UNIVERSITY OF Southampton

University of Southampton Research Repository
ePrints Soton

Copyright © and Moral Rights for this thesis are retained by the author and/or other copyright owners. A copy can be downloaded for personal non-commercial research or study, without prior permission or charge. This thesis cannot be reproduced or quoted extensively from without first obtaining permission in writing from the copyright holder/s. The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the copyright holders.

When referring to this work, full bibliographic details including the author, title, awarding institution and date of the thesis must be given e.g.

AUTHOR (year of submission) "Full thesis title", University of Southampton, name of the University School or Department, PhD Thesis, pagination

http://eprints.soton.ac.uk

UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL AND HUMAN SCIENCES
Division of Economics

Essays in Labour Economics

by

Panagiotis Giannarakis

A document submitted in partial fulfillment for the PhD thesis

This Doctoral Thesis is dedicated to the memory of my beloved Grandma, Mrs. Ioanna Giannaraki (1929-2015). A strong woman who raised and supported me all these years and made this Ph.D. thesis to become feasible. Also to my beloved Grandpa, Mr. Panagiotis Giannarakis (1914-2004). A true hero in the Greek resistance during WWII and a role model in my teenage life.

"*Εις μνήμην του* Παππού *και της* Γιαγιάς *μου* Παναγιώτη *και Ιωάννας* Γιανναράκη..."

Ιθάκη

“Σα βγεις στον πηγαιμό για την Ιθάκη, να εύχεσαι νάναι μακρύς ο δρόμος, γεμάτος περιπέτειες, γεμάτος γνώσεις. Τους Λαιστρυγόνας και τους Κύκλωπας, τον θυμωμένο Ποσειδώνα *μη φοβάσαι, τέτοια στον δρόμο σου ποτέ σου δεν θα βρεις, αν μέν' η σκέψις σου υψηλή, αν εκλεκτή συγκίνησις το πνεύμα και το σώμα σου αγγίζει. Τους Λαιστρυγόνας και τους Κύκλωπας, τον άγριο* Ποσειδώνα *δεν θα συναντήσεις, αν δεν τους κουβανείς μες στην ψυχή σου, αν η ψυχή σου δεν τους στήνει εμπρός σου.*

Να εύχεσαι νάναι μακρύς ο δρόμος. Πολλά *τα καλοκαιρινά πρωιά να είναι που με τι ευχαρίστησι, με τι χαρά θα μπαίνεις σε λιμένας πρωτοειδωμένους· να σταματήσεις σ' εμπορεία* Φοινικικά, *και τες καλές πραγμάτειες ν' αποκτήσεις, σεντέφια και κοράλλια, κεχριμπάρια κ' έβενους, και ηδονικά μυρωδικά κάθε λογής, όσο μπορείς πιο άφθονα ηδονικά μυρωδικά· σε* *πόλεις Αιγυπτιακές πολλές να πας, να μάθεις και να μάθεις απ' τους σπουδαγμένους.*

Πάντα στον νου σου νάχεις την Ιθάκη. Το φθάσιμον εκεί είν' ο προορισμός σου. Αλλά μη βιάζεις το ταξείδι διόλου. Καλλίτερα χρόνια πολλά να διαρκέσει· και γέρος πια ν' αράξεις στο νησί, πλούσιος με όσα κέρδισες στον δρόμο, μη προσδοκώντας πλούτη να σε δώσει η Ιθάκη.

Η Ιθάκη σ' έδωσε τ' ωραίο ταξείδι. Χωρίς αυτήν δεν θάβγαινες στον δρόμο. 'Αλλα δεν έχει να σε δώσει πια.

Κι αν πτωχική την βρεις, η Ιθάκη δεν σε γέλασε. 'Ετσι σοφός που έγινες, με τόση πείρα, ήδη θα το κατάλαβες η Ιθάκες τι σημαίνουν."

Κωνσταντίνος Π. *Καβάφης (*1911*)*

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF SOCIAL AND HUMAN SCIENCES
DIVISION OF ECONOMICS

Doctor of Philosophy

ESSAYS IN LABOUR ECONOMICS
by Panagiotis Giannarakis

In this Ph.D. thesis I attempt to investigate in more depth, important topics in labour economics for the UK economy. In the first two chapters, I explore the effect of involuntary job separations on earnings and on aggregate productivity in the UK. In the third chapter, I investigate the efficiency of matchings between firms and workers in the UK's labour market. I highlight the efficiency of formal and informal channels during searching and finding a job.

More specifically in the first chapter, I exploit household data for the UK economy to estimate the magnitude and the temporal pattern of displaced workers earnings for the UK economy. By linking the British Household Panel Survey" with the Understanding Society" dataset, I have been able to extract a unique dataset of worker's employment histories for the UK from 1990 to 2011. In this chapter, I estimate the contribution of wage cuts and of the reductions in hours of working on the earning losses that are observed after a job separation. From the empirical estimations, I observe the following results: short run income losses for displaced workers with an unemployment flow after a displacement are about 19 percent and are reduced from 18 to 15 percent the following 3 years. The losses are higher for college educated workers than that with lower eduction. Finally, after decomposing income, a remarkable result is that these losses are mainly driven by cuts in wages (80%-90%) and not by reduction in the hours of working.

In the second chapter, I exploit the effect of involuntary job separations on aggregate productivity for the UK economy (as output per hour worked). More specifically, human capital has been found to be important for aggregate productivity, and large individual human capital losses are associated with job displacements. I investigate the role of involuntary job separations (since displacements have increased during the 2008 financial crisis) on the UK's productivity puzzle. By using the same dataset as in Chapter 1, I observe the following results: displacements of high tenured workers (more than 2 years in the same job prior to the separation) can explain on average the 27 percent of the post-crisis gap, if aggregate labour productivity had followed the path of the pre-2008 trend. Furthermore, almost the 78 percent of this effect can be explained by the drop in wages of college educated workers and the rest 22 percent by the drop in wages of non-college educated workers.

Finally, in the last chapter of this Ph.D. thesis, I empirically examine the workers' choice of using different channels of search during seeking for a job. I focus on the UK's labour market where the usage of referrals as a search channel is by 50% lower than that in the US. I estimate matching functions for 6 different channels and also introduce a new method in the literature which handles better possible endogeneity issues. By using the "Quarterly Labour Force Survey" and the "Vacancy Survey" datasets, the results show that the most efficient channel are referrals and the second most efficient one is the channel "Job advertisements". The channel with the lower matching efficiency is "Jobcenter, jobmarket or training and employment agency office".

Contents

List of Tables

List of Figures

Declaration of Authorship

I, Panagiotis Giannarakis, declare that the thesis entitled *Essays in Labour Economics* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Either none of this work has been published before submission, or parts of this work have been published as:

    –

Signed: ....

Date: ....

Acknowledgements

I would like to thank my good supervisor Dr Alessandro Mennuni for his great support and guidance especially during my third and fourth year of my Ph.D. program. Moreover, he helped and supported me very much during the last one year and a half, where I had to deal with the loss of my beloved Grandma. He had a major contribution in all parts of my Ph.D. thesis and without him, probably the completion of my Ph.D. thesis would have been impossible.

Also, I would like to thank my previous supervisor Professor John Knowles, for giving me the opportunity to enter to this Ph.D. program and achieve some of my dreams. With an excellent guidance the first two years of my Ph.D. program, he tried to give me all the necessary tools and knowledge for producing high standards of research in Economics and also led to a successful upgrade from M.Phil. to Ph.D. at the University of Southampton. Special thanks to Professor Manolis Galenianos and Dr Thomas Gall, who were my external and my internal examiner, respectively, in the Viva examination. They reviewed my Ph.D. thesis and made some very useful comments for corrections and improvements of this Ph.D. Thesis. Also I would like to thanks Dr. Panos Nanos for the great support and encouragement especially the first three years of my Ph.D. program. I would like to thank also Professor Paul Klein and Dr. Roman Sustek for the comments and the suggestions that they did on my second chapter of this Ph.D. thesis.

I would like to thank very much my beloved Grandma Ioanna Giannaraki. She raised me with the right principles and she supported me all these years especially during my studies in the UK. Without her, all my effort to come to the UK and extend my knowledge and my studies beyond Greece, would have been impossible. Unfortunately, for about a year she didn't manage to see me completing this Ph.D. thesis and left on the 29th of March 2015. But, I hope that up from the sky she can see me and maybe she feels proud about her grandson. Also, I would like to thank my Grandpa Panagiotis Giannarakis, a true hero in the Greek resistance during the WWII, who gave me all the necessary tools and principles to jump from my teenage to my adult life. My grandpa left on the 25th of October 2004 and he was a role model in my teenage life.

Finally, I would like to thank very much all my friends and relatives who have support me all these years. Special thanks to my father Panagiotis Giannarakis, my mother Maria Koutsourelaki, my two sisters Ioanna Nektaria Giannaraki and Emmanouela Giannaraki. Special thanks also to Sotia Georgiou, George Kotsampasakis, and to my friends which I made in Crete Motakis Giannis, Theodorakis George, Belas Kostas, Neratsakis Spyros, Thanasis Rentzios, Artemis Gramvousaki, Maria Grigoraki, Anna Tzouganaki, Michael Fronimakis, Odisseas Mathioudakis, George Xalakatevakis, Stamatis Konstantoulakis, Giannis Konstantoulakis, Antonis Kalogerakis, Vasilis Vasiliadis, Alexandros Karakostas, Evangelos Mitrokostas, Nikos Vlahakis, Christos Manoledakis, Olga, Maria and George Pentari, and Father George Petrakis. Special thanks to Eleni & Giannis Tsakiris, Giannis Leventakis, Marios Giannaris and all my relatives from Stalos. I would like to thank also my friends from the Master Luis Pinedo, Stefano Soccorsi, Katerina Tsakou, Thanos Papathanasiou, Dimitris Xanthopoulos, Zaira Koskina, Vaggelis Karkalakis, Haley Jackman. My friends from the Ph.D., the amazing friends Dafni Papoutsaki, Maria Kyriacou, and Nicholas Lazarou. My good friends Andres

Luengo, Carlos A. Pineda, Marcos Gomez, Jason Hilton, Elif Kara, Michael Kearns. Also Burak Kaan Demirta, Hao Xu, Rossella Icardi, Katarzyna Bech, Omar De La Riva, Yahia S. El-Horbaty, Kristine Nilsen, Adriana Duta, Tom Rushby, Fiona Wairimu Ngarachu, Dilek Yldz, Melike Alper, Giorgos Dritsakis, Jana Farrugia-Sadeh, Andrea Giovannetti, Ioanna Magklassis, Lena Magklassis, and Evangelos Mazomenos.

I would like to thank all the academic staff of the Department of Economics in the University of Crete who gave me the necessary tools and knowledge to achieve my dreams in England and especially Pr Milonakis Dimitris, Dr Nikolaidis Evangelos, Dr Tserkezos Dikaios, Pr Yiannopoulos Andreas, Pr Papadopoulos Athanasios, Pr Petrakis Emmanuel, Dr Genius Margarita, Dr Giannellis Nikolaos, and Dr Tsiotas Georgios.

I would like also to thank all the academic staff of the Department of Economics for the support and the great collaboration all these years and especially to Dr Emanuela Lotti, Dr Manos Mentzakis, Pr Jackline Wahba, Dr Jan Podivinsky, Dr Zacharias Maniadis, Dr Carmine Ornaghi, Pr Miltos Makris, Pr Jean-Yves Pitarakis, Dr Christos Ioannou, Dr Maksymilian Kwiek and Dr Spyros Galanis.

Finally, I would like to thank all the administrative staff in the University of Southampton for their great support all these years.

1

Introduction

In this Ph.D. thesis I attempt to investigate deeper important topics in labour economics for the UK economy. In the first chapter, I explore the effect of involuntary job separations on earnings and on wages. Furthermore, I quantify what is the contribution of wage cuts and hours of working decreases on earning losses followed by an involuntary job separation. In the second chapter, I am accounting how much of the UK's productivity puzzle can be explained by job displacements. Finally, in the third chapter, I investigate the efficiency of matchings from formal or informal channels between firms and workers in the UK's labour market.

The chapters of my Ph.D. thesis elaborate into the broader area of applied labour economics with a special focus on the UK economy. In the first two chapters, I investigate issues on job separations and in the third, issues on how firms and job seekers match in the labour market. These research areas are arising from a growing literature which investigates in depth job flows and their effect on the economy (see for instance **?**). These papers highlight the role of flows in and out from unemployment or from employment and investigate the mechanisms that drives them. So, this literature motivate me to investigate further on job finding and separation issues such as, on involuntary job separations and on the hiring methods between firms and workers.

In terms of literature on job flows, Hall (1995) uses data from Job Openings and Labour Turnover Survey (JOLTS) and estimates job-finding and separation rates for the US for the past 50 years. In another paper, Hall (2000) finds that the increases in the unemployment rate of the US are not due to a high separation rate but, more due to the fact that job finding rate is too low. Furthermore, **?** is the first researcher who introduces a new measurement of estimating the transition probabilities in and out of employment and unemployment. By using data from the Bureau of Labour Statistics (BLS) he estimates the job finding and the job separation rate in the US. **?** finds that the job separation probability is nearly acyclical and the job finding probability is strongly procyclical. **?** replicate the methodology introduced by **?** (using the Current Population Survey data) and they find evidence that inflow rates are on the contrary countercyclical, especially for workers who experienced layoffs. They also find that outflow rates are procyclical. Finally, they suggest that these evidence differ from **?** due to some measurement errors in the past literature and they propose ways to refine the methodology which was introduced by Shimer.

