, own injury,} \\ \text{school/training.} \\ \textbf{Other (O)} \text{ - Left work for some other reason.} \end{cases}
$$

The UK Labour Force Survey

Like the CPS for the US, the LFS is a household-based survey that is used as the backbone for UK government labour force statistics. While the survey was originally used for cross-sectional analysis, in 1992 the survey introduced a longitudinal component.[10] Following this reform, survey

---

[9]This information is based on recalling past labour market spells. Perry (1972a) shows that recall over short periods like those used here are unlikely to significantly impact the flows.

[10]A longitudinal component, at a lower frequency, implicitly exists preceding this period by the use of retrospective data, see Elsby et al. (2016). The retrospective technique used in that paper cannot be used to estimate each separation type by reason or the job-to-job probability.

participants are sampled for five consecutive quarters. This reform allows for the estimation of quarterly labour market flows. I use the period between 1996q1 and 2016q4.[11]

I follow Gomes (2012) and assign job-to-job transitions using a tenure approach. A job-to-job transition occurs when an individual is employed at time $t-1$ and, since the survey is quarterly, has less than three months tenure at time t.

Like the SIPP, the LFS provides the reason why the worker has separated from their previous employer for both currently employed and non-employed workers. I categorise the reasons for separating, r, in the following way.

Involuntary (I) - Dismissed, made redundant, temporary job finished.

Voluntary (V)
$$\begin{cases}\text{\textbf{Quit (Q)}} \text{ - Resigned, took voluntary redundancy.} \\ \text{\textbf{Personal (P)}} \text{ - Took early retirement, retired, gave up work} \\ \text{for health reasons, gave up work for family or personal reasons.} \\ \text{\textbf{Other (O)}} \text{ - Left work for some other reason.}\end{cases}$$

The LFS also provides rich information regarding on the job search. Workers are asked whether they are searching for another job, the number of methods used, and the reason for searching. I categorise the reason for search as follows

Uncertain - Present job may come to an end, and present job is to fill time before you find another.
Unsatisfactory - Pay unsatisfactory in present job, journey unsatisfactory in present job, wants longer hours than in present job, wants shorter hours than in present job and other aspects of present job unsatisfactory.
Other - Other reasons.

See Appendix B.3 for further details of each of the data sets. See Appendix B.1 for a discussion and adjustments for time aggregation, margin error and seasonality. The main results, and figures in this section, are adjusted for margin error and seasonality. I provide additional results where I also adjust for time aggregation.

---

[11]I begin in 1996q1 because this is the period where the reason for separation was introduced, which takes center stage in my analysis.

3.3.2 Worker flows in the UK and US

It is instructive to first describe the dynamics of worker flows in the US and UK. The probability of transitioning from state i at time $t-1$ to state j at time t is given as

$$p_t^{ij} = \frac{IJ_t}{I_{t-1}}, \tag{3.2}$$

where IJ_t represents the stock moving from state i to state j between $t-1$ and t, and I_{t-1} represents the stock in state i at $t-1$. Appendix B.6 shows the US and UK worker flows.

As is well documented, the job-to-job and unemployment to employment transition rates are procyclical, and the employment to unemployment rate is countercyclical.[12] As well as this, transitions into the labour force exhibit clear cyclicality. Recessions come with rises and falls in transitions from inactivity into unemployment and employment, respectively.

3.3.3 Decomposing the ins of unemployment

We begin with the basic decomposition from Nagypal (2008), as in (3.1)

$$p_t^{eu} = p_t^{sep} p_t^{lf|sep} (1 - p_t^{jj|lfsep}). \tag{3.3}$$

Component (i) is the *Separation* probability. Component (ii) is the *LF|Sep* probability. Component (iii) is the *JJ|LFSep* probability. As well as transitions from employment to unemployment, inactivity to unemployment transitions can be decomposed in a similar manner. Workers who move into the labour force during recessions are more likely to find themselves unemployed because of the drop in the job finding rate. In the same vein, the inactivity to unemployment probability can be decomposed as follows

$$p_t^{nu} = p_t^{entry} (1 - p_t^{e|entry}). \tag{3.4}$$

Component (a), the *Entry* probability, represents the probability of entering the labour force. Component (b), the *E|Entry* probability, represents the probability of moving into employment

---

[12]See Fallick and Fleischman (2004) and Shimer (2005b) for job-to-job transitions in the US and Gomes (2012) for job-to-job transitions in the UK.

conditional on entering the labour force.[13] See Section B.4 for a flow diagram of the overall decomposed ins of unemployment.
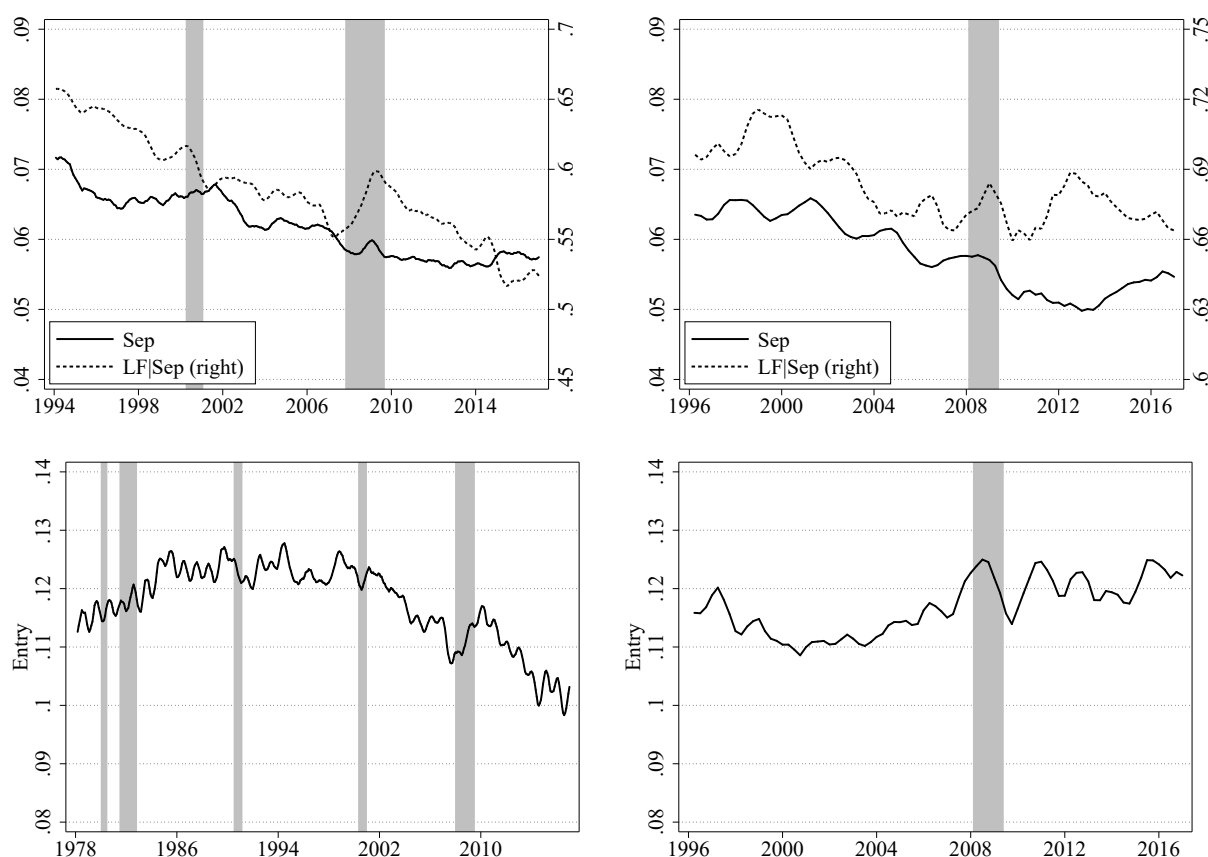
FIGURE 3.1: The job separation and labour force entry probabilities in the US (left) and UK (right).

Note: Probabilities adjusted for margin error and seasonality. Shaded areas denote officially defined US and UK recessions. Source: Author calculations using the CPS and Two Quarter LFS. Ages 16-64/59. US 1994m1-2016m12 (left) and 1978m1-2016m12 (right), UK 1996q1-2016q4, respectively.

Figure 3.1 shows the separation, (i) and (ii), and entry, (a), components of the ins of unemployment in the US and UK. As can be seen, these probabilities vary little over the cycle. While employment to unemployment and inactivity to unemployment transitions are countercyclical, the overall rates at which workers separate from their employer or enter the labour force are comparatively acyclical.

Figure 3.2 shows the job finding, $JJ|LFSep$ and $E|Entry$, components of the ins of unemployment in the US and UK, accompanied with the respective unemployment to employment transition

---

[13]The components of equation (3.4) are calculated by: $p_t^{entry} = \frac{Entry_t}{N_{t-1}}$ and $p_t^{e|entry} = \frac{EEntry_t}{Entry_t}$. $Entry_t$ constitutes the stock of all those who enter the labour force between $t-1$ and t. $EEntry_t$ constitutes the stock of all those who enter the labour force between $t-1$ and t and are in employment at t.
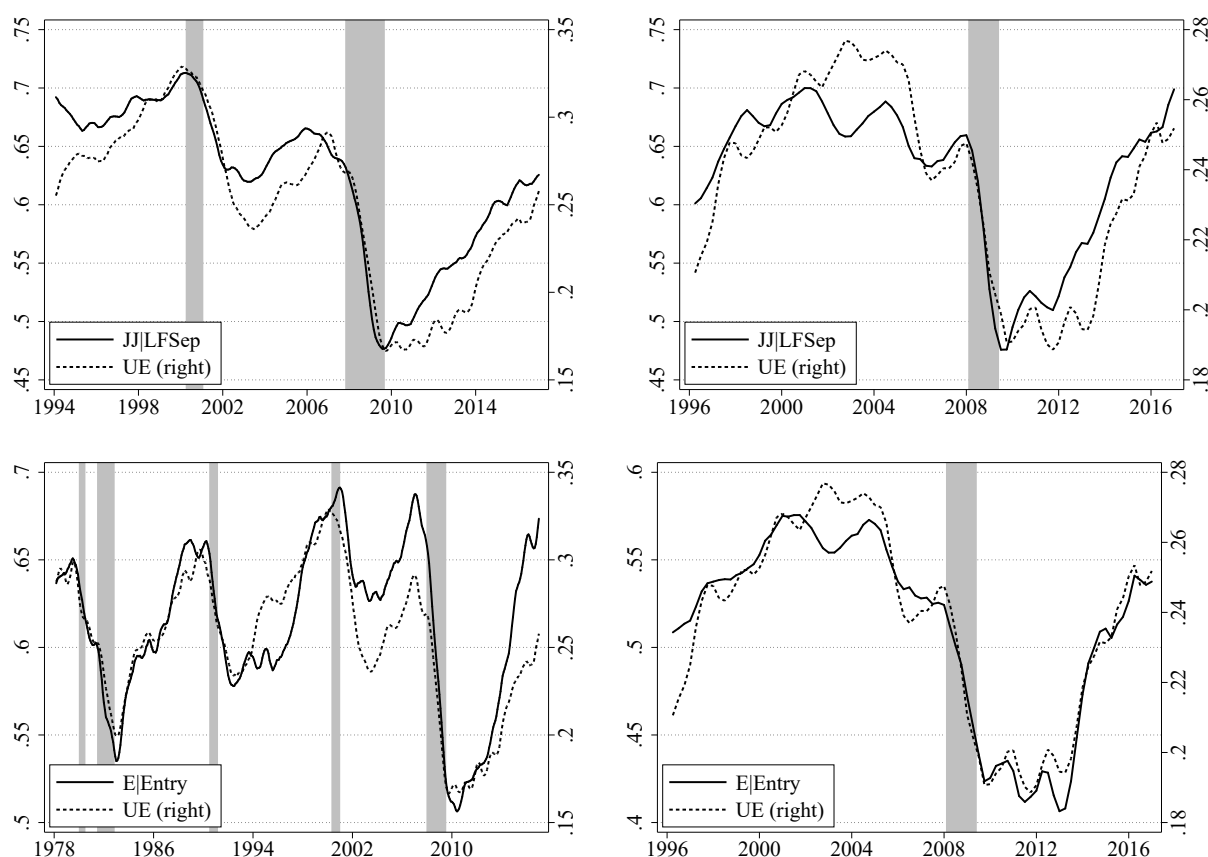
FIGURE 3.2: The job finding rates conditional on separating from a job and remaining in the labour force or entering the labour force in the US (left) and UK (right).

Note: Probabilities adjusted for margin error and seasonality. Shaded areas denote officially defined UK and US recessions. Source: Author calculations using the CPS and Two Quarter LFS. Ages 16-64/59. US 1994m1-2016m12 (top) and 1978m1-2016m12 (bottom). UK 1996q1-2016q4.

probabilities. The job finding components closely track the respective unemployment to employment transition probabilities. Figures 3.1 and 3.2 suggest that the fall in job finding is the main driver behind the increased ins of unemployment during recessions. The next section argues that this conclusion may be premature.

3.3.4 Accounting for reasons for separation

From the previous evidence it is tempting to conclude that the separation component of the employment to unemployment probability is unaffected by the cycle. This would be inaccurate. As documented by Akerlof et al. (1988), Anderson and Meyer (1994) and Davis et al. (2012) among others, voluntary separations fall in recessions and involuntary separations rise in recessions.

Elsby et al. (2010) points out that not accounting for compositional changes in the reason for separation can lead one to overstate the role of the job finding component of the employment to unemployment probability.[14] It is also important to assess the overall role of layoffs in the economy, as cyclical differences in voluntary and involuntary separations may dampen the role of layoffs when focusing on overall separations. Using the categorisations of reasons described in Section 3.3.1, I can account for compositional changes in the reason for separation, and assess the role of layoffs separately by adapting (3.1)

$$p_t^{eu} = \sum_r p_t^{sep^r} p_t^{lf|sep^r} (1 - p_t^{jj|lfsep^r}).[15] \tag{3.5}$$

Figure 3.3 shows the time series of each component of (3.5) for the US and UK. The top row of Figure 3.3 plots the time series of the involuntary separation and voluntary separation probabilities. What we see is a clear reduction in voluntary separations and a clear increase in involuntary separations during each recession. Figure 3.1 simply points out that these two types of separations offset each other, resulting in an overall acyclical separation probability.

The second row plots the time series of the involuntary and voluntary $LF|Sep$ probabilities. They largely confirm the conclusions made in the aggregate - following a voluntary or involuntary job separation, the probability that a worker will subsequently remain in the labour force is independent of the cycle.

---

[14]See Elsby et al. (2010) Section IIc.

[15]The components of equation (3.1) are calculated by: $p_t^{sep^r} = \frac{Sep_t^r}{E_{t-1}}$, $p_t^{lf|sep^r} = \frac{LFSep_t^r}{Sep_t}$ and $p_t^{jj|lfsep^r} = \frac{JJLFSep_t^r}{LFSep_t^r}$. Sep_t^r constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r. $LFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r and are in the labour force at t. $JJLFSep_t^r$ constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r and are in employment at t.
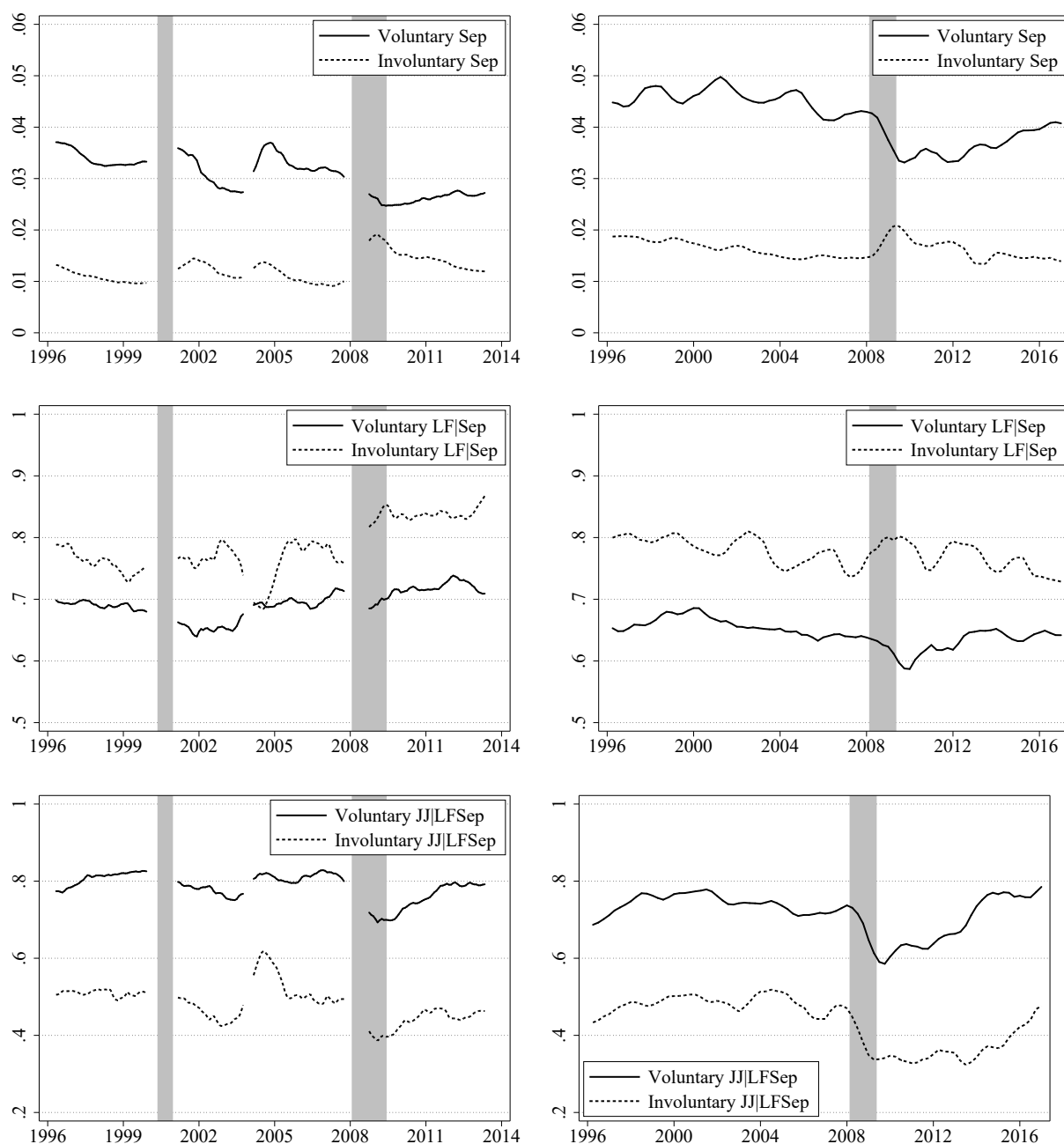
FIGURE 3.3: The US (left) and UK (right) voluntary and involuntary: separation, labour force given separation and job-to-job given labour force separation probabilities.

Note: Probabilities adjusted for margin error and seasonality. Shaded areas denote officially defined US and UK recessions. Source: Author calculations using the SIPP and Two Quarter LFS. Ages 16-64/59. US 1996m4-2013m5. UK 1996q1-2016q4.

The final row plots the time series of the involuntary and voluntary $JJ|LFSep$ probabilities. Notice that voluntary separations that remain in the labour force are more likely to subsequently

be in future employment than involuntary separations. This observation, coupled with the fact the involuntary separations rise in recessions and voluntary separations fall, will result in the changing composition of the reason for separation contributing to reductions in the *JJ|LFSep* probability. Because of these two facts, a procyclical aggregate *JJ|LFSep* probability, as seen in Figure 3.2, does not necessarily imply that the *JJ|LFSep* probability disaggregated by each reason is procyclical. If this changing composition effect explained all the drop of the aggregate *JJ|LFSep* probability during a recession, then the *JJ|LFSep* probabilities disaggregated by reason would be acyclical. As we can see from Figure 3.3, this is not true. We see clear reductions in the probability of subsequently finding employment, for each reason for separation.

I now turn to the decomposition of unemployment variation to quantitatively assess the role of the decomposed ins of unemployment.

3.4 Decomposition of unemployment variation

In this section I explain how it is possible to assess the impact of the fluctuations of the decomposed ins of unemployment on overall labour market state rate dynamics. To do this, I adapt a non-steady state variance decomposition described by Elsby et al. (2015).

3.4.1 Methodology

The following first-order Markov process describes the evolution of the three state variables where: e is the employment-to-population rate, u is the unemployment-to-population rate and n is the inactivity-to-population rate. p_t^{ij} describes the probability of moving from state i to j during period t.

$$
\begin{bmatrix} e \\ u \\ n \end{bmatrix}_t =
\begin{bmatrix}
1 - p^{eu} - p^{en} & p^{ue} & p^{ne} \\
p^{eu} & 1 - p^{ue} - p^{un} & p^{nu} \\
p^{en} & p^{un} & 1 - p^{ne} - p^{nu}
\end{bmatrix}_t
\begin{bmatrix} e \\ u \\ n \end{bmatrix}_{t-1}
\tag{3.6}
$$

Substituting in for the decomposed employment outflow and labour force entry probabilities described in Section 3.3, and exploiting the fact that $e_t + u_t + n_t = 1$, results in the following reduced dynamic system

$$
\underbrace{\begin{bmatrix} e \\ u \end{bmatrix}_t}_{s_t} =
\underbrace{\begin{bmatrix}
1 - \sum_r \left[p^{sep^r}(1 - p^{sep^r} p^{lf|sep^r} p^{jj|lfsep^r}) \right] - p^{entry} p^{e|entry} & p^{ue} - p^{entry} p^{e|entry} \\
\sum_r \left[p^{sep^r} p^{lf|sep^r}(1 - p^{jj|lfsep^r}) \right] - p^{entry}(1 - p^{e|entry}) & 1 - p^{ue} - p^{un} - p^{entry}(1 - p^{e|entry})
\end{bmatrix}_t}_{P_t}
\underbrace{\begin{bmatrix} e \\ u \end{bmatrix}_{t-1}}_{s_{t-1}}
$$

$$+\underbrace{\begin{bmatrix} p^{entry}p^{e|entry} \\ p^{entry}(1-p^{e|entry}) \end{bmatrix}_t}_{q_t}. \tag{3.7}$$

The limiting distribution, or steady state, of the Markov process is then given as

$$\bar{s}_t = (I - P_t)^{-1}q_t. \tag{3.8}$$

To see how the changes in steady state rates are affected by changes in the flow probabilities, I take a first order approximation around the previous periods flows giving

$$\bar{s}_t \approx \bar{s}_{t-1} + \sum_{y \in Y} \frac{\partial \bar{s}_t}{\partial p_t^y}(p_t^y - p_{t-1}^y) : Y = \{ui, sep^r, lf|sep^r, jj|lf\&sep^r, entry, e|entry\}_{i \neq u, \forall r}. \tag{3.9}$$

Elsby et al. (2015) show that $\triangle \bar{s}$ and $\triangle s$ are related through

$$\triangle s_t = A_t \triangle \bar{s}_t + B_t \triangle s_{t-1}, \tag{3.10}$$

where $A_t = (I - P_t)$ and $B_t = (I - P_t)P_{t-1}(I - P_{t-1})^{-1}$. Iterating back, equation (3.10) can be represented as the following

$$\triangle s_{t,k} = \sum_{t=0}^{t-1}(\prod_{n=0}^{k-1}B_{t-n})A_{t-k}\triangle \bar{s}_{t-k} + \prod_{k=0}^{t-1}B_{t-k}\triangle s_0. \tag{3.11}$$

Using equations (3.9) and (3.11) we can now run a non-steady state decomposition because (ignoring the second term on the RHS of (3.11) which describes the initial deviation from steady state)

$$\triangle s_{t,k} \approx \sum_{t=0}^{t-1}(\prod_{n=0}^{k-1}B_{t-n})A_{t-k}\sum_{y \in Y}\frac{d\bar{s}_t}{dp_t^y}\triangle p_t^y. \tag{3.12}$$

The non-steady state variance decomposition is then

$$var(\triangle s_{t,k}) \approx \sum_{y \in Y}cov(\sum_{t=0}^{t-1}(\prod_{n=0}^{k-1}B_{t-n})A_{t-k}\frac{\partial \bar{s}_t}{\partial p_t^y}\triangle p_t^y, \triangle s_t). \tag{3.13}$$

The percentage of the fluctuations of the unemployment-to-population ratio that can be accounted for by fluctuations in the total $JJ|LFSep$ probability, for example, can be calculated using

$$C_u^{jj|lf\&sep} = \frac{\sum_r cov(\sum_{t=0}^{t-1}(\prod_{n=0}^{k-1}B_{t-n})A_{t-k}\frac{\partial \bar{u}_t}{\partial p_t^{jj|lf\&sep^r}}\triangle p_t^{jj|lf\&sep^r}, \triangle u_t)}{var(\triangle u_t)}. \tag{3.14}$$

The decomposition above applies to the contribution of worker flows to the dynamics of the unemployment-to-population ratio. To estimate the impact of the worker flows to the dynamics of the unemployment rate, it is possible to take the following approximation

$$\triangle u_t^{rate} \approx (1 - u_{t-1}^{rate}) \frac{\triangle u_t}{(e_{t-1} + u_{t-1})} - u_{t-1}^{rate} \frac{\triangle e_t}{(e_{t-1} + u_{t-1})}.^{16} \qquad (3.15)$$

3.4.2 Results

Table 3.1 shows the results of the decomposition of the unemployment rate using the system described by (3.7) (III) for the US (left, SIPP) and UK (right). I compare the decomposition of this system with two others: (I) a standard three-state system and (II) an extension of the standard system that splits the employment outflow probabilities by type of separation (middle). Beginning with (I), this is perhaps the logical progression to understand unemployment dynamics using worker flows. I use this progression to highlight the differences in interpretation that one would glean from each system. The interpretation of the top left cell is: the past and present fluctuations in the employment to unemployment probability contributes to 37.8% of the dynamics of the US unemployment rate.[17]

System (I) shows that variations in the flows between employment and unemployment and between unemployment and inactivity contribute to around two-thirds and a third of unemployment dynamics, respectively. These results are broadly consistent with recent worker flow analyses for the US and UK.[18] From this system, it is difficult to understand the overall importance of layoffs and job finding. In particular, we may, possibly inaccurately, conclude that layoffs contribute to around a third of unemployment variation in the US and UK.

Next, system (II) splits the employment outflow probabilities by voluntary and involuntary reasons. We find that involuntary and voluntary employment to unemployment flows both contribute positively to unemployment variation, with the larger contribution coming from the involuntary transition. This may lead us to conclude that increased involuntary separations is the main driver behind increased employment to unemployment flows, and that recessions come with a mass of workers quitting their jobs in order to move into unemployment. The latter result is contradictory to evidence from Figure 3.3 that shows that voluntary separations fall in recessions. These conclusions can only be made by ignoring job-to-job transitions.

---

[16] See Appendix B.1 for details.

[17] I will sidestep the issue of time aggregation here but will address this in the next subsection.

[18] See Elsby et al. (2015) and Razzu and Singleton (2016) for the US using the CPS and Smith (2012), Gomes (2012), Elsby et al. (2016), Singleton (2017) and Lale and Borowczyk-Martins (2018) for the UK.

Finally, system (III) shows the results after incorporating the decomposed ins of unemployment. Much like in system (II) involuntary separations contribute positively to unemployment dynamics (US 21.6% and UK 13.8%) but unlike in system (II) voluntary separations contribute negatively to unemployment dynamics (US -5.3% and UK -15.9%). The $LF|Sep$ probability, component (ii), is cyclically unimportant. And the job finding component of the employment to unemployment probability contributes significantly to unemployment variation (US 19.4% and UK 30.9%). These results suggest that job-to-job transitions are critical in the story of unemployment dynamics.

I find that entry into the labour force is mildly procyclical contributing negatively to unemployment variation (US -3.1% and UK -4.1%), and job finding at the participation margin contributes significantly to unemployment dynamics (US 16.4% and UK 22.7%).

Changes in the job finding components of the ins of unemployment may be due to other forces that are not necessarily due to fluctuations in the job finding probability. If we do make this assumption, however, we find that the role of job finding changes significantly as move from system (I) to system (III), as shown in the final two rows. The contribution of job finding at least doubles.

Time aggregation

Part of the contribution that comes through the $JJ|LFSep$ and $E|Entry$ probabilities would be attributed to fluctuations in the unemployment to employment probability if we could observe each individuals labour market status every second. This is because some of those who I categorise as making a job to job or inactivity to employment transition may have experienced a spell of unemployment in between. We expect, therefore, to see a reduction in the contributions of the $JJ|LFSep$ and $E|Entry$ transitions, and an increase in the contribution of the unemployment to employment transitions. Table B.51 shows the continuous time analog of column (III) in Table 3.1, and confirms this expectation. The differences in the contributions of the Sep, $LF|Sep$, $JJ|LFSep$, $Entry$ and $E|Entry$ rates in the continuous time environment compared to the discrete time environment are small, however.

Heterogeneity

As suggested by Darby et al. (1985), reductions in the job finding probability during a recession may be contributed to by compositional shifts in the pool of individuals looking for employment - from individuals who are more effective at finding work, to individuals who are less effective at finding work. In Appendix B.2 I assess the role of compositional changes in worker type including: age, sex, education, relationship to head of household, whether searching on the

Probability	US			UK		
	I	**II**	**III**	**I**	**II**	**III**
e to u	37.8			33.5		
e to n	0.1			-1.1		
e to u^v		8.5			9.4	
e to u^i		31.2			20.4	
e to n^v		-0.8			-1.1	
e to n^i		1.3			0.6	
sep^v			-5.3			-15.9
sep^i			21.6			13.8
$lf\|sep^v$			0.2			1.1
$lf\|sep^i$			3.1			1.2
$jj\|lfsep^v$			11.9			20.8
$jj\|lfsep^i$			7.5			10.1
u to e	32.4	32.4	32.4	30.9	30.9	30.9
u to n	17.5	17.5	17.5	17.5	17.5	17.5
n to e	-0.7	-0.7		4.6	4.6	
n to u	14.0	14.0		14.2	14.2	
$entry$			-3.1			-4.1
$e\|entry$			16.4			22.7
Residual	-2.0	-1.1	-2.4	-0.4	-3.5	-0.7
$\sum_r jj\|lfsep^r$			19.4			30.9
u to $e + n$ to e	31.7	31.7		35.5	35.5	
u to $e + e\|entry$ $+ \sum_r jj\|lfsep^r$			68.2			85.5

TABLE 3.1: Contribution to unemployment rate variation - standard vs extended systems.

Note: Calculations based on margin error and seasonally adjusted probabilities. I: standard system. II: employment outflows by reason. III: system described by (3.7). sep^v, for example, refers to the voluntary separation probability. sep^i, for example, refers to the involuntary separation probability. The interpretation of the top left cell is: the past and present fluctuations in the employment to unemployment probability contributes to 37.8% of the dynamics of the unemployment rate. Source: Author calculations using the SIPP and Two-Quarter LFS. Ages 16-64/59. US 1996m4-2013m5. UK 1996q1-2016q4.

job, the reason for searching on the job, and the reason for separation. I find no evidence that compositional shifts in observable characteristics, other than the reason for separation, are contributing to fluctuations in the job finding components of the ins of unemployment.

3.5 Further discussion

This section provides evidence for the story detailed in this paper, discusses possible other stories, and outlines the relevance of this work to past and future empirical and theoretical analyses.

3.5.1 Evidence using on the job search

The story of Section 3.2 argues that evidence that job finding impacts employment to unemployment transitions would show that workers increase search before becoming unemployed. Chapter 2 shows this for involuntary separations, and that the reason for the increased search is because the worker "thinks their job may end". Here I show evidence for increased search for workers who separate voluntarily, both into a new job and to unemployment. And that the increased search is almost entirely due to workers being "dissatisfied" for both the voluntary job-to-job and employment to unemployment transitions.

I first show that on the job search is a good indicator for both job-to-job and employment to unemployment transitions, and this remains for workers who separate involuntarily and voluntarily. I estimate the following linear probability model using the on the job search information in the UK LFS.

$$Transition_{it} = \alpha_t + X_{it}\beta + \gamma OJS_{it-1} + \varepsilon_{it}, \tag{3.16}$$

where $Transition_{it}$ is a binary variable, taking the value of zero if the worker remains in the current job and one if the individual moves into a new job/unemployment/inactivity. α_t is a time fixed effect, X_{it} contains controls, and ε_{it} is the error. OJS_{it-1} takes a value of zero if the individual declares to be searching and zero otherwise. Table 3.2 shows the results.

We can see that job search is a good indicator for whether a worker will make a job to job transition or move into unemployment, be it voluntarily or involuntarily. Workers are 7.56 and 2.58 percentage points more likely to switch jobs voluntarily and involuntarily, respectively, if they are searching; and 1.73 and 2.50 percentage points more likely to transition into unemployment voluntarily and involuntarily, respectively, if they are searching. We see a similar pattern for transitions into inactivity, but with a much smaller magnitude. Those who are looking for new

jobs are in employment relationships that are more likely to dissolve the next period, whether the worker is pushed out or the worker quits.

	All			Voluntary			Involuntary		
	jj	*eu*	*en*	*jj*	*eu*	*en*	*jj*	*eu*	*en*
OJS	.1212**	.0450**	.0036**	.0756**	.0173**	.0021**	.0258**	.0250**	.0025**
	(.0010)	(.0006)	(.0004)	(.0008)	(.0004)	(.0003)	(.0005)	(.0005)	(.0002)
N (mil.)	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5

TABLE 3.2: On-the-job search and separations.

Note: Each regression includes controls for sex, age, job tenure, skill (two types) and time. Standard errors in parentheses. 1996Q1 - 2016Q1. *, ** indicate statistical significance at 5% and 1% levels, respectively.

As is shown in Chapter 2, workers increase search before they are fired, which results in job switching following layoffs. How does on the job search change before workers quit to a new job, and to unemployment? To answer this, I follow a similar technique in the job loss literature and Chapter 2, and compare workers who separate to a control group. The control group consists of workers who never separate from their job during the entire five quarters of the survey. Between 1995 and 2016, this leaves me with 288,821 individuals in the control group. It is important to note that some of the control group may experience a separation in quarter six. The experimental group consists of workers who remain at their job from quarter one to quarter four, and quit during the final quarter. This leaves me with 1,482 quit events that satisfy the above. Using these restrictions I estimate the following distributed lag model.

$$s_{it} = a_i + \gamma_t + X_{it}\beta + \sum_{k=1}^{3} \delta^{-k} D_{it}^{-k} + u_{it}. \tag{3.17}$$

s_{it} is an indicator variable representing three variables. It takes the value 1 if the individual reports to be searching, searching because they think their job may end (Uncertain search), or searching because they are Unsatisfied and 0 if not. I have categorised these two broad motives using the reported reasons described in the previous subsection. α_i and γ_t are individual and time fixed effects, respectively. X_{it} contains observables - a quartic in age. D^{-k} takes the value of 1 if the individual quits in k quarters and 0 otherwise. The stream of δ^{-k} gives the percentage change in

search incidence *k* quarters before the quit relative to their search incidence four quarters before the quit and that of the control group.

Table 3.3 shows the results. In columns one and two, we find that search during the quarter prior to the quit increases significantly for both workers who quit into unemployment (17.4 percentage points), and for workers who quit to a new job (13 percentage points). Columns three and four show the same regression for workers searching because they think their job may end. The increase in search is far smaller and almost negligible. Finally, columns five and six show the results for unsatisfied search. Unsatisfied search is the main explanation for the rise in search prior to voluntary employment to unemployment or voluntary job-to-job transitions. These results show that the search patterns before the quit are very similar for those who move to a new job or into unemployment.

