ESSAYS ON CAREER MOBILITY IN THE UK LABOUR MARKET

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Abstract

This thesis consists of three substantial chapters on topics related to occupational and industrial mobility.

Using quarterly data of the Labour Force Survey (LFS) from 1992 to 2013, Chapter 2 documents the mobility across occupations and industries (referred to as career change). The findings suggest that occupational and industrial mobility are surprisingly high. Both occupational and industrial mobility are procyclical. The majority of instances of career change are associated with wage growth. During an expansion, a career changer's wage grows more than someone who stays in their career. However, this does not apply if the career changer was unemployed and then hired during a recession. The evidence suggests that career mobility during a business cycle is important for understanding the labour market flows and wage growth.

The use of interviewing method may affect the accuracy of the data. The dependent interviewing is introduced in the survey, and is helpful in reducing the measurement errors. Chapter 3 uses data from British Household Panel Survey (BHPS) and UK Household Longitudinal Survey (UKHLS) to examine the robustness of the results obtained by using LFS. The procyclicality of occupational and industrial mobility are reassured when the change of interviewing method is controlled for. The further detailed occupational and industrial classification is applied, and the pro-cyclicality of occupational and industrial mobility is found in the further detailing of classifications.

Given the solid evidence found in Chaper 2 and 3, Chapter 4 develops a theoretical model to understand the mechanism of workers' reallocation. Aggregate productivity shock, sectoral productivity shock and preference shock are included in order to investigate reallocation through business cycle, net mobility and gross

mobility respectively. This model shows the procyclicality of gross mobility between sectors, which is consistent with the findings in Chapter 2 and 3. This chapter also explains the higher level of unemployment during recession.

This thesis undertakes a comprehensive analysis of the occupational and industrial mobility in the UK using both empirical and theoretical methods. Limitations of this thesis and suggestions for future research are provided.

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Chapter 1

Introduction

1.1 Motivation

The nature of economy is that it changes all the time. This leads people to consider two questions: how to keep their job and when to change to another job. Regarding the first question, people can essentially improve their skills and capabilities to reduce the risk of getting fired. However, regarding the second question, it is important for people to observe the performance of the economy in order to get a good job since economic expansion always accompanies better job opportunities.

People have to consider whether or not to stay in their profession - their occupation or industry - when they are seeking a job. The possibility of them being hired in another profession during a boom period is increased because the labour market demand is so strong. However, the incentive to change profession decreases during the boom period because jobs in their current profession may be easier to secure.

People change their profess due to different reasons, and these reasons can be simply categorised into two types. The first type concerns the individual's character, for example, a better fit with the individual's skill, a better location, or the individuals' preference. The second type stems mainly from the economic situation, such as aggregate productivity and technology improvement.

Another interesting question is whether workers receive lower wages after they change their profess. Workers are normally paid more because of greater experience and accumulation of human capital. However, once workers change their profess, are they still paid as well as the previous job?

According to the description above, we know that the economic situation affects the worker's decision regarding their career choices. but we do not know *how* it affects their decision. Does a better economy encourage workers to be more adventurous in their career choices?

The individual's profess can be widely defined from different aspects, but in this thesis, I mainly use the occupation and the industry of the worker job as a measurement to identify worker's reallocation behavior. The occupational and industrial reallocation in this thesis are hereafter referred to as a career change..

The research of reallocation across occupation and industries in the US has been documented in the existing literature, but a comprehensive research of reallocation in the UK is urgently needed. This thesis focuses on the occupational and industrial reallocation in the UK, and contributes to fill the gap of the existing literature.

In economic theory, labour and capital are the most common resources in the process of production, and this also emphasizes the importance of labour. The demand and supply of labour involve complex factors and has attracted many researchers into this area. Labour economics is an area that uses economic analysis to understand the interaction between firms, workers and the government. It involves microeconomic and macroeconomic techniques. There are diversified subjects in this area, and unemployment is a crucial one. The other subjects include wages, labor force participation and human capital, etc.

Empirical analysis and theoretical analysis are applied in this thesis. From the empirical aspect, this thesis applies three core datasets to capture a comprehensive view of the labour market in the UK. The Labour force Survey (LFS) is a quarterly dataset providing individuals' employment circumstances, and it is available from 1992. The British Household Panel Survey (BHPS) is a multi-purpose study and is helpful to track workers' long term behavior. The BHPS contains individuals' employment histories and is published every year from 1992 to 2008. The United Kingdom Household Longitudinal Study (UKHLS) is a successor of the BHPS and began in 2009. The UKHLS includes a wider sample than the BHPS. The empirical analysis provides robust features, which motivate me to explore the mechanism behind the features with a theoretical model.

Given the background, the availability of data allows me to examine workers' behaviour regarding changing career. The substantive chapters in this thesis focus on the above research aspects and aim to answer the following research questions:

What is the level of career mobility in the UK, and what is the relationship between career mobility and business cycle? Do wages grow after switching occupation or industry? What is the reason for workers wanting to switch occupation and industry? Who changes careers and where is the destination for career changing?

1.2 Chapter Overview

Chapter 2 is a paper published with Carlos Carrillo-Tudela, Ludo Visschers and Bart Hobijn. All authors have extensively contributed to the paper presented in this chapter. Initially, this published paper was only one chapter of my thesis. We modified and extended this chapter in the form of a journal article and have been published by the *European Economic Review.* I contributed to the conception and design of the work and acquired, analysed and interpreted the data. I also critically revised the paper for important rational content. My contribution to this paper is therefore substantial and recognised.

Using quarterly data of the UK from 1993 to 2012, Chapter 2 documents how the extent of worker reallocation across occupations or industries (a *career change*, in the parlance of this paper) is high and procyclical. This holds true after controlling for workers' previous labour market status and for changes in the composition of who gets hired over the business cycle. Our evidence suggests that a large part of this reallocation reflects excess churn in the labour market. We also find that the majority of career changes come with wage increases. During the economic expansion, wage increases were typically larger for those who changed careers than for those who did not. During the recession, this was not true for career changers who were hired from unemployment. Our evidence suggests that understanding career changes over the business cycle is important for explaining labour market flows and the cyclicality of wage growth.

The method of survey interviewing may overestimate the measure of occupational mobility. The independent interviewing involves asking the participants every time they join the survey, whether or not their employment status has changed. However, the dependent interviewing only updates the participants' status if they change their employment status. If the participants' status does not change at all, their employment status will be transferred from last survey. The errors may occur because of the inconsistency of the participants' responses and the typos of the survey interviewer. The datasets that applied in Chapter 3 consist of independent interviewing from 1992 to 2005 and dependent interviewing from 2006 to 2012. Cheaper 3 confirms the robustness of the results found in Chapter 2, and reaffirm the procyclical feature of occupational and industrial mobility.

After I find and reaffirm the procyclical feature of occupational and industrial mobility, Chapter 4 develops a theoretical model to explore and understand the mechanism behind these findings. A direct search method with Mortensen-Pissaride search and matching framework are applied to investigate the cyclicality of individuals' moving decisions between sectors. A job separation cut-off and a sector reallocation cut-off are used to determine whether workers became unemployed within sector or across the sectors. Aggregate productivity shock, sector productivity shock and preference shock are used to understand the force of mobility. I find that the job separation and sectoral reallocation cut-off are affected by the aggregate productivity, and this may conclude that the sectoral mobility is procyclical under some circumstances. This is helpful for understanding the findings in Chapter 2 and Chapter 3. Finally, Chapter 5 briefly summarises the main findings of each chapter, and and provides the limitations of the thesis and suggestions for future research.

Chapter 2

The Extent and Cyclicality of Career Changes: Evidence for the U.K.

The Extent and Cyclicality of Career Changes: Evidence for the U.K.*

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‡The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

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2.1 Introduction

One of the most important functions of the labour market is to pair the right set of workers with the right set of jobs. This assignment process, however, is slowed down by frictions that impede the reallocation of labour resources. For example, moving costs, re-training, learning about one's ability, information frictions about the location of workers or jobs, among others, can be important barriers for efficient resource reallocation. The result of these frictions is that we observe large concurrent flows of workers changing jobs directly from employer-to-employer as well as through spells of unemployment. As documented by Davis (1987) and Jolivet et. al (2006), among others, this excess churning is a common feature of all labour markets in OECD countries.

The extent of reallocation is not necessarily constant over the business cycle. In one view, recessions are times in which the labour market is "cleansed" by speeding up the reallocation of workers, something that was prevented from occurring by frictions during the proceeding expansions (See, for example, Lilien, 1982, Mortensen and Pissarides, 1994, Caballero and Hammour, 1994, Groshen and Potter, 2003, and Jaimovich and Siu, 2014). This view is appealing because it provides a possible explanation for why unemployment is persistently high in recessions. It simply takes workers time to switch, e.g., from jobs in industries and occupations for which demand is in secular decline to jobs in growing segments of the labour market.

However, this is not the only view of the reallocative effects of recessions. Barlevy (2002) argues that, since employment-to-employment transitions are large and procyclical, economic expansions, rather than recessions, are times in which labour resources tend to reallocate to better uses. In his view recessions have a "sullying" rather than "cleansing" effect on reallocation.

In this paper, we study two specific dimensions of reallocation: occupational and sectoral mobility of workers. If recessions have an important reallocative impact then occupational and sectoral mobility of workers are likely to be two important channels through which this reallocation occurs.[1] In this context we interpret a career as a sequence of jobs a worker has in the same industry and occupation. A career change is a case in which a worker changes employer and starts a new job in either a different industry or occupation from the one he or she was previously employed in.

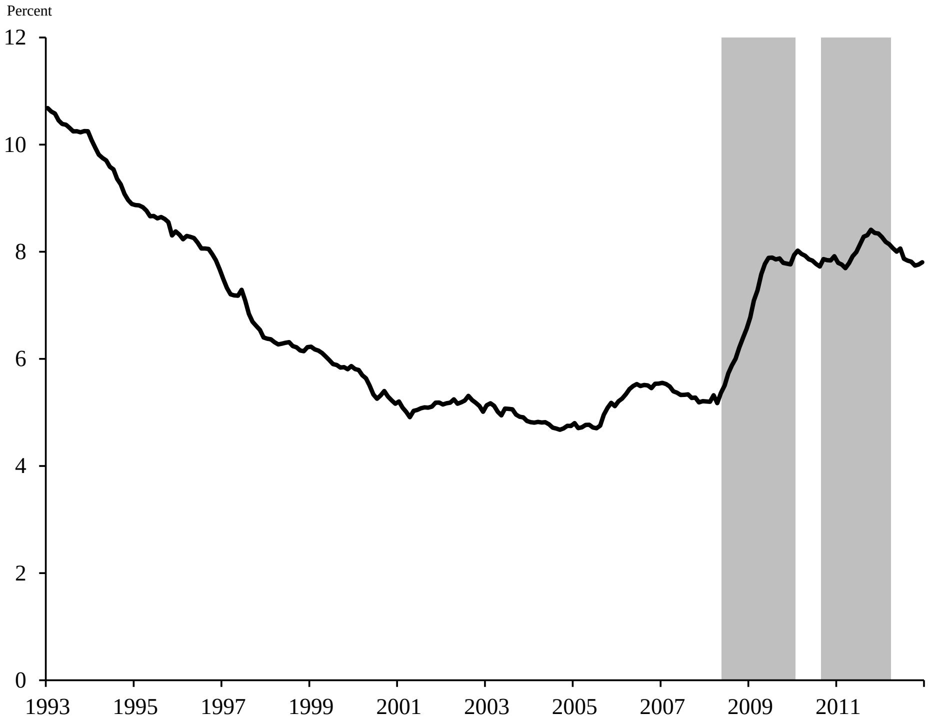
We focus on career changes in the U.K labour market over the period from 1993 to 2012. The U.K. is an interesting country to look at for our purposes because it has one of the most flexible labour markets in Europe and exhibits one of the highest levels of worker turnover in the OECD (see Jolivet et. al, 2006). This high level of turnover suggests that the U.K. labour market facilitates reallocation at a higher rate than those in other European countries.

Figure 2.1 shows the evolution of the U.K. unemployment rate during the period that we study, from 1993 through 2013. It shows that this period can be split up into four distinct episodes. The first episode is a period of economic expansion until 2001, during which the unemployment rate declined by about 4 percentage points.[2] The second is a period of slow growth following 2001, when the U.K. economy skirted a recession and the unemployment rate blipped up marginally. The third episode is the economic expansion from 2002 until the start of the Great Recession in 2008, in which the unemployment rate remained centered around 5%.

Lastly, the Great Recession and its aftermath make up the final episode. Figure 2.1 shows that the unemployment rate increased by 3 percentage points during that period. It is the *number* and *rate* of industry and occupation changes, as well as the associated wage changes, in this final episode that we compare with the earlier parts of our sample. For this, we use individual-level data from the U.K. Quarterly Labour Force Survey.

[1] For example, Pissarides (2003) partly ascribes the persistent outward shift of the U.K. Beveridge curve in the early 1980's to delayed sectoral reallocation in the wake of the fast decline of manufacturing that happened during the deep recession at the beginning of the decade.

[2] Recession dates are taken from Economic Cycle Research Institute (ECRI, 2014).



Source: U.K. LFS. Recession-shading are U.K. recession dates from ECRI. Monthly data, seasonally adjusted, 3-month centered moving average.

Figure 2.1: Unemployment rate in the United Kingdom.

We present our evidence at two levels of detail. In the first part of our analysis we focus on aggregate patterns and uncover facts on (*i*) the extent of career changes in the labour market and (*ii*) how they fluctuate over the business cycle. In the second part we look closer at individual-level patterns that can shine a light on what drives these career changes. In this part we document (*i*) who change careers, (*ii*) which industries and occupations they come from and go to, and (*iii*) whether they do so at higher or lower wage gains than those who switch employers but stay in the same career. Five main findings emerge from our analysis of the U.K. Labour Force Survey.

The extent of career changes is high. A worker who changes employers has around a 50% chance of switching to another occupation or industry. The rates of career changes are remarkably similar for those that change employers with or without an intervening spell of non-employment. Career changes in large part reflect excess churning in the labour market: the actual net mobility across industries and occupations due to career switches only amounts to 10% and 15% of the overall flows between occupations and industries respectively. This evidence on career mobility is in line with Longhi and Taylor (2011) who, using the same data source as us, find that the extent of occupational mobility in the U.K. is high.[3] The U.K. is not an exception. Industry and occupational mobility rates are also high in the United States (see Moscarini and Thomsson, 2007, Moscarini and Vella, 2008, Kambourov and Manovskii, 2008, and Hobijn, 2012, for example.)

Career changes decrease in recessions: The total *number* of workers that change careers and the probability of a career change are procyclical. Moreover, for a worker, the *probability* of a career change is also procyclical, whether conditioning on changing employers directly, or on experiencing an intervening spell of non-participation, or a spell of unemployment. In this sense the cyclicality of career changes in the U.K. is similar to that in the U.S. For the U.S. Murphy and Topel (1987), Carrillo-Tudela, Hobijn and Visschers (2014), and Carrillo-Tudela and Visschers (2014) have all documented that the occupational and industry mobility is procyclical.[4] Moreover, just like in the U.S., excess churning in the U.K. is the main driver of the cyclicality of overall mobility across occupations or industries. This is because employer-to-employer transitions, that account for the bulk of this churning, are procyclical. Moscarini and Thomsson (2007), Moscarini and Vella (2008) and Kambourov and Manovskii (2008), document these dynamics for the U.S. labour market.

Characteristics of career changers: Career changes are more likely for (*i*) those workers actively searching for a job, (*ii*) those that made voluntary transitions

[3]We build on Longhi and Taylor (2011) by considering worker mobility across occupations *and* industries and their associated wage changes, taking into account three different labour market statuses and business cycle fluctuations.

[4]The present paper builds on our previous work by providing a more comprehensive evaluation of career changes and their implications for wage changes.

(i.e. those who 'resigned' from jobs, or gave up for 'family or personal reasons', as opposed to those that were made 'redundant' or 'dismissed') and (*iii*) those workers that work part-time or as temps. Though models of on-the-job search with multiple job types (as in Pissarides, 1994, Akerlof, Rose, and Yellen, 1988, Barlevy, 2002, Menzio and Shi, 2011, Hagedorn and Manovskii, 2013, and Moscarini and Postel-Vinay, 2013, among others) do not specifically focus on career changes, and do not include a formal occupational or industry choice, they do imply that quits are procyclical. Our evidence suggests that many of these quits in the U.K. result in career switches. This is, however, not only the case for employment-to-employment transitions. Career changes are also very common for hires out of non-employment. In terms of underlying demographics, young workers and women are more prone to change careers than their older and male counterparts. Even after accounting for these characteristics, the propensity to change careers for workers that start a new job remains procyclical. Thus, our results are not due to changes in the composition of who gets hired over the business cycle.

Career Paths: Across occupations, career changes that involve an upgrade in the skill level are more likely through direct employer-to-employer transitions. On the contrary, career changes that involve a step down in skill level are more likely after spells of non-employment. Further, career changes tend to move workers from routine to non-routine employment. Our results also show that these movements did not accelerate during the Great Recession.

Wage changes upon career changes: The majority of career changes come with wage increases and these wage increases tend to be bigger than for those workers that change jobs but remain in the same career. The wage gains for those who got hired out of unemployment and changed occupations fell during the recession and became smaller than the wage gains of those who did not change occupations. Several studies have linked wage gains to employer-to-employer transitions (Akerlof, Rose, and Yellen, 1998, and Hagedorn and Manovskii, 2013). Our evidence here suggests that such wage gains disproportionately get realized by workers changing careers rather than continuing in the same one.

These findings provide evidence as to which theories would be able to best explain labour market reallocation through occupational and industry mobility of workers.

Our evidence shows that outcomes for career changers are different from those who remain in the same career when changing jobs. This suggests that understanding career changes over the business cycle is important for explaining the cyclicality labour turnover and wage growth. Most current models of labour turnover, like those that allow for on-the-job search mentioned above, provide theories of why turnover is highly procyclical. Though these theories have heterogenous jobs, none of them explicitly considers a career change decision. Recent models, like Carrillo-Tudela and Visschers (2014) and Groes, Kircher, and Manovskii (2015), do contain a career change margin and help us better understand the incidence of career changes over the business cycle and across the income distribution, respectively.

Taken together, the facts we document are consistent with the view that the Great Recession and its aftermath has affected workers across a large set of industries and occupations, with a broad-based shortfall in economic activity preventing workers from pursuing alternate careers at substantial wage gains. In this sense, our results are consistent with the "sullying" effect of recessions put forward by Barlevy (2002). Of course, career changes are only one form of reallocation of labour and other resources. Thus, our results do not imply that recessions have no cleansing effect at all but rather that such a cleansing is not happening through worker reallocation across occupations and industries. This is important, because it means we find little support in the U.K. data for recent theories of job polarization (Jaimovich and Siu, 2014) that point to occupational mobility between routine and non-routine jobs during recessions as the major driving force of the secular decline in routine jobs.

The rest of the paper is structured as follows. In the next section we discuss the

Quarterly U.K. Labour Force Survey, the definitions of the main variables, as well as the level of aggregation of the industry and occupational classifications that we use. In Section 2.3 we present the aggregate evidence and focus on broad patterns in the level and cyclicality of career changes in the U.K. In Section 2.4 we present individual-level evidence and discuss what it suggests about the reasons for career switches. Finally, we end with a brief discussion of the theoretical implications of the facts we document in Section 2.5.

2.2 Data

The data we use are from the U.K. Quarterly Labour Force Survey (LFS) and cover the period 1993Q1-2012Q3. The LFS has a rotating panel structure, depicted in Figure 2.2, in which individuals that live on the sampled address are followed for a maximum of 5 quarters, also referred to as waves. Each quarter, one-fifth of the sample of addresses is replaced by an incoming rotation group, or cohort. From this sample, we consider all male workers between 16 and 65 years of age and all female workers between 16 and 60 years of age with an ongoing career.[5]

In each wave, the respondents provide information about, among other things, their labour market status as well as their occupation and the industry they work in if they are employed. If non-employed, they provide the occupation and industry of their previous job.[6] Because we are interested in those workers who switch employers and potentially change careers, and because non-employed workers provide information on previous employment, we need observations on workers only for two consecutive quarters. Thus, we use the two-quarter (2Q) longitudinal sample of the LFS. Figure 2.2 depicts two quarters of this sample as long-dashed rectangles, labeled “2Q”. As can be seen from the figure, because of the rotating panel structure

[5]We only include workers that provide information on occupation or industry.

[6]Note that around 10% of workers that start jobs with a new employer do not report information on occupation or industry. These are mainly young workers for whom this is, presumably, their first job.

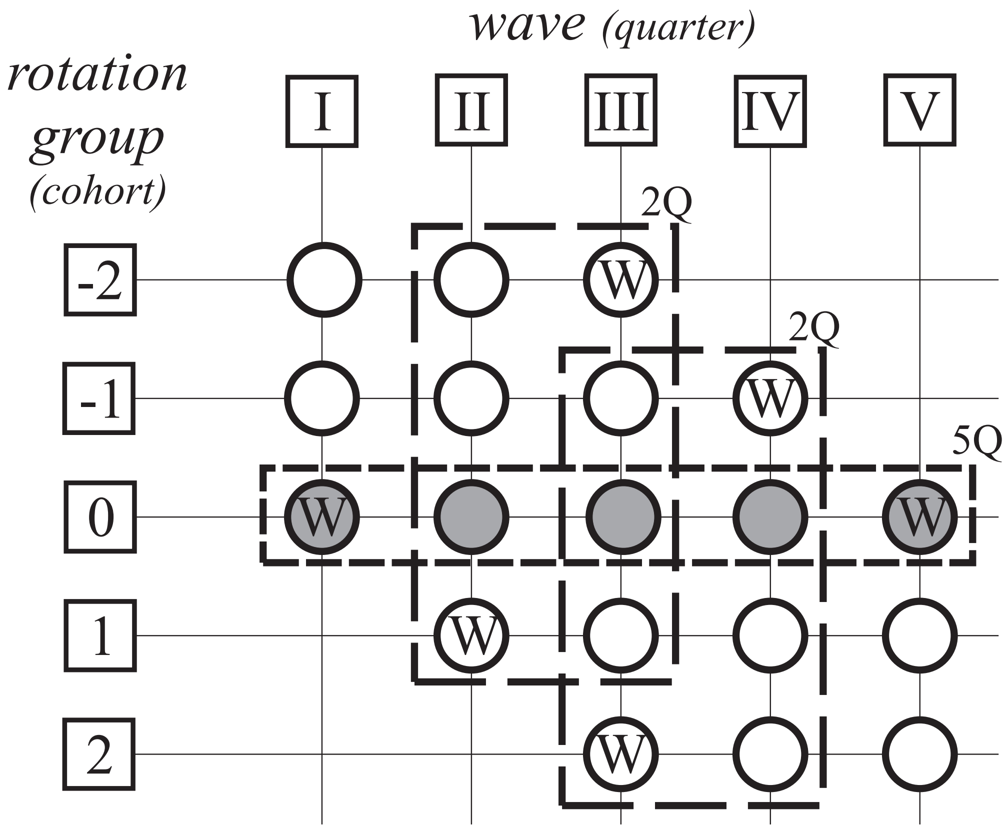


Figure 2.2: Rotating panel structure of U.K. Quarterly Labour Force Survey.

and sample attrition, the 2Q sample is smaller than the quarterly cross-section. It consists of about 60,000 individuals each quarter.[7]

Occupation and Industrial Classifications To code occupations, the U.K. LFS uses the Standard Occupational Classification (SOC). The occupational coding system was redefined in 2001, from the SOC 1990 to the SOC 2000, which was used until the end of 2010. A drawback of this revision is that the SOC 1990 and SOC 2000 are not fully compatible. To reduce potential incompatibility errors we focus on mobility across 1-digit or major occupational groups. These groups are listed in Table 2.1 for both the SOC 1990 and SOC 2000. At this level of aggregation, the disagreement between the two SOC is of 26.5 percent.

The disagreement between the two classifications introduces a level shift in some

[7]More information about the U.K. Quarterly Labour Force Survey can be found in Office for National Statistics (2011a, 2011b).

Table 2.1: One-digit Occupational Codes

SOC 1990	SOC 2000
1. Managers and administrators	1. Managers and senior officials^{n}
2. Professional occupations	2. Professional occupations^{n}
3. Associate professional occ.	3. Associate professional and technical occ.^{n}
4. Clerical and secretarial occ.	4. Administrative and secretarial occ.^{r}
5. Craft and related occupations	5. Skilled trades occupations^{r}
6. Personal and protective service occ.	6. Personal service occupations^{r}
7. Sales occupations	7. Sales and customer service occupations^{r}
8. Plant and machine operatives	8. Process, plant and machine operatives^{r}
9. Other occupations	9. Elementary occupations^{r}

Note: ^{n} are non-routine occupations and ^{r} are routine occupations.

of the occupational series at the time of the switch from SOC 1990 to SOC 2000. To correct for this shift, we adjust all 5-quarter centered moving average series by running an OLS regression on the log of the corresponding series with respect to a linear time trend, the log of output per worker and a dummy which takes a value of zero before 2000Q4, and one after. We then use the coefficient estimate of the dummy variable (irrespectively if it was significant or not) to adjust the series up to 2000Q4.[8]

To code industries, the U.K. LFS uses the Standard Industrial Classification (SIC). In this case the U.K. LFS does provide homogenised industry information for workers for the entire sample period based on the SIC 1992.[9] We focus on industrial mobility on broad industrial sectors, which roughly corresponds to a one-digit aggregation level, with 17 categories displayed in Table 2.2.

Wage Analysis For the last part of our analysis, we also consider the change in wages when workers switch occupations or industries. The wage measure we use is the self-reported gross weekly earnings, deflated using the CPI. Individuals in the LFS only report their wages in the first and fifth waves. These are depicted

[8] There is no occupational information for 2001Q1. Moreover, because our sample is very short after 2010, such splicing is not possible for the latter period when the occupational definitions shifted to the SOC 2010. Consequently, we end the sample used to calculate results for occupations in 2010Q4.

[9] The U.K. LFS did not ask respondents about their industry of employment before 1994, and therefore our results for industries cover 1994-2012.

Table 2.2: Industry Classification

Homogenised SIC	
1. Agriculture, forestry	10. Financial intermediation
2. Fishing	11. Real estate, renting
3. Mining and quarrying	12. Public administration
4. Manufacturing	13. Education
5. Electricity, gas and water	14. Health and social work
6. Construction	15. Other community service activities
7. Wholesale and retail trade	16. Private households
8. Hotels and restaurants	17. Extra-territorial organisations and bodies
9. Transport, distribution	

by the circles labeled "W" in Figure 2.2. Because they report their wages one year apart, we can calculate annual wage growth for these workers. However, to do so requires us to follow these workers for the full five quarters that they are in the LFS. This sample is known as the five-quarter longitudinal sample and is depicted by the short-dashed rectangle labeled "5Q" in the figure. This sample contains, on average, about 11,000 individuals. Using this sample we condition the wage analysis on employer changes through employment, unemployment or inactivity based only on uninterrupted spells.[10] We aggregate all these transitions to analyse the wage changes among all workers.

2.2.1 Level and probability of career changes

We record a *career change* when a worker changed employer *and* reported an occupation or industry in the new job that is different from the occupation or industry reported in the last job held. Then, what is flagged as a career change depends on the level of aggregation of the occupation and industry classifications used. Because we use the major occupation and industry classifications discussed above,

[10]That is, for employer-to-employer (EE) transitions, we consider workers with employment histories (within the 5-quarters) of $E_1E_2E_2E_2E_2$, $E_1E_1E_2E_2E_2$, $E_1E_1E_1E_2E_2$, or $E_1E_1E_1E_1E_2$, where E_1 denotes the first employer and E_2 the second employer. For employment to unemployment to employment (EUE) transition, we consider workers with employment histories of $E_1UE_2E_2E_2$, $E_1E_1UE_2E_2$, $E_1E_1E_1UE_2$, $E_1UUE_2E_2$, E_1UUUE_2, or $E_1E_1UUE_2$. For employment to non-participation to employment (EIE) transitions we consider employment histories with the same structure as for EUE transitions.

the career changes we flag capture a substantial change in the nature of a worker's job.[11]

Since mobility across employers and careers can occur with or without intervening spells of non-employment, we analyse mobility across jobs by considering employment to employment (EE) transitions, unemployment to employment (UE) transitions, and inactivity (non-participant in the labour force) to employment (IE) transitions. We denote the labour market status of a worker in the quarter before he or she starts a new job as $S \in \{E, U, I\}$. Conditioning on labour market status history is informative, because it is a signal of the reason why a worker might decide to pursue a different career.

Throughout, we split the three types of flows, EE, UE, and IE, up by *career movers*, denoted by m, and *career stayers*, denoted by s. Career movers are those workers that work for a new employer in either a different occupation or industry as they worked in before. Career stayers are workers that start a new job in the same occupation and industry they worked in previously. In terms of this notation, EE_{t+1} is the total number of workers that move from one employer in quarter t to another in quarter $t+1$, $EE_{t+1}^{(m)}$ is the number of those workers who are career $m$overs, and $EE_{t+1}^{(s)}$ is the number of career $s$tayers.[12]

These definitions allow us to consider the quarterly proportion of all new hires that experienced a change in occupation or industry in period $t+1$, given that in period t their labour market state was $S \in \{E, U, I\}$. Namely,

$$HS_t^{(m)} = \frac{SE_{t+1}^{(m)}}{SE_{t+1}}. \tag{2.1}$$

Aggregating over all three labour market statuses, $S \in \{E, U, I\}$, we obtain that

[11]Because of the address being the sampling unit of the LFS, we do not capture career changes in which people move to a different address. In that case they drop out of the sample. Moreover, given the quarterly nature of the data in the LFS, we are unable to record a worker's transitions within any given quarter and hence our estimates e.g. could miss jobs that begin and end within a quarter.

[12]We similarly define UE_t, $UE_t^{(m)}$, $UE_t^{(s)}$, IE_t, $IE_t^{(m)}$, and $IE_t^{(s)}$.

the proportion of total hires that are career movers is given by

$$H_t^{(m)} = \frac{UE_{t+1}^{(m)} + IE_{t+1}^{(m)} + EE_{t+1}^{(m)}}{UE_{t+1} + IE_{t+1} + EE_{t+1}}. \tag{2.2}$$

We use these measures as estimates of the probability of a career change conditional on starting a new job, the previous labour market status, and being in an ongoing career. The levels of the flows and these estimated career change probabilities are the main statistics we focus on in our analysis. That is, we focus on two measures of the incidence of career changes. The *levels*, $SE_t^{(m)}$ for $S \in \{E, U, I\}$, inform us about the extent of reallocation going on in the economy, while the *rates*, $HS_t^{(m)}$ for $S \in \{E, U, I\}$, approximate the probabilities that individual workers switch careers conditional on getting hired out of a particular labor market status.

2.2.2 Net mobility

Theories that emphasize the cleansing effect of recessions on the labour market emphasize how downturns accelerate the shift in labour market resources from segments that are in structural decline to those that are on a positive long-run trend. These are theories that focus on the net mobility of workers across professions and sectors.

Net mobility is given by

$$NM_t = \sum_{i=1}^{K} |I_{i,t} - O_{i,t}|, \tag{2.3}$$

where $I_{i,t}$ is the number of career movers that start a new career in sector (or occupation), i. Similarly, $O_{i,t}$ is the number of workers that leave sector (or occupation) i to pursue a different career.

To put this net mobility in the context of the magnitude of overall flows in the labour market, we follow Davis and Haltiwanger (1992) and analyze excess reallocation. That is, we quantify by how much the total gross reallocation measured by the flows introduced in the previous subsection exceeds the minimum flows needed to achieve the net shift in the observed allocation of workers across occupations and industries.

In particular, we use the following proxy of the fraction of gross reallocation needed to achieve the net reallocation in the data. This net mobility rate, nm_t, is defined as

$$nm_t = \sum_{i=1}^{K} \Big[\frac{|I_{i,t} - O_{i,t}|}{I_{i,t} + O_{i,t}}\Big]\omega_{i,t}, \tag{2.4}$$

where we weigh the sector (or occupation) specific flows by the employment share of the respective industry or occupation at time t, $\omega_{i,t}$. Our data allow us to compute separate quarterly series, NM_t and nm_t, for occupations and industries.

2.3 The Extent and Cyclicality of Career Changes

In this section we investigate both the level as well as the cyclical fluctuations of the incidence of career changes in the U.K. labour market. In the first subsection we focus on the level and report long-run averages over our whole sample period. In the second subsection we shift our focus to how the prevalence of career changes moves over the business cycle.

2.3.1 Long-run averages

The U.K. labour market displays a surprising degree of churning. Over our sample period, the sum of career movers and stayers is on average 1.3 million per quarter. This amounts to 4.5% of the U.K.'s working age population. Of those who get hired and have a previous career, 43% come directly from a previous employer, 29% are hired out of unemployment, and 29% were out of the labour force. These numbers are in line with Gomes (2012).

What is even more striking is the high share of these hires that involve a career

Table 2.3: Probability of career change, $HS^{(m)}$.

		Occupation	Industry
1.	**All workers**	0.49	0.53
2.	**Employed Workers,** $HE^{(m)}$	0.47	0.52
3.	Voluntary mobility	0.48	0.52
4.	Involuntary mobility	0.44	0.51
5.	Active search	0.53	0.59
6.	Non active search	0.46	0.49
7.	**Unemployed Workers,** $HU^{(m)}$	0.51	0.56
8.	Unemp duration $< 2Q$	0.50	0.54
9.	Unemp duration $\geq 2Q$	0.56	0.61
10.	**Inactive Workers,** $HI^{(m)}$	0.49	0.50
11.	Want a job	0.50	0.52
12.	Don't want a job	0.47	0.48

Note: Shares reported are averages over all quarters in 1993Q1-2012Q3 sample for which data are available.

change. Table 2.3 shows the average fraction of these hires that we classify as a career change. As can be seen from the top row of the table, 49% of those workers with a previous career who start a new job do so in a different (major) occupation from which they worked in before. This fraction is even higher for industries, for which the majority, 53%, of such hires involve a switch in major industry.

The similarities in the extent of career changes across occupations or industries arises mostly because the majority of career movers change occupations and industries at the same time. For example, on average 75% of workers who changed occupations also changed industries and 70% of workers who changed industries also changed occupations.

Though high, these numbers are in line with evidence for the United States. For example, Carrillo-Tudela, Hobijn and Visschers (2014), using data from the Current Population Survey, and Carrillo-Tudela and Visschers (2014), who rely on the Survey of Income and Program Participation, both find that about half of the hires in the United States involve a career change as well.

One caveat is important to note. Reporting errors, more so for occupations than for industries, are common in surveys like the U.K. LFS. If estimates from other datasets are applied to our results for the U.K. LFS, then, maybe even as much as a quarter, of the career moves that we measure could be due to workers misreporting their occupation and/or industry in the survey.[13] However, even if this is true, this would still mean that about a third of all hires of persons with previous work experience involves them changing either the industry or profession that they work in. Even after such a drastic downward adjustment, this would imply that more than one percent of the U.K. working age population switches careers every quarter.

Rows 2 and up of Table 2.3 list the probability of a career change conditional on the labour market status of the worker in the quarter before she or he starts a new job. As can be seen from the table, the average probability of a career change is around 50% for each of these types of hires.

Two groups of workers stand out as having a higher probability of switching careers than others. The first consists of workers who make an EE transition and who actively searched for the new position in the old job. These are more likely workers who actively pursue a voluntary change in their career path. To be specific, career or job changes are categorised as *voluntary* when workers report in the LFS that they left their previous employer because they "resigned", went to "education or training" or "gave up for family or personal reasons". *Involuntary* career or job changes are made by those workers who left their last job because they were "dismissed", "made redundant/took voluntary redundancy", "temporary job finished" and "gave up work for health reasons". Finally, workers in the *other* group are those who left their last job because they "took early retirement", "retired" and due to "other reasons".[14] Active search encompasses all activities that involve

[13]Mellow and Sider (1993) estimate a misreporting rate of about 20% for major occupations and 8% for major industry sector in the Current Population Survey for the U.S. Lynn and Sala (2006) find similar misreporting rates for the BHPS in the U.K.