For the rest of the world, **?** estimate the unemployment dynamics in fourteen OECD countries and find that the 15 percent of the unemployment variation in the Anglo-Saxon countries are due to inflows in unemployment and the rest 85 percent to outflows. In the continental European and Nordic economies the relationship is different and inflows contribute by 45 percent of the variation in unemployment and the rest 55 percent is due to outflows. **?** estimate the unemployment dynamics in three European countries, which are the United Kingdom, France and Spain. For the UK economy they find that in the pool of unemployment, inflows is the higher contribution than outflows after mid 1980s but, its significance subsided again in the late 1990s and 2000s. Moreover, they find that outflow rates drive entire the unemployment dynamics in France. Finally, in Spain there is a significant contribution on dynamics of unemployment from both inflows and outflows. For the UK economy, Smith (2011) uses the British Household Panel Survey from 1988 to 2008 and finds that the 57 percent of the unemployment dynamics are due to inflows and only the 40 percent due to outflows. These results show that job separations play a crucial role in the UK on determining the level of unemployment and gives further motivation in this Ph.D. thesis.

Moreover, Fujita and Ramey (2009) by using the CPS gross flow data estimate the unemployment dynamics in the US and find the contribution of job finding and separation rates on them. A notable result from this paper is that Fujita and Ramey (2009) find a negative correlation of productivity with cyclical changes in the separation rate. Furthermore, productivity has a positive correlation with job finding rate. This result motivates me for a broader research on the aggregate effect of job separations on labour productivity, which I do in the second chapter of this thesis.

A direct effect of volatility in the employment dynamics are changes in the matching efficiency between worker and employers. So, the last chapter of this Ph.D. thesis also focuses in the broader area of applied labour economics, but is more concentrated in the area of search and matching theory. **?** along with **?** set up a theoretical framework on the concept of the matching functions and develop the well known Diamond-Mortensen-Pissarides model (Nobel Price in economics in 2010). The literature and the labour market equilibrium model with search and matching frictions is well presented in **?**. Moreover, in the well-known book "Equilibrium Unemployment Theory" Pissarides (2000) introduces more heterogeneity to the model.

Further motivation about a prior research on formal and informal hiring methods is coming from Granovetter (1995) who highlights the importance of friends, relatives and networks on the labour market. He finds that the 56% of male white-collar workers used referrals to find their current job (data from a Boston suburb). For the US, also Holzer (1987c) find that more than the 85% of the unemployed and new workers are using personal contact as a search method.

From the above literature, we can understand the important role of job flows and employment dynamics in the labour market. For that reason, I am motivating to investigate further interesting issues on labour economics such as, job displacements and hiring methods. These issues play a fundamental role in the labour market.

Therefore, the aim of this Ph.D. thesis is to address important topics in labour economics. A research in these topics seems critical since in the last decades a mass technological change has been observed globally. The massive growth in technology has rapidly changed the structure of the labour market, as well. New technological innovations and production methods have altered the wage distribution and the inequality in developed economies globally. For instance, Acemoglu (2002b) and Acemoglu (2002a) highlight that technological progress increases the inequality since it favours high skilled workers. Moreover, in some countries such in the UK, there is evidence that during the current crisis there is a shift to less productive sectors (see for instance Martin and Rowthorn (2012) and Martin (2011)).

As a result of the above described technological progress, over time there is a massive change firstly in the job requirements and also new jobs demand new qualifications (as part of a higher job creation and destruction rates). The latter and also the current economic crisis leads to increase in the job flows, to changes in the job finding and separation probabilities and to changes in the hiring methods both from job seekers and employers. These changes will eventually affect wages, labour productivity and the matching efficiency between unemployed and firms. For that reason, a deeper analysis of the overall effect of involuntary job separations, and of the matching process between employers and workers is very important for a better understanding of how the real economy works. The current Ph.D. thesis, attempts to combine these broad areas of research on labour economics and contribute to the literature by providing empirical evidence on the effect of involuntary job separations and the usage of formal and informal hiring channels by firms and job seekers in the UK's labour market.

1.1 Earning Losses due to Involuntary Separations.

In the first chapter of this Ph.D. thesis, I investigate the labour outcomes from involuntary job separations. Involuntary job separations or displacements are defined in this thesis as workers who experienced at least one job separation with the cause to be either a firing or a redundancy. In the literature there are many papers that investigate what are the effects of involuntary job separations on earnings and wages. Furthermore, lately there is also an extensive focus from policy makers to enlighten earning losses that are occurring due to job displacements.

For the US economy there is an extensive literature focusing on involuntary job separations. For instance Monks and Pizer (1998) use data for the period 1971 to 1990 taken from the U.S. National Longitudinal Surveys and they find a positive trend in the probability of job turnover. Furthermore, the positive trend is driven by involuntary job separations and the effect of voluntary job separation is insignificant. Polsky (1999) extents the literature by using data from the US Panel Study of Income Dynamics for the periods 1976-81 and 1986-91. He finds that job separations are behaving pretty stable for that period but there was a statistical significant increase in the involuntary job separations.

Furthermore, some literature (see Jacobson et al. (1993a), Neal (1995), and Couch and Placzek (2010)) focuses on involuntary job separations that are part of a plan closure or a mass layoff event. To understand what is a mass layoff, *WARN* defines the event where a reduction in labour force: “(A) is not the result of a plant closing; and (B) results in an employment loss at the single site of employment during any 30-day period for (i) at least 33 percent of the employees (excluding any part-time employees); and (ii) at least 50 employees (excluding any part-time employees); or (iii) at least 500 employees excluding any part-time employees (see also McKittrick and Schnairsohn (2008))”. They use this definition since in some cases, limitations in administrative data cause problems on identifying if the displaced worker left from the job voluntary or involuntary (Jacobson et al. (1993a)). Therefore, the cause of the separation cannot be distinguished between quit, retirement, firing or redundancy. The idea is that the majority of displaced workers who experience a mass layoff event have higher probability to lose their jobs involuntary than voluntary, and not because of their lower performance. They support that economic reasons led to their displacements. On the other hand, Hijzen et al. (2010) highlight that even in the latter case there is a selection problem from the firm side: low performing (or low productive) firms will have higher probability to close or to produce a mass layoff event.

In terms of results, all the recent studies conclude that there are sustained losses in earnings after an involuntary job separation. But the volume of these losses depends on the data that are used and differences across countries, states, industries, age and sex are observed. For instance, Ruhm (1991) uses data from the Michigan Panel Study of Income Dynamics and is the first who is suggesting that workers who experience a displacement event suffer from ”long lasting scars”. In his findings, displaced workers are earning 10-13% less than non-displaced workers. Note that non-displaced is a worker who is continuously employed and did not experienced a displacement event.

The first paper, however, which sets up the methodological standards for estimating earning losses after a displacement is coming from Jacobson et al. (1993a), who are using administrative data in Pennsylvania state from 1975-1985. In their influential paper *Earnings Losses of Displaced Workers*, they estimate the impact of a mass layoff event on future earnings. In these estimates they consider only job separations due to firm closures or to at least 25% reduction of the labour force of companies that made redundancies. In their findings, a 40% decrease in earnings is observed in the short run to a worker who experiences a mass layoff event (one year after the separation). These earning losses are persistent in the long run, as well. They find a 25% decrease in earnings of a displaced worker from a mass layoff event, 6 years after the separation. Finally, they conclude that these losses should be driven from losses in the accumulated firm-specific human capital that have occurred after the displacement. These losses in human capital made the displaced worker less productive as he would have been, if not displaced. Jacobson et al. (1993a) are using a very tractable empirical strategy for measuring earning losses after a displacement which is a fixed effect model. This model is used from other papers which are estimating earning losses after a displacement and is a quite standard empirical procedure in the literature. I use the same strategy, as well, to estimate the earning losses from involuntary job separations (firings or redundancies) in the UK economy.

One critique to the above estimates of Jacobson et al. (1993a), is that the empirical results cannot be generalised (Couch and Placzek (2010)). During the period that the data cover, high unemployment in a heavily industrialised state is observed and the job separation in the manufacturing sector is disproportionate higher than before. Thus, its questionable if those results are in fact true in periods of economic growth or in states (or countries) which are dominated by the service sector. For that reason, Couch and Placzek (2010) are using administrative data to replicate Jacobson et al. (1993a). They find more conservative and robust results for the state of Connecticut. Covering the period between 1993 and 2004, which is during more moderate times than Jacobson et al. (1993a), they find only 32% immediate earning losses after a mass layoff event, and 14% in the long run (6 years after a separation). There are other relative studies which are using different US data sets for estimating earning losses after a job separation with the results varying across states and data sets, as well. The main ones are Topel (1990), Carrington (1993), Neal (1995), Stevens (1997), Couch (1998), Chan and Stevens (1999, 2004), Kletzer and Fairlie (2003), and Jacobson et al. (2005, 1993b).

Jung and Kuhn (2012) go one step further and separate the earning losses after a job separation into three components. These components are the *selection effect*, the *extensive margin effect* and the *wage loss effect*. Selection effects which cause an upward bias can account for the 30% of the estimated earning losses. 20% is due to the fact that a worker after its first involuntary job separation has a higher probability to get displaced again in the future. The rest 50% is due to gaining lower wage in the new job. Furthermore, they apply an interesting decomposition of the last effect and they find that the 85% of the wage losses are due to losses in firm-specific human capital and the rest 15% due to losses in worker-specific human capital. In this chapter I can argue that my measures do not suffer from the *extensive margin effect*. This should be the case since in my data, I measure the earning losses for workers who experience only their first job separation. By eliminating this effect, I can ensure that the larger component of earning losses is the *wage loss effect*.

On the other hand, for the rest of the world the literature on earning losses after a displacement is more limited than that in the US. A remarkable finding in most European studies is that the volume of earning losses after a displacement is smaller from the findings for the US economy. For instance lower earning losses are observed by Eliason and Storrie (2006), Huttunen et al. (2011) and Ichino et al. (2013), who are using large administrative data from Sweden, Norway, and Austria respectively or from household surveys such as Couch and Placzek (2010) for Germany and Balestra and Backes-Gellner (2012) for Switzerland who find smaller negative impact on earnings or wages after a separation. Many other studies are included in Kuhn (2002) with similar findings.

It is worth to mention that, in the literature, there are many papers that find differences in the earning path after a displacement across education, age groups, unemployment duration and sex. For instance, Farber (2005), by using the "Displaced Workers Survey" (DWS) from 1981-2003, finds that a displacement event have different effect on workers' post-displacement earnings across educational categories for the US labour market. More specifically, for the period 1981-91, he finds that low educated workers suffer from larger earning losses than high educated workers. After 2001, however, this effect is been reversed, with high educated workers suffering larger losses than low educated workers. The latter findings are in line with the results of this paper.

In addition, Farber (2005) finds a very strong relationship between pre-displacement tenure and the drop in earnings after a displacement. Earning losses after a displacement are larger for those workers with a high tenure in their previous job than than for those workers who had low tenure in their previous jobs. Kletzer (1989) and Addison and Portugal (1989) (both studies use data from DWS for the years 1979-84) find a positive correlation between previous job tenure and earning losses after a displacement. Addison and Portugal (1989) also find that a higher post-displacement unemployment duration had a larger impact on earning losses after an involuntary job separation. For Britain, Borland et al. (2002) use the BHPS dataset for the years 1991-1996, just as the current research does for the period 1990-2011, and finds that older workers and those with a higher duration of unemployment after a job separation experience larger pay cuts than the average. It is noteworthy that the majority of the abovementioned findings are again in line with the results of the current paper.

Farber (2005) finds that job-loss rates among younger and less educated workers are higher than those of older and more educated workers. The results of that paper also show that the earning losses which occur after a job separation is relatively large for older displaced workers since it is more likely that they have accumulated more specific human capital than younger workers before their displacement. Furthermore, Farber (2005) finds that, after their displacement, women have lower unemployment and employment rates than men. For Britain, Borland et al. (2002) find that the earning losses for women who experience a displacement event is around twice larger than that of men. The above results are also in line with my findings across gender, and different age groups.

For the UK, except from the current research, there are another two papers which are investigating losses in earning due to separations. The first one is Borland et al. (2002) who is using the BHPS data set for a limited period of 5 years (1991-1996). They find that on average a 2 to 14 percent penalty in wages is observed after a separation. Furthermore, workers who had a period of non employment after the displacement are experiencing larger losses. Since the period is limited up to 5 years, the estimation of earning losses by the fixed effect model of Jacobson et al. (1993a) cannot extract robust results in the long run (5 years after the separation). The reason is that only the long run effect of displacements that occurred within 1991 on earnings can be observed until 1996, which makes the sample limited.

The second one is coming from Hijzen et al. (2010) who are using administrative data from New Earning Survey (NES) and the Inter-Departmental Business Register (IDBR). They observe 18 to 35 percent losses in earnings from workers that lost their job due to a firm closure and only 14 to 25 percent from a mass layoff event. In terms of data limitation, this administrative data set (as commonly happens) does not contain information about what is the reason which makes a worker separate from his job and become either unemployed or to drop out from the labour force (Hijzen et al. (2010)). So, it is not known if a displacement is voluntary or involuntary which is an important distinction in terms of earning losses.

In general, the negative magnitude in earning losses after an involuntary separation should be expected to be quite larger than voluntary separations (Balestra and Backes-Gellner (2012)). Only household data, as the BHPS, provide this information since the reason of leaving a job is being asked to each individual who experiences a job separation. This chapter is less ambitious than the previous literature and I am documenting more stylised facts rather than identifying unbiased estimates of earning losses after a displacement. It worth to mention though that there is no evidence in all the previous studies if earning losses are driven by cuts in wages or by decreases in hours of working, which this chapter attempts to highlight.

As I mentioned above, in terms of findings, the majority of this literature conclude that there are long run losses in earnings after an involuntary job separation. More specifically, these studies have extracted very interesting empirical results. Jacobson et al. (1993a), for instance, in their influential paper *Earnings Losses of Displaced Workers*, find 40% short-run and 25% long-run earning losses for high tenured workers experiencing a mass layoff event (Pennsylvania state: 1975-1985). Many other papers have come to the same conclusion of firm-specific human capital losses due to job separation)[1]. The latter implies that losses in firm-specific human capital should be reflected on wages as well. But, in the literature, there have been no further investigations regarding what drives these earnings losses after job separations. So, one challenging question is the following: is it the case that the losses in income after a displacement are driven by wage cuts, as human capital theory suggests, or by cuts in hours of working? This chapter tries to answer the question raised above by quantifying the contribution of wage cuts and decreases in hours of working on earning losses after displacements.