	All		Uncertain		Unsatisfied or other	
	eu	*jj*	*eu*	*jj*	*eu*	*jj*
δ^{-1}	.174**	.130**	.023**	.009**	.136**	.126**
	(.015)	(.006)	(.005)	(.002)	(.013)	(.006)
δ^{-2}	.055**	.067**	.014**	.005**	.028*	.065**
	(.015)	(.007)	(.005)	(.002)	(.013)	(.0006)
δ^{-3}	.059**	.008	-.004	.001	.032**	.008
	(.015)	(.007)	(.005)	(.002)	(.013)	(.006)
N (mil.)	1.16	1.16	1.16	1.16	1.16	1.16

TABLE 3.3: Search before the quit.

The top left coefficient reads, the proportion of workers who report to be searching is 17.4 percentage points higher for those who quit their job in one quarter relative to those who do not and the proportion searching four quarters before the quit. Note: Standard errors in parentheses. All regressions include a quartic in age, and time and person fixed effects. 1995Q1 - 2016Q1. *, ** indicate statistical significance at 5% and 1% levels, respectively.

The implication being that if job finding falls, as it does in a recession, search is less likely to be matched with new employment and so more likely to result in unemployment. We can see direct evidence of this by augmenting (3.16). I run the following for workers in the recessionary period in the UK (2008Q3 - 2009Q2) and not in a recessionary period (2006Q3 - 2007Q2, 2010Q3 - 2011Q2).

$$Transition_{it} = \alpha_t + X_{it}\beta + \gamma_1 OJS_{it-1} * R_t + \gamma_2 OJS_{it-1} + \gamma_3 R_t + \varepsilon_{it}, \qquad (3.18)$$

Table 3.4 shows the results. Firstly, recessions reduce job-to-job transitions, increase employment to unemployment transitions, and slightly increase employment to inactivity transitions, as documented in the previous subsection. If the worker is searching in a recession, however, the job-to-job transition probability falls more and the employment to unemployment transition increases more. Similar results emerge when splitting the transitions by reason. Relative to those searching out of a recession, those who are searching on the job in a recession are more likely to quit into unemployment and less likely to quit to a new job. Those who are searching on the job in a recession are also more likely to be sacked and move into unemployment, and less likely to move into new employment, although the last coefficient is imprecisely estimated.

	All			Voluntary			Involuntary		
	jj	eu	en	jj	eu	en	jj	eu	en
OJS	.1095**	.0465**	.0059**	. 0602**	.0146**	.0038**	.0223**	.0241**	.0032**
	(.0016)	(.0011)	(.0014)	(.0010)	(.0006)	(.0009)	(.0006)	(.0008)	(.0006)
R	-.0038**	.0034**	.0003	-.0024**	.0001	.0009	.0006	.0041**	.0009**
	(.0006)	(.0004)	(.0005)	(.0004)	(.0002)	(.0004)	(.0146)	(.0003)	(.0002)
$OJS*R$	-.0148**	.0155**	-.0052*	-.0160**	.0040**	-.0036*	-.0007	.0184**	-.0020
	(.0027)	(.0019)	(.0024)	(.0018)	(.0011)	(.0019)	(.0011)	(.0014)	(.0011)
N (thous.)	323	318	320	318	315	318	315	316	315

TABLE 3.4: On-the-job search and separations during a recession.

Each regression includes controls for sex, age, job tenure, skill (two types) and time. Standard errors in parentheses. Recessionary period is 2008Q2 - 2009Q2, and the non-recessionary period is 2006Q2 - 2007Q2 and 2010Q2 - 2011Q2. *, ** indicate statistical significance at 5% and 1% levels, respectively.

These results argue that job-to-job transitions and employment to unemployment transitions are related through the job finding rate. More search prior to an employment to unemployment transition suggests that the lack of job finding, in part, resulted in the employment to unemployment transition. As job finding falls in recessions, those workers who were searching prior to the job finishing, are more likely to experience an unemployment spell.

3.5.2 Other stories

While I have presented a story that reductions in the job finding rate can contribute to the increase in the ins of unemployment during recessions, inferring causality without the aid of a model would be incorrect.

One possible reason for the drop in job finding of potential job-to-job transitions could be due to differences in the type of layoff during recessions and expansions. If layoffs are more likely to be unforeseen in recessions, workers are more likely to experience unemployment, not just because of the drop in job finding, but because workers have less time to find new employment whilst still employed. This mechanism is present in Garibaldi (2004). He shows that, in a model of advance notice, in the style of Pissarides (2000), firms are more likely to opt for fixed firing costs in recessions as opposed to providing advance notice. This is due to the reduced job finding rate in recessions, increasing the likelihood that the firm must pay the worker for the entire length of notice.

It may also be the case that workers who have separated in recessions are *unobservably* different than those have separated in expansions. If those who separate in expansions are better at finding jobs than those who separate in recessions, this will give rise to procyclical job-to-job transitions conditional on separation. Ahn and Hamilton (2016) argues that unobserved heterogeneity is a particularly important feature of business cycles.

3.5.3 Empirical

Understanding the driving forces behind the fluctuations in unemployment has become a controversial issue. Do movements out of unemployment or into unemployment drive unemployment dynamics? Darby et al. (1986) wrote in their title "... The Ins Win" - the ins drive unemployment fluctuations. Contrary to this, Shimer (2012) argues that the outs win. In some sense both of these conclusions could be true, if the outs of unemployment in fact describe the overall job finding probability (the terms 'outs' and 'job finding' are often used interchangeably). To understand this, I will very briefly discuss the methodology pioneered by Shimer (2012). In his framework he developed novel methods to estimate the ins and outs of unemployment using aggregate data.[19]

---

[19]There is a vast number of studies that attempt to understand the dynamics of unemployment in a two state framework. These include Petrongolo and Pissarides (2008), Elsby et al. (2009), Elsby et al. (2010, 2013) and Smith (2012)

He shows that the evolution of unemployment can be described as

$$u_t = (1 - F_{t-1})u_{t-1} + u_t^s, \tag{3.19}$$

where F is the probability of finding a job and u^s is the percentage of the labour force who are in short term unemployment. The short term unemployed proxy the ins of unemployment. He finds that the ins of unemployment are much less important than the outs. Using a similar technique, Elsby et al. (2013) analyse the ins and outs of unemployment for thirteen OECD countries.[20] They find that the ins of unemployment in some countries contribute more to unemployment variation than the outs.

The results of this paper show that the fluctuations in the percentage of short term unemployed, the ins, are impacted by fluctuations in the job finding probability. This is because, during recessions, the reductions in the job finding probability drives an increased number of the employed and inactive to transition into unemployment following job separation or labour force entry and inflate the impact of the ins. In other words, the ins are important, not just because of an increase in layoffs during a recession, but also because of a reduction in the job finding probability of potential job-to-job and inactivity to employment movers.

The analysis in this paper is superior to preceding literature that has decomposed the employment to unemployment transition for four main reasons. First, I have shown direct evidence using on the job search in the UK, that search increases significantly before workers quit their job and move to a new job, but also to move to unemployment. And I have shown that the rationale for the increased search is consistent across these two destinations of the quit. Second, I have disaggregated separations into layoffs and voluntary separations. This has allowed me to account for compositional changes in the reason for separation, but also to assess the individual role that layoffs play in the story of unemployment dynamics. Third, I have studied the problem in a three state world, and noted that transitions into the labour force are susceptible to fluctuations in job finding in a similar manner as separations, showing that overall entry into the labour market changes very little over the business cycle, but that job finding conditional on entry changes considerably. Finally, I have conducted the analysis out of steady-state and provided significant evidence that these results are not driven by compositional shifts in demographic or job characteristics.

---

[20]They extend Shimer's analysis to assess the dynamics of the ins and outs of unemployment out of steady state.

3.5.4 Theory

In the standard model of on-the-job search, workers switch employers if they find a new employer who offers a sufficiently high wage.[21] Once they have found an employer who is willing to offer a sufficiently high wage they will separate and make the transition. Evidence from the SIPP suggests that approximately a third of job-to-job transitions are due to a worker "quitting to take up a new job", and that a non-trivial fraction of job-to-job transitions actually proceed involuntary, firm driven, separations. Ahn and Shao (2017) document that the intensity of on-the-job search increased during the Great Recession as workers insured themselves against the increased probability of losing a job.[22] This evidence suggests that job-to-job transitions do not occur only as a means to increase wages, but also through an inadequate relationship breaking and the worker finding a job quickly enough to avoid a spell of unemployment. This paper pushes for a bigger emphasis in modelling the job-to-job transition as not just a method to climb the waged job-ladder, but also through a mechanism to allow a worker to escape a spell of unemployment following the worker-firm match dissolution.[23]

Krusell et al. (2017) build a model of the labour market that includes transitions across the three labour market states. Their model predicts countercyclical inactivity to unemployment transitions. The reason is precisely because of procyclical job finding: *During good times the increase in job opportunity arrival rates implies that marginal N workers are more likely to receive offers that take them into E, thus decreasing the flow of these workers into U*. In this paper, I have decomposed inactivity to unemployment flows, to capture this feature.

3.6 Conclusion

Recent worker flows analyses have studied the variations in transitions between employment, unemployment and inactivity, in order to understand the cyclical nature of unemployment. In

---

[21]See Burdett and Mortensen (1998).

[22]Krause and Lubik (2010) have shown that procyclical on-the-job search can help search models replicate the observed volatility of unemployment and vacancies (Shimer (2005a)).

[23]An example of a model that shows that a fall in job finding can result in an increase in separations into unemployment is shown in Nagypal (2005). Workers lose their job when the match hits a lower threshold, but before this threshold is reached, search much harder to avoid unemployment spells. She shows that, unlike the standard job ladder model, this model is able to capture the extent of job-to-job transitions. This mechanism can also help models predict job-to-job transitions with wage cuts. See Jolivet et al. (2006) and Tjaden and Wellschmeid (2014) for an adaptation of the standard model to include this observation. The setup is that workers can make three transitions: (i) a shock that forces the individual into unemployment, (ii) on-the-job search that gives the individual the option of making a job-to-job transition, and (iii) another shock that forces a worker to make a job-to-job transition independent of whether the wage increases or decreases. The intuition of (iii) is often described as a notice shock.

this paper, I argue that analysing the ins and outs of unemployment is not necessarily informative for understanding the relative contributions of job finding and job separations. To address this, I decompose the ins of unemployment into distinct job separation/labour force entry and job finding components and assess their cyclical dynamics separately, where I importantly take into account the different reasons for separations. I find that changes in the job finding probability of potential job-to-job transitions, is at least as important as layoffs in driving the increase in employment to unemployment transitions during recessions, while procyclical quits play a moderating role in recessions.

Finally, I provide evidence using information regarding on the job search in the UK, that employment to unemployment transitions and job-to-job transitions are intimately related through the ability to find jobs. Workers increase search incidence before separating from their jobs for any reason - some employment to unemployment transitions would have instead resulted in a job switch if they had been lucky enough to line up a new job before the separation occurred.

Chapter 4

The ins and outs of the gender unemployment gap in the OECD

Note: This paper is joint work with Reamonn Lydon. He has agreed that this paper represents a significant contribution on my part and can appear in this thesis. The views expressed in this paper are those of the authors only and do not necessarily reflect the views of the Central Bank of Ireland or the ESCB.

4.1 Introduction

Why do recessions impact males and females differently? This question drew a lot of attention in the media in the US following the Great Recession, as the unemployment rate rose significantly more for males over females.[1] A stronger increase in male unemployment is not unique to the Great Recession in the US and, in fact, similar patterns, but to varying extents, seem to be present in many other developed economies.[2] For example, over the last 4 decades, for Australia, Denmark, France, Spain and the US, the variance of the percentage change in unemployment is over twice as large for males than for females, but only slightly larger for Japan and New Zealand (see Table 4.1).

The disparity in unemployment dynamics between genders may be due to two forces, differences in the variations of the flows into unemployment (variations in the inflow gap), or differences in the variations of the flows out of unemployment (variations in the outflow gap). Understanding which of these forces is most important, can help highlight the underlying causes for the asymmetric impact that recessions have by gender, and may inform future gender-based analysis of labour markets and policy making. In this paper, we quantify the role of both of these forces for a large group of countries over a long period using publicly available data.

We use harmonised data from the Organisation for Economic Cooperation and Development (OECD) to estimate the ins and outs of unemployment by gender for 18 countries over the last

---

[1]See articles from the Economist and The New York Times.

[2]A large amount of studies, predominantly in the US and UK, have noted that the male unemployment rate is significantly more volatile than the female unemployment rate. See Clark (1980), Blank (1989), Peiro (2012), Hoynes (2012), Razzu and Singleton (2016) and Albanesi and Sahin (2018) for examples.

	Aus	Bel	Can	Den	Fra	Ger	Ire	Ita	Jap
$\dfrac{var\left(\Delta log(u_M)\right)}{var\left(\Delta log(u_F)\right)}$	2.97	1.64	1.93	2.87	2.17	1.39	1.58	1.71	1.27
	Lux	Neth	NZ	Nor	Por	Spa	Swe	UK	US
$\dfrac{var\left(\Delta log(u_M)\right)}{var\left(\Delta log(u_F)\right)}$	0.96	1.60	1.24	1.58	1.91	2.30	1.37	1.75	2.10

TABLE 4.1: Variance of male unemployment change relative to female unemployment change. Source: OECD (2018b). Annual data over the last 4 decades. See Table 4.2 for the exact periods.

4 decades or so. Using the unemployment flows, we perform a non-steady-state decomposition of unemployment variation for both genders and for variations in the gender unemployment rate gap (the percentage change in the male unemployment rate minus the percentage change in the female unemployment rate). The results indicate that for all countries, the dynamics of the gender unemployment gap can be predominantly explained by variations in the inflow gap. To understand why male unemployment rates tend to rise proportionately more in recessions, therefore, one must pay close attention to why the percentage increase in the male inflow rate is greater than the percentage increase in female inflow rate. We provide evidence that gender composition by sector is a prominent explanation for this result. There has been a tendency to treat unemployment inflows, or separations, as irrelevant in the US following the influential work of Hall (2005) and Shimer (2012). Yet, when concerning the dynamics of the gender unemployment gap, in fact the opposite is true for all countries under study.

In Section 4.2, we outline the derivation of the aggregate unemployment flows using data on unemployment duration from the OECD. When constructing unemployment flows using OECD data following Shimer (2012), the estimates can become very noisy for countries with slow moving labour markets, especially when splitting the data by gender. To rectify this issue, following Elsby et al. (2013), we make use of all the available data on unemployment duration provided by the OECD, to create a weighted average of derived flow rates.[3] The gender unemployment flows show interesting commonalities by country. For all countries, apart from Germany and Norway, inflows into unemployment are on average larger for females than for males, but the relative size of the outflows are varied. In all English speaking countries, females experience higher rates of movements out of unemployment compared to males. This is not true, however, for Continental European and Nordic countries with some experiencing faster movements out of unemployment for women and some for men. On average, among all countries, females have higher transition

---

[3]The OECD provides information on the stocks of the unemployed with duration of less than one, three, six and twelve months.

rates into and out of unemployment. Concerning changes in the unemployment flows between 2007 and 2009, for all countries apart from France, the percentage increase in the unemployment inflow is larger for males than for females, but the percentage fall in the unemployment outflow does not follow a similar clear pattern.

Using the estimated flows, we perform a non-steady-state variance decomposition of unemployment variation by gender, which allows us to decompose variations in the gender unemployment gap. In line with Elsby et al. (2013), who focus on all workers, we find that the relative contributions of the ins and outs differ markedly between countries. For example, for Netherlands and Italy, the outs of unemployment for males drive 14% and 76% of unemployment variation, respectively. The ins (outs) of unemployment contribute more (less) to unemployment variation for males than for females for two thirds of the sample. The only countries that clearly depart from this pattern are either Continental European or Nordic. As an example of how different the picture can be between genders, in the UK, the inflow:outflow contribution for males and females is 43:57 and 83:21, respectively - for males, the ins and outs are equally important, while for females the outs of unemployment drive the vast majority of unemployment dynamics. The results indicate that male and female unemployment dynamics can be very different.

Despite the fact that we find different contributions of ins and outs for the variation in unemployment of males and females between different countries, when we look at the dynamics of the gender unemployment gap a clear and consistent pattern emerges between all countries in our sample. Variations in the inflow gap, drives the majority of the dynamics of the gender unemployment gap. In fact, more than 80% of dynamics of the gender unemployment gap is explained by variations in the inflow gap for 14 of the 18 countries. Focusing on the Great Recession, the percentage rise in unemployment relative to 2007 is larger for males than for females for almost all countries. Using the decomposition framework, we show graphically, that the rise in the gender unemployment gap is predominantly due to a larger increase in inflows for males than for females for most countries.

In Section 4.5 we take a step back and ask what the underlying story is behind these results. We focus on the role of the male-female sector composition, asking, are male dominated sectors hit harder in recessions relative to female dominated sectors? To be precise, we ask the following question: What is the relationship between the male sector share, and the cyclicality of that sectors output? We compile sector specific data from the OECD (and BLS for the US) on output and sectoral composition, and find a consistent fact for all countries. There is a positive relationship between the male sector share and the correlation of sector output with overall output. This fact provides a candidate explanation for the results documented in this paper. Males tend to sort into

sectors that are more susceptible to economic swings, which in turn increases the average precarity of male jobs in recessions relative to females.

A large body of work has focused on understanding the changes in the ins and outs of unemployment from the perspective a representative worker.[4] Despite a lot of media attention regarding changes in the disparity in gender unemployment during the Great Recession, the literature is relatively sparse when it comes to the ins and outs of unemployment by gender.[5] Albanesi and Sahin (2018) study changes in the gender unemployment gap in the US. They show that (among other things) approximately half of the increase in the gender unemployment gap during recessions can be attributed to differences in industry composition by gender. This final observation clearly squares well the results described in the previous paragraph, albeit applied to a much larger set of countries.

Razzu and Singleton (2016) study the dynamics of UK and US unemployment using a flows based approach. They show that differences in the variations of transitions at the participation margin explain a non negligible proportion of the dynamics of the unemployment gap. In this paper, we only consider a two-state world which disallows us to asses differing participation decisions. Analysing a two-state world, however, allows for the study of a larger group of countries over a longer period, using harmonised OECD data. We also show in Section 4.6, using data on flows at the participation margin from a sub-sample of countries in this study, that avoiding non-participation is not likely to significantly affect the results. Another related study is Koutentakis (2015), who estimates the ins and outs of unemployment for ten OECD countries by gender in a similar manner as we do in this paper.[6] He does not focus on the dynamics of unemployment over the business cycle, but instead asks why the unemployment rate is greater for females than males in some countries. He argues that the steady-state female relative to male unemployment rate is positive for some countries predominantly because of larger unemployment inflows for females. Azmat et al. (2006), however, argues that both employment to unemployment and unemployment to employment transitions are important in explaining differences in unemployment rate across countries in the OECD, especially the Mediterranean countries. While this is very important, it does not say anything with regards to the origins of the asymmetric impact that recessions have by gender, to which this study is focused.

---

[4]Perry (1972b), Darby et al. (1985), Darby et al. (1986), Davis and Haltiwanger (1992), Hall (2005), Bachmann (2005), Petrongolo and Pissarides (2008), Nagypal (2008), Elsby et al. (2009), Elsby et al. (2010), Fujita and Ramey (2009), Elsby et al. (2011), Smith (2012), Shimer (2012), Gomes (2012) and Chapter 3 to name a few.

[5]There is clearly a vast literature studying gender disparities in other labour market variables, such as the wages and hours worked, and how these vary over time and between countries. See Olivetti and Petrongolo (2008, 2014, 2016) for a review of and examples of the fantastic work in this area.

[6]Although he does not make use of all available data on unemployment durations.

We provide a discussion of any inaccuracies with the analysis. In particular, the baseline decomposition measures the contribution of the underlying flows to logarithmic deviations in the unemployment gap. A modest change to the decomposition method allows us to assess non-logarithmic deviations in the unemployment gap. We find that the two decompositions provide qualitatively similar results. We also provide evidence that ignoring the participation margin is unlikely to significantly affect the conclusions.

The remainder of this paper is structured as follows. Section 4.2 outlines the derivation of the flow rates. Section 4.3 describes the non-steady-state variance decomposition of unemployment and the gender unemployment gap, and Section 4.4 describes the results. Section 4.5 shows that a candidate explanation for differing dynamics of male and female unemployment is due to sector composition. Section 4.6 provides presents robustness tests and a discussion. Finally, Section 4.7 concludes.

4.2 Estimating unemployment flows with aggregate data

In this section we outline the derivation of the unemployment flows following Elsby et al. (2013). We focus on 18 OECD countries: Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the United Kingdom, and the United States, over all the available data. The data covers the last 4 decades or so, ending in 2018 for all countries (see Table 4.2 for the start year for each country).

The derivation makes use of two different pieces of information. (i) annual unemployment rates, OECD (2018b), and (ii) the annual percentage of the unemployed with less than d months of unemployment duration, given as $u_t^{<d}$, OECD (2018c). To begin, consider the following two-state world of unemployment variation:

$$\dot{u}_t = s_t(1 - u_t) - f_t u_t, \tag{4.1}$$

where u_t is the unemployment rate at time t, $\dot{u}_t$ is the change in the unemployment rate over one month at time t, s_t is the monthly unemployment inflow rate from employment at time t, and f_t is the monthly unemployment outflow rate into employment at time t. Solving (4.1) forward twelve months, we arrive at

$$u_t = \frac{s_t}{s_t + f_t}\left(1 - e^{-12(s_t + f_t)}\right) + e^{-12(s_t + f_t)}u_{t-12}. \tag{4.2}$$

This describes a recursive relationship between unemployment now and unemployment one year ago. Notice that, $1 - e^{-12(s_t + f_t)}$ converges to one as the flow rates increase, which results in the unemployment rate at time t approaching steady-state.[7] This is because the speed of convergence to the limiting distribution of the Markov process is faster the larger the joint level of flow rates.

Using information provided by the OECD on what percentage of the unemployed have been in unemployment for less than one month, $u_t^{<1}$, we can also write a recursive relationship of unemployment as:

$$u_{t+1} - u_t = u_{t+1}^{<1} - F_t u_t, \tag{4.3}$$

where F_t is the monthly outflow probability. Rearranging, the monthly unemployment outflow probability can be written as:

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^{<1}}{u_t}. \tag{4.4}$$

Assuming that workers leave and enter unemployment following a Poisson point process, the monthly unemployment outflow rate is:

$$f_t = -ln(1 - F_t). \tag{4.5}$$

Finally, using (C.16), s_t can also be solved for numerically.

The problem with estimating unemployment flows using the OECD data in this manner, as noted by Elsby et al. (2013), is that for many countries in the sample, few workers are in their first month of unemployment at any one point in time. Or $u_t^{<1}$ can be very small. This can result in noisy estimates of the flow rates for countries with slow moving labour markets. This is especially problematic when splitting the flows by gender as we do in this paper, which reduces the sample sizes. To counteract this, we follow Elsby et al. (2013) and use all the available data on unemployment duration provided by the OECD. See Section C.3 for further information regarding the full estimation process.

4.2.1 The unemployment flows by gender

Figure 4.1 shows the unemployment rates over time for each country. There has been a clear convergence in unemployment rates for Belgium, France, Italy, Netherlands and Spain, during the end of the twentieth and beginning of the twenty first centuries. The country that stands out with regards to the experience during the Great Recession by gender is Ireland. The unemployment rate rose to 18% for males and 13% for females. These disparities in unemployment dynamics are

---

[7]See Section C.4 for further details.

our focus in this paper. Which flow is driving these differences in labour market experience by gender over time?

Figure 4.2 shows the estimated inflow and outflow rates for each country. In Table 4.2, we present the main points in order for ease of exposition. Table 4.2 shows the average estimated inflow and outflow rates by gender for all the countries under consideration. The magnitudes are very similar to the estimated unemployment flows, not by gender, in Elsby et al. (2013). In line with the findings of Koutentakis (2015), we find that for almost all countries, apart from Germany and Norway, inflows into unemployment are on average larger for females than for males. We do not observe such a clear pattern for the outflows - in Spain, the outflow is on average 28% larger for males than for females and in Ireland, the outflow is on average 37% lower for males than for females. Notice that the for English speaking countries and Japan, there are faster movements for females relative to males in both directions, but that for Continental Europe and Nordic economies the picture is varied. In general, on average, females experience both faster movements into unemployment and faster movements out of unemployment. This an interesting result, but one should not take this to mean that, on average, females are fired at a faster rate than males. There are other reasons as to why workers move into unemployment. Workers may enter the labour force or voluntarily leave their employer. We cannot disentangle between these different types of inflows using the OECD data.

On the right side of Table 4.2, we report the average annual percentage change in the unemployment flows between 2007 and 2009, in order to gauge which flows responded more during the Great Recession. We find stark differences between males and females. For all countries, apart from France, the percentage increase in the inflow was larger for males than for females. This is epitomised by Ireland, where males experienced a 46 percentage point (pp) larger increase in the unemployment inflow relative to females. In fact, on average, the change in the inflow during the most recent recession was actually slightly negative for females, but large and positive for males. With regards to outflows, however, we do not observe a common pattern. The fall in outflows was larger for ten out of the eighteen countries for females and on average the difference in the percentage changes in the outflows is close to zero. Table 4.2 is suggestive evidence that variations in the inflows into unemployment play a larger role for male unemployment dynamics relative to female unemployment dynamics, and is perhaps the main driver behind different variations in the unemployment gap between countries. These results square well with Hoynes (2012), who shows that males experienced larger increases in the rates of layoff during the Great Recession in the US. In the next section, we formally decompose the dynamics of the gender unemployment gap into components attributed to differences in the variations of the flows into unemployment, and to differences in the variations of the flows out of unemployment.
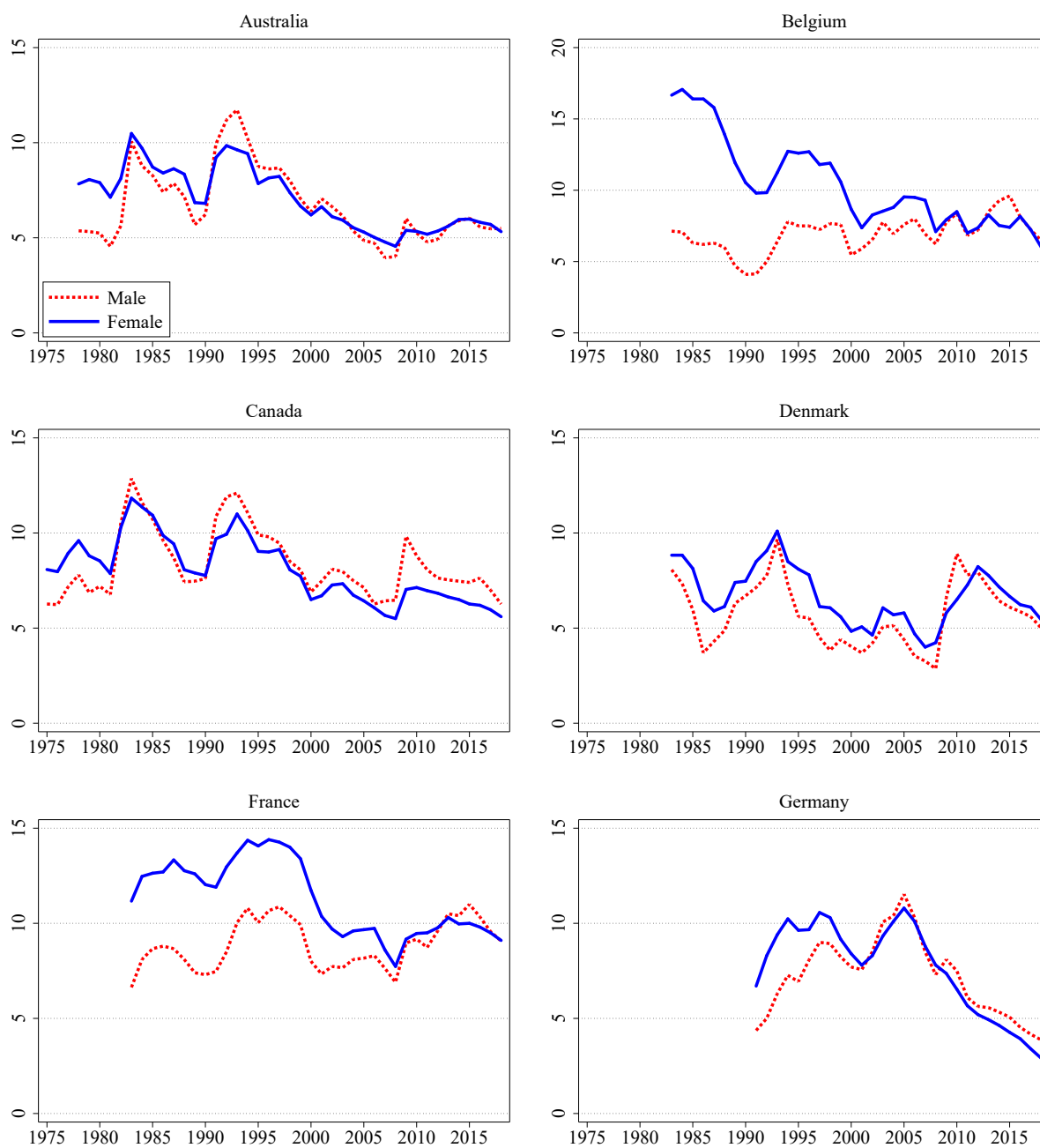
FIGURE 4.1: Unemployment rate by gender across the OECD
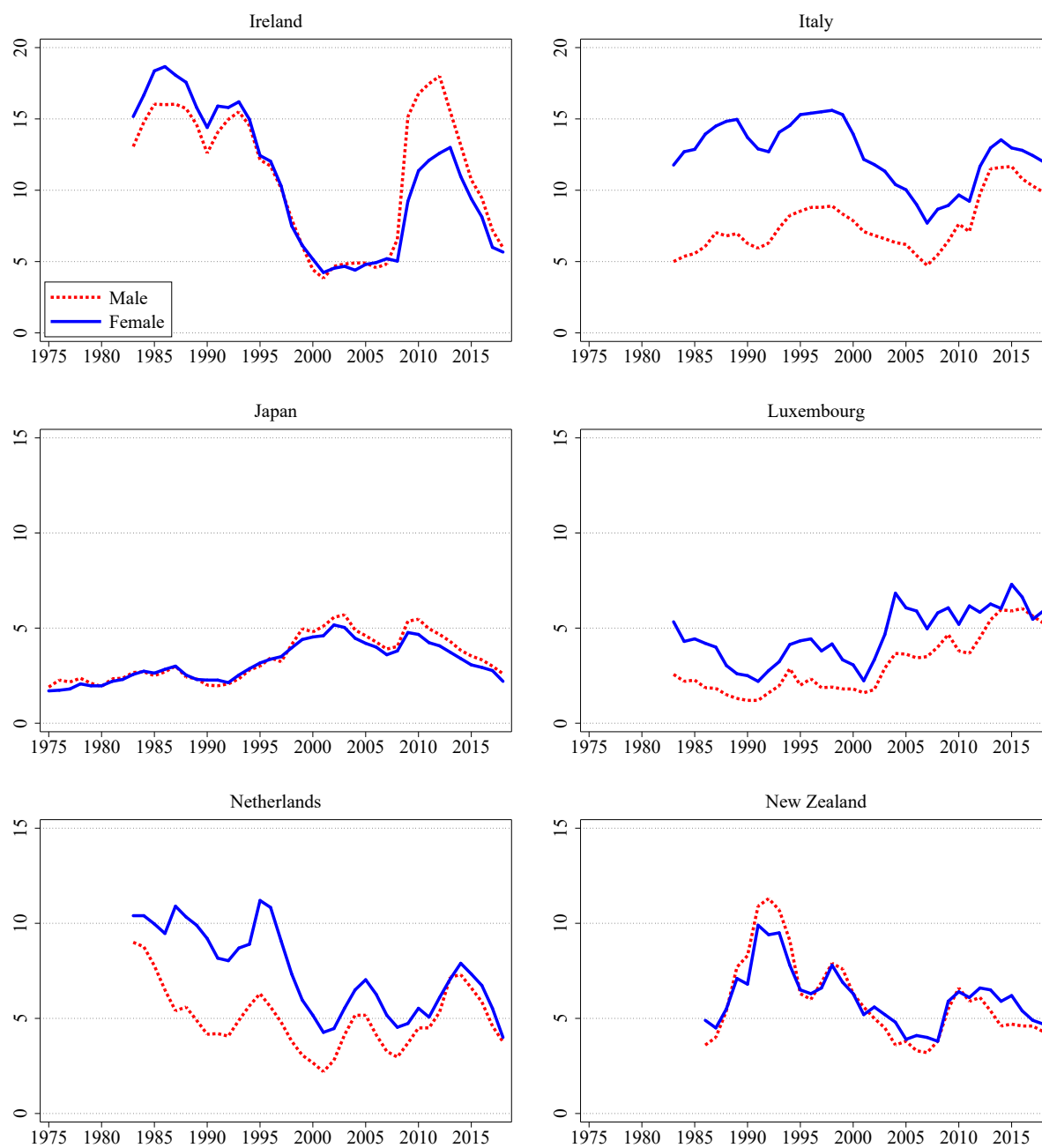Source: OECD (2018b)

FIGURE 4.1: Unemployment rate by gender across the OECD continued
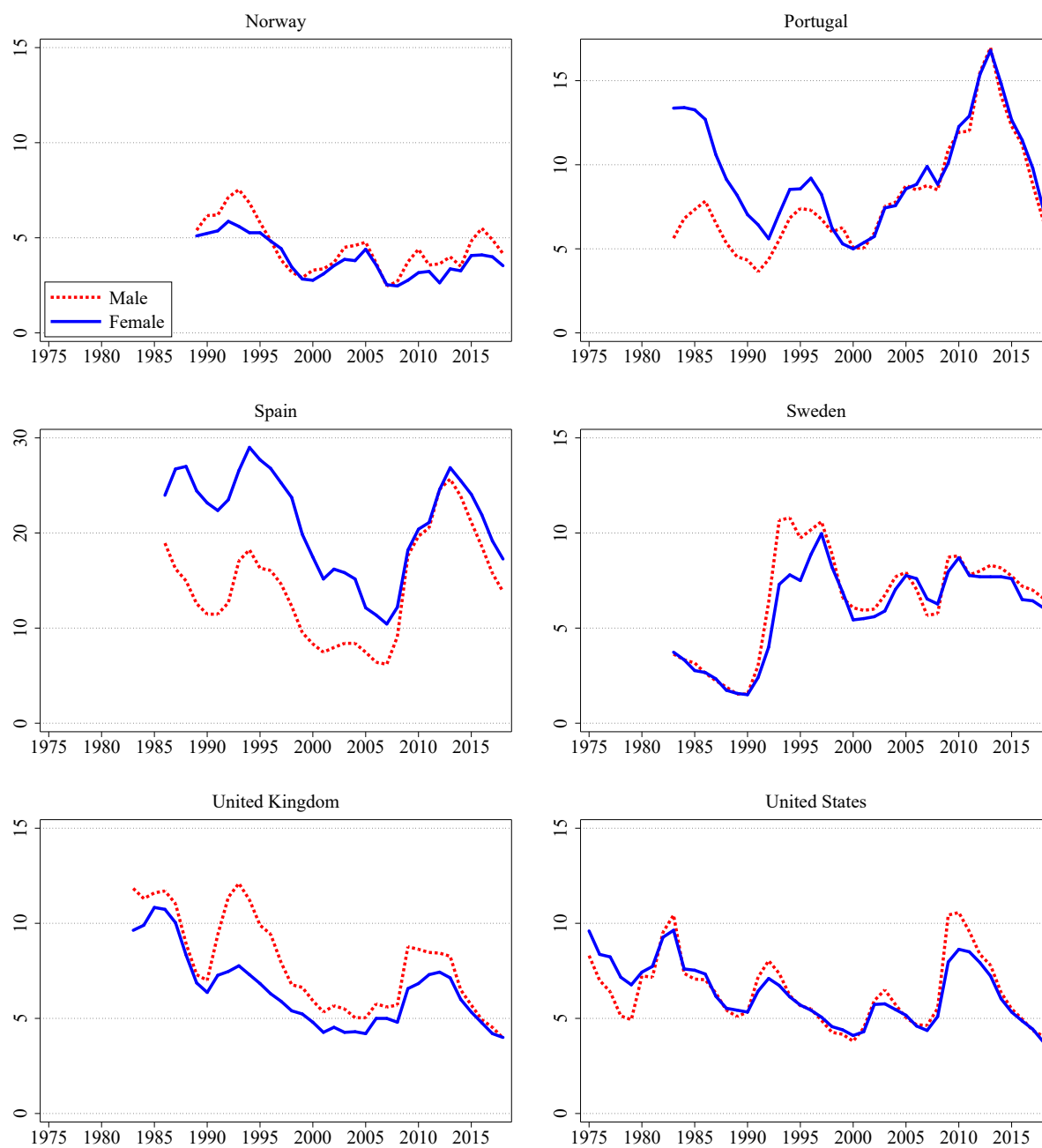Source: OECD (2018b)

FIGURE 4.1: Unemployment rate by gender across the OECD continued
Source: OECD (2018b)

	Start year	Average monthly flows						Average annual % Δ in flows between 2007 and 2009					
		s^M	s^F	f^M	f^F	$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	s^M	s^F	f^M	f^F	$s^M - s^F$	$f^M - f^F$
Australia	1978	1.79	2.01	24.78	26.68	0.89	0.93	5.20	1.69	-16.80	-4.86	3.51	-11.94
Belgium	1984	0.38	0.48	4.90	4.47	0.79	1.10	7.82	-24.57	-13.03	-13.16	32.39	0.13
Canada	1976	3.39	3.67	37.70	42.71	0.93	0.88	7.08	-0.57	-14.07	-10.85	7.65	-3.21
Denmark	1984	0.72	0.83	12.32	11.92	0.87	1.03	51.64	12.74	-8.61	-7.99	38.90	-0.62
France	1975	0.50	0.59	5.06	4.60	0.85	1.10	-3.33	1.06	-29.96	-21.05	-4.39	-8.92
Germany	1983	0.49	0.48	6.14	5.85	1.01	1.05	10.67	-12.02	-2.58	-6.23	22.68	3.65
Ireland	1984	0.56	0.81	5.01	7.92	0.69	0.63	62.34	16.72	-33.86	-27.12	45.61	-6.74
Italy	1983	0.38	0.58	4.48	4.07	0.65	1.10	16.09	-0.93	-16.26	-21.37	17.03	5.11
Japan	1977	0.34	0.51	10.68	15.99	0.68	0.67	20.75	10.73	-11.43	-11.34	10.02	-0.09
Luxembourg	1984	0.35	0.55	9.56	10.52	0.64	0.91	39.58	0.88	19.92	-21.72	38.70	41.64
Netherlands	1985	0.31	0.45	5.74	5.54	0.70	1.04	12.66	3.61	-13.04	-2.28	9.05	-10.76
New Zealand	1987	1.09	1.25	14.77	17.66	0.87	0.84	23.30	12.88	-6.32	-8.31	10.42	1.98
Norway	1983	0.77	0.74	17.70	19.75	1.03	0.90	20.24	-9.73	-4.51	-15.05	29.97	10.54
Portugal	1986	0.57	0.59	6.93	6.03	0.96	1.15	20.81	-14.88	-3.57	-14.18	35.69	10.61
Spain	1977	1.35	1.61	8.78	6.84	0.84	1.28	18.56	-0.40	-56.18	-39.28	18.96	-16.90
Sweden	1976	0.92	0.93	14.19	14.91	0.99	0.95	16.92	-4.34	-13.54	-16.26	21.25	2.72
United Kingdom	1983	0.68	0.76	8.48	11.74	0.90	0.72	20.79	-2.85	-15.67	-19.41	23.64	3.74
United States	1969	2.78	3.61	45.46	54.91	0.77	0.83	11.84	-0.08	-28.88	-29.80	11.92	0.93
Total average		0.97	1.14	13.48	15.12	0.84	0.95	20.16	-0.56	-14.91	-16.13	20.72	1.21

TABLE 4.2: The average estimates of annual unemployment flow rates by gender, and changes in the flows during the Great Recession.