[14]Overall, voluntary employer changes account for 48% of total EE transitions, while involuntary employer changes account for 24% and the remainder by the 'other' category. From those employed workers that experienced a voluntary or involuntary separation, over 85% found another

the worker to contact or actively pursue job opportunities rather than browse job opportunities that are available. This is the definition of job search that defines a person without a job as being unemployed. The specific LFS answers that result in a person being classified as an active searcher are listed in the Appendix.

The second group of workers with a higher probability of moving to a different career are those who were unemployed for two quarters or more in the quarter before they started their new jobs. These transitions most likely reflect involuntary career decisions that occur in long spells of unemployment. Such career changes are often emphasized as driving up the natural rate of unemployment in the short-run in the wake of a recession due to mismatch in the labour market. Recent studies show that mismatch can only account for a small part of overall fluctuations in the unemployment rate.[15]

Most studies of mismatch in the labour market compare the composition of job openings by industry and occupation with the composition of the pool of unemployed workers. This assumes that it is the pool of unemployed workers that are required to make all the adjustments to make the skill composition of the labour supply adjust to the composition of skills demanded. It turns out that more than half of the workers that get hired out of unemployment end up making such an adjustment. Moreover, our results suggest that the large number of EE career switchers helps to accelerate this adjustment process.

By providing a measure of the gap between the skill requirements needed to fill the stock of job openings and the skill composition of the pool of unemployed, measures of mismatch are a proxy for the *net* amount of reallocation needed in the labour market to equilibrate the supply of and demand for skills. However, gross mobility between careers far exceeds net mobility. The average net mobility rates, nm_t, over our sample period are 10% for occupations and 13% across industries.[16]

job without an intervening spell of non-employment.

[15] See, for example, Smith (2012) and Patterson, Şahin, Topa, and Violante (2013) for a quantitative analysis of this type of mismatch in the U.K.

[16] The small contribution of net mobility is also present when considering transitions only

This echoes the findings for the U.S. of Jovanovic and Moffit (1990), Kambourov and Manovskii (2008) and Auray et. al (2014), who show that net mobility accounts for only a small proportion of gross mobility across industries and occupations.

2.3.2 Cyclical fluctuations

Whether recession are times of accelerated or of relatively slow reallocation in the labour market can, of course, not be gleaned from the long-run averages we reported so far. To answer this question we now present evidence on the fluctuations, in deviation from these averages, in the extent and probabilities of career changes over our sample period.

The evidence on the extent of career changes is depicted in Figure 2.3.[17] It plots the six types of hires of workers with ongoing careers. The bottom three shaded areas are the career movers coming from unemployment, $UE^{(m)}$, employment, $EE^{(m)}$, and inactivity, $IE^{(m)}$, respectively. The top three shaded areas plot the same flows but then for career stayers instead. The solid line in the middle is the number of career movers in the quarter, while the dashed line on top is the sum of career movers and stayers.

The first thing to take away from this figure is that overall turnover for workers with previous work experience is procyclical. This can be seen from the fact that the dashed line in the figure follows almost exactly the reverse pattern as the unemployment rate in Figure 2.1. The procyclicality of turnover in our data is mainly driven by people who move directly from one employer to another employer, i.e. by $EE^{(m)}$ and $EE^{(s)}$. As can be seen from Figure 2.3, the bulk of the hires of workers with an ongoing career are EE hires. This is consistent with the turnover

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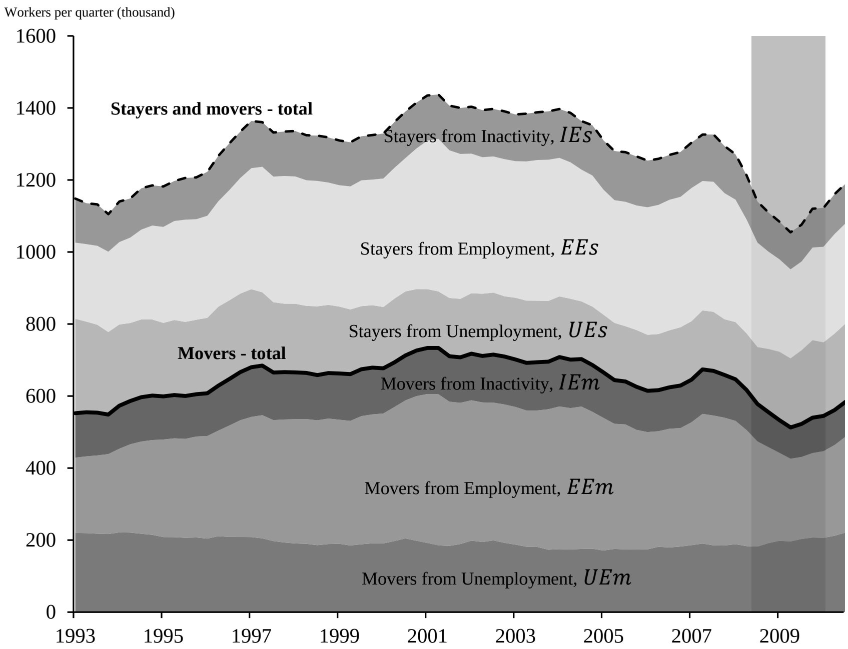
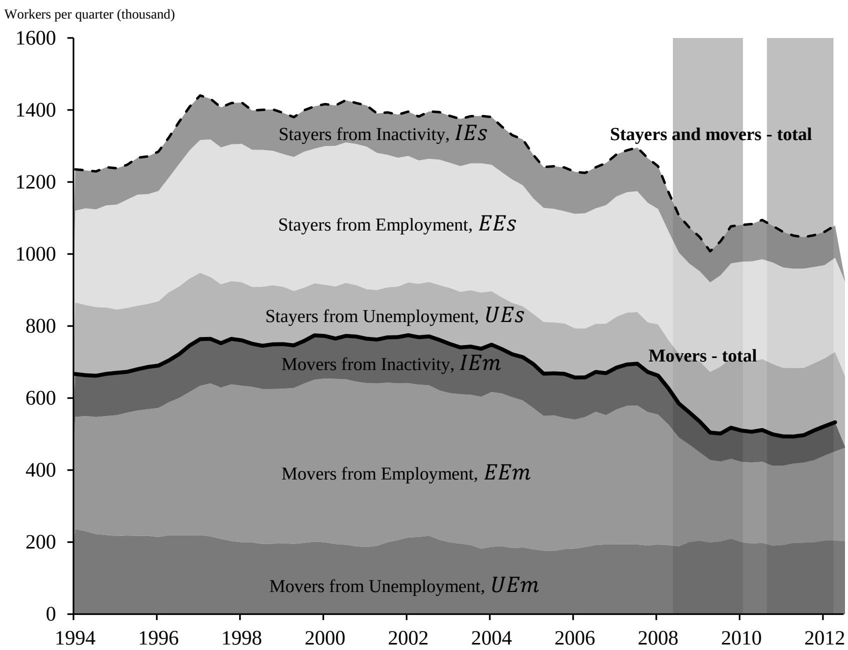
through unemployment or only through employment. For the former case, the average net mobility rates are 17% for occupations and 20% for industries; while for the latter the rates are 12% for occupations and 15% for industries.

[17] Throughout we show time series that are 5-quarter *centered* moving averages. Though this allows for symmetric centering, it could induce residual seasonality in our time series. However, tests for such seasonality do not reject the null hypothesis of its absence.



Occupations



Industries

Figure 2.3: Hires of workers with ongoing careers, by career movers and stayers. Source: U.K. LFS and authors calculations. Recession-shading are U.K. recession dates from ECRI. Quarterly series, centered 5-quarter moving averages.

estimates for the U.K. in Hobijn and Şahin (2013) and for the United States.[18]

The solid line in Figure 2.3 reveals that, just like overall turnover, the number of career changes is procyclical. Employer-to-employer transitions, $EE^{(m)}$, also make up the majority of career changes. The main driving force behind the incidence of career changes over the business cycle is that the number of workers that change employers to pursue a different career declines substantially when the unemployment rate spikes.

This force is partly offset by the fact that the number of workers that change careers after a spell of unemployment increases during and in the wake of recessions. However, in the aftermath of the Great Recession this uptick in career changes after unemployment, $UE^{(m)}$, was rather small. It pales in comparison to the decline in $EE^{(m)}$ flows during the same period and thus contributed very little to the fluctuations in reallocation in the labour market over the last business cycle.

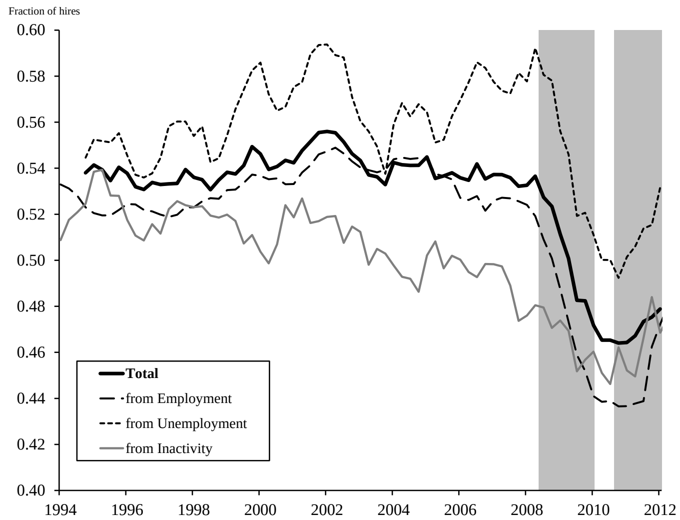
Moreover, if one compares the number of $UE^{(m)}$ and $UE^{(s)}$ transitions in Figure 2.3, one can see that the number of workers that find a job after being unemployed and remain in the same career, increases more during recessions than the number of unemployed that end up taking a job in a different industry or occupation. This suggests that the probability of a career change for those workers hired out of unemployment actually declines rather than increases during the recession.

This is shown to be the case in Figure 2.4. It plots the time series of the unconditional probability of a career change for hires with previous work experience, $H^{(m)}$, as well as this probability conditional on what labour market state they were hired from, i.e. $HS^{(m)}$ for $S \in \{U, E, I\}$. The bold line in the figure shows that $H^{(m)}$ declined during the recession for both occupation and industry changes. This decline is starker for changes across industries, shown in panel (b), than for changes across occupations, in panel (a). The short-dashed line is the probability that a hire out of unemployment changes careers. This probability also declined

[18] See Lazear and Spletzer (2012) for evidence for the United States, for example.

substantially during the Great Recession.

Occupations



Industries

Figure 2.4: Probability of career change: Hm, and HSm for $S \in \{U, E, I\}$.
Source: U.K. LFS and authors calculations. Recession-shading are U.K. recession dates from ECRI. Quarterly series, centered 5-quarter moving averages.

Above, we have focused on comparing the Great Recession with the previous episodes in the data. The procyclicality of the level and probability of career changes that we documented, however, is also robust to other ways of business cycle accounting. For example, it also shows up if one uses the Hodrick-Prescott (1997) filter to distinguish between trend and cycle in the unemployment rate and the time series plotted in Figures 2.3 and 2.4.[19]

One possible explanation for the procyclicality of the propensity to change careers out of unemployment is the increased incidence of workers being recalled to their previous job during downturns. For example, Fujita and Moscarini (2012) find that, in the U.S., those workers that become unemployed after being permanently separated from their previous jobs are much more likely to make an occupational change than those that were on layoff and recalled within 3 months. However, in the UK such recall practice is minimal and, hence, is thus not likely to affect the results presented here.

What could be more pertinent is that, on the supply side, those workers who get laid off in recessions would first look for a job that is similar to the one they lost and only slowly broaden their search.[20] However, as Carrillo-Tudela and Visschers (2014) argue, workers take into account that they may be less likely to start a particularly successful career path during a recession, which reduces their incentives to change careers at any duration.

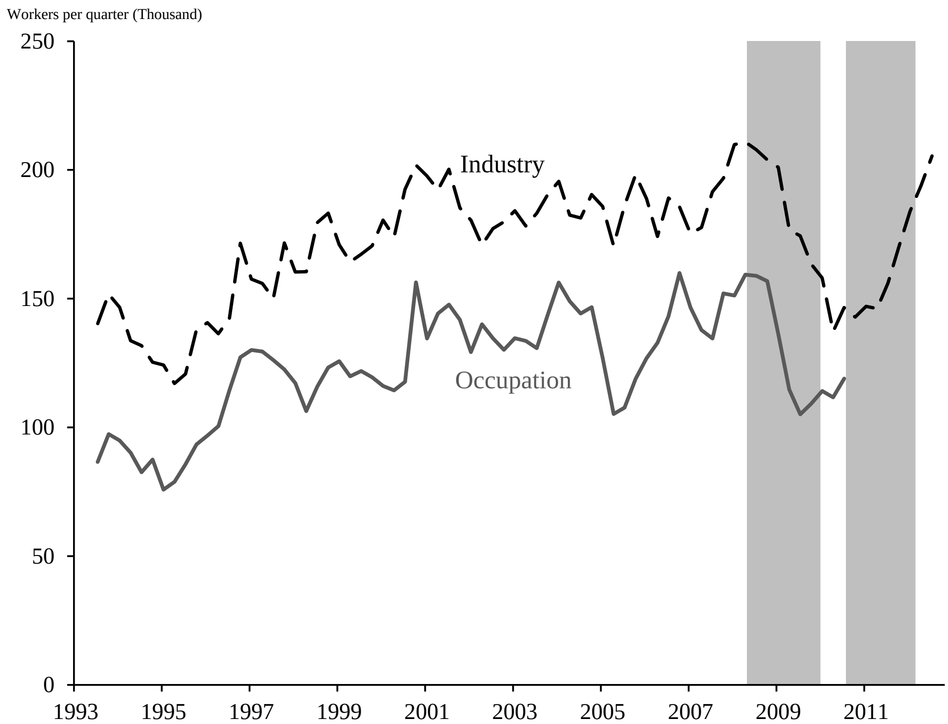
On the labour demand side, because of the increased size of the pool of unemployed workers in recessions, employers would be more likely to find candidates that more closely match the career profile they are looking for. Some studies, like Ravenna and Walsh (2012) and Sedláček (2014), suggest that employers also get more selective in their hiring practices during downturns. Such an increase in the pickiness of employers about who they hire in downturns also affects the opportunities of those who are employed and are looking to change jobs and pursue a different career. These effects could result in a decline in the fraction of EE transitions that result in a switch in industry or occupation during recessions, as can be seen from the long-dashed line in Figure 2.4.

Another way to gauge the relative importance of these effects is to look at

[19]It also shows up when regressing the log of these series with respect to a constant, the log of output per worker or of the unemployment rate and a time trend.

[20]Indeed, the number of unemployed workers who found a job after an unemployment spell of less than 6 months and changed careers actually decreased during the Great Recession.

the fluctuations in net mobility, NM, over the business cycle. Net mobility for both occupations and industries is plotted in Figure 2.5. If recessions had a major "cleansing" effect that resulted in a substantial shift in workers from occupations and industries in secular decline to those for which demand is booming, then net mobility would increase during the recession as well during the subsequent recovery. This is because during the recovery workers would, gradually perhaps, find jobs in careers different from those that they were in before. It is exactly this slow adjustment during the recovery that is often pointed to as a source of the jobless recoveries from the last three recessions in the U.S. (Groshen and Potter, 2003, and Jaimovich and Siu, 2014)



Source: U.K. LFS. Recession-shading are U.K. recession dates from ECRI. Quarterly data, 5-month centered moving average.

Figure 2.5: Net mobility, NM_t, for career changes to different occupations and industries.

However, as Figure 2.5 shows, there is no such persistent spike in net mobility. Net mobility briefly went up at the onset of the Great Recession, but then declined to levels rather lower than typical values in the period 2001-2008Q1. While the early rise coincided with the wave of layoffs described by Elsby and Smith (2010), by the end of the recession net mobility rate had fallen deeply, however. From this low level, net sectoral mobility started to increase again during the 2010-2011 recession, only reaching pre-recession levels at the end of the second recession. The increase in net mobility in 2010 and 2011 is mainly due to workers flowing towards services sectors. The main contributors to this increase are all in the service sector (in order of importance): (*i*) Real estate, renting and business activities; (*ii*) Health and social work; (*iii*) Education; (*iv*) Wholesale and Retail Trade including Repairs; and (*v*) Transport, storage and distribution.

This evidence on net mobility, together with that on the level and probability of career changes presented above, is in line with Barlevy's (2002) interpretation of the role of business cycle for labour market dynamics, here for career changes, rather than job changes. He argues that, because labour turnover is higher during expansions than during downturns, the reallocation of labour market resources is procyclical rather than countercyclical.

Our interpretation of the above results is that, in terms of worker reallocation across occupations and industries, recessions do *not* appear to be times of accelerated labour market reallocation which is prevented from happening during expansions due to frictions. Instead, in a recession, workers seem to stay put in their respective occupations and industries when labour market opportunities for them dry up during downturns.

2.4 Career Changes: Why, Who, Where, and at What Wage Gains?

In this section we dive into the details underlying these aggregates and use additional information from the U.K. LFS to analyse the reasons for the career changes, who changes careers, what they do before and after the career change, and how the change affects their wages. This turns out to yield further evidence supportive of the "sullying effect" of recessions through the lenses of career changes.

2.4.1 Reasons for career change

Unfortunately, the U.K. LFS survey does not directly ask respondents who take jobs in a different occupation or industry about the specific reason for their career change. However, some of the questions asked allow us to indirectly infer some of the potential reasons. In particular, we revisit the questions we first focused on in Table 2.3. That is, for those who move directly from one employer to another we consider whether this move was voluntary and whether or not they had been actively searching for a job before they switched. For those who were unemployed in the quarter before they started their new job, we consider the duration of their unemployment spell in that quarter.

Because EE flows account for the bulk of the turnover in Figure 2.3, we focus on the evidence for this switchers first. Figure 2.6 divides up the EE flows into movers and stayers and classifies them by whether or not they made a voluntary EE switch, panels (a) and (c), and by whether they were actively searching on the job before they made the switch, panels (b) and (d).

The first thing that stands out from the figure is that the bulk of EE transitions are voluntary. Moreover, the vast majority of EE transitions is not the result of the worker actively searching for another job but rather of the worker getting a job offer without searching. We interpret these two facts as suggesting that a lot of job changes are voluntary quits that could occur as result of employers contacting workers. Recent evidence for the U.S. also shows that many workers get hired without ever reporting to be actively looking for a job (see Topa et al., 2014, and Carrillo-Tudela et al., 2015, for example).

It is the procyclicality of this type of hires that makes labour turnover move with the business cycle. This is also the type of hire that accounts for the procyclicality

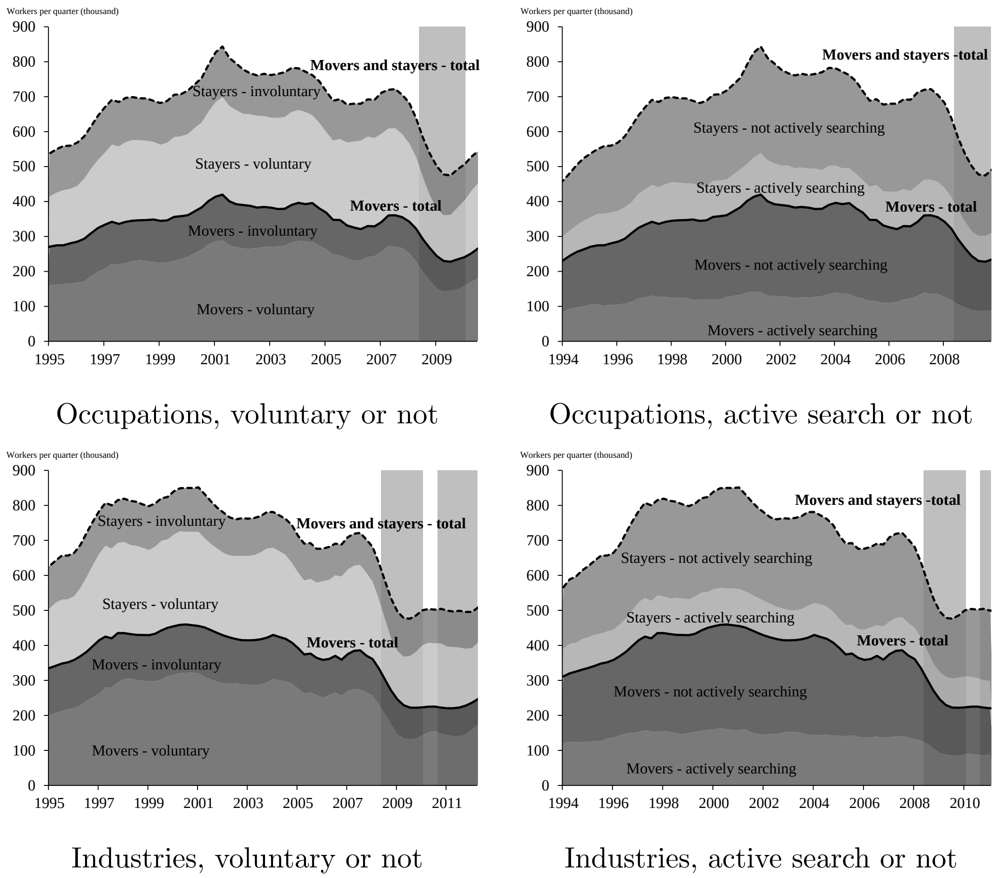
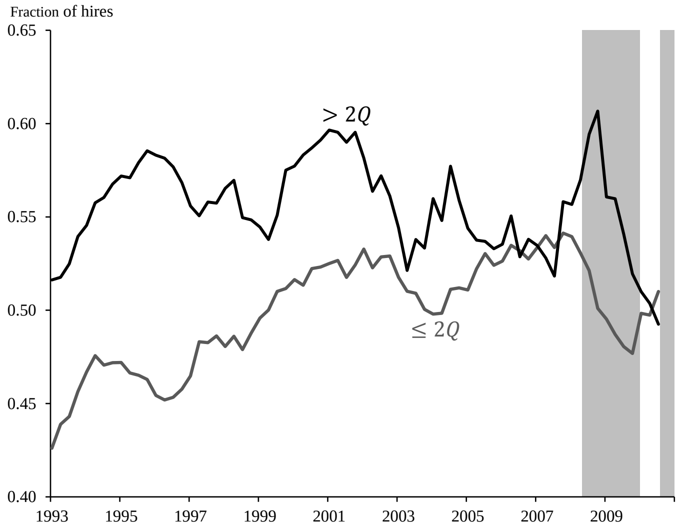


Figure 2.6: Composition of EE by movers, stayers, and whether job transition was voluntary or result of active search.

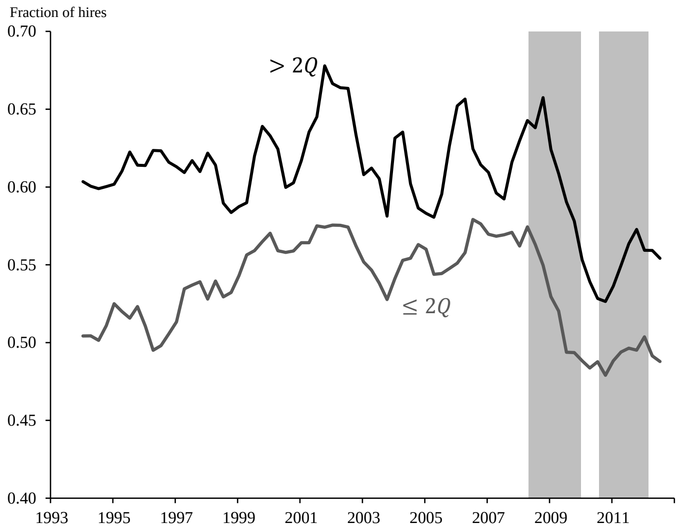
of $EE^{(m)}$ flows. This can be seen from the fluctuations in the numbers of voluntary movers, in panels (a) and (c), and of movers that did not actively search for a job, in panels (b) and (d). Thus, Figure 2.3 and 2.6 jointly point to voluntary EE career changes due to workers being recruited for rather than finding a new job as the main driving force behind the procyclicality of career changes.

This type of voluntary job and career switches occurs side by side to those that are the result of workers being displaced and changing careers after a spell of unemployment. Figure 2.7 splits up the probability of a career change for hires out of unemployment, $HU^{(m)}$ plotted as the short-dashed line in Figure 2.4, by whether the worker was unemployed for less or more than 2-quarters before finding a new job. These two series are denoted by $\leq 2Q$ and $> 2Q$ respectively.

Comparing the $\leq 2Q$ and $> 2Q$ probabilities in the figure for the entire period, it



Occupations



Industries

Figure 2.7: HUm for workers finding jobs after spells shorter and longer than 2 quarters.

Source: U.K. LFS and authors calculations. Recession-shading are U.K. recession dates from ECRI. Quarterly series, centered 5-quarter moving averages.

is clear that those whose are unemployed for longer change careers more frequently. This is consistent with the finding of Faberman and Kudlyak (2012), who, using data from an on-line job-search website, find that workers apply more to vacancies outside their usual occupational field as their spell duration increases.

What is surprising is that the decline in $HU^{(m)}$ in Figure 2.4 is not only because those who find a job after a short unemployment spell in the recession are more likely to find a job similar to the one they had before. Even the probability of a career change for those with unemployment spells longer than two quarters declined during the Great Recession.[21]

This contrasts with the common perception, as expressed in Jaimovich and Siu (2014), that recessions are times of accelerated involuntary structural transformation. During such times a large number of workers supposedly gets displaced from jobs that will never come back and thus are forced to look for and take jobs in sectors and occupations different from those they worked in before.

One possible explanation for why the incidence of career changes among hires out of unemployment does not spike in the recession is that workers that get displaced from jobs that are in secular decline might decide to drop out of the labour force rather than to switch careers. This is especially a concern in the United States, where the labour force participation rate dropped by more than 3 percentage points in the five years after the start of the Great Recession.[22] Such flows to inactivity, however, are not likely to be important in the U.K. where the labour force participation rate actually increased between 2007 and 2012.

2.4.2 Who changes careers?

Of course, the discussion in the previous subsection focuses on the Great Recession versus the rest of the sample. In addition, the evidence presented does not condition on other factors that might be correlated with the variables used to proxy for different reasons for a career change. Here we show that the procyclicality of

[21] At the beginning of the recession, looking at occupations, there is a temporary increase in the probability of an career change among those workers who, at that point, found a job after being unemployed for more than 2 quarters. Note that at this early moment in the recession, only few workers are covered by this statistic, and (or because) a large part of them have entered unemployed before the start of the recession. Instead, for the typical long-term unemployed of the Great Recession, who will only find a job after the second quarter of 2008, the probability of a career change is decreased substantially relative to its average value.

[22] See Daly et al. (2012), for example, for discussion of the decline of the U.S. labour force participation rate.

the probability of career changes, shown in Figures 2.4 and 2.7, is statistically significant even if one considers the whole sample and also corrects for factors that affect the probability of a career switch.

We do so by presenting Probit estimates derived from a model where the dependent variable is whether or not the hire of a worker with previous work experience results in a career change. The explanatory variables include a set of worker characteristics, properties of the job the worker is hired in, and variables that proxy for the potential reasons for why the worker changed careers or not. Because the availability of some of the variables related to the reasons for the career change depends on the labour market status of the worker before he or she accepted the new job, we present the Probit estimates not only for all hires but also condition them on what labour market status the worker had in the quarter before starting the new job. The estimation results are presented in Table 2.4.[23]

In terms of the effects of human capital on the probability of a career change, we find that age decreases the probability of a career change, suggesting the importance of on-the-job human capital accumulation. Educational attainment, however, affects occupations and industries differently. Across occupations, high and medium skilled workers have a higher probability of a career change than low skilled workers (our reference category). Across industries, we find that low skilled workers have a higher probability of a career change than medium and high skilled workers. These results seem to arise from differences in the impact of skill levels by employment status. Across occupations, it is only the unemployed for which high and medium skilled workers have a higher probability of a career change. Across industries, low skilled workers have a higher probability of changing career when mobility is through employment or inactivity, but not through unemployment.

Table 2.4 also shows the effects of different types of job characteristics on the probability of a career change. This probability increases if the worker obtains

[23]Details about the definitions of the explanatory variables are provided in the Appendix.

Table 2.4: Probit estimates for Hm.

	Dependent variable Hire results in career change, $Y_i = 1$, or not, $Y_i = 0$.								
		Occupations 1993-2010				**Industries 1994-2012**			
		All	**E**	**U**	**I**	**All**	**E**	**U**	**I**
		I	II	III	IV	V	VI	VII	VIII
1.	agg urate	-0.59***	-1.10***	-0.79**	-0.24	-1.38***	-1.83***	-1.64***	-0.44
2.	reg-agg urate	-0.59***	-0.53	-1.10**	-0.27	-0.41*	-0.51	-0.57	0.23
3.	age	−0.01***	−0.01***	-0.01***	0.00	-0.01***	-0.01***	-0.01***	0.01**
4.	age^2	0.06***	0.10***	0.08***	-0.09***	0.05***	0.12***	0.06**	-0.12***
5.	mar/cohab	-0.03***	-0.02***	-0.03***	-0.02*	-0.03***	-0.02**	-0.02*	-0.02*
6.	nchild	−0.00	−0.01*	−0.01	0.00	−0.00	0.002	−0.01	−0.00
7.	spell dur		-0.002	0.03***			-0.01***	0.03***	
8.	female	0.01**	0.02***	-0.01	0.002	0.07***	0.07***	0.06***	0.03***
9.	high skilled	0.03***	0.01	0.04***	0.01	-0.05***	-0.08***	-0.00	-0.04**
10.	med skilled	0.02***	0.01	0.03***	-0.001	-0.01***	-0.03***	0.02**	-0.02**
11.	ft job	-0.04***	-0.01*	-0.07***	-0.04***	-0.04***	-0.04***	-0.04***	-0.07***
12.	temporary	0.02***	0.06***	-0.03***	0.01	0.04***	0.08***	-0.01	0.01
13.	unemployed	0.04***				0.03***			
14.	inactive	-0.01**				-0.06***			
15.	invol		-0.03***				-0.02**		
16.	other		-0.02***				-0.03***		
17.	job centre		0.02				0.09***		
18.	ads		0.07***	0.02***			0.10***	0.02*	
19.	direct app		0.03*	-0.03**			0.02	-0.08***	
20.	family/friend		0.04**	-0.04***			0.02	-0.07***	
21.	other method		0.04**	-0.01			0.02	-0.04**	
22.	want a job				0.03***				0.05***
23.	no. of obs.	77303	34272	19619	14298	83995	37210	21458	15103
24.	pseudo-R^2	0.023	0.040	0.023	0.034	0.035	0.051	0.031	0.040

Note: Sample includes all hires of workers with a previous career in our sample. Regional and previous occ/ind dummies included in all specifications. Coefficients reported are marginal probabilities and the one for age^2 is multiplied by 1000. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

a part-time versus a full-time job or if the worker obtains a temporary versus a permanent job.[24] Women have a higher probability of a career change than men. Furthermore, the larger the household someone is part of, the less likely a person is to change careers. That is, Hm is lower for persons who are married or cohabitate.

[24]The exception is that for unemployed workers obtaining a permanent job increases the probability of a career change.

It also decreases, although not significantly, in the number of children.

The Probit estimates also reaffirm the results found in Table 2.3 and Figures 2.3, 2.6, and 2.7. We find that for employed workers, career changes are more likely among those employed workers that made voluntary EE transitions and among those that were actively searching for a job (our baseline category with respect to all the search channels). Unemployed workers are more likely to make career changes than employed (our baseline category) or inactive workers, while a career change through unemployment is more likely to occur at longer unemployment spells.

Using individual-level data in the Probit regression allows us to shine a more detailed light on search method workers employed to find their new jobs and how it affects their chance of changing careers. In particular, the explanatory variables listed in Rows 18 through 21 get at this.[25] We find that those workers who find jobs responding to ads are more likely to change careers than those who find jobs through other means.

Conditioning on the worker-, job-, and search- characteristics does not erase the significance of the procyclicality of career changes. This suggests that the business cycle movements in occupational and industry mobility of workers are not the result of the composition of the group of workers with a previous career that gets hired changing with the cycle.

As can be seen from the marginal probability estimates reported in Row 1 and columns I and V of Table 2.4, a one percentage point increase in the unemployment rate reduces $H^{(m)}$ by 0.6 percentage points for occupations and 1.4 percentage points for industries.[26] Contrary to the discussion above, these results are based on the whole sample period and not only on comparing the Great Recession and its aftermath with the preceding episodes in the data.

[25] The baseline category "direct application to employers".

[26] Because these are marginal probability estimates, this interpretation is for the "average" hire in terms of the covariates in our sample.

The higher sensitivity of occupational switches compared to industry switches to the aggregate unemployment rate is offset by the higher sensitivity of occupational mobility with respect to the regional component of the unemployment rate, reported in Row 2 of Table 2.4. Taking the results of Rows 1 and 2 of Table 2.4 together both occupational as well as industry mobility comove very significantly with labour market conditions.

2.4.3 Origins and Destinations

Another way to gauge the reasons for career switches is to consider what type of job in which industry and occupation workers come from and what type of job they end up in. This is what we explore in this subsection. We focus on three aspects of the origins and destinations of career changers in our data. The first is whether the jobs are full- or part-time. The second is what industry and occupation career changers come from and which ones they go to. Finally, we refine the occupation analysis by considering whether the occupations are routine or non-routine.

Full- versus part-time jobs So far, we have documented that most career changes result from voluntary labour turnover and that the share of career changes that is voluntary is procyclical. That is, during downturns a higher fraction of career changes is involuntary (see Figure 2.6). This cyclical behaviour of voluntary career changes is mirrored by the extent to which occupational mobility results in full- or part-time jobs.

Career changes turn out to be an important mechanism through which workers move between part-time and full-time jobs and, on net, contribute positively to part-time and to full-time job flows.[27] On average 65% of hires resulted in a full-time job and 35% of hires resulted in a part-time job during the 1993-2007 pe-

[27]For recent investigations of cyclical fluctuations in full/part-time jobs, see e.g Borowczyk-Martins and Lale (2015), and Singleton (2015).

riod. These hires are disproportionately people who change occupations.[28] Career *movers* on average get a full-time job in 60% and a part-time job in 40% of the time.

For those that switch directly between employers we know both their full-time status before and after they get hired and can thus infer whether their full-time status changed when switching jobs. Using these data, we find that on average 13% workers making an EE transition move from part-time into full-time employment, while 7% move from full-time to part-time employment during the 1993-2007 period. The bulk of changes in the full-time nature of work, in either direction, involves a career change. Of those who moved from part-time into full-time employment, 66% changed careers; while from those that moved from full-time to part-time employment 59% changed careers.

During the Great Recession, however, the incidence of part-time work increased. On average 37% of hires now resulted in a part-time job, while 63% of hires resulted in a full-time job. Consistent with this, the net contribution of career changes to part-time-to-full-time flows declined during the same period.[29]

Thus, if we would consider part-time jobs to be typically less desirable than full-time jobs, then the shift in the full-time/part-time composition of career movers' new jobs during the recession reflects a relative worsening of outcomes associated with changing careers in downturns and thus a deceleration of the pace with which workers move to higher quality jobs during those periods. Note, however, that the shift in the full-time/part-time composition is much less pronounced than the shift in terms of voluntary versus involuntary turnover, depicted in Figure 2.6.

Industries and occupations Above, we suggested that transitions from part-time to full-time jobs are generally considered a step up the job ladder while the

[28]In our analysis of full- versus part-time jobs we limit ourselves to career moves that involve a change in occupation.

[29]In the exposition here we contrast the Great Recession with the period before. Unreported regression results show that the cyclicality of the incidence of part-time employment we discuss here is present over our whole sample period.

reverse are considered a step down. To paint a more detailed picture of the job ladders that career changers are on, we consider the origins and destinations of their career moves here in terms of industry and occupation. We do so, by constructing industry and occupation transition matrices for workers' career changes. These matrices provide useful information on the mobility patterns of workers as they shed light on the potential importance of individual occupations or industries in driving overall mobility.