More specifically, this chapter is contributing in the literature by investigating the behaviour of earnings before and after an involuntary job displacement in the UK economy. It documents what the earnings losses after a job separation at the individual level are, as well as how much of these losses are driven by wage cuts and by reductions in hours of working after a job displacement occurs at the aggregate level. Jacobson et al. (1993a) highlight the importance of this kind of research since they mention that *"..lack of data prevent us from decomposing earnings losses into effects due to lower wages and reduced hours"*. This research can overcome the data limitations of some past papers and fill this gap in the literature by estimating the contributions of wage cuts

[1] See for instance Kletzer (1989, 1998), Neal (1995), Carrington (1993) and Couch and Placzek (2010)

and decreases in hours of working on earnings losses.

In terms of empirical analysis at an individual level, I follow the standard methodology of estimating earning losses after an involuntary job separation (see, for instance, Jacobson et al. (1993a), and Couch and Placzek (2010)). I estimate earning losses after a displacement for different groups of workers depending on their pre-displacement tenure, their unemployment duration after the displacement, and their level of education. I sort the sample into these subgroups since many past papers find differences in earning paths after a displacement depending on tenure, education, and unemployment duration.

In the analysis, I use a large unbalanced panel with thousands of individuals where standard panel regression techniques cannot be applied (Cameron and Triverdi (2005)). For that reason, I run a fixed effect model with Driscoll-Kraay standard errors and observe the following results: the monthly real labour income losses for high tenured (more than two years in the same job before the separation) displaced workers with an unemployment flow after the involuntary separation is almost 19% one year after the separation; and, that that figure reduces from 18% to 15% during the following 3 years. Five years after the displacement income losses are decreased to 6 percent. The wage losses on the other hand are smaller. Workers who are included in this group are experience a 15 percent short-run wage cuts. These cuts are reduced to 5% in the long-run. For a job-to-job flow following an involuntary job separation, the losses both in income and wages are much smaller and, in the long-run, income and wages almost reach their potential level if the worker had not been displaced. Note that this chapter defines an involuntary job separation as the event where a worker loses his or her job because either the company made a redundancy or the worker got fired.

Since I estimate the earning losses after a job separation at the individual level, the distinguished methodology of this chapter for addressing the role of wage cuts on income is that I decompose labour income into its two components: wages and hours of working. In most administrative data, this is not possible since a variable which gives information on hourly wages is missing from the employment histories. I do this decomposition by running two counterfactual exercises. In the first one, I keep the post-displacement wages equal to those before the displacement and measure the post-displacement earnings by using the actual post-displacement hours of working. After that, I compare the actual earnings with the estimated earnings had the post-displacement wages been fixed. The percentage change between actual and estimated earnings is the contribution of hours of working on earning losses after a displacement. On the other hand, in the second counterfactual, I keep fixed the post-displacement hours of working with those before the displacement and allow post-displacement wages to fluctuate over time. With that counterfactual, I can measure the contribution of cuts in wages on earning losses after a displacement. I find that high tenured workers who had an unemployment spell following an involuntary job separation experience large and sustained income losses and wage cuts in the post-displacement period. Furthermore, on average, 85 percent of the income losses are purely driven by wage cuts, with only 6 percent being purely driven by decreases in hours of working. Finally, these losses are much smaller for individuals who had a job-to-job flow after the separation; nevertheless, the contribution of wages on these losses are almost 86 percent.

1.2 Can Job Displacements explain the UK's Productivity Puzzle?

In the second chapter of this Ph.D. thesis, I am investigating the possible aggregate effects from involuntary job separations. I am interested on this research since at a micro level there are many papers which are arguing that a displaced worker will become less productive in the new job as he would have been if not displaced. More specifically, as described above, previous studies on job displacements have extracted very interesting empirical results. Jacobson et al. (1993a) find a 40% short-run and 25% long-run earning losses for high tenured workers who experience a mass layoff event (Pennsylvania state: 1975-1985). They conclude that this *"lost attribute might be some form of specific human capital"*. Many other papers arrive at the same conclusion; i.e. that there are firm-specific human capital losses due to job separation (Kletzer (1989, 1998), Neal (1995), Carrington (1993), and more recently, Couch and Placzek (2010)). For more details about this literature see also Abowd et al. (2009).

Jung and Kuhn (2012) go one step further and separate the earning losses which occur after a job separation into three components. These components are the *selection effect*, the *extensive margin effect* and the *wage loss effect*. *Selection effect* which cause an upward bias can account the 30% of the estimated earning losses. 20% is due to the fact that worker, after their first involuntary job separation, have higher probability to experience a displacement event again in the future. The remaining 50% is due to gaining lower wage in the new job. Furthermore, they conduct an interesting decomposition of the last effect. They find that 85% of the wage losses are due to losses in firm-specific human capital and that the remaining 15% are due to losses in worker-specific human capital. In this paper, I can argue that my measures do not suffer from the *extensive margin effect*. This should be the case since I measure the post- and pre-displacement levels of wages, earnings, working hours, etc., for workers who have only experienced their first job separation. By eliminating this effect, I can ensure that the larger component of earning losses referred to in this research is due to the *wage loss effect*. This is due to some short of losses in the specific human capital after the involuntary job separation. In the literature, however, there is a gap between translating the individual productivity losses due to displacements, into their aggregate effects, which this chapter attempts to cover.

Further motivation about a primary focus on the UK economy comes from three papers which estimate earning losses after a job separation at the individual level. Their results encourage me to investigate the aggregate effect that displacements have on the UK's labour productivity. All these studies confirm the general findings of Jacobson et al. (1993a); i.e. that there are productivity losses after job separations. The first paper that motivates me is Borland et al. (2002). According to their findings, on average, there is a 2 to 14 percent penalty in wages observed after a separation (1991-1996). Larger losses are, thus, estimated between workers who had a period of non-employment after displacement. The second one is coming from Hijzen et al. (2010). They observe 18 to 35 percent losses in earnings from workers that lost their jobs due to a firm closure and only 14 to 25 percent losses from a mass layoff event (1994-2003).

I present more recent stylised facts in Chapter 1. In this Chapter, I give more insides about the separation effect on earnings, for the UK between 1991 and 2011. I estimated that, on average, high tenured employees experience 18% short-run and 12% long-run earning losses after an involuntary job separation. The short-run losses are larger for college educated workers than for those with no college education. Nevertheless, earnings of college educated workers are recovering quicker. Moreover, at an aggregate level, the earning losses which accrued after a job separation were 86% driven by wage cuts[2]. These results may imply that, and for the UK economy, individual productivity losses occurred after a displacement. Furthermore, these losses should vary across high and low educated workers. The above findings drive this chapter to further investigate about any aggregate effect of displacements on the UK's productivity during the 2008 recession.

But the question is why should we be interested on a primary research for the UK economy? I argue that involuntary job separations should have played a role in determining the post-crisis productivity. I observe that in the UK during the current crisis the fraction of displaced employed workers who had more than two years of tenure in their previous job, has increased by 50% and that their wages have decreased by about 16% relatively to that before the crisis. At this point it will be beneficial to describe the UK economy and the productivity puzzle that has been created during the recent crisis. In the first quarter of 2008, the UK entered one of the deepest recessions in its modern history. During this crisis, real GDP and labour productivity (as output per hour

[2]I decompose earnings losses into wage cuts and working hours decreases.

worked) dropped by over 7%, with the UKs economy only starting to recover following the trough of the crisis in 2009Q2. After the trough, real GDP began to recover fast and finally reached its pre-crisis trend. Surprisingly, though, productivity did not follow the same path. More specifically, during the last 5 years, the UK experienced almost zero growth in labour productivity, following a 2.5% annual growth rate in the pre crisis period. This zero growth in labour productivity is due to the fact that both employment and total hours worked are recovering faster than real GDP. This has been called the UK's productivity puzzle and recently has attracted the attention of many researchers who are trying to give plausible explanations to this puzzle (e.g. Blundell et al. (2014), Gregg et al. (2014), Oulton and Sebastia-Barriel (2013), Goodridge et al. (2013) and Barnett et al. (2014)[3]).

Perhaps surprisingly, though, the literature does not consider displacements as being a factor which has the potentiality of explaining part of the UK's productivity puzzle. I argue that involuntary job separations should have played a role in explaining part of the UK's productivity puzzle since, in the UK, during the current crisis, I observe a large increase in the fraction of displaced workers with a severe drop in their wages in comparison with that before 2008. Further motivation for a focus on the UK is coming from the following findings: in the US a productivity puzzle is not observed since after the recession both GDP and output per hour worked recovered strongly (see Hughes and Saleheen (2012) and Oulton and Sebastia-Barriel (2013), among others). Furthermore, involuntary job separations increased only by 23% in comparison with the UK where the effect was almost 2 and a half times larger. Thus, since in the UK we observe zero growth in productivity, it makes stronger the argument that the UK productivity puzzle may related with displacements.

This chapter attempts to make a contribution to the growing literature on the UK's productivity puzzle. It aims to provide more insights and highlight the role of displacements on post-crisis productivity. In the literature there are many papers which attempt

[3]See also: Martin (2011), Martin and Rowthorn (2012), Pessoa and Reenen (2013).

to explain this puzzle. For instance, Blundell et al. (2014) find that aggregate labour productivity should have been affected by the increase in the labour supply and by flexible wages. They conclude that the reduction in wages (which implies a reduction in labour productivity) cannot be explained by compositional changes in the labour force. These studies do not, however, focus on any compositional changes to the displaced and non-displaced groups; something which might have affected labour productivity. Gregg et al. (2014) find that, in recent years, real wages have been much more sensitive to negative shocks than in previous recessions.

Furthermore, Pessoa and Reenen (2013) argue that, since real wages dropped during the crisis, a labour-capital substitution exists which has made the UK economy less productive. They find that capital shallowing explains the 68% of the puzzle. On the other hand, there are other papers such as Martin and Rowthorn (2012) and Martin (2011), which suggest that compositional changes in the labour force in favour of low-skilled workers and less productive sectors account for 33% of the puzzle. Goodridge et al. (2014) challenge the capital shallowing and the supply-side hypotheses and argue that this puzzle is, actually, a TFP puzzle, claiming that that would explain 33% of the UK's productivity puzzle. Furthermore, Oulton and Sebastia-Barriel (2013) argue that the recession and the financial crisis have caused permanent damage on the aggregate productivity of the UK. They find that the banking crises have decreased the short-run growth of labour productivity by around 0.65% each year, as well as the long-run level by around 1%.

From the above literature we can observe that displacements in the UK have been ignored on the explanation of the productivity puzzle. The aim of this chapter is to give more insight as to why output per hour worked did not catch up its pre-2008 trend. In particular, I study the possible role that involuntary job separations (or displacements) of high tenured workers had on post-2008 productivity; an aspect which the literature has ignored so far. Since, in the UK, during the current crisis, I observe that the fraction of displaced employed workers who had more than two years of tenure in their previous job, has increased by 50% and that their wages have decreased by about 16% relatively to that before the crisis, it becomes natural to ask to what extent these productivity losses for workers who have experienced a displacement event can explain the UK's productivity puzzle.

As I mentioned above, one possible reason why displacements should matter for productivity comes from Jacobson et al. (1993a)(among many others), who suggest that, after a job separation, the high tenured displaced workers lose some of their accumulated, firm-specific human capital. These individual human capital losses make these workers less productive in their new job vis-a-vis how they would have been if they had not been displaced. Intuitively, these human capital and productivity losses should be important at an aggregate level as well. Some evidence has been provided by Fujita and Ramey (2009) who find a negative correlation in productivity and cyclical changes in the job separation rate. Further motivation comes from the past literature, which studies the effect of compositional changes on the labour force and the role of human capital at the aggregate level. Acemoglu and Autor (2012) in their interesting review of the magnum opus (as they characterised it) of Goldin and Katz (2009), "*The Race between Education and Technology*", underline the fundamental role of human capital in determining the economic growth of an economy (in their case, the USA). By running a careful accounting exercise, they measure that, on average, 15 percent of the USs economic growth is due to increases in human capital. Moreover, compositional changes are also important for business cycle fluctuations. Some empirical evidence are coming from Jaimovich and Siu (2009), who show that changes in the labour composition by age, affect the business cycle volatility (for the US and other G7 economies), and Mennuni (2013) who finds that age, gender and educational redistributions altered aggregate volatility (US: 1967-2013).

It is not very surprising that the empirical results of this chapter show that the displacements of high tenured workers (i.e. workers who had more than 2 years at the same job prior to the separation) can explain, on average, 27% of the post-crisis gap between actual productivity and potential productivity if productivity had followed the pre-2008 trend. Furthermore, 78 percent of this effect can be explained by job separations of college educated workers, with the remaining 22 percent being able to be explained by separations of non-college educated workers.

In the literature there are papers that built models based on the idea that, during a recession, there is a "cleansing" out effect of firms and workers which are less efficient and less productive, as well as a redirection of the economy into more efficient production arrangements[4]. This literature contrasts with my empirical findings from the UK economy. On the other hand, Barlevy (2002) points out that empirical evidence finds that job quality is pro-cyclical. The new jobs that are created during a recession have a higher probability of being temporary and low-paying. Furthermore, empirical evidence has shown that the new jobs that are created during recessions are more likely to have lower than the average productivity of a match between workers and employers during a more normal period. Bowlus (1993) and Davis et al. (1996) find that there is a higher probability of a job destruction for new jobs created during a recession than new jobs created during an expansion. The latter implies that firms during a recession are unlikely to keep the same short of production arrangements in the long run. In addition, Bowlus (1993) (in line with Bils (1985) and Shin (1994)) find that the new jobs that are created during a recession are generated from the lower wage pool of workers; something which implies that these workers are not that productive. The results of the current study that the displacements of college educated workers can explain the 21 percent of the UK's productivity puzzle, are in line with the above empirical evidence.