Note: All series end in 2018.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

4.3 Decomposition method

In this section we outline how it is possible to decompose the non-steady-state variations of unemployment into components attributed to variations in the two unemployment flows, following Elsby et al. (2013). By taking a log-linear approximation of (C.16), the non-steady-state logarithmic variations in the unemployment rate can be written as:

$$\triangle ln(u_t) = \lambda_{t-12}\Big\{(1-u^*_{t-12})[\triangle ln(s_t) - \triangle ln(f_t)] + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}\triangle ln(u_{t-12})\Big\} + \varepsilon_t, \qquad (4.6)$$

where $\lambda = (1-e^{-12(s_t+f_t)})$. (4.6) describes a recursive relationship regarding variations in logarithmic unemployment out of steady-state. Notice that, as λ converges to one, the second term within the braces converges to zero and (4.6) collapses to its steady-state counterpart. The steady-state approximation is used in many papers including Elsby et al. (2009) and Fujita and Ramey (2009). Why do we need a non-steady-state decomposition here? The reason is two-fold. First, assuming that countries with slow flows into and out of unemployment, like many in the sample in this paper, are in steady-state, results in large errors from the decomposition. Second, because unemployment flows are, in general, slightly larger for females than males, the convergence to steady-state should be faster for females and so the errors for males are likely to be larger. In Section C.5 we show that both of these assertions are broadly true in the OECD data. To draw comparisons of unemployment dynamics between genders across many countries, therefore, requires a decomposition out of steady-state. Using (4.6), the following measures describing the percentage contributions of four distinct components are calculated:

$$\beta_f = \frac{Cov(\Delta ln(u_t), C_{f_t})}{Var(\Delta ln(u_t))}, \ \beta_s = \frac{Cov(\Delta ln(u_t), C_{s_t})}{Var(\Delta ln(u_t))}, \ \beta_0 = \frac{Cov(\Delta ln(u_t), C_{0_t})}{Var(\Delta ln(u_t))}, \ \beta_\varepsilon = \frac{Cov(\Delta ln(u_t), \varepsilon)}{Var(\Delta ln(u_t))},$$
$$(4.7)$$

where

$$C_{f_t} = \lambda_{t-12}\Big\{-(1-u^*_{t-12})\Delta ln(f_t) + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{f_{t-12}}\Big\} \text{ with } C_{f_0} = 0,$$

$$C_{s_t} = \lambda_{t-12}\Big\{(1-u^*_{t-12})\Delta ln(s_t) + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{s_{t-12}}\Big\} \text{ with } C_{s_0} = 0,$$

and

$$C_{0_t} = \lambda_{t-12}\frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{0_{t-12}} \text{ with } C_{0_0} = \Delta ln(u_0).$$

C_{s_t} and C_{f_t} describe the contributions of the contemporaneous and past variations of the ins and outs of unemployment to unemployment variation, respectively. C_0 describes deviations attributable to initial deviations from steady-state. Precisely, β_s and β_f are the percentage contribution

FIGURE 4.2: The percentage estimated monthly inflow and outflow rates by gender across the OECD

Note: Unemployment outflows on the left hand axis. Unemployment inflows on the right hand axis. Axes are in logarithmic scales.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

FIGURE 4.2: The percentage estimated monthly inflow and outflow rates by gender across the OECD continued

Note: Unemployment outflows on the left hand axis. Unemployment inflows on the right hand axis. Axes are in logarithmic scales.

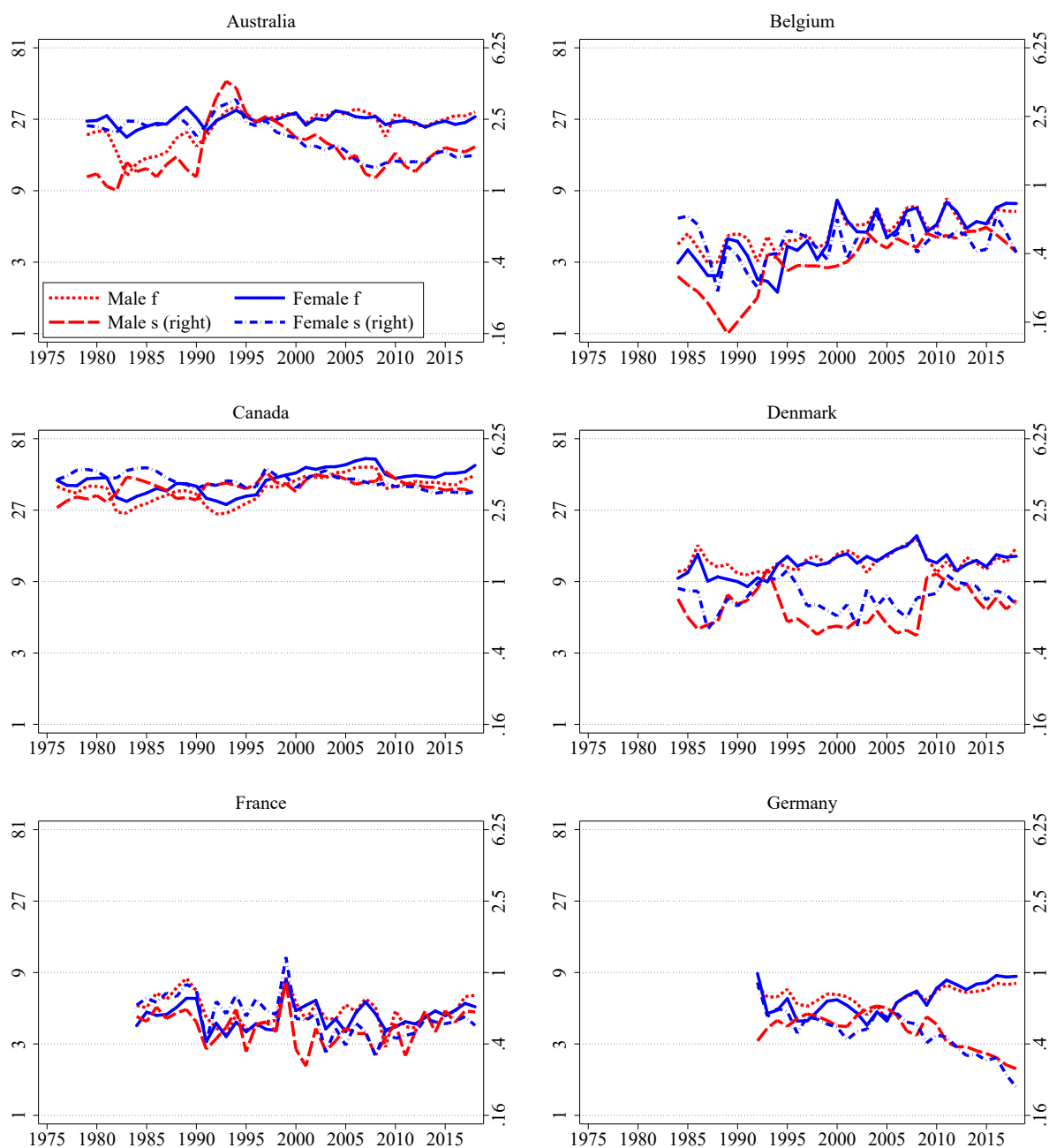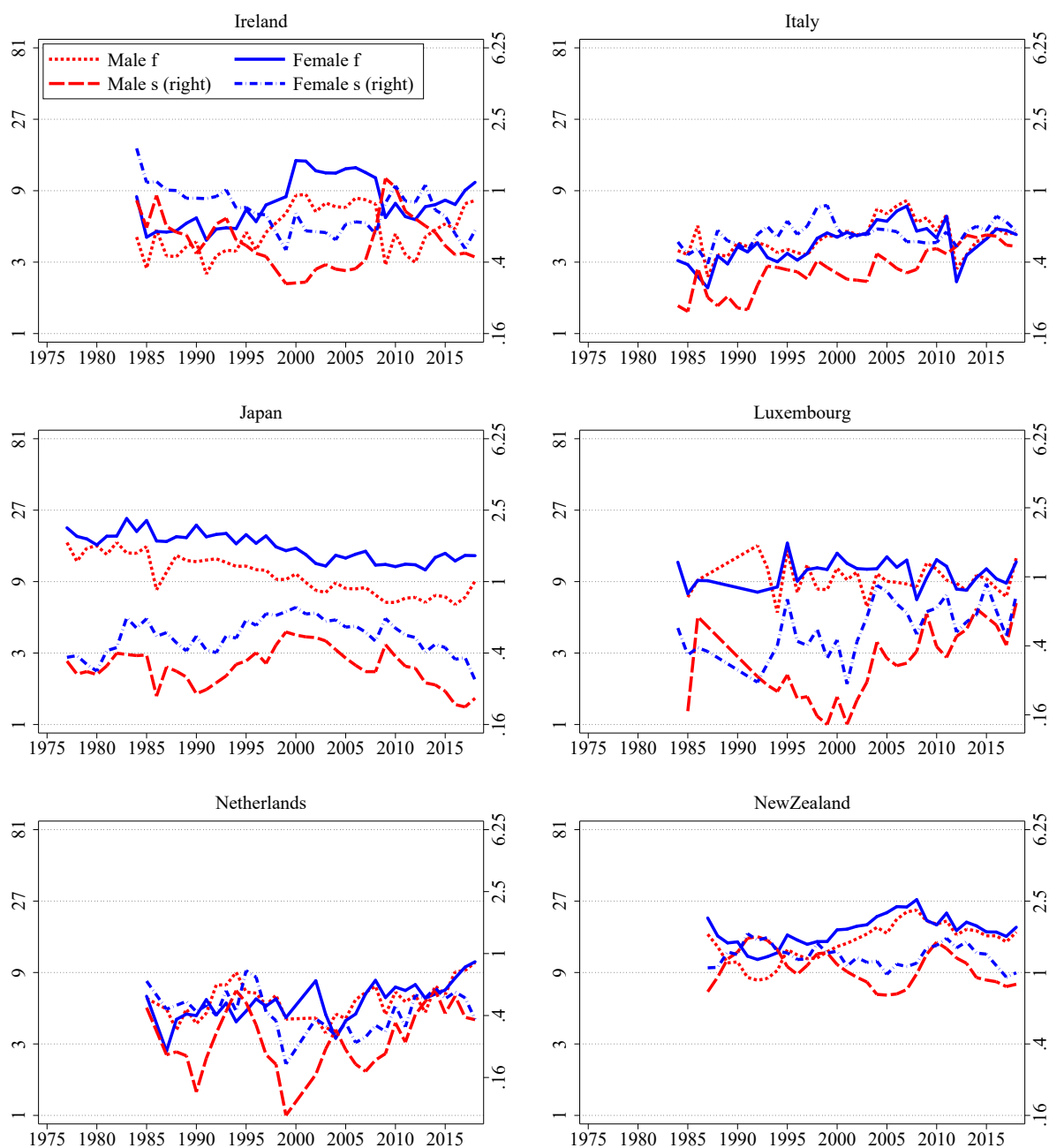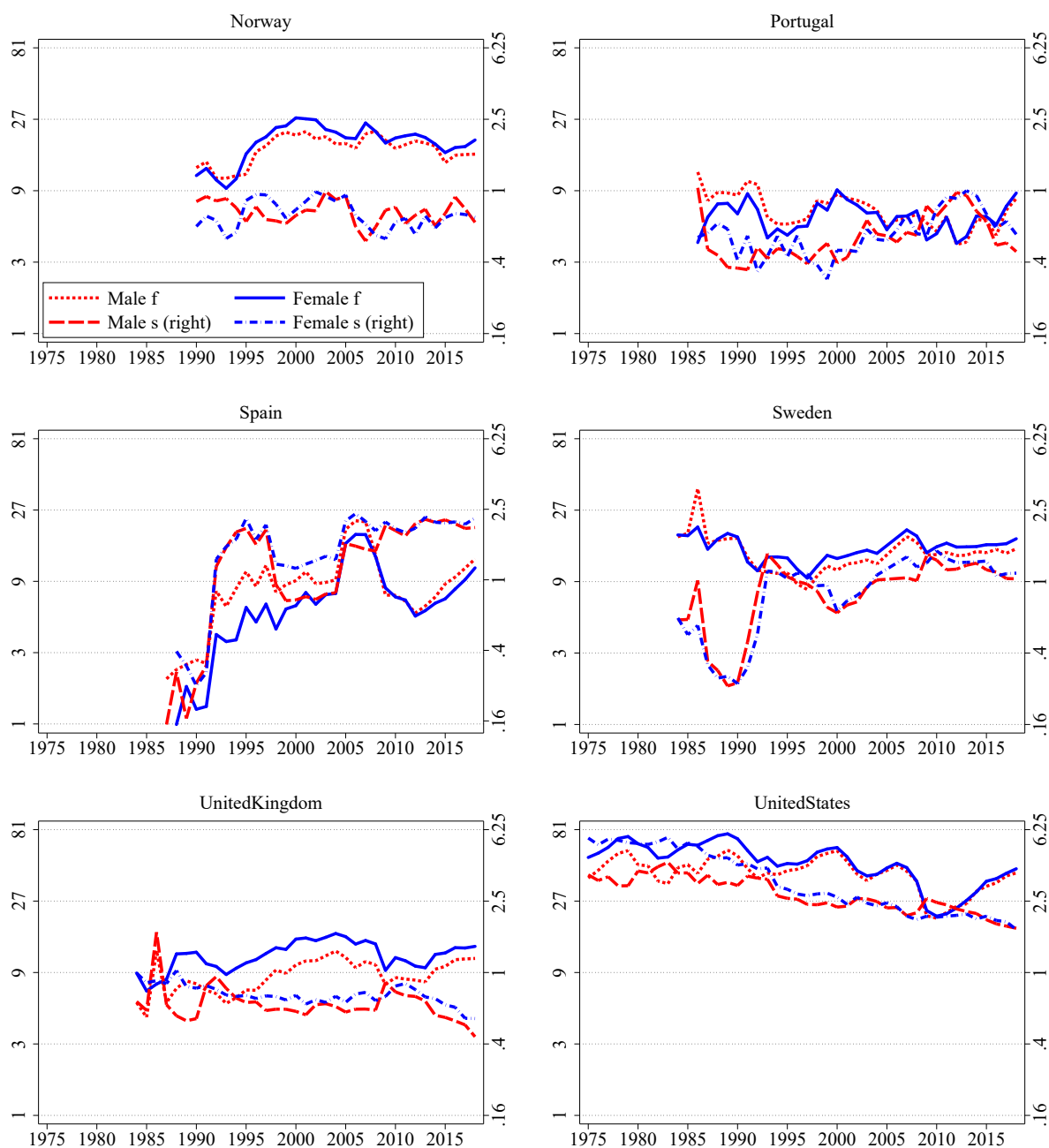Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

FIGURE 4.2: The percentage estimated monthly inflow and outflow rates by gender across the OECD continued

Note: Unemployment outflows on the left hand axis. Unemployment inflows on the right hand axis. Axes are in logarithmic scales.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

of the contemporaneous and past deviations in the ins and outs of unemployment to unemployment variation, respectively. β_0 describes the percentage contribution of initial deviations to unemployment variation, which tends to zero as the length of time increases. β_ε is the percent of unemployment variation left unexplained.

To decompose the percentage variations in the gender unemployment gap, begin with the gender unemployment gap as:

$$ln(u_t)^{Gap} = ln(u_t^M) - ln(u_t^F). \tag{4.8}$$

The deviations in the unemployment gap can, therefore, be written as:

$$\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F). \tag{4.9}$$

This gap reads, to a close approximation, the percentage change in the male unemployment rate minus the percentage change in the female unemployment rate. It is a simple extension to decompose the unemployment gap using the above methodology. For example, the percentage contributions of differences in the proportionate variations in the ins, the inflow gap, to fluctuations in the unemployment gap is calculated as

$$\beta_s^{Gap} = \frac{Cov(\Delta ln(u_t)^{Gap}, C_{s_t}^{Gap})}{Var(\Delta ln(u_t)^{Gap})}, \tag{4.10}$$

where $C_{s_t}^{Gap} = C_{s_t}^M - C_{s_t}^F$. It is worth noting that this decomposition of the unemployment gap pertains to differences in the percentage deviations in unemployment between genders. That is, if the male unemployment rate rose from 0.05 to 0.0505, and the female unemployment rate rose from 0.1 to 0.11, $\triangle ln(u_t)^{Gap} = 0$. In Section 4.6, we present a decomposition and results for deviations in unemployment rates as opposed to logarithmic deviations in unemployment rates, and show that the results remain qualitatively similar. In the next section, we present the results of the decomposition for all eighteen countries over the last 4 decades or so.

4.4 Results

Table 4.3 shows the results for the decomposition of unemployment rate variation by gender and of the gender unemployment gap. For clarification on interpretation, for male unemployment in Australia, the results read: variations in the inflows contribute to 37% of unemployment variation, variations in the outflows contribute to 66% of unemployment variation, 0% of unemployment

variation can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the variations in the unemployment rate. In line with Elsby et al. (2013), the first observation is that countries in the OECD experience very different labour market dynamics. For example, concentrating on males, for Netherlands and Italy, the outs of unemployment drive 14% and 76% of unemployment variation, respectively. A complete understanding of unemployment dynamics across countries, therefore, requires that we pay close attention to both the unemployment outflow and the unemployment inflow.

We can see clear differences in how different countries' labour markets operate, but what about differences between genders within countries? The column β_s^M-β_s^F, shows the male relative to female contributions of the ins to unemployment variation.[8] For two thirds of the countries, variations in the ins of unemployment contribute more to male unemployment variation than to female unemployment variation. Two economies that clearly divert from this trend are Japan and Luxembourg - in the latter, the ins contribute to 31% and 89% of male and female unemployment variation, respectively. On average, the ins of unemployment contribute 6% more to male unemployment variation than to female unemployment variation. As an example of how different the picture can be between genders, for the UK, the inflow:outflow contribution split to unemployment variation for males and females, respectively, is 57:43 and 21:83. These are drastically different. For males, inflows and outflows are equally important, and for females, changes in the outflows drive the vast majority of unemployment dynamics. There is clear heterogeneity in the ins and outs of unemployment between genders and by country.

The main purpose of this paper is to understand which flows contribute more to the dynamics of the unemployment gap, to which we now turn. Again, the gap that we refer to here is, differences in the logarithmic deviations in the unemployment rates between males and females. To be clear on interpretation, β_f^{Gap} for Australia reads, variations in the the outflow gap (differences in the variations of the outflows between gender) contribute to 24% of the variations in the unemployment gap. Notice that, for all countries, the contribution of variations in the inflow gap is greater than 50%. In fact, more than 80% of dynamics of the unemployment gap is explained by variations in the inflow gap for 14 of the 18 countries.[9] This is a remarkable result. When trying to understand why male and female unemployment rates change disproportionately over the cycle, one generally need only understand why the inflow is more volatile for one gender over the other.

---

[8]Notice that this would be the negative of the relative outflow measure when initial deviations from steady-state and the error play no role.

[9]The negative values associated with contributions of variations in the outflow gap, means that if the outs behaved identically for males and females, then the unemployment gap would be more volatile.

4.4.1 Focus on Recessions

Given the period of data, containing many downturns in some countries, the results do not necessarily hold when looking at any single sub-period. Using the framework described in Section 4.3, we can focus in on sub periods in the data, to see which of the flows contributed to any disproportionate changes in the unemployment rates for males and females during salient time periods. Figure 4.3 shows graphical analysis of the 1990-1995 and 2007-2012 periods using the framework described in Section 4.3. The solid lines in Figure 4.3 show the change in the gender unemployment gap relative to 1990 and 2007 for each country. More precisely, the solid line shows, the percentage change in the unemployment rate for males minus the percentage change in the unemployment rate for females relative to 1990 and 2007. A reading of 20, for example, means that the percentage increase in the male unemployment rate was 20 pp larger than the percentage increase in the female unemployment rate. The long dashed line shows the contribution to the unemployment gap of variations of the inflow gap, or C_{st}, and the short dashed line shows the contribution to the unemployment gap of variations of the outflow gap, or C_{ft}. The two dashed lines should approximately sum to the solid line since the contributions of initial deviations and the errors are in general small.

Looking at the solid line in Figure 4.3, for the majority of countries, we can see that the unemployment rate rose proportionately more for males than for females during the 1991 recession and the Great Recession. There is clear heterogeneity in the strength of the rise by country, however. In Ireland and Spain, the percentage rise in the male unemployment rate was almost 60 pp larger for males than for females in the Great Recession. For Japan and France, however, the proportionate difference in the rise between males and females was relatively small in the Great Recession.

Moving to the contributions, the larger rise in the ins for males is the main explanation for the rise in the gender unemployment gap during the 1991 recession and the Great Recession for most countries. Interestingly, the contribution of the outs is often negative, as we saw in general in the previous subsection. This means that, if the outflows for males followed the same pattern as the outflows for females, all else the same, then the rise in the gender unemployment gap during the 1991 recession and Great Recession would have been larger.[10]

---

[10]These results square well with Hoynes (2012) who shows that the layoff rate rose more for males than for females during the Great Recession in the US.
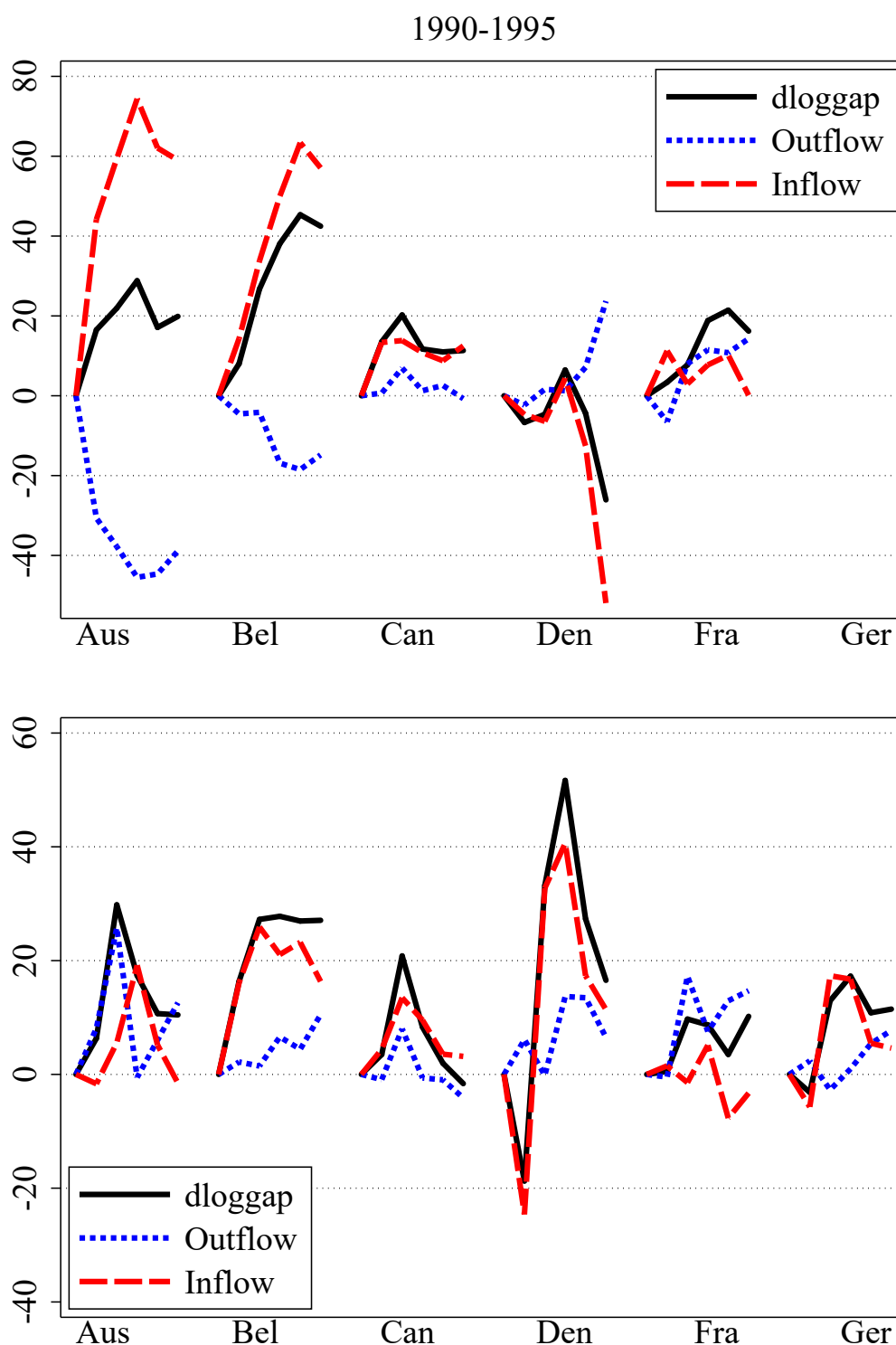
FIGURE 4.3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods

Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

1990-1995

FIGURE 4.3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods continued

Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

FIGURE 4.3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods continued

Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

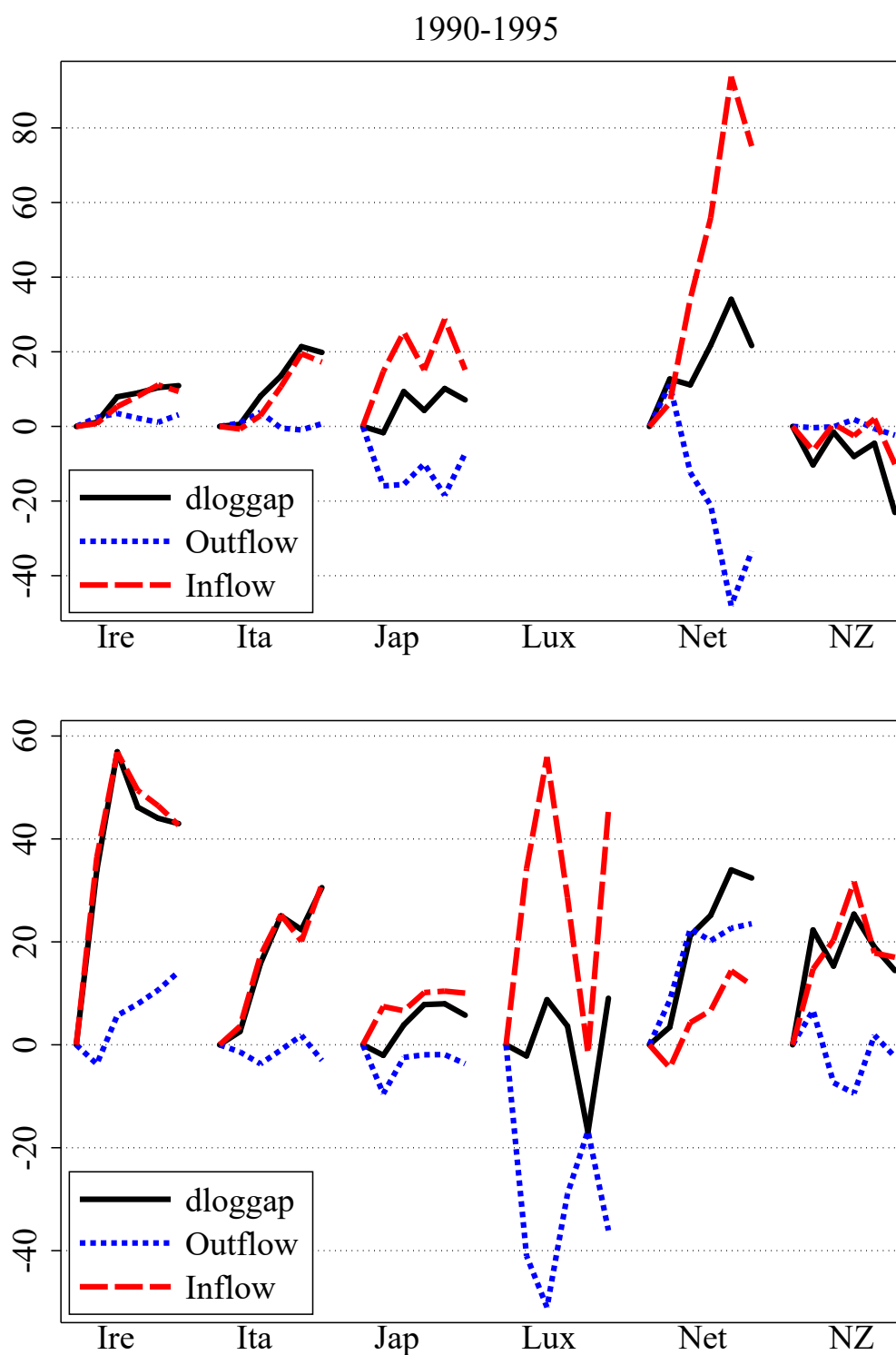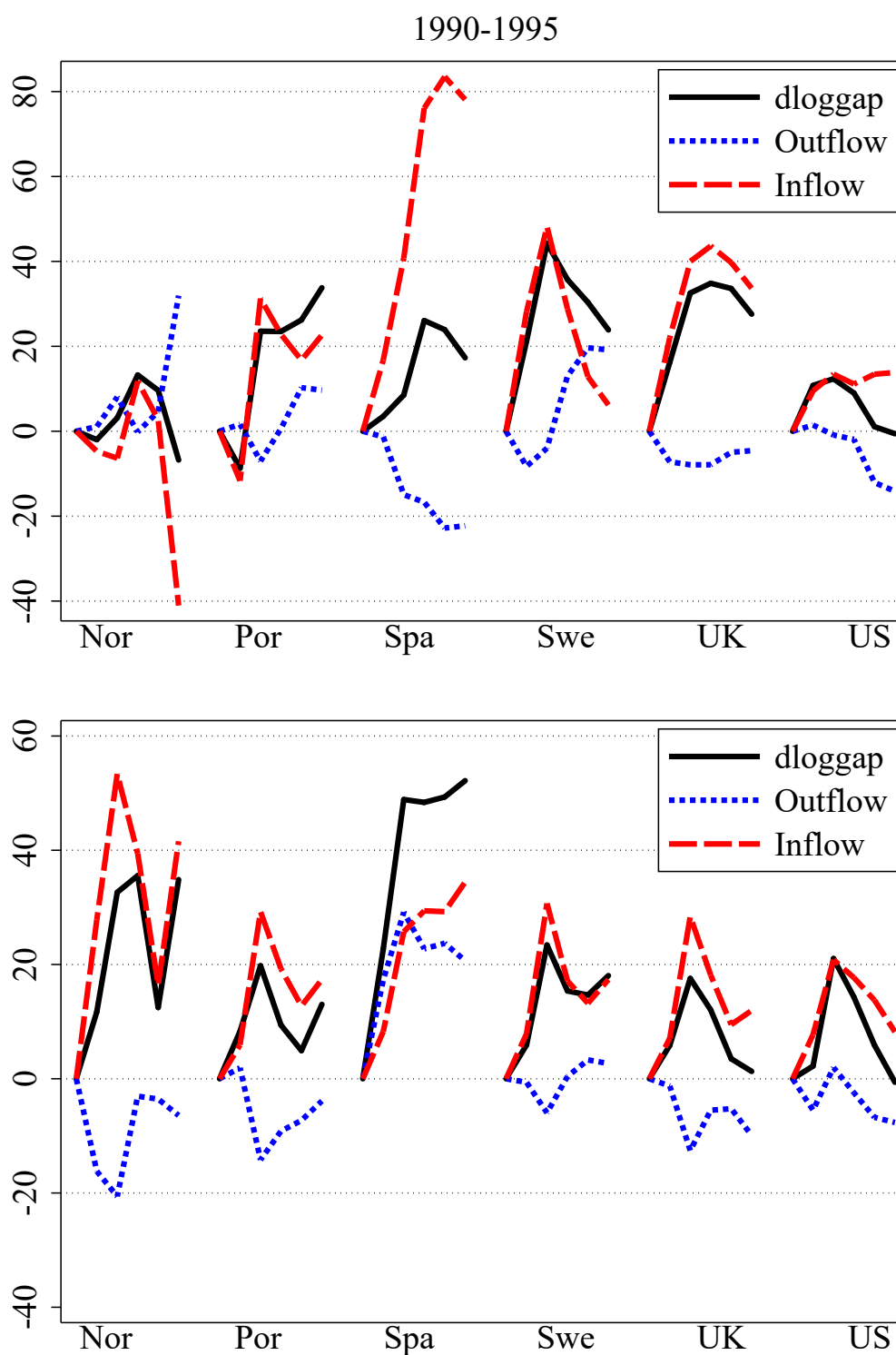|	Males				Females				Gap				
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε	$\beta_s^M - \beta_s^F$	β_f	β_s	β_0	β_ε
Australia	0.37	0.66	0.00	-0.02	0.53	0.48	0.00	-0.01	0.17	0.24	0.80	0.00	-0.04
Belgium	0.53	0.38	0.00	0.09	0.59	0.44	0.00	-0.03	-0.06	0.01	0.98	0.01	0.01
Canada	0.60	0.42	0.00	-0.01	0.66	0.34	0.00	-0.01	0.08	0.36	0.66	0.00	-0.02
Denmark	0.38	0.61	0.00	0.00	0.34	0.66	0.00	0.00	-0.06	-0.09	1.09	0.01	0.00
France	0.54	0.58	0.02	-0.14	0.36	0.69	0.02	-0.07	-0.11	0.50	0.58	0.01	-0.09
Germany	0.47	0.51	0.04	-0.02	0.84	0.12	0.06	-0.02	0.39	-0.58	1.62	-0.01	-0.03
Ireland	0.57	0.47	0.04	-0.10	0.67	0.35	0.03	-0.06	0.12	-0.02	1.05	0.02	-0.03
Italy	0.76	0.33	0.01	-0.10	1.01	0.11	0.02	-0.14	0.21	0.04	1.01	0.01	-0.05
Japan	0.51	0.48	0.00	0.01	0.30	0.70	0.00	0.00	-0.22	-0.11	1.11	0.00	0.00
Luxembourg	0.69	0.31	0.01	-0.01	0.11	0.89	0.00	-0.02	-0.59	0.05	0.90	0.04	0.03
Netherlands	0.14	0.78	0.06	-0.01	0.42	0.62	0.00	-0.01	0.16	-0.20	0.99	0.05	0.07
New Zealand	0.49	0.57	0.05	-0.11	0.52	0.51	0.02	-0.05	0.06	0.16	0.73	0.02	0.10
Norway	0.39	0.60	0.00	0.00	0.41	0.58	0.00	0.00	0.02	-0.12	1.13	0.00	0.00
Portugal	0.41	0.59	0.00	0.00	0.55	0.44	0.01	0.00	0.15	-0.32	1.32	-0.01	0.01
Spain	0.57	0.51	0.00	-0.08	0.84	0.17	0.00	-0.02	0.33	0.23	0.87	0.00	-0.10
Sweden	0.26	0.73	0.00	0.00	0.22	0.76	0.00	0.03	-0.02	-0.21	1.23	0.00	0.00
United Kingdom	0.43	0.57	0.00	0.00	0.83	0.21	0.00	-0.04	0.37	-0.24	1.19	0.01	0.03
United States	0.67	0.34	0.00	-0.02	0.79	0.22	0.00	-0.01	0.12	0.37	0.64	0.00	-0.02
Average	0.49	0.52	0.01	-0.03	0.56	0.46	0.01	-0.03	0.06	0.00	0.99	0.01	-0.01

TABLE 4.3: Contributions to unemployment variation for males, females and the gender unemployment gap

Note: Gender unemployment gap is defined as $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$. The interpretation of the Male results for Australia read: Variations in the outflows contribute to 37% of unemployment variation, variations in the inflows contribute to 66% of unemployment variation, 0% of unemployment variation can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the variations in the unemployment rate.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

4.5 Towards understanding the underlying mechanism

We have shown that the cyclical changes in the gender unemployment gap appear to be predominantly, in a lot of cases entirely, explained by differing volatilities of flows into unemployment. What is the underlying explanation for this result? In this section we document a key consistent fact across all countries: There is a positive relationship between the share of males in a sector, and the correlation of that sectors output with aggregate output.