Table 2.5 shows the transition matrix for workers changing careers across occupations.[30]

Table 2.5: Transition Matrix: Occupations

			High Skill			Medium Skill			Low Skill		Misc.
	From	To	Managers 1.	Professional Occupations 2.	Asscociate Professional Technical Occ 3.	Clerical/Admin Secretarial Occ 4.	Sales Occupations 5.	Personal Serv. Occupations 6.	Craft/Skilled Trade Related Occ 7.	Plant and Machine Operatives 8.	Elementary/ Other Occupations 9.
1.	**Managers**	**Total**	**0.46**	**0.07**	**0.10**	**0.11**	**0.08**	**0.05**	**0.04**	**0.04**	**0.05**
		EE	0.53	0.07	0.10	0.10	0.07	0.03	0.04	0.03	0.04
		UE	0.38	0.06	0.11	0.14	0.09	0.06	0.04	0.05	0.07
		IE	0.38	0.08	0.10	0.13	0.09	0.07	0.04	0.04	0.07
2.	**Professional Occupations**	**Total**	**0.07**	**0.68**	**0.08**	**0.05**	**0.02**	**0.03**	**0.02**	**0.01**	**0.02**
		EE	0.09	0.71	0.08	0.04	0.02	0.02	0.02	0.01	0.01
		UE	0.07	0.60	0.11	0.06	0.04	0.04	0.03	0.03	0.04
		IE	0.04	0.68	0.07	0.07	0.02	0.04	0.03	0.01	0.03
3.	**Asscociate Professional Technical Occ**	**Total**	**0.09**	**0.09**	**0.50**	**0.10**	**0.06**	**0.05**	**0.03**	**0.03**	**0.05**
		EE	0.10	0.09	0.54	0.09	0.05	0.05	0.03	0.02	0.04
		UE	0.07	0.09	0.44	0.12	0.08	0.05	0.04	0.04	0.07
		IE	0.05	0.07	0.50	0.12	0.07	0.06	0.03	0.03	0.06
4.	**Clerical/Admin Secretarial Occ**	**Total**	**0.06**	**0.03**	**0.07**	**0.54**	**0.10**	**0.07**	**0.02**	**0.03**	**0.07**
		EE	0.08	0.03	0.08	0.58	0.09	0.05	0.02	0.03	0.05
		UE	0.04	0.03	0.07	0.50	0.12	0.07	0.03	0.04	0.09
		IE	0.05	0.04	0.06	0.50	0.11	0.11	0.02	0.02	0.10
5.	**Sales Occupations**	**Total**	**0.05**	**0.02**	**0.06**	**0.16**	**0.39**	**0.10**	**0.03**	**0.04**	**0.14**
		EE	0.06	0.02	0.07	0.18	0.37	0.11	0.03	0.04	0.12
		UE	0.04	0.02	0.06	0.15	0.41	0.09	0.03	0.05	0.16
		IE	0.03	0.03	0.05	0.12	0.44	0.12	0.02	0.03	0.16
6.	**Personal Serv Occupations**	**Total**	**0.03**	**0.03**	**0.06**	**0.09**	**0.10**	**0.51**	**0.02**	**0.04**	**0.11**
		EE	0.04	0.03	0.06	0.09	0.11	0.50	0.02	0.05	0.10
		UE	0.02	0.02	0.04	0.08	0.11	0.50	0.03	0.05	0.13
		IE	0.03	0.03	0.06	0.08	0.08	0.55	0.02	0.02	0.13
7.	**Craft/Skilled Trade & related Occ**	**Total**	**0.02**	**0.02**	**0.03**	**0.03**	**0.04**	**0.03**	**0.60**	**0.11**	**0.12**
		EE	0.03	0.02	0.03	0.03	0.03	0.03	0.63	0.11	0.10
		UE	0.01	0.02	0.02	0.03	0.04	0.03	0.58	0.12	0.14
		IE	0.03	0.03	0.04	0.04	0.05	0.05	0.56	0.07	0.14
8.	**Plant and Machine Operatives**	**Total**	**0.02**	**0.01**	**0.03**	**0.05**	**0.06**	**0.06**	**0.11**	**0.49**	**0.18**
		EE	0.03	0.01	0.03	0.05	0.06	0.05	0.11	0.51	0.16
		UE	0.01	0.01	0.03	0.05	0.07	0.05	0.10	0.47	0.21
		IE	0.02	0.02	0.04	0.05	0.07	0.08	0.08	0.44	0.20
9.	**Elementary/ Other Occupations**	**Total**	**0.02**	**0.01**	**0.04**	**0.08**	**0.12**	**0.09**	**0.07**	**0.09**	**0.48**
		EE	0.02	0.02	0.04	0.09	0.14	0.10	0.07	0.11	0.42
		UE	0.01	0.01	0.03	0.07	0.10	0.07	0.08	0.11	0.52
		IE	0.02	0.01	0.03	0.07	0.11	0.10	0.04	0.04	0.57

[30] To construct the transition matrix for occupations we have combined the SOC 1990 and SOC 2000 occupation classifications. We do this as our results hardly change when considering a separate transition matrix for each classification. Furthermore, we present the results for the entire period of study and not before and during the Great Recession, as the transitions matrices for the Great Recession period have the same characteristics as those for the pre-recession period. For the sake of brevity, we limit ourselves to the discussion of origins and destinations for occupations here.

This matrix shows that all occupations exhibit a high degree of mobility. The dark-shaded cells list the fraction of hires that get hired in the same major occupation as they were working in before. Looking at the numbers for all hires, labeled as "Total", the probability of a career change ranges from 61% for sales occupations to 32% for professional occupations.

Across occupations, however, we observe some clustering by skill level. To show this, we group together those occupations that require similar skill levels. This results in three groups of high-, medium, and low skilled occupations. The first two groups consist of three major occupation codes and the last group consists of two major occupation codes. Career changes within each of these groups are highlighted in light grey as the block diagonal in the transition matrix. As can be seen, the transition probabilities in the grey cells tend to be higher than those in the other cells. There are two destination occupations that are notable exceptions to this pattern. First, a substantial number of career changes out of high-skill occupations result in jobs in "Clerical and administrative" jobs. Second, the miscellaneous ninth category absorbs a large number of career switchers from middle-skilled jobs.[31]

Although we observe similar non-diagonal probabilities between rows in the transition matrix, we also observe that workers are more likely to stay within their skill category or move to the highest skill category after an EE transition and more likely to move to a lower skill category through a UE or IE transition.[32] These patterns suggest that workers tend to move more often to occupations that demand skills closer to the ones they can supply. However, conditional on moving to a different skill category, workers are more likely to make career changes that involve an upgrade in the skill level through direct EE transitions, while career changes that

[31] These patterns for occupational transitions are remarkably similar to those documented in Hobijn (2012) for the U.S.

[32] When making a career change outside a given skill category, workers in high skill occupations are more likely to move to an occupation in the medium skill category; workers in the medium skill category are more likely to move to an occupation in the low skill category. However, workers in the low skill category are more likely to move to an occupation in the medium skill category. The exception are those workers in the clerical/admin and secretarial occupations, who are more likely to move to an occupation in the high skill category conditional on a career change.

involve a lower skill level are more likely through spells of non-employment. This evidence reinforces the view that occupational mobility through EE transitions are more likely to be voluntary career changes in which workers mostly pursue upward career moves, while occupational mobility through non-employment are more likely to be involuntary career changes.

Routine and non-routine occupations One particular type of occupational mobility that has been emphasized in the recent literature is that between occupations that involve routine and those that involve non-routine tasks. The distinction between these two types of occupations is relevant for the "Polarization" hypothesis (See Autor (2003), Acemoglu and Autor (2011), Autor and Dorn (2013), among others). This hypothesis is that, over the last decades, job tasks that can be captured easily by a set of explicit of simple instructions or rules, i.e. 'routine tasks', have been increasingly taken over by computers and machines. As a result, employment in those occupations in which workers are mainly executing routine tasks, summarily called 'routine occupations', has declined. In its place, employment has risen at the bottom of the wage distribution, in occupations that require physical labour, yet with tasks that cannot easily be captured in routines to be automated. This includes simple service jobs that require physical eye-hand coordination and physical navigation, typically under the heading 'non-routine manual' jobs. Employment has also risen higher in the wage distribution, where tasks require knowledge acquisition and creative thinking, with jobs put under the 'non-routine cognitive' header.[33] Jaimovich and Siu (2014) argue that this secular process of job polarization accelerates during recessions when many routine jobs are permanently destroyed and workers in those jobs are forced to pursue other careers. In this way, they claim, the cycle is actually the trend, since this type of job polarization during

[33]With routine jobs in these occupations mostly located in the middle segment of the wage distribution, employment gains at the low end of the wage distribution, in non-cognitive manual and at the high end of the wage distribution, in cognitive non-routine job imply a 'hollowing out' of the middle, which is often referred to as 'job polarization'.

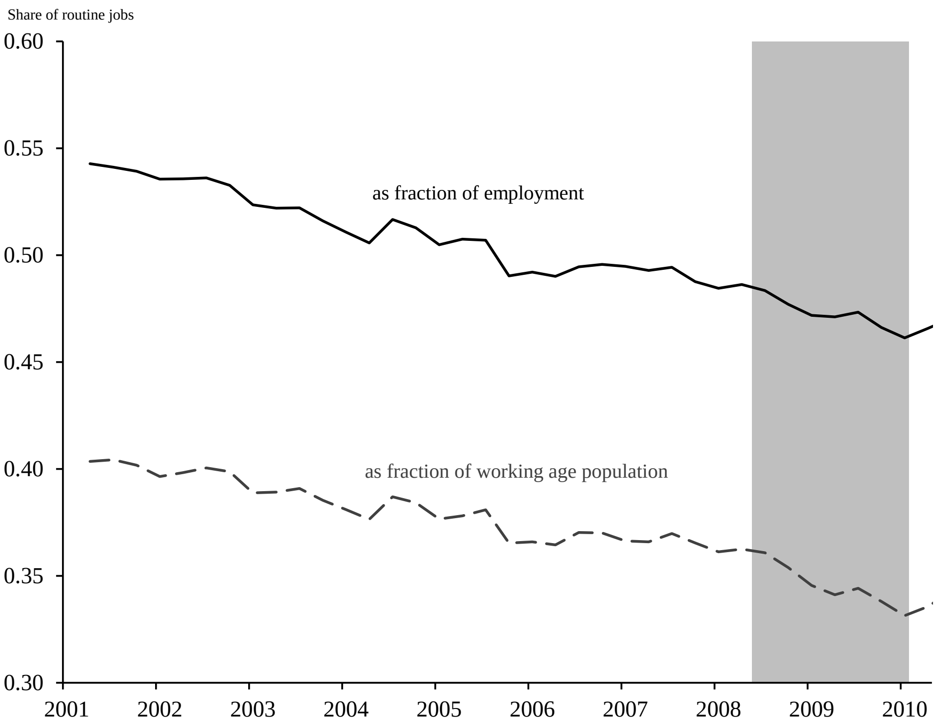
recessions is not reversed during expansions.

To consider whether job polarization is happening in the U.K. labour market and to what extent it is reflected in workers switching from careers in routine to non-routine occupations, we split up the post-2000 data by occupation into routine and non-routine occupations, following Acemoglu and Autor (2011). The second column of Table 2.1 contains a marker that signifies which SOC 2000 occupations are classified in which category.

Figure 2.8 shows employment in routine occupations as both a share of the working age population as well as of total employment. The figure shows that the share of employment in 'routine occupations' has steadily declined in the U.K., similar to that in the U.S. (Jaimovich and Siu, 2014). However, there was no acceleration in this trend during the Great Recession, as the "trend-is-the-cycle" hypothesis would suggest. In fact, using more formal regression-based techniques we find no significant cyclical component in the routine share series plotted in Figure 2.8. This is in line with the evidence for the U.S. in Foote and Ryan (2014).

Figure 2.9 shows the time series of career changes that result in a switch between routine and non-routine occupations. The first thing that stands out from this figure is the excess churning we already saw in terms of the net mobility measure in Figure 2.5. The net change in routine employment induced by these career switches is negative and contributes to the trend decline shown in Figure 2.8. Just like in the U.S. (Cortes et al., 2014) IE and UE flows contribute the bulk of this net decline. Most importantly, however, is the observation that the share of routine to non-routine career switches does not increase significantly during the recession, indicating that, in terms of career switches, there is no evidence that the long-run downward trend in the share of routine employment accelerates during recessions. In fact, the overall turnover between these two categories of occupations seems to have declined in the recession.

Of course, the data in Figure 2.9 only includes workers who have been employed

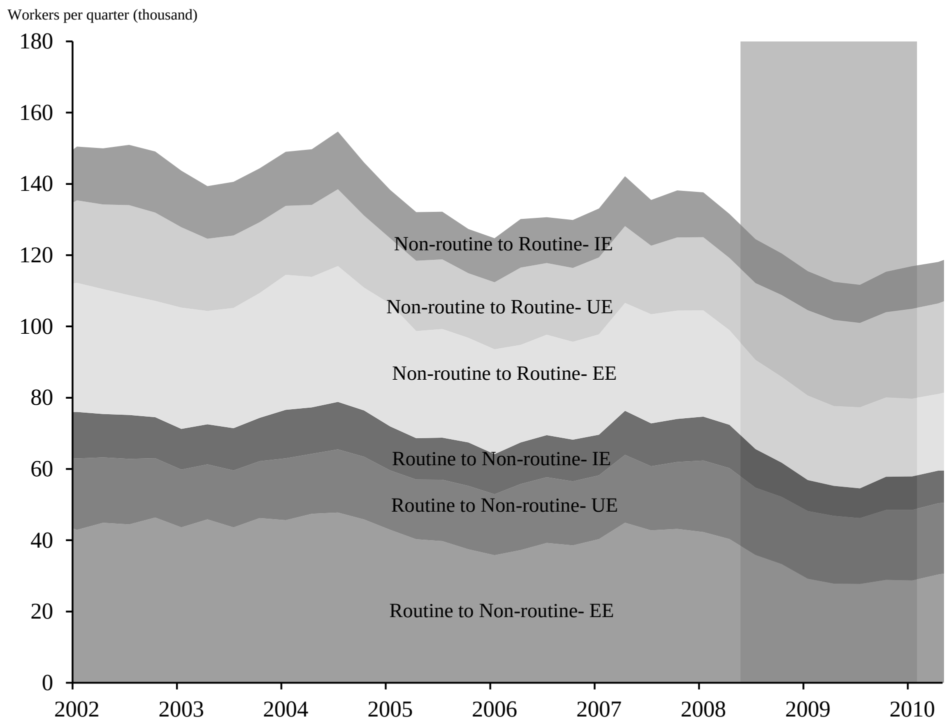


Note: Routine occupations in SOC 2000 listed in Table 2.1.

Figure 2.8: Shares of working age population and total employment working in routine occupations.

before at some point, and are hired again. This means that adjustment in the overall level of routine employment could also come about by a diminishing inflow into routine occupations by labour market entrants, and by an increased outflow of retirees from these occupations is not visible in our statistics. Cortes et al. (2014), for example, emphasize that such a cohort effect is an important driver behind the trend decline in routine employment in the United States. However, the lack of a cyclical pattern in Figure 2.9 suggests that this cohort effect most likely also does not fluctuate a lot over the business cycle.

Thus, our analysis for the U.K. is supportive of the same conclusion that Albanesi et al. (2013) draw for the U.S.; weakness in the labor market in the Great Recession was shared by non-routine and routine occupations alike, did not disproportionately affect routine occupations, nor did it accelerate the secular decline in routine jobs.



Note: Routine occupations in SOC 2000 listed in Table 2.1.

Figure 2.9: Number of career switches between routine and non-routine occupations.

2.4.4 Wage gains

Thus far, we have shown that career switches make up a substantial fraction labour market turnover, and of voluntary turnover in particular. Recent theoretical (Hagedorn and Manovskii, 2013) and empirical (Daly, Hobijn, and Wiles, 2012) studies have emphasized the importance of voluntary turnover and employer-to-employer transitions for understanding the cyclical behaviour of wage growth. Our data suggest that distinguishing between career switchers and stayers would refine our understanding of wage growth over the business cycle even more.

To see why, consider Tables 2.6 and 2.7, which summarize the distribution of percent real wage changes for job switchers, conditional on moving careers or staying in the same career, for the whole sample as well as for the three main periods in our sample.[34] Because we are interested in wage *changes*, our analysis only includes

[34] Recall that these wages are self-reported gross weakly earnings, deflated using the CPI.

hires for which we have data in waves 1 and 5 of the survey, depicted in Figure 2.2. In particular, that means that for workers who flow through unemployment, we only have wage changes for those with an unemployment spell shorter than 4 quarters.

Table 2.6: Probability of positive real wage growth by percentile of wage in previous job

	Quartile of the wage before changing jobs		**Occupations** Movers I	Stayers II	**Industries** Movers III	Stayers IV
1.	0^{th}-25^{th}	**Total**	**78.5**	**67.0**	**79.9**	**65.5**
		EE	80.3	71.8	81.1	69.7
		EUE	80.7	69.2	78.8	67.6
2.	25^{th}-50^{th}	**Total**	**56.9**	**51.1**	**57.5**	**51.1**
		EE	56.7	48.7	57.9	49.4
		EUE	55.1	55.3	62.3	50.9
3.	50^{th}-75^{th}	**Total**	**37.6**	**46.1**	**36.1**	**46.3**
		EE	35.8	44.3	34.7	44.5
		EUE	40.1	40.8	34.5	47.0
4.	75^{th}-100^{th}	**Total**	**27.0**	**35.8**	**26.4**	**37.2**
		EE	27.2	35.2	26.4	36.5
		EUE	23.6	34.3	23.4	34.5

Note: Percent of workers that receive a wage increase after changing jobs for all job changes in the sample.

Long-run perspective Table 2.6 shows the probability that the hire of a worker with previous work experience results in a wage gain. The table lists this probability conditional on whether the hire involves a change in career and on the level of the wage earned in the previous job, measured in terms of the percentile of the wage

Given that the LFS only provides wage information on its 5 quarter sample and only for a worker's Q1 and Q5 interview wave, we are not able to subdivide the analysis by demographic or job characteristics or by the other stratifications we used in the previous sections without running into small sample problems. We also focus our attention to those workers that made EE or UE transitions given the small sample of those workers making IE transitions for which we have wage information. Further information about Q1 and Q5 wages is only available as from 1996. Further, we also checked whether the cyclicality of our Hm rates is robust if we changed to the 5-quarter sample. Across occupations and industries we find that Hm, HEm and HUm are procyclical; while HIm is acyclical.

distribution. The probability of a positive wage gain is much higher for workers who earned a low wage in their previous jobs. More importantly, for those workers this probability is also higher when they change careers than when they did not. For workers making an above-median wage, however, the probability of obtaining a positive wage growth when changing employer is closer to 30% but now is higher for those who do not change careers. This suggests that a large part of the voluntary career mobility through employer-to-employer moves that we document is workers moving up the job ladder to progress their careers.[35]

Where Table 2.6 provides information about the sign of the wage change, the columns for the "Whole sample" in Table 2.7 show the distribution of the magnitude of wage changes.[36] The first takeaway from this table is the large degree of *dispersion* in wage growth that results from a change in employers. Below the 50th percentile of each distribution, workers can experience large negative wage losses when moving employers, while above the 50th percentile workers experience large wage gains.[37]

The most striking feature of the distributions shown in Table 2.7 is that the dispersion of wage gains is larger for career movers than for career stayers. This also holds true when we condition on whether the worker changed employers through an intervening spell of unemployment or not. Relative to stayers those who changed careers have higher wage growth at and above the 50th percentile of the wage growth distribution; while the opposite happens below the 50th percentile. This

[35]Indeed, when adding the quartile of the wage earned in the previous job as an explanatory variable to the Probit analysis reported in subsection 4.2, we find that the probability of a career change through an EE transition deceases with the wage earned in the previous job.

[36]Note that these tables convey different information than the one presented in Longhi and Taylor (2013). For occupational movers, they compare the average wage in the worker's previous occupation with the average wage in the worker's new occupation. Using this information they distinguish between upward or downward occupational mobility by workers' employment status. In contrast, we compute the difference in the wages the *individual* obtains from changing occupation. This allows us to understand the relative gains for the individual of a career change.

[37]These numbers are consistent with the large set of evidence that finds re-employment wage loses for displaced workers (see Jacobson, et al. 1993) and wage gains for workers that undergo direct EE transitions (see Topel and Ward, 1992). The actual wage losses due to displacement are likely underestimated in our data since our sample only contains unemployment spells that lasted shorter than 4 quarters.

evidence again supports our interpretation that workers typically change careers for wage gains bigger than for those that stayed in the same occupation. It might seem counterintuitive that career changes through unemployment do tend to lead to positive wage gains that are larger than those obtained by unemployed workers who will stay in the same career. However, this evidence is not inconsistent with a theory in which these potentially larger wage gains can only be obtained after a costly reallocation process which only becomes worthwhile after job prospects in the original career have deteriorated sufficiently (see, for example, Carrillo-Tudela and Visschers, 2014).

Table 2.7: Distribution of real wage changes for hires: 1997-end of sample

		Whole sample		**1997-2000**		**2001-2007**		**2008-end**	
Percentile		**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**	**Stayers**
					(a) Occupations				
25th	**Total**	**-16.4**	**-13.0**	**-13.0**	**-9.6**	**-16.0**	**-11.3**	**-24.0**	**-22.1**
	EUE	-32.4	-22.9	-32.5	-18.7	-27.4	-21.6	-48.9	-29.5
	EE	-10.9	-8.2	-7.4	-5.1	-12.2	-6.6	-12.8	-16.7
50th	**Total**	**10.7**	**6.8**	**16.8**	**10.8**	**9.7**	**6.0**	**2.6**	**2.0**
	EUE	-2.1	-3.0	1.3	1.8	1.1	-3.4	-19.6	-10.5
	EE	13.4	9.6	19.1	13.4	11.7	8.8	8.5	4.9
75th	**Total**	**54.8**	**33.6**	**71.8**	**40.5**	**49.1**	**30.9**	**42.0**	**29.9**
	EUE	48.3	28.7	59.0	33.4	54.9	26.6	6.5	27.2
	EE	56.8	34.6	75.5	41.1	50.1	32.4	44.3	29.8
					(b) Industries				
25th	**Total**	**-17.0**	**-12.5**	**-12.5**	**-9.3**	**-16.3**	**-12.3**	**-22.4**	**-15.8**
	EUE	-29.7	-24.7	-30.1	-19.9	-27.2	-23.2	-33.7	-31.6
	EE	-11.7	-7.1	-7.7	-4.5	-12.0	-7.5	-14.8	-8.9
50th	**Total**	**9.8**	**6.7**	**15.2**	**11.1**	**8.6**	**6.6**	**6.9**	**2.8**
	EUE	-2.1	-2.7	2.4	4.8	0.5	-2.4	-10.6	-10.4
	EE	12.4	9.2	17.7	13.4	11.2	8.7	9.5	6.0
75th	**Total**	**54.3**	**32.1**	**69.0**	**40.7**	**48.3**	**30.3**	**50.5**	**26.9**
	EUE	42.4	27.6	46.8	41.6	49.7	26.8	26.0	15.9
	EE	55.0	32.5	66.3	40.6	49.8	31.0	53.2	27.7

Note: Percentile of the distribution percent wage changes. Reported are averages of the quarterly time series of percentiles over the sample periods listed. Wage data only available after 2007.

Cyclical patterns The last six columns of Table 2.7 show how the distribution of wage changes varies over different business cycle episodes in the U.K. labour market. Across occupations and industries the wage growth distribution of those workers that change careers through unemployment shifts down during the recession. The decrease is stronger across occupations than industries. Further, the shift in the wage growth distribution of those who changed occupations through unemployment is sufficiently big that their wage gains are now below the wage gains of career stayers even at the 75th percentile of the wage growth distribution. In contrast, the wage growth distribution of workers that changed employers directly through an EE transitions or those that changed employers through unemployment but did not undertake a career change, do not seem to respond as much to business cycle conditions.[38]

The evidence presented suggests that career changers have a higher probability of a substantially large wage increase than career stayers. However, during the recession the wage gains of occupational changers decrease to the point that, for unemployed workers, these have become smaller than the wage gains from changing employer in the same occupation. As argued, for example, in Carrillo-Tudela and Visschers (2014), the decrease in the gains of reallocation can help explain the drop in the probability of a career change during the recession, documented in subsection 3.2.

Thus, the procyclicality of the incidence of career changes and the associated wage gains that we document suggest that adding a career change margin to our models of labour market fluctuations will help improve our understanding of the, not well-understood, link between unemployment, labour turnover, and aggregate wage growth.[39]

[38]These observations are also confirmed when regressing the wage growth of workers on output per worker and a time trend, showing that these patterns are not particular to the Great Recession.

[39]Of course, some of aggregate wage growth is drive by a composition effect (Solon, Barsky, and Parker, 1994, and Daly, Hobijn, and Wiles, 2012). This is the same composition effect that partially drives the procyclicality of career changes. For our understanding of aggregate time series it is important to have theoretical models that capture the main sources of (self-)selection that drives this composition effect.

2.5 Discussion and Conclusion

Overall, the patterns in the UK LFS suggest that in good times career changes imply a chance to improve a worker's position in the labour market. In downturns the gains associated with career changes appear to diminish. From a theory perspective one can build on Carrillo-Tudela and Visschers (2014) and Wiczer (2013) to reconcile these patterns using a framework that incorporates heterogeneity in labour market conditions, costly mobility choices between labour markets (career changes) and business cycle shocks. In such a framework, fluctuations in the expected net returns to a career change induce workers to adjust their mobility choices. In downturns, when net returns are low, workers decide to stay in their careers and wait for conditions to improve instead of changing to a new occupation or industry.

In such a framework two motives for job mobility can arise: (i) workers may move to other jobs because their current employment conditions worsen while outside opportunities stay the same; (ii) workers may move because outside opportunities improve while current employment conditions are unaffected. Although both reasons may be at work, they are not necessarily two sides of the same coin. Aggregate conditions may interact differently with the idiosyncratic shocks to workers' current employment, than with the stochastic arrival of new employment opportunities in different occupations or industries.

In these models, adverse shocks to current employment could then generate 'involuntary' transitions, through which workers try to recover the loss of prospects in their current job. Increased opportunities elsewhere could draw workers to 'voluntarily' change their jobs and careers. The 'pull' of the latter kind of opportunities can be especially strong in booms, in line with the evidence presented in this paper; while the mobility 'push' associated with the shocks behind 'involuntary' transitions could be especially relevant in recessions.

Taken together, career changes are different from other hires in terms of their cyclicality, their associated (wage) gains and the cyclical variations in these gains.

Incorporating a career-mobility dimension in equilibrium business cycle models of the labor market can be a promising direction to contribute to our understanding of the overall behaviour of labour turnover and wage growth over the business cycle, and could help guide better policy responses to business cycle fluctuations.

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Appendix

In this appendix we supplement the description of the U.K. Quarterly Labour Force Survey provided in the main text. In particular, we describe how we constructed the different categories we used to described workers' search activities, unemployment durations and the variables used in the probit regressions.

Search Activity In the U.K. LFS employed workers are asked whether they were actively searching for a job or not and which search channels did they use. We categorise workers as using a "job centre" when they declared that their main method of search was "visit a job centre, job market or jobs and benefit centres", "visit a job club", "have your name on the books of a private employment agency", or "visit a careers office". Workers in the category "ads" were those that declared that their main method of search was "advertise for jobs in newspapers and journals", "answer advertisements in newspapers and journals", "study situations vacant in newspapers or journals". Workers in the category "direct applications" were those whose main method was "apply directly to employers". Workers in the category "ask a friend or relative" correspond to those that declared their main method of search to be "ask friends, relatives, colleagues or trade unions about jobs". The last category "do anything else" includes those who responded "wait for the results of an application for a job", "look for premises or equipment", "seek any kind of permit", "try to get a loan or other financial backing for a job or business", and "do anything else to find work". Among the employed, 77% of workers that made an employer-to-employer transition declared they were not actively searching for a job and the reminder 33% did.

Workers who declared themselves as non-participants in the labour market were considered to "want a job" if they were seeking but unavailable because they were a student, looking after family, temporarily sick or injured, long-term sick or disabled or due to other reasons or no reasons given. In addition we categorise as wanting a job those non-participants that are not seeking, but would like to work and are waiting for results of job applications, believe no jobs are available, have not looked, are a student, looking after family, temporarily sick or injured, long-term sick or disabled, or no reason given. Those who "do not want a job" are those workers that declared they are not seeking, would not want to work and are waiting for results of job applications, do not need or want a job, are a student, looking after family, temporarily sick or injured, long-term sick or disabled, retired or or due to other reasons or no reasons given. Although there are many reasons why a worker declares him or herself out of the labour force, for those that want or do not want a job, there are three main reasons: being either a student, looking after family or long-term sick.[40]

Unemployment Duration To construct the category of unemployed workers that found a job within the first 2 quarters of their unemployment spell and the category of those that found a job after that, we use the following categorical variable for the duration of unemployment: (1) Less than 3 months, (2) 3 months but less that 6 months, (3) 6 months but less than 12 months, (4) 1 year but less than 2 years, (5) 2 years but less than 3 years, (6) 3 years but less than 4 years, (7) 4 years but less than 5 years, (8) 5 years or more. We label workers in (1) and (2) as "less than or equal to 2 quarters" and the rest as "more than 2 quarters".

Probit Analysis To further analyse the workers' likelihood of a career change, we use the latent variable model

$$P_{ij} = \mathbf{x}_i' \beta_{\mathbf{j}} + \varepsilon_{ij}, \tag{2.5}$$

[40]In particular, 75% of workers who wanted a job are in these three categories, while 82% of those that did not want a job are in these categories. Among the inactive, those that want a job represent on average 30% of the non-participants, and those that do not want a job the remainder 70%.

where P_{ij} is the latent variable that measures the probability of an occupational or industry change, ε_{ij} is i.i.d and follows a multivariate normal distribution, i represent individuals and j outcomes. For all those workers that changed employers (through employment or non-employment), the dependent variable takes the value of zero if the worker did not change occupation or industry and one if the worker did.

The vector $\mathbf{x}_i$ describes the explanatory variables. It includes variables which capture the effects of aggregate and local economic conditions through the aggregate unemployment rate, and the deviations of the regional unemployment rates from the aggregate unemployment rate in each quarter. The effects of workers' human capital through a quadratic on age, different skill categories and the duration of the job or unemployment spell. The skill categories are dummy variables that take the value of one if the worker has the corresponding skill level and zero otherwise. The high skilled category groups all those workers that have post school degrees, ranging from teaching qualifications to graduate studies. The medium skilled category groups all workers that achieved between a O-level or GCSE qualification to an A-level or equivalent qualification. The low skilled category groups all individuals with an educational attainment below O-levels or GCSE. For unemployed workers, the spell duration indicates the duration of unemployment and includes the eight categories mentioned above. For employed workers, this variable denotes the duration of employment with current employer in months. We also include a set of variables that measure further demographics such as a dummy for marital status,[41] the number of children, and a dummy for gender. We also con-

[41]The classification of marital status before 2006Q2 has five options: (1) Single, never married, (2) Married, living with husband/wife, (3) Married, separated from husband/wife, (4) Divorced, and (5) Widowed. We set the value of this variable is one if the respondents marital status is (2), otherwise the value of this variable is zero. The classification of marital status after 2006Q2 has nine options. The first five options are identical to the previous classification. The additional options are (6) A civil partner in a legally-recognised Civil Partnership, (7) In a legally-recognised Civil Partnership and separated from his/her civil partner, (8) Formerly a civil partner, the Civil Partnership now legally dissolved, and (9) A surviving civil partner: his/her partner having since died. Under the classification of marital status after 2006Q2, we set the value of "mar/cohab" to one if a respondent whose marital status is (2) or (6), and zero otherwise.

sider dummies for full-time jobs and whether the job was temporary or permanent. We include dummies for employment status and whether the change of employer was for involuntary or for other reasons, where we take voluntary reasons as our baseline category. Finally, we include dummies for the methods of job search and whether non-participants declared they wanted a job or not. All dummies take the value of one if the respective worker-, job-, and search- characteristic is equal to the label of the dummy. Otherwise, the dummy takes the value of zero.

Chapter 3

Are the occupational and industrial mobility overestimated? An evidence from BHPS.

3.1 Introduction

The mechanism of the labour market is an important topic for a labour economist. Over the past two decades, researchers in this field have widely debated the impact of unemployment on reallocation. There are two major effects discussed: the sullying effect and cleansing effect. [1] During a recession, the reallocation speeds up because new jobs in the expanding sector are opening and the existing jobs in the decreasing sector are closing. The force that pushes people from the decreasing sector to the expanding sector is called the cleansing effect. The process of reallocation could be between occupations and industries, and hence the measurement of reallocation becomes an important issue that needs to be considered. The occupational and industrial mobility is not uniquely defined. Researchers use different formulas to calculate it. Here, we use the number of occupational (industrial) movers divided by the summation of occupational (industrial) mover and stayer as occupational (industrial) mobility. [2] In order to measure the process of reallocation, we assume that the data is correctly and accurately collected and transformed. However, this assumption may not be true. Some factors lead to wrongly collected data, such as misunderstandings between interviewers and participants.

Pearles (2004) suggested that dependent interviewing can detect how wrong we were in the measurement of occupational mobility. However, the independent interviewing was applied in earlier surveys of BHPS. This interviewing method works as respondents answer the questionnaire without any information fed forward. Respondents have to answer each question even though their circumstances did not change at all. For example, respondents provide the description of their occupations in a wave. In the following wave, these respondents still need to repeat the description of occupation and relevant questions, even though they did not change their job. Since the survey interview runs once a year, some participant

[1] See Barlevy (2002) and Caballero and Hammour (1994).

[2] Carrillo-Tudela et al. (2016) and Carrillo-Tudela and Visschers (2013) use the same method to calculate occupational (industrial) mobility.

were unable to provide exactly the same description as the one in the previous wave. Therefore, independent interviewing may prolong the time of interview, and potentially contain measurement errors.

A modified design of questioning method is introduced: dependent interviewing is designed to shorten the interview time and increase the accuracy of the data collected. In some circumstances, respondents were provided the information they answered in the previous wave. If the respondents have not changed their circumstances since the last wave, then the information provided in the previous wave is used as the answer in the current wave. This questioning method is called dependent interviewing as the participant's answer depends on the circumstances of the previous wave. Since the answers from the previous wave were directly transfered, this design can shorten the interview time and avoid boring the interviewee. The interviewer can also avoid the measurement error due to the consistent description if the respondent did not change job.

The change of questioning method is a very important issue for researchers' analysis. If the questioning method considerably influences the feature of market reallocation, researchers should exclude this factor and modify the argument. However, the effect of changing questioning method on the reallocation is still poorly understood, and ignorance of this effect would result in a misleading conclusion.

In order to address this problem, I apply a dummy variable indicating the period of dependent interviewing. Given the Probit model has been provided in the last chapter, I include this dummy variable into the estimation in order to discover its role regarding the occupational and industrial mobility. Since workers may change their job via different channels of transition, the effect of changing questioning method may vary differently depending on the channels. In this chapter, I will also examine the cases of job changers, employer-to-employer transition, and non-employment transition in order to obtain a complete understanding.

This study is the first paper to document the effect of dependent interviewing on the occupational and industrial reallocation. Whether the change of questioning method affects the measurement of reallocation will be discussed in a later part of this research.

The aim of this research is to test whether the questioning method affects the measurement of reallocation. Since the independent interviewing was applied in the period 1991-2005 and the dependent interviewing was used in the period 2006-2014, I can detect if the level of reallocation was disturbed by the change of questioning method. I also investigate whether the procyclicality of occupational and industrial mobility is still robust considering the change of questioning method.

This study is organized as follows. The relevant literature is discussed in section 3.2. In section 3.3, a description of BHPS and UKHLS can be found, and the occupational and industrial classification. In section 3.4, I demonstrate the design of dependent interviewing, and discuss why dependent interviewing is used. In Section 3.5, I apply Probit models to examine the reallocations considering the change of questioning method. I firstly provide the estimation of occupational and industrial reallocation by considering workers who were employed in two consecutive waves in order to obtain a general view of the effect of dependent interviewing. I then focus on the cases of all workers who experienced job change, workers who experience employer-to-employer transition and workers who experience non-employment transition to analyse whether the reallocation behaviors are different across the jobs finding channels . I am especially interested in the effect of aa change of question method on the reallocation measurement, as the significance of this effect can help us to detect the robustness of the reallocation measurement as well. Finally, Section 6 summarises and concludes our findings.