[4]See for instance Hall (1995, 2000), Mortensen and Pissarides (1994), Caballero and Hammour (1994); Caballero et al. (1996), Gomes et al. (2001), and Jaimovich and Siu (2012).

1.3 Matchings through formal and informal channels: The UK case.

In the last chapter of this Ph.D. thesis, I investigate the role of personal contacts in the labour market of the UK. There are many papers in the literature that examine the role of friends, relatives and networks in the labour market. Rees (1966) is one of the first researchers who argues that there might be a preference towards informal job matching methods from both the unemployed, who are searching for jobs, and employers. Granovetter (1995) highlights the importance of referrals on the labour market, finding that 56% of male white-collar workers in a Boston suburb use referrals to find their current job (data from a Boston suburb). For the US, Holzer (1987c) finds that the 85% of the unemployed workers used personal contacts among other methods while searching for a job and the 87% of new workers found their current job through referrals (data from National Longitudinal Survey of Youth for the years 1981-1982).

Furthermore, Lin et al. (1981) use survey data and obtain that the 59% of the workers found their current job from referrals (Albany, New York). Similar results are coming from Bridges and Villemez (1986) who use employed survey data in the Chicago SMSA (1981). Elliott (1999) finds that the 77% of unemployed (aged between 21 and 64) use referrals as one of their searching channel (data from Multi-City Study of Urban Inequality which includes the metropolitan areas of Atlanta, Boston, Detroit and Los Angeles and this paper considers only low educated workers). Corcoran et al. (1980) use data from the Panel Study of Income Dynamics and find that more than 50% of all workers found their current job through referrals. Furthermore, 24 studies surveyed by Bewley (1999) brings this number from 30 to 60 percent.

Similar results as that in the US are extracted internationally. Wahba and Zenou (2005) obtain the following results: about one third of the Egyptian workers find their current job through personal contacts and 52% of the job seekers use this channel while searching for a job (Labour Market Survey for the year 1998). Alon (1997) also finds high fraction of unemployed who are using referrals as a searching method in Israel whereas Addison and Portugal (1989) by using the Labour Force Survey find a smaller usage of friends and relatives in the Portuguese labour market (about 25 percent). Pellizzari (2010) is inline with Addison and Portugal (1989) and finds that only between 25 to 40 percent of the employed find their current job by using personal contacts in 14 European countries (data from the European Community Household Panel for the years 1994 to 1999). Finally, Gregg et al. (2014) use the UK's Labour Force Survey for the year 1992 and report that the 70% of unemployed use referrals while searching for a job. The latter estimates are about 15% smaller than my estimates for the period of $2000-2015$[5].

From the firm side, many papers have documented the extensive usage of personal contacts by employers while recruiting potential workers for a job vacancy. For instance, Marsden and Gorman (2001) use data from the National Organizations Survey and find that from 37 to 53 percent of employers advertise new job vacancies through the personal network of their current employees. Holzer (1987a) uses data from the Employment Opportunity Pilot Project, and he finds that 36% of the firms use personal network during the recruitment process for hiring new workers. Data from Chicago-area surveys of firms show that personal network of employees are used by 65 to 88 percent of their current employers during the hiring period (see Neckerman and Kirschenman (1991) and Miller and Rosenbaum (1997)). Finally, Fernandez et al. (2000) and Fernandez and Castilla (2001) find that referrals is extensively used as a hiring method[6].

The usage of referrals as a searching channel for a job also varies across different demographic groups. For instance, since there is a higher probability for low educated and

[5]For more details about the literature on referrals until 2011 see Topa (2011)

[6]Both studies (Fernandez et al. (2000) and Fernandez and Castilla (2001)) use data from the Phone Customer Services Representative for the years between 1995 to 1996. These are data of hires for entry level jobs at a large phone center within a global financial services institution.

low income workers to lose their job, as Elsby et al. (2010) document, these groups of workers are using referrals more intensively while searching for a job (see also Kuzubas (2010)). On the other hand, Pellizzari (2010) proposes that the higher usage of friends, relatives and personal contacts from low type job seekers might be due to differential adverse selection and due to problems in signaling across different occupations and education levels. There are many other papers that find a higher usage of networks for low type job seekers[7]. Elliott (1999) obtains that referrals are used significantly more intensively by unemployed from high poverty neighborhoods than those who reside in low poverty neighborhoods. The latter job seekers have higher probability to use formal hiring channels than informal. For Atlanta, Green et al. (1995) find that low income unemployed have a higher probability to use personal contacts for finding a job than that of a high income. There is also evidence that job seekers in blue-collar occupations are more likely to use referrals than the job seekers in white-collar occupations (see for instance Corcoran et al. (1980) and Rees and Shultz (1970)).

Furthermore, some papers investigate the gender differences in the usage of referrals by job seekers, where the results are mixed. Some of them find that men are more likely to use friends, relatives and networks while searching for a job than women job seekers (Corcoran et al. (1980), Bortnick and Ports (1992), Bradshaw (1973), Ports (1993)). On the other hand, there are findings that are controversial to the above results and suggest that women job seekers use more informal methods than men (Moore (1990) and Marsden and Campbell (1990) among others). Furthermore, there are studies which find that young job seekers with little or no experience have higher probability to use friends and relatives as a searching method (Corcoran et al. (1980), Marsden and Hurlbert (1988), Wegener (1991)). However, there are other papers which support that there are no significant differences in the usage of informal methods between age groups (see Hilaski (1971) and Falcon (1995))[8].

[7] See for instance Datcher (1983), Ornstein (1976), Corcoran et al. (1980) and Marx and Leicht (1992).

[8] There is also an extensive literature on the differences in the usage of formal and informal channels by job seekers across different racial and ethnic groups such as: Corcoran et al. (1980), Datcher (1983, 2006), Green et al. (1999), Holzer (1987b), Marx and Leicht (1992) and Korenman and Turner (1996).

In terms of labour outcomes, there are several studies which find that personal contacts increase the job finding rate of employees. Topa (2001) using Census data for the city of Chicago (1980 and 1990) finds that a one standard deviation increase in neighborhood employment raises job finding rate from 0.6 to 1.3 percent and these results are stronger for low educated workers. By using confidential longitudinal data from the 1979 National Longitudinal Survey of Youth (NLSY), Weinberg et al. (2004) find that a one standard deviation increase in neighborhood employment increases the annual total hours worked by 9.5 percent. Bayer et al. (2008) using the US Census of population for the Boston metropolitan area (1990) arrive to the following result: a one standard deviation increase in potential personal contacts increase labour income from 2% to 3.7% and total weekly hours from 0.3 to 1.8 hours for men and labour force participation from 0.8% to 3.6% for women.

Granovetter (1995) argues that weak ties offer better information to job seekers about perspective jobs and also higher wage outcome than strong ties. Moreover, Montgomery (1991) finds that weak ties increase the reservation wage of an employee. Schmutte (2015) obtains that for job seekers a significant amount of job offers are received through referrals. He finds also that for non-native workers the magnitude of the effect of personal contacts on the quality of the job is almost two times stronger than that from natives, and that non-native workers are more likely to use social networks to find a work[9]. Conley and Topa (2007) use the same data sources as Schmutte (2015) and extract that the average wage premium in a worker's network has a positive effect on the wage premia of an individual worker who is part of this network. Additionally, they find that referrals generate the 10% of the offers for a job to potential workers. For the UK labour market, Cappellari and Tatsiramos (2010) find that one additional employed friend increases the job finding rate by 3.7% and the wages by 5% (British Household Panel Survey from 1992 to 2003).

[9]Data from Longitudinal Employer Household Dynamics Program of the US Census Bureau linked to data on workers Census blocks of residence from the Statistical Administrative Records System.

In the UK, my estimates from the "Quarterly Labour Force Survey" (QLFS) for the years between 2001 and 2015 are quite lower than that obtained from the US. Across 6 different channels of searching for jobs, referrals are used only by about 54% of unemployed persons. Furthermore, as a labour outcome, 26% of new workers found their current job through referrals. So, in this paper, I empirically investigate what is the matching efficiency across different channels of search and highlight the role of referrals on the UK's labour market.

Since there is a lower fraction of job seekers and workers who are using informal channels while looking for a job in the UK than in the US, in this chapter, I estimate whether there are any significant differences in the efficiencies between matchings through referrals and matchings through formal channels. Therefore, the broader question that this research attempts to answer is whether referrals in the UK have the highest matching efficiency. To my knowledge, this is the first paper which estimates matching efficiencies through different channels of search. I focus on the UK economy, and I follow the standard methodology which is used in the literature (see, for instance, Galenianos (2014) and Sahin et al. (2014)), but I also introduce an alternative estimation which handles possible endogeneity issues in the estimations better. By using the "Quarterly Labour Force Survey" (QLFS) and the "Vacancy Survey" datasets for the years between 2001 and 2015, I tackle these broader questions by estimating a matching function where both the workers and the firms can meet through several channels.

In the literature, there are papers which estimate the matching functions at an aggregate level, but also across industries and occupations. The majority of the past papers estimate matching functions in the form of a Cobb-Douglas. For instance, Barnichon and Figura (2015, 2011) estimate an aggregate matching function in the form of a Cobb-Douglas for the US economy and find that the aggregate matching efficiency across time to be between 0.7 and 1.1. Davis et al. (2013) also estimate Cobb-Douglas matching functions with a common elasticity (as I do) and industry-specific efficiency parameters, finding variation in the matching efficiencies across industries for the US (data from JOLTS for 2001-2011). Galenianos (2014) estimates a Cobb-Douglas matching function across sectors of the US economy and finds that the matching efficiency across industries varies from 0.78 to 1.89, depending on the sector[10]. Sahin et al. (2014) investigate mismatches in the US labour market and, by using data on hires from the JOLTS database, estimate industry-specific matching efficiencies to be between 0.76 and 1.71 before the crisis and between 0.7 and 1.87 after the crisis. Furthermore, by using data on hires from CPS, they estimate industry-specific matching efficiencies between 0.33 and 0.5 before and after the crisis. Furthermore, they estimate occupation-specific matching efficiencies between 0.32 and 0.58 before the crisis, and between 0.33 and 0.63 after the crisis. Sahin et al. (2014) impose matching functions in the form of a Cobb-Douglas, as Galenianos (2014) does, since they estimate the elasticity of substitution for a general CES matching function to be statistically close to 1.

Patterson et al. (2013) also investigate mismatches in the UK labour market by using data from the "Vacancy Survey", the "Jobcentre Plus Vacancy Statistics" and "Labour Force Survey". They follow the methodology introduced by Sahin et al. (2014), and estimate sectoral matching efficiencies from between 0.43 and 0.66 for the pre-crisis period and between 0.4 and 0.57 for the post-crisis period. It is worth to note that also Patterson et al. (2013) impose a Cobb-Douglas matching function[11].

According to my knowledge, however, the current research is the only one which investigates the aggregate matching efficiency of both formal and informal searching channels in the labour market. This researchs primary focus is the UK economy. I follow Galenianos (2014) and Sahin et al. (2014) in estimating the matching efficien-

[10]Galenianos (2014) uses monthly data from 2001 to 2011 of industry-specific unemployed taken from the CPS, and of hires and industry-specific vacancies taken from JOLTS.

[11]More studies on estimation of aggregate matching functions can be found in Petrongolo and Pissarides (2001).

cies across different search channels by assuming that the matching functions are in the form of a Cobb-Douglas. For the purpose of estimating the matching efficiencies across channels, I follow the standard methodology that is used in the literature. On the other hand, Borowczyk-Martins et al. (2013) argue that this estimation methodology (i.e. of matching functions) could suffer from possible endogeneity biases stemming from the search behaviours of both job seekers and employers. For that reason, I introduce an alternative methodology which can reduce this potential bias. Finally, I also follow Sahin et al. (2014), who suggest that one should model the matching efficiency dynamics through structural breaks and time-varying polynomials in order to handle this potential bias in the estimates. According to Sahin et al. (2014) and Borowczyk-Martins et al. (2013), the latter methodology is more robust to endogeneity issues compared to all of the other methodologies. The estimates of the matching efficiencies from these three different methodologies are quite similar, and the ranking of the matching efficiencies across channels is the same independently from the methodology that I used. In all the estimations, I find that referrals have the highest matching efficiency. The channel "Job Advertisement" has the second highest matching efficiency and "Direct Applications" have the third highest matching efficiency. The channel "Private employment agency or business", on the other hand, has a low matching efficiency. Finally, the searching channel with the lowest matching efficiency is "Jobcenter, Jobmarket, etc.".

2

Are Earning Losses after Involuntary Separations, Wage Driven? The UK Case.

2.1 Introduction

Lately, there has been an extensive focus from both researchers and policymakers on lightening earning losses caused by job displacements (or job separations). The majority of previous literatures conclude that there are long-run losses in earnings after an involuntary job separation (Jacobson et al. (1993a), Neal (1995), Couch and Placzek (2010)). More specifically, these studies have extracted very interesting empirical results. Jacobson et al. (1993a), for instance, in their influential paper *Earnings Losses of Displaced Workers*, find 40% short-run and 25% long-run earning losses for high tenured workers experiencing a mass layoff event (Pennsylvania state: 1975-1985)[1].

[1] *WARN* defines a *mass layoff* as a reduction in labour force that: (A) is not the result of a plant closing; and (B) results in an employment loss at the single site of employment during any 30-day period for (i)

They conclude that this *"lost attribute might be some form of specific human capital"*. Many other papers have come to the same conclusion of firm-specific human capital losses due to job separation)[2]. The latter implies that losses in firm-specific human capital should be reflected on wages as well. But, in the literature, there have been no further investigations regarding what drives these earnings losses after job separations. So, one challenging question is the following: is it the case that the losses in income after a displacement are driven by wage cuts, as human capital theory suggests, or by cuts in hours of working? This chapter tries to answer the question raised above by quantifying the contribution of wage cuts and decreases in hours of working on earning losses after displacements.