In the US Albanesi and Sahin (2018) show that if you assign the male industry composition to the female labour force, then the rise in the gender unemployment gap during recessions would fall by about a half. That is, males tend to be in jobs that are more susceptible to economic swings than females. This suggests that output in male dominated sectors shows more cyclicality than output in female dominated sectors. To assess whether this fact is true for all countries, we compile data from the OECD on male-female sector shares, a time series of output in those sectors, and output in the aggregate.[11]

We detrend the output data using a Hodrick Prescott filter on quarterly data. We then correlate the cyclical components of sector and aggregate output, and plot these against the percentage of males by sector. Figure 4.5 shows the results of this exercise, where we have grouped all Continental European countries into one figure, and English speaking countries and South Korea into another. We find a clear positive relationship between these two measures. A regression of the correlation of sector output with overall output on the male sector share with country fixed effects, reveals a coefficient of 0.69 with a standard error of 0.11 - a 1 percentage point increase in the share of males in a sector is associated with a 0.69 percentage point increase in the correlation of a sectors output with overall output.

Figure 4.6 shows the the figure for the UK and US, with the points representing the sectors named. Again, we see a clear positive association between the two measures.[12] Output in male dominated sectors, such as Construction and Manufacturing, show a strong correlation with aggregate output. Whereas output in female dominated sectors, such as health care and education, show a weaker correlation with aggregate output over the cycle. These observations suggests an underlying story for the results on the gender unemployment gap for all countries that are documented in this paper, and reaffirms the sector story made by Albanesi and Sahin (2018) in

---

[11]Sectors that we adopt in the OECD data are, Agriculture, forestry and fishing; Industry; Manufacturing; Construction; Distribution, trade, accommodation and food services; IT and communications; Finance and insurance; Real estate; Scientific and administration; Public admin, health and education.

[12]In the Appendix we show a clear positive association for almost all countries included in Figure 4.5.
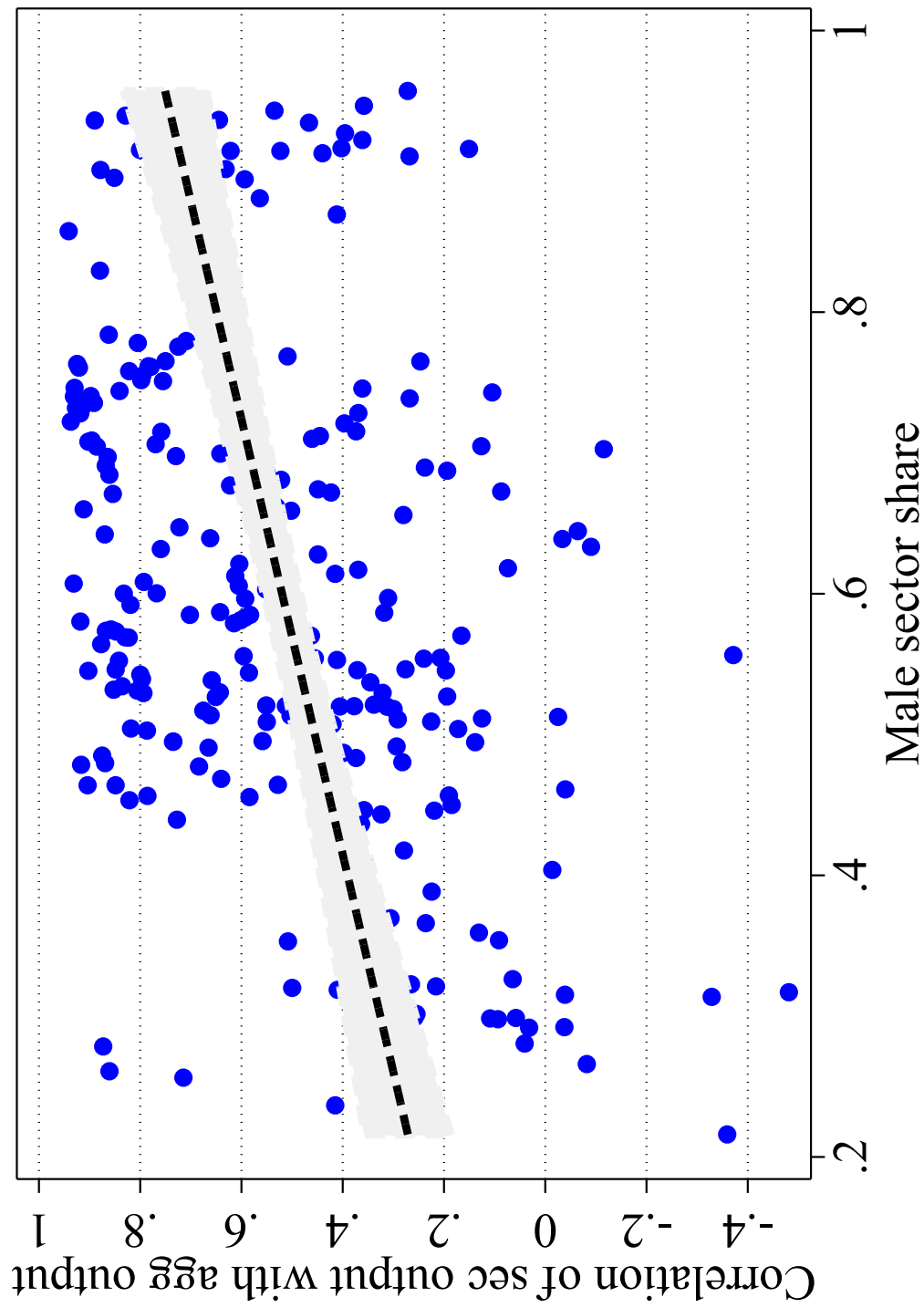
FIGURE 4.4: Relationship between male share and the correlation of sector output with overall output. Note: Countries included are Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom and United States. Excluded Agricultural sector.

FIGURE 4.5: Relationship between male share and the correlation of sector output with overall output for Continental European (top), and English speaking and South Korea (bottom).
Note: Countries included in the top figure are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain and Sweden. Countries included in the bottom figure are Canada, Ireland, Japan, United Kingdom and United States. Excluded Agricultural sector.
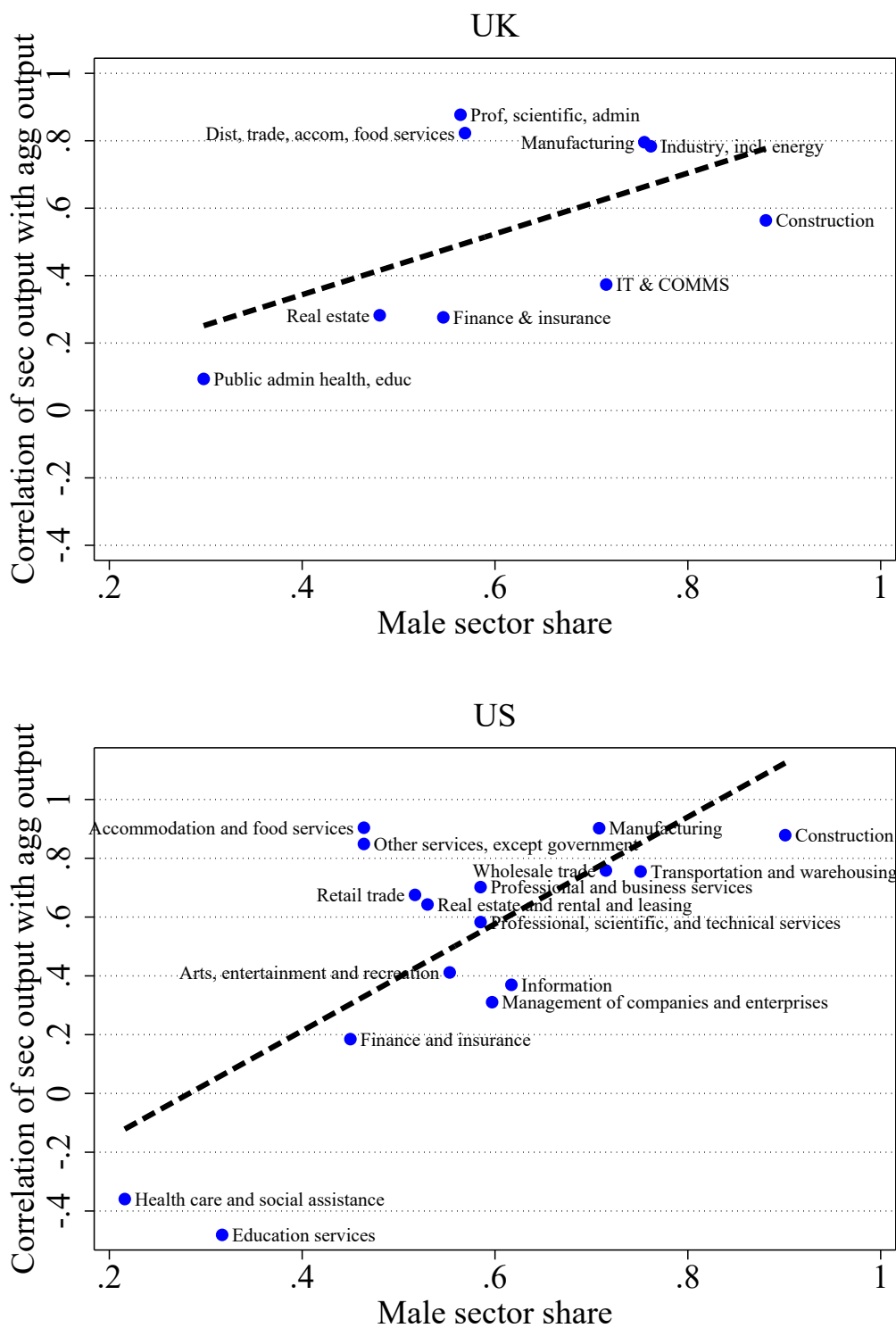
FIGURE 4.6: Relationship between male share and the correlation of sector output with overall output for UK (top), and US (bottom).

Note: Excluded Agricultural sector.

the US: males are hired into sectors that are more susceptible to economic swings, which in turn means the average precarity of male jobs falls more in recessions relative to females.

4.6 Further discussion and robustness

The preceding sections have demonstrated that the differing cyclicality of the inflow between males and females is the main explanation for the dynamics of the unemployment gap, and that one of the underlying explanations for this is the male-female composition by sector. In this section, we discuss whether any simplifications from the analysis may affect these results, and provide recent related statistics regarding the 2020 crisis.

Logarithmic vs non-logarithmic (levels) decomposition

The baseline decomposition is one of differences in logarithmic deviations in the unemployment rates by sex. What if we were instead interested in differences in deviations in the unemployment rates by sex. We can assess whether an analysis of levels results in any clear differences using a slight modification of the decomposition in Section 4.3. We write down changes in the unemployment rate as

$$\Delta u_t = (1 - e^{-12(s_t + f_t)})\Delta u_t^* + e^{-12(s_t + f_t)}\Delta u_{t-12} + \varepsilon_t. \tag{4.11}$$

As with the logarithmic decomposition, changes are equal to a distributed lag of changes in the steady state level, and also an initial condition. Notice that

$$\Delta u_t^M - \Delta u_t^F = u_t^{Gap} - u_{t-t}^{Gap} = \Delta u_t^{Gap}, \tag{4.12}$$

where $u_t^{Gap} = u_t^M - u_t^F$. This, therefore, allows us to determine the contributions of deviations in inflow gap and outflow gap to changes in unemployment gap.[13] Table C.11 shows the results using this decomposition compared with the logarithmic decomposition described in Section 4.3. The results are very similar.

The participation entry margin

The analysis in this paper has been conducted from a two state perspective, employment and unemployment. Elsby et al. (2015) show that flows at the participation margin, into and out of inactivity, are important for understanding the overall dynamics of unemployment. It is

---

[13]We provide further mathematical details in Section C.4.

plausible, therefore, that the results documented previously are due to flows between participation and non-participation.

In Section 4.2, the main piece of information used to estimate the unemployment flows is unemployment by duration, in particular the percent of the labour force who have been unemployed for less than one month. This stock contains workers who have just left their job and moved into unemployment, but also workers who have just entered the labour force and moved into unemployment. Taking into account flows into and out of the labour force, we can write the steady state unemployment rate as

$$u_t^* = \frac{s_t}{s_t + f_t} = \frac{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne} + \lambda_t^{nu}}}{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne} + \lambda_t^{nu}} + \lambda_t^{ue} + \frac{\lambda_t^{un}\lambda_t^{ne}}{\lambda_t^{ne} + \lambda_t^{nu}}}, \tag{4.13}$$

where λ_t^{ij} represents the monthly transition probability from state i to state j at time t, and e and n refer to employment and inactivity rates at time t. The separation and job finding rates are inflated by flows from inactivity. It is possible that some of the contributions of the inflows to the dynamics of the unemployment gap, should be attributed to variations of transitions at the participation entry margin.

Here we assess whether the percentage increase in the inactivity to unemployment rate during recessions is stronger for males than for females for a select few countries. The reality of the added worker effect would suggest the opposite (see recent work on the added worker effect in Mankart and Oikonomou (2016)) - females are more likely to enter unemployment from inactivity during recessions to mitigate the consequences of spousal job loss. This would mean that the contribution of employment to unemployment transitions is actually downward biased.

We collect data on inactivity to unemployment transitions from Ireland, the UK and the US. Figure 4.7 shows the log changes in the inactivity to unemployment transition probability from 2007 - 2012, relative to 2007, for each country. If the dynamics of the unemployment gap are driven by differences in variations of the inactivity to unemployment transitions between genders as opposed to employment to unemployment transitions, we would expect to find larger percentage increases in inactivity to unemployment transitions for males over females. There is no clear evidence of this for this sub-sample of countries. In fact, for the UK the rise is far larger for females than males.
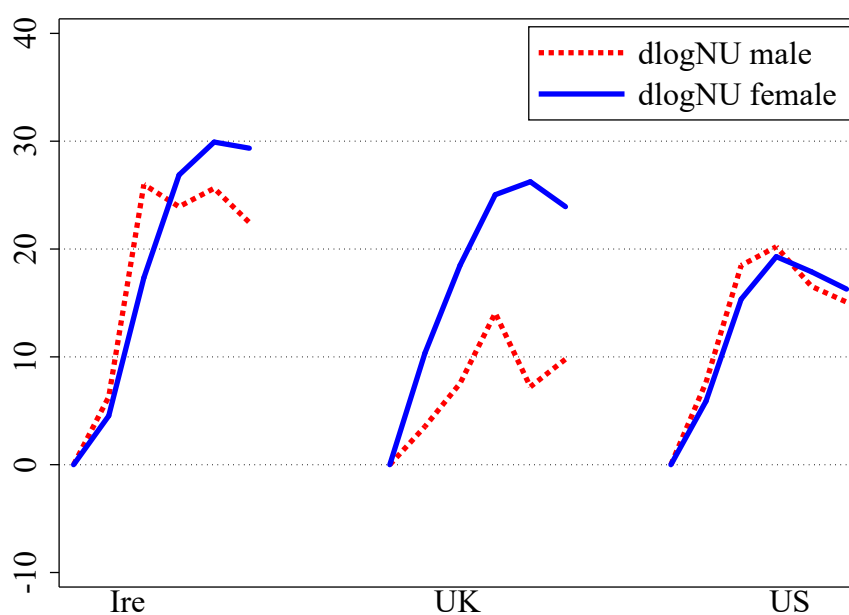
FIGURE 4.7: The percentage change in the inactivity to unemployment probability between 2007-2012, relative to 2007.
Source: Data compiled from the Irish LFS and UK LFS, author calculations. US data taken from BLS (2018).

Time aggregation

Using the OECD data, we are only able to estimate annual flows, a relatively low frequency. Estimating flows with low frequency data may create issues of time aggregation - one may miss many transitions between survey dates. Shimer (2012) shows, however, that the technique used for estimating the inflow in this paper corrects for this bias. It is possible, however, that the outflow measure misses some exits from unemployment. This is likely to be negligible for two reasons. First, any biases will be significant if inflows back into unemployment are large. As we have seen in Table 4.2, the inflows are very small and so the number of outflows that are missed is likely small. Second, because we are focusing on differences between genders, any small biases will affect both males and females in a similar way. It is likely, therefore, that the impact of time aggregation is very small.

Cross country comparison

Because of the difference in available data, some countries in the sample have longer periods, and some short. Unemployment flows for the US can be estimated for 5 decades, and unemployment flows for New Zealand can only be estimated for just over 3 decades. It is of interest to see if

the results are similar when looking at a more recent period that is common to all, for example 2000-2018.[14] Table C.12 shows the results for the entire period and the 2000-2018 period accompanied with the ratio of unemployment flows between males and females. First, focusing on the unemployment flows, the difference in the size of the inflows has reduced in recent times on average suggesting a convergence in the trend of males and female outcomes in recent times (Albanesi and Sahin (2018)). The contributions to changes in the unemployment gap, however, are very similar. The results described in Section 4.4 are not driven by any one sub-period in the data and seem to persist even when the average inflows between males and females converge.

4.7 Conclusion

This paper has assessed why the variance of unemployment is so markedly different between genders in many labour markets. The disparity is due to either, differences in the variations of flows into unemployment, or differences in variations of flows out of unemployment. Using publicly available harmonised data from 18 OECD countries over the last 4 decades or so, we have shown that the variations in the gender unemployment gap are mostly due to differences in the variations of the inflows for males relative to females. In fact, more than 80% of dynamics of the unemployment gap is explained by differences in the variations of the ins for 14 of the 18 countries. Using data on output by sector and male sector share, we have also found that sectors that employ more males, seem to more susceptible to economic swings. Which is a consistent result across all countries.

These results paint a clear and simple picture behind the dynamics of the gender unemployment gap across countries in the OECD. Males tend to sort into sectors where output declines more in recessions. This in turn increases the average precarity of a male's job more than for a female. Which increases unemployment inflows more for males then for females.

Sectoral composition, however, is undoubtedly not the only explanation behind why males tend to experience greater increases in inflows during recessions. Avenues for future work should be to uncover further asymmetric features behind male and female unemployment inflow dynamics.

---

[14]The OECD has gone to great lengths to harmonise the statistics, precisely so cross-country comparisons can be made. In particular, for unemployment, the OECD have created a blanket criteria to assign a survey participant as unemployed, precisely the information used in this paper.

Chapter 5

Conclusion

This thesis presents three essays, each related to aspects of labour market dynamics. Chapter 2 provides considerable evidence that workers can anticipate job loss in the UK labour market, and respond by changing search behaviour to avoid unemployment. The chapter then proceeds to develop a job ladder model where workers may receive information of impending job loss. The model estimates reveal that between a half and two-thirds of workers have knowledge of impending layoff, on average about three months in advance of unemployment. Counterfactuals show that the ability to anticipate job loss provides sizeable welfare gains to workers, with the most important behavioural change being to increase search. Chapter 3 and Chapter 4 both study questions related to unemployment dynamics using the flows approach. Chapter 3 argues that to understand why the unemployment rate rises during recessions and falls during expansions, incorporating job-to-job transitions is paramount for a full understanding of the role of changes in job finding and changes in layoffs. Finally, Chapter 4 studies why variations in unemployment rates are so markedly different between genders across a large group of countries over the last four decades. The results reveal that larger rises in unemployment inflows for males is the main driver. The chapter then proceeds to show that a candidate explanation for this result is gender composition by sector: males tend to be in sectors that are more susceptible to economic swings, which in turn increases the average precarity of male jobs more than females in recessions.

To focus on Chapter 2, more work is needed into understanding how workers change their behaviour before job loss. Displacement is one of the most fundamental features of a well functioning economy, that on average provides significant hardship to whomever it falls upon. But not all workers fare so badly following layoff. Those who find work quickly, without even transitioning into unemployment, seem to experience much smaller earnings losses in the short and long run, as shown in Chapter 2. Policies devoted to promoting faster reallocation to new employment may be extremely beneficial to workers, whilst maintaining labour market dynamism. Studying these policy questions in a context where workers can anticipate unemployment seems like a fruitful direction for further study.

107

Appendix A

A.1 Further empirical details

Subjective elicitations

Here I provide more information regarding anticipatory behaviour using subjective elicitations in the BHPS. In waves 2, 4, 6 and 8, workers are asked how likely they are to lose their job in the next year. Possible answers are, Very Unlikely, Unlikely, Likely, and Very Likely. Table A.11 shows the proportions of each answer given for all workers and those who subsequently do lose their job. Around 8% of individuals think they are likely or very likely to lose their job in the next year. Inline with Figure 2.3, for workers who lose their job in the subsequent 12 months, more high skill than low skill workers report that they are very likely to lose their job.

	Very unlikely	Unlikely	Likely	Very likely
		All employed		
All	54.50	37.78	5.69	2.03
Low skill	53.16	38.72	6.10	2.02
High skill	55.93	36.78	5.25	2.04
		Within 12 months of layoff		
All	28.19	34.75	17.55	19.50
Low skill	31.31	34.09	17.51	17.09
High skill	23.65	35.71	17.61	23.03

TABLE A.11: Answer by percentages to job security question

Note: Question - in the next 12 months, how likely do you think it is that you will become unemployed? High skill is defined as those who have more than A levels.
Source: Data from the BHPS.

How are these elicitations connected to actual job insecurity? While elicitations are clearly subjective and likely imperfect, we can use these measures to assess whether workers have valid

information of impending job loss, and to see whether workers who declare that their job is insecure are also more likely to switch jobs involuntarily. To do so I run the following linear probability model

$$y_{it} = \alpha_i + \gamma_t + X_{it}\beta + \delta_U U_{it} + \delta_L L_{it} + \delta_{VL} VL_{it} + \varepsilon_{it}, \tag{A.1}$$

where y_{it} is either, an indicator variable taking the value 1 if the individual moves to unemployment between periods t and t+1 and 0 if the worker remains at their employer, or taking the value 1 if the individual moves to a new employer involuntarily between periods t and t+1 and 0 if the worker remains at their employer. α_i and γ_t are individual and time fixed effects, respectively. X_{it} contains observables - a quartic in age. The variables of interest are whether a worker describes the likelihood of losing their job in the next 12 months as, Unlikely (U), Likely (L), and Very Likely (VL). The coefficients, should be interpreted as relative to saying that the likelihood of your job terminating is Very Unlikely.

	All *eu*	Low skill *eu*	High skill *eu*	All *jji*	Low skill *jji*	High skill *jji*
δ_U	.004**	.005**	.004**	.002*	.001	.005**
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
δ_L	.032**	.033**	.033**	.024**	.022**	.028**
	(.002)	(.003)	(.003)	(.002)	(.003)	(.002)
δ_{VL}	.163**	.169**	.160**	.175**	.170**	.182**
	(.004)	(.006)	(.005)	(.003)	(.005)	(.004)
N	126,766	61,861	64,905	125,799	61,365	64,434

TABLE A.12: Job security elicitations and outcomes

Note: The top left coefficient reads, those who report their job to be unlikely to end in the next twelve months are 0.4 percentage points more likely to lose their job in the next twelve months than those who report that their job is very unlikely to end. Standard errors in parentheses. All regressions include a quartic polynomial in age, person dummies, and time dummies as controls. High skill is defined as those who have more than A levels. *, ** indicate statistical significance at 5% and 1% levels, respectively.
Source: Data from the BHPS.

Table A.12 shows the results for both transitions and by education. Focusing on columns 1 to 3, workers subjective reading of their own job insecurity has important explanatory power. The probability that a worker will move into unemployment for those who report that they are very likely to lose their job is around 16 percentage points larger than those who report that their job is very unlikely to end. Moving to columns 4 to 6, the probability that a worker will switch

jobs involuntarily for those who report that they are very likely to lose their job is around 17.5 percentage points larger than those who report that their job is very unlikely to end.

These results provide two insights, firstly workers have clear private information of impending job loss and respond by increasing the likelihood of switching a job involuntarily. Second, ignoring involuntary job-to-job transitions will result in significantly underestimating the explanatory power of a worker's subjective reading of their own job insecurity.

The costs of job loss and pre-layoff search in numbers

	All layoffs				Layoffs to employment		
	y		y		y		y
δ_{-4}	.024	δ_6	-.128**	δ_{-4}	.032	δ_6	-.031
	(.017)		(.021)		(.026)		(.032)
δ_{-3}	.020	δ_7	-.105**	δ_{-3}	.031	δ_7	-.034
	(.017)		(.022)		(.026)		(.035)
δ_{-2}	.027	δ_8	-.115**	δ_{-2}	.025	δ_8	-.022
	(.017)		(.023)		(.025)		(.038)
δ_{-1}	.010	δ_9	-.086**	δ_{-1}	.005	δ_9	.011
	(.017)		(.025)		(.025)		(.041)
δ_0	-.413**	δ_{10}	-.061**	δ_0	-.149**	δ_{10}	-.024
	(.017)		(.027)		(.025)		(.043)
δ_1	-.274**	age	.231**	δ_1	-.143**	age	.235**
	(.017)		(.040)		(.026)		(.041)
δ_2	-.211**	age^2	-.008**	δ_2	-.082**	age^2	-.009**
	(.018)		(.002)		(.027)		(.002)
δ_3	-.176**	age^3	.000	δ_3	-.082**	age^3	.000
	(.018)		(.000)		(.028)		(.000)
δ_4	-.143**	age^4	-.000	δ_4	-.023	age^4	-.000
	(.019)		(.000)		(.029)		(.000)
δ_5	-.127**			δ_5	-.036		
	(.020)				(.031)		
N	355,494				348,424		

TABLE A.13: The empirical costs of job loss for all job losers and those who switch jobs following layoff

Note: The top left coefficient reads, workers who will be laid off in four years time earn 2.4% more than those who will not be laid off in four years time. Standard errors in parentheses. Both regressions include individual and time fixed effects. *, ** indicate statistical significance at 5% and 1% levels, respectively.

	All	Think	Skill Low	Skill High	Tenure Low	Tenure High	Firm size Small	Firm size Large	Age 25-40	Age 41-55	Sex Male	Sex Female
δ^{-1}	.203**	.158**	.169**	.316**	.184**	.210**	.202**	.180**	.202**	.204**	.179**	.241**
	(.007)	(.002)	(.008)	(.016)	(.016)	(.008)	(.015)	(.016)	(.012)	(.009)	(.009)	(.012)
δ^{-2}	.042**	.025**	.029**	.085**	.060**	.035**	.048**	.051**	.041**	.039**	.038**	.048**
	(.007)	(.002)	(.008)	(.016)	(.016)	(.008)	(.015)	(.016)	(.011)	(.009)	(.009)	(.011)
δ^{-3}	.008	.007**	.003	.024	.040**	-.005	.024	.020	.015	-.001	.006	.011
	(.007)	(.002)	(.008)	(.016)	(.016)	(.008)	(.015)	(.016)	(.011)	(.009)	(.009)	(.011)
N (m.)	1.16	1.16	.84	.33	.22	.94	.19	.24	.51	.65	.60	.56

TABLE A.14: Pre-layoff search by different types

Note: The top left coefficient reads, the proportion of workers who report to be searching is 20.3 percentage points higher for those who lose their job in one quarter relative to those who do not and the proportion searching four quarters before job loss. Note: Standard errors in parentheses. All regressions include a polynomial in age, and time and person fixed effects. 1995Q1 - 2016Q1. *, ** indicate statistical significance at 5% and 1% levels, respectively.