3.2 Literature review

Approximately 930,000 thousands workers move into employment, and 877,000 workers move out of employment in the UK each quarter (Gomes, 2012). When workers change their job, they have to face the issue of whether they need to switch their occupation or industry. A sector may become less competitive or productive, and fewer workers may be needed within this sector. This forces workers to look for job opportunities in different occupations or industries. For example, the sector of agriculture is not as important as before, and the service sector has become the most important sector in the current economy. This change of economic structure reflects the development of the economy. After acknowledging the importance of sectoral adjustment, researchers can properly understand workers' difficulties of seeking job and career adjustment, and confirm whether the career adjustment is properly analyzed with the survey answers collected.

How occupational and industrial data are collected in surveys is an elementary point here. Respondents are asked to describe their work, and their verbal answers are coded by a coder or a computer program to be assigned into a occupational (industrial) unit of standard occupational (industrial) classification. However, such a process may result in measurement errors from a number of sources. For example, respondents may provide incomplete descriptions, and interviewers keep inaccurate records (Laurie and Moon, 2003; Lynn and Sala, 2006; Moscarini and Thomsson, 2007). Also, different coders may subjectively allocate one description into a different occupational or industrial unit. To solve this conflict, the inter-coder reliability is introduced: examine the consistence of the assigned coding unit from different coders in terms of the same occupational and industrial description, and calculate the agreement rate. However, the agreement rates for occupational data between two different coders are at a far from acceptable level (Laurie and Moon, 2003).

Annette, Laurie and Uhrig (2007) suggest that, the measurement error are probably due to the independent interviewing and the coders' misclassification. To assess the effects of measurement error on the mobility rates, we must examine, in detail, the questioning design that has been used to collect the participant's responses.

We use an inherent longitudinal dimension survey which allows us to examine the reason why people switch the type of work they do, and how people climb the career ladder during their life (Bukodi and Dex, 2010; Evans, 1999; Harper, 1995). However, the complexities inherent in the process of occupational and industrial data collection make the data quality worse. Typically, respondents report their description of occupation and industry each year, and their answers are coded into an occupational and industrial unit. According to the process of coding mentioned above, the occupational and industrial coding may be erroneous in any given wave. The erroneous coding that occurs in any wave will further decrease the accurance of mobility measurement that is based on two-consecutive-wave data (Sullivan, 2009).

Perales (2014) has shown that independent interviewing causes measurement error. All respondents have to answer each question independently each wave, and provide the description of their occupation. Since respondents may not remember the exact description of their occupation provided in the last wave, they may provide a slightly different description of the occupation despite not having changed their job. This measurement error has been identified as the primary reason for erroneous analysis.

Occupational and industrial structure are considered as indications of economic development. The change of occupational structure is a reflection of social community change, and the change of employment among industries is the modification of economic structure. Changing occupation or industry is a costly and risky process for workers because they not only lose their human capital but also pay the opportunity cost. Workers only switch career if they will gain higher utility from the new career compared with all the costs, including search cost and economy cost, associated with this change. In empirical literature, the wage growth is thus usually considered as a useful proxy.

Empirically, a comparison of the occupational and industrial codes assigned between different survey waves is used to distinguish mobility from stability. The empirical evidence from the US and the UK shows that workers frequently change their career. Parrado, Caner and Wolff (2007) and Kambourov and Manovskii (2008) report that the occupational mobility rate is between 10 % and 20 % each year in the US, and the more disaggregated the classification used is, the higher the mobility rate is. Moscarini and Thomsson (2007) find that the occupational mobility rate is even higher, at 35 % per month in the US. Carrillo-Tudela and Visschers (2013) provide the latest finding that the occupational mobility rate has reached 40 % in the US. While Kambourov and Manovskii (2008) report that industrial mobility was 10 % annually in the period 1969-1997 in the US, and Greenaway, Upward and Wright (2000) report that the industrial mobility rate is between 6 % -10 % annually in the UK. However, Carrillo-Tudela et al. (2016) report that the industrial mobility is considerably higher - 40 % in the UK..

For the reason outlined above, the implementation of dependent interviewing might reduces the level of measurement error. Annette, Laurie and Uhrig (2007) claim that dependent interviewing significantly reduce the level of measurement error, and they use the feature of dependent interviewing to confirm if the data are reliable and robust.

Generally, researchers assume that respondents perfectly remember their actual employment history, and the information provided by them is not affected by the questioning method. However, such a questionable assumption can not be supported by the findings from Perales (2014). He shows that the questioning method affects the measurement error. Most research neglect the impact of measurement error on the mobility measurements. Such unawareness is common to most researchers, therefore understanding its effects on the consistency of longitudinal surveys enables us to improve our knowledge and therefore improve the accuracy of data collection. Instead of intentionally avoiding the measurement error, this issue should be examined more carefully. It is also advantageous to investigate whether changing the questioning method affects each mobility measurement or not as this examination can be seen as a gauge when we review the existing literature.

This study aims to provide an examination of career change with the change of questioning method. It would be helpful to have a better and more profound understand of the validity and robustness of different mobility measurements in future studies.

3.3 Data and mobility measurements

3.3.1 BHPS and UKHLS

The British Household Panel Survey (BHPS) is a multi-purpose study which covers the period from 1991 to 2008. It interviews people annually, therefore it has provided 18 waves of datasets. The BHPS is a UK-wide survey: it consisted of around 5,500 households and 10,000 individuals from Great Britain in the earlier stage. 3,000 households from both Scotland and Wales has been added into the sample since 1999, and another 1,900 households from Northern Ireland were added in since 2001.

Participants of the BHPS in 2008 were asked if they would consider joining a new and wider-range survey, the UK Households Longitudinal Study (UKHLS), conducted by the Understanding Society. Around 80% participants of the BHPS participants jointed the UKHLS, and this extension is useful for researchers to investigate participants' short-term and long-term behavior.

The UKHLS, the main survey of the Understanding Society, began in 2009 and is a multi-topic household survey. It collects a wide range of information on many topics, such as employment history, healthy condition, education, lifestyle, etc. This survey is considered as a successor of the BHPS, and its sample size is bigger. The UKHLS consists of around 40,000 households and 100,000 individuals.

When the UKHLS began, the BHPS participants in the 18th wave had only completed their interviews for a few months. Since two interviews within a short period may cause an extra burden on the participant, the samples of the BHPS are integrated into the UKHLS, after 2010 which is the UKHLS Wave 2.

For the UKHLS, the particpants are interviewed annually, but the data collection period of each wave is two years. From UKHLS wave 2 onwards, given that the data collection period of the BHPS is one year, BHPS samples are interviewed in the first year of each wave for the UKHLS and non-BHPS samples are interviewed in the second year of each wave. The timing of UKHLS and BHPS integration is shown in Table 3.6. To link the UKHLS with the BHPS, given that the latest UKHLS is updated to 2014, researchers could track the samples of the BHPS over more than two decades. In the UKHLS, each wave is collected every 24 months. The participants are interviewed around the same time each year, but the collection period of each wave overlapps. For example, the first wave of UKHLS was collected between January 2009 and January 2011, and then the second wave was collected between January 2010 and January 2012, and so on.

3.3.2 Standard occupational classification

The BHPS provides the codes of worker's jobs in terms of Standard Occupational Classification 1990 (SOC 1990) from 1991 to 2008, and the codes in terms of Standard Occupational Classification 2000 (SOC2000) from 2001 to 2008. The codes of occupational classification are given according to how the job is performed and what skill is required. In SOC 1990, there are 9 major groups with 1-digit codes, 77 minor groups with 2-digit codes and 371 unit groups with 3-digit codes. In SOC2000, there are 9 major groups with 1-digit codes, 81 minor groups with 2-digit codes and 353 unit groups with 3-digit codes. Comparing SOC1990 and SOC2000, the number of major groups, minor groups and unit groups are similar.

3.3.3 Standard industrial classification

The information of the firms that participants work for is used to identify the industry classification of a worker's job. According to these firms' productivity categories, the codes of industrial classification will be given in terms of Standard Industrial Classification. The classification scheme has been modified regularly, as industry and commerce has changed considerably over the past few decades. In the BHPS, the worker's code based on Standard Industrial Classification 1980 (SIC1980) is available from 1991 to 2001, and the code based on Standard Industrial Classification 1992 (SIC1992) is available from 2001 to 2008. In the UKHLS, Standard Industrial Classification 2007 (SIC2007) is adopted to classify the industry of the worker's job at the beginning of the survey (2009), and information of SIC1992 is not provided afterwards. There are 10 divisions (1-digit level) and 60 classes (2-digit) in SIC 1980. SIC 1992 changes the names of the hierarchy levels and includes 17 sections (1-digit level) and 60 divisions (2-digit level). SIC 2007 is divided into 21 sections (1-digit level) and 88 divisions (2-digit level). The 1-digit level of the industrial classifications for SIC 1980, 1992 and 2007 are shown in Table 3.7.

3.3.4 Dependent interviewing

Dependent interviewing is a different questioning method from independent interviewing. Participants were provided with their responses from the previous interview before answering the questions. If their circumstance has not changed, the answer from the previous wave will be transfered to the current wave.

For the respondents, it can be tedious and redundant to repeat their answer if their situation has not changed since the previous wave, which is required in the independent interviewing. In the longitudinal survey, the respondents become bored if they spend hours in the interview repeating the same answers as the previous wave. The participants therefore may refuse to join future interviews. This repetitiveness of answering leads the participants to believe that the survey is not listening to them.

Dependent interviewing is designed to reduce the coding and reporting errors by using previous information. For example, participants use different words to describe the same occupation and industry at different waves, because they can't remember precisely how they answered before, and they might be referring to different occupations and industries across interviews. Errors that arise from different descriptions of the same job leads to inconsistencies across waves and results in biases in the estimation.

The design of dependent interviewing also provides a way to check the participant's answers. In some cases, the interviewer made the key-in error. For example, the interviewer may key in an additional zero for the respondent's earnings. In terms of the process of dependent interviewing, respondents were given the previous information of their earnings to confirm if it is still true. This process allows the interviewer or respondents to capture key-in errors.

The important feature of dependent interviewing is to remind the respondent what their previous information is. This reminder could effectively reduce the misreporting in their answer. The previous information can efficiently help participants recall what they have done in the previous year because it provides a step-by-step method to refresh the participant's memory .

Dependent interviewing was implemented in wave 16 of the BHPS (year 2006) and all waves of the UKHLS. It was used in the current employment section and employment history section. This provides valuable data for labour economists, especially for researchers comparing the data across waves. The consistency of information and measurement is an important issue when researchers work on a longitudinal study and can be helpful to guarantee the reliability of the research

. The implementation of dependent interviewing not only improves the quality of data, but also saves precious time for both interviewer and respondents.

3.3.5 Measurements of mobilities

I use three measurements to discuss the career mobility. CE_t^m is the number of workers who have a different occupational or industrial code between a given survey wave t and the previous wave $t-1$, and CE_t^s is the number of workers who have the same occupational or industrial code. Therefore, C_t^m is inferred as the percentage of workers who have a different occupational or industrial code given that workers are continuously employed in two adjacent waves.

$$C_t^m = \frac{CE_t^m}{CE_t^m + CE_t^s} \tag{3.1}$$

JC_t^m represents the number of workers who change their job and have a different occupational or industrial code, and JC_t^s is the number of job changers who have the same occupational or industrial codes. K_t^m incorporates information on job changes and indicates the percentage of job changers who switch their career over the employment. J_t^m is the proportion of job changers who have different codes; this is the one that most researchers use to measure career mobility.

$$K_t^m = \frac{JC_t^m}{CE_t^m + CE_t^s} \tag{3.2}$$

$$J_t^m = \frac{JC_t^m}{JC_t^m + JC_t^s} \tag{3.3}$$

Figure 3.1 shows the percentage of workers who were continuously employed in two adjacent years and have a different occupational code between 1992-2014 with SOC 1990. Each line shows the results for a different level of aggregation of the SOC 1990 classification. A solid line is for a 1-digit level of classification, a long-dash line for a 2-digit level of classification, and the short-dash line is for the

3-digit level of classification.

There are many interesting points according to the figure. Firstly, the occupational change is obviously high. 40 % of all workers have changed occupations in terms of 3-digit level occupational classification between 1999 and 2005. Secondly, there is a small increase in C^m, around 5 % from 1992 to 2005. Thirdly, the more the applied classification is disaggregated, the higher rates of occupational change observed, such that the 3-digit level has higher rates of occupational change.

Around 40 % of workers are found to be changing occupations in terms of 3-digit level of classification each year, but only 20 % of workers change occupation in terms of 1-digit level classification. Furthermore and most importantly, the introduction of dependent interviewing dramatically reduces the percentage of occupational change. For example, the rates of occupational change at the 3-digit level, which were 40 % - 45 %, drop to 15 %. This also appears in 2-digit and 1-digit level classification, where they drop to 10 % and 12 % respectively.

The slump associated with the introduction of dependent interviewing shown above is not only related to with SOC 1990. Figure 3.2 suggests the slump in 2007 is still significant when using SOC 2000. The ratios of occupational change with SOC2000 from 2002-2005 is around 20 %, 30% and 35 % for 1-digit, 2-digit and 3-digit classification respectively. After introducing dependent interviewing from 2006, the ratios of occupational change drop to around 10 %, which is a similar level to the ratios with SOC 1990. These ratios are slightly smaller than the ratios with SOC 1990. After 2010, the ratios of occupational change become very stable at 10 %, and the difference between 1-digit and 3-digit codes is within 2 %.

Results in Figure 3.3 show the percentage of industrial change, and consists of SIC1980, SIC1992 and SIC2007. A solid line indicates the percentage of industrial change with 1-digit level of industrial classification, and the long dash line indicates the mobility rate using 2-digit level classification. Around 15 % of workers changed their industry in terms of 1-digit level industrial classification between 1992 and

20005, and 25 % of workers changed their industries in terms of 2-digit level. When the dependent interviewing is introduced, the percentage of industrial change drops dramatically to less than 10 % and becomes stable at around 5 %. The difference of the ratios between 1-digit and 2-digit coding is around 10 % when the independent interviewing is applied, but this difference is significantly reduced to 1% after introducing dependent interviewing. We also find that the ratio of industrial change is smaller than occupational change. Figure 3.3 also suggests that the introduction of dependent interviewing significantly reduces the percentage of industrial change for the workers who were employed in consecutive waves with a different industrial classification (1-digit level and 2-digit level).

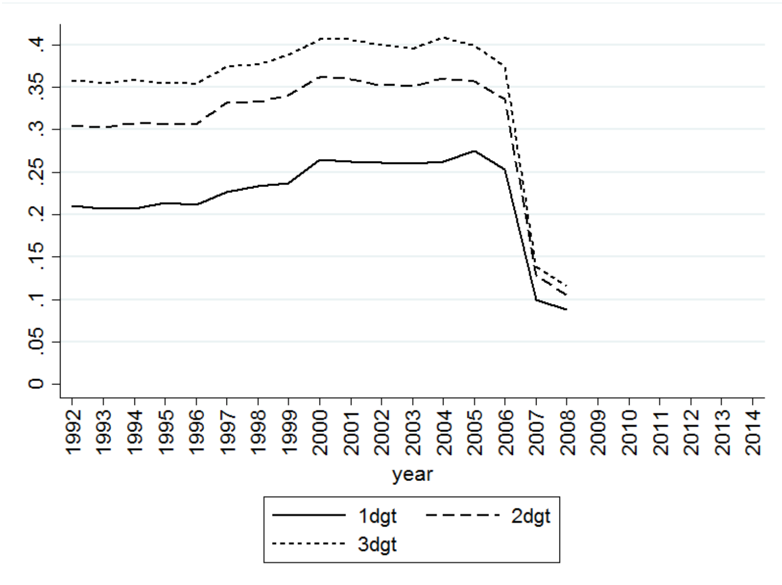

Figure 3.1: Time series of C^m with SOC1990

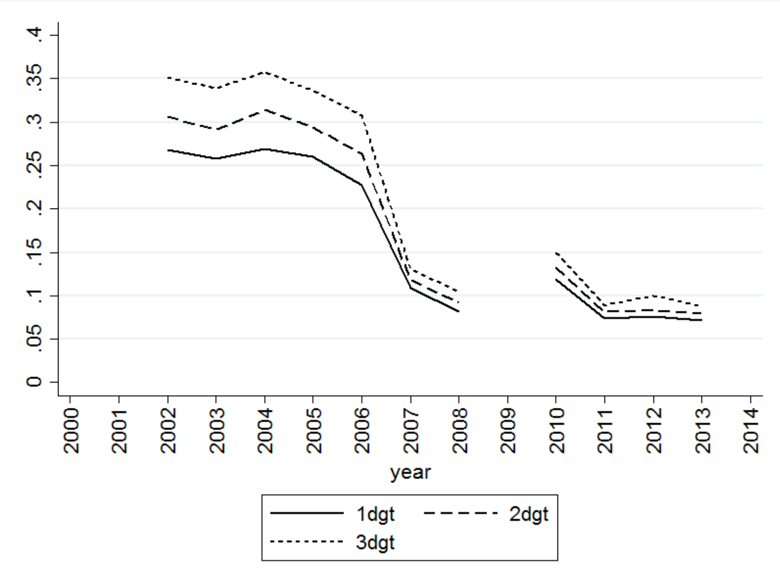

Figure 3.2: Time series of C^m with SOC2000

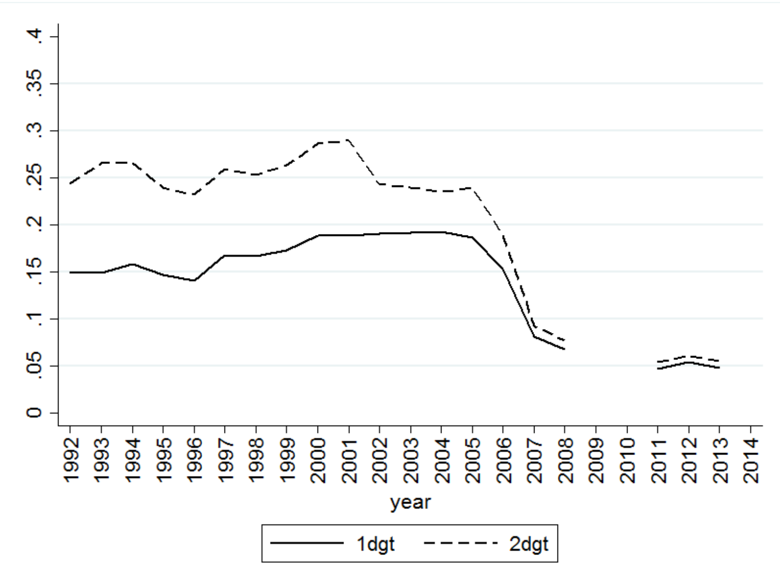

Figure 3.3: Time series of C^m for industry

Unexpectedly, the reduction in the percentage of occupational and industrial change in Figure 3.1 - 3.3 demonstrates an interesting effect: the rates reduce only slightly in 2006, considerably slump in 2007 and then become stable after 2008. Perales (2014) provides the reasons why the application of dependent interviewing in 2006 did not cause an immediate drop in the percentage of occupational change.

Firstly, many workers did not have valid occupational or industrial descriptions to be fed forward from 2005 for dependent interviewing in 2006. Since the longitudinal consistency is poor, this increases the rate of occupational or industrial change in 2006. That is to say, the impact of dependent interviewing on the rate of career change can not be completely displayed given that the linkage of the information between 2005 and 2006 is not sufficient. Secondly, a number of workers were assigned different occupational codes in 2006, even though they have confirmed that their occupation was the same as in 2005 via dependent interviewing. Thirdly, during dependent interviewing in 2006, the BHPS undertook work to improve the efficiency of the verbatim occupational descriptions provided in 2005. This might lead some respondents to erroneously report an occupational change. The BHPS has to confirm the job title and occupational description provided by workers because the descriptions may be unreadable, misspelled, or too long. The BHPS may have to edit the description in order to classify the worker's occupation. For example, respondents may provide a long description of their job, and the BHPS will shorten this description and use the key feature of it to classify the respondent's occupation. The trend of occupational mobility rate in 2006 may be prettified by the errors associated with the complex transition from independent interviewing. 2006 is a transition period for dependent interviewing because there is much information from the previous wave that was not well recorded, which may increase the suspicious occupational change in 2006. Given the descriptions will not need to be checked unless new information has been updated, during the editing process, many editing errors occur. However, from 2007, the information collected by dependent interviewing is built up well and organized. The percentage of occupational and industrial change (career change) becomes stable after this point. Therefore, the unexpected slump in occupational rate occurs in 2007 and becomes stable after 2008.

Now, I turn my attention to K^m by using the definition of career change that incorporates information on job changes. The rate of career change in Figure 3.4 - Figure 3.6 is defined as the following: the number of workers who experienced job change with different occupations divided by the number of workers who were employed in consecutive two waves. This ratio can help us to understand whether mobility rate defined by job changers over whole employment is affected by the dependent interviewing. A few interesting findings need to be pointed out. Firstly, compared with Figure 3.1 - 3.3, the rates are almost half in Figure 3.4 - Figure 3.6 within the period of independent interviewing, while they are at a similar level within the period of dependent interviewing. Secondly, the slump also appears when the dependent interviewing was introduced. The level of the drop is not as remarkable as Figure 3.1 - 3.3, but it is still observable. Thirdly, rates of career change are comparable to those in Figure 3.1 - 3.3. This suggests that, within the independent interviewing period, using job change information could fractionally correct the spurious career change due to measurement errors as we can observe that the range of the slump is smaller.

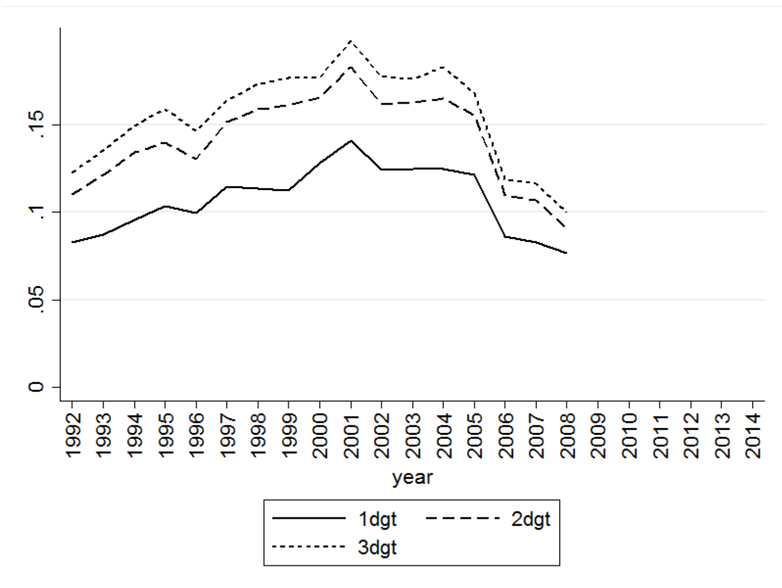

Figure 3.4: Time series of K^m with SOC1990

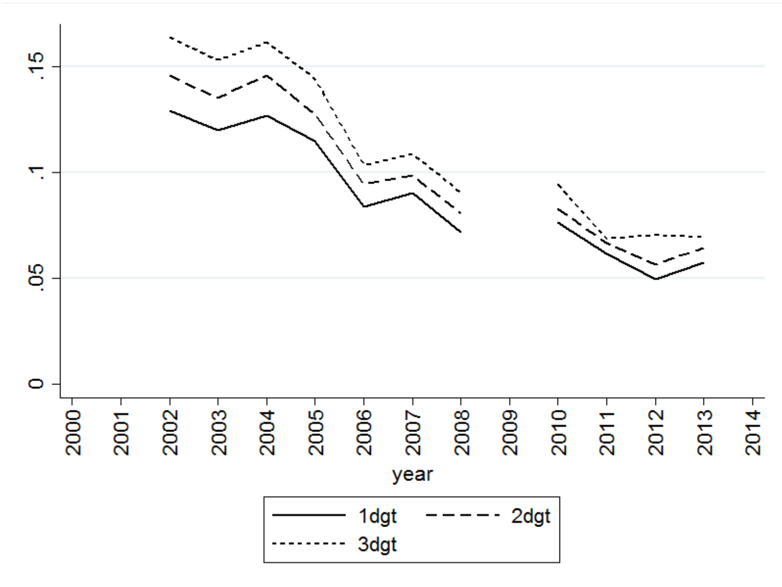

Figure 3.5: Time series of K^m with SOC2000

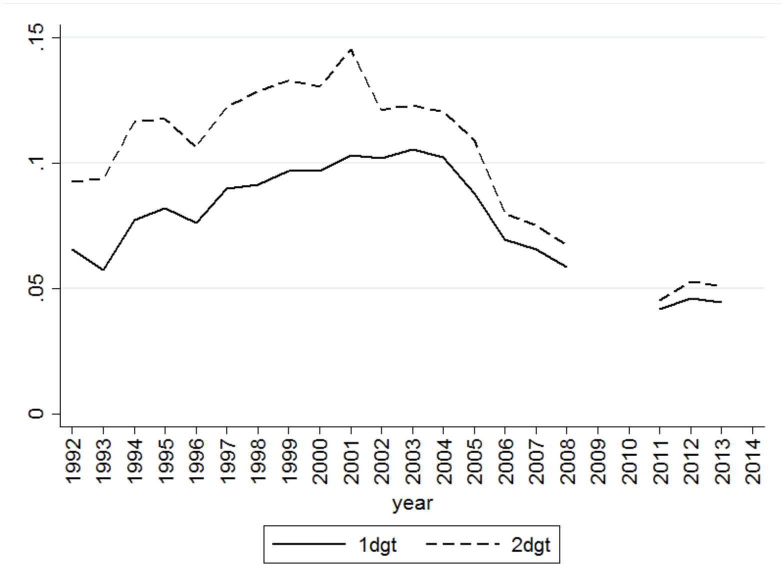

Figure 3.6: Time series of K^m for industry

The occupational and industrial mobility trend for the job changers will now be discussed. Here, the mobility rate is defined as the number of job changers who experience occupational or industrial change (career change) divided by the total number of job changers. The lines in Figure 3.7 - Figure 3.9 indicate that there is no significant slump when the dependent interviewing is introduced. The mobility rate increases in 2006, decreases in 2007, and then slightly increases again in 2008. The stable trend that it appears the dependent interviewing captured in Figure 3.1 - Figure 3.6 is not evident in in Figure 3.7 - Figure 3.9.

The lines in Figure 3.7 - Figure 3.9 suggest that the occupational and industrial mobility are quite high, more than 40 % in terms of 1-digit classification. The more disaggregated the classification used, the higher the mobility rate is. The mobility rate using SOC 1990 is around 60 % for the 3-digit level, and around 55 % for the 2-digit level. The mobility rate using SOC2000 is between 55 % -60 % for the 3-digit level before 2008, and between 50 % -55 % after 2010. The mobility rate using the 2-digit level SOC2000 is between 50 % - 55 % before 2008, and 45 % - 50% after 2010. The mobility rate using the 2-digit level of SOC 2000 is 5 % higher than the mobility rate using the 1-digit level of SOC 2000. The industrial mobility rate is between 40 % - 45 % for the 2-digit level, and around 35 % for the 1-digit level. The industrial mobility is smaller than occupational mobility. The greater the detail of classification used, the higher the mobility rate is. The difference of occupational mobility between 1-digit and 3-digit classification is around 20 %, and this difference is not dramatically reduced when the dependent interviewing is applied. For industrial mobility, the difference between 1-digit and 2-digit classification narrows from 1992 to 2002, and maintains around 10% afterwards.

These strongly suggest that using different measurements obtains quite different results. Using the proportion of job changers who experience career change (occupational and industrial change) to calculate the mobility rate is not affected by the change of questioning method. Figure 3.1 - Figure 3.6 provide interesting evidence to show that the dependent interviewing reduces the mobility rate dramatically, which suggests that the literature may overestimate the occupational mobility. However, I found that this is not the case when using the proportion of job changers who experience career change as a measurement. This raises a question: which measurement is more appropriate to represent the essence of career mobility? Compared with the first measurement of mobility rate Eq 3.1, the second measurement Eq 3.2 may correct measurement errors caused by the independent interviewing, and make the mobility rate within the dependent interviewing period more comparable. This suggests that the questioning mechanism of dependent interviewing can detect whether workers really change their occupations or industries. However, the second measurement Eq 3.2 still does not give us an idea of mobility rate. The proportion of job changers who switch occupations or industries is the essence of the career mobility rate. Therefore, I examine the third measurement Eq 3.3 and find that the change of questioning method no longer breaks the trend of occupational and industrial mobility. The third measurement calculates the proportion of job changers who switch their career, which demonstrates the essence of the mobility rate that most researchers used.

The first and second measurements adopt workers who were employed in two consecutive waves which also contains workers who do not change their job at all. However, this type of worker should not be included into the sample that we adopted to calculate the mobility rate. Information about job change can eliminate the measurement errors, from the first measurement to the second. From the second measurement to the third measurement, the proportion of job changers who switch their career allows us to observe the real behavior of workers who were changing their job, and reflects the process of workers' decisions on career switching.

In the following section, I will use an econometric model to investigate the robustness of the results provided in chapter 2. I use a Probit model to examine whether the change of questioning method changes the workers' occupations and industries. I use two types of sample to investigate the effect of the change in questioning method. One uses the samples who were employed in two consecutive waves, and the other uses the samples who experience job change. A job changer could change his job within the same employer. For example, he can be promoted to another position with the same employer. However, I exclude the workers who change jobs with the same employer in the next section because I would like to use a more restricted definition of changing job to understand the estimated feature. Using the sample of changing jobs across different employers is also helpful to compare the results in Chapter 2. In addition, I will divide the job-changers into two groups in terms of the channel in which workers found their next job. The first one is the employer-to-employer transition, and the second one is the non-employment transition. Workers who obtain their next job without any spell of unemployment or inactivity are classified as belonging to the former category, while workers who find their next job with a spell of employment or inactivity are categorised in the latter category. This division allows us to understand the incentive of career change for these two types of workers.

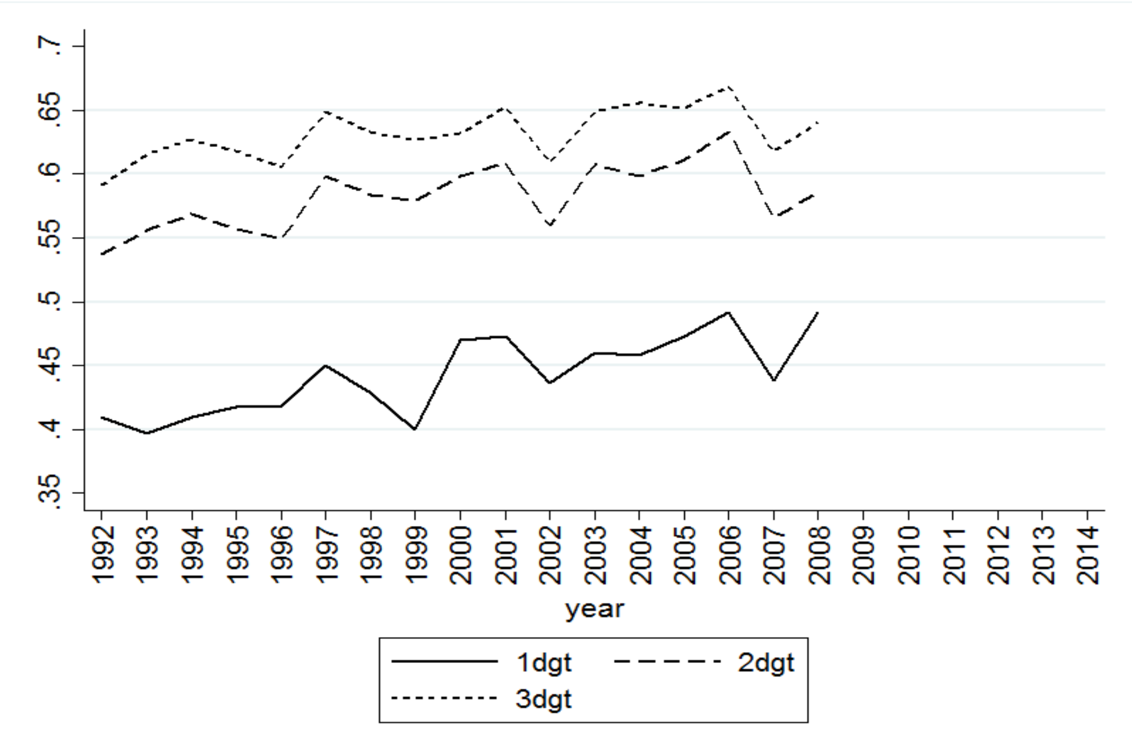

Figure 3.7: Time series of J^m with SOC1990

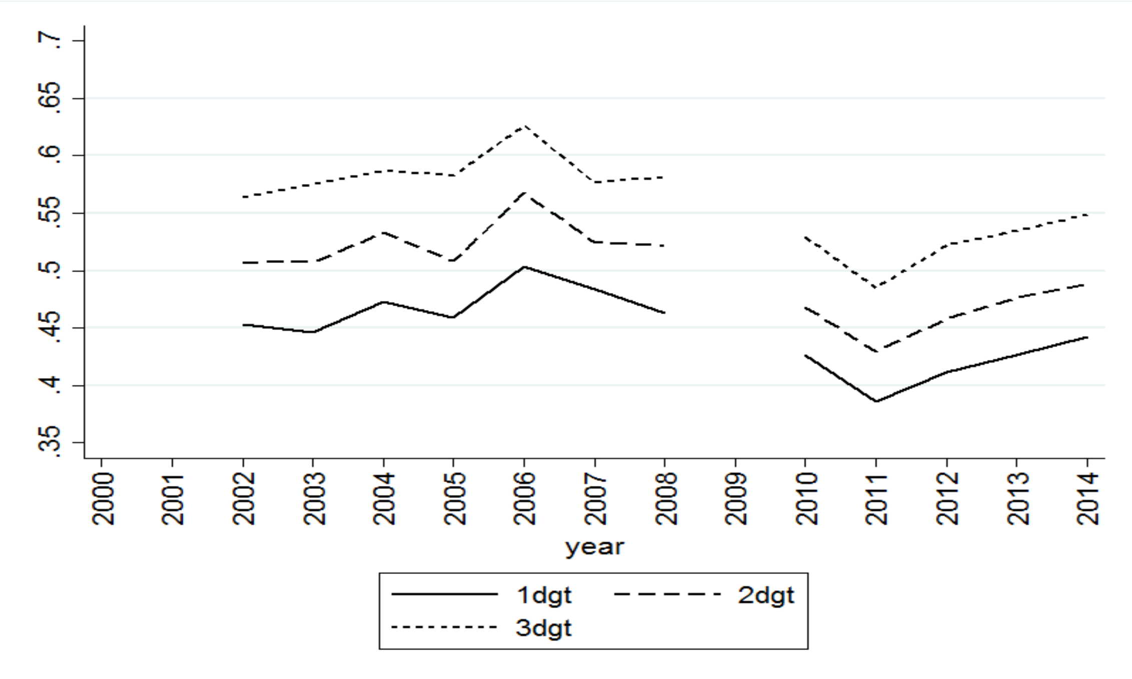

Figure 3.8: Time series of J^m with SOC2000

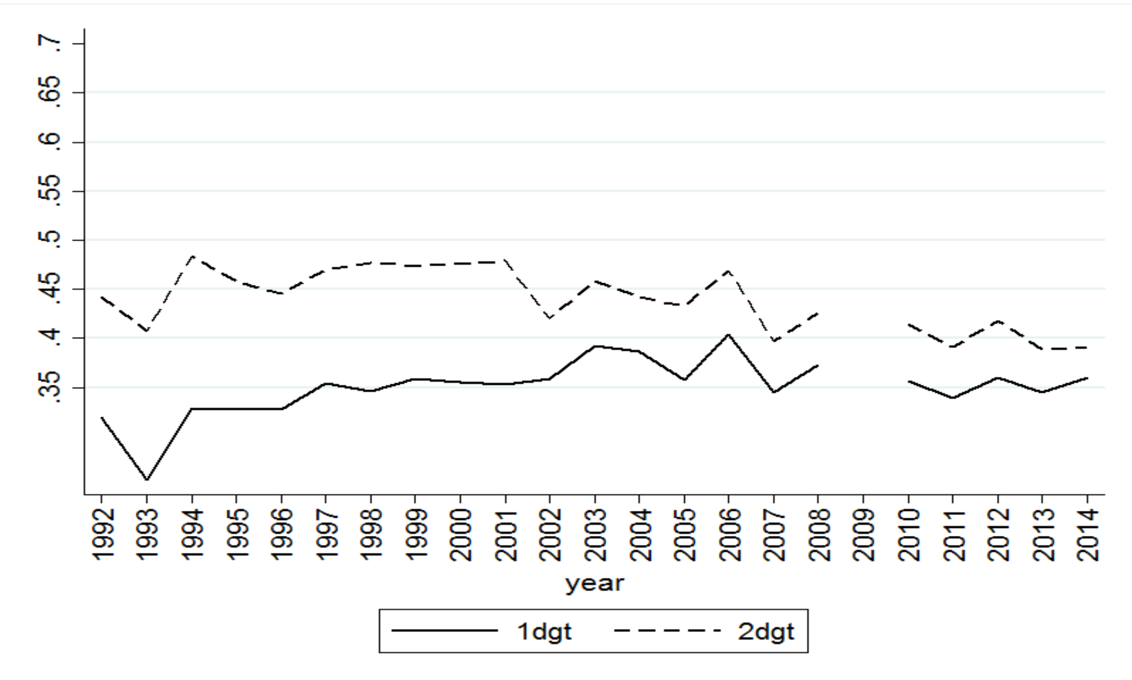

Figure 3.9: Time series of J^m for industry

3.3.6 Placebo regression with LFS

From the figures mentioned above, we observe the slump that occurs in 2007 from Figure 3.1 - Figure 3.6. The main reason for this is the change of interviewing method from 2007 in the BHPS. In order to confirm the change of interviewing method causing this slump, I use the same period of LFS data to examine whether the same slump occurs as well. If the slump is observed in the LFS, we have to reconsider whether there is another factor causing the slump which is coincidentally simultaneous to the change of interviewing method in 2007. I adopt a simple econometric model to examine whether the measures of mobility dramatically decrease after 2007 with the LFS. In Table 3.1, I use three variables to measure cyclical business: gross domestic production(GDP), output per worker (Opw) and unemployment rate (Urate). A dummy variable, Break, equals 1 if the time is after 2006 quarter 4, otherwise 0. Since there is no change of interviewing method in the LFS, the coefficient of Break should be insignificant. I regress the three measures of mobility on the measurements of business cycle, Break and time trend (Time_trend). Columns 1-3 in Table 3.1 shows that the coefficient of Break is statistically insignificant when I use GDP as the performance measure of the business cycle. There is no significant effect affecting any of the occupational mobility measurements (C^m, K^m and J^m) from 2007, and this implies that the slump of C^m and K^m with BHPS data does not occur with LFS data. If there is a factor generally affecting C^m and K^m, the effect could be observed in both of the LFS and the BHPS. If this factor is observed from the BHPs, but not observed in the LFS, then it should be a specific factor for the BHPS. According to the figures above, the change of interviewing method is the reason for this. Columns 4-6 in Table 3.1 are the results using output per worker as the measurement of business cycles, and Columns 7-9 are the results using unemployment rate as the measurement of cyclical business. The effects of Break from Columns 4-9 are all insignificant which confirms the finding of Columns 1-3. There is no dramatic change of occupational mobility (C^m, K^m, and J^m) between the period before and after 2007 as there was no change in the interview method in the LFS. The same results are obtained when the estimations with the information of industrial mobility are applied. Furthermore, this paper adds the Break dummy into the Probit model in Chapter 2 to understand whether the insignificance of Break could be observed in terms of the individual level. The coefficients of Break are all insignificant for the sample of continuously employed in consecutive two quarters, the sample of job changers, the sample of employed-to-employed transition, the sample of unemployed-to-employed transition and the sample of inactive-to-employed transition, no matter if it is occupational or industrial movement.