This research makes a contribution to the literature by investigating the behaviour of earnings before and after an involuntary job displacement in the UK economy. It documents what the earnings losses after a job separation at the individual level are, as well as how much of these losses are driven by wage cuts and by reductions in hours of working after a job displacement occurs at the aggregate level. Jacobson et al. (1993a) highlight the importance of this kind of research since they mention that *"..lack of data prevent us from decomposing earnings losses into effects due to lower wages and reduced hours"*. This chapter can overcome the data limitations of some past papers and fill this gap in the literature by estimating the contributions of wage cuts and decreases in hours of working on earnings losses. In terms of results, I find that high tenured workers who had an unemployment spell following an involuntary job separation experience large and sustained income losses and wage cuts in the post-displacement period. Furthermore, on average, 85 percent of the income losses are purely driven by wage cuts, with only 6 percent being purely driven by decreases in hours of working. Finally, these losses are much smaller for individuals who had a job-to-job flow after the separation; nevertheless, the contribution of wages on these losses are almost 86 percent.

at least 33 percent of the employees (excluding any part-time employees); and (ii) at least 50 employees (excluding any part-time employees); or (iii) at least 500 employees (excluding any part-time employees). See also McKittrick and Schnairsohn (2008).

[2] See for instance Kletzer (1989, 1998), Neal (1995), Carrington (1993) and Couch and Placzek (2010)

A research conducted on the UK economy for the purpose of studying earning losses after job displacements is quite salient since there were two recessions which occurred during the period between 1990 and 2011; it is also quite salient because one can observe the results of displacement events on earnings, not only at the regional level, but at the country level as wellsomething which many papers fail to focus on (see for instance Jacobson et al. (1993a) and Couch and Placzek (2010)). In order to tackle the question raised above, this chapter uses the "British Household Panel Survey" dataset (BHPS) for the years between 1990 and 2011. I also link this dataset with its last two waves, which are contained in the "Understanding Society" dataset. The latter makes the data that this research uses a long panel including the 2008 crisis. To my knowledge, this is the first attempt to create employment histories in the UK for the 1990-2011 period. Another contribution of this chapter is that it is the first, to my knowledge, which examines the behaviour of earnings, of wages, and of hours of working for the UK economy by using the BHPS dataset.

In terms of empirical analysis at an individual level, I follow the standard methodology of estimating earning losses after an involuntary job separation (see, for instance, Jacobson et al. (1993a), and Couch and Placzek (2010)). I estimate earning losses after a displacement for different groups of workers depending on their pre-displacement tenure, their unemployment duration after the displacement, and their level of education. I sort the sample into these subgroups since many past papers find differences in earning paths after a displacement depending on tenure, education, and unemployment duration.

In the analysis, I use a large unbalanced panel with thousands of individuals where standard panel regression techniques cannot be applied (Cameron and Triverdi (2005)). For that reason, I run a fixed effect model with Driscoll-Kraay standard errors and observe the following results: the monthly real labour income losses for high tenured (more than two years in the same job before the separation) displaced workers with an unemployment flow after the involuntary separation is almost 19% one year after the separation; and, that that figure reduces from 18% to 15% during the following 3 years. Five years after the displacement income losses are decreased to 6 percent. The wage losses on the other hand are smaller. Workers who are included in this group are experience a 15 percent short-run wage cuts. These cuts are reduced to 5% in the long-run. For a job-to-job flow following an involuntary job separation, the losses both in income and wages are much smaller and, in the long-run, income and wages almost reach their potential level if the worker had not been displaced. Note that this research defines an involuntary job separation as the event where a worker loses his or her job because either the company made a redundancy or the worker got fired.

Since I estimate the earning losses after a job separation at the individual level, the distinguished methodology of this chapter for addressing the role of wage cuts on income is that I decompose labour income into its two components: wages and hours of working. In most administrative data, this is not possible since a variable which gives information on hourly wages is missing from the employment histories. I do this decomposition by running two counterfactual exercises. In the first one, I keep the post-displacement wages equal to those before the displacement and measure the post-displacement earnings by using the actual post-displacement hours of working. After that, I compare the actual earnings with the estimated earnings had the post-displacement wages been fixed. The percentage change between actual and estimated earnings is the contribution of hours of working on earning losses after a displacement. On the other hand, in the second counterfactual, I keep fixed the post-displacement hours of working with those before the displacement and allow post-displacement wages to fluctuate over time. With that counterfactual, I can measure the contribution of cuts in wages on earning losses after a displacement.

It is worth mentioning that, in the literature, there are many papers that find differences in the earning path after a displacement across education, age groups, unemployment duration and sex. For instance, Farber (2005), by using the “Displaced Workers

Survey" (DWS) from 1981-2003, finds that a displacement event has different effect on workers' post-displacement earnings across educational categories for the US labour market. More specifically, for the period 1981-91, he finds that low educated workers suffer from larger earning losses than high educated workers. After 2001, however, this effect is been reversed, with high educated workers suffering larger losses than low educated workers. The latter findings are in line with the results of this paper.

In addition, Farber (2005) finds a very strong relationship between pre-displacement tenure and the drop in earnings after a displacement. Earning losses after a displacement are larger for those workers with a high tenure in their previous job than for those workers who had low tenure in their previous jobs. Kletzer (1989) and Addison and Portugal (1989) (both studies use data from DWS for the years 1979-84) find a positive correlation between previous job tenure and earning losses after a displacement. Addison and Portugal (1989) also find that a higher post-displacement unemployment duration had a larger impact on earning losses after an involuntary job separation. For Britain, Borland et al. (2002) use the BHPS dataset for the years 1991-1996, just as the current research does for the period 1990-2011, and finds that older workers and those with a higher duration of unemployment after a job separation experience larger pay cuts than the average. It is noteworthy, that the majority of the abovementioned findings are again in line with the results of the current paper.

Farber (2005) finds that job-loss rates among younger and less educated workers are higher than those of older and more educated workers. The results of that chapter also show that the earning losses which occur after a job separation are relatively large for older displaced workers since it is more likely that they have accumulated more specific human capital than younger workers before their displacement. Furthermore, Farber (2005) finds that, after their displacement, women have lower unemployment and employment rates than men. For Britain, Borland et al. (2002) find that the earning losses for women who experience a displacement event is around twice larger than that of men. The above results are also in line with my findings across gender, and different age groups.

As discussed above, the findings in the past literature suggest that there are differences in earning paths after a displacement across education, age groups, unemployment duration, and sex. I am also investigating whether this is the case for the UK's labour market. As a first step in my analysis, I consider two different groups of displaced workers. Workers who found a job right after the involuntary separation - and thus had a job-to-job flow - and workers who had an unemployment spell in between jobs after they got displaced. I consider high-tenured workers who were continuously employed with the same employer for at least 2 or 3 years before the separation. Finally, I find whether there are any differences in the contribution of wages on earning paths after a displacement for college vis-a-vis non-college educated workers.

The first group consists of workers who had a job-to-job flow following an involuntary job separation. From my estimates, the drop in earnings for workers who experience such a flow after a displacement are more severe for those with more than 3 years of pre-displacement tenure than those with more than 2 years. On average, workers with 2 years of pre-displacement tenure experience a 9.7% earnings loss in the first 3 years after an involuntary job separation and 14.1% for those with 3 years of tenure. Furthermore, we can observe that total hours of working do not differ much after the displacement from that before the displacement. This demonstrates the crucial role of wage cuts on earning losses. On average, 83% of the drop in earnings for both groups of worker are purely driven by wage cuts. Furthermore, in most of the cases after a displacement, there is no reduction in the total hours of working.

I also separate this group of workers into two subgroups, college and non-college educated displaced workers, and run the same counterfactuals. A notable result is that, on average, college educated workers do not face losses after a job-to-job separation and changes in earnings are driven both by changes in hours of working and in wages.

On the other hand, for non-college educated workers, there is observed, on average, a 17.9% earnings loss in the first year after the separation for displaced workers with at least 2 years of pre-displacement tenure, and 24.7% for displaced workers with at least 3 years of pre-displacement tenure. Finally, these losses are, on average, 85% driven by wage cuts.

The second group consists of workers who had an unemployment spell, after the displacement and before finding a new job. For this group of worker, one can observe that there is a higher magnitude (i.e. 3 percentage points) in the drop of earnings for workers with more than 3 years of pre-displacement tenure than for those with more than 2 years of pre-displacement tenure (20.5% versus 17.5%, respectively). Furthermore, these losses are 80% purely driven by wage cuts independently from tenure. For this period, only 2% of the earning gap, on average, is purely driven by decreases in working hours.

In my analysis, I also investigate the role of unemployment duration on earnings following a displacement. Thus, I run the same counterfactuals for workers with different unemployment durations. Due to data limitations, I chose the median of the unemployment duration which, in this case, is 3 months. As expected, the magnitude of losses is larger for workers with more than three months of unemployment after a job separation than that with less than (or equal to) 3 months. For the short-run unemployed, these losses are, on average, 10.6 percent for workers with over two years of tenure and 11.8 percent for workers with over three years of tenure. For the long-run unemployed, the losses are, on average, 27.5 percent for workers with over two years of tenure and 34.3 percent for workers with over three years of tenure.

It should be mentioned that the contribution of wages on the earning losses for workers with short unemployment durations are, on average, from 35 to 40 percent higher (depending on tenure) than those workers with long durations of unemployment. More specifically, the contribution that cuts in wages have on earning losses is 108% for those who are unemployed for short periods of time (or short unemployed) and 70.5% for those who are unemployed for long periods of time (or long unemployed). These results show that the hours of working for the short unemployed are either stable or actually increasing after the displacement.

I also split this sample of workers into high and low according to their education. The results for college educated workers with over two years of tenure contradict the ones with a job-to-job flow. There is a large drop in earnings for college educated workers after a job separation but, after the first year, their earnings recover quickly and have the tendency to reach their pre-displacement level of earnings. On the other hand, the short-run losses for non-college educated workers is less than that of college educated workers but are, nevertheless, more stable in the long-run and do not recover. The above results imply that the earnings of high type workers have a more severe short-run effect (the drop is larger) than for the low type, but their earnings recover faster than the low type. Finally, another notable result is that the drop that high type displaced workers experience in their earnings is almost purely driven from wage cuts (more than 100%), whereas, for low type workers only by 61% . If we consider workers with more than 3 years of tenure, on the other hand, the results are different. There is a larger drop in earnings for high type workers with more than 3 years of tenure after a job separation from those who have at least 2 years of tenure. After the first year, though, their earnings losses are sustained and do not recover. The same is true for the earning recovery of low type workers with more than 3 years of tenure where the magnitude of losses is smaller than that of high type workers. As a final remark, we can see that the drop in earnings is almost 95% purely due to wage cuts for high type workers with more than 3 years of tenure and only 66% due to wage cuts for low type workers.

Furthermore, female displaced workers who had a job-to-job flow after a displacement do not face any losses in their earnings; instead they experience small gains. The drop in earnings in a job-to-job displacement for men are severe and large. On average, workers with at least 2 years of pre-displacement tenure experience a 16.5% earning loss in the first 3 years after an involuntary job separation, whereas those with 3 years of tenure experience a 21.6% earning loss . These losses for male displaced workers are almost purely wage-driven. The results for female displaced workers who had an E-U-E flow are in contradiction with those who had a job-to-job flow. There is a large drop in earnings for female workers after a job separation which is, on average, 26.8% in the first year, whereas, for men, it is smaller (19.2%). It is noteworthy that the drop in earnings of female workers are purely 60.4% driven by cuts in wages and 36.5% driven by reductions in hours of working, whereas, for male displaced workers, 81.5% of earning losses are driven by wage cuts, with their hours of working actually increasing.

If I split the sample into three different age groups, the results are not always well determined because of the small sample size - something which was noted by Borland et al. (2002) as well. In this case, there is a large drop in earnings for young displaced worker who had a job-to-job flow; middle aged displaced workers do not suffer from any losses after a displacement; and old workers face smaller losses in their earnings. The main finding is that the earning losses for young workers are almost purely driven by wage cuts, whereas, in the first 2 years after the displacement of old workers, earning losses are 78% driven by wage cuts and 20% driven by decreases in hours of working. On the other hand, the drop in earnings for the three age groups of worker who had an unemployment spell after the displacement and before finding a new job (a E-U-E flow) were, in most cases, an expected result based on the past literature. The drop in earnings are higher for old displaced workers (37% in the first two years), quite smaller for middle aged workers (18%), and young workers almost do not suffer from any losses after a displacement. The main finding for these groups of worker is that the earning losses for middle aged workers are almost purely driven by wage cuts, whereas, in the first 2 years after the displacement of old workers, 53% is purely driven by wage cuts and 31% are driven by decreases in hours of working.

Note that, for all of these estimates, I compare the pre-displacement earnings with that of the post-displacement earnings. I am aware that these stylised facts do not show the actual difference between the post-displacement earnings and the potential earnings had the workers not been displaced, since I do not control for individual and demographic characteristics. Furthermore, I expect that the magnitude of these losses to be 1 to 2 percent higher than that from my estimates had I take into account that the growth rates of earnings and wages in a non-displaced group (continuously employed in the same firm) was, on average, 1% per year. The above counterfactuals do not account for this effect in the estimates.

In the next section, the literature review is presented and, in the third part, a detailed description of the data is provided. In the fourth section, the statistical model for estimating labour income and earning losses and the decomposition of earnings into its components is presented. The empirical results are presented in the fifth section of this chapter. And, finally, in the last section, I summarise the findings of this paper.