Value functions
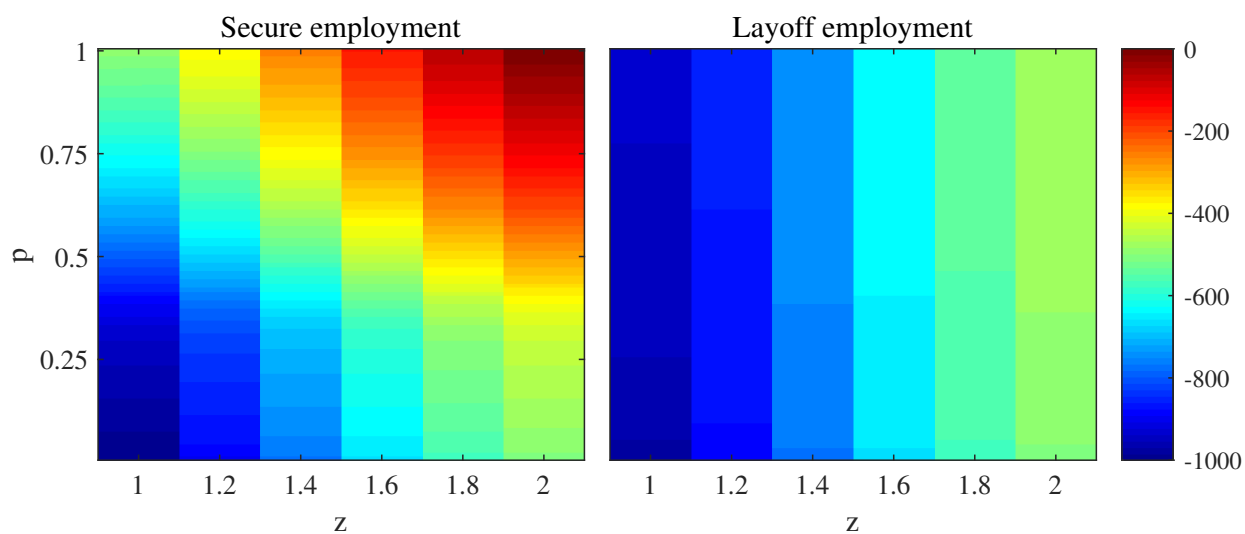
FIGURE A.11: Value functions with zero assets: secure employment and layoff employment

Note: Showing values for $V_i(p,z,a=0)$. p is the firm productivity. z is human capital level. The worker has zero assets, $a=0$.
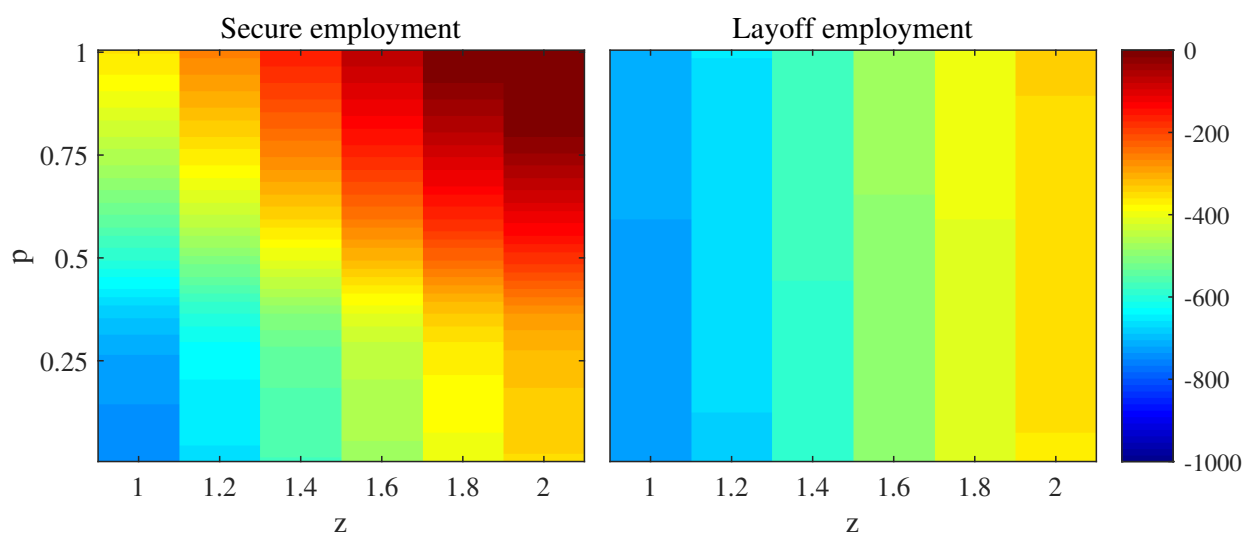
FIGURE A.12: Value functions with significant assets: secure employment and layoff employment

Note: Showing values for $V_i(p,z,a=100)$. p is the firm productivity. z is human capital level. The worker has an asset level with approximately four lots of the average annual income, $a=100$.
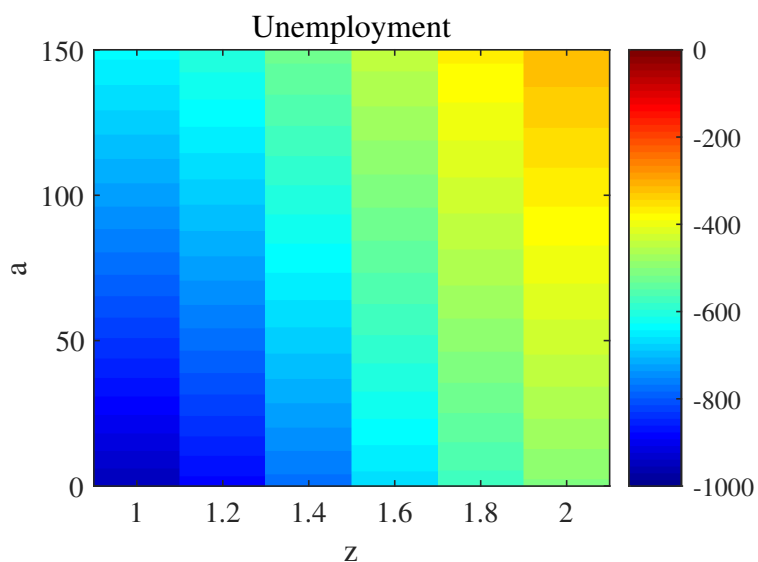
FIGURE A.13: Value functions: unemployment

Note: Showing values for $V_u(z,a)$. z is human capital level. a is the asset level.
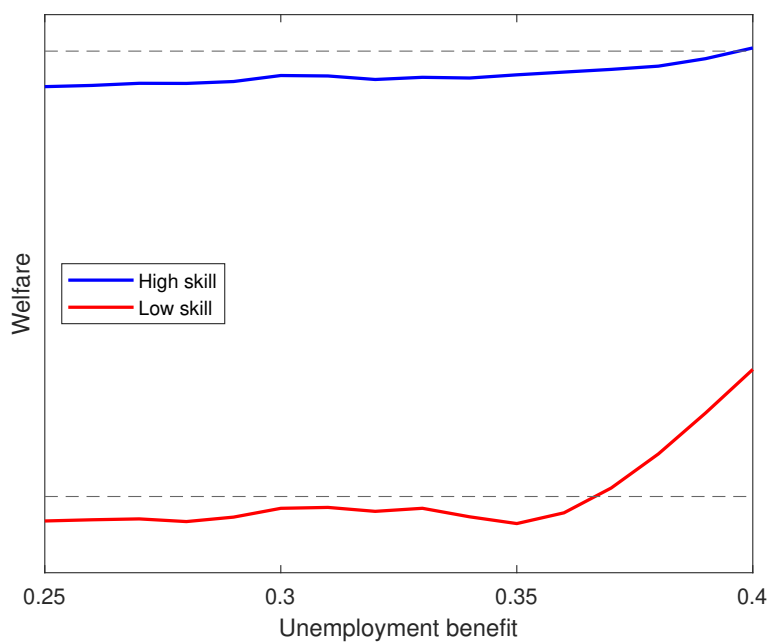
FIGURE A.14: Changes in non-financed unemployment benefits

Note: These figures are used to calculate unemployment benefits in column 3 in Table 2.6. The dotted lines represent the welfare in the baseline economy for low skill at the bottom, and high skill at the top.

Switching off human capital dynamics

Figure A.15 shows the model losses in Section 2.6 without stochastic human capital compared to those with stochastic human capital. The overall earnings losses, shown in the left hand panel, quickly dissipate when workers do not lose human capital in unemployment. As argued by the majority of the literature, stochastic human capital is an important feature to incorporate in models that aim to replicate the unemployment scar.

We can also see that the costs of job loss for those who switch jobs is not affected by variations in human capital. This highlights that the incorporation of human capital in the model raises the value of anticipating job loss, since the costs of unemployment are increased.
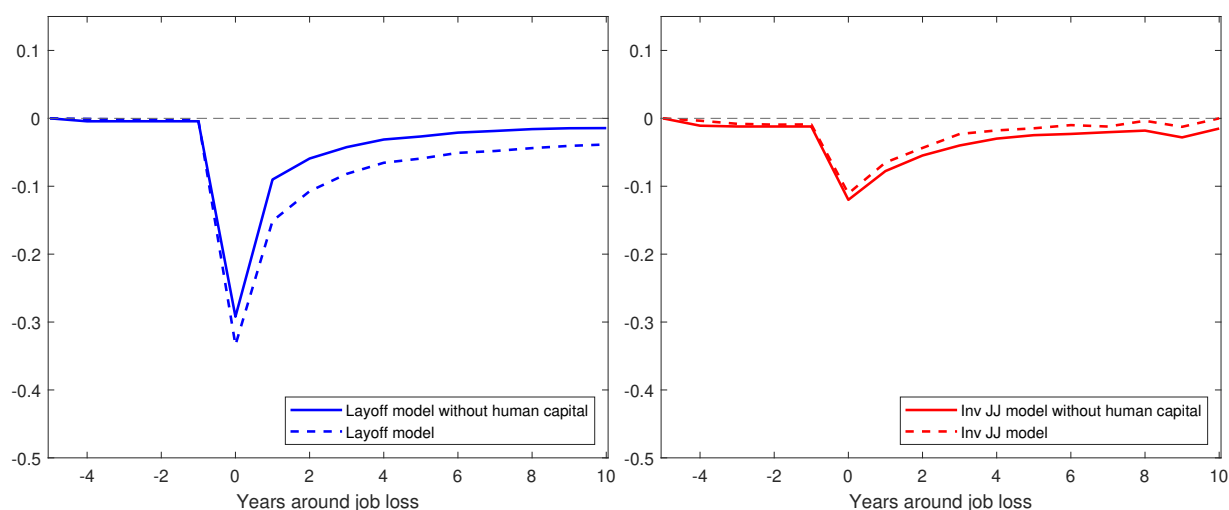
FIGURE A.15: Earnings losses: model with and without stochastic human capital

Further figures on notice periods
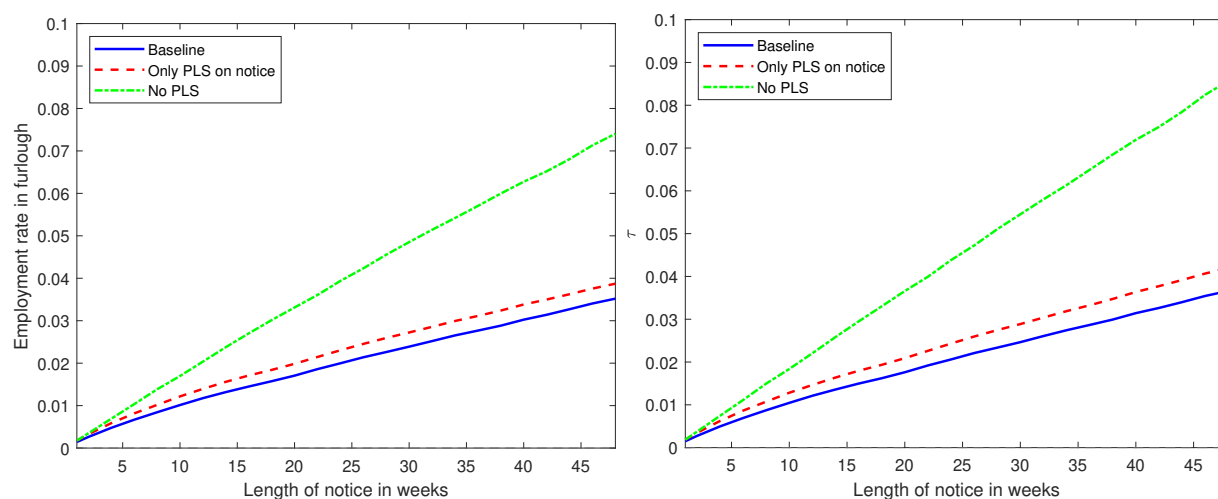
FIGURE A.16: The employment rate on notice and the required tax rate to finance the scheme

Note: τ is required tax rate that the government must use in order to finance the three schemes and balance the budget. The horizontal axis shows $\frac{1}{\delta_N}$.

Unemployment benefit-welfare schedule

Does this distortion impact the optimal level of benefits? In Figure A.17, I present how welfare in the economy changes relative to the estimated model with unemployment benefits equal to 0.25, for all, low and high skill workers separately. The model suggests that aggregate welfare is always falling in unemployment benefits taxed through labour income. The distortion in the schedule brought on by pre-layoff search is small.

A Low skilled

B High skilled

C All workers
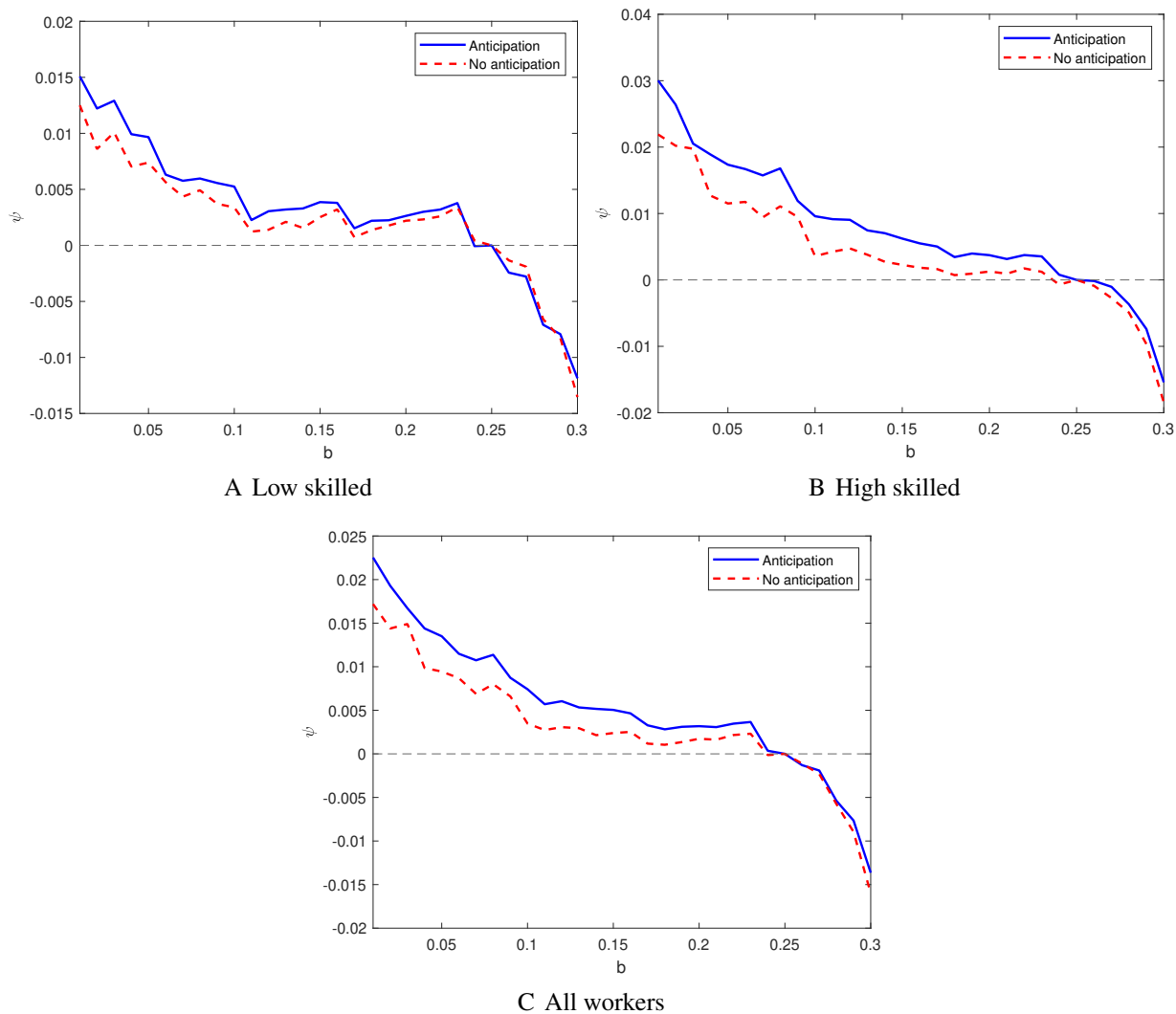
FIGURE A.17: Optimal unemployment benefits

Note: b does not represent the unemployment replacement rate. The replacement rate at a value of $b = 0.25$ is approximately 0.5.

A.2 Survey questions and categorisations

In the text, I make use of information on the reasons for separation provided by the worker. Here I describe how I categorise whether a worker leaves their job voluntarily or involuntarily, and also why a worker is searching on the job.

LFS

In the LFS I use information on the reported reason for separation for the last job to estimate the pre-layoff search in the data, and also as moments to fit with the model. I define separations as involuntary and voluntary using the following categorisations.

Question: Why did you leave your last job?

Involuntary - *Dismissed, made redundant*
Voluntary - *Resigned, took voluntary redundancy*.

Workers also provide other answers that I ignore when calculating the ratio of involuntary separations to overall separations as a moment in the data. The ignored answers are

Temporary job finished, took early retirement, retired, gave up work for health reasons, gave up work for family or personal reasons, left work for some other reason.

I also make use of information on why a worker is searching. In Figure 2.2, I describe how the proportion of workers who report to be working because they think their job may end. We can see this highlighted in the following list.

Question: Why are you searching for a new job?

Present job may come to an end, *present job to fill time before finding another, pay unsatisfactory, journey unsatisfactory, wants longer hours, other aspects unsatisfactory, searching for some other reason*.

BHPS

To estimate the cost of job loss for those making involuntary job to job transitions, as seen in Figure 2.1, I need to categorise involuntary separations in the BHPS. I do so using the following categorisations that are consistent with those in the LFS

Question: Which of the statements on the card best describes why you stopped doing that job?

Involuntary - *Made redundant, dismissed/sacked*

Other reasons that workers give are

Temporary job ended, promoted, left for a better job, took retirement, health reasons, left to have a baby, look after family, look after another person, moved area, started college/university, other reason.

A.3 Mathematical details

Proof of Proposition 1(i) and (ii)

In order to show that $p_L(p,z,a) \leq p$ and $s_L(p,z,a) \geq s_S(p,z,a)$, from (2.10) and (2.11), we must show that

$$V_L(p,z,a) \leq V_S(p,z,a) \; \forall \; p \in [p_U(z,a),1]. \tag{A.2}$$

I first show that $p_U(z,a)$ is unique. By taking the derivative of (2.7) and (2.8) and two applications of the envelope theorem, we have

$$\frac{\partial V_S(p,z,a)}{\partial p} = \frac{\partial u}{\partial c}\frac{dc}{dp} + \beta \, \mathbb{E}\left[\frac{\partial V_S(p,z',a')}{\partial p}\big(1 - \delta - s_S(p,z,a)\lambda[1 - F(p)]\big) + \delta\phi\frac{\partial V_L(p,z',a')}{\partial p} \right], \tag{A.3}$$

and

$$\frac{\partial V_L(p,z,a)}{\partial p} = \frac{\partial u}{\partial c}\frac{dc}{dp} + \beta \, \mathbb{E}\left[\frac{\partial V_L(p,z',a')}{\partial p}\big(1 - \delta_L - s_L(p,z,a)\lambda[1 - F(p_L)]\big) \right]. \tag{A.4}$$

Since $\frac{\partial u}{\partial c}\frac{dc}{dp} > 0$, it follows that (A.3) and (A.4) are both positive.[1] Since $\frac{\partial V_U(z,a)}{\partial p} = 0$, there must be a unique productivity that a worker in unemployment is willing to accept. So $\forall p \in (p_U^*(z,a),1]$, $V_S(p,z,a) > V_U(z,a)$. In layoff employment a higher weight is placed on the value of unemployment, which implies that $\forall p \in (p_U(z,a),1]$, $V_S(p,z,a) > V_L(p,z,a)$. ‖

Proof of Proposition 1(iii)

Lemma 1: *when $w(p,z) = pz$, without stochastic human capital, $p_U(z,a) = b/z$.*

Begin with the definition $V_S(p_U(z,a),z,a) - V_U(z,a) = 0$,

$$u\big(c(p_U(z,a),z,a)\big) - u\big(c(z,a)\big) + \beta \Bigg[(1 - \delta)(V_S(p_U^*(z,a),z,a') - V_U(z,a'))$$

$$+ s_S(p_U^*(z,a),z,a)\lambda \int_p V_S(x,z,a') - V_S(p,z,a')dF(x) - s_U(z,a)\lambda \int_p V_S(x,z,a') - V_U(z,a')dF(x) \Bigg]$$

$$+ \kappa(s_S(p_U^*(z,a),z,a)) - \kappa(s_U(z,a)) = 0. \tag{A.5}$$

---

[1]Following the same process, it is straight forward to show that $\frac{\partial V_S(p,z,a)}{\partial z} > 0$, $\frac{\partial V_L(p,z,a)}{\partial z} > 0$, $\frac{\partial V_S(p,z,a)}{\partial a} > 0$ and $\frac{\partial V_L(p,z,a)}{\partial a} > 0$, since $\frac{dc}{dz} > 0$ and $\frac{dc}{da} > 0$.

Looking at (2.9) and (2.10), and assuming that at this point the asset choice is independent of the state, $s_S(p_U(z,a),z,a) = s_U(z,a)$ and $V_S(p_U(z,a),z,a') - V_U(z,a') = 0$, (A.5) collapses to

$$u\big(c(p_U(z,a),z,a) = u\big(c(z,a)\big). \tag{A.6}$$

Looking at (2.12) and (2.13), and assuming that at this point the search effort is the same, $a'_S(p_U(z,a),z,a) = a'_U(z,a)$. (A.5) again, collapses to (A.6). ‖

Lemma 1 states that, in a world without human capital,

$$\frac{\partial u(c(b,z,a))}{\partial c} > \frac{\partial u(c(p,z,a))}{\partial c} \ \forall \ p \in (b/z,1]. \tag{A.7}$$

I re-wright the relevant Euler equations for the readers ease, where $\phi = 1$.

$$\frac{\partial u}{\partial c} = (1+r)\beta\left[\frac{\partial u_S}{\partial c_S}\left(1-\delta\right) + \delta\frac{\partial u_U}{\partial c_U} + s_S(p,z,a)\lambda\int\frac{\partial u_S}{\partial c_S}(x) - \frac{\partial u_S}{\partial c_S}dF(x)\right] \tag{A.8}$$

and

$$\frac{\partial u}{\partial c} = (1+r)\beta\left[\frac{\partial u_L}{\partial c_L}\left(1-\delta_L\right) + \delta_L\frac{\partial u_U}{\partial c_U} + s_L(p,z,a)\lambda\int\frac{\partial u_S}{\partial c_S}(x) - \frac{\partial u_L}{\partial c_L}dF(x)\right].^2 \tag{A.9}$$

Since, the LHS of (A.8) and (A.9) are of the same functional form, it follows that $a'_L \geq a'_S$ if the RHS of (A.9) is weakly greater than the RHS of (A.8) - if the RHS is greater in (A.9) than (A.8), it will result in a movement up the marginal cost line.

From lemma 1, $a'_S(b/z,z,a) = a'_U(z,a)$. The exact same process implies that $a'_S(b/z,z,a) = a'_L(p/z,z,a)$. Because of (A.7), and $\delta_L > \delta$, $p > b/z$ implies that the RHS of (A.9) is greater than the RHS of (A.8). ‖

Derivation of (2.19) and further discussion of pre-layoff search dynamics

Here I describe how to derive (2.19). As stated in the text, we are interested in the following probability

$$P(\text{In layoff employment at time } t-j \mid \text{Laid off at time } t) = P(LOEmp_{t-j}|LO_t). \tag{A.10}$$

---

[2]It is sufficient to show the case when $\phi = 1$, as I have shown in (A.8).

This probability tells us the proportion of workers who are in layoff employment during the period j periods prior to losing their job. Using Bayes' rule we have

$$P(LOEmp_{t-j}|LO_t) = \frac{P(LO_t|LOEmp_{t-j})P(LOEmp_{t-j})}{P(LO_t)}. \tag{A.11}$$

Inline with the pre-layoff search documented in the paper, all these probabilities should be interpreted as given that a worker is employed in either secure or layoff employment states between $t-T$ and t. The probabilities on the right hand side can be derived in steady state. $P(LO_t|LOEmp_{t-j})$ is equal to the probability of not leaving layoff employment for $j-1$ periods, $(1-\delta_L-\bar{s}_L\lambda\overline{F}(\overline{p}_L))^{j-1}$, multiplied by the probability of being laid off, $\delta_L+\bar{s}_L\lambda\overline{F}(\overline{p}_L)$ (remembering that any transition out of layoff employment is defined as a layoff)

$$P(LO_t|LOEmp_{t-j}) = (1-\delta_L-\bar{s}_L\lambda\overline{F}(\overline{p}_L))^{j-1}(\delta_L+\bar{s}_L\lambda\overline{F}(\overline{p}_L)), \tag{A.12}$$

where $\bar{s}_L\lambda$ denotes the average job finding probability for all workers in layoff employment, and $\overline{F}(\overline{p}_L)$ denotes the average job acceptance probability. We can derive the proportion of the employed in layoff employment, $P(LOEmp_{t-j})$, by writing the markov chain describing the dynamics of the three labour market states and then solving for the limiting distribution. The markov chain is written as

$$\begin{bmatrix} P(Sec\hat{E}mp) \\ P(LO\hat{E}mp) \\ P(Un\hat{e}mp) \end{bmatrix}_t = \begin{bmatrix} 1-\delta & \bar{s}_L\lambda\overline{F}(\overline{p}_L) & \bar{s}_U\lambda\overline{F}(\overline{p}_U) \\ \delta\phi & 1-\bar{s}_L\lambda\overline{F}(\overline{p}_L)-\delta_L & 0 \\ \delta(1-\phi) & \delta_L & 1-\bar{s}_U\lambda\overline{F}(\overline{p}_U) \end{bmatrix}_t \begin{bmatrix} P(Sec\hat{E}mp) \\ P(LO\hat{E}mp) \\ P(Un\hat{e}mp) \end{bmatrix}_{t-1}. \tag{A.13}$$

Since $P(Sec\hat{E}mp)_t + P(LO\hat{E}mp)_t + P(Un\hat{e}mp)_t = 1$, we can reduce the matrix and solve for steady state. The steady state probability of being in layoff employment as a percentage of the employment pool is given as

$$\frac{P(LO\hat{E}mp)}{P(LO\hat{E}mp)+P(Sec\hat{E}mp)} = P(LOEmp) = P(LOEmp_{t-j}) = \frac{\delta\phi}{\delta\phi+\delta_L+\bar{s}_L\lambda\overline{F}(\overline{p}_L)}. \tag{A.14}$$

Finally, the probability of being laid off, $P(LO_t)$, in steady state is given as

$$P(LO_t) = P(LOEmp)(\delta_L+s_L\lambda\overline{F}(\overline{p}_L))+P(SecEmp)\delta(1-\phi) \tag{A.15}$$

Incorporating the steady state rate probabilities, one can arrive at the following layoff probability

$$P(LO_t) = P(LO) = \frac{\delta(\delta_L + \bar{s}_L \lambda \overline{F}(\overline{p}_L))}{\delta\phi + \delta_L + \bar{s}_L \lambda \overline{F}(\overline{p}_L)}. \tag{A.16}$$

Combining these probabilities, it is straight forward to see that

$$P(LOEmp_{t-j}|LO_t) = \frac{P(LO_t|LOEmp_{t-j})P(LOEmp_{t-j})}{P(LO_t)} = (1 - \delta_L - \bar{s}_L \lambda \overline{F}(\overline{p}_L))^{j-1}\phi. \tag{A.17}$$

As described in Section 2.3, the model analogue of *PLS* (pre-layoff search) can be written as

$$PLS_{t-jT} = \big(P(Search|LOEmp) - P(Search|SecEmp)\big)P(LOEmp_{t-j}|LO_t). \tag{A.18}$$

We know that $P(Search|LOEmp) - P(Search|SecEmp)$ is positive, since $s_L(p,z,a) \geq s_S(p,z,a)$, where this difference essentially determines how many workers actually react "enough" to the realisation of increased job insecurity such that they would deem themselves as actually searching on the job - $P(Search|LOEmp)$ is not necessarily equal to 1. The level of $P(Search|LOEmp)$ is determined by the model structure, parameterisations, and the cutoff rule that is used to match the proportion of the employed who are searching in the data. The probability is particularly important in determining ϕ. Remember that $P(LOEmp_{t-1}|LO_t) = \phi$. Using (A.18), we can write

$$\phi = \frac{PLS_{t-1T}}{P(Search|LOEmp) - P(Search|SecEmp)}. \tag{A.19}$$

Notice that, as the denominator decreases - fewer workers in layoff employment respond enough to the increased likelihood of unemployment to be deemed as searching - ϕ must increase in order to match the level of pre-layoff search just before job loss, PLS_{t-1T}.

Finally, note that the pre-layoff search documented in Section 2.2 is at a quarterly frequency, while the model frequency is a week. There is, therefore, a slight discrepancy between pre-layoff search in the data and that derived here. Let us assume that layoffs are equally likely across all weeks in a quarter, and that a quarter is equal to 12 weeks. Pre-layoff search i quarters before job loss, where j represents the number of weeks before job loss as above, is given as

$$\begin{aligned}
PLS_{t-i} &= \frac{\sum_{j=1}^{12} PLS_{t-j-12(i-1)}}{12} \\
&= \big(P(Search|LOEmp) - P(Search|SecEmp)\big)\phi \frac{\sum_{j=1}^{12}(1 - \delta_L - \bar{s}_L \lambda \overline{F}(\overline{p}_L))^{j-1+12(i-1)}}{12}.
\end{aligned} \tag{A.20}$$

Notice that the ratio of pre-layoff search at consecutive quarters can be simplified to

$$\frac{PLS_{t-(i-1)}}{PLS_{t-i}} = (1 - \delta_L - \bar{s}_L \lambda \overline{F}(\overline{p}_L))^{12}. \tag{A.21}$$

The ratio of pre-layoff search between two consecutive quarters is equal to probability of remaining in layoff employment, raised to the power of the number of periods within the quarter.

Derivation of search effort

Here I derive search effort in secure employment as a function of the model parameters. Begin with search effort as a function of the value functions, and evaluate the underlying integral by integration by parts giving

$$
\begin{aligned}
s_S(p,z,a) &= \gamma \left(\beta \, \mathbb{E}_{z'|z} \left[\lambda \int_p V_S(x,z',a_S') - V_S(p,z',a_S') dF(x) \right] \right) \\
&= \gamma \left(\beta \, \mathbb{E}_{z'|z} \left[\lambda \int_p \frac{\partial V_S(x,z',a_U')}{\partial x} \overline{F}(x) dx \right] \right).
\end{aligned}
\tag{A.22}
$$

The second equals sign is true under the assumption that, if $V_U(z,a) = V_S(p_U(z,a),z,a)$, then $\mathbb{E} V_U(z',a') = \mathbb{E} V_S(p_U(z,a),z',a')$. In reality this is only approximately true because human capital falls in unemployment and increases in employment. Now all we need is the derivative of the value function with respect to productivity. Under the same assumption, we can rearrange equation (A.3) and (A.4), respectively, as

$$\frac{\partial V_S(p,z,a)}{\partial p} = \frac{\frac{\partial u}{\partial c}\frac{dc}{dp} + \beta \delta \phi \frac{\partial V_L(p,z,a)}{\partial p}}{1 - \beta(1 - \delta - s_S(p,z,a)\lambda \overline{F}(p))}, \tag{A.23}$$

and

$$\frac{\partial V_L(p,z,a)}{\partial p} = \frac{\frac{\partial u}{\partial c}\frac{dc}{dp}}{1 - \beta(1 - \delta_L - s_L(p,z,a)\lambda \overline{F}(p_L(p,z,a)))}. \tag{A.24}$$

The derivative of the value function with respect to p in secure employment is a function of the same derivative in layoff employment. This reflects the increased security gained from anticipatory behaviour, which increases the gains from an increase in productivity in secure employment. Substituting (A.24) into (A.23), and then into (A.22), and using the parameterised cost of search

function, results in search effort as a function of the model parameters, given as

$$s_S(p,z,a) = \left(\beta \, \mathbb{E}_{z'|z} \left[\frac{\lambda}{\kappa_0} \int_p \frac{\frac{\partial u}{\partial c}\frac{dc}{dp} + \frac{\beta \delta \phi \frac{\partial u}{\partial c}\frac{dc}{dp}}{1-\beta[1-\delta_L-\lambda s_L(x,z',a'_L)\overline{F}(p_L(x,z',a'_L))]}\overline{F}(p_L(x,z',a'_L))}{1-\beta[1-\delta-\lambda s_S(x,z',a'_S)\overline{F}(x)]} \overline{F}(x) dx \right] \right)^{\kappa_1}. \qquad (A.25)$$

Under the same assumptions, search effort for the unemployed and those in layoff employment have the same functional form but are instead integrated over the respective reservation productivities, $p_U(z,a)$ for the unemployed and $p_L(p,z,a)$ for the layoff employed.

Including notice in the model

To include notice in the model, now only those who are in notice can transition into unemployment, where the notice ends with probability δ_N. There is no change to the value function for the unemployed. The other value functions, secure employment and stable employment now become

$$V_S(p,z,a) = \max_{s_S,a'_S} \left\{ u(a(1+r) + w(p,z) - a'_S) - \kappa(s_S) + \beta \, \mathbb{E}_{z'|z} \left[V_S(p,z',a'_S) \right. \right.$$
$$\left. \left. + s_S \lambda \int_p \left(V_S(x,z',a'_S) - V_S(p,z',a'_S) \right) dF(x) + \delta \left(\phi V_L(p,z',a'_S) + (1-\phi)V_N(z',a'_S) - V_S(p,z',a'_S) \right) \right] \right\},$$

$$(A.26)$$

and

$$V_L(p,z,a) = \max_{s_L,a'_L} \left\{ u(a(1+r) + w(p,z) - a'_L) - \kappa(s_L) + \beta \, \mathbb{E}_{z'|z} \left[V_L(p,z',a'_L) \right. \right.$$
$$\left. \left. + s_L \lambda \int_{p_L(p,z',a'_L)} \left(V_S(x,z',a'_L) - V_L(p,z',a'_L) \right) dF(x) + \delta_L \left(V_N(p,z',a'_L) - V_L(p,z',a'_L) \right) \right] \right\}.$$

$$(A.27)$$

V_N is the present discounted value of notice employment and given as

$$V_N(p,z,a) = \max_{s_N,a'_N} \left\{ u(a(1+r) + w(p,z) - a'_N) - \kappa(s_N) + \beta \, \mathbb{E}_{z'|z} \left[V_N(p,z',a'_N) \right. \right.$$
$$\left. \left. + s_N \lambda \int_{p_N(p,z',a'_N)} \left(V_S(x,z',a'_N) - V_N(p,z',a'_N) \right) dF(x) + \delta_N \left(V_U(z',a'_N) - V_N(p,z',a'_N) \right) \right] \right\}.$$

$$(A.28)$$

c_0 and welfare

When determining welfare, the cost of search function plays an important role, especially when determining the value of realising job insecurity has increased. c_0 should, therefore, play an important role in the value of welfare. This is true but imprecise. What really matters is the following ratio, that I pin down in the estimation procedure,

$$\frac{\lambda^{1+\kappa_1}}{\kappa_0^{\kappa_1}}. \tag{A.29}$$

We can write down optimal search effort, s^* in any state as $s^* = \tilde{s}^* \left(\frac{\lambda}{\kappa_0}\right)^{\kappa_1}$. Using this representation, we can write $\kappa(s^*) = \frac{\lambda^{1+\kappa_1}}{\kappa_0^{\kappa_1}} \frac{\tilde{s}^{*1+\kappa_1}}{1+\kappa_1}$. Notice that the first ratio on the right hand side is related to the average length of an unemployment spell. Remember that $ulength = \frac{\kappa_0^{\kappa_1}}{\lambda^{1+\kappa_1}} \left(\int \int \lambda \tilde{s}_U(z,a) \overline{F}(p_U(z,a)) g(z,a) dz da \right)$ where $\tilde{s}_U(z,a) \left(\frac{\lambda}{\kappa_0}\right)^{\kappa_1} = s_U(z,a)$. What matters, therefore, is the ratio $\frac{\lambda^{1+\kappa_1}}{\kappa_0^{\kappa_1}}$, which I pin down with c_0, given a value for λ and κ_1.

A.4 Threshold

The method that is used to determine which workers are "searching" and which are "not searching", is shown graphically in Figure A.41. Those who I deem as searching are greater than a determined threshold such that the proportion searching is equal to that shown in Table 2.1. The threshold search intensities are 0.1359 and 0.2062 for low and high skill workers, respectively. If we take these numbers seriously, despite search incidence being lower for low skill workers, they have a lower threshold by which search effort would translate into a reported incidence of search.
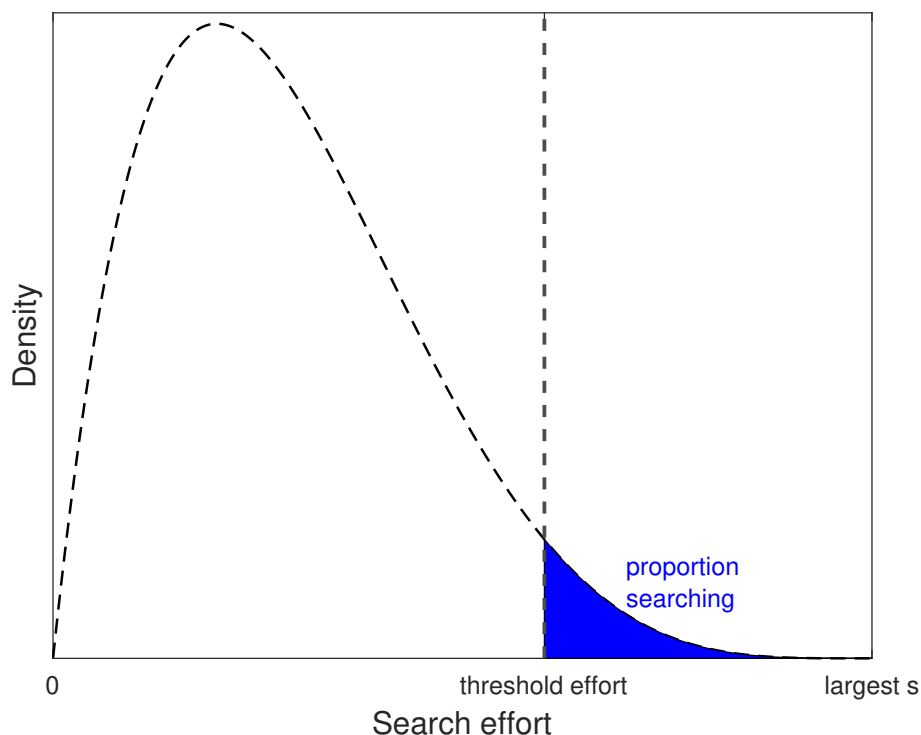
FIGURE A.41: Threshold search effort in the model

Note: The threshold search effort determines the point through which workers are described as "searching" and "not searching". This is set such that the shaded region in the figure is equal to the proportion of the employed who are searching with effort greater than this point are equal to the proportion of the employed who are searching in Table 2.1. Those below are deemed "not searching" but can still receive job offers.