Table 3.1: Estimates for C^m, K^m, J^m with Labour Force survey

Occupation									
	C^m	K^m	J^m	C^m	K^m	J^m	C^m	K^m	J^m
GDP	0.182*	0.0982**	0.697**						
	(1.98)	(2.04)	(2.48)						
Opw				0.000774*	0.000534**	0.00309**			
				(1.76)	(2.34)	(2.29)			
Urate							-0.00136*	-0.00138***	-0.00438*
							(-1.82)	(-3.77)	(-1.89)
Break	0.00200	-0.00159	-0.00209	0.00165	-0.00142	-0.00304	0.00376	0.00148	0.00194
	(0.69)	(-1.05)	(-0.24)	(0.57)	(-0.95)	(-0.34)	(1.06)	(0.85)	(0.18)
Time_trend	0.000353	-0.000245**	-0.00100	0.000415*	-0.000264**	-0.000821	0.000646***	-0.000145***	0.000196
	(1.63)	(-2.14)	(-1.51)	(1.99)	(-2.44)	(-1.28)	(7.51)	(-3.45)	(0.73)
N	67	67	67	67	67	67	67	67	67
R2	0.874	0.243	0.264	0.873	0.258	0.254	0.873	0.342	0.236
pseudo R2									
Log llik.	248.5	291.5	173.5	248.1	292.2	173.0	248.2	296.2	172.2
Industry									
	C^m	K^m	J^m	C^m	K^m	J^m	C^m	K^m	J^m
GDP	0.192*	0.0962***	1.373***						
	(1.78)	(3.13)	(7.74)						
Opw				0.000562*	0.000454***	0.00610***			
				(1.69)	(2.91)	(6.84)			
Urate							-0.00292	-0.00129***	-0.0125***
							(-1.65)	(-4.84)	(-7.31)
Break	0.0121	-0.00183	-0.00866	0.0106	-0.00189	-0.0110	0.0186	0.000830	0.00883
	(1.17)	(-1.33)	(-1.14)	(1.19)	(-1.39)	(-1.44)	(1.26)	(0.56)	(0.92)
Time_trend	-0.000386	-0.000313***	-0.00318***	-0.000212	-0.000299***	-0.00283***	-0.000175	-0.000195***	-0.00110***
	(-1.39)	(-4.45)	(-7.66)	(-1.31)	(-4.21)	(-6.85)	(-0.99)	(-6.16)	(-5.81)
N	74	74	74	74	74	74	74	74	74
R2	0.068	0.633	0.704	0.060	0.634	0.679	0.086	0.675	0.686
pseudo R2									
Log llik.	192.7	325.4	200.2	192.4	325.4	197.2	193.5	329.9	198.0

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, t statistics in parentheses

3.4 Empirical Evidence

3.4.1 Models

This section contains the main empirical results of the research. In particular, I document the robustness test of occupational and industrial mobility in the UK using the data from the BHPS between 1991-2008 and the UKHLS between 2009-2014. The discontinuity data collection from independent interviewing to dependent interviewing allows us to check the robustness of the measurement.

As discussed above, the level of occupational mobility before 2006 obtained from independent interviewing is substantially higher than the one obtained from the dependent interviewing after 2006. As suggested by Figure 3.1 - 3.6, the presence of a mobility slump in 2007 is caused by the implementation of dependent interviewing and the coding error that occurs during transition from independent interviewing to dependent interviewing. Thus, in order to investigate the effects of the change in the questioning method after 2007, I propose the following model:

$$y_i = X_i\beta_j + \epsilon_{ij}$$

where the variable y_i indicates whether the worker changes occupation or industry, and the vector X describes the explanatory variables. ϵ_{ij} is i.i.d and follows a multivariate normal distribution, i represents individuals and j outcomes. y_i is a binary variable which is assigned the value of one if the individual i switches his occupation/industry in time t and is zero otherwise.

$$y_i = \begin{cases} 1 & \text{if the worker changes his occupation/industry} \\ 0 & \text{if the worker remains in his occupation/industry} \end{cases}$$

and

$$
\begin{aligned}
X_i\beta_j = \quad \beta_0 \quad & +\beta_1 agg\_urate + \beta_2 reg\_agg\_urate + \beta_3 age + \beta_4 age\_sq \\
+ \quad & \beta_5 Break + \beta_6 mar\_cohab + \beta_7 num\_child + \beta_8 ft\_job \\
+ \quad & \beta_9 female + \beta_{10} temporary + \beta_{11} E2E + \beta_{12} Non\_emp \\
+ \quad & \beta_{13} H\_edu + \beta_{14} M\_edu \qquad (3.4)
\end{aligned}
$$

I model an individual's occupational or industrial switch depending on a set of individual characteristics, properties of the job the worker is hired for and the macroeconomic situation, etc. Since the significant impact caused by the change of questioning method on the occupational/ industrial mobility occurs in 2007, I include the dummy variable *Break*, which is assigned the value of one if the time span covers the period 2007-2014, and zero otherwise. This dummy variable actually captures the change of questioning method. Furthermore, the individual's last occupation/industry and his/her resident area are controlled within this model. [3]

The complete list of variables is shown in Table 3.8. Workers who possess a higher education degree or equivalent qualification are classified as high-skilled workers. Middle-skilled workers indicates the workers who have a O-level or equivalent qualification. Workers whose educational qualification are below O-level are defined as low-skilled.

3.4.2 Continuously employed in two adjacent waves

The estimation result in Table 3.2 is for the workers who were continuously employed in the adjacent survey waves. The first column uses the 1-digit level of occupational classification to identify whether the worker's occupation at time t is

[3] The areas of individual's resident are shown as the following: North West, North East, Yorkshire & Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland and Northern Ireland.

different from his occupation at time $t-1$. The second column uses the 2-digit level of occupational information to identify the switcher, and the third column uses the 3-digit level of occupational information. For defining the industrial change, the fourth column uses 1-digit industrial classification and the fifth column uses 2-digit classification.

The main result tells us that the interview method of questioning has a significant impact on the career change. Since a majority part of the samples do not experience job change, the significance of $Break$ indicates the measurement error exists, as $Break$ captures the change of questioning method. The negative sign of $Break$ is consistent with the findings suggested by Figure 3.1 - Figure 3.6. It shows that change of questioning method reduces occupational and industrial mobility. The number of occupational and industrial switchers dramatically falls during the period in which dependent interviewing applied. This implies that the application of dependent interviewing has a considerable impact on the measurement of occupational and industrial change.

In Table 3.2, a change of questioning method is associated with a 16-25 % decrease in the occupational changing probability. The probability of 1-digit occupational change decreases around 16%, 2-digit level decrease 21%, and 3-digit level decreases 24 %. The more detailed the level is, the higher the coefficient of $Break$ becomes. These results are consistent with the discussion above, and show that the dependent interviewing is a major factor that affects occupational data. I also found that the marginal effect of $Break$ for occupational change is larger than industrial mobility, which is consistent with the discussions of Figure 3.1 - 3.6.

The results in Table 3.2 show that employer-to-employer transition significantly increases the probability of occupational and industrial switch. Transition through non-employment also has a significant effect on the career change (occupational and industrial change). Compared with staying in the same job, transition through employer-to-employer or through non-employment statistically increases the possibility of moving to another occupation or industry. This also motivates me to investigate career mobility transition through employer-to-employer and the cases of transition through non-employment.

3.4.3 Job changer

In the results from Table 3.3, occupational mobility is captured by changes in occupational codes for job changers. In order to compared this with the results of Chapter 2, the job changers here refers to workers who experience transition through employer-to-employer, or through non-employment. Therefore, workers who change job within the same employer are excluded to avoid confusion caused from the sample selection.

Here, Table 3.3 shows the most important results of this research: a change of questioning method, the variable of *Break*, has no statistically significant impact on occupational and industrial mobility. The questioning method does not affect the occupational and industrial mobility when we consider the workers who experience job change as a sample. This result provides a robust examination of the research question we were asking in this study. [4] It shows that the measurement of occupational and industrial mobility we were using is not affected by dependent interviewing. This is a vigorous support of the argument made in Chapter 2.

The results in Table 3.3 also show the aggregate unemployed rate has a significant impact on occupational mobility, which strengthens the argument about the pro-cyclicality of occupational mobility. The regional component of the unemployment is significant in industrial mobility rather than in occupational mobility. The effects of the business cycle are statistically significant through all levels (1-digit level, 2-digit level and 3-digit level). The more detailed the level of occupational coding is , less stronger the impact of cyclical business becomes. This tells us that the business cycle is more important for workers when a major occupational

[4] Question: which measurement is more appropriate to represent the essence of career mobility?

Table 3.2: Probit model for the workers who were continuously employed in two adjacent waves (with and without job change)

	Occupation			Industry	
	1dgt	2dgt	3dgt	1dgt	2dgt
agg_urate	-0.00402**	-0.00176	-0.00197	-0.00322***	0.000584
	(-2.20)	(-1.06)	(-1.57)	(-2.73)	(0.36)
reg_agg_urate	0.00140	-0.0000471	0.00298	-0.00285*	-0.00213
	(0.58)	(-0.02)	(0.89)	(-1.73)	(-0.93)
age_2	-0.00334***	-0.00411***	-0.00331**	-0.00285***	-0.00213**
	(-3.71)	(-3.69)	(-2.26)	(-3.62)	(-1.97)
age_sq	0.0000249**	0.0000299**	0.0000197	0.0000251**	0.0000162
	(2.21)	(2.16)	(1.11)	(2.55)	(1.26)
Break (d)	-0.161***	-0.210***	-0.242***	-0.104***	-0.178***
	(-23.61)	(-15.96)	(-10.32)	(-14.87)	(-14.49)
mar_cohab (d)	-0.00538	-0.00382	-0.00594	-0.00601**	-0.00680***
	(-1.46)	(-0.84)	(-1.23)	(-2.52)	(-2.62)
num_child	-0.000221	0.000471	0.00174	-0.00218*	-0.00234**
	(-0.14)	(0.24)	(0.76)	(-1.95)	(-2.14)
female (d)	-0.0247***	-0.0157***	-0.0114***	-0.0104***	-0.00390
	(-4.82)	(-4.16)	(-3.40)	(-4.23)	(-1.39)
ft_job (d)	0.00864**	0.00526	0.00732	-0.0168***	-0.0272***
	(2.29)	(1.32)	(1.52)	(-3.46)	(-6.49)
temporary (d)	0.0210***	0.0380***	0.0399***	0.0287***	0.0438***
	(3.67)	(4.83)	(4.23)	(6.59)	(7.15)
E2E (d)	0.343***	0.409***	0.459***	0.333***	0.412***
	(8.26)	(9.33)	(9.89)	(12.14)	(13.12)
Non_emp (d)	0.293***	0.349***	0.396***	0.364***	0.439***
	(8.18)	(8.90)	(8.73)	(8.47)	(8.76)
H_edu (d)	0.00874*	0.00832	0.0129**	-0.0138***	-0.0124***
	(1.73)	(1.56)	(2.17)	(-6.30)	(-4.03)
M_edu (d)	0.0156***	0.0143**	0.0161**	-0.00252	-0.000803
	(3.53)	(2.56)	(2.23)	(-0.88)	(-0.20)
Regions	Yes	Yes	Yes	Yes	Yes
Last OCC/IND	Yes	Yes	Yes	Yes	Yes
N	84317	84317	84200	81709	81659
pseudo R^2	0.168	0.228	0.258	0.226	0.266
Log llik.	-29637.9	-31828.7	-32891.6	-21228.1	-25003.4

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
t statistics in parentheses

change applies rather than when a minor occupational change applies. During the economic boom period, people have more courage to step into another occupation which is highly distinctive from their current occupation. The impact of the business cycle on occupational mobility is due to the difficulty of workers' job seeking. If it is during the economic recession period, it is harder for workers to be reemployed. This difficulty forces workers to widely seek jobs from other occupation in order to find a job sooner.

Comparing with a part-time job, a full-time job statistically decreases the probability of occupational and industrial mobility. A temporary job has a statistical impact on increasing industrial mobility, but it has no impact on occupational mobility. I also find that age decreases the probability of occupational and industrial change. This suggests the importance of human capital accumulation on occupational and industrial change. Also, women do not have a higher probability of career changing than men.

3.4.4 Employer-to-employer transition

According to the results in Table 3.2, the transition channel increases the probability of occupational and industrial change. Here, I decompose the previous sample, and only use workers who experience employer-to-employer transition as a sample. This sample selection can help us to understand the behavior of career change for the workers who were searching on the job, and allows us to compare with the results provided in Chapter 2. Table 3.4 provides similar results of Probit estimation with the results in Table 3.3. The procyclicality of occupational is still found to be significant for the employer-to-employer transition, and the procyclicality of industrial mobility mainly relies on the regional component of unemployment. The variable of *Break*, the change of questioning method, does not play a significant role in the occupational and industrial mobility.

The marginal effect of aggregate unemployment on occupational mobility is

Table 3.3: Probit model for job changers

	Occupation			Industry	
	1dgt	2dgt	3dgt	1dgt	2dgt
agg_urate	-0.01553***	-0.01444***	-0.01297***	-0.00423	-0.00042
	(-5.67)	(-4.25)	(-3.23)	(-0.58)	(-0.08)
reg_agg_urate	-0.01543	-0.01698	-0.01003	-0.02332**	-0.02704**
	(-0.92)	(-1.25)	(-0.74)	(-1.96)	(-2.16)
age_2	-0.01381***	-0.02043***	-0.01824***	-0.01159***	-0.01243**
	(-2.95)	(-3.93)	(-4.42)	(-2.59)	(-2.09)
age_sq	0.00014**	0.00022***	0.00019***	0.00012*	0.00012
	(2.35)	(3.29)	(3.65)	(1.93)	(1.57)
Break (d)	-0.00321	-0.01416	-0.01346	0.03222	-0.04078
	(-0.25)	(-0.87)	(-0.74)	(1.03)	(-1.38)
mar_cohab (d)	-0.01815	-0.00610	-0.00352	-0.04584**	-0.03032
	(-0.89)	(-0.33)	(-0.20)	(-2.46)	(-1.62)
num_child	-0.00232	0.00595	0.00515	-0.00640	-0.00720
	(-0.24)	(0.57)	(0.51)	(-1.02)	(-1.03)
ft_job (d)	-0.04580***	-0.04103***	-0.03159*	-0.07246***	-0.07715***
	(-2.97)	(-2.67)	(-1.76)	(-5.16)	(-6.06)
female (d)	-0.01288	0.01533	0.00787	0.01337	0.03813*
	(-0.87)	(0.95)	(0.48)	(0.64)	(1.79)
temporary (d)	0.00633	0.03323	0.02036	0.04953***	0.06004***
	(0.32)	(1.36)	(0.95)	(3.17)	(3.03)
Non_emp (d)	0.00342	-0.01090	-0.00085	-0.00114	-0.00157
	(0.30)	(-1.04)	(-0.06)	(-0.09)	(-0.11)
H_edu (d)	0.02208	0.02435	0.02924	-0.09806***	-0.09124***
	(1.01)	(1.08)	(1.16)	(-7.10)	(-4.63)
M_edu (d)	0.04663**	0.04361**	0.04569*	0.00413	0.00833
	(2.36)	(2.02)	(1.72)	(0.25)	(0.41)
Regions	Yes	Yes	Yes	Yes	Yes
Last OCC/IND	Yes	Yes	Yes	Yes	Yes
N	8065	8060	7828	7775	7769
pseudo R^2	0.031	0.076	0.028	0.042	0.072
Log llik.	-5367.92	-5148.73	-5189.56	-5147.37	-4926.72

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
t statistics in parentheses

stronger for 1-digit classification than for 2-digit and 3-digit classification. When workers experience major occupational change, the business cycle plays a more important role in the major group (1-digit level) than the minor group (2-digit level), and unit (3-digit level) occupational change. This reminds us that workers' considerations depend on how far they move their career, and what occupation and industry they move to: more considerations are needed.

The marginal effect of aggregate unemployment (business cycle) on occupational mobility for EE transition is larger than the marginal effect for job changers. Workers who experience EE transition are more sensitive than job changers. Job changers consist of the number of EE transitions and the number of non-employment transition. Given that the marginal effect for EE transition is larger than for job changers, it is worth knowing the marginal effect of the business cycle for non-employment transition as well.

A full-time job makes workers statistically less likely to attempt occupational and industrial change. Workers who experience on-the-job transition have a low possibility to change their major (1-digit level) and minor occupational group (2-digit level) if the workers' previous job was full-time. However, a full-time job does not affect workers' decisions on unit occupational change (3-digit level). Elder workers have less attempts to change their occupational and industrial attachment. A temporary job enhances workers' occupational change in the minor and unit group (2-digit and 3-digit level). Marriage only decreases the probability of major industrial changing, and there is no significant effect of marriage on occupational mobility. The number of children does not affect career adjustment, which is consistent with the findings from the LFS.

However, education attainment affects occupational and industrial change differently. Across occupations, medium-level skilled workers have a higher probability to become switchers than low-level skilled workers as our reference category. For the industries, low skilled workers have a higher probability to become industrial switchers than high skilled workers.

3.4.5 Non-employment transition

Let's focus on the workers who experience non-employment transition. The sample size of transition through unemployment and the sample size of transition through inactivity are not sufficiently large enough to have a proper investigation. A small sample size may lead to a biased result and conclusion. Therefore, I include the transition through unemployment and inactivity together to analyze the estimation. In 3.5, the procyclicality of occupational and industrial mobility can still be observed, and the change of questioning method does not affect the probability of occupational and industrial change. For the occupational mobility, the marginal effect of aggregate unemployment (business cycle) is bigger for the more detailed occupational classification, and the opposite is true for EE transition. The business cycle increases the probability of changing occupation within unit groups (3 digit level), rather than major groups (1-digit level). For the industrial mobility, the aggregate non-employment becomes significant for unemployed workers when they experience major industrial change, and the regional component of unemployment no longer has an effect on industrial change any more.

Educational attainment, however, affects occupational and industrial mobility differently. Across occupations, high and medium skilled workers do not have a higher probability than low skilled workers of changing occupation. Across industries, higher skilled workers have a lower probability of changing industry than low skilled workers. These results are different from the results of on-the-job searching workers, and also show that education attachment has a different effect on career change according to different channels of transition.

The effect of temporary jobs on career change disappears for non-employed workers while this effect is positively significant for EE transition. Full-time jobs only increase the probability of major occupational change, and do not affect the

Table 3.4: Probit model for EE transition

	Occupation			Industry	
	1dgt	2dgt	3dgt	1dgt	2dgt
agg_urate	-0.0184***	-0.0158***	-0.0151**	0.00326	0.00700
	(-5.19)	(-3.94)	(-2.38)	(0.37)	(0.96)
reg_agg_urate	-0.0109	-0.0180	-0.0121	-0.0238*	-0.0276*
	(-0.56)	(-1.01)	(-0.80)	(-1.80)	(-1.79)
age_2	-0.0184***	-0.0251***	-0.0204***	-0.0165***	-0.0199***
	(-3.20)	(-4.50)	(-3.90)	(-3.04)	(-3.05)
age_sq	0.000206***	0.000282***	0.000229***	0.000184***	0.000222***
	(2.83)	(4.00)	(3.41)	(2.63)	(2.64)
Break (d)	-0.00207	-0.00649	-0.0123	0.0194	-0.0552
	(-0.14)	(-0.36)	(-0.48)	(0.58)	(-1.53)
mar_cohab (d)	-0.00271	0.00996	0.00961	-0.0412*	-0.0234
	(-0.12)	(0.55)	(0.48)	(-1.96)	(-1.14)
num_child	-0.00286	0.00503	0.00507	-0.00887	-0.00968
	(-0.27)	(0.42)	(0.40)	(-1.29)	(-1.27)
female (d)	-0.0119	0.0238	0.0181	0.00939	0.0397
	(-0.74)	(1.33)	(0.89)	(0.39)	(1.53)
ft_job (d)	-0.0380*	-0.0666***	-0.0574***	-0.129***	-0.128***
	(-1.80)	(-3.70)	(-2.81)	(-7.51)	(-10.10)
temporary (d)	0.0400	0.0541*	0.0433*	0.0502***	0.0420**
	(1.62)	(1.83)	(1.72)	(2.70)	(2.45)
H_edu (d)	0.0171	0.00480	0.0173	-0.0727***	-0.0825***
	(0.59)	(0.18)	(0.60)	(-4.57)	(-4.30)
M_edu (d)	0.0585**	0.0485**	0.0577*	0.0310	0.0177
	(2.48)	(2.04)	(1.88)	(1.53)	(0.85)
Regions	Yes	Yes	Yes	Yes	Yes
Last OCC/IND	Yes	Yes	Yes	Yes	Yes
N	5663	5628	5454	5494	5479
pseudo R^2	0.039	0.080	0.116	0.053	0.090
Log llik.	-3730.3	-3586.7	-3307.1	-3589.6	-3423.3

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
t statistics in parentheses

industrial mobility for unemployed workers. The effect of workers' age on the probability of occupational and industrial change disappears for non-employed workers. Female workers do not have a significantly higher probability of occupational and industrial change than male workers. After observing and analyzing the results which correspond to all the independent variables, I found that the crucial factors which influence career change for non-employment workers are aggregate unemployment (business cycle) and education attachment. These findings are also helpful to understand the non-employed workers' career adjustment in the economic recession.

3.5 Summary and conclusion

Using the sample that was employed in consecutive waves, I found that the occupational and industrial mobility dramatically fall when dependent interviewing is introduced. This phenomenon is observed in Figure 3.1 - Figure 3.6 , and concrete results are obtained from the econometric model. There is a huge difference of occupational mobility rate between the 3-digit and 1-digit level during the period 1992-2006, but this difference has dramatically shrunk over the period 2007-2014 with the size of difference falling from 15 % to 5 %. This phenomenon indicates that the measurement error does indeed exist. Comparing the coefficients of questioning method changes, I found that a more disaggregated classification increases the dependent interviewing impact on occupational and industrial mobility. This estimation result is consistent with what the features of Figures 3.1 - 3.6 suggested.

I also found that the change of questioning method does not affect the occupational and industrial mobility if I use the sample who experienced job change, no matter if it is through employer-to-employer transition or non-unemployment transition. The impact of dependent interviewing on the probability of career change occurs only with the sample of workers who were employed in consecutive waves,

Table 3.5: Probit model for non-employment

	Occupation			Industry	
	1dgt	2dgt	3dgt	1dgt	2dgt
agg_urate	-0.01232***	-0.01464***	-0.01518*	-0.01790***	-0.01245
	(-2.89)	(-2.75)	(-1.68)	(-2.90)	(-1.57)
reg_agg_urate	-0.02842	-0.01135	-0.00386	-0.01522	-0.02476
	(-1.19)	(-0.62)	(-0.14)	(-0.65)	(-1.19)
age_2	-0.00275	-0.00972	-0.01016	0.00080	0.00157
	(-0.34)	(-1.09)	(-1.17)	(0.11)	(0.17)
age_sq	-0.00002	0.00007	0.00006	-0.00004	-0.00005
	(-0.16)	(0.58)	(0.51)	(-0.43)	(-0.38)
Break (d)	-0.00292	-0.03591	-0.00439	0.03978	-0.01147
	(-0.13)	(-1.60)	(-0.15)	(1.18)	(-0.40)
mar_cohab (d)	-0.04541*	-0.03340	-0.02384	-0.04688	-0.04126
	(-1.67)	(-1.24)	(-0.88)	(-1.39)	(-1.11)
num_child	0.00018	0.00419	0.00222	-0.00371	-0.00091
	(0.01)	(0.26)	(0.15)	(-0.26)	(-0.06)
ft_job (d)	-0.05679**	-0.04321	-0.04693	-0.00366	-0.00543
	(-2.00)	(-1.57)	(-1.37)	(-0.14)	(-0.18)
female (d)	-0.01079	-0.00326	-0.03307	0.00141	0.01774
	(-0.40)	(-0.09)	(-0.89)	(0.05)	(0.53)
temporary (d)	-0.00769	-0.00524	-0.00572	0.02073	0.03028
	(-0.26)	(-0.17)	(-0.22)	(0.90)	(1.04)
H_edu (d)	0.02980	0.05899*	0.04438	-0.12791***	-0.11109**
	(0.75)	(1.91)	(1.35)	(-4.46)	(-2.39)
M_edu (d)	0.00701	0.01773	0.00416	-0.04621	-0.02579
	(0.18)	(0.58)	(0.14)	(-1.54)	(-0.54)
Regions	Yes	Yes	Yes	Yes	Yes
Last OCC/IND	Yes	Yes	Yes	Yes	Yes
N	2390	2363	2147	2267	2241
pseudo R^2	0.026	0.088	0.062	0.051	0.080
Log llik.	-1605.33	-1482.25	-1366.24	-1490.12	-1391.65

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
t statistics in parentheses

and most of this sample are workers who did not experience job change. An appropriate definition of occupational or industrial mobility should consider the worker who experiences job change as a sample, otherwise it will misconstrue the meaning of career ladder and career mobility. The occupational and industrial change for people who do not experience job change could be considered as a measurement error, collection error or coding error etc. These errors can be excluded by introducing of dependent interviewing when we investigate the occupational and industrial mobility. For the people who experience job change, the occupational and industrial mobility are not affected by the implementation of dependent interviewing. This proves that the measurement used in Chapter 2 is robust and solid.

The procyclicality of occupational mobility is confirmed by aggregate unemployment for job changers, while the procyclicality of industrial mobility is confirmed by the performance of regional unemployment against aggregate unemployment. The procyclicality of occupational mobility is essentially consistent with the findings using LFS. The cyclicality of industrial mobility relies more on the performance of regional unemployment than aggregate unemployment. Although the aim of this chapter is to investigate the effect of dependent interviewing on the occupational and industrial measurement, I still find strong support for the procyclicality of career adjustment. The procyclicality of career mobility is, thus, supported via estimations using the LFS, BHPS and UKHLS. This also helps us address our arguments in a sounder manner.

In this study, I examine the robustness of the occupational and industrial mobility measurement in the UK by applying dependent interviewing. This study evidences that procyclicality of career mobility is solid in the UK. Some surveys use dependent interviewing as the questioning method in the US and Canada: the US Current Population Survey (CPS), the US Survey of Income and Program Participation (SIPP) and the Canadian Survey of Labour and Income Dynamics (SLID). It is also valuable to analyze the occupational and industrial mobility with the surveys mentioned above. This will help us to understand the strength of the measurement and the situation of career change in the US and Canada. Then we can obtain a wider and more completed view about occupational and industrial mobility across different counties.

In this study, I combine the transition through unemployment and inactive together in estimation because the sample size is not sufficient to investigate these two transition separately. A good way to increase the sample size is to include every transition within a year. However, this will require higher quality of data. It's not easy for participants to remember the details of employment history took place within a year. Then, the reliability of data collection will be challenged. This situation also indicates the advantages of using Quarterly LFS to analyze career mobility. Each move of employment can be recorded easily when respondent's memory is still fresh. In addition, the sample size is sufficient to be decomposed further for more specified analysis.

There are still quite a few topics worth investigating in the future. For example, how wage changes depend on career changes is an important topic in labour economics. I provide evidence that dependent interviewing does not affect the measurement of occupational and industrial mobility when samples via EE transition and non-employment transition are adopted, and it is also interesting to investigate if dependent interviewing directly or indirectly affects the wage gains via occupational or industrial change. Furthermore, researchers also are interested in repeat mobility. For example, what is a worker's occupational and industrial choice if he was an occupational mover in the previous wave and is currently seeking for a new job? Does an occupational mover have a higher probability of always being an occupational mover? I leave these topics for future research.

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Table 3.6: Timing of collection

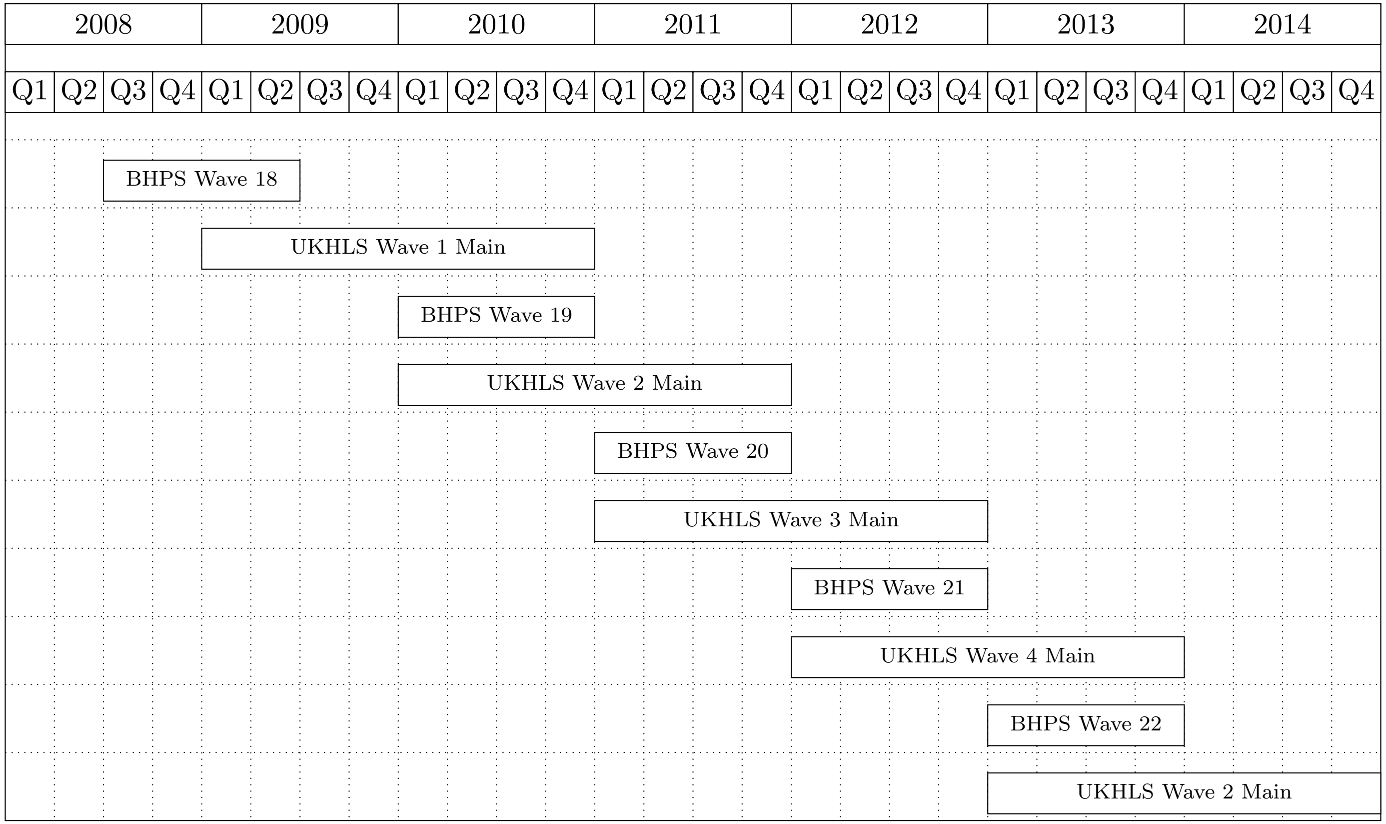


Table 3.7: The classification of SIC 1980, 1992, and 2007 (section tier)

	SIC1980	SIC1992	SIC2007
1	Agriculture, forestry & fishing	Agriculture, Hunting and Forestry	Agriculture, forestry and fishing
2	Energy & water supplies	Fishing	Mining and quarrying
3	Extraction of minerals & ores other than fuels; manufacture of metals, mineral products & chemicals	Mining and Quarrying	Manufacturing
4	Metal goods, engineering & vehicles industries	Manufacturing	Electricity, gas, air cond supply
5	Other manufacturing industries	Electricity, Gas and Water Supply	Water supply, sewerage, waste
6	Construction	Construction	Construction
7	Distribution, hotels & catering (repairs)	Wholesale and Retail Trade: Repair of Motor Vehicles, Motorcycles and Personal Household Goods	Wholesale, retail, repair of vehicles
8	Transport & communication	Hotels and Restaurants	Transport and storage
9	Banking, finance, insurance, business services & leasing	Transport, Storage and Communication	Accommodation and food services
10	Other services	Financial Intermediation	Information and communication
11		Real Estate, Renting and Business Activities	Financial and insurance activities
12		Public Administration and Defence: Compulsory Social Security	Real estate activities
13		Education	Prof, scientific, technical activities
14		Health and Social Work	Admin and support services
15		Other Community, Social and Personal Service Activities	Public admin and defence
16		Private Households with Employed Persons	Education
17		Extra-Territorial Organisations and Bodies	Health and social work
18			Arts, entertainment and recreation
19			Other service activities
20			Households as employers
21			Extraterritorial organisation

Table 3.8: The description of variables

Variable	Description
agg_rate:	The aggregate unemployment rate.
reg_agg_rate:	The regional unemployment rate minus the aggregate unemployment rate.
Age:	the participant's age
Age_sq:	the square of the participant's age
Mar_cohab:	Dummy; equals 1 if a respondent is classified as married or cohabitated, else 0
num_child:	the number of children
Break:	Dummy, equals 1 if the dependent interviewing is applied.
female:	Dummy; equals 1 if a participant is female, else 0.
H_edu:	Dummy; equals 1 if a worker has a higher education/qualification.
M_edu:	Dummy; equals 1 if a worker has a middle education/qualification.
ft_job:	Dummy; equals 1 if an employed worker's last job is a full time job. Otherwise the value of this variable is zero if an employed worker's last job is part-time job. ft_job equals 1 if a non-employed worker's current job is a full time job. Otherwise the value of this variable is zero if a non-employed worker's current job is part-time job.
Temporary:	Dummy; equals 1 if an employed worker's last job is a temporary job. Otherwise the value of this variable is zero if an employed worker's last job is a permanent job. Temporary equals 1 if a non-employed worker's current job is a temporary job. Otherwise the value of this variable is zero if a non-employed worker's current job is a permanent job.
E2E:	Dummy; equals 1 if the workers change their job via employer-to-employer transition, else 0
Non_emp:	Dummy; equals 1 if the worker's previous employment status is unemployment or inactive, else 0

Chapter 4

Sectoral Mobility and Unemployment with Heterogeneous Disutility of Work

4.1 Introduction

The Great Recession has attracted economists' attention to intersectoral mobility frictions in explaining aggregate unemployment. Some have argued that the increase of reallocation has contributed to the high and persistent level of unemployment. When workers need to reallocate to other sectors, they have to spend some time becoming familiar with another labour market. This process is time-consuming and unemployment might rise as workers accomplish this slow transition. This hypothesis forms the basis for theories of the natural unemployment and an explanation for its fluctuations in Lilien (1982) .