2.2 Previous Literature

This chapter attempts to contribute to the growing literature of the earning losses after an involuntary job separation. It aims to give more insides and to highlight the contribution of wages and hours of working on the drop of earnings that are observed after a displacement event for the UK economy. For the US economy there is an extensive literature focusing on involuntary job separations. For instance Monks and Pizer (1998) use data for the period 1971 to 1990 taken from the U.S. National Longitudinal Surveys and they find a positive trend in the probability of job turnover. Furthermore, the positive trend is driven by involuntary job separations and the effect of voluntary job separation is insignificant. Polsky (1999) extents the literature by using data from the US Panel Study of Income Dynamics for the periods 1976-81 and 1986-91. He finds that job separations are behaving pretty stable for that period but there was a statistical significant increase in the involuntary job separations.

There are many other papers which are measuring earning losses after an involuntary displacement. The main focus of these papers are on workers who have experienced an involuntary separation due to a firm closure or to a mass layoff event[3]. The literature usually considers firm closures or a mass layoff events where displacements are assumed to be exogenous and the whole workforce is affected. They use this definition of displaced workers since usually in the data there is not a direct distinction between high and low productive workers. But as Hijzen et al. (2010) highlight, even in this case there is a selection problem from the firm side. It should be expected that the low performing (or low productive) firms will have higher probability to close or to produce a mass layoff event.

All the recent studies conclude that there are sustained losses in earnings after an involuntary job separation. But the volume of these losses depends on the data that are used and differences across countries, states, industries, age and sex are observed. For instance, Ruhm (1991) uses data from the Michigan Panel Study of Income Dynamics and is the first who is suggesting that workers who experience a displacement event suffer from ”long lasting scars”. In his findings, displaced workers are earning 10-13% less than non-displaced workers[4].

The first paper, however, which sets up the methodological standards for estimating earning losses after a displacement is coming from Jacobson et al. (1993a), who are

[3]“WARN” defines a “mass layoff” as a reduction in labour force that: (A) is not the result of a plant closing; and (B) results in an employment loss at the single site of employment during any 30-day period for (i) at least 33 percent of the employees (excluding any part-time employees); and (ii) at least 50 employees (excluding any part-time employees); or (iii) at least 500 employees (excluding any part-time employees)(see: McKittrick and Schnairsohn (2008)).

[4]Non-displaced is a worker who is continuously employed and did not experienced a displacement event.

using administrative data in Pennsylvania state from 1975-1985. They estimate the impact of a mass layoff event on future earnings. In these estimates they consider only job separations due to firm closures or to at least 25% reduction of the labour force of companies that made redundancies. In their findings, a 40% decrease in earnings is observed in the short run to a worker who experiences a mass layoff event (one year after the separation). These earning losses are persistent in the long run, as well. They find a 25% decrease in earnings of a displaced worker from a mass layoff event, 6 years after the separation. Finally, they conclude that these losses should be driven from losses in the accumulated firm-specific human capital that have occurred after the displacement. These losses in human capital made the displaced worker less productive as he would have been, if not displaced. Jacobson et al. (1993a) are using a very tractable empirical strategy for measuring earning losses after a displacement which is a fixed effect model. This model is used from other papers which are estimating earning losses after a displacement and is a quite standard empirical procedure in the literature. I use the same strategy, as well, to estimate the earning losses from involuntary job separations (firings or redundancies) in the UK economy. The fixed effect model is described in more details in the empirical strategy section.

One critique to the above estimates of Jacobson et al. (1993a), is that the empirical results cannot be generalised (Couch and Placzek (2010)). During the period that the data cover, high unemployment in a heavily industrialised state is observed and the job separation in the manufacturing sector is disproportionate higher than before. Thus, its questionable if those results are in fact true in periods of economic growth or in states (or countries) which are dominated by the service sector. For that reason, Couch and Placzek (2010) are using administrative data to replicate Jacobson et al. (1993a). They find more conservative and robust results for the state of Connecticut. Covering the period between 1993 and 2004, which is during more moderate times than Jacobson et al. (1993a), they find only 32% immediate earning losses after a mass layoff event, and 14% in the long run (6 years after a separation). There are other relative studies which are using different US data sets for estimating earning losses after a job separation with the results varying across states and data sets, as well. The main ones are Topel (1990), Carrington (1993), Neal (1995), Stevens (1997), Couch (1998), Chan and Stevens (1999, 2004), Kletzer and Fairlie (2003), and Jacobson et al. (2005, 1993b).

Jung and Kuhn (2012) go one step further and separate the earning losses after a job separation into three components. These components are the *selection effect*, the *extensive margin effect* and the *wage loss effect*. Selection effects which cause an upward bias can account for the 30% of the estimated earning losses. 20% is due to the fact that a worker after its first involuntary job separation has a higher probability to get displaced again in the future. The rest 50% is due to gaining lower wage in the new job. Furthermore, they apply an interesting decomposition of the last effect and they find that the 85% of the wage losses are due to losses in firm-specific human capital and the rest 15% due to losses in worker-specific human capital. In this chapter I can argue that my measures do not suffer from the *extensive margin effect*. This should be the case since in my data, I measure the earning losses for workers who experience only their first job separation. By eliminating this effect, I can ensure that the larger component of earning losses is the *wage loss effect*.

On the other hand, for the rest of the world the literature on earning losses after a displacement is more limited than that in the US. A remarkable finding in most European studies is that the volume of earning losses after a displacement is smaller from the findings for the US economy. For instance lower earning losses are observed by Eliason and Storrie (2006), Huttunen et al. (2011) and Ichino et al. (2013), who are using large administrative data from Sweden, Norway, and Austria respectively or from household surveys such as Couch and Placzek (2010) for Germany and Balestra and Backes-Gellner (2012) for Switzerland who find smaller negative impact on earnings or wages after a separation. Many other studies are included in Kuhn (2002) with similar findings.

For the UK, except from the current research, there are another two papers which are investigating losses in earning due to separations. The first one is Borland et al. (2002) who is using the BHPS data set for a limited period of 5 years (1991-1996). They find that on average a 2 to 14 percent penalty in wages is observed after a separation. Furthermore, workers who had a period of non employment after the displacement are experiencing larger losses. Since the period is limited up to 5 years, the estimation of earning losses by the fixed effect model of Jacobson et al. (1993a) cannot extract robust results in the long run (5 years after the separation). The reason is that only the long run effect of displacements that occurred within 1991 on earnings can be observed until 1996, which makes the sample limited.

The second one is coming from Hijzen et al. (2010) who are using administrative data from New Earning Survey (NES) and the Inter-Departmental Business Register (IDBR). They observe 18 to 35 percent losses in earnings from workers that lost their job due to a firm closure and only 14 to 25 percent from a mass layoff event. In terms of data limitation, this administrative data set (as commonly happens) does not contain information about what is the reason which makes a worker separate from his job and become either unemployed or to drop out from the labour force (Hijzen et al. (2010)). So, it is not known if a displacement is voluntary or involuntary which is an important distinction in terms of earning losses.

In general, the negative magnitude in earning losses after an involuntary separation should be expected to be quite larger than voluntary separations (Balestra and Backes-Gellner (2012)). Only household data, as the BHPS, provide this information since the reason of leaving a job is being asked to each individual who experiences a job separation. This chapter is less ambitious than the previous literature and I am documenting more stylised facts rather than identifying unbiased estimates of earning losses after a displacement. It worth mentioning though that there is no evidence in all the previous studies if earning losses are driven by cuts in wages or by decreases in hours of working, which this research attempts to highlight.

2.3 Data

The data that are used in this chapter are household UK data provided by the Institute for Social and Economic Research of the University of Essex. I use the British Household Panel Survey (BHPS) and construct employment and earning histories in a panel form. For the employment histories, I follow and improve the methodology which is used by Smith (2011) and for the earning histories by Smith (2013) (in these papers, there is a more detailed description of the data). BHPS is a long panel with quite rich data on working histories, labour and non labour income, wages, hours of working, individual and job characteristics and Macroeconomic and local market indicators. Individuals can be followed at most for 20 years, starting from the end of 1990 to the end of 2011 (waves 1-20). Worth noting that it is the first analysis which can measure flows in and out of unemployment for the period until 2011 including the current economic crisis. For making the sample representative of Great Britain (excluding Scotland) this analysis uses longitudinal weights.

The first contribution of this chapter, in terms of data, is that I improve the methodology that is introduced by Paull (2002) and Smith (2011) for constructing the panel from the BHPS dataset. On average, I gain 5 to 15 percent more information than Smith (2011). Furthermore, I link this dataset with new releases which are included in a different dataset (with different structure). This dataset is the ”Understanding Society” and to my knowledge, is the first attempt to create employment histories in the UK for a period of time from 1990 to 2011.

More specifically, I improve the construction of the data set by gaining 15% more information in the employment histories than Smith has in her papers (Smith (2011), Smith (2013)). For data inconsistencies, Smith follows the reconciliation method which is introduced by Paull (2002). This method is the following: ”The start date for the second spell in overlapping spells was set to the end date of the first spell. If the spells had the same start date or the first spell began after the second, the second spell is dropped.” (See Paull (2002) Appendix B, point C). The latter implies that if an individual is employed for the whole period in one wave (i.e wave A) and has the same job in the subsequent wave (i.e wave B), then clearly the spell in wave B overlaps wave A. For instance, lets assume that an individual was interviewed in August 2004 and stated that the starting date of his current job was on September 2001 (defined as wave A for the purpose of this example). Next year, in August 2005 the same individual is interviewed again (defined as wave B). This individual stated that he has remained in the same job that he had last year. He also has to report again the starting date of his current job which will be September 2001. So, for this example the first employment spell (wave A) starts on September 2001 and finishes on August 2004 and the second spell (wave B) starts on September 2001 and finishes on August 2005. Clearly, wave B overlaps wave A and according to the above described methodology we have to drop wave A. However, by deleting the spell in wave A, as Smith does, very important information on growth in earnings, wages, hours of working, benefits, etc. over time (from wave to wave) is lost. The same occurs for individuals who are currently unemployed or out of the labour force.

The above methodology can be a critique on Smith (2013) where she makes estimations on earnings, wages, hours of working without taking into consideration a possible growth on these variables over time (or over waves). I improve the methodology of constructing the data firstly by not following the method for overlapping spells, as Smith does. In this paper, I keep both waves and only drop from the second wave (wave B) all the information that overlaps with the previous wave (wave A). Therefore, in the above example, I keep wave A (September 2001 to August 2004) and from wave B I keep only the information that does not overlap with the previous wave (wave B). So, the starting date of wave B will be August 2004, and the ending date August 2005.

Worth mentioning that Smith has less than 132,000 spells. On the other hand, this research, by following the above described methodology, constructs more than 243,000 spells for the first 18 waves and overall almost 270,000 spells. These spells are converted into a monthly panel for each individual of at most 256 months. 32,869 individuals create a rich data set with 4,436,077 monthly spells.

In addition, this chapter gains from 5% to 15% more information by applying the following rule: from subsequent waves, for instance wave A & B, the employment history of an individual in his last spell of wave A should always be the same as the first spell of wave B, as soon as the individual's employment status did not change. For instance, let us assume that in wave A an individual got interviewed on August 2004 and stated that he was employed from January 2004, reporting also earnings, hours of working, etc. Next year (wave B) in August 2005 he got interviewed again and he stated that he didn't change employment status from wave A and was employed until March 2005. After that he lost his job and became unemployed until August 2005. By construction of the BHPS dataset for the first spell in wave B (August 2004-March 2005) the individual did not report hours of working. However, since he didn't change employment for this period from wave A, it must be the case that this missing information can be replaced from the previous wave A. So, lost information on hours of working, wages, etc. which are not reported if an individual will change employment status within wave B (this information is reported only in the last spell of each wave but not in the previous spells of this wave), can be regained by using the complete information of the last spell from wave A.

Furthermore, a demanding goal was to link the data obtained from the BHPS with that of the Understanding Societys, which is the continuation of the original sample for waves 19 and 20. In that attempt, unfortunately, quite important information for this research was lost from the construction of the new survey. In the new survey, the Understanding Societys data has complete information for the last spell of each wave but, disappointingly, does not contain information on earnings, benefits, industrial and occupation classifications for the spells within a wave. For instance, if a worker changes his or her employment status four times during a single year (within the same wave), complete information regarding their earnings, etc., is only provided at the last spell and offers limited information for all the other spells. One issue which could potentially influence the results of this chapter is the classification of college and non-college educated workers. In the original BHPS dataset, there is a variable which uses the International Standard Classification of Education (ISCED) as a measurement. Unfortunately, in the Understanding Societys dataset, there is no direct variable for that distinction; furthermore, in the Appendix A, it is explained how an education variable is generated.

Another issue which can legitimately be raised is why this chapter does not use the Labour Force Survey (LFS), which is a larger dataset than BHPS. The reason that the BHPS is used is that, unlike LFS, the BHPS portrays employment histories better and more holistically. In the survey, it asks the exact date of any employment flows into employment (E), unemployment (U), and out of the labour force (O) within a wave. Furthermore, it can follows the same individual across time without imposing any restrictions in the length of the time period that this individual will be interviewed. So, there is a complete history of each individual for at most 20 years. On the other hand, in the LFS, only a quarter of information about employment status (i.e. the employment status at the time of the interview) for, at most, 5 subsequent quarters is provided. It is, thus, obvious that a long-run estimation of the earnings after a displacement (5 years after) is impossible to be generated using the LFS.