A.5 Details on the numerical solution and estimation process

The challenge of solving a model with assets is that one cannot solve a function with an asset space of infinite length. Discretisation is necessary, where the number of grid points in the asset space must be sufficiently large to allow individuals to change their asset holdings. I solve the model numerically using a combination of iterative and interpolation techniques of which I outline next.

I choose a sparse grid of 100 points for $p \in [0,1]$, 6 points for $z \in [1,2]$ and, 1501 points for $a \in [0,150]$. There are, therefore, $100 * 6 * 1501 = 900,600$ points on the grid. I pick an initial parameter set, and values for the three value functions, V_j^0 and, optimally chosen search efforts, s_j^0. I choose initial value functions with four arguments, p, z, a and a'. a is set to be 4 equally distanced points on the grid, whereas a' takes 1,501. Using (2.6), (2.7) and (2.8), I can then calculate $V_j^1 = T_v(V_j^0)$ for all possible combinations of optimally chosen assets, which has $100 * 6 * 4 * 1501 = 3,602,400$ points. This procedure is inefficient since workers cannot increase their assets by much each period if they would like to since consumption must be positive. We can, therefore, look at a smaller amount of points around a for a'. In the computation, I choose 12 points around a, meaning that the number of points to be solved is just $100 * 6 * 4 * 24 = 57,600$, speeding the algorithm by a factor of approximately 60. I then pick a'_j such that it maximises V_j^1 at all $100 * 6 * 4 = 2,400$ points.

Using the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), for each unique productivity and human capital combination, I interpolate each value function for intermediate asset values for a. One could opt for a different interpolating procedure. The benefit of using the PCHIP procedure is to maintain monotonicity of the value functions, with no overshoots and less oscillation. Performing the interpolation leaves me with value functions with three arguments, p, z and a, and optimally chosen assets with the same three arguments. I repeat this procedure, calculating $V_j^{t+1} = T_v(V_j^t)$, until $\left|V_j^{t+1} - V_j^t\right| < \varepsilon_v$, where Blackwell's sufficient conditions for the Contraction Mapping Theorem apply, and a unique solution for the value functions exist, see Stokey and Lucas (1989). Once the value functions have converged, using (2.9), (2.10) and (2.11), I calculate new search efforts, $s_j^1 = T_S(s_j^0)$. I then loop back over the calculation of the value functions until $\left|V_j^{t+1} - V_j^t\right| < \varepsilon_v$ and $\left|s_j^{t+1} - s_j^t\right| < \varepsilon_S$. The above description can be summarised by the following six step procedure.

1. Begin with numbers for value functions and search efforts where value functions have four inputs: p, z, a and a'

2. Calculate new values over all inputs and pick the optimal asset level a'

3. Interpolate intermediate numbers for dimension *a* over the entire grid of possible assets

4. Repeat steps 2 to 3 until the value functions convergence

5. Calculate search efforts

6. Repeat steps 2 to 5 until value functions and search efforts converge

Using the solution method described above, it is possible to estimate the parameters of the model using the simulated method of moments. To do so, I choose salient moments from the data described in 2.5, solve the model using the above procedure, and simulate $20,000$ worker histories over $30 * 48$ weeks. I then calculate the same moments as in the data from the simulated panel. Following this, I choose optimisation procedures to pick parameter values to minimise the criterion function, shown in equation (2.23). I use the Nelder-Mead simplex directed search algorithm to search for a local minimum given the chosen initial set of "sensibly" chosen parameter values. The above description can be summarised by the following six step procedure.

1. Make "sensible" guesses for the parameter values

2. Numerically solve the model using the above procedure

3. Simulate a dataset of $20,000$ individuals over $30 * 48$ weeks

4. Calculate the same moments as in the empirical data using the simulated data and calculate the criterion function, shown in equation (2.23)

5. Pick new parameter values using optimisation procedures

6. Iterate over steps 2 to 5 until the criterion is minimised

Once the parameters are recovered, the associated standard errors are calculated in the following manner. Under mild regularity conditions, Gourieroux et al. (1993), $\sqrt{N}(\hat{\theta} - \theta) \sim \mathcal{N}(0, 2Var(\theta))$, where

$$Var(\theta) = \left[J'\Sigma J\right]^{-1}J'\Sigma W\Sigma J\left[J'\Sigma J\right]^{-1}, \tag{A.30}$$

where $J = \frac{\partial m(\theta)}{\partial \theta}$ and Σ is the variance covariance matrix of the empirical moments. I calculate the variance covariance matrix using bootstrapping with 2000 iterations with $N = 100,000$. I report standard errors based on the asymptotic variance-covariance matrix $N^{-1}2Var(\hat{\theta})$. Elements of the jacobian matrix, $\frac{\partial m(\hat{\theta})}{\partial \hat{\theta}}$, are estimated numerically by perturbing the parameter values and estimating the resultant slope.

Appendix B

B.1 Data adjustments and mathematical details

I remain consistent with recent literature and implement an adjustment for margin error. Margin error is an inaccuracy that describes the differences in the actual changes in the labour market state rates and those explained by the probability measures. To make the adjustment I follow Elsby et al. (2015) and minimize the weighted squared difference between the raw and margin error adjusted probabilities.

Shimer (2012) claims that time aggregation can significantly impact the measured cyclicality of flows data. Time aggregation is the issue that observed transitions from the data miss transitions between periods. To describe this idea for the job-to-job mover, imagine that an individual is employed and interviewed at time $t - 1$, moves into unemployment immediately following the interview, and then finds a job immediately prior to their interview at time t. I would define this as a job-to-job transition, which is incorrect. To account for this measurement error, I make the standard adjustment shown by Shimer (2012) coupled with an adjustment for the job-to-job probability shown by Mukoyama (2014).[1]

I adjust the transition probabilities for seasonality by applying the commonly used X13 Arima SEATS procedure provided by the US Census Bureau, and then smooth the data using a centered yearly moving average.

Margin error

The results throughout this paper are based on margin error adjusted flows. The adjustment changes the probabilities to be consistent with the changes in the labour market stocks. I follow

---

[1]While the Shimer (2012) adjustment for time aggregation has become common practice in the dynamics literature. Gomes (2015) shows the inconsistencies between the implementation of this adjustment procedure on data with different frequencies - continuous time hazards derived using quarterly data (divided by 3) and monthly data are not equal, which is of direct importance in my analysis for comparison between the UK and US results. Fortunately, the author finds that the contribution to unemployment fluctuations of the continuous time hazards derived at different frequencies are quantitatively similar.

Elsby et al. (2015) and pick p_t, the vector of transition probabilities, that solves the following for each period:

$$min_{p_t}(p_t - \hat{p}_t)'\hat{W}_t^{-1}(p_t - \hat{p}_t) : \triangle s_t = X_{t-1}p_t. \tag{B.1}$$

This minimises the weighted squared distance between the adjusted probability vector, p, from its counterpart derived from the data, $\hat{p}$, subject to the changes in the stocks equalling those explained by the adjusted transition probabilities. In my analysis I keep the job-to-job probability unadjusted for margin error.

To calculate the adjusted components of the employment to unemployment decomposition for each reason, I make sure the ratio of each reason for the unadjusted case is the same for adjusted case. For example, the adjusted employment-to-unemployment probability for reason r is

$$p_t^{eu^r} = \frac{\hat{p}_t^{eu^r}}{\hat{p}_t^{eu}} p_t^{eu} \tag{B.2}$$

Time aggregation: adjustment and methodology

For robustness, I assess the impact of the fluctuations of the corresponding hazard rates to the dynamics of unemployment. I outline the adjustments and decomposition method below.

Adjustment

To estimate the continuous time hazard rates, I apply the standard time aggregation adjustment shown by Shimer (2012) accompanied by an adjustment for the job-to-job probability shown by Mukoyama (2014). I firstly outline the Shimer (2012) adjustment.

The aim is to recover the instantaneous transition matrix, $F_{t+\tau} : \tau \in [0,1]$, from it's discrete time counterpart. It is possible to see the relationship between F_t and P_t by solving the following differential equation

$$\dot{\tilde{s}}_{t+\tau} = \tilde{F}_{t+\tau}\tilde{s}_{t+\tau}. \tag{B.3}$$

This has solution

$$\tilde{s}_{t+1} = e^{\tilde{F}_{t+1}} \tilde{s}_t. \tag{B.4}$$

Since

$$\tilde{s}_{t+1} = \tilde{P}_{t+1} \tilde{s}_t, \tag{B.5}$$

we therefore have

$$e^{\tilde{F}_{t+1}} = \tilde{P}_{t+1}. \tag{B.6}$$

If P_{t+1} can be represented in this way - the matrix exponential of another matrix - then it is described as being embeddable. P_{t+1} is only embeddable if its eigenvalues are; real, positive and distinct (which is fortunately always the case for my data). If these conditions are satisfied, $\tilde{F}_{t+1}$ is then just the matrix logarithm of its corresponding discrete time transition matrix, $\tilde{P}_{t+1}$.

Mukoyama (2014) develops a method to adjust the job-to-job probability for time aggregation which I describe here. Let $E^0_{t+\tau}$ be all those who remain in employment and do not move from job to job between t and $t + \tau$. The evolution of $E^0_{t+\tau}$ follows

$$\dot{E}^0_{t+\tau} = -(\lambda^{jj}_{t+\tau} + \lambda^{eu}_{t+\tau} + \lambda^{en}_{t+\tau})E^0_{t+\tau}. \tag{B.7}$$

This has solution

$$E^0_{t+1} = e^{-(\lambda^{jj}_{t+1} + \lambda^{eu}_{t+1} + \lambda^{en}_{t+1})}, \tag{B.8}$$

where $E^0_t = 1$.

Next, consider the fraction of workers who have moved from job to job exactly once and have never changed their labour market state between time t and $t + \tau$. Call this fraction of the employed, $E^1_{t+\tau}$. The evolution of $E^1_{t+\tau}$ follows

$$\dot{E}^1_{t+\tau} = \lambda^{jj}_{t+\tau}E^0_{t+\tau} - (\lambda^{jj}_{t+\tau} + \lambda^{eu}_{t+\tau} + \lambda^{en}_{t+\tau})E^1_{t+\tau}. \tag{B.9}$$

This has solution

$$E^1_{t+1} = \lambda^{jj}_{t+1} e^{(-(\lambda^{jj}_{t+1} + \lambda^{eu}_{t+1} + \lambda^{en}_{t+1}))}, \tag{B.10}$$

where $E^1_t = 0$. It is then possible to form the following relationship

$$p^{jj}_{t+1} = \underbrace{E^1_{t+1}}_{A} + \underbrace{p^{ee}_{t+1} - E^0_{t+1} - E^1_{t+1}}_{B}.^2 \tag{B.11}$$

A, as said above, corresponds to all those who move from job to job just once and do not leave employment. B corresponds to all those who move from job to job more than once and switch states more than once ending back up in employment. Using (B.8), (B.10) and (B.11), λ^{jj} can then be solved for analytically as

$$\lambda^{jj}_t = -\log(p^{ee}_t - p^{jj}_t) - \lambda^{eu}_t - \lambda^{en}_t. \tag{B.12}$$

To estimate the instantaneous transitions disaggregated by reason, I assume the proportion of each type of instantaneous separation is the same as that seen in the data. For example, the job-to-job hazard for reason r is

$$\lambda^{jj^r} = \lambda^{jj}_t \frac{p^{jj^r}_t}{p^{jj}_t}. \tag{B.13}$$

Methodology

It is possible to assess the impact of the fluctuations of the derived hazard rates (shown above) in a continuous time environment, where the changes in the labour market state rates evolve by the following reduced system

$$\underbrace{\begin{bmatrix} \dot{e} \\ \dot{u} \end{bmatrix}_{t+\tau}}_{\dot{s}_{t+\tau}} = \underbrace{\begin{bmatrix} -\sum_{r \in R}[\lambda^{sep^r}(1 - \lambda^{sep^r} \lambda^{lf|sep^r} \lambda^{jj|lfsep^r})] - \lambda^{entry}\lambda^{e|entry} & \lambda^{ue} - \lambda^{entry}\lambda^{e|entry} \\ \sum_{r \in R}[\lambda^{sep^r}\lambda^{lf|sep^r}(1 - \lambda^{jj|lfsep^r})] - \lambda^{entry}(1 - \lambda^{e|entry}) & -\lambda^{ue} - \lambda^{un} - \lambda^{entry}(1 - \lambda^{e|entry}) \end{bmatrix}_{t+\tau}}_{F_{t+\tau}} \underbrace{\begin{bmatrix} e \\ u \end{bmatrix}_{t+\tau}}_{s_{t+\tau}}$$

---

[2]Mukoyama (2014) considers also the impact of recalls which I do not incorporate here.

$$+ \underbrace{\begin{bmatrix} \lambda^{entry} \lambda^{e|entry} \\ \lambda^{entry}(1 - \lambda^{e|entry}) \end{bmatrix}_{t+\tau}}_{h_{t+\tau}},$$ (B.14)

where $\lambda_t^{sep^r} = \lambda_t^{eu^r} + \lambda_t^{en^r} + \lambda_t^{jj^r}$, $\lambda_t^{lf|sep^r} = \frac{\lambda_t^{eu^r} + \lambda_t^{jj^r}}{\lambda_t^{eu^r} + \lambda_t^{en^r} + \lambda_t^{jj^r}}$, $\lambda_t^{jj|lfsep^r} = \frac{\lambda_t^{jj^r}}{\lambda_t^{eu^r} + \lambda_t^{jj^r}}$, $\lambda_t^{entry} = \lambda_t^{ne} + \lambda_t^{nu}$ and $\lambda_t^{e|entry} = \frac{\lambda_t^{ne}}{\lambda_t^{ne} + \lambda_t^{nu}}$. The interpretation of the three ratios are slightly different than there corresponding discretised counterparts. $\lambda_t^{lf|sep^r}$ represents the proportion of separations (into another job, unemployment or inactivity), that transition directly into employment or unemployment. $\lambda_t^{jj|lfsep^r}$ represents the proportion of separations that remain in the labour force (into another job or unemployment), that transition directly to another job without an intervening spell of unemployment. $\lambda_t^{e|entry}$ represents the proportion of entrants that transition directly into employment. The steady state of the above system is equal to

$$\bar{s}_t = (-F_t)^{-1} h_t.$$ (B.15)

The decomposition is then identical to the discrete case from here.

Decomposing Δu_t^{rate}

The decomposition is straight forward.

$$\Delta u_t^{rate} = \frac{u_t}{e_t + u_t} - \frac{u_{t-1}}{e_{t-1} + u_{t-1}} = \frac{u_t(e_{t-1} + u_{t-1}) - u_{t-1}(e_t + u_t)}{(e_t + u_t)(e_{t-1} + u_{t-1})} = \frac{u_t e_{t-1} - u_{t-1} e_t}{(e_t + u_t)(e_{t-1} + u_{t-1})}.$$ (B.16)

Add $u_t e_t - u_t e_t$ to the numerator and the rest follows.

$$\frac{u_t e_{t-1} - u_{t-1} e_t + u_t e_t - u_t e_t}{(e_t + u_t)(e_{t-1} + u_{t-1})} \approx \frac{e_{t-1}}{e_{t-1} + u_{t-1}} \frac{\triangle u_t}{e_{t-1} + u_{t-1}} - \frac{u_{t-1}}{e_{t-1} + u_{t-1}} \frac{\triangle e_t}{e_{t-1} + u_{t-1}}.$$ (B.17)

B.2 Heterogeneity

To assess the changing composition effect, I follow the same method as Shimer (2012) and decompose probability $d \in \{jj|lfsep, e|entry, ue\}$ as

$$p_t^d = \sum_g w_{g,t}^d p_{g,t}^d, \tag{B.18}$$

where g corresponds to the type of the individual and $w_{g,t}^d$ corresponds to the percentage of those type g individuals who separated and remained in the labour force, entered the labour force, or are in the unemployment pool at time t. I estimate the composition effect by keeping $p_{g,t}^d$ fixed at the average and allow $w_{g,t}^d$ to vary. The composition effect is given as

$$C_{type}^d = \frac{cov(\sum_g \overline{p}_{g,t}^d \, w_{g,t}^d, \, p_t^d)}{var(p_t^d)}. \tag{B.19}$$

Table B.21 shows the three probabilities disaggregated by potential salient types: age, sex, education, relationship to head of household, reason for separation from last job, reason for on-the-job search and tenure, and also shows the magnitude of the composition effect for each type. The interpretation of the US $C_{age}^{jj|lfsep}$, for example, is: compositional shifts in the age of those who separate and remain in the labour force contribute to 2.8% of the fluctuations in the $JJ|LFSep$ probability. The remainder of this section discusses the salient results.

B.2.1 Job separation

On-the-job search

The workhorse job search model of job-to-job transitions, the job-ladder model, would predict that employed job search is procyclical.[3] The theoretical reductions in on-the-job search during a recession, may be the explanation why the $JJ|LFSep$ probability also drops. The LFS provides a unique opportunity to assess this channel because of the detailed on-the-job search information.

From Table B.21, the results show that fluctuations in on-the-job search behaviour do not play a role in contributing to the procyclicality of the $JJ|LFSep$ probability (-0.6%). Why not? Figure B.21 provides an explanation for this. First, the left panel shows the percentage of employed

---

[3]See Burdett and Mortensen (1998) for the job ladder model. On-the-job search would be predicted to be procyclical due to the complimentary between search effort and job finding. The incentives to search are lower when the job offer arrival rate is lower.

searching on the job in the UK. There is no clear fall in on-the-job search during the Great Recession. Second, the right panel disaggregates by reason for search. During the Great Recession, we see a clear rise in uncertain on-the-job search. This apparent countercyclical nature of on the job search dovetails nicely with new evidence from Ahn and Shao (2017), who shows that the time devoted to search on the job rose during the Great Recession in the US.

Reason for separation

We have already seen that there is a clear shift in the type of separation from voluntary to involuntary during the Great Recession. In the above analysis, I argue that the incorporation of the reasons for separation is of high importance to accurately understand the impact of the job finding component of the employment to unemployment probability. Table B.21 confirms this. The changing composition of the reason for separation contributes to 38.6% and 21.8% of the fluctuations in the $JJ|LFSep$ probability for the US and UK, respectively.

B.2.2 labour force entry

Education

Economic theory suggests that during expansions, the increased opportunities pull more highly qualified individuals into the labour market.[4] Since the level of education is positively associated with the ability to find employment (see Table B.21), the possible changes in average education levels may contribute to more labour force entrants transitioning into unemployment during a recession. Table B.21 provides no evidence for this - the contribution of changes in education to the fluctuations in the $E|Entry$ probability is, if anything, negative.

Added worker

The added worker effect argues that inactive household members, or partners, are more likely to enter the labour market following job loss of another member of their household.[5] If added workers are less likely to find employment upon labour force entry, then the added worker effect may explain why job finding at the participation margin is procyclical. I study this effect using the variable, *relationship to the head of household*, which defines whether an individual is a *head*, *partner* or *child*. Actually, partners have a higher job finding rate following entry into the labour

---

[4] See Pissarides (2000) chapter 7.

[5] Mankart and Oikonomou (2016) conclude that the added worker effect has increased over the last three decades.

force. As is then expected, I find no evidence that a proxy for measuring the impact of the added worker effect can explain procyclical job finding at the participation margin.

This section provides a battery of evidence that compositional changes in observable types, other than the reason for separation, do not contribute significantly to the dynamics of each of the job finding probabilities. However, to claim that heterogeneity is unimportant in the story of labour market dynamics would be false. As we have seen, and has been shown consistently in the literature, the probability of continuing to search from unemployment increases during recessions. Elsby et al. (2015) conclude that this feature is primarily the result of a switching composition of the unemployment pool during a recession, from individuals who are less attached to the labour force, to individuals who are more attached. This section also only studies variations in observables. Ahn and Hamilton (2016) argue that unobservables play a particularly important role in the story of unemployment dynamics.

FIGURE B.21: On-the-job search in the UK. Note: The left panel shows the proportion of the employed who are searching. The right panel shows the proportion of the employed who are searching for each reason. Proportions adjusted for seasonality. The shaded area denotes the officially defined UK Great Recession. Source: Author calculations using Two Quarter LFS. Ages 16-64/59. 1996q1-2016q4.

Type	US			UK		
	$p_g^{jj\|lfsep}$	$p_g^{e\|entry}$	p_g^{ue}	$p_g^{jj\|lfsep}$	$p_g^{e\|entry}$	p_g^{ue}
AGE						
$16-20$	71.5	64.9	18.4	59.9	57.0	28.6
$21-30$	71.9	63.8	19.6	68.3	52.8	30.3
$31-40$	69.8	61.5	19.0	69.8	49.0	24.9
$41-50$	66.4	61.9	18.3	64.0	50.1	24.5
$51-64/59$	65.7	65.2	17.2	55.3	54.6	20.3
C_{age}^d	2.8	1.0	1.1	0.4	-1.7	-0.7
SEX						
Male	68.4	62.9	19.0	62.1	50.9	25.7
Female	71.3	64.4	18.3	68.8	55.9	19.9
C_{sex}^d	0.8	0.3	0.0	0.8	0.6	0.1
EDUCATION						
Degree or more	76.7	59.0	21.7	71.5	62.0	37.1
More than school	71.4	67.5	20.5	68.4	62.1	31.5
School or less	65.0	72.8	17.1	60.1	48.5	22.9
C_{ed}^d	-3.0	-2.9	-4.2	-6.5	-5.6	-7.1
RELATIONSHIP TO HEAD OF HOUSEHOLD						
Head				64.6	45.1	23.2
Partner				71.6	58.8	29.8
Child				61.0	57.2	30.2
C_{hhd}^d				0.1	0.4	1.8
REASON FOR SEPARATION FROM LAST JOB						
Voluntary	82.0			75.8	54.4	34.7
Involuntary	49.2			45.6	44.7	27.6
Personal	81.1			50.4	53.1	23.7
Other	66.7			78.3	58.8	32.1
Never had a job					55.4	21.9
C_{reas}^d	38.6			21.8	0.7	4.3
REASON FOR ON-THE-JOB SEARCH						
Worried				62.2		
Unsatisfactory				69.1		
Other				72.2		
Not searching				63.2		
C_{ojs}^d				-0.6		
TENURE (months)						
Less than 3				57.8		
$3-12$				61.3		
Greater than 12				67.6		
C_{ten}^d				-3.0		

TABLE B.21: Heterogeneity of the job finding probabilities. Note: Probabilities based on measures unadjusted for margin error and seasonality. The reason measure for the unemployment-to-employment probability refers to the reason they separated from the job they had before $t-1$ if they had one. The interpretation of $C_{age}^{jj|lfsep}$ for the UK is: changes in the composition of *Age* contribute to 0.4% of the fluctuations in the *JJ|LFSep* probability. Source: Author calculations using Two-Quarter LFS and the SIPP. Ages 16-64/59. The data spans 1996q1-2016q4 for the LFS and 1996m4-2013m5 for the SIPP.

B.3 Further description of the data

The Current Population Survey

The CPS flows are based on code from Robert Shimer. Please see Shimer (2012) for further details.

The Survey of Income and Program Participation

The wealth of precise information in the SIPP makes it a very useful survey to use to analyse unemployment dynamics, but it also makes it easy to be inconsistent between projects in the literature. To estimate the worker flows, I use a similar method to that of Nagypal (2008).

A worker is defined as employed if in the last week of the month they are *with job/bus - working*, or are *with job/bus - not on layoff or absent without pay*. A worker is defined as unemployed if in the last week of the month they are *with job/bus - on layoff or absent without pay*, or have *no job/bus - looking for work or on layoff*. A worker is defined as inactive if in the last week of the month they have *no job/bus - not looking and not on layoff*. The number of people who move from state to state can be estimated using this categorisation.

I estimate job-to-job transitions starting with the employer-employee identifier. These are EENO1, EENO2, EBNO1 and EBNO2. The first two refer to two different jobs that the survey participant is attached to during the wave. The last two refer to two different businesses that the survey participant is attached to during the wave. A survey participant can also have a contingent job that is not assigned an employer-employee identifier. Attached to each identifier is a start date and, if the job ended during the wave, an end date. Using these dates it is possible to determine whether a job was held at the end of a month. I then assign a job that was held at the end of the month as the main job if the hours that are attached to that job are higher than any other. If they work equal hours at two, three or all of their jobs then the main job is assigned to the job that the worker has held for the longest.

Using this definition of a main job, a job-to-job transition is given as a change in the employees main job. If the employer is employed at time $t-1$ and t and the employer identifier has changed. I also make sure that a separation has occurred because they are not holding the previous job anymore. If a survey participant separates from their employer, they attach a reason for making the transition which I categorise as seen in Section 3.4. Each month around half of separations have missing reasons, which is very prominent at the seem. I impute the missing reasons using a multinomial logit based on an individual's: age, sex, tenure in last job, education, indicator for part time work, the month and whether the separation occurred at the seem.

An issue that is unique to the SIPP is known as seam bias: individuals are much more likely to say that they transitioned from state to state in between waves than another month not in between waves. In between the first three months and final three months of each panel, each month will

have exactly one rotation group who is at the seam. I make the standard assumption that the impact of the seem is constant throughout the panel. Given this assumption, an adjustment for the seam bias can be made by removing the first three and last three months from each panel.

The SIPP data have missing periods between panels. Between the 1996 and 2001 panel there are 14 months missing, between the 2001 panel and 2004 panel there are 4 months missing, and between the 2004 and 2008 panel there are 11 months missing. The X13 Arima SEATS procedure used to seasonally adjust the data interpolates the missing observations between the panels. Estimation of the missing observations between the panels is performed by a "skipping" approach. A maximum likelihood estimation of the process is carried out by skipping the observations which then uses the fixed point smoother for interpolation of the missing values.

The UK Labour Force Survey

Job-to-job transitions are simply a change in the main job. The tenure method on its own will give an inaccurate understanding of separations because they may not in fact be separations at all but just a change in the individuals main job. I assign whether a separation occurred with a job-to-job transition if the individual gave a reason as to why they left their job in the last three months or they had had only one job in the second period.

Each period around a quarter of separations have missing reasons. For each two-quarter data set I impute the missing reasons using a multinomial logit based on an individual's: age, sex, tenure in last job, education and indicator for part time work.

B.4 The decomposed ins of unemployment
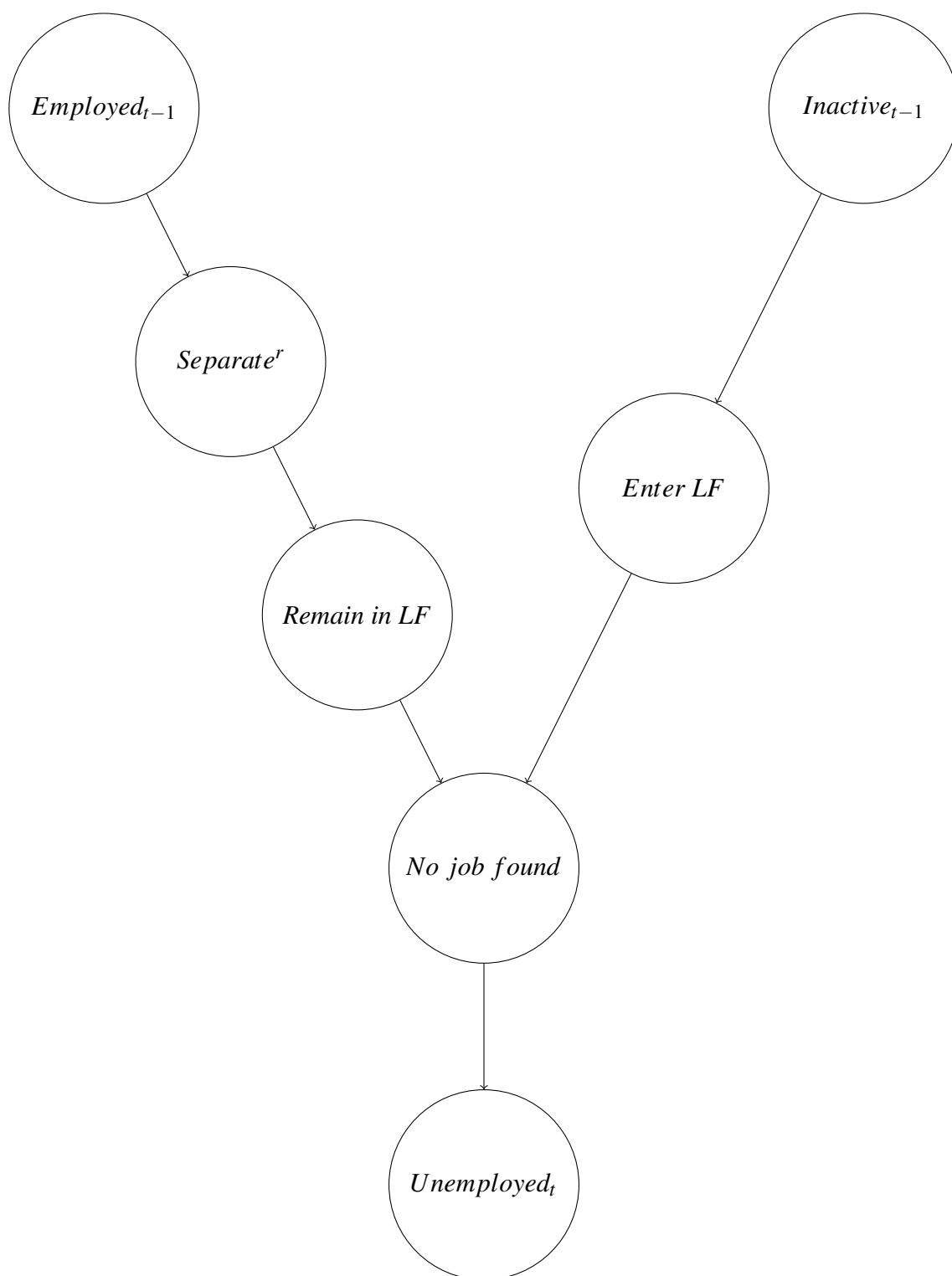
FIGURE B.41: The decomposed ins of unemployment

B.5 Additional tables

Probability	US Unadj	US TA	UK Unadj	UK TA
sep^v	-5.3	-8.3	-15.9	-17.6
sep^i	21.6	23.6	13.8	13.5
$lf\|sep^v$	0.2	0.6	1.1	0.8
$lf\|sep^i$	3.1	1.0	1.2	0.9
$\sum_r jj\|lfsep^r$	19.4	16.9	31.9	27.0
u to e	32.4	39.5	30.9	42.1
u to n	17.5	22.1	17.5	28.4
$entry$	-3.1	-4.2	-4.1	-6.9
$e\|entry$	16.4	14.0	22.7	16.5
Residual	-2.4	-5.3	-0.7	5.0
job finding	68.2	70.4	85.5	85.6

TABLE B.51: Contribution to unemployment rate variation - time aggregation adjusted rates. Note: Calculations based on margin error and seasonally adjusted probabilities. **Unadj**: Unadjusted. **TA**: Time aggregation adjusted. The first and third columns are the baseline results shown in Table 3.1. sep^v, for example, refers to the voluntary separation probability. sep^i, for example, refers to the involuntary separation probability. The interpretation of the top left cell is: the past and present fluctuations in the voluntary separation probability contributes to -5.3% of the dynamics of the unemployment rate. Source: Author calculations using the SIPP and Two-Quarter LFS. Ages 16-64/59. SIPP 1996m4-2013m5. LFS 1996q1-2016q4.

B.6 Additional figures
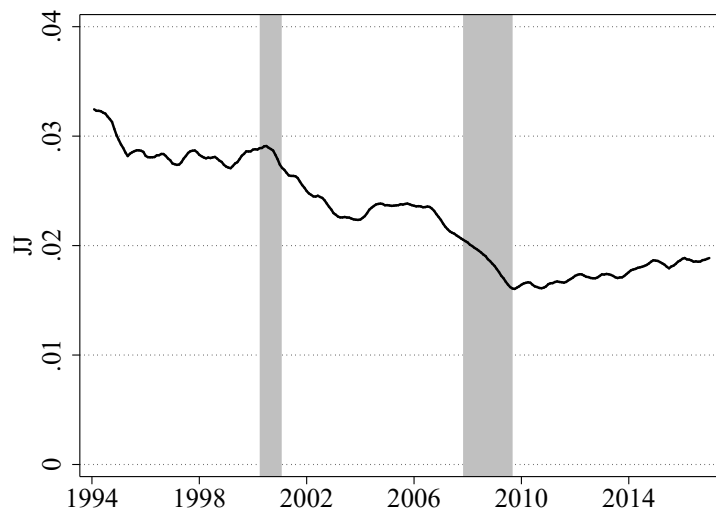
FIGURE B.61: The CPS US monthly job-to-job transition probability. Note: Probabilities adjusted for seasonality. Shaded areas denote officially defined US recessions. Source: Author calculations using the CPS, ages 16-64/59, 1994m1-2016m12.

FIGURE B.62: The SIPP US monthly job-to-job transition probability. Note: Probability adjusted for seasonality. Shaded areas denote officially defined US recessions. Source: Author calculations using the SIPP, ages 16-64/59, 1996m4-2013m5.