This paper constructs a two-sector equilibrium business cycle model, in which different types of unemployment arise in different labour markets. I use this model to analyse how unemployed workers' reallocation decisions change with individual and aggregate conditions. This model considers a two-sector economy by introducing aggregate productivity shocks, sectoral productivity shock and preference shock. This paper distinguishes between 'search', 'reallocation'and 'rest'unemployment in the labour markets with search frictions, and also studies how workers' preferences within a sector affect their reallocation decisions when unemployed.

This paper shows that rest unemployment is the important driver of aggregate unemployment fluctuations. For example, in a recession, a large proportion of workers with a high disutility of work in their sector become rest unemployed, and face no immediate job prospects. Meanwhile, the existing pool of rest unemployed workers find the current labour sub-market less profitable and would like to reallocate. This increases the size of aggregate unemployment and decreases the overall job finding rate.

A key aspect of the model in this paper is the role of workers' disutility in the labour market. Workers will decide to discontinue the job if their disutility is higher than a separation cutoff. Reallocation decisions are also summarised by a reallocation cutoff. The cyclical property of the model is determined by the relative position of the separation and reallocation cutoffs, and these cutoffs vary with aggregate productivity. Only when the separation cutoff is below the reallocation cutoff, do search, rest and reallocation unemployment coexist within a sector. Workers whose disutility are above the reallocation cutoff move to another sector in order to search for better opportunities. The variation of cutoffs with aggregate productivity then determines the response of the three types of unemployment.

A two-sector search model of labour reallocation which features gross flows and net flows is developed in this paper. In both sector, firms and workers are matched according to the same matching technology. Matches are endogenously separated by a preference shock. The reallocation choice is determined by sectoral job finding rates and wages, but also by an individual disutility component. If a worker decides to move to another sector, he spends additional time in unemployment before he becomes available to the new sector's labour market. This model distinguishes between unemployment due to movers and unemployment due to stayers, and helps us understand if the unemployment is caused by reallocation.

The remainder of this paper is organized as follows. Section 4.2 presents the motivating evidence on sectoral mobility. I provide the discussion of sectoral preference in Section 4.3 and the related literature in Section 4.4. The proposed model is discussed and the theory's implications are developed in section 4.5. A numerical example is calibrated and provided in section 4.6. Section 4.7 is the conclusion. Proofs are provided in the Appendix.

4.2 Sectoral mobility through unemployment

A Beveridge curve describes the relationship between the ratio of job vacancy and unemployed worker in a U-V graph. [1] A Beveridge curve tells us that there is

[1]Since the U and V axises are using the number of vacancy and unemployed workers divided by the labour force, a higher value indicates the level of mismatch on the market. For example,

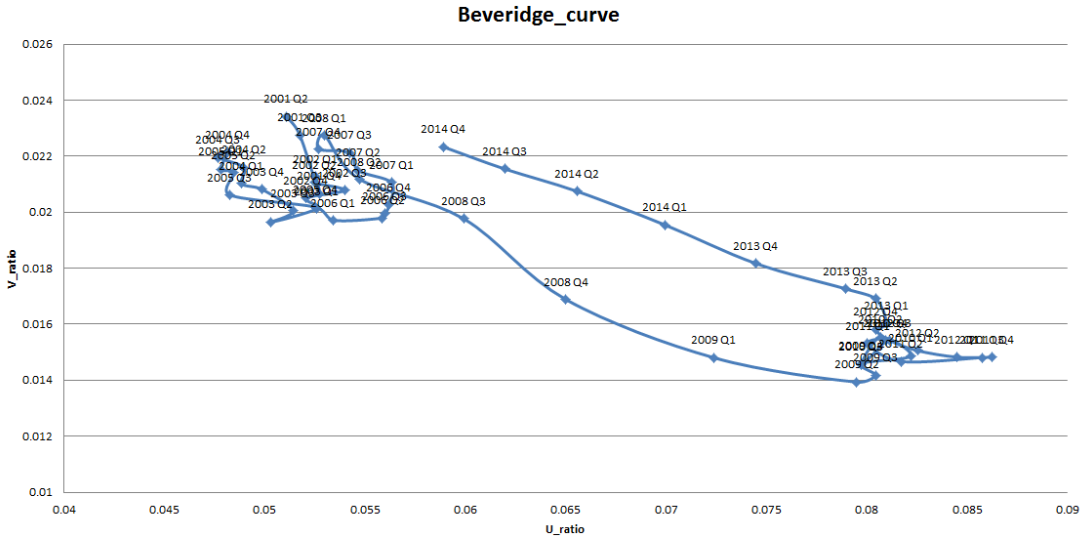


Figure 4.1: Beveridge Curve in the UK

higher vacancy and lower unemployment during a boom period, and lower vacancy and higher unemployment during recession. The mismatch will push the Beveridge curve outward, and an improvement in the matching process will return the curve to its original position.

The Beveridge curve introduces the importance of mismatch and implies that the search friction is one of the reasons causing the mismatch. This paper applies the LFS quarterly dataset from 1994-2012 to draw the Beveridge curve and the situation of mismatch in the UK is found in Figure 4.1.

Another important reason for mismatch is that workers' skills are not identical. For example, different industries needs different skills. Lilien (1982) explains that different sectors need different types of workers, and this inter-sector match-

if the V is equal to one and no unemployed worker find a job, it means that the number of vacancies is equal to the number of the laobur force, and it is also called a perfect mismatch. It says that firms provide many vacancies, but no unemployed workers can get a match or find any job. This case is also an extreme case which illustrates the concept of seriousness of mismatch in the market. On the other hand, if the U ratio is equal to 1, then all workers are unemployed workers and no vacancy is posted, which implies another extreme case of mismatch. Even if the number of vacancy and unemployed workers are the same and high value, let's say 0.8, this also implies there is an incredible high mismatch on the market. We may think about this issue in the opposite way, what if the ratio of vacancy (V) and unemployed workers (U) are very low, let's say 0.0001, then this suggests the market is highly efficient and there is a lack of mismatch because most of the vacancies and unemployed are matched. This efficient match leads to few vacancies and unemployed workers left in the market.

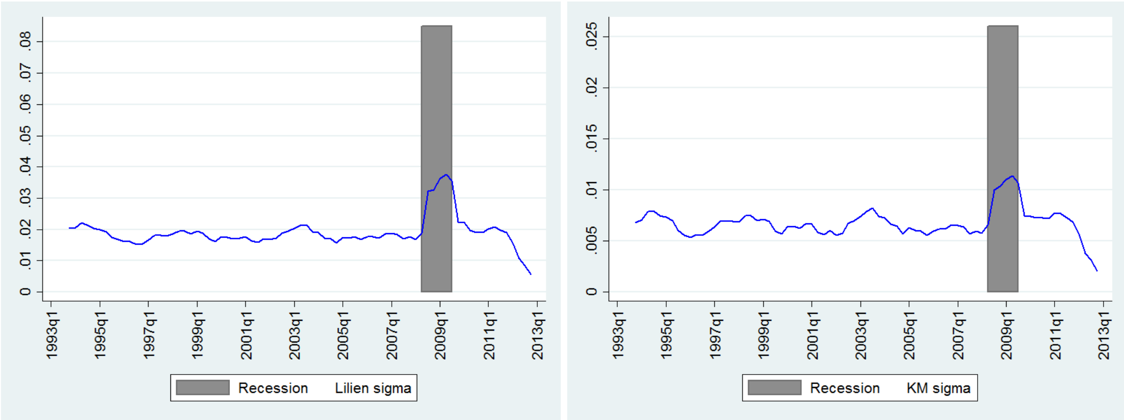
ing causes the fluctuation of unemployment. His paper attracts the attention of economists to understand and discuss the reallocation among the sectors.

Inter-sectoral matching is different from the intra-sectoral matching, as sectoral shift may push the Beveridge curve outward. [2] Lilien (1982) explains that an increase in the dispersion of sectoral shocks leads to net labor reallocation, then this process increases unemployment due to frictional inter-sectoral mobility. The sectoral shock releases workers from employment to unemployment, and some workers move to another sector. Carrillo-Tudela and Visschers (2013) assume that inter-sectoral movers stay in unemployment longer than stayers; the process of inter-sectoral movement takes time to be reallocated, thus generating unemployment. This statement claims that inter-sectoral movers result in higher unemployment. The correlation between the amount of movers (or the proportion of movers who found jobs through unemployment) and unemployment is thus expected to be positive.

Net mobility The sectoral shifts can be measured by net mobility. Lilien (1982) constructs a proxy to measure sectoral shifts, which is defined as the following formula : $Lilien_{\sigma} = [\sum_{i=1}^{N} \frac{x_{it}}{X_t}(\triangle log x_{it} - \triangle log X_t)^2]^{\frac{1}{2}}$ where N is the number of industries, x_{it} is employment in sector i and X_t is aggregate employment. This index is also regarded as the proxy for the net flow among sectors. Kambourov and Manovskii (2008) define the net mobility as one-half of the sum of the absolute changes in occupational employment shares. I apply the same formula for measuring the net industrial mobility, thus the definition of net mobility is as follows: $KM_{\sigma} = \frac{1}{2}\sum_{i=1}|s_{i,t} - s_{i,t-1}|$ where $s_{i,t}$ is the fraction of employment in industry i in quarter t. The net mobility is captured by $Lilien_{\sigma}$ and KM_{σ} as portrayed in Figure 4.2 .

Figure 4.2 indicates that net mobility is significantly high during the recession

[2] The sectoral shifts indicates that the inter-sectoral matching is more important. Given that inter-sectoral matching is less efficient than intra-sectoral matching, the aggregate matching efficiency decreases and pushes the Beveridge curve outwards.



(a) (b)

Figure 4.2: The series of Net mobility defined by Lilien (1982) and Kambourov and Manovskii (2008)

with the data of the LFS UK. This impression encourages us to adopt an econometric regression examining the cyclicality of net mobility. Generally, there are three variables to measure business cycle: GDP, output per worker (Opw) and unemployment rate (Urate). This paper regresses the log of net mobility defined above on the log of measurement of business cycle, time trend and quarter dummies. The robust result is obtained and shows that net mobility is counter-cyclical (see Table 4.1). An important finding is that higher net mobility comes with higher unemployment. That is to say, net mobility is counter-cyclical.

Interestingly, one of the major findings of my second and third chapters shows that gross mobility is pro-cyclical. An interesting phenomenon is found, but rarely discussed: net mobility is counter-cyclical and gross mobility is pro-cyclical. This contrast between the cyclicality of net and gross mobility motivates us to investigate this situation. Additionally, this interesting result is also found in the USA. [3] The consistency of the findings in the UK and USA greatly increase the research value and make a contribution to the literature.

[3]See Lilien (1982), Murphy and Topel (1987), Kambourov and Manovskii (2008) and Carrillo-Tudela and Visschers (2013).

Table 4.1: The cyclicality of industrial net mobility

	Lilen	KM	Lilen	KM	Lilen	KM
log_GDP	-1.432*	-1.588**				
	(-1.94)	(-2.06)				
log_Opw			-2.288**	-2.530**		
			(-2.13)	(-2.25)		
log_Urate					0.259*	0.258*
					(1.91)	(1.81)
Time_trend	0.0110**	0.0114**	0.0115**	0.0119**	0.00274*	0.00221
	(2.38)	(2.36)	(2.57)	(2.54)	(1.97)	(1.51)
constant	12.26	13.14	4.420	4.414	-3.730***	-4.667***
	(1.43)	(1.46)	(1.07)	(1.02)	(-8.81)	(-10.46)
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	73	73	73	73	73	73
R^2	0.160	0.122	0.168	0.132	0.158	0.110

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Net mobility rate

From now on, I use 'sector'instead of 'industry 'in order to maintain the consistency of the expression in the theoretical model and empirical data. Net mobility can help us understand how much reallocation is contributed by the sectoral shifts. If gross flow is equal to net flow, then we can conclude that all the reallocation is due to sectoral shift. On the other hand, if net mobility can explain little about gross mobility, for example, inflow to a sector is equal to the outflow from this sector, then we can conclude that the sectoral shift explains nothing regarding the decision of workers' reallocation. [4] I construct a net mobility rate as follows:

$$nm_t = \sum_{i=1}^{K} \left[\frac{|\mathbf{I}_{i,t} - \mathbf{O}_{i,t}|}{[\mathbf{I}_{i,t} + \mathbf{O}_{i,t}]}\right] w_{i,t}$$

where K is the number of sectors and $I_{i,t}$ is the number of inflow to sector i. $O_{i,t}$ is the number of outflow from sector i. I weight a sector by $w_{i,t}$, which is the employment share of the respective industry or occupation at time t. I find that net mobility only accounts for 13 percent of gross mobility across sectors. Net mobility contributes a small part of gross mobility.

The net mobility is driven by the sectoral shifts, but the worker's mobility decision is not mainly driven by the sectoral shocks. In fact, the worker's mobility is mainly driven by the idiosyncratic factors, which also suggests that gross mobility is more important. [5]

Lilien (1982) tells us that the sectoral shifts happened in the recession, and

[4] When inflow to a sector is equal to the outflow from this sector, the net flow is zero. Gross flow is calculated as the number of inflow plus the number of outflow, and captures the behavior of worker's reallocation. Net flow of each industry is the measurement of sectoral shift. Therefore, sectoral shift cannot sufficiently explain the gross flow.

[5] Jovanovic and Moffitt (1990) and Auray, Lkhagvasuren and Terracol (2014) show that workers' mobility decisions across industries are not primarily driven by industry-wide shocks. The importance here is defined as the explanatory ability. Sectoral shock causing net mobility only explains 13% of gross mobility. So the sectoral shock is not the main factor to motivate workers changing sector. Given that the net mobility cannot sufficiently explain the work's flow, we need to pay more attention to the components of gross mobility. Therefore, gross mobility has a higher explanatory ability of worker's flow than net mobility.

we should expect more inter-sector reallocation in the recession. But when we examine the data of whole reallocation, which is defined as gross mobility in my study, the inter-sector reallocation is pro-cyclical, not counter-cyclical as we may suppose. This introduces the motivation of this chapter. Meanwhile, I also find the net mobility (flow) can only explain a small part of whole reallocation (gross mobility). This fact inspires me to think that the worker's reallocation may not only be caused by the sectoral shift, but also the other factors, for example, the idiosyncratic shock, the preference or human capital.

Since net mobility only accounts for a small part of gross mobility, I have been aware that there is something else that affects workers' reallocation decisions. If the unemployment is mainly caused by the time-consuming process of reallocation, the net mobility should not only explain a small part of gross mobility. There must be something else to explain the rest part of unemployment. That is why the preference is introduced to explain the gross mobility.

4.3 Sectoral Preference

Net mobility which is cause by the sectoral shock can only explain 13 % of gross mobility. The gross worker flows are in excess of net worker flows. Additionally, workers are moving in and out of sectors, and 'churning 'around sectors. These findings tell us that the sectoral shock is not the dominate force to push workers moving, and there is another reason that makes workers move. Therefore, I find some information which helps us tackle this issue with the LFS. Employed workers provide the reason why they look for another job. There are several options here for this multiple question: 1. Present job may come to an end, 2. Present job is to fill in time before finding another job, 3. Pay unsatisfactory in present job, 4. Journey to work unsatisfactory in present job, 5. Respondent wants to work longer hours than in present job, 6. Respondent wants to work shorter hours than in present job, 7. Other aspects of present job unsatisfactory, 8. Respondent wants to change occupation/sector, 9. Other reasons. I find that around 18% of employed workers who are looking for a job prefer to change their occupation or sector. 27% of employed job seekers are ending their present job or filling in time before finding a better job. 45% of employed job seekers were looking for a job because of unsatisfaction with the present job, and the main unsatisfactory factor is the pay in the present job, which is 14%. From these statistics, I find that the number of job seekers due to the preference of occupation/sector is larger than the number of job seekers due to the unsatisfactory pay. This surprising finding, especially in the UK labour market, motivates this paper to introduce the preference shock into the model. Moreover, Pilossoph (2012) uses 'taste shock 'which is sector-specific to discuss the intersectional reallocation. She interpreted taste shock as anything that might keep workers in a sector that is not related to the wage or ease of finding a job. Essentially, Pilossoph (2012) introduced the concept of 'sectoral preference 'into her model. This paper also adopts sectoral preference to analyse the sectoral reallocation, especially to explain the cyclical feature of net mobility which was not fully discussed in Pilossoph (2012).

4.4 Literature

The model in this chapter is based on three key pieces of literature: Lucas and Prescott (1974), Mortensen and Pissarides (1994) and Carrillo-Tudela and Visschers (2013). Lucas and Prescott (1974) propose a framework where workers seek jobs among different 'islands '. Each island could be represented as an industry, an occupation, or a city. When shocks are realized on each island, workers within each island have to decide whether to stay or move to another island. If they decide to leave, then they mush spend some time on the move. Workers transfer from a declining sector to an expanding sector and search for job opportunities.

This transition period is regarded as the cause of unemployment. Since the island model successfully captures the feature of the workers' transition behavior, there has been a huge body of literature relating to this model over the past two decades. Rogerson (2005), as a simple extension of Lucas and Prescott (1974), uses a two-sector model to investigate sectoral mobility. He assumes that workers leave a declining sector and simply become non-employed, which is different from Lucas and Prescott (1974).

The model of Mortensen and Pissarides (1994), an MP model, is a classic search and matching model. An MP model simulates the occurrence of the matching process between individual job vacancies and unemployed workers. In order to consider the endogenous separation, an idiosyncratic component is introduced to investigate the labour market after the shock arrival. If a serious negative shock comes to the market, firms would destroy some job opportunities since those jobs are non-profitable. Contrarily, a positive shock increases the possibility for firms to open more vacancy opportunities. By setting up a reservation productivity, an MP model can endogenize separation, thus contribute to the theory of unemployment. An MP model also considers the bilateral bargain to examine the effect of bargaining power in the labour market.

Carrillo-Tudela and Visschers (2013) do not only consider the idiosyncratic shock to worker's occupation (referred to as worker-occupation specific productivity), but also the aggregate productivity shocks to the economy. They extend the model of Lucas and Prescott (1974) and include search and matching frictions as in Pissarides (2000). Comparing the random search method in the MP model, Carrillo-Tudela and Visschers (2013) apply a tractable direct-search model, where the equilibrium has a block recursive structure and the equilibrium of mobility decision only depends on the aggregate states. In their model, they assume that unemployed workers who leave their original occupation are randomly assigned to a new island, and this means that the decision to leave only depends on the expectation value of new draw from a different occupation.

I model the sectoral mobility based on these models mentioned above. This combination is helpful to understand the feature of inter-sectoral labour mobility frictions in unemployment. [6] In particular, this paper can be considered as an expansion of Carrillo-Tudela and Visschers (2013), but I focus on the cyclicality of sectoral mobility instead of only focusing on a single sector.

Moen (1997) provides a framework of directed search (also called competitive search). He assumes that all firms publicly provide the full information of their job offers. Higher productivity firms offer a higher wage and attract more workers. After firms have posted wage offers in the sub-market, unemployed workers can choose a specific sub-market to visit. Therefore, this setting can lead the unemployed worker's search towards the most suitable job or preferred job.

There are several pieces of literature that examine how workers' specific occupational/sectoral knowledge affects the reallocation decisions over a business cycle.

Pilossoph (2012) develops a multi-sector search model of intersectoral labour reallocation and capture the features of both gross and net mobility. She models the worker's sectoral switching decision by taking advantage of the Type I Extreme Value Distributions. In her model, the idiosyncratic shocks are considered as 'taste shocks '. Since she assumes that the taste shocks follow Type I Extreme Value Distributions, she can integrate out the future taste shocks. Consequently, all value functions are independent of workers' future taste shocks, thus obtaining a simplified model.

Dvorkin (2013) uses a dynamic discrete choice model with random utility to investigate the reallocation decisions during the business cycle. [7] He proposes a multi-sectoral business cycle model of labour reallocation and unemployment to investigate whether sectoral shocks are caused by business cycles. An island model

[6] This paper is a combination by Lucas and Prescott (1974), Pissarides (2000) and Carrillo-Tudela and Visschers (2013).

[7] Dvorkin (2013) also assume idiosyncratic shock is distributed as the Type I Extreme Value Distributions.

with aggregation and sectoral shocks is adopted in his analysis. He found that an aggregate shock explains a substantial part of cyclical movement in GDP and unemployment.

Chang (2011) adopts a similar strategy which is to differentiate the effects of aggregate shock and sectoral shock on the economy, but she introduces intra-firm wage bargaining, instead of bilateral bargaining, into the Diamond-Mortensen-Pissarides model. Chang (2011) also finds that a structural change has limited impact on the aggregate unemployment.

4.5 Model

4.5.1 Framework and assumptions

The model is specified in discrete time, and time $t = 0, 1, 2, \ldots$. There are two sectors and these are indexed by $j = \{0, 1\}$. The sectoral productivity is denoted as z_j and $z_j \in [\underline{z}, \overline{z}]$. In this model, there is a continuum of infinitely lived risk-neutral workers within each sector. At any time t workers within a sector j are different in terms of worker's preference on the sector. This preference regarded as disutility is denoted by x in Trigari (2009), Hornstein, Krusell and Violante (2011) and Cole and Rogerson (1999). Higher disutility decreases the worker's expected value of employment and unemployment.

According to the setting of the model, workers are randomly given their sectoral disutility x, and preference is sector-specified. Once the disutility is given, workers retain it until he/her enter the process of reallocation. That is to say, workers retain their disutility, no matter if they are employed or unemployed before reallocation. The disutility x is consistent through the whole period of employment, where $x \in [\underline{x}, \overline{x}]$. The preference shock, x follows an iid distribution $F(x)$ with the possibility $(1 - \gamma)$. Worker's preference x evolves over time following a common first-order stationary Markov process, where $F(x_{t+1}|x_t)$ denotes its transition law with x_t

and $x_{t+1} \in [\underline{x}, \overline{x}]$, $\underline{x} > 0$ and $\overline{x} < \infty$. Every unemployed worker receives the benefit b each period. All agents discount the future using the same discount factor β. All firms use only labour as the input and operate under a constant return to scale technology. All firms are identical within a sector, but the workers are heterogeneous with individual disutility.

The production function consists of two components, the aggregate productivity p_t and the sectoral-specific productivity, z_j. I assume p_t follows a first-order stationary Markov process with $p_t \in [\underline{p}, \overline{p}]$, $\underline{p} > 0$ and $\overline{p} < \infty$ in this chapter, the same as Carrillo-Tudela and Visschers (2013). I also assume z_t follows a first-order stationary Markov process with $z_t \in [\underline{z}, \overline{z}]$, $\underline{z} > 0$ and $\overline{z} < \infty$. The production function is given by $y(p_t, z_{jt}) = p_t \, z_{jt}$. Furthermore, the production function is a continuous differentiable and strictly increasing in p and z.

Posting and matching

Following Carrillo-Tudela and Visschers (2013), I assume that workers with different pairs(z_j, x) do not congest each other in the matching process. Each pair of (z_j, x) indicates a sub-market. In each submarket, firms post contracts to which they are committed. Unemployed workers and advertising firms then match with frictions as in Moen (1997). This framework is called a directed search model. A matching function, which is a constant return to scale, manages the matches between unemployed workers and vacancies within each sector. Each sub-market has the same matching technology. All firms can freely enter the market and post a vacancy with cost k each period.

Given the above, I assume that all labour markets have the same matching function, $m(v, u)$ with the particular form: $m(v, u) = v^{\eta} u^{1-\eta}$, where $(1-\eta) \in (0, 1)$ is the elasticity of the matching function. u is the number of workers searching within a submarket and v the number of firms who have posted a contract in the submarket. Let $\theta = \frac{v}{u}$ denote the labour submarket tightness, the probability that vacancies within a submarket turn into jobs is given by $q(\theta) = \frac{m(v,u)}{v} = \theta^{\eta-1}$, and the probability that job seekers find jobs within a submarket is given by $\lambda(\theta) = \frac{m(v,u)}{u}$.

Reallocation

After the shock is realized, a worker may discontinue his relationship with the firm, and he becomes unemployed. The unemployed worker can stay unemployed and search for a job in his current sector. Instead of searching for jobs in the current sector, unemployed workers also can decide to pay a cost c and start to search for a job in another sector. This behavior is called the reallocation process. [8] Only unemployed workers can be reallocated into different sectors in this model. Workers must spend time and resources to discover the condition of another sector. When an unemployed worker decides to reallocate, his preference in the new sector is drawn from distribution $F(x)$. According to Carrillo-Tudela and Visschers (2013), $F(x)$ is assumed ex-ante and the same for all sectors. After a worker receives his new preference, he has to stay in one period of unemployment before deciding to reallocate once again or to start searching for a job in the new sector. A worker can not recall his disutility x once he has left his sector.

The timing of events is described as follows. At the beginning of a period, the new values of p, z and x are realized. The period can be separated into four stages: separation, reallocation, search and matching and production. Given the above narratives, Figure 4.3 summarises the timing of the events within a period for a given sector.

[8] Carrillo-Tudela and Visschers (2013)

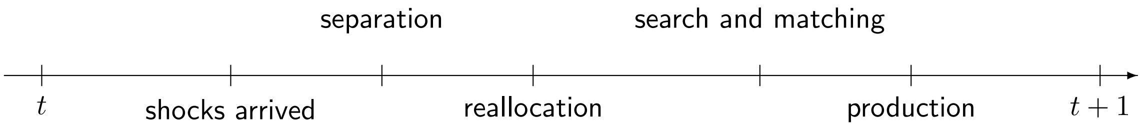


Figure 4.3: Timing of events

4.5.2 Agents' decisions

Worker's problem

Consider an employed worker currently characterized by the sector-specific productivity z with the disutility $\phi_e x$ generated from working, and ϕ_e is the scale of disutility while workers are employed, and is a positive parameter. x refers to disutility as mentioned in section 4.5.1. A worker in a job with sector-specified productivity z_j enjoys the expected value of employment, $W^E(p, z_j, x)$, given the worker's wage w, is described by :

$$\begin{aligned} W^E(p, z_j, x) &= w(p, z_j, x) - \phi_e x + \\ &\beta\, \mathbb{E}_{p', z_j', x'} \Big[\max_{\rho_E} \{ (1 - \rho_E(p', z_j', x')) W^U(p, z_j', x') + \rho_E(p', z_j', x') W^E(p', z_j', x') \} \Big] \end{aligned} \tag{4.1}$$

where ρ_E is the job separation decision parameter, it takes the value of δ when $W^E(p, z_j', x') \geq W^U(p, z_j', x')$ and the value of zero otherwise. [9] When a preference shock arrives, the worker's disutility moves from its initial value x to a new value x'. Eq(4.1) shows that if the new disutility is in the range $\underline{x} \leq x' \leq x^s$, ($x^s$ is the job separation level of the disutility) ,the worker remains employed. If x' is higher than the separation level of the disutility x^s, he discontinues his job and becomes unemployed with an expected return W^U.

Now consider an unemployed worker currently characterized by a sector-specified productivity z_j with the disutility $\phi_u x$. ϕ_u is the scale of disutility while workers are unemployed, and $0 < \phi_u, 0 < \phi_e$. The value function of this worker is given

[9] Carrillo-Tudela and Visschers (2013), $\delta \in (0, 1)$

by:

$$W^U(p, z_j, x) = b - \phi_u x + \tag{4.2}$$
$$\beta\, \mathbb{E}_{p', z_j', x'} \Big[\max_{\rho_U} \{ (1 - \rho_U(p', z_j', x')) \hat{W}^U(p', z_j', \tilde{x}), \rho_U(p', z_j', x') R(p', z_{1-j}') \} \, dF(\tilde{x}) \Big]$$

$$\hat{W}^U(p, z_j, x) = \lambda(\theta(p, z_j, x)) W^E(p, z_j, x) + (1 - \lambda(\theta(p, z_j, x))) W^U(p, z_j, x)$$
$$R(p) = -c + \int_{\underline{x}}^{\overline{x}} \hat{W}^U(p, z_{1-j}, \tilde{x}) \, dF(\tilde{x})$$

Unemployed workers can decide to start a reallocation process towards another sector by paying a cost c. ρ_U is the reallocation decision variable. If workers decide to reallocate, then ρ_U is one, otherwise zero. If unemployed workers' expected value is higher than the value of reallocation, they will stay with the current sector. Otherwise, they will exit the current sector and jump into another sector. Once workers decide to be reallocated, they will stay in the current sector until the end of the period.

In Eq(4.2), the value of unemployment consists with the flow utility of unemployment $b - \phi_u x$, plus the discounted expected value of the next period which is the reallocation stage. The term $-c + \int_{\underline{x}}^{\overline{x}} \hat{W}^U(p, z_{1-j}, x) \, dF(x)$ denotes the expected net utility of reallocation that samples a new preference x in a different sector $1 - j$. The unemployed worker has the value of $\lambda(\theta(p, z_j, x)) W^E(p, z_j, x) + (1 - \lambda(\theta(p, z_j, x))) W^U(p, z_j, x)$ as his expected gain if he stays in his current sector.

4.5.3 Firm's problem

Consider a firm in sector j, currently employing a worker within sectoral productivity z_j. The firm's expected lifetime discount profit can therefore be expressed as the following:

$$J(p, z_j, x) = [y(p, z_j) - w(p, z_j, x)] \\ + \beta \mathbb{E}_{p', z'_j, x'} \Big[\max_{\rho_J} \{ [(1 - \rho_J(p', z'_j, x'))J(p', z'_j, x') + \rho_J(p', z'_j, x')V(p', z'_j, x')] \} \Big] \tag{4.3}$$

where ρ_J takes the value of zero when $J(p', z'_j, x') \geq V(p', z'_j, x')$, otherwise one. When the worker's preference shock arrives, the firm continue to produce if $J(p, z_j, x) \geq V(p, z_j, x)$, or destroy the job with a zero return otherwise. Now consider a firm posting a vacancy in labor market sector j at the start of the search and matching stage. The expected value of a vacancy is described by:

$$V(p, z_j, x) = -k + q(\theta(p, z_j, x))J(p, z_j, x) + (1 - q(\theta(p, z_j, x)))V(p, z_j, x) \tag{4.4}$$

4.5.4 Wages determination

I apply the assumption that wages are determined by Nash Bargaining according to Carrillo-Tudela and Visschers (2013). The wage which is derived from the Nash bargaining solution is to maximise the weighted product of the worker's and the firm's net return from the job match. Nash Bargaining implies that the wage, $w(p, z_j, x)$, results in

$$(1 - \alpha)[W^E(p, z_j, x) - W^U(p, z_j, x)] = \alpha J(p, z_j, x) \tag{4.5}$$

where $\alpha \in [0, 1]$ denotes the worker's exogenous bargaining power. In what follows, the Hosios condition applies here, such that $1 - \alpha = \eta$, where η denotes to the elasticity of the job finding probability with respect to labour market tightness. This guarantees that firms post efficient number of vacancies in labour markets.

4.5.5 Worker flows

The evolution of the number of workers is a result of optimal vacancy posting, separation and reallocation decisions. I define $x_j^r \equiv x^r(z_j)$ and $j = \{0, 1\}$ as abbreviate notation. The number of unemployed workers in the market (z_j, x) at the beginning of next next period is given by

$$u_{t+1}(z_j, x)dx = \int_{\underline{x}}^{\overline{x}} (1 - \lambda(\theta(p, z_j, \tilde{x})))(1 - \rho_U(p, z_j, \tilde{x}))u_j(\tilde{x})\, dF(x|\tilde{x})d\tilde{x}$$
$$+ \int_{\underline{x}}^{\overline{x}} \rho_E e_j(\tilde{x})\, dF(x|\tilde{x})d\tilde{x} + \int_{\underline{x}}^{\overline{x}} \rho_U(z_{1-j}, \tilde{x})u_{1-j}(\tilde{x})\, d\tilde{x}\, dF(x) \tag{4.6}$$

where e_j is the number of employment in sector j. The first term on the right hand side of Eq 4.6 is the number of unemployed workers who do not reallocate to a different sector and do not find a job. The second term represents the number of employed workers who separate from the unemployment. The third term is the unemployment from outside of sector j when reallocating.

The number of employed workers characterized by (z, x) at the beginning of the next period is given by

$$e_{t+1}(z_j, x) = \int_{\underline{x}}^{\overline{x}} \lambda(\theta(p, z_j, \tilde{x})(1 - \rho_U(p, z_j, \tilde{x}))u_j(\tilde{x})\, dF(x|\tilde{x})d\tilde{x} \tag{4.7}$$
$$+ \int_{\underline{x}}^{\overline{x}} (1 - \rho_E)e_j(p, \tilde{x})\, dF(x|\tilde{x})d\tilde{x}$$

The first term on the right hand side of Eq 4.7 is the number of unemployed workers who find a job. The second term is the number of employed workers who are still employed.

4.5.6 Equilibrium

I focus on the equilibrium in which the value functions, and decisions of workers and firms in both sectors only depend on $\{p_t, z_{jt}\}$ and the worker's employment status.

Definition: A Block Recursive Equilibrium (BRE) is structured by a set of value functions $W^U(p,z,x)$, $W^E(p,z,x)$ $J(p,z,x)$, ρ_U, ρ_E, ρ_J (resp. workers' reallocation, separation decisions and firms' layoff decision), submarket tightness $\theta(p,z,x)$, wages $w(p,z,x)$, laws of motion of p, z and x for both sectors, and laws of motion for the distribution of unemployed and employed workers in both sectors, such that

- The value functions and decision rules follow the firm's and worker's problems described in Eq(4.1)-Eq(4.4).
- Labour market tightness $\theta(p,z_j,x)$ is consistent with free entry on each labor market. If the expected profits determining $\theta(p,z,x)$ on labour markets is negative, then $\theta(p,z,x)=0$.
- Wages can be solved out according to Eq(4.1) - eq(4.5)
- The flow equations Eq(4.6)-Eq(4.7) are solvable given that the above three terms have been fulfilled.