2.4 Methods

2.4.1 Definition of Earnings and Wages Losses and Statistical Model

In this section I define what are the earnings and wage losses and present briefly the statistical methodology that I am using for estimating these losses after an involuntary separation. For the measures of monthly earning losses I use the net weekly labour income times 4.33. For the measures of the hourly wage rates I use the net weekly labour income and I divide it by the total weekly hours worked, including overtime. Both measures are deflated to 2010 prices. Furthermore, I follow the previous literature which sets up the methods for estimating earning losses after a displacement and mainly from Jacobson et al. (1993a) and Couch and Placzek (2010). In these papers, they are using a sample of workers who have been displaced and they construct a counterfactual: what would have been their earnings if they had not experienced a displacement event. Then they look into the differences between the actual post-displacement earnings and the potential earnings if the displacement event had not occurred by estimating a panel. More specifically, let me denote y_{it} as the earnings (or the hourly wages) of a worker *i* at time *t*, and $D_{i,s}$ a dummy variable which is equal to one if a worker *i* has been displaced at date *s*, and zero otherwise. They define the following as a loss:

$$E(y_{it}|D_{i,s}=1, I_{i,s-p}) - E(y_{it}|D_{i,s}=0, \forall s, I_{i,s-p}) \tag{2.4.1}$$

With $I_{i,s-p}$ to be an information set available at time $s-p$. This information set contains individual-specific earnings determinants independently if the worker experiences a displacement event, and *p* is sufficiently large to ensure that the events which lead to a separation started after the date *s-p*.

Since our data cover a long period of time containing many individuals, the goal is to obtain a clear pattern of earnings across time and across displaced workers. To achieve that, Jacobson et al. (1993a) use a series of dummy variables D_{it}^n which represent the period of time that a worker got displaced. For each individual *i*, these dummy variables will be equal to one if in period *t* this worker has been displaced *n* quarters before the displacement. Note that *n* can be negative, representing the quarters before a first displacement has occurred. The focus is on these dummy variables, since a displaced worker in 1997 who got displaced 3 years before is as much in the same position as a worker in 2006 who got displaced in 2003 (Jacobson et al. (1993a)). For the purpose of this study, I am using a fixed effect model with worker-specific time trends $\alpha_i t$ and controls for fixed and time-varying characteristics. These controls are limited to age and age squared, as (Jacobson et al. (1993a)) also do. So, the fixed effect model is:

$$y_{it} = \gamma_i + \alpha_i t + \eta_t + x_{it}\beta + \sum_{n \geq -k} \xi_n D_{it}^n + \varepsilon_{it} \tag{2.4.2}$$

Where *n* represents that the displacement occurred *k* quarters before or -*k* quarters after *t*. γ_i is the "fixed effect", which shows the effect of permanent differences between displaced workers in unobserved and observed characteristics. η_t captures the general time pattern of earnings, and the vector x contains the controls that are used for this research. ξ_n represents the effect of displacements on earnings *n* quarters prior separation, and ε_{it} is the error term which is assumed to be uncorrelated across time and individuals and has constant variance. The least square estimations of the parameters in 2.4.2 (including the fixed effects) are unbiased and this approach generalises the widely used "difference in difference" technique (Jacobson et al. (1993a))[5].

[5] A technique which is using a "control" group of non-displaced and compares their earnings with the "treatment" group of displaced workers.

2.4.2 Decomposition of Earnings

For estimating the contribution of wage cuts and decreases in hours of working on earning losses after a job separation, I decompose the earnings following the bellow counterfactual exercises. Firstly, I keep the post-displacement wages equal to that before the displacement and measure the post-displacement earnings by using the post-displacement actual hours of working. Then I compare the actual earnings with this estimated earnings (if I keep wages fixed). The percentage change between actual and estimated post-displacement earnings is the contribution of hours of working on earnings. On the other hand, in the second counterfactual exercise, I keep the post-displacement hours of working fixed with that before the displacement and allow wages to fluctuate over time. With that counterfactual I measure the contribution of wages on earnings.

In mathematical terms the way to measure how much of the earning losses is purely driven by wage cuts or purely driven by decreases in hours of working I do the following: we know that earnings are equal with the product of wages times the hours of working. So the pre-displacement earnings (E) are equal to the product of pre-displacement wages (w) times the pre-displacement hours of working (h). So, $E = wh$. The same is true for the post-displacement earnings E^d which are equal to the post-displacement wages (w^d) times the post-displacement hours of working (h^d), and so $E^d = w^d h^d$. Then, the potential post-displacement earnings by using the pre-displacement hours of working will be equal to $E_h^p = w^d h$. And the potential post-displacement earnings by using the pre-displacement level of wages will be equal to $E_w^p = wh^d$.

The earning gap between pre-displacement and post-displacement period is equal to $\Delta E^d / E^d = (E - E^d)/E^d$. The earning gap that is created purely by wage cuts is equal to $\Delta E_h^p / E_h^p = (E - E_h^p)/E_h^p$ and the earning gap that is created purely by decreases in hours of working is equal to $\Delta E_w^p / E_w^p = (E - E_w^p)/E_w^p$. The question is what is the change in earnings, if wages change by Δw, and hours of working by Δh? To answer this question I do the following:

$$\begin{aligned} E + \Delta E &= (w + \Delta w)(h + \Delta h) = wh + w\Delta h + h\Delta w + \Delta w \Delta h \overset{E=wh}{\Leftrightarrow} \\ \Delta E &= w\Delta h + h\Delta w + \Delta w \Delta h \Leftrightarrow \\ \frac{\Delta E}{E} &= \frac{w\Delta h}{wh} + \frac{h\Delta w}{wh} + \frac{\Delta w \Delta h}{wh} \end{aligned} \tag{2.4.3}$$

And so:

$$\frac{\Delta E}{E} = \frac{\Delta h}{h} + \frac{\Delta w}{w} + \frac{\Delta w}{w}\frac{\Delta h}{h} \tag{2.4.4}$$

Where $\frac{\Delta E_h^p}{E_h^p} = \frac{E - E_h^p}{E_h^p} = \frac{wh - w^d h}{w^d h} = \frac{w - w^d}{w^d} = \frac{\Delta w}{w^d}$ and $\frac{\Delta E_w^p}{E_w^p} = \frac{E - E_w^p}{E_w^p} = \frac{wh - wh^d}{wh^d} = \frac{h - h^d}{h^d} = \frac{\Delta h}{h^d}$ and the last two components on the right hand side of 2.4.4 are the interactions between wages and hours of working.

2.4.2.1 An example of measuring the contribution of wages and hours of working on earnings losses

For a deeper understanding of the decomposition of earning losses into wage cuts and decreases in hours of working, I give an arithmetic example. Let's assume that the pre-displacement earnings of a worker who experienced a job displacement is equal to $E = wh = 1000$. From that, the hourly wage was equal to $w = 4$ and the total monthly hours of working were $h = 250$. On the other hand, N quarters after the displacement, his post-displacement wage was equal to $w^d = 3$ and the post-displacement hours of working equal to $h^d = 200$. So, the post-displacement earnings were equal to $E^d = w^d h^d = 3 * 200 = 600$. Then, the potential post-displacement earnings by using the pre-displacement hours of working would have been equal to $E_h^p = w^d h = 3 * 250 = 750$, and the potential post-displacement earnings by using the pre-displacement level of wages would have been equal to $E_w^p = wh^d = 4 * 200 = 800$.

With the same logic as above, the earning gap between pre-displacement and post-displacement period is equal to $\Delta E/E^d = (E - E^d)/E^d = (1000 - 600)/600 = 0.667$ or 66.7%. The earning gap that is created purely by wage cuts is equal to $\Delta E_h^p/E_h^p = (E - E_h^p)/E_h^p = (1000 - 750)/750 = 0.333$ or 33.3% and the earning gap that is created purely by decreases in hours of working is equal to $\Delta E_w^p/E_w^p = (E - E_w^p)/E_w^p = (1000 - 800)/800 = 0.25$ or 25%. This means that the 33.3% out of the 66.7% (which is equal to 50%) of the earning losses are created purely by wage cuts, and the 25% out of the 66.7% (which is equal to 37.5%) of the earning losses are created purely by decreases in hours of working. The rest 12.5% is a residual.

2.5 Empirical Results

2.5.1 Earning Losses after a Displacement

2.5.1.1 Introduction

In this section, I present the empirical results from the statistical model of estimating labour income and wages losses after a displacement which is described above. Firstly, I present the estimation output from three different models (Models 1-3) and conclude that the third model is the appropriate one that I am going to use for the rest of the chapter. In model 1, I run a robust estimate of the variance-covariance matrix (VCE) in a fixed effect estimation for the case where: $N \nrightarrow \infty$, $T \rightarrow \infty$. In model 2, I run a Feasible Generalised Least Squares (FGLS) estimation for the case where: $N \nrightarrow \infty$, $T \rightarrow \infty$. Finally, in model 3 (which is the model that I am using for the rest of the empirical analysis), I run a Fixed Effect regression with Driscoll-Kraay standard errors, where $N \to \infty$ and $T \to \infty$[6]. I run these estimations for three different groups of separators: I) for all the displacements, II) for the job to job flows following a displacement and III) for the displacements which include an unemployment spell after the separation. In the Appendix A, Tables A.1, A.2, A.3, A.4, A.5 and A.6 show the estimation outputs of the labour income and wages paths, respectively for these three models. At this point, I keep the analysis simple (as Jacobson et al. (1993a) and Couch and Placzek (2010) do) and I control only for age, age squared and time. To estimate the models described in the previous section, I consider only workers with a high tenure before the displacement: the worker has to work continuously in the same job for at least 2 years before the separation.

2.5.1.2 Empirical Estimations of Labour Income Losses after an Involuntary Separation

This part presents the empirical estimations of labour income losses followed an involuntary job separation for high tenured workers who find a job after a displacement. I do three different estimations. In the first one, there are only displaced workers who found a job (noted as E), but they had a flow which includes an unemployment spell (noted as U) right after the involuntary separation (noted as E-U-E). In the second one, I include workers with a job to job flow following the separation (noted as E-E), and in the third one, I include all the separations. As expected, the losses are larger and significant for separators with a flow which includes an unemployment spell right after the involuntary separation (first group) and quite smaller for the rest of the groups. Furthermore, I also run the same estimations by separating the sample into high (or college) and low (or non-college) educated workers. It is remarkable that the income losses path of these two groups of workers are not the same neither in levels nor in percentage terms. High type workers are suffering larger and substantial income losses than that from the low

[6]For more details about these models and a discussion on the selection of model 3 as the most appropriate one, see Appendix A.

educated workers.

Table 2.1: Estimated monthly earnings before and after an involuntary job separation, for different groups of workers

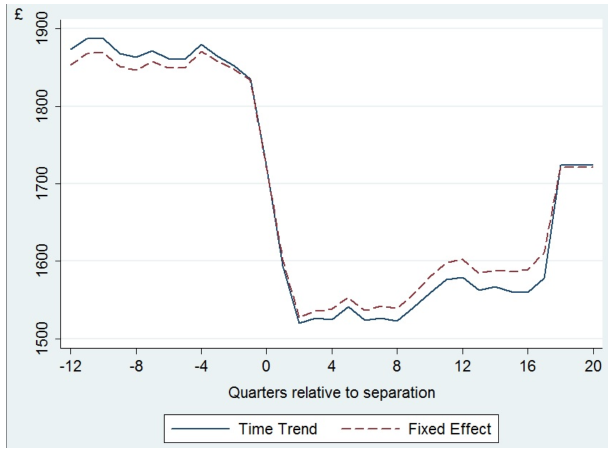
	Displacement				
	Before	After			
Group		1 Quarter	1 Year	2-4 years	5 Years
E-U-E					
All	1870	1594	1525	1551	1725
College	2600	2128	2048	2075	2138
Non-College	1615	1404	1346	1373	1522
E-E					
All	1808	1797	1737	1745	1775
College	2479	2476	2476	2476	2476
Non-College	1500	1500	1408	1444	1471
Both					
All	1847	1798	1678	1694	1764
College	2506	2304	2306	2294	2340
Non-College	1546	1509	1376	1408	1509

The results of this empirical analysis for all the different groups of workers can be found in Table 2.1. This Table shows the estimated monthly earnings before and (1 quarter, 1, 2 to 4, and 5 years) after an involuntary job separation, for E-U-E flows, for E-E flows and for both of them. In addition, I split these samples into two subsamples for each group according to their education (college and non-college education). Note that the estimated monthly earnings before the displacement is taken as the average earnings of the last 3 years before the separation[7]. The percentage drop of earnings 1 quarter, 1, 2 to 4, and 5 years after the separation are presented in Table 2.2, and more

[7] I use this method to avoid a possible downwards bias in the estimated losses. This downward bias

Table 2.2: Earning and wage losses (in percentage terms) after an involuntary job separation, for different groups of workers.

Quarters After Separation	1 Quarter		1 Year		2-4 years		5 Years	
Group	Earnings	Wages	Earnings	Wages	Earnings	Wages	Earnings	Wages
E-U-E								
All	14.61	14.33	18.34	16.05	16.90	15.67	7.63	5.9
College	17.71	20.3	20.79	20.82	19.72	21.58	17.32	19.33
Non-College	13.04	11.22	16.68	12.89	14.93	11.84	5.74	3.65
E-E								
All	0.50	0	3.81	3.39	3.33	5.27	1.67	0
College	12.90	0.64	12.90	0.64	12.90	3.68	12.90	0.64
Non-College	0.00	0	6.17	6.49	3.77	5.59	1.96	0
Both								
All	0.50	2.96	7.11	9.08	6.19	10.02	2.32	2.96
College	8.03	4.56	7.97	4.56	8.43	11.05	6.61	4.56
Non-College	2.12	1.61	10.72	9.41	8.67	8.45	2.12	1.61



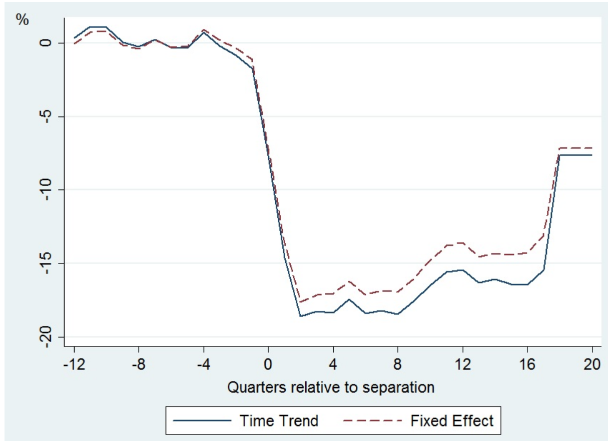
Data: (BHPS, 1990-2011)

Figure 2.1: Monthly real income losses for separators with a flow which includes an unemployment spell (E-U-E) (monthly earnings in pounds).

specifically in the columns noted as *Earnings*.