FIGURE B.63: The UK quarterly job-to-job transition probability. Note: Probability adjusted for seasonality. The shaded area denotes the officially defined UK Great Recession. Source: Author calculations using Two Quarter LFS, ages 16-64/59, 1996q1-2016q4.
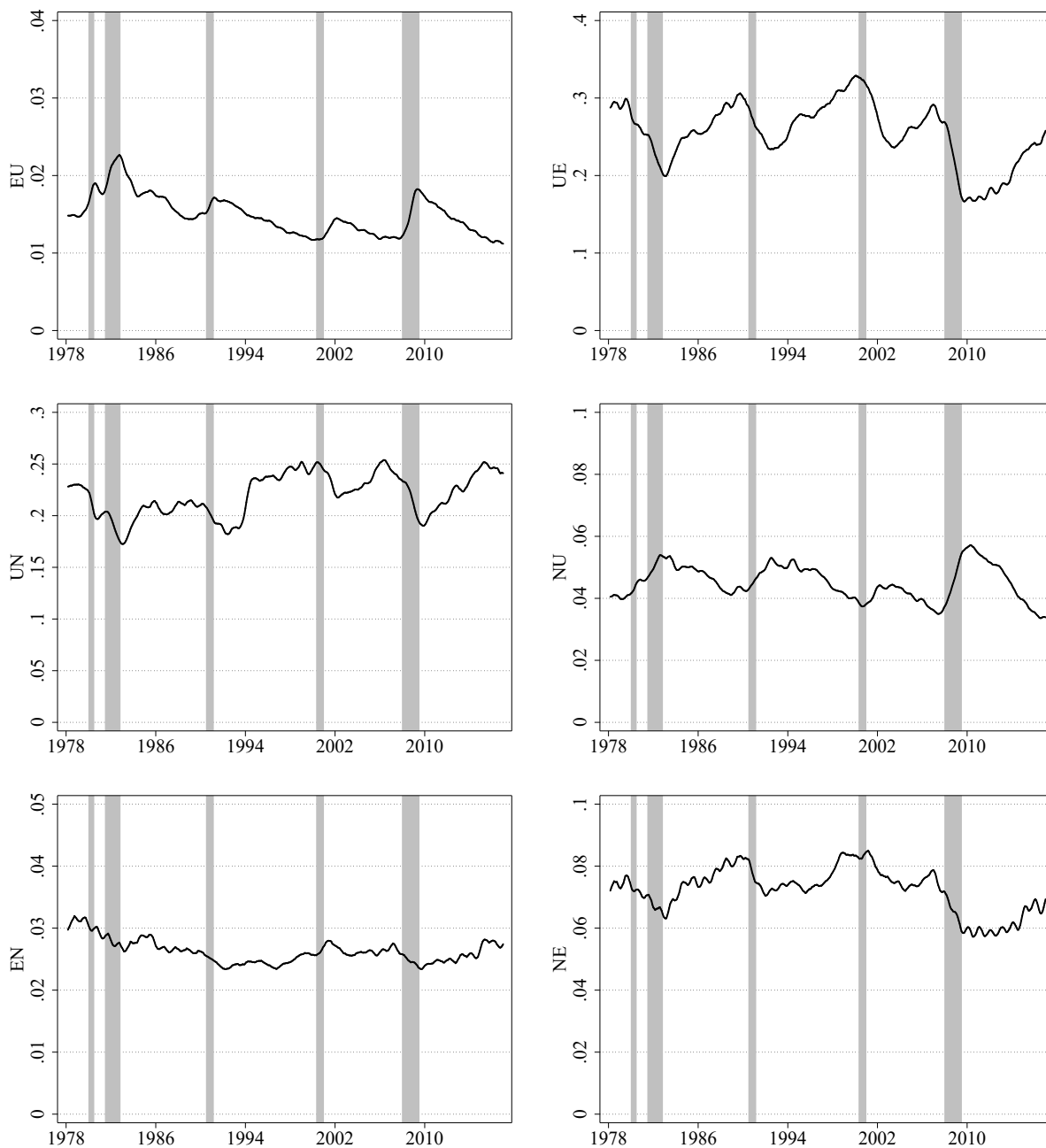
FIGURE B.64: The CPS US monthly worker flows. Note: Probabilities adjusted for margin error and seasonality. Shaded areas denote officially defined US recessions. Source: Author calculations using the CPS, ages 16-64/59, 1978m1-2016m12.
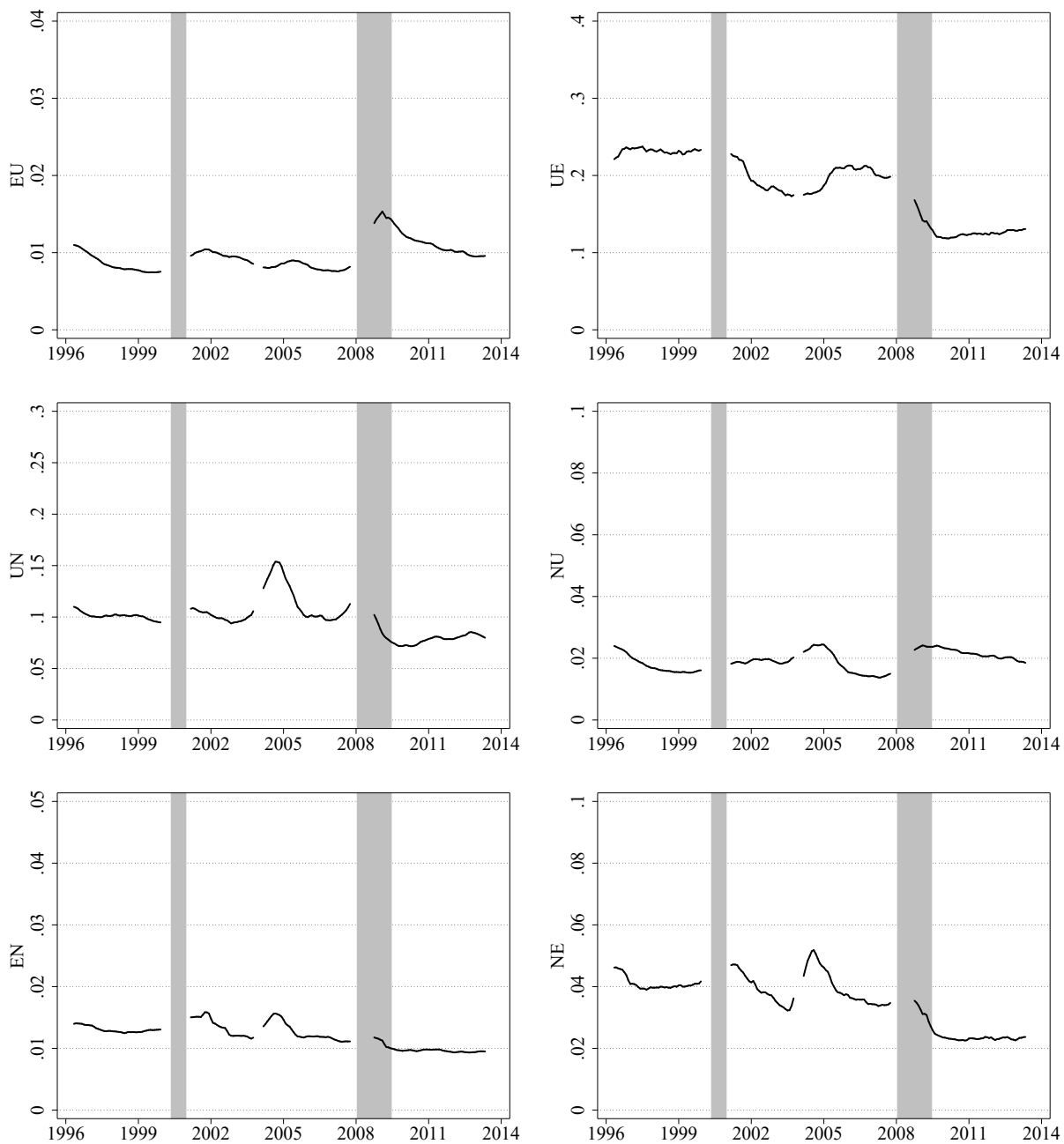
FIGURE B.65: The SIPP US monthly worker flows. Note: Probabilities adjusted for margin error and seasonality. Shaded areas denote officially defined US recessions. Source: Author calculations using the SIPP, ages 16-64/59, 1996m4-2013m5.

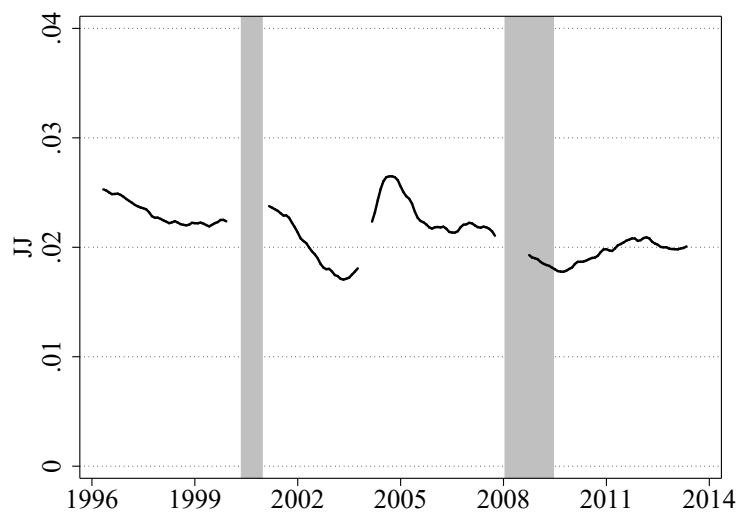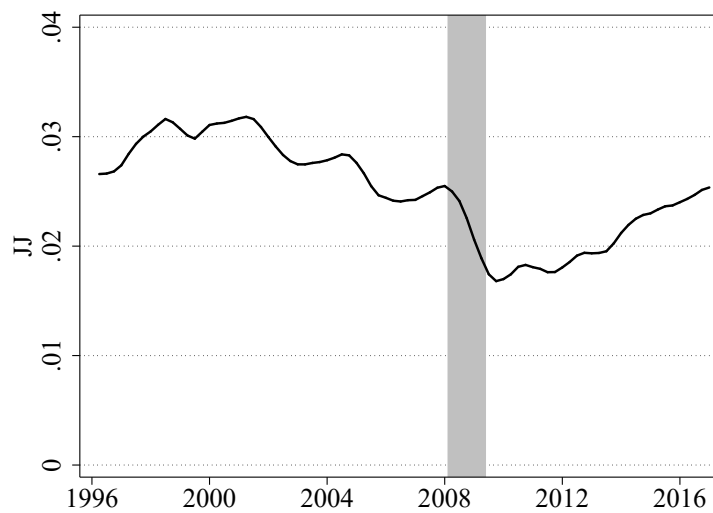FIGURE B.66: The UK quarterly worker flows. Note: Probabilities adjusted for margin error and seasonality. The shaded area denotes the officially defined UK Great Recession. Source: Author calculations using Two Quarter LFS, ages 16-64/59, 1996q1-2016q4.
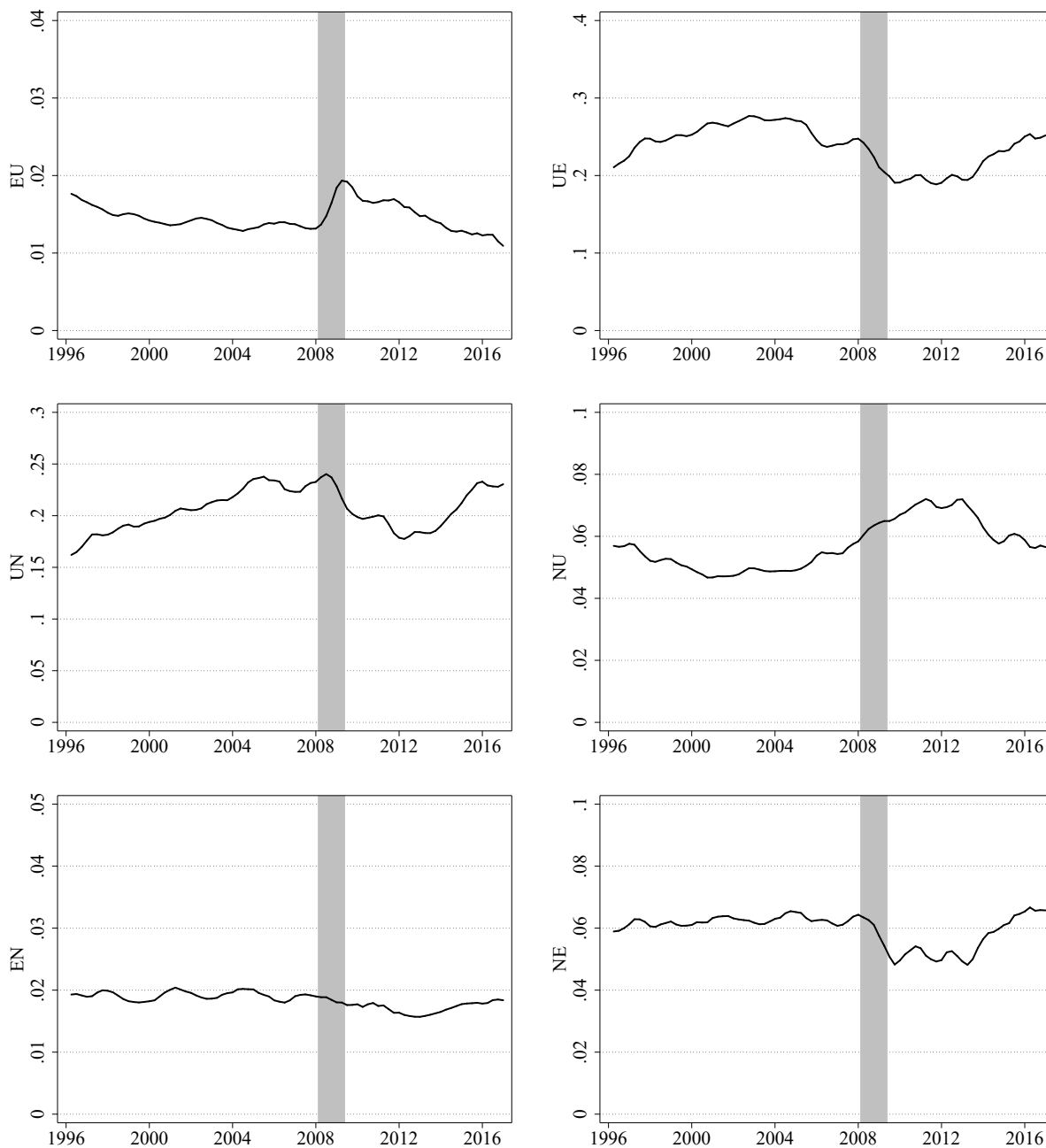
Appendix C

C.1 More tables

	Non-logarithmic gap				Logarithmic gap			
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	-0.01	1.03	0.00	-0.02	0.24	0.80	0.00	-0.04
Belgium	-0.03	1.02	0.00	0.01	0.01	0.98	0.01	0.01
Canada	0.43	0.58	0.00	0.00	0.36	0.66	0.00	-0.02
Denmark	-0.07	1.09	0.01	-0.03	-0.09	1.09	0.01	0.00
France	0.44	0.54	0.01	0.01	0.50	0.58	0.01	-0.09
Germany	-0.15	1.23	-0.02	-0.06	-0.58	1.62	-0.01	-0.03
Ireland	0.42	0.73	0.00	-0.15	-0.02	1.05	0.02	-0.03
Italy	0.07	0.92	0.05	-0.03	0.04	1.01	0.01	-0.05
Japan	-0.12	1.12	0.00	0.00	-0.11	1.11	0.00	0.00
Luxembourg	0.08	0.99	0.00	-0.07	0.05	0.90	0.04	0.03
Netherlands	0.20	0.96	-0.01	-0.15	-0.20	0.99	0.05	0.07
New Zealand	0.09	0.98	0.01	-0.07	0.16	0.73	0.02	0.10
Norway	-0.23	1.22	0.00	0.01	-0.12	1.13	0.00	0.00
Portugal	-0.11	1.03	0.00	0.07	-0.32	1.32	-0.01	0.01
Spain	0.58	0.37	0.24	-0.19	0.23	0.87	0.00	-0.10
Sweden	0.23	0.82	0.00	-0.05	-0.21	1.23	0.00	0.00
United Kingdom	-0.28	1.28	0.02	-0.01	-0.24	1.19	0.01	0.03
United States	0.49	0.52	0.00	0.00	0.37	0.64	0.00	-0.02
Average	0.11	0.91	0.02	-0.04	0.00	0.99	0.01	-0.01

TABLE C.11: Comparison between the non-logarithmic and logarithmic deviations in the unemployment gap.

Note: The non-logarithmic unemployment gap refers to $\Delta u_t^{Gap} = \Delta u_t^M - \Delta u_t^F$, and the contributions are estimated using (4.11). The logarithmic unemployment gap refers to $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, and the contributions are estimated using (4.6). The interpretation of the non-logarithmic results for Australia are: Differences in the variations in the outflows between males and females contribute to -1% of the dynamics of the unemployment gap, differences in the variations in the inflows between males and females contribute to 1.03% of the dynamics of the unemployment gap, 0% of the dynamics of the unemployment gap can be attributed to differences in initial deviations from steady-state between males and females, and changes in the error contribute to -2% of the dynamics of the unemployment gap.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

| | Entire period | | | | | | | 2000-2018 | | | | | |
| | | | Gap | | | | | | | Gap | | | |
	$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	β_f	β_s	β_0	β_ε		$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	β_f	β_s	β_0	β_ε
Australia	0.89	0.93	0.24	0.80	0.00	-0.04		1.02	1.04	0.48	0.55	0.00	-0.03
Belgium	0.79	1.10	0.01	0.98	0.01	0.01		0.93	0.99	0.08	0.90	0.00	0.02
Canada	0.93	0.88	0.36	0.66	0.00	-0.02		1.02	0.88	0.42	0.60	0.00	-0.01
Denmark	0.87	1.03	-0.09	1.09	0.01	0.00		0.90	0.99	-0.11	1.11	0.00	0.00
France	0.85	1.10	0.50	0.58	0.01	-0.09		0.96	1.04	0.56	0.62	0.00	-0.18
Germany	1.01	1.05	-0.58	1.62	-0.01	-0.03		1.09	0.98	-0.28	1.33	0.00	-0.06
Ireland	0.69	0.63	-0.02	1.05	0.02	-0.03		0.75	0.63	-0.05	1.06	0.02	-0.03
Italy	0.65	1.10	0.04	1.01	0.01	-0.05		0.75	1.07	-0.16	1.07	0.00	0.09
Japan	0.68	0.67	-0.11	1.11	0.00	0.00		0.67	0.60	-0.26	1.33	0.00	-0.07
Luxembourg	0.64	0.91	0.05	0.90	0.04	0.03		0.66	0.88	0.14	0.92	0.00	-0.06
Netherlands	0.70	1.04	-0.20	0.99	0.05	0.07		0.80	0.94	0.08	0.65	0.05	0.10
New Zealand	0.87	0.84	0.16	0.73	0.02	0.10		0.82	0.88	0.22	0.70	0.00	0.08
Norway	1.03	0.90	-0.12	1.13	0.00	0.00		1.02	0.87	0.00	1.00	0.00	0.00
Portugal	0.96	1.15	-0.32	1.32	-0.01	0.01		0.95	0.99	-0.36	1.26	0.00	0.11
Spain	0.84	1.28	0.23	0.87	0.00	-0.10		0.85	1.18	0.48	0.57	0.00	-0.05
Sweden	0.99	0.95	-0.21	1.23	0.00	0.00		0.93	0.89	-0.24	1.24	-0.01	-0.02
United Kingdom	0.90	0.72	-0.24	1.19	0.01	0.03		0.89	0.76	-0.42	1.36	0.00	0.06
United States	0.77	0.83	0.37	0.64	0.00	-0.02		1.03	0.96	0.32	0.72	0.00	-0.04
Average	0.84	0.95	0.00	0.99	0.01	-0.01		0.89	0.92	0.05	0.94	0.00	-0.01

TABLE C.12: Contributions to the dynamics of the unemployment gap for different periods and the relative inflows and outflows

Note: The interpretation of the Male results for Australia read: Differences in the proportionate variations in the outflows between males and females contribute to 24% of the dynamics of the unemployment gap, differences in the proportionate variations in the inflows between males and females contribute to 80% of the dynamics of the unemployment gap, 0% of the dynamics of the unemployment gap can be attributed to differences in initial deviations from steady-state between males and females, and changes in the error contribute to -4% of dynamics of the unemployment gap.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

C.2 More figures

FIGURE C.21: Relationship between male share and the correlation of sector output with overall output by country
Note: Excluded agricultural sector.

FIGURE C.21: Relationship between male share and the correlation of sector output with overall output by country continued

Note: Excluded agricultural sector.

FIGURE C.21: Relationship between male share and the correlation of sector output with overall output by country continued
Note: Excluded agricultural sector.

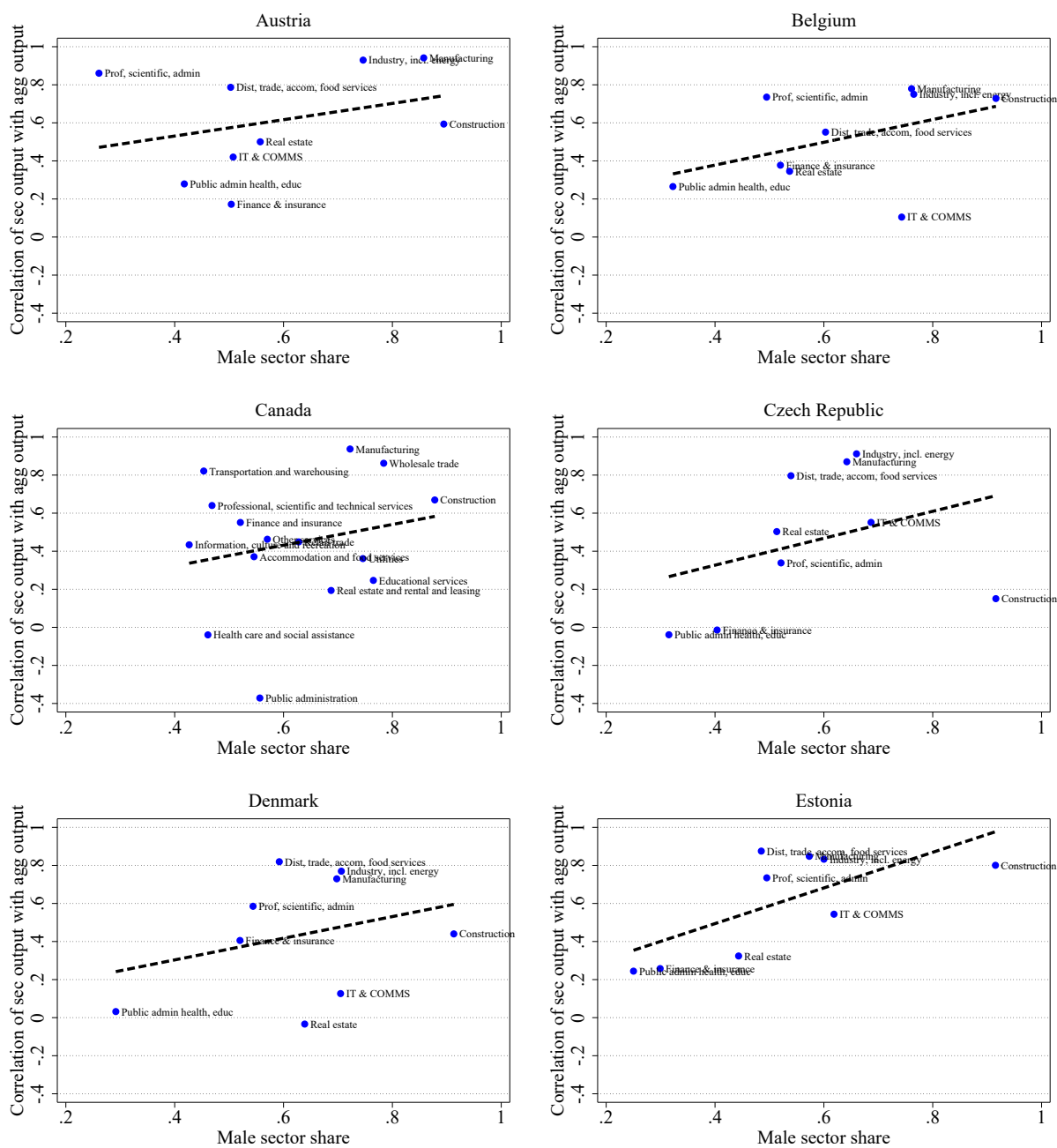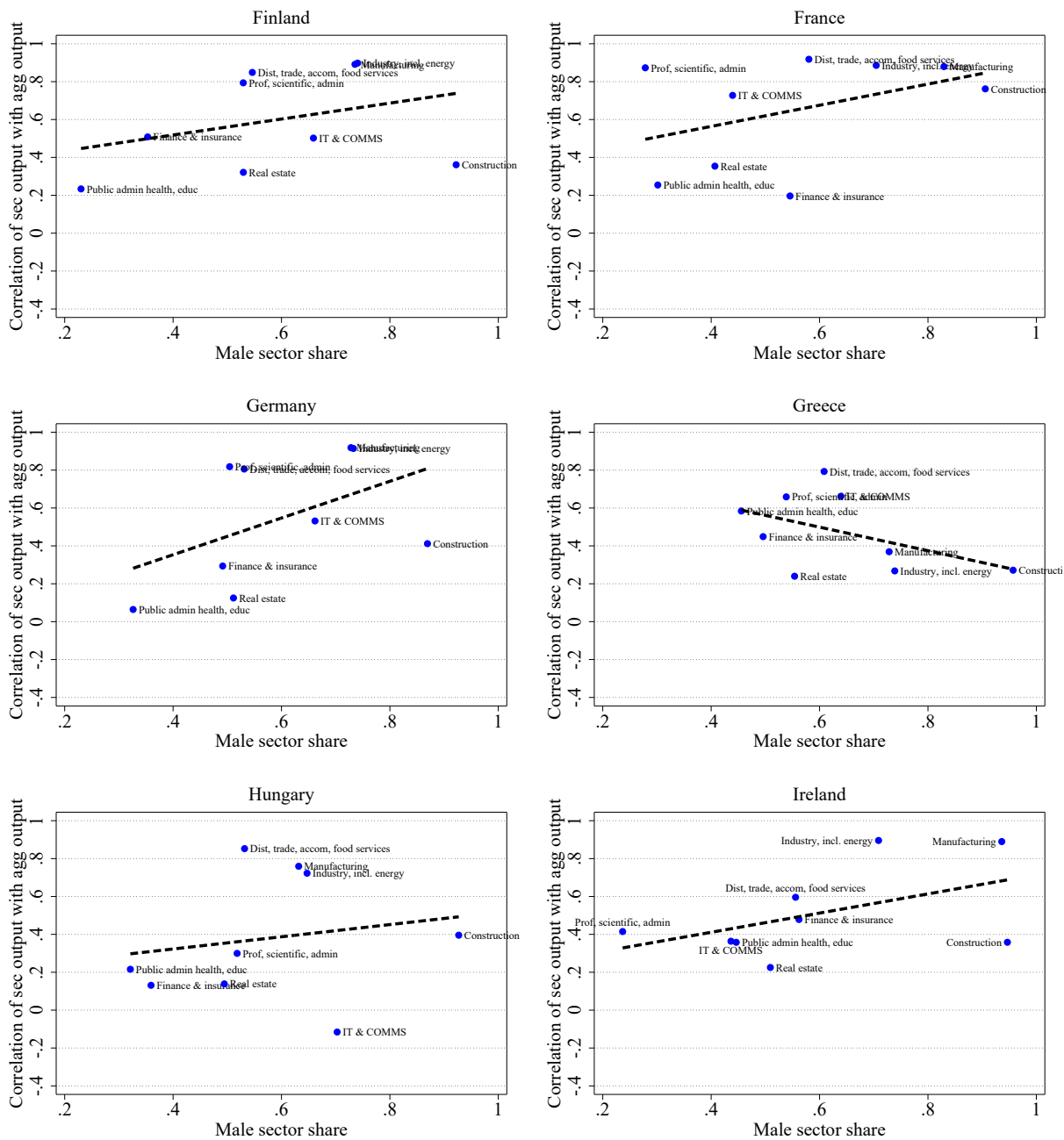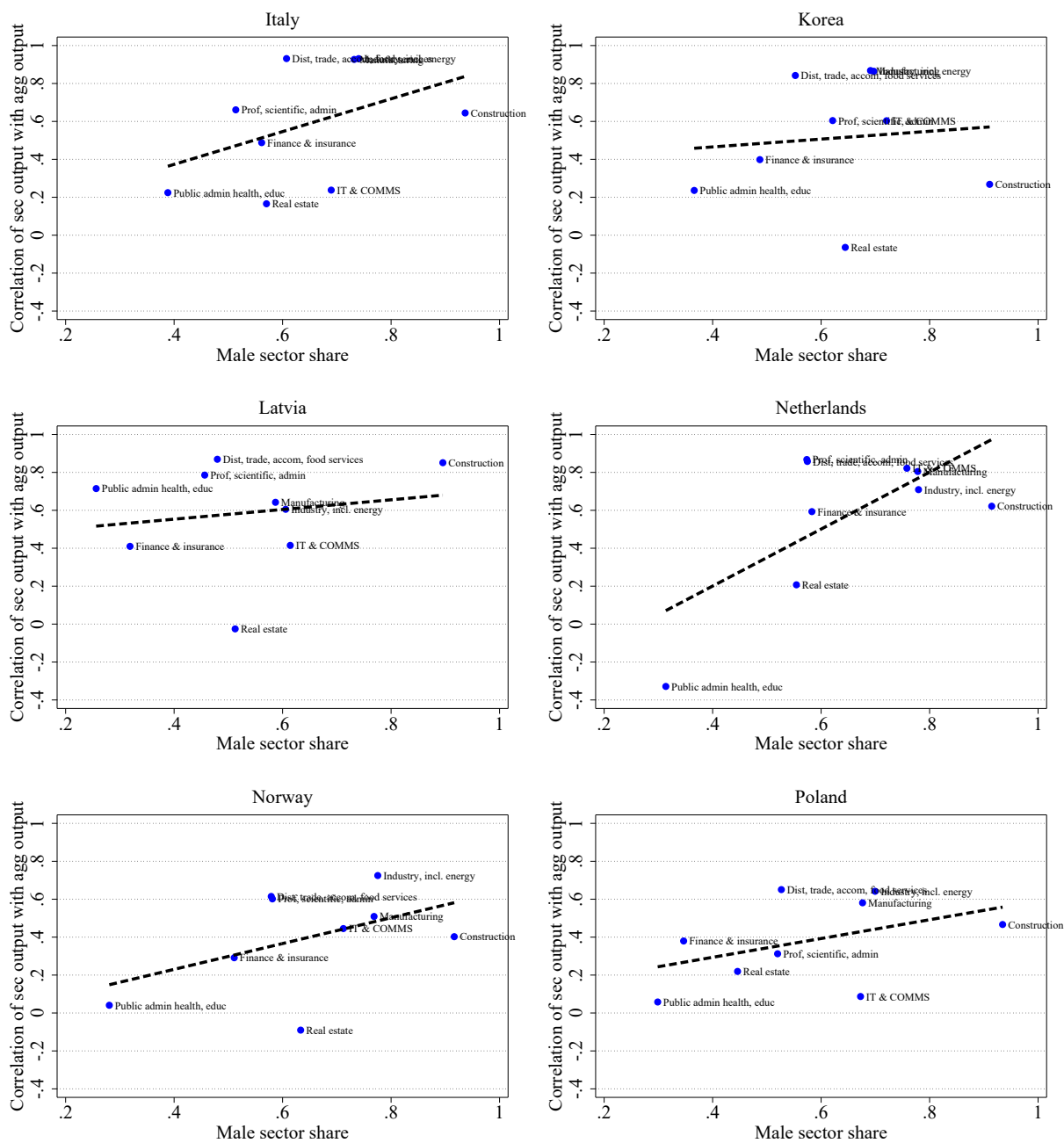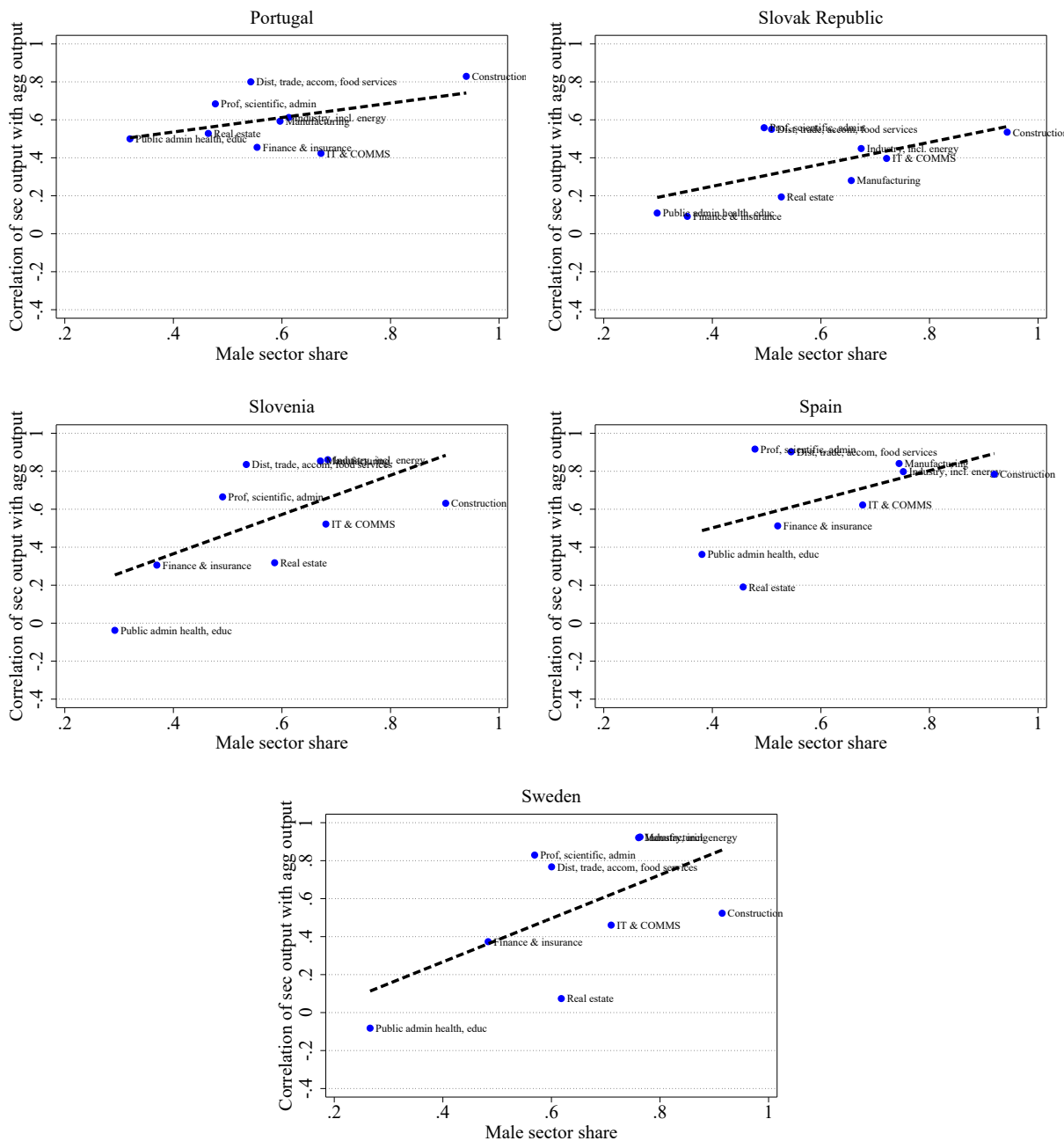FIGURE C.21: Relationship between male share and the correlation of sector output with overall output by country continued

Note: Excluded agricultural sector.

C.3 Further information on the outflow estimation process

For completeness, here we provide more information regarding the estimation process for the unemployment outflow. It should be made clear that this process exactly follows Elsby et al. (2013), but by gender, and is not a contribution of this paper. One does not have to use information on unemployment duration of less than one month to estimate the monthly outflow rate. The OECD provides information on unemployment duration of less than one, three, six and twelve months. To see how any of these duration methods can be used to estimate the monthly unemployment outflow rate, begin with

$$u_{t+d} - u_t = u_{t+d}^{<d} - F_t^{<d} u_t. \tag{C.1}$$

where $u_{t+d}^{<d}$ is the percentage of the unemployed at time $t+d$ and have been there for less than d months, and $F_t^{<d}$ is the probability of leaving unemployment in less than d months. Rearranging, we find

$$F_t^{<d} = 1 - \frac{u_{t+d} - u_{t+d}^{<d}}{u_t}, \tag{C.2}$$

which relates to the corresponding monthly outflow rate as

$$f_t^{<d} = \frac{-ln(1 - F_t^{<d})}{d}, \tag{C.3}$$

leaving us with outflow rate measures $f_t^{<1}, f_t^{<3}, f_t^{<6}$, and $f_t^{<12}$. The aim is to use a weighted sum of these outflows as f_t. Notice that these rates are not necessarily the same. If $f_t^{<1} > f_t^{<3} > f_t^{<6} > f_t^{<12}$, or the outflow rate exhibits negative duration dependence, then estimates of the outflow rates with large durations, for example $f_t^{<12}$, will not provide consistent estimates of the aggregate outflow rates. Only when duration dependence is not present, can all information on unemployment durations be used.