Existence and uniqueness

The operator T is a contraction that maps $M(p,z_j,x)$ and $W^U(p,z_j,x)$ as shown in Appendix 4.9.1. Given this result and the contraction mapping theorem, a unique fixed point $(M(p,z_j,x),W^U(p,z_j,x))$ exists. The existence of x_j^s can also be established. [10] All equilibrium value functions and decision rules can then be derived from this fixed point. We then see the following: $W^E(p,z_j,x)=M(p,z_j,x)-J(p,z_j,x)$ and $J(p,z_j,x)=(1-\eta)(M(p,z_j,x)-W^U(p,z_j,x))=\frac{k}{q(\theta(p,z_j,x))}$. This implies that $W^E(p,z_j,x),J(p,z_j,x)$ and $\theta(p,z_j,x)$ can be found from the unique pattern of $M(p,z,x)$ and $W^U(p,z_j,x)$. Given the equation of workers flow from Eq(4.6) and Eq(4.7), the number of unemployed and employed at a steady state

[10] For the proof, please see Appendix 4.9.1.

can also be constructed. By completing these steps we prove the existence and uniqueness of an equilibrium.

4.6 Implications

The strategy of analyzing the cyclicality is similar to that in the literature. [11] Assume that the aggregate productivity is constant and permanently fixed, and also use the comparative statics of this situation responding to a one-time unexpected permanent change in aggregate productivity, sectoral productivity, reallocation cost and unemployment benefit respectively. This is a standard method to capture the intuition of the responses to a persistent shock process.

4.6.1 Search, rest unemployment and reallocation

This study distinguishes search unemployment, rest unemployment and reallocation in labour markets. Additionally, I find that worker's disutility affects their reallocation decisions differently when they are unemployed, by considering an economy with two sectors.

There is much literature discussing the search unemployment, rest unemployment or reallocation. It could be helpful to briefly introduce the concept of search and rest unemployment in my model before I convey the main content. The process of seeking a job is costly, and a successful job match takes time in the labour market. This is called the search friction in the labour market. The unemployment caused by the search friction is defined as search unemployment in this paper.

The relative position of the cutoff functions indicates the composition of employment status in a sector. Figure 4.4 depicts the features corresponding to different cases. I will show that x^r is decreasing and x^s is increasing with p in a later section of this study. If workers' disutility x is lower than x^s and x^r, workers want

[11] Carrillo-Tudela and Visschers (2013)

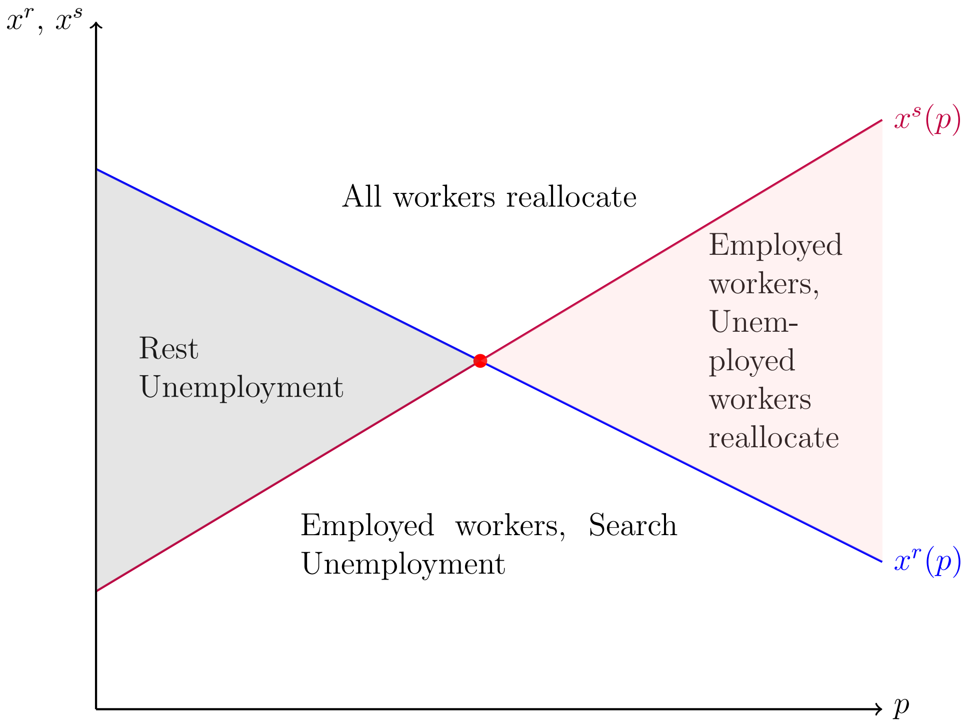


Figure 4.4: The relative positions of the reallocation and separation cutoff

to remain in the sector, and have the opportunity to be employed. In this case, search-friction unemployment occurs because the process of search and matching is time costly. If worker's disutility is in the range $x^s < x < x^r$, workers are counted as rest unemployed. This implies that workers are willing to break existing job matches, and the unemployed workers would like to stay in their current sector. If worker's disutility x is in the range of $x^r < x < x^s$, employed workers will stay in their job and current sector, but unemployed workers will move to another sector. If worker's disutility x is higher than the separation x^s and reallocation cutoff x^r, employed workers will stay in their job and unemployed workers will reallocate. [12]

The separation cutoff function x^s characterizes endogenous separations. However, the x refers to worker's disutility in a sector, rather than to a match-specific idiosyncratic productivity with a firm. This difference implies that when the worker becomes unemployed, his disutility x is not lost and is not reset when re-entering

[12]If $(\delta + \lambda(\theta)) \leq 1$, for all p, z in equilibrium, there exists a unique cutoff function $x^s(p, z_j)$ that depends on p and z_j. such that $\rho_{_E} = \rho_{_J} = 1$ if and only if $x_j < x^s_j$, and $\rho_{_E} = \rho_{_J} = 0$ otherwise. For the proof, please see in Appendix 4.9.2

employment in the same sector. The worker's disutility x continues to shape his outcomes in unemployment as well.

Reallocation cutoff

A worker decides to reallocate when the expected value of staying unemployed in his current sector falls below the expected value of reallocation. Assumption 1 guarantees that $W^U(p, z_j, x)$ from eq(4.2) is decreasing in x, and $\max\{\lambda(\theta(p, z_j, x))(W^E(p, z_j, x) - W^U(p, z_j, x)), 0\}$ is decreasing in x as well. Given that $R_j(p, z_{1-j})$ is constant with x, there exists a reallocation cutoff function $z^r(p)$ such that workers will reallocate if and only if $x > x^r(p, z_j)$ for every p and z_j, where $x^r_j(p, z_j)$ satisfies

$$\begin{aligned} W^U(p, z_j, x^r) + \quad \max \quad & \{\lambda(\theta(p, z_j, x^r))(W^E(p, z_j, x^r) - W^U(p, z_j, x^r)), 0\} \\ &= -c + \int_{\underline{x}}^{\overline{x}} W^U(p, z_{1-j}, x)\, dF(x) \equiv R_j(p, z_{1-j}) \end{aligned} \tag{4.8}$$

4.6.2 Reservation cutoffs for separations and reallocation cyclicality of reallocation

Now consider the impact of search frictions on the slope of x^r. I now focus on a more general case of $x^r > x^s$.

Lemma 4.6.1. *Consider a stationary economy, where there is no sectoral and preference shock. Given an unexpected, permanent increase in p, then*

$$\begin{aligned} \frac{dx^r_j}{dp} &= \frac{-1}{1-(1-F(x^r_j))(1-F(x^r_{1-j}))} \times \\ & \beta k \frac{1-\eta}{\eta}\Big[(1-F(x^r_{1-j}))\int_{\underline{x}}^{x^r_j} \frac{d\theta(p, z_j, x)}{dp}\, dF(x) + [\int_{\underline{x}}^{x^r_{1-j}} \frac{d\theta(p, z_{1-j}, x)}{dp}\, dF(x)]\Big] \end{aligned} \tag{4.9}$$

where $\frac{d\theta(p,z_j,x)}{dp}$ *and* $\frac{d\theta(p,z_{1-j},x)}{dp}$ *is positive.*

- *For β is small enough to 0 or η is close to 1, the reallocation is independent from aggregate productivity shock.*

- *If the discount factor β is not small enough, then $\frac{dx^r}{dp} < 0$ indicates that the reallocation is procyclical.*

For the detail of proof, please see Appendix 4.9.4

Cyclicality of job separation

Lemma 4.6.2. *Consider an economy where is no sectoral and preference shock. If $x^s(p) < x^r(p)$, then $\frac{dx^s(p)}{dp} = \frac{1}{\phi_e - \phi_u} y_p(p, z_j) > 0$. If $x^s(p) > x^r(p)$ it holds that*

$$\frac{dx_j^s}{dp} = \frac{1}{\phi_e}\Big[y_p(p, z_j) - \frac{\beta\lambda(\theta(p, z_j, x_j^r))}{1 - \beta + \beta\lambda(\theta(p, z_j, x_j^r))}\Big(y_p(p, z_j) - (\phi_e - \phi_u)\frac{dx_j^r(p)}{dp}\Big) + \frac{dx_j^r(p)}{dp}\Big] \tag{4.10}$$

- *Given $x^s(p) > x^r(p)$ and $\frac{dx_j^r(p)}{dp} < 0$, the sign of $\frac{dx_j^s(p)}{dp} > 0$ depends on $\frac{dx^s}{dp}$*

For the detail of proof, please see Appendix 4.9.5

4.6.3 Sectoral shock and net mobility

Lemma 4.6.3. *Consider a stationary economy, where is no aggregate and preference shock. Given an unexpected, permanent increase in z_j, then*

$$\frac{dx_j^r}{dz_j} = \frac{\frac{1-\eta}{\eta}k\frac{\theta(p,z_j,x^r)}{w(p,z_j,x^r)-b-(\phi_e-\phi_u)x^r}\frac{dy(p,z_j)}{dz_j}}{\frac{1-\eta}{\eta}k\frac{(\phi_e-\phi_u)\theta(p,z_j,x^r)}{w(p,z_j,x^r)-b-(\phi_e-\phi_u)x_j^r}+1} \quad ,$$

$$\frac{dx_j^s}{dz_j} > 0 \quad ,$$

$$\frac{dx_{1-j}^r}{dz_j} = -\beta k\frac{1-\eta}{\eta}\int_{\underline{x}}^{x_j^r}\frac{\theta(p, z_j, x)}{w(p, z_j, x) - b - (\phi_e - \phi_u)x}\frac{dy(p, z_j)}{dz_j}\,dF(x) < 0$$

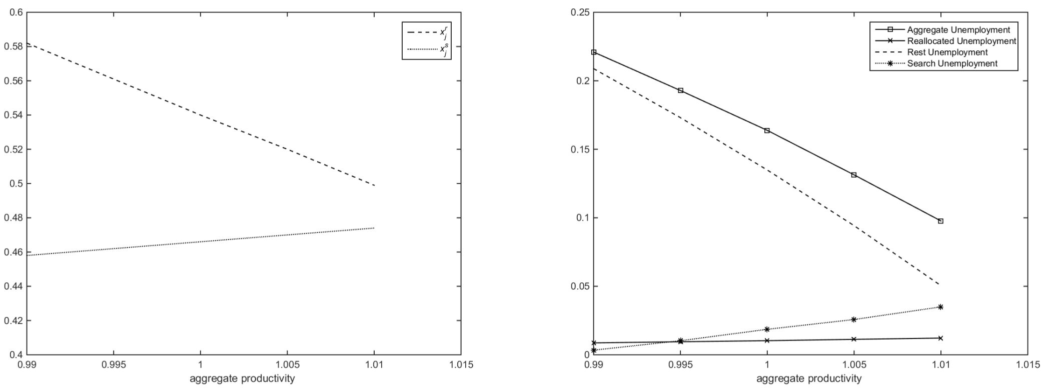
- *Given $\lambda(\theta(p, z_j, x^r)) = 0$, the reallocation cutoff is independent from the sectoral shock in sector j.*

An increase in productivity z_j followed by sectoral shock leads to more employed workers in sector j, and z_j does not affect the separation cutoff in sector $1-j$. The proportion of employment in sector j increases with a positive z_j. This implies the net mobility caused by the sectoral shock in terms of the definition of net mobility outlined by Lilien (1982). On the other hand, an increase in sectoral productivity in sector j z_j decreases the reallocation cutoff in another sector, which implies that more unemployed workers in sector $1-j$ move to sector j. Meanwhile, less unemployed workers move from sector j to sector $1-j$ because sector $1-j$ is less attractive. This results in net inflow to sector j. For the proof, please see Appendix 4.9.6

4.7 Numerical example

To study aggregate outcomes of unemployment and reallocation, a numerical example is provided to illustrate the properties of the model in the case of $x^r > x^s$. I also present simulated numbers of rest unemployment, search unemployment and reallocation. This is to illustrate the effects of aggregate and sectoral productivity. The parameters of the model are chosen as follows: The discount factor is 0.99 which implies the quarterly interest rate is 0.01. I obtained and applied several parameters from Carrillo-Tudela and Visschers (2013). The cost of posting a vacancy was set as 14.319, and the reallocation cost was set as 3.58. The job destruction rate is 0.0002, and the bargaining power was set as 0.048. The unemployment benefit b was set as 0.39 which was obtained from Krause and Lubik (2006). The scale of sectoral disutility for employees is 1.419, and for unemployed workers it is 0.111 which is obtained from Shimer (2013).

There are two ways in which a worker's preference could be changed: one is the arrival of preference shock, and the other is through the process of reallocation. Assume that there is no aggregate and sectoral shock, then preference shock arrives



(a) (b)

Figure 4.5: The reallocation and separtation cut-off and decomposition of unemployment rate with change of aggregate productivity

with a rate of γ. Given the separation and reallocation cut-off, the only force driving reallocation between sectors would be the preference shock. Unemployed workers will move across sectors once the preference shock arrives, and the proportion of each sectoral employment over the whole employment does not change significantly.

I use the same parameters mentioned above assuming there is no preference shock all the time in order to capture the trace of the model. This assumption allows us to observe the simplest and crucial motivation of workers' reallocation. In an extreme case where a worker can redraw his preference every period, he is not willing to be reallocated because he just needs to wait a few periods until he can redraw a disutility that is low enough to stay in the same sector. On the other hand, if a worker redraws his disutility only through the process of reallocation, we can capture the sample whose reallocation is motivated by the condition of labour market, not the preference shock. The simulated statistic (mean) is drawn from 10000 samples and each sample has 80 quarters span. For the initial condition, 5000 samples were randomly assigned the worker's preference in both sector j and $1 - j$. The simulated numbers of employment, unemployment and reallocation are presented in terms of different cases later.

The cyclical feature of reallocation cut-off and separation cut-off

Figure 4.5 presents the solution of the model in this paper and the comparative statics of changes in aggregate productivity. The equilibrium value of reallocation cut-off x^r for both sectors decreases with higher aggregate productivity. If a worker's disutility is higher than the reallocation cut-off, he will move to another sector next period. This numerical result tells us that a higher aggregate productivity will decrease reallocation cut-off, therefore raising the number of reallocations. This result is consistent with the proposition I discussed above. [13] For the sector j where the sector productivity is lower, the value of reallocation cut-off decreases from 0.5820 to 0.478, and the value of reallocation cut-off for sector $1 - j$ is from 0.586 to 0.482. A higher-productivity sector has a higher reallocation cut-off, and then more workers are willing to stay in the sector.

For separation cut-off, both sectors increases with aggregate productivity, and this implies that the unemployment rate is decreasing. Unemployed workers whose disutility is below the separation cut-off x^s are search unemployed. Those workers whose disutility was between separation cut-off x^s and reallocation cut-off x^r are rest unemployed, and those workers whose disutility was above reallocation cut-off are reallocated unemployed. From the simulated results, rest unemployment represents the majority of aggregate unemployment, and it constitutes around 75.3 % of aggregate unemployment. Search and reallocation unemployment only accounts for 15.7% and 8.9 %, respectively. In the numerical simulation, when the aggregate productivity or sectoral productivity develops, the reallocation and separation cut-off change as well. This pushes workers to transit among search, rest and reallocation unemployment.

Figure 4.5 also shows that the search unemployment rate based on the simulated model is increasing. In the case of $x^s < x^r$, a higher aggregate productivity leads

[13] Please see Lemma 4.6.1

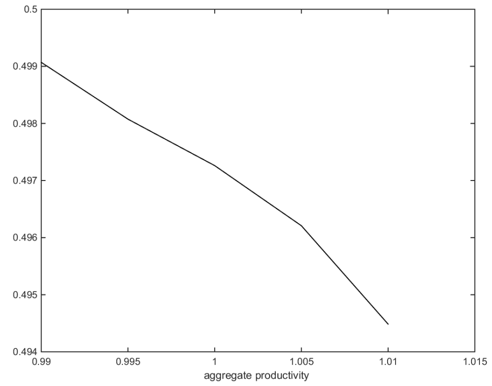


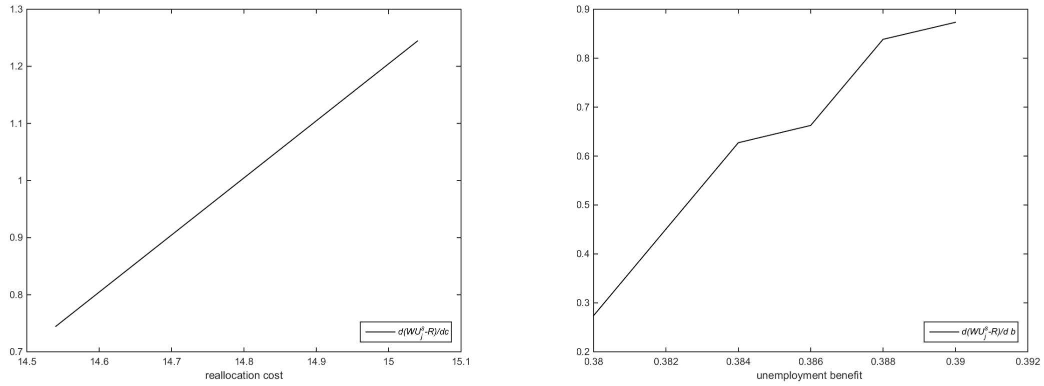
Figure 4.6: Proportion of sectoral employment with different aggregate productivity

to a smaller rest unemployment because reallocation cut-off decreases and separation cut-off increases with aggregate productivity. The search unemployment even exceeds the rest unemployment, and it may form the majority of unemployment after a specific level of aggregate productivity is achieved. The reallocation unemployment increases with aggregate productivity, and this is consistent with the empirical findings of Carrillo-Tudela et al. (2016).

Figure 4.6 shows that the proportion of sector j is 0.49 which is smaller than half because sectoral productivity in sector j is smaller than productivity in sector $1-j$. This also tells us that a higher sectoral-productivity sector has more capability to employ more workers. Therefore, changes of sectroal productivity may affect the employment of each sector, and hence drive net mobility among sectors. The unemployment is not necessarily lower in the sector whose productivity is lower.

Changing reallocation cost c and unemployment benefit b

Changing reallocation cost or unemployment benefit will affect the relative gains of waiting. The distance between expect value of unemployed $W^U(x_j^s)$ and expect value of reallocation R increases with reallocation cost and unemployment benefit. Figure 4.7 presents consistent results. Additionally, the distance between $W^U(x_j^s)$ and R has an impact on the distance between reallocation cut-off x^r and separation



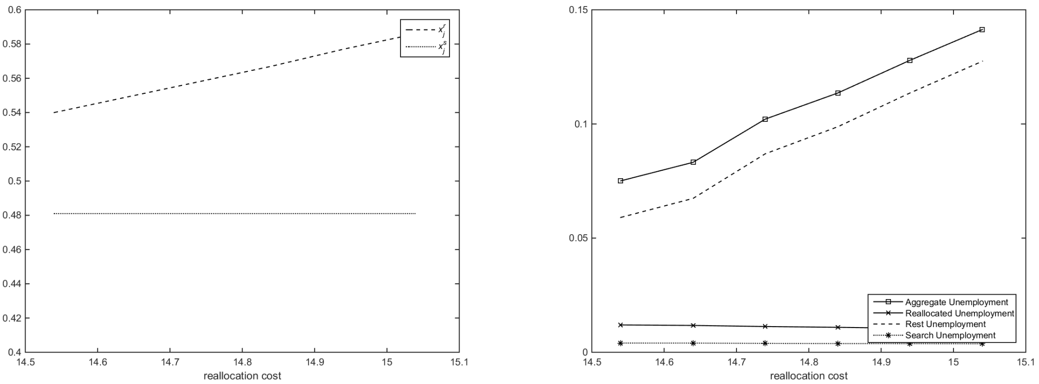
(a) (b)

Figure 4.7: The distance of $W^U(x_j^s) - R$ with regard to the change of reallocation cost and unemployment benefit

cut-off x^s. These will be discussed as follows.

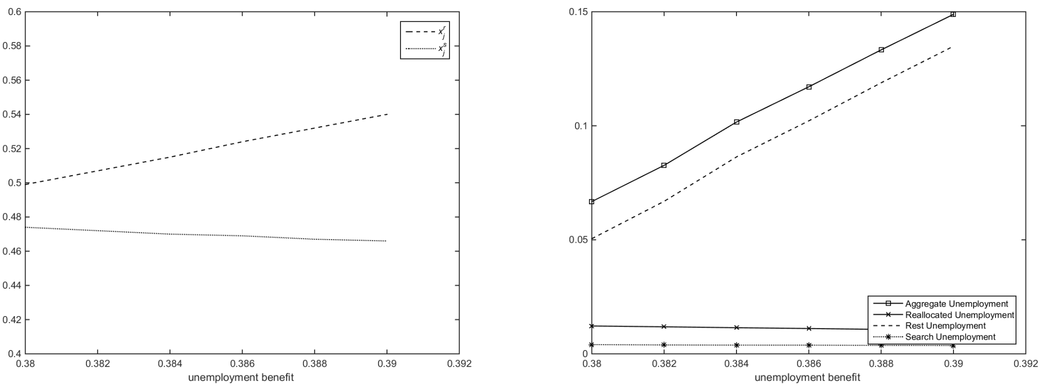
If the reallocation cost is too high, a worker would prefer to wait until the preference shock arrives. In Figure 4.8, I found that the difference between the value of separation cut-off x^s and the value of reallocation cut-off x^r increases with the higher reallocation cost. The intuition is that the higher reallocation cost will increase the reallocation cut-off x^r and less unemployed workers are urged to move to another sector. The rest unemployment increases while the reallocation cost is high. This situation also occurs in sector $1-j$, so the rest unemployment in sector $1-j$ also increases but the reallocation unemployment is decreasing. In total, we can observe that the reallocation unemployment is reduced.

Figure 4.9 shows that an increase of unemployment benefit will increase the value of being unemployed and reduce the match surplus, and this leads to a lower separation cut-off. The reallocation cut-off increases with higher unemployment benefit. Figure 4.9 shows that the separation cut-off x^s decreases with unemployment benefit, but the reallocation cut-off x^r with unemployment benefit. From the theoretical view, I find that the movement of separation cut-off is stronger than the reallocation cut-off. On the other hand, the simulated example presents consistent results: the difference between the separation and reallocation cut-off is greater



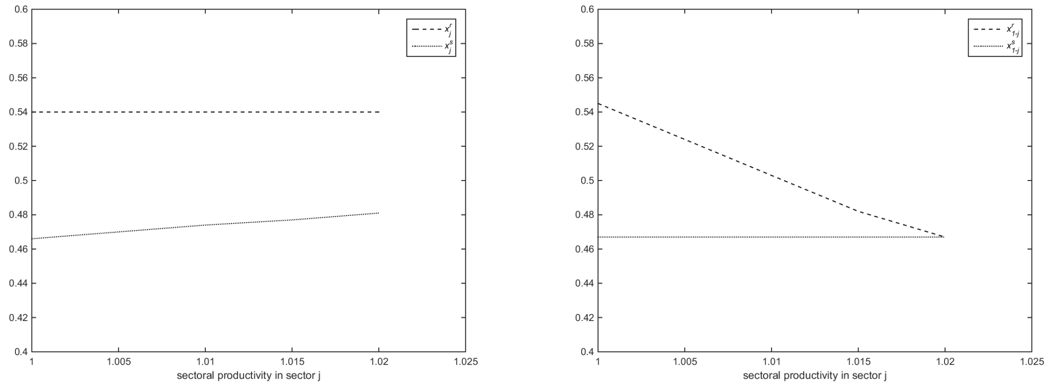
(a) (b)

Figure 4.8: The reallocation and separtation cut-off and decomposition of unemployment rate with change of reallocation cost



(a) (b)

Figure 4.9: The reallocation and separtation cut-off and decomposition of unemployment rate with change of unemployment benefit



(a) (b)

Figure 4.10: The reallocation and separtation cut-off and decomposition of unemployment rate with change of sectoral productivity

with higher unemployment benefit, and reallocation unemployment increases as well. The increasing distance between separation cut-off with reallocation cut-off and the increasing rest unemployment occurs in sector $1-j$ while the unemployment benefit increases.

Change of Sectoral Productivity

To emphasize the net mobility, the result of sectoral employment is demonstrated in this subsection. Net mobility is driven by the shift of sectoral productivity. The shift of secotral productivity attracts more workers from another sector. Meanwhile workers are more willing to stay because the job offers from another sector are less attractive. I start with a simulated model with changing sectoral productivity in sector j from 1 to 1.02, and the sector productivity in sector $1-j$ is set as 1.001. Figure 4.10 displays the separation cut-off x^s and reallocation cut-off x^r in sector j and sector $1-j$. The distance between separation cut-off and reallocation cut-off in sector j is smaller due to the increase of separation cut-off as higher sectoral productivity. This is one force to reduce the rest unemployment in sector j. However, higher sectoral productivity in sector j also decreases the reallocation cut-off in sector $1-j$. This force squeezes the rest unemployed in sector $1-j$ and drives them to move to sector j, which dominates the decrease of rest unemployment that originally occurs in sector j. As a result, the unemployment in sector j increases. This explains the reason why the higher productivity sector has a higher unemployment rate, and the lower productivity sector has a lower unemployment rate. Figure 4.11 illustrates that the higher productivity sector has a higher unemployment rate as sectoral productivity in sector j increases. The higher productivity sector has a higher job finding rate in average, so more workers are willing to be search unemployed in sector j. This result is consistent with the finding in Lkhagvasuren and Nitulescu (2013). For example, the labour productivity of the Mining sector is higher than the labour productivity of the Construction sector in 2009, and I also find the unemployment rate in the Mining sector is higher than the Construction sector.

According to Figure 4.12, we can see that sectoral productivity increases the proportion of sectoral employment in sector j over the whole employment. It shows that a higher sectoral productivity is associated with a higher share of sectoral employment. The absolute value of sectoral employment proportion growth in each sector is used to measure the net reallocation/mobility in the literature. The raising of sectoral productivity increases the proportion of sectoral employment in sector j and reduces the proportion of sectoral employment in sector $1-j$, thus the measure of net reallocation increases. From this example, we have a clear picture that the shift of sectoral productivity drives the net reallocation.

Furthermore, I observe that many unemployed workers are reallocated from sector $1-j$ to sector j, but the aggregate unemployment rate increases with higher sectoral productivity. In the literature, the process of reallocation is time consuming, and promotes the unemployment rate. However, the improvement of sectoral productivity simultaneously increases the capability of sectoral employment, which allows more unemployed worker to be employed. In my simulated model, the improvement of sectoral productivity does not bring massive unemployment as a

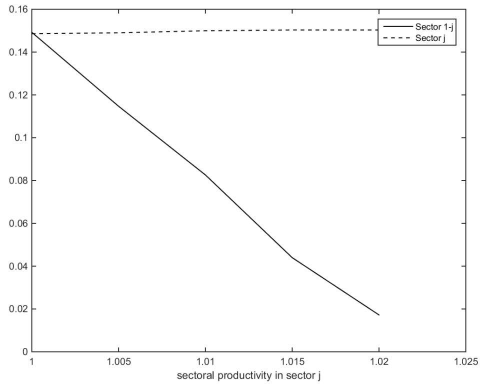


Figure 4.11: Sectoral unemployment rate

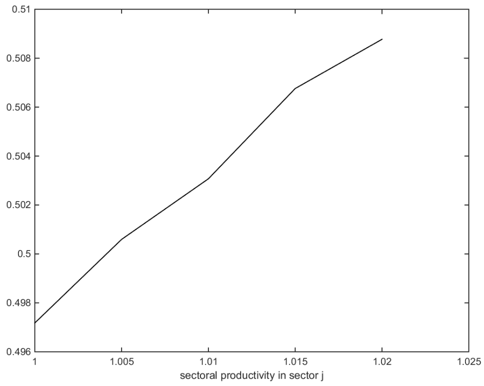


Figure 4.12: Proportion of sectoral employment

result.

It is valuable to compare the reallocation between the aggregate shock and the sectoral shock. Aggregate shock affects the productivity in both sectors, but sectoral shock only directly affects one sector. The raising of aggregate productivity lowers the reallocation cut-off for both sectors, and generates less reallocation unemployment. The shift of sectoral productivity in sector j does not affect unemployment workers' movement to sector $1-j$, but attracts more unemployed workers moving from sector $1-j$ to sector j. This effect of sectoral shock generates more unemployed workers' reallocation than aggregate shock. Higher sectoral productivity attracts the reallocation unemployment from outside of the sector. Higher sectoral productivity also increases the sectoral employment due to the capability, thus the labour force of sector j increases as well.

If sectoral productivity in sector j is extraordinarily big compared to sectoral productivity in sector $1-j$, then we can observe that every unemployed worker in sector $1-j$ would like to move to sector j and no workers from sector j are willing move to sector $1-j$.

Cyclical features of gross and net mobility

I simulate my model with aggregate productivity shock and preference shock to understand the gross and net mobility. The result in Table 4.2 suggests that the calibrated model can explain the finding that gross mobility is procyclical and net mobility is countercyclical in the LFS. Specifically, the correlation coefficient between the reallocation rate and the unemployment rate is negative -0.594, and the correlation coefficient between the net mobility, (no matter if measurements are used from Lilen or KM), and the unemployment rate is positive (0.73 for Lilen and 0.59 for KM). In order to confirm the robustness of the cyclical property of gross and net mobility, I regress the gross and net mobility on the unemployment rate and time trend. The effect of the unemployment rate is significantly negative on the number of reallocation, and it is significantly positive on the net mobility. This confirms that gross mobility is procyclical and net mobility is counter-cyclical.

Pilossoph (2012) uses a multisector equilibrium search model with taste shock to simulate the labour reallocation in the housing boom, but the procyclicality of gross mobility does not occur in the simulation. Pilossoph (2012) further shows that aggregate gross reallocation over the entire period is basically unchanged, while gross reallocation has been lower during the housing boom and slightly higher in the burst. I use a direct-search model with preference shock to simulate the behavior of workers' reallocation. The simulated model produces the result that the reallocation rate is procyclical and net mobility is countercyclical. Higher aggregate productivity lowers the reallocation cut-off of disutility, and more workers are willing to switch their sector. The net mobility uses the growth of sectoral employment share over whole employment as a measure. I also find that the counter cyclical nature of net mobility is due to the process of hiring and discharging. When recession comes, the employed worker whose disutility is higher than the separation cut-off is discharged immediately because his job is no longer profitable. Although unemployed workers are still employed with the speed of job finding rate,

Table 4.2: correlation and estimates with unemployment rate for Lilen and KM

	correlation	Urate	t statistic
Lilen	0.733	0.0000194	8.58
KM	0.59	21.75	5.2

the amount of workers who were discharged dominates the amount of unemployed workers who find jobs in the recession. Firms hire more unemployed workers in the boom, and this causes the sectoral adjustment. On the other hand, it takes time for the unemployed to get employed because unemployed workers need to spend time seeking jobs. Even though the job finding rate is higher in the boom period, unemployed workers still take time searching jobs before they are employed. Therefore, the sectoral adjustment is slower in the boom. Net mobility essentially is for measuring the sectoral adjustment. To summarise my discussions above, the fact that employed workers could be discharged immediately in the recession leads to sectoral adjustment. However, it takes time for unemployed workers to be hired, no matter if this is in the recession or boom period, so the effect of hiring workers on sectoral adjustment will not occur immediately. That is why net mobility is counter-cyclical.

4.8 Conclusion

This study presents a tractable equilibrium framework to investigate how unemployed workers' reallocation and separation decisions affect the aggregate unemployment rate over the business cycle. In particular, I reaffirm the important role of rest unemployment as an explanation of the unemployment fluctuation.

Rest unemployment emphasizes the value of waiting for local labour market conditions when workers make reallocation decisions. This implies that workers are not eager to be reallocated, even through they face no job prospects. The reasons behind this scenario are the reallocation friction due to an irreversible cost and the uncertainty of the net returns of reallocation.

Through the theoretical section and numerical example, this study shows that the sectoral shock triggers the net mobility, which implies the structural change of economy. There is little literature using a direct search framework to investigate the sectoral mobility, and this method can help us to understand the feature of sectoral mobility.

This paper also explains that gross mobility is caused by the preference shock. In an economy where is no aggregate and sectoral shock, the reallocation and separation cutoff is consistently permanent. The preference shock can push unemployed workers moving between sector j and sector $1 - j$. The only factor that triggers unemployed workers moving to another sector is the changing of the worker's preference, which is caused by preference shock.

This study also emphasises the model's implications for career mobility from several dimensions. It illustrates that a lower disutility make workers more willing to stay in the current sector because they have a higher possibility of finding a job. Since the cutoff of reallocation is affected by the aggregate productivity, the amount of rest unemployment causes the fluctuation of aggregate unemployment

There are still many aspects I can expand on regarding the topic of this paper. How workers' career change is always an important topic in labour economics. I have provided the theoretical work, in which unemployed workers' preference shock explains gross mobility and sectoral shock deciphering net mobility, but it is also interesting to investigate how employed workers respond to aggregate, sectoral and preference shock. This will be done as part of my future work. From the empirical result, I find that the employed worker's occupational and sectoral mobility is procyclical, so it is valuable to build up a corresponding theoretical body of work in the future. Furthermore, researchers also are interested in expanding the two-sector framework to a multiple-sector framework. For example, if workers face multiple offers from many different sectors, then how will workers choose? Workers could pick up the highest expected value offer, or randomly pick up one offer from them. This paper focuses on unemployed worker's reallocation decisions, however unemployed workers may decide to leave the labour market, therefore a threshold of non-participation could be included into the model, and the cyclicality feature of the non-participation rate can be investigated as part of any future work.

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4.9 Appendix

4.9.1 Existence and Uniqueness

Assumption 1: $F(x'|x) < F(x'|\tilde{x})$, for all x,x' if $x > \tilde{x}$

This assumption allows that lower x today implies (on average) lower x tomorrow. [14] In the proof of existence, I use this assumption to show that the operator T is a contraction that maps $M(p, z_j, x)$ and $W^U(p, z_j, x)$ who are decreasing in x into itself.

Step 1 Proof that the operator T is a contraction function:

Let $M(p, z, x) \equiv W^E(p, z, x) + J(p, z, x)$ denote the value of match. And define the operator T that maps the value function $\Gamma(p, z, x, n)$ for $n = 0, 1$ into the same function space, such that $\Gamma(p, z, x, 0) = M(p, z, x), \Gamma(p, z, x, 1) = W^U(p, z, x)$, as [15]

$$T(\Gamma(p, x, 0)) = y(p, z) - \phi_e x + \beta \mathbb{E}_{p',z',x'} \Big[\max\{[M(p', z', x'), W^U(p', z', x')\}] \Big] \tag{4.11}$$

$$T(\Gamma(p, x, 1)) = b - \phi_u x + \tag{4.12}$$

$$\beta \mathbb{E}_{p',z',x'} \Big[\max\{ \int W^U(p', z_{1-j}, \tilde{x})\, dF(\tilde{x}) - c, (S^T(p', z', x') + W^U(p', z', x'))\} \Big]$$

$$S^T \equiv \lambda(\theta(p', z', x')) \Big(M(p', z', x) - W^U(p', z', x) \Big) - \theta(p', z', x)k.$$

First we show that the operator T maps continuous functions into continu-

[14] The case that higher x today leads to higher (on average) tomorrow's x, if $x < \tilde{x}$, can be described by the following equation: $P(X > x') > P(Y > x')$, where X is random variable given the previous status is x and Y the random variable given the previous status is $\tilde{x}$. It follows that : $1 - F(x'|x) > 1 - F(x'|\tilde{x})$, then $F(x'|x) < F(x'|\tilde{x})$. The formula of expectation value is given as $E[X] = \int_{\underline{x}}^{\overline{x}} x' f(x')\, dx' = \underline{x} + \int_{\underline{x}}^{\overline{x}} [1 - F(x'|x)]\, dx'$ Similarly, $E[Y] = \underline{x} + \int_{\underline{x}}^{\overline{x}} [1 - F(x'|\tilde{x})]\, dx'$. It follows that $E[X] > E[Y]$ if $x > \tilde{x}$. Therefore, a higher today's x implies (on average) higher x tomorrow.