Before we test for duration dependence define the following two vectors

$$\mathbf{f}_t = \begin{bmatrix} f_t^{<1} & f_t^{<3} & f_t^{<6} & f_t^{<12} \end{bmatrix}' \tag{C.4}$$

and

$$\mathbf{u}_t = \begin{bmatrix} u_{1,t} & u_{3,t} & u_{6,t} & u_{12,t} & u_{\infty,t} & u_{t-3} & u_{t-6} & u_{t-12} \end{bmatrix}', \tag{C.5}$$

and let $\mathbf{V}_t$ be the associated covariance matrix of $\mathbf{u}_t$. $u_{1,t}$ is the fraction of the unemployed who have been unemployed for less than one month, $u_{3,t}$ is the fraction of the unemployed who have been unemployed for less than three months but more than one month, $u_{6,t}$ is the fraction of the unemployed who have been unemployed for less than six months but more than three months, $u_{12,t}$ is the fraction of the unemployed who have been unemployed for less than twelve months but more than size months, $u_{\infty,t}$ is the fraction of the unemployed who have been unemployed for more than twelve months. u_{t-3}, for example, is the unemployment rate at time $t-3$.

With the covariance matrix in hand, it is possible to use the Delta-method to write down the approximate distribution of $\hat{\mathbf{f}}_t$ as $\hat{\mathbf{f}}_t \sim N(\mathbf{f}_t, \frac{1}{n}D_{f,t}V_t D'_{f,t})$, where $D_{f,t}$ is the gradient matrix as in Elsby et al. (2013). This distribution will be used in the hypothesis test and the optimal weighting of the four outflow measures for the estimated outflow rate. The hypothesis test is

$$H_0 : \mathbf{f}_t = f\mathbf{i}, \tag{C.6}$$

where f is a scalar, $\mathbf{i}$ is a vector of ones. Using

$$M_f = \begin{bmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix} \tag{C.7}$$

under the null-hypothesis, it is the case that $\mathbf{M}_f \hat{\mathbf{f}}_t \sim N(0, \frac{1}{n}\mathbf{M}_f \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}'_{f,t} \mathbf{M}'_f$. It follows that $g_t \sim \chi^2(3)$, where $g_t = n\hat{\mathbf{f}}' \mathbf{M}'_f (\mathbf{M}_f \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}'_{f,t} \mathbf{M}'_f)^{-1} \mathbf{M}_f \hat{\mathbf{f}}_t$.

For the test we need the number of individuals in each survey. For the countries that crossover with Elsby et al. (2013), we use the same n but divided by 2 for males and females. For Belgium the number of households interviewed is approximately 14,625, so we use $n = 16,750$. For Denmark the number of individuals interviewed is approximately 40,000 so $n = 20,000$. For Luxembourg, the number of households interviewed is approximately 11,250, so we use $n = 13,500$. Finally, for Netherlands, the number of households interviewed is approximately 50,000, so we use $n = 58750$. We test the null at the 5% significance level. See Table C.33 for the results. The results for the male sample are to reject the null for Australia, Canada, France, Netherlands, Spain and the US. The results are fortunately the same for the female sample but that for the Netherlands the hypothesis is not rejected. For countries where the null is rejected, we use $f_t^{<1}$ as the outflow rate. For the case of the Netherlands, for both males and females, we use $f_t^{<1}$ as my estimate for the unemployment outflow rate.

If the null is not rejected we calculate optimal weights following Elsby et al. (2013). We want to pick the vector of weights, $\mathbf{w}$, to estimate

$$\hat{f}_t = \mathbf{w}'_t \hat{\mathbf{f}}_t \; s.t. \; \mathbf{w}'_t \mathbf{i} = 1, \tag{C.8}$$

i.e. the estimated aggregate outflow, is a weighted sum of the four outflow measures. Given this constraint, $\mathbf{w}$ minimises

$$V_{f,t} = \mathbf{w}'_t \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}'_{f,t} \mathbf{w}_t. \tag{C.9}$$

To take care of the constraint, define the vector

$$\tilde{\mathbf{w}}_t = \begin{bmatrix} w_t^{<1} & w_t^{<3} & w_t^{<6} \end{bmatrix}, \tag{C.10}$$

	n	Male		Female	
		P-value	H0 Rejected?	P-value	H0 Rejected?
Australia	28,500	1.9	Yes	0.8	Yes
Belgium	16,750	49.3		32.1	
Canada	67,500	0.0	Yes	0.0	Yes
Denmark	20,000	10.2		10.4	
France	75,000	4.7	Yes	1.7	Yes
Germany	82,500	11.6		15.6	
Ireland	48,750	23.4		21.0	
Italy	30,000	52.8		21.9	
Japan	50,000	48.4		39.1	
Luxembourg	13,500	68.9		49.2	
Netherlands	58,750	9.1		2.1	Yes
New Zealand	20,000	12.1		5.0	
Norway	12,000	35.8		32.2	
Portugal	26,250	28.6		24.5	
Spain	92,500	0.1	Yes	0.0	Yes
Sweden	10,000	27.8		26.5	
United Kingdom	60,000	8.7		7.6	
United States	65,000	0.0	Yes	0.0	Yes

TABLE C.33: The approximate number of individuals in each survey and the outcome of the hypothesis test for each country.

Note: n is based on the respective labour force surveys and when there is overlap corresponds to the same numbers used in Elsby et al. (2013) divided by 2. For Netherlands, we proceed assuming that the test was also rejected for Males.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

so $w_t^{<12}$ is 1, less the sum of the other three weights. The objective function can be written as:

$$V_{f,t} = \mathbf{e}_1' \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}_{f,t}' \mathbf{e}_1 + 2\mathbf{e}_1' \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}_{f,t}' \mathbf{M}_w \tilde{\mathbf{w}}_t + \tilde{\mathbf{w}}_t' \mathbf{M}_w' \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}_{f,t}' \mathbf{M}_w \tilde{\mathbf{w}}_t, \qquad \text{(C.11)}$$

which results in the optimal set of weights as:

$$\tilde{\mathbf{w}}_t = -(\mathbf{M}_w' \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}_{f,t}' \mathbf{M}_w)^{-1} \mathbf{M}_w' \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}_{f,t}' \mathbf{e}_1. \qquad \text{(C.12)}$$

C.4 Further mathematical details

Here we provide derivations of important equations in the paper.

C.4.1 Unemployment and steady state

Here we describe how one of the main equations in the text is obtained, first shown in Shimer (2012),

$$u_t = \left(1 - e^{-12(s_t + f_t)}\right)u_t^* + e^{-12(s_t + f_t)}u_{t-12}. \tag{C.13}$$

Start with

$$\frac{du_t}{dt} = s_t(1 - u_t) - f_t u_t \Rightarrow \frac{du_t}{dt} + (s_t + f_t)u_t = s_t. \tag{C.14}$$

This is a first order linear differential equation in u. If we make the assumption that flows are not changing within a period, say τ months, the solution can be written as

$$u_t = u_t^* + ce^{-\tau(f_t + s_t)}, \tag{C.15}$$

where c is the constant of integration. c represents initial deviations from steady state $c = u_{t-\tau} - u_t^*$. Substiting c into (C.15) and setting $\tau = 12$ months gives (C.13).

C.4.2 Non-logarithmic decomposition

In order to asses deviations in unemployment rates as opposed to logarithmic deviations we write down a decomposition in levels. Begin with (C.13)

$$u_t = \left(1 - e^{-12(s_t + f_t)}\right)u_t^* + e^{-12(s_t + f_t)}u_{t-12}. \tag{C.16}$$

First-differencing and letting $e^{-12(s_t + f_t)} \approx e^{-12(s_{t-1} + f_{t-1})}$, we have

$$\Delta u_t = (1 - e^{-12(s_t + f_t)})\Delta u_t^* + e^{-12(s_t + f_t)}\Delta u_{t-12} + \varepsilon. \tag{C.17}$$

Now all we need is a categorisation for Δu_t^*. As is shown in Petrongolo and Pissarides (2008) and Smith (2012), among others, it is straightforward to show that

$$\Delta u_t^* = (1 - u_t^*)u_{t-12}^* \frac{\Delta s_t}{s_{t-12}} - (1 - u_{t-12}^*)u_t^* \frac{\Delta f_t}{f_{t-12}}. \tag{C.18}$$

We show the derivation for completeness. Begin with the twelve month changes in unemployment

$$\Delta u_t^* = \frac{s_t}{s_t + f_t} - \frac{s_{t-12}}{s_{t-12} + f_{t-12}} = \frac{s_t(s_{t-12} + f_{t-12}) - s_{t-12}(s_t + f_t)}{(s_t + f_t)(s_{t-12} + f_{t-12})} = \frac{s_t f_{t-12} - s_{t-12} f_t}{(s_t + f_t)(s_{t-12} + f_{t-12})}. \tag{C.19}$$

Including $s_t f_t - s_t f_t$ in the numerator we have

$$\Delta u_t^* = \frac{s_t f_t - s_t f_t + s_t f_{t-12} - s_{t-12} f_t}{(s_t + f_t)(s_{t-12} + f_{t-12})} = \frac{\Delta s_t f_t}{(s_t + f_t)(s_{t-12} + f_{t-12})} + \frac{\Delta f_t s_t}{(s_t + f_t)(s_{t-12} + f_{t-12})}$$
$$= \frac{\Delta s_t}{s_{t-12}} \frac{f_t}{s_t + f_t} \frac{s_{t-12}}{s_{t-12} + f_{t-12}} + \frac{\Delta f_t}{f_{t-12}} \frac{s_t}{s_t + f_t} \frac{f_{t-12}}{s_{t-12} + f_{t-12}},$$

(C.20)

which is equivalent to (C.18), where the final equality follows from multiplying the first ratio by s_{t-1}/s_{t-1} and the second by f_{t-1}/f_{t-1}. Combining (C.17) and (C.18), we can write the contributions of the inflows and outflows, respectively, as

$$C_{s_t} = \left(1 - e^{-12(s_t + f_t)}\right)(1 - u_t^*)u_{t-12}^* \frac{\Delta s_t}{s_{t-12}} + e^{-12(s_t + f_t)} C_{s_{t-12}},$$

(C.21)

and

$$C_{f_t} = -\left(1 - e^{-12(s_t + f_t)}\right)(1 - u_{t-12}^*)u_t^* \frac{\Delta f_t}{f_{t-12}} + e^{-12(s_t + f_t)} C_{f_{t-12}},$$

(C.22)

where $C_{s_0} = C_{f_0} = 0$. Finally, the contribution of initial deviations is given as

$$C_{0_t} = e^{-12(s_t + f_t)} C_{0_{t-12}} \quad \text{with} \quad C_{0_0} = \Delta u_0.$$

(C.23)

Smith (2012) also provides a non-logarithmic decomposition. We have found that when using her decomposition, the errors are large, so we resort to this decomposition. Table C.44 shows the results when applying this decomposition method.

	Males				Females			
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	0.24	0.77	0.00	-0.01	0.50	0.50	0.00	0.00
Belgium	0.56	0.41	0.00	0.03	0.60	0.28	-0.01	0.13
Canada	0.60	0.40	0.00	0.00	0.66	0.34	0.00	0.00
Denmark	0.41	0.60	0.01	-0.01	0.39	0.62	0.00	-0.01
France	0.71	0.21	0.02	0.06	0.89	0.05	0.02	0.04
Germany	0.51	0.48	0.03	-0.02	0.81	0.12	0.12	-0.05
Ireland	0.65	0.34	0.03	-0.01	0.66	0.28	0.05	0.01
Italy	0.60	0.33	0.00	0.06	0.58	0.30	0.03	0.10
Japan	0.42	0.58	0.00	0.00	0.36	0.63	0.00	0.01
Luxembourg	0.59	0.47	0.00	-0.05	0.07	0.92	0.01	0.00
Netherlands	0.15	0.82	-0.02	0.05	0.29	0.80	-0.01	-0.07
New Zealand	0.66	0.68	0.00	-0.35	0.56	0.57	0.00	-0.13
Norway	0.42	0.56	0.00	0.02	0.43	0.56	0.00	0.01
Portugal	0.49	0.53	0.00	-0.02	0.52	0.41	0.00	0.07
Spain	0.48	0.51	0.03	-0.02	0.51	0.57	-0.02	-0.07
Sweden	0.32	0.68	0.00	-0.00	0.16	0.81	0.00	0.02
United Kingdom	0.50	0.49	0.00	0.01	0.93	0.03	0.01	0.03
United States	0.72	0.28	0.00	0.00	0.78	0.22	0.00	0.00
Average	0.50	0.51	0.01	-0.01	0.54	0.45	0.01	0.01

TABLE C.44: Contributions to unemployment variations for males and females using the non-logarithmic decomposition.

Note: The interpretation of the male results for Australia are: Variations in the outflows contribute to 24% of the dynamics of the unemployment rate, variations in the inflows contribute to 77% of the dynamics of the unemployment rate, 0% of the dynamics of the unemployment rate can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the dynamics of the unemployment rate.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

C.5 Steady-state vs non-steady-state

If the economy remains in steady-state in all periods notice that the baseline decomposition in the text collapses to:

$$\Delta ln(u_t) = (1 - u_{t-1}^*)[\Delta lns_t - \Delta lnf_t] + \varepsilon. \tag{C.24}$$

Table C.65 shows the results when using the steady-state and non-steady-state decomposition for males and females. The steady-state decomposition is not suitable for two reasons. First because flows are relatively small for many of the countries, the convergence to steady-state is slow. This results in very large errors as we can see. Secondly, because the unemployment flows are, in general, slightly larger for females relative to males, the convergence to steady-state is quicker for females relative to males. This is likely to result in slightly larger errors for males relative to females. We can see that this is in general true - the average absolute value of the error for males and females is 0.35 and 0.31, respectively.

C.6 Differences during the 2020 crisis

The crisis in 2020 seems likely to devastate labour markets as economies around the world attempt to minimise the number of lives lost through various social distancing policies. Figure C.62 shows the unemployment rate by gender for the US and Canada, where the last date is April 2020. The rise in unemployment during the current crisis is incredible. It dwarfs the unemployment rise in any economic downturn over the entirety of available data from the OECD. As we have discussed in this paper, typically, the unemployment rate rises proportionately more for males than females in recessions. This trend seems to have reversed during the 2020 crisis. The female unemployment rate rose significantly more than for males. If the results in the current paper extend to the 2020 crisis, then the reason for the larger rise in female unemployment is predominantly due to a proportionately larger rise in females separating from their jobs and flowing into unemployment, and the types of industries that are being affected in the current crisis are different to those affected in crises over the past four decades, which are more likely to employ women over men.
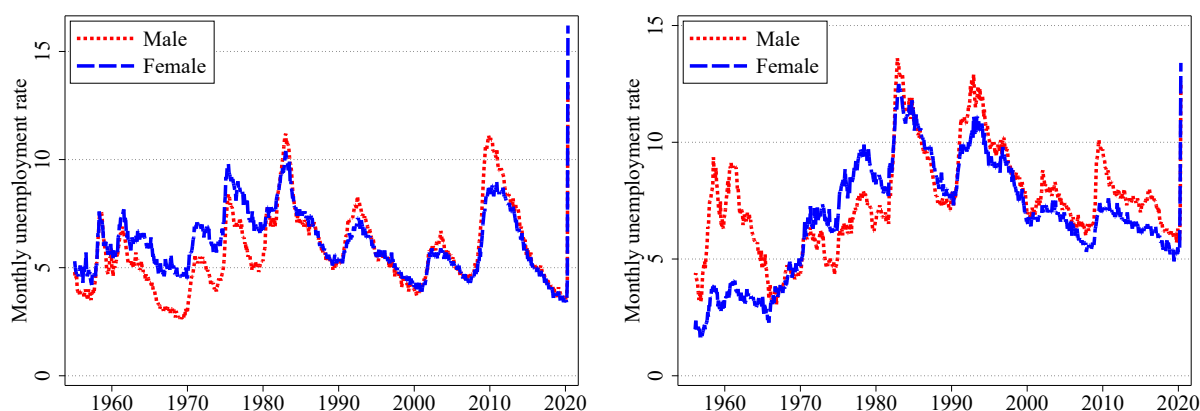

FIGURE C.62: The monthly unemployment rate by gender in the US (left) and Canada (right)
Source: Data compiled from OECD (2018b).

| | Steady-state | | | | | | Non-steady-state | | | | | | | |
| | Males | | | Females | | | Males | | | | Females | | | |
	β_f	β_s	β_ε	β_f	β_s	β_ε	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	0.38	0.73	-0.11	0.53	0.51	-0.04	0.37	0.66	0.00	-0.02	0.53	0.48	0.00	-0.01
Belgium	1.14	0.59	-0.73	0.93	0.91	-0.85	0.53	0.38	0.00	0.09	0.59	0.44	0.00	-0.03
Canada	0.60	0.42	-0.02	0.67	0.34	-0.01	0.60	0.42	0.00	-0.01	0.66	0.34	0.00	-0.01
Denmark	0.46	0.71	-0.17	0.39	0.82	-0.21	0.38	0.61	0.00	0.00	0.34	0.66	0.00	0.00
France	0.28	1.75	-1.03	-0.21	2.09	-0.89	0.54	0.58	0.02	-0.14	0.36	0.69	0.02	-0.07
Germany	0.69	0.75	-0.44	0.97	0.31	-0.28	0.47	0.51	0.04	-0.02	0.84	0.12	0.06	-0.02
Ireland	0.91	0.58	-0.49	0.84	0.47	-0.31	0.57	0.47	0.04	-0.10	0.67	0.35	0.03	-0.06
Italy	1.34	0.52	-0.86	1.62	0.28	-0.90	0.76	0.33	0.01	-0.10	1.01	0.11	0.02	-0.14
Japan	0.63	0.66	-0.29	0.32	0.80	-0.12	0.51	0.48	0.00	0.01	0.30	0.70	0.00	0.00
Luxembourg	1.09	0.42	-0.51	0.11	1.20	-0.31	0.69	0.31	0.01	-0.01	0.11	0.89	0.00	-0.02
Netherlands	0.23	1.11	-0.34	0.42	1.07	-0.48	0.14	0.78	0.06	-0.01	0.42	0.62	0.00	-0.01
New Zealand	0.56	0.63	-0.19	0.56	0.58	-0.14	0.49	0.57	0.05	-0.11	0.52	0.51	0.02	-0.05
Norway	0.42	0.65	-0.08	0.43	0.64	-0.07	0.39	0.60	0.00	0.00	0.41	0.58	0.00	0.00
Portugal	0.69	0.70	-0.39	0.69	0.71	-0.41	0.41	0.59	0.00	0.00	0.55	0.44	0.01	0.00
Spain	0.73	0.51	-0.24	1.13	0.16	-0.29	0.57	0.51	0.00	-0.08	0.84	0.17	0.00	-0.02
Sweden	0.29	0.81	-0.10	0.21	0.88	-0.09	0.26	0.73	0.00	0.00	0.22	0.76	0.00	0.03
United Kingdom	0.55	0.76	-0.32	0.95	0.24	-0.19	0.43	0.57	0.00	0.00	0.83	0.21	0.00	-0.04
United States	0.68	0.34	-0.02	0.79	0.22	-0.01	0.67	0.34	0.00	-0.02	0.79	0.22	0.00	-0.01

TABLE C.65: Contributions to unemployment variation

Note: The interpretation of the Male steady-state results for Australia read: Variations in the outflows contribute to 38% of unemployment variation, variations in the inflows contribute to 73% of unemployment variation, and changes in the error contribute to -11% of the variations in the unemployment rate.

Source: Author calculations based on data compiled from OECD (2018b) and OECD (2018c).

Bibliography

Bibliography

Ahn, H. J., and J. D. Hamilton. 2016. "Heterogeneity and unemployment dynamics." *Finance and Economics Discussion Series 2016-012. Washington: Board of Governors of the Federal Reserve System, http://dx.doi.org/10.17016/FEDS.2016.012.*

Ahn, H. J., and L. Shao. 2017. "Precautionary On-the-Job Search over the Business Cycle." *Finance and Economics Discussion Seires*, 025.

Akerlof, A. G., A. K. Rose, and J. L. Yellen. 1988. "Job switching and job satisfaction in the U.S. labor market." *Brookings Papers on Economic Activity*, 2 495–594.

Albanesi, S., and A. Sahin. 2018. "The Gender Unemployment Gap." *Review of Economics Dynamics*, 30 47–67.

Alvarez, F., and M. Veracierto. 2001. "Severance payments in an economy with frictions." *Journal of Monetary Economics*, 47(3): 477–498.

Anderson, P. M., and B. D. Meyer. 1994. "The extent and consequences of job turnover." *Brookings Papers on Economic Activity: Microeconomics* 177–236.

Azmat, G., M. Guell, and A. Manning. 2006. "Gender gaps in unemployment rates in OECD countries." *Journal of Labor Economics*, 24(1): 1–37.

Bachmann, R. 2005. "Labour market dynamics in Germany: hirings, separations and job-to-job transitions over the business cycle." *mimeo*.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin. 2014. "Tenure, experience, human capital, and wages: a tractable equilibrium search model of wage dynamics." *American Economic Review*, 104(6): 1551–1596.

Bagger, J., and R. Lentz. 2019. "An empirical model of wage dispersion." *Review of Economic Studies*, 86(1): 153–190.

Basten, C., A. Fagereng, and K. Telle. 2016. "Saving and portfolio allocation before and after job loss." *Journal of Money, Credit and Banking*, 48(2-3): 293–324.

Benito, A. 2006. "Does job insecurity affect household consumption?." *Oxford Economic Papers*, 58(1): 157–181.

Blank, R. M. 1989. "Disaggregating the effect of the business cycle on the distribution of income." *Economica*, 56(222): 141–163.

BLS. 2018. "Bureau of Labor Statisitcs." *Current Population Survey: Worker flows.*

Bryan, M., and S. Longhi. 2018. "Couples labour supply responses to job loss: growth and recession compared." *The Manchester School*, 86(3): 333–357.

Burdett, K., C. Carrillo-Tudela, and M. Coles. 2020. "The cost of job loss." *Review of Economic Studies*, 87(4): 1757–1798.

Burdett, K., and D. T. Mortensen. 1998. "Wage differentials, employer size, and unemployment." *International Economic Review*, 39(2): 257–273.

Burgess, P., and S. Low. 1992. "Preunemployment job search and advance job loss notice." *Journal of Labor Economics*, 10(3): 258–287.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin. 2006. "Wage Bargaining with On-the-job Search: Theory and Evidence." *Econometrica*, 74(2): 323–364.

Carrillo-Tudela, C., and E. Smith. 2017. "Search capital." *Review of Economic Dynamics*, 23 191–211.

Clark, L. H., Kim B Summers. 1980. "Demographic Difference in Cyclical Employment Variation." *The Journal of Human Resources*, 16(1): 61–79.

Couch, K., and D. Placzek. 2010. "Earnings losses of displaced workers revisited." *American Economic Review*, 100(1): 572–589.

Cozzi, M., and G. Fella. 2016. "Job displacement risk and severance pay." *Journal of Monetary Economics*, 84 166–181.

Crossley, T., and C. O'Dea. 2010. "The wealth and saving of UK families on the eve of the crisis." *Institute for Fiscal Studies*.

Daniel, H. 1987. "The costs of worker displacement." *Quarterly Journal of Economics*, 102(1): 51–75.

Darby, M., J. Haltiwanger, and M. Plant. 1985. "Unemployment rate dynamics and persistent and persistent unemployment under rational expectations." *American Economic Review*, 75(4): 614–637.

Darby, M., J. Haltiwanger, and M. Plant. 1986. "The Ins and Outs of Unemployment: The Ins Win." *NBER Working Paper*.

Davis, S., J. Faberman, and J. Haltiwanger. 2012. "Labor market flows in the cross section and over time." *Journal of Monetary Economics*, 59 1–18.

Davis, S., and J. Haltiwanger. 1992. "Gross job creation, gross job destruction, and employment reallocation." *Quarterly Journal of Economics*, 107(3): 818–863.

Davis, S., and T. Von Wachter. 2011. "Recessions and the cost of job loss." *Brookings Papers on Economic Activity*, 43(2): 1–72.

Elsby, M., B. Hobijn, and A. Sahin. 2010. "The labor market in the great recession." *Brookings Papers on Economic Activity*, 2 1–48.

Elsby, M., B. Hobijn, and A. Sahin. 2013. "Unemployment Dynamics in the OECD." *NBER Working Paper*.

Elsby, M., B. Hobijn, and A. Sahin. 2015. "On The Importance of the Participation Margin for Labor Market Fluctuations." *Journal of Monetary Economics*, 72 64–82.

Elsby, M., R. Michaels, and G. Solon. 2009. "The Ins and Outs of Cyclical Unemployment." *American Economic Journal: Macroeconomics*, 72 64–82.

Elsby, M., J. C. Smith, and J. Wadsworth. 2011. "The role of worker flows in the dynamics and distribution of UK unemployment." *Oxford Review of Economic Policy*, 27(2): 338–363.

Elsby, M., J. C. Smith, and J. Wadsworth. 2016. "Population Growth, Immigration, and Labour Market dynamics." *mimeo*.

Faberman, J. R., A. I. Mueller, A. Şahin, and G. Topa. 2020. "Job search behavior among the employed and non-employed." *National Bureau of Economic Research Working Paper*(23731): .

Fallick, B., and C. A. Fleischman. 2004. "Employer-to-Employer Flows in the US Labor Market: The Complete Picture of Gross Worker Flows." *Federal Reserve Board of Governors Working Paper*, 34.

Fujita, S. 2012. "An empirical analysis of on-the-job search and job-to-job transitions." *Working Paper 10-34/R*.

Fujita, S., and G. Ramey. 2009. "The Cyclicality of Separation and Job Finding Rates." *International Economic Review*, 50(2): 414–430.

Garibaldi, P. 2004. "Search Unemployment with Advance Notice." *Macroeconomic Dynamics*, 8(1): 51–75.

Gomes, P. 2012. "Labour Market Flows: Facts from the United Kingdom." *Labour Economics*, 19 165–175.

Gomes, P. 2015. "The Importance of Frequency in Estimating Labour Market Transition Rates." *IZA Journal of Labor Economics*, 4:6.

Gong, X. 2011. "The added worker effect for married women in Australia." *Economic Record*, 87(278): 414–426.

Gottfries, A. 2021. "Bargaining with Renegotiation in Models with On-the-Job Search." *mimeo*.

Gourieroux, C., A. Monfort, and E. Renault. 1993. "Indirect Inference." *Journal of Applied Econometrics*, 8 S85–S118.

Gruber, J. 1997. "The consumption smoothing benefits of unemployment insurance." *American Economic Review*, 87(1): 192–205.

Guvenen, F., F. Karahan, S. Ozkan, and J. Song. 2015. "What Do Data on Millions of U.S. Workers Reveal About Life-Cycle Earnings Risk?." *NBER Working Paper*(20913): .

Hall, R. 2005. "Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years." *NBER Macroeconomics Annual*, 20 101–137.

Hansen, G., and A. Imrohoroglu. 1990. "The role of unemployment insurance in an economy and liquidity constraints and moral hazard." *Journal of Political Economy*, 100(1): 118–142.

Hendren, N. 2017. "Knowledge of future job loss and implications for unemployment insurance." *American Economic Review*, 107(7): 1778–1823.

Hoynes, D. L. . S. J., Hilary Miller. 2012. "Who suffers during recessions?." *Journal of Economic Perspectives*, 26(3): 27–47.

Hubmer, J. 2018. "The job ladder and its implications for earnings risk." *Review of Economic Dynamics*, 29(2018): 172–194.

Jacobson, L., R. Lalonde, and D. Sullivan. 1993. "Earnings losses of displaced workers." *American Economic Review*, 83(4): 685–709.

Jarosch, G. 2021. "Searching for Job Security and the Consequences of Job Loss." *National Bureau of Economic Research Working Paper*(28481): .

Jolivet, G., F. Postel-Vinay, and J.-M. Robin. 2006. "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US." *European Economic Review*, 50(4): 877–907.

Jung, P., and M. Kuhn. 2018. "Earnings losses and labor mobility over the life cycle." *Journal of the European Economic Association*, 17(3): 678–724.

Koutentakis, F. 2015. "Gender Unemployment Dynamics: Evidence from Ten Advanced Econmies." *Labour Economics*, 29(1): 15–31.

Krause, M., and T. Lubik. 2010. "On-the-Job Search and the Cyclical Dynamics of the Labor Market." *Federal Reserve Bank of Richmond*, 12.

Krolikowski, P. 2017. "Job ladders and earnings of displaced workers." *American Economic Journal: Macroeconomics*, 9(2): 1–31.

Krusell, P., T. Mukoyama, R. Rogerson, and A. Şahin. 2017. "Gross worker flows over the business cycle." *American Economic Review*, 107(11): 3447–3476.

Krusell, P., T. Mukoyama, and A. Sahin. 2010. "Labor-Market Matching with Precautionary Savings and Aggregate Fluctuations." *Review of Economic Studies*, 77(4): 1477–1507.

Lale, E., and D. Borowczyk-Martins. 2018. "Employment adjustment and part-time jobs: The U.S. and the U.K. in the Great Recession." *American Economic Journal: Macroeconomics*, forthcoming.

Lise, J. 2013. "On-the-job search and precautionary savings." *Review of Economic Studies*, 80(3): 1086–1113.

Liu, K. 2019. "Wage risk and the value of job mobility in early employment careers." *Journal of Labor Economics*, 37(1): 139–185.

Ljungqvist, L., and J. Sargent. 1998. "The European Unemployment Dilemma." *Journal of Political Economy*, 106(3): 514–550.

Longhi, S., and M. Taylor. 2010. "Employed and Unemployed Job Seekers and the Business Cycle." *Oxford Bulletin of Economics and Statistics*, 76(4): .

Low, H., C. Meghir, and L. Pistaferri. 2010. "Wage risk and employment risk over the life cycle." *American Economic Review*, 100(4): 1432–1467.

Mankart, J., and R. Oikonomou. 2016. "The rise of the added worker effect." *Economics Letters*, 143 48–51.

Mukoyama, T. 2014. "The cyclicality of JJ transitions and its implications for aggregate productivity." *Journal of Economic Dynamics & Control*, 39 1–17.

Nagypal, E. 2005. "On the extent of job-to-job transitions." *mimeo*.

Nagypal, E. 2008. "Worker reallocation over the business cycle: the importance of employer-employer transitions." *mimeo*.

Nord, S., and Y. Ting. 1991. "The impact of advance notice of plant closings on earnings and the probability of unemployment." *Industrial & Labor Relations Review*, 44(4): 681–691.

OECD. 2018a. "Organisation for economic cooperation and development." *Social Protection and Well-being.*

OECD. 2018b. "Organisation for economic cooperation and development." *Labour Force Statistics: Short-Term Statistics.*

OECD. 2018c. "Organisation for Economic Cooperation and Development." *Labour Force statistics: Unemployment by Duration.*

Olivetti, C., and B. Petrongolo. 2008. "Unequal pay or unequal employment? A cross-country analysis of gender gaps." *Journal of Labor Economics*, 26 621–654.

Olivetti, C., and B. Petrongolo. 2014. "Gender gaps across countries and skills: Demand, supply and the industry structure." *Review of Economic Dynamics*, 17 842–859.

Olivetti, C., and B. Petrongolo. 2016. "The evolution of the gender gap in industrialized countries." *Annual Review of Economics*, 8 405–434.

Peiro, J. . T. G. M., Amado Belaire Franch. 2012. "Unemployment, cycle and gender." *Journal of Macroeconomics*, 34(4): 1167–1175.

Perry, G. L. 1972a. "Biases in the reporting of labour market dynamics." *Institute for Fiscal Studies Working Paper*, 02/10.

Perry, G. L. 1972b. "Unemployment Flows in the U.S. Labour Market." *BPEA*, 2 245–278.

Petrongolo, B., and C. Pissarides. 2008. "The Ins and Outs of European Unemployment." *American Economic Review P&P*, 98(2): 256–262.

Pissarides, C. 1994. "Search Unemployment with On-the-job Search." *The Review of Economic Studies*, 61(3): 457–475.

Pissarides, C. 2000. "Equilibrium Unemployment Theory, second edition." *MIT Press*.

Pissarides, C., and J. Wadsworth. 1994. "On-the-job search: some empirical evidence from Britain." *European Economic Review*, 38(2): 385–401.

Postel-Vinay, R., and J.-M. Robin. 2002. "The distribution of earnings in an equilibrium search model with state-dependent offers and counteroffers." *International Economic Review*, 43(4): 989–1016.

Razzu, G., and C. Singleton. 2016. "Gender and the business cycle: An analysis of labour markets in the US and UK." *Journal of Macroeconomics*, 47 131–146.

Rogerson, R., and M. Schindler. 2002. "The welfare costs of worker displacement." *Journal of Monetary Economics*, 49(6): 1213–1234.

Schwerdt, G. 2011. "Labor turnover before plant closure:"Leaving the sinking ship" vs."Captain throwing ballast overboard"." *Labour Economics*, 18 93–101.

Shimer, R. 2005a. "The cyclical behavior of equilibrium unemployment and vacancies." *American Economic Review*, 95(1): 25–49.

Shimer, R. 2005b. "The cyclicality of hires, separations, and job-to-job transitions." *Federal Reserve Bank of St. Louis*, 87(4): 493–507.

Shimer, R. 2006. "On-the-job search and strategic bargaining." *European Economic Review*, 50(4): 811–830.

Shimer, R. 2012. "Reassessing the Ins and Outs of Unemployment." *Review of Economic Dynamics*, 15(2): 127–148.

Singleton, C. 2017. "Long-Term Unemployment and the Great Recession: Evidence from UK Stocks and Flows." *Scottish Journal of Political Economy*, forthcoming.

Slichter, S. H. 1919. "The turnover of factory labor." *New York: D. Appleton and Company*.

Smith, J. C. 2012. "The Ins and Outs of UK Unemployment." *The Economic Journal*, 121(552): 402–444.

Statista. 2018. "Statista." *United Kingdom expenditure on unemployment benefits*.

Stephens Jr, M. 2001. "The long-run consumption effects of earnings shocks ." *Review of Economics and Statistics*, 83(1): 28–36.

Stephens Jr, M. 2002. "Worker displacement and the added worker effect." *Journal of Labor Economics*, 20(3): 504–537.

Stephens Jr, M. 2004. "Job loss expectations, realizations, and household consumption behavior." *Review of Economics and Statistics*, 86(1): 253–269.

Stevens, A. H. 1997. "Persistent effects of job displacement: The importance of multiple job losses." *Journal of Labor Economics*, 15(1): 165–188.

Stokey, L. N., and E. R. Lucas. 1989. "Recursive Methods in Economic Dynamics." *Cambridge, MA: with Edward C. Prescott, Harvard University Press, 1989*.

Swaim, P., and M. Podgursky. 1990. "Advance notice and job search: The value of an early start." *The journal of human resources*, 25(2): 147–178.

Tjaden, V., and F. Wellschmeid. 2014. "Quantifying the contribution of search to wage inequality." *American Economic Journal: Macroeconomics*, 6(1): 134–161.

UKGov. 2020. "UK Government." *Making staff redundant: Giving staff notice*.

Upward, R., and P. Wright. 2017. "Don't look down: The consequences of job loss in a flexible labour market." *Economica*, 2019(86): 166–200.