[15] S^T is obtained by the following:

$$\lambda(\theta)(W^E(p, z, x) - W^U(p, z, x)) = \lambda(\theta)(W^E(p, z, x) - W^U(p, z, x)) + \lambda(\theta)J - \lambda(\theta)J$$
$$= \lambda(\theta)(W^E(p, z, x) - W^U(p, z, x)) + \lambda(\theta)J - \theta k = \lambda(M(p, z, x) - W^U(p, z, x)) - \theta k = S^T$$

From equation above, I also obtain $\lambda W^E + (1 - \lambda)W^U = S^T + W^U$

ous functions. Since $\theta \in [0,1]$ for all p, z, x and $W^U(p,z,x), M(p,z,x), \lambda(\theta)$ and $S(p,z,x)$ are continuous functions. Since $\max\{M(p,z,x), W^U(p,z,x)\}$ is also a continuous function, it follows that T maps continuous functions into continuous functions. Moreover, since the domain of p, z, x is bounded, the resulting continuous functions are bounded as well.

To show that T defines a contraction, consdier two functions Γ, Γ', such that $\|\Gamma - \Gamma'\|_{\sup} < \epsilon$. Then, it follows that $\|M(p,z,x) - M'(p,z,x)\|_{\sup} < \epsilon$ and $\|W^U(p,z,x) - W^{U'}(p,z,x)\|_{\sup} < \epsilon$. where W^U, M are part of Γ as defined above. Since $\|\max\{a,b\} - \max\{a',b'\}\| < \max\{\|a-a'\|, \|b-b'\|\}$, as long as the terms over which to maximize do not change by more than ϵ in absolute value, the maximized value does not change by more ϵ. It is straightforwardly to obtain that $\|T(\Gamma(p,x,0)) - T(\Gamma'(p,x,0))\|_{\sup} < \tau\epsilon$. [16] The maximum value of $\max\{\int W^U(p', z_{1-j}, \tilde{x})\, dF(\tilde{x}) - c, S^T(p', z', x') - W^U(p', z', x')\}$ is needed to identify whether Eq(4.11) is a contraction. The first part can be established readily: $\|\int \Big(W^U(p, z_{1-j}, x) - W^{U'}(p, z_{1-j}, x)\Big)\, dF(x)\|_{\sup} < \epsilon$.

Next step is to show that the value of $\|S(p,z,x) + W^U(p,z,x) - S'(p,z,x) - W^{U'}(p,z,x)\|_{\sup}$ is smaller than ϵ as well. Given $\|M(p,z,x) - M'(p,z,x)\|_{\sup} < \epsilon$ and $\|W^U(p,z,x) - W^{U'}(p,z,x)\|_{\sup} < \epsilon$, it still is not clear that $M(p,z,x) - M'(p,z,x)$ is bigger or smaller than $W^U(p,z,x) - W^{U'}(p,z,x)$. Consider the first case that $M - M' > W - W'$,where M stand for $M(p,z,x)$ and W stand for $W^U(p,z,x)$, and we also have $\epsilon > W' - W \geq M' - M > -\epsilon$ in hand. Set $M'' = W' + (M - W) > M'$ and $W'' = M' - (M - W) < W'$

Since $S(M - W) = \lambda(\theta)(M - W) - \theta k$, we have that

$$-\epsilon < M - M' < W - W' < \epsilon$$

$$\Rightarrow -\epsilon < W'' - W < W - W' < \epsilon$$

[16]Since we know $\|\max\{a,b\} - \max\{a',b'\}\| < \max\{\|a-a'\|, \|b-b'\|\}$, it follows that $\|\max\{M, W^U\} - \max\{M', W^{U'}\}\| < \max\{\|M - M'\|, \|W^U - W^{U'}\|\}$. Therefore, I can obtain $\|T(\Gamma(p,x,0)) - T(\Gamma'(p,x,0))\|_{\sup} = \|\max\{M, W^U\} - \max\{M', W^{U'}\}\| = \epsilon < \epsilon$, where $0 < \tau < 1$

$$
\begin{aligned}
\Rightarrow -\epsilon &< S(M' - W'') + W'' - S(M - W) - W \\
&\leq S(M' - W') + W' - S(M - W) - W \\
&\leq S(M'' - W') + W' - S(M - W) - W < \epsilon \qquad (4.13)
\end{aligned}
$$

where $S(M' - W'') = S(M - W) = S(M'' - W')$.

Note that the outer inequalities follow because $M - M' > -\epsilon, W - W' < \epsilon$. Now consider the second case that $M' - W' > M - W \geq 0$.

$$
\begin{aligned}
&\epsilon > M - M' > W - W' > -\epsilon \\
&\Rightarrow \epsilon > W'' - W > W - W' > -\epsilon
\end{aligned}
$$

$$
\begin{aligned}
\epsilon > S(M' - W'') + W'' - S(M - W) - W &> S(M' - W') + W' - S(M - W) - W \\
&> S(M'' - W') + W' - S(M - W) - W < \epsilon
\end{aligned} \qquad (4.14)
$$

Both of cases support that

$\|S(p, z, x) + W^U(p', z', x) - S'(p, z, x) - W^{U'}(p', z', x)\|_{\sup} < \epsilon$

It then follows that $\|T(\Gamma(p, x, 1)) - T(\Gamma'(p, x, 1))\|_{\sup} < \tau\epsilon$, where $0 < \tau < 1$, for all p, z, x. Hence, the operator T is a contraction. Now, it is trivial to show that if M and W^U are decreasing in x, T maps them into decreasing function. This follows since the $\max\{M(p', z', x'), W^U(p', z', x')\}$ is also a decreasing function. Assumption 1 is needed so higher x today implies (on average) higher x tomorrow. Since the value of reallocation is constant in x, a reservation policy for reallocation follows immediately.

Step 2 Given that T is a contraction, and Banach's Fixed Point Theorem,a unique fixed point $(M^*(p, z, x), W^{U^*}(p, z, x))$ of the mapping T exists. [17] From the fixed point function $M^*(p, z, x)$ and $W^{U^*}(p, z, x)$ and free entry condition, we

[17] The fixed point of $(M^*(p, z, x), W^{U^*}(p, z, x))$ satisfies that $M^*(p, z, x) = T(M^*(p, z, x))$ and $W^{U^*}(p, z, x) = T(W^{U^*}(p, z, x))$

can define the function $J(p,z,x) = \max\{(1-\alpha)[M(p,z,x) - W^U(p,z,x)], 0\} = \max\{k/q(\theta(p,z,x)), 0\}$, and we can obtain $\theta^*(p,z,x)$ and $J^*(p,z,x)$ Finally, $w^*(p,z,x)$ derived using Eq(4.5) given all other functions.

4.9.2 Existence of Separation Cutoff

Consider the same operator T defined in the proof of Proposition 4.9.1, but now the relevant state space is given by (p, z_j, x). I now want to show that the operator T maps the subspace of functions Γ into itself with $M(p,x)$ decreasing weakly faster in x than $W(p,z_j,x)$. To show this , take $M(p,z_j,x)$ and $W^U(p,z_j,x)$ such that $M(p,z_j,x) - W^U(p,z_j,x)$ is decreasing in x and let x^s denote a reservation productivity such that for $x > x^s$ a firm-worker match decide to terminate. Using $\lambda(\theta)(M - W^U) - \theta k = \lambda(\theta)(M - W^U) - \lambda'(\theta)(M - W^U)\theta = \lambda(\theta)(1-\eta)(M - W^U)$, I can construct the following:

$$
\begin{aligned}
&T(\Gamma(p,z_j,x,0)) - T(\Gamma(p,z_j,x,1)) = \qquad (4.15)\\
&y(p,z_j) - (\phi_e - \phi_u)x - b + \beta\mathbb{E}_{p',z_j',x'}\Big[\max\{M(p',z_j',x') - W^U(p',z_j',x'), 0\} - \\
&\max\Big\{\int W^U(p',z_{1-j},\tilde{x})\,dF(\tilde{x}) - c - W^U(p',z_j',x'), \lambda(\theta)(1-\eta)(M(p',z_j',x') - W^U(p',z_j',x'))\Big\}\Big]
\end{aligned}
$$

The first part of the proof shows the conditions under which $T(\Gamma(p,z_j,x,0)) - T(\Gamma(p,z_j,x,1))$ is weakly decreasing in x. Because the elements of the relevant domain are restricted to have $W^U(p,z_j,x)$ decreasing in x, and $M(p,z_j,x) - W^U(p,z_j,x)$ is decreasing in x.

*Case*1 Consider the range of tomorrow's $x' \in [\underline{x}(p',z_j'), x^r(p',z_j'))$, where $x^r(p',z_j') < x^s(p')$. In this case, workers are employed and are not willing to reallocate next period. the term under the expectation sign in the above equation reduces to $(1-\delta)[M(p',z_j',x') - W^U(p',z_j',x')] - \lambda(\theta(p',z_j',x'))(1-\eta)[M(p',z_j',x') - W^U(p',z_j',x')]$

Take derivative of x, then [18]

$$
\begin{aligned}
&\frac{d\,(1-\delta)[M(p',z'_j,x')-W^U(p',z'_j,x')]-\lambda(\theta)(1-\eta)[M(p',z'_j,x')-W^U(p',z'_j,x')]}{dx'}\\
&=\frac{d(1-\delta)(M-W^U)}{dx'}-\frac{d\,[\lambda(\theta)(1-\eta)(M-W^U)]}{dx'}\\
&=\frac{d(1-\delta)(M-W^U)}{dx'}-\frac{d(\lambda(\theta)(1-\eta)[M-W^U])}{d\theta}\frac{d\theta}{d(M-W^U)}\frac{d(M-W^U)}{dx'}\\
&=\frac{d(1-\delta)(M-W^U)}{dx'}-\frac{(1-\eta)}{\eta}k\frac{\eta\,\lambda(\theta)}{(1-\eta)k}\frac{d(M-W^U)}{dx'}\\
&=(1-\delta-\lambda(\theta))\frac{d(M-W^U)}{dx'} \qquad (4.16)
\end{aligned}
$$

Given $\frac{d(M-W^U)}{dx'}<0$ and $(1-\delta-\lambda(\theta))\geq 0$, then the derivative of last equation with respect to x' is negative.

*Case*2 Now suppose tomorrow's $x'\in[x^r(p',z'_j),x^s(p',z'_j))$. In this case, workers are employed and willing to reallocate next period. The entire term under the expectation sign is equal to

$$(1-\delta)[M(p',z'_j,x')-W^U(p',z'_j,x')]-\int W^U(p',z_{1-j},\tilde{x})\,dF(\tilde{x})+c+W^U(p',z'_j,x')$$

and this term is weakly decreasing in x', because $(M(p',z'_j,x')-W^U(p',z'_j,x'))$ is weakly decreasing in x', and so is $W^U(p',z'_j,x')$.

Case 3 Now suppose tomorrow's $x'\in[x^s(p',z'_j),x^r(p',z'_j))$. The workers are unemployed and are not willing to reallocate. The term under the expectation sign becomes zero (as $M(p',z'_j,x')-W^U(p',z'_j,x')=0$), and is therefore constant in x'.

Case 4 Now suppose tomorrow's $x'\geq\max\{x^r(p',z'_j),x^s(p',z'_j)\}$. In this case,

[18]Given$(1-\eta)(M(x)-W^U(x))=\frac{1-\eta}{\eta}J=\frac{1-\eta}{\eta}\frac{k}{q(\theta)}$, , I can obtain $\lambda(\theta(x))(1-\eta)(M(x)-W^U(x))=\frac{1-\eta}{\eta}k\theta$, and $\frac{d\theta}{d(M-W^U)}=\frac{\eta}{1-\eta}\frac{\lambda(\theta)}{k}$. It follows that $\frac{d}{d(M(x)-W^U(x))}(\lambda(\theta(x))(1-\eta)(M(x)-W^U(x)))=\frac{d(\lambda(\theta(x))(1-\eta)(M(x)-W^U(x)))}{d\theta}\frac{d\theta}{d(M-W^U)}=\lambda(\theta)$

workers are unemployed and willing to reallocate. The term under the expectation sign reduces to $-\int W^U(p', z_{1-j}, \tilde{x})\, dF(\tilde{x}) + c + W^U(p', z_j', x')$, which is decreasing in x'.

Given Assumption 1, the independence of z of p, and that the term under the expectation sign are decreasing in x', given any p' and z_j'. Together with the term of $y(p, z_j) - b - (\phi_e - \phi_u)x$ is decreasing in x, given $(\phi_e - \phi_u) > 0$, it must be that $T(\Gamma(p, z_j, x, 0)) - T(\Gamma(p, z_j', x, 1))$ is also decreasing in x. The fixed point difference $M - W^U$ must also be strictly decreasing in x.

4.9.3 Wage equation

$$\lambda(p, z_j, x)(W^E(p, z_j, x) - W^U(p, z_j, x)) = \frac{(1-\eta)\theta(p, z_j, x)k}{\eta} \tag{4.17}$$

The free entry condition holds for all sector, then

$$V(p, z_j, x) = 0 \Rightarrow J(p, z_j, x) = \frac{k}{q(\theta(p, z_j, x))} \tag{4.18}$$

Pissarides wage equation: Given that an employed worker's value in steady state is

$$W^E(p, z_j, x) = w(p, z_j, x) - \phi_e x + \beta[W^E(p, z_j, x)]$$

then

$$\begin{aligned} W^E(p, z_j, x) - W^U(p, z_j, x) &= [w(p, z_j, x) - (\phi_e - \phi_u)x - b] \\ &\quad -\beta\lambda(\theta(p, z_j, x))(W^E(p, z_j, x) - W^U(p, z_j, x)) + \beta(W^E(p, z_j, x) - W^U(p, z_j, x)) \\ \Rightarrow W^E(p, z_j, x) - W^U(p, z, x) &= \frac{[w(p, z_j, x) - (\phi_e - \phi_u)x - b]}{1 - \beta + \beta\lambda(\theta(p, z_j, x))} \end{aligned} \tag{4.19}$$

In terms of Hosios condition, we have

$$\frac{\eta}{(1-\eta)}\frac{[w(p,z_j,x)-(\phi_e-\phi_u)x-b]}{1-\beta+\beta\lambda(\theta(p,z_j,x))}=\frac{k}{q(\theta(p,z_j,x))} \tag{4.20}$$

Additionally, the value of firm in steady state can be rewritten as following

$$J(p,z_j,x)=\frac{y(p,z_j)-w(p,z_j,x)}{1-\beta}=\frac{k}{q(\theta(p,z,x))} \tag{4.21}$$

Simultaneously solve the Eq(4.20) and Eq(4.21), we find

$$w(p,z_j,x)=y(p,z_j)-\frac{k}{q(\theta(p,z_j,x))}(1-\beta) \tag{4.22}$$

Substituting Eq(4.22) in Eq(4.20), we find

$$\eta(y(p,z_j)-b-\phi_u x)-\frac{k}{q(\theta(p,z_j,x))}(1-\beta)-\beta\theta(p,z_j,x)(1-\eta)k=0 \tag{4.23}$$

If we replace the middle term with $y(p,z_j)-w(p,z_j,x)$ in Eq(4.22), we can get the pissarides wage equation

$$w=(1-\eta)pz_j+\eta b+\eta(\phi_e-\phi_u)x+\beta(1-\eta)\theta(p,z_j,x)k \tag{4.24}$$

4.9.4 Proof of the cyclicality of reallocation

Proof.

Given that $R(p)$ is constant in x, there exists a reallocation cutoff function x^r such that workers reallocate if and only $x < x^r(p)$ for every p, where $x^r(p)$ satisfies:

$$\hat{W}^U(p, z_j, x^r) = \lambda(\theta(p, z_j, x^r))W^E(p, z_j, x^r) + (1-\lambda(\theta(p, z_j, x^r)))W^U(p, z_j, x^r) = R(p)$$

Unemployed workers reallocate if and only if $x < x^r(p)$ satisfies $\hat{W}^U(p, z_j, x^r) = -c + \int_{\underline{x}}^{\overline{x}} W^U(p, z_{1-j}, \tilde{x})\, dF(\tilde{x})$

For the reallocation cutoff, we know that

$$\begin{aligned} &-c + \textstyle\int_{\underline{x}}^{\overline{x}} W^U(p, z_{1-j}, \tilde{x})\, dF(\tilde{z}) \\ &\quad = \hat{W}^U(p, z_j, x^r) = \lambda(\theta(p, z_j, x^r))(W^E((p, z_j, x^r)) - W^U((p, z_j, x^r)) + W^U(p, z_j, x^r)) \end{aligned}$$

Substituting $W^U(p, z_j, x) = \frac{1}{1-\beta}\big(b - \phi_u x + \beta\lambda(\theta(p, z_j, x))(W^E(p, z_j, x) - W^U(p, z_j, x))\big)$ into last equation, I can find

$$\begin{aligned} -c + \int_{\underline{x}}^{\overline{z}} &\max\{W^U(p, z_{1-j}, x), W^U(p, z_{1-j}, x^r)\} dF(x) \\ &= \lambda(\theta(p, z_j, x^r))(W^E(p, z_j, x^r) - W^U(p, z_j, x^r)) + W^U(p, z_j, x^r) \quad (4.25) \end{aligned}$$

Define $\theta_j^r = \theta(p, z_j, x^r)$ and x_{1-j}^r is the reallocation cutoff in sector $1-j$

$$\begin{aligned} \frac{(1-\eta)k\theta_j^r}{\eta} - x_j^r + \int_{\underline{x}}^{x_{1-j}^r} x\, dF(x) + (1 - F(x_{1-j}^r))x_{1-j}^r + (1-\beta)c + \quad (4.26) \\ \beta k \frac{1-\eta}{\eta}[\int_{\underline{x}}^{x_{1-j}^r} \theta(p, z_{1-j}, x)\, dF(x) + (1 - F(x_{1-j}^r))\theta(p, z_{1-j}, x^r)] = 0 \equiv RE \end{aligned}$$

Use the implicit function theorem, then I can obtain the following equation:

$$\begin{aligned} \frac{dx_j^r}{dp} = -\frac{1}{\frac{(1-\eta)}{\eta}\frac{d\theta(p,x_j^r)}{dx_j^r}k - 1} \times \Big[\frac{(1-\eta)}{\eta}\frac{d\theta(p, x_j^r)}{dp}k + (1 - F(x_{1-j}^r)\frac{dx_{1-j}^r}{dp} \quad (4.27) \\ -\beta k\frac{1-\eta}{\eta}[\int_{\underline{x}}^{x_{1-j}^r} \frac{d\theta(p, z_{1-j}, x)}{dp}\, dF(x) + (1 - F(x_{1-j}^r))\frac{d\theta(p, x_{1-j}^r)}{dp}]\Big] \end{aligned}$$

Since $q(\theta(p,z_j,x)) = \frac{v^\eta u^\eta}{v} = \theta(p,z_j,x)^{\eta-1}$, Eq(4.23) can be re-writen as

$$\theta(p,z_j,x)^{\eta-1}\frac{\eta[y(p,z_j) - b - (\phi_e - \phi_u)x] - \beta(1-\eta)\theta(p,z_j,x)k}{1-\beta} - k = 0 \quad (4.28)$$

Take derivative of Eq(4.28) with respect to p and x, I find

$$\frac{d\theta(p,z_j,x)}{dp} = \frac{\theta(p,z_j,x)}{w(p,z_j,x) - b - (\phi_e - \phi_u)x}\frac{dy(p,z_j)}{dp} \quad (4.29)$$

$$\frac{d\theta(p,z_j,x)}{dx} = \frac{-(\phi_e - \phi_u)\theta(p,z_j,x)}{w(p,z_j,x) - b - (\phi_e - \phi_u)x} \quad (4.30)$$

the two equations above imply that θ is increasing in p and decreasing in z. Note that

$$\lim_{x\uparrow w^{-1}(y;p,z_j)} \frac{\theta(p,z_j,x)}{w(p,z_j,x) - b - (\phi_e - \phi_u)x} = \frac{\lambda(\theta(p,z_j,x))}{1-\beta(1-\lambda(\theta(p,z_j,x)))} = 0 \quad (4.31)$$

because $\theta(p,z_j,x) \downarrow 0$, as $w(p,z_j,x^r) \uparrow y(p,z_j)$.

$$\left.\frac{d\theta(p,z_j,x)}{dp}\right|_{x=x_j^r} = \frac{\theta(p,z_j,x^r)}{w(p,z_j,x^r) - b - (\phi_e - \phi_u)x^r}\frac{dy(p,z_j)}{dp} = 0 \quad (4.32)$$

$$\left.\frac{d\theta(p,z_j,x)}{dx}\right|_{x=x_j^r} = \frac{-(\phi_e - \phi_u)\theta(p,z_j,x^r)}{w(p,z_j,x^r) - b - (\phi_e - \phi_u)x^r} = 0 \quad (4.33)$$

$$\frac{dx_j^r}{dp} = \Big[(1 - F(x_{1-j}^r)\frac{dx_{1-j}^r}{dp} - \beta k\frac{1-\eta}{\eta}[\int_{\underline{x}}^{x_{1-j}^r} \frac{d\theta(p, z_{1-j}, x)}{dp} dF(x)]\Big] \quad (4.34)$$

$$\frac{dx_{1-j}^r}{dp} = \Big[(1 - F(x_j^r)\frac{dx_j^r}{dp} - \beta k\frac{1-\eta}{\eta}[\int_{\underline{x}}^{x_j^r} \frac{d\theta(p, z_j, x)}{dp} dF(x)]\Big] \quad (4.35)$$

Substitute (4.34) with (4.35), then

$$\begin{aligned}\frac{dx_j^r}{dp} &= \frac{-1}{1-(1-F(x_j^r))(1-F(x_{1-j}^r))} \times & (4.36)\\ &\beta k\frac{1-\eta}{\eta}\Big[(1-F(x_{1-j}^r))\int_{\underline{x}}^{x_j^r} \frac{d\theta(p, z_j, x)}{dp} dF(x) + [\int_{\underline{x}}^{x_{1-j}^r} \frac{d\theta(p, z_{1-j}, x)}{dp} dF(x)]\Big]\end{aligned}$$

□

And $\frac{d\theta(p,z,x)}{dp}$ is decreasing in x.

4.9.5 Proof of The cyclicality of separation

Case 1 In the case of random z, and a one-time unexpected permanent shock to p,

If $x^r > x^s$,the value of being unemployed does not depend directly on the value of reallocation, but depends on the island-specific value of unemployment.

And define $\theta^s \equiv \theta(p, x^s)$ And define $\theta(p, x_j^s) \equiv \theta(p, z_j, x^s)$

All islands with rest unemployment have the same value of unemployments of productivity: $W^U(p, z_j, x) = \frac{b-x_j^s}{1-\beta}$ The value of a match at the cutoff of separation x^s implies that workers are unemployed, thus $M(p, x^s(p)) = W^U(p, x^s)$

$$M(p, z_j, x^s) = y(p, z) - \phi_e x_j^s + \beta[M(p, z, x^s)] \Rightarrow (1-\beta)W^U(p, z, x^s) = y(p, z) - \phi_e x^s$$

Use the implicit function theory to take derivative of last equation, then we can obtain

$$\frac{dx^s(p)}{dp} = \frac{1}{\phi_e - \phi_u} y_p(p, z_j) > 0 \tag{4.37}$$

Separations are countercyclical

Case 2 If $x^r < x^s$, implies that workers separate endogenously to reallocate

$$R(p, z_{1-j}) = W^U(p, z_j, x^r) = \frac{b - \phi_u x_j^r + \beta k \theta(p, z_j, x^r) \frac{1-\eta}{\eta}}{1-\beta}$$

Take derivative with respect to p, I find

$$\frac{dR(p, z_{1-j})}{dp} = \frac{\beta k(1-\eta)}{(1-\beta)\eta} \frac{\theta(p, z_j, x^r)}{w(p, z_j, x^r) - b - (\phi_e - \phi_u)x_j^r} \Big(y_p(p, z_j) - (\phi_e - \phi_u) \frac{dx_j^r(p)}{dp}) \Big) \\ - \frac{1}{1-\beta} \frac{dx_j^r}{dp} \tag{4.38}$$

we can rewrite the last equation as following

$$\frac{dR(p, z_{1-j})}{dp} = \frac{\beta \lambda(\theta(p, z_j, x^r))}{(1-\beta)(1-\beta(1-\lambda(\theta(p, z_j, x^r))))} \Big(y_p(p, z_j) - (\phi_e - \phi_u) \frac{dx_j^r}{dp} \Big) \\ - \frac{1}{1-\beta} \frac{dx_j^r}{dp} \tag{4.39}$$

All unemployed workers would like to reallocate, thus $M(p, z_j, x^s) = W^U(p, z_j, x^s) = W^U(p, z_j, x^r) = R(p, z_{1-j})$.

$$M(p, z_j, x^s) = y(p, z_j) - \phi_e x_j^s + \beta[W^U(p, z_j, x^s)] \Rightarrow M(p, x_j^s) = y(p, z_j) - \phi_e x_j^s + \beta[W^U(p, x_j^r)]$$

$$R(p, z_{1-j}) = y(p, z_j) - \phi_e x_j^s + \beta R(p, z_{1-j}) \Rightarrow (1-\beta)R(p, z_{1-j}) = y(p, z_j) - \phi_e x_j^s$$

$$(1-\beta)\frac{dR(p, z_{1-j})}{dp} = \Big(y_p(p, z_j) - \phi_e \frac{dx_j^s(p)}{dp} \Big) \tag{4.40}$$

Substituting Eq(4.39) into Eq(4.40) and rearranging the result, I can get the following equation

Take partial derivative with p of last two equation, and rearrange the results , then I can get the following result.

$$\frac{dx_j^s}{dp}=\frac{1}{\phi_e}\Big[y_p(p,z_j)-\frac{\beta\lambda(\theta(p,z_j,x_j^r))}{1-\beta+\beta\lambda(\theta(p,z_j,x_j^r))}\Big(y_p(p,z_j)-(\phi_e-\phi_u)\frac{dx_j^r(p)}{dp}\Big)+\frac{dx_j^r(p)}{dp}\Big] \tag{4.41}$$

4.9.6 Sectoral shock and net mobility

Case 1 $x^r > x^s$

$$\frac{d\theta(p,z_j,x)}{dz_j}=\frac{\theta(p,z_j,x)}{w(p,z_j,x)-b-(\phi_e-\phi_u)x}\frac{dy(p,z_j)}{dz_j} \tag{4.42}$$

Take derivative of (4.26) with respect to z_j, we can obtain :

$$\frac{dx_j^r}{dz_j}=-\frac{\frac{1-\eta}{\eta}k\frac{\theta(p,z_j,x^r)}{w(p,z_j,x^r)-b-(\phi_e-\phi_u)x^r}\frac{dy(p,z_j)}{dz_j}}{\frac{1-\eta}{\eta}k\frac{-(\phi_e-\phi_u)\theta(p,z_j,x^r)}{w(p,z_j,x^r)-b-(\phi_e-\phi_u)x_j^r}-1}=0$$

$$\begin{aligned}\frac{dx_{1-j}^r}{dz_j}&=-\frac{(1-F(x_j^r))\frac{dx_j^r}{dz_j}-\beta k\frac{1-\eta}{\eta}[\int_{\underline{x}}^{x_j^r}\frac{d\theta(p,z_j,x)}{dz_j}dF(x)+(1-F(x_j^r))\frac{d\theta(p,x_j^r)}{dz_j}]}{\frac{1-\eta}{\eta}k\frac{-(\phi_e-\phi_u)\theta(p,z_{1-j},x^r)}{w(p,z_{1-j},x^r)-b-(\phi_e-\phi_u)x_{1-j}^r}-1}\\
&=-\beta k\frac{1-\eta}{\eta}\int_{\underline{x}}^{x_j^r}\frac{d\theta(p,z_j,x)}{dz_j}dF(x)<0\\
&=-\beta k\frac{1-\eta}{\eta}\int_{\underline{x}}^{x_j^r}\frac{\theta(p,z_j,x)}{w(p,z_j,x)-b-(\phi_e-\phi_u)x}\frac{dy(p,z_j)}{dz_j}dF(x)<0\end{aligned} \tag{4.43}$$

Separation cutoff

$$M(p,z_j,x^s)=y(p,z)-\phi_e x_j^s+\beta[M(p,z,x^s)]\Rightarrow(1-\beta)W^U(p,z,x^s)=y(p,z)-\phi_e x^s$$

$$\frac{dx_j^s(p)}{dz_j}=\frac{1}{\phi_e-\phi_u}y_z(p,z_j)\ >0 \tag{4.44}$$

Case 2 If $x^r < x^s$, implies that workers separate endogenously to reallocate

$$R(p, z_{1-j}) = W^U(p, z_j, x^r) = \frac{b - x_j^r + \beta k \theta(p, z_j, x^r)\frac{1-\eta}{\eta}}{1-\beta}$$

Take derivative with respect to p, I find

$$\frac{dR(p, z_{1-j})}{dz_j} = \frac{dW^U(p, z_j, x^r)}{dz_j}$$
$$= \frac{\beta k(1-\eta)}{(1-\beta)\eta} \frac{\theta(p, z_j, x^r)}{w(p, z_j, x^r) - b - (\phi_e - \phi_u)x_j^r} \Big(y_z(p, z_j) - (\phi_e - \phi_u)\frac{dx_j^r(p)}{dz_j}) \Big)$$
$$- \frac{1}{1-\beta} \frac{dx_j^r}{dz_j} \tag{4.45}$$

we can rewrite the last equation as following

$$\frac{dW^U(p, z_j, x^r)}{dz_j} = \frac{\beta \lambda(\theta(p, z_j, x^r))}{(1-\beta)(1-\beta(1-\lambda(\theta(p, z_j, x^r))))} \Big(y_z(p, z_j) - (\phi_e - \phi_u)\frac{dx_j^r}{dz_j} \Big)$$
$$- \frac{1}{1-\beta} \frac{dx_j^r}{dz_j} \tag{4.46}$$

All unemployed workers would like to reallocate, thus $M(p, z_j, x^s) = W^U(p, z_j, x^s) = W^U(p, z_j, x^r)$.

$$M(p, z_j, x^s) = y(p, z_j) - \phi_e x_j^s + \beta[W^U(p, z_j, x^s)] \Rightarrow M(p, x_j^s) = y(p, z_j) - \phi_e x_j^s + \beta[W^U(p, x_j^r)]$$
$$W^U(p, z_j, x^r) = y(p, z_j) - \phi_e x_j^s + \beta W^U(p, z_j, x^r)) \Rightarrow (1-\beta)W^U(p, z_j, x^r)) = y(p, z_j) - \phi_e x_j^s$$
$$(1-\beta)\frac{dW^U(p, z_j, x^r)}{dz_j} = \Big(y_z(p, z_j) - \phi_e \frac{dx_j^s(p)}{dz_j} \Big) \tag{4.47}$$

Substituting Eq(4.46) into Eq(4.47) and rearranging the result, I can get the following equation

$$\frac{dx_j^s}{dz_j} = \frac{1}{\phi_e}\Big[y_z(p, z_j) - \frac{\beta \lambda(\theta(p, z_j, x_j^r))}{1-\beta+\beta\lambda(\theta(p, z_j, x_j^r))} \Big(y_z(p, z_j) - (\phi_e - \phi_u)\frac{dx_j^r(p)}{dz_j} \Big) + \frac{dx_j^r(p)}{dz_j} \Big] \tag{4.48}$$

Given $\frac{dx_j^r}{dz_j} = 0$ and $\lambda(\theta(p, z_j, x^r)) = 0$, we can obtain $\frac{dx_j^s}{dz_j} = \frac{1}{\phi} y_z(p, z_j) > 0$

Chapter 5

Conclusion

5.1 Introduction

This thesis has focused on career mobility in the labour market in the UK. Chapter 2 use a quarterly LFS dataset to confirm that career mobility is procyclical. Chapter 3 applied yearly BHPS and UKHLS datasets to confirm the procyclicality of career mobility while Chapter 4 developed a theoretical model to explore and understand the reasons behind the evidence of Chapter 2 and Chapter 3.

5.2 Main findings

Chapter 2 presents the first comprehensive investigation of occupational and industrial mobility in the UK. I recorded that the level of career mobility is surprisingly high. The evidence shows that the reallocation is churning in the UK labour market. In the literature, workers' career mobility is due to the change of economic structure. However, the churning of the labour market we observed in the UK cannot be explained by the change of economic structure; there is another reason pushing worker's mobility across occupations and industries. This has motivated me to develop a theoretical model in order to tackle the complexity of mobility. I documented the procyclical of career mobility using the LFS, no matter which transition channel, and confirmed this feature with the econometric model. Employed workers who voluntarily left their last job have a higher probability to change career than those who were involuntarily left their job. Unemployed workers whose unemployment duration is longer than two quarters have a higher possibility to change career than those whose duration is shorter than two quarters. Inactive workers who want a job have a higher possibility to change career than those who do not want a job. A career changer's wage increases more than the career stayer during economic expansion.

Chapter 3 is the first research to detect the effect of interviewing method on the career mobility. The dataset consists of BHPS and UKHLS, which allows me to investigate the career mobility with a long-term viewpoint. The combination of the BHPS and UKHLS contributes to tracking the individuals' behaviour for more than twenty years, and contributes to observing the business cycle. I reassure the procyclicality of career mobility by controlling the change of interviewing method. This feature is found with 1-digit, 2-digit and 3-digit level occupational classification, and with 1-digit and 2-digit industrial classification. This implies the evidence is robust and reliable. This chapter contributes to determining the effect of changing interview method on the definition of career mobility. Given that the mobility is defined as the changing of classification, no matter whether workers have changed job or not,the dependent interviewing significantly reduces the level of mobility. However, if we define the mobility as the changing of classification for job changers, then we can conclude that the change of interviewing methods does not affect the career mobility. This result eliminates the concerns from the literature. At the same time, the results support the findings in Chapter 2. The career mobilities are still surprisingly high.

Chapter 4 places the sectoral productivity shock and preference shock into a direct-search model, which help us to distinguish the net mobility and gross mobility. The reallocation cutoff is affected by the aggregate productivity, and this cutoff changes the individual's attempt to move between sectors. This result helps us to understand not only the fact of churning gross mobility observed by the data, but also the change of sectoral employment. The increasing reallocation cost reduces the individual's incentive to switch sector and makes them stay in the sector longer because the waiting cost is lower than before. Higher unemployment benefit also reduces the worker's attempts to switch his sector. The rest unemployment is a major part of total unemployment. Rest-Unemployed workers have a very low chance of finding a job , but they still prefer to stay in the sector. The reason is that their expected value of waiting in the sector is higher than moving to another sector. On the other hand, the increase of a sector productivity will attract more inflow into the sector than the outflow. This result helps us to understand the procyclicality of career mobility in terms of the shift of aggregate productivity. It also presents the mechanism of net mobility and gross mobility, and provides us with a framework to review the literature.

5.3 Future studies

In this thesis, the theoretical framework only allows workers to reallocate across sectors via unemployment. However, according to the empirical evidence, we can observe many workers moving via employed to employed transition. In Chapter 3, we compare the job information between two consecutive waves to identify the career mobility. There are some cases in which workers are employed in many other jobs within two consecutive waves. However, the dataset only captures part of the job information over the waves; job information within two consecutive wave is not sufficient to be appropriately analysed. It would also be interesting to include the inactive concept into the model, for example, a cutoff of worker who quit the labour market. This would be helpful to understand the intuition of transition from inactive to employment.