Figure 2.1 shows the monthly real labour income losses (in 2010 prices) for high tenured displaced workers with an unemployment flow after the involuntary separation, and the second and third columns of Table A.7 (see Appendix A) show these estimation outputs with Driscoll-Kraay standard errors for the cases with and without time trends. I find that displaced workers who are included in this group are suffering from substantial and persistent income losses following a separation. The estimated level of monthly real labour income before the displacement is on about 1870 pounds and one year after the displacement 1550 pounds. This result implies an immediate monthly losses of about 400 pounds, 1 to 4 quarters after a separation. These losses can be translated to an almost 19 percent reduction in income one year after the separation and are shown in Figure 2.2. The losses which are presented in the tables are in percentage terms and normalised around zero, by taking the difference between the average estimated pre dis-

can be due to the fact that in most of the cases I observe a drop in earnings 1 to 2 quarters before the displacement. The same findings are highlighted from the past literature (see for instance Jacobson et al. (1993a) and Couch and Placzek (2010)).

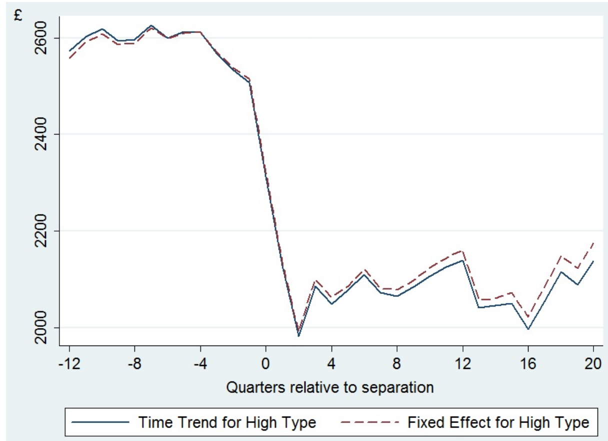


Data: (BHPS, 1990-2011)

Figure 2.2: Monthly real income losses in % terms for separators with a flow which includes an unemployment spell (E-U-E).

placement labour income (over the last 3 years) with the estimated labour income for each quarter. As we can see from the same figures, these losses are persistent until the fourth year after the separation (from 18 to 15 percent) and reduced on the fifth year to 6 percent. Finally, controlling for worker-specific time trends we can observe that these losses are larger (see blue line in Figures 2.1 and 2.2). Thus, as Jacobson et al. (1993a) highlight, these results do not come from employers systematically layoff employees with slower growth in labour income. Moreover, we can see from the same figure that labour income have a tendency to recover fast and after a decade may return to its expected level.

For this group of workers, I also separate the sample into high and low type workers according to their level of education and run the same estimations. Figures 2.3 and 2.4 show the expected real monthly labour income for high tenured displaced workers with an unemployment flow after the involuntary separation, for college and non-college displaced workers. In the Appendix A, the fourth and fifth columns of Table A.7 represent the estimation outputs of fixed-effect regressions with Driscoll-Kraay standard errors for the cases with and without time trends.

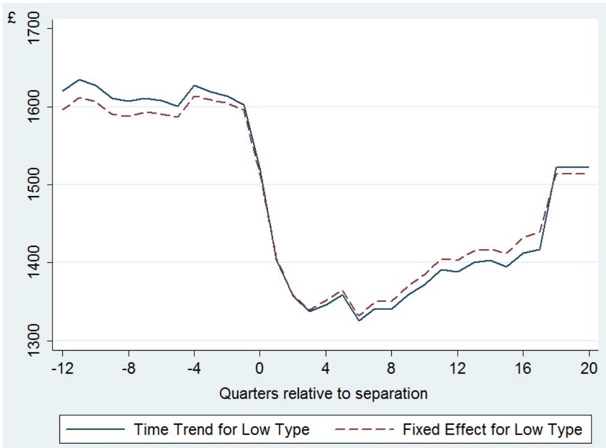


Data: (BHPS, 1990-2011)

Figure 2.3: Monthly real income losses for separators with a flow which includes an unemployment spell (E-U-E) for high educated workers (in pounds).

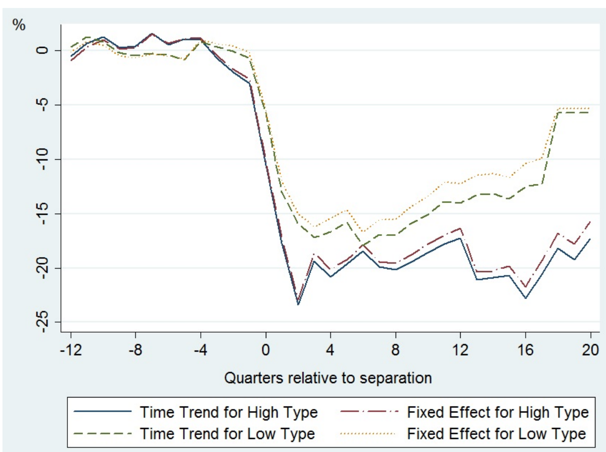
From Figure 2.3 we observe that the estimated income before the displacement for high educated workers is about 2600 pounds and is reduced on average 600 pounds to reach a post-displacement level of about 2000, one quarter after the separation and 2100, 1 year after the separation. From Figure 2.5 and the blue and red lines we can see that these losses represent 23 and 20 percent drop from the pre-displacement level of income, 1 and 4 quarters after the separation, respectively. In the long run, we can observe that these losses are sustained to 19 percent, which represents income losses of about 500 pounds each month. Furthermore, we can see from the same figure that labour income for high type workers have no tendency to return to their expected level after the 5th year of the displacement but remaining to about 19 percent less from that in the pre-displacement period.

On the other hand, labour income of low educated displaced workers is behaving quite differently from that of high educated workers. Figure 2.3 (see also sixth and seventh columns of Table A.7 which is in the Appendix A) shows that the estimated income



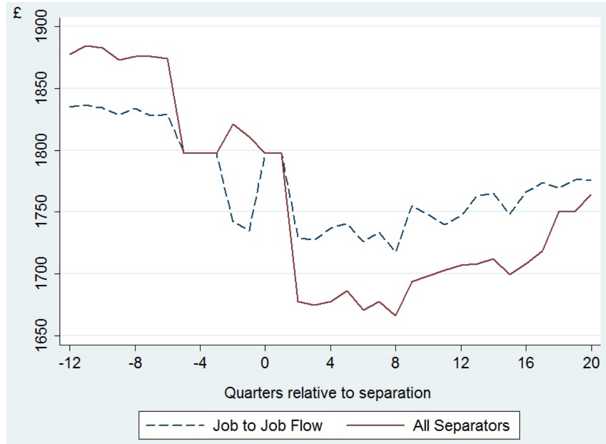
Data: (BHPS, 1990-2011)

Figure 2.4: Monthly real income losses for separators with a flow which includes an unemployment spell (E-U-E) for low educated workers (monthly earnings in pounds).



Data: (BHPS, 1990-2011)

Figure 2.5: Monthly real income losses in % terms for separators with a flow which includes an unemployment spell (E-U-E) for high and low educated workers.

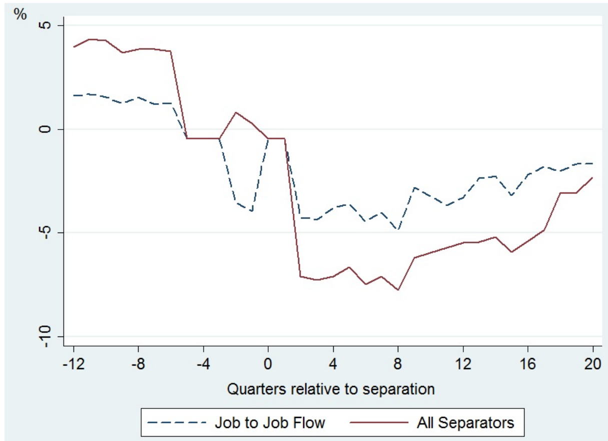


Data: (BHPS, 1990-2011)

Figure 2.6: Monthly real income losses for separators with a job to job flow (E-E) and for all the separated workers (monthly earnings in pounds).

before the displacement for low educated worker is about 1600 pounds, and is reduced to 1350 (a drop of 250 pounds) one and four quarters after the job separation. In the green and yellow lines of Figure 2.5 we can observe that these losses represent only a 16 percent drop from the pre-displacement level of income, 1 year after the separation. The interesting fact for this case is that in the long run, we can observe that these losses are reduced to 5 percent which represents expected income losses of about 100 pounds each month.

Furthermore, Figure 2.5 represents the differences between high and low educated workers in percentage terms. As we can see from this figure, labour income for low type workers has the tendency to return to its expected level after the 5th year of the displacement, driving the result that we observe in Figure 2.2. A final point is that 3 quarters before the displacement there is a drop in the income of high type workers whereas the income of low type is more stable. The reason can be either that before the separation the college educated worker faced a reduction in either the hourly wages or in the hours of working.



Data: (BHPS, 1990-2011)

Figure 2.7: Monthly real income losses in % terms for separators with a job to job flow (E-E) and for all the separated workers (monthly earnings).

For the second group, which includes all the displaced workers who had a job to job flow following an involuntary job separation, the losses are very small. We can see these estimated losses in Table A.8 (see Appendix A) and in the blue line of Figure 2.6 (estimates with a time trend)[8]. I find that the level of monthly income before the displacement for displaced workers who had a job to job flow is on about 1800 pounds and one year after the displacement on about 1740 pounds. This result implies a very small short run monthly losses of about 40 pounds 1 to 4 quarters after a separation. These losses can be translated to an almost 4% reduction in income one year after the separation and are shown in the blue line of Figure 2.7. As we can see from the same figures, these losses are becoming smaller in the long run (1760 pounds) which can be translated to only 2% income losses after a job to job flow. So, we can conclude that in this displaced group, income 5 years after the separation has almost returned to its expected level.

Finally, as it is expected, for the last group which includes all the separators, the

[8]Note that the estimates without a time trend show that most of the dummy variables of D_{it}^{n} are statistical insignificant.

losses are quite bigger than that in the estimations of the previous group[9]. These estimated losses are presented in Table A.9 (see Appendix A) and in the red line of Figure 2.6[10]. Monthly income before the displacement for all the displaced workers is about 1800 pounds and one year after the displacement about 1670 pounds. This result implies short run monthly losses of about 230 pounds, 1 year after a separation and almost a 7.5% reduction in the labour income (see Figure 2.7). As we can see from the same figures, these losses are becoming smaller in the long run (1750 pounds) which can be translated to only 2.7% income losses after an involuntary job separation. So, we can conclude that, and in this case, income 5 years after the separation has almost returned to its expected level.

2.5.1.3 Empirical Estimations of Hourly Wages Losses after an Involuntary Separation

Since I analysed the effect of involuntary job separations on earnings, in this part I produce the same estimations for the hourly wage rates. Therefore, firstly I present the wage cuts followed by a displacement for workers who found a job after a displacement (either E-E or E-U-E). As I mentioned in the previous section, I run three different estimations, for high tenured (more than two years) displaced workers with: a flow which includes an unemployment spell right after the involuntary separation (E-U-E), with a job to job flow following the separation (E-E), and in the last one with all the separators. As expected, the results are quite similar to the ones in the labour income case and the wage losses are large for the first group and smaller for the other two groups. I also run the same estimations by separating the sample into high and low educated workers and I find that the wage losses of high type workers are larger and sustained than that from the low educated workers.

[9]In this group belongs both the separators who had a flow which includes an unemployment spell and also the separators with a job to job flow following an involuntary job separation.

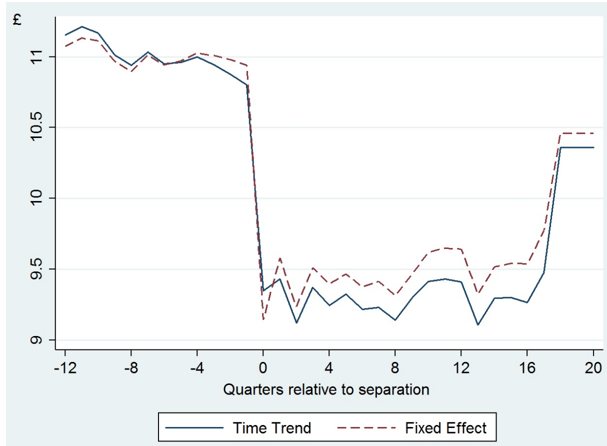
[10]Note that these estimates are with time trend. And in this case, estimates without a time trend are showing that most of the dummy variables of D_{it}^{n} are statistically insignificant.

Table 2.3: Estimated real hourly wage rates before and after an involuntary job separation, for different groups of workers.

	Displacement				
	Before	After			
Group		1 Quarter	1 Year	2-4 years	5 Years
E-U-E					
All	11.01	9.43	9.24	9.29	10.36
College	16.11	12.85	12.76	12.64	13
Non-College	9.31	8.27	8.12	8.21	8.98
E-E					
All	11.23	11.23	10.85	10.64	11.23
College	15.7	15.6	15.6	15.12	15.6
Non-College	9.29	9.29	8.69	8.77	9.29
Both					
All	11.15	10.82	10.14	10.03	10.82
College	15.78	15.06	15.06	14.03	15.06
Non-College	9.3	9.15	8.42	8.51	9.15

As in the previous case, the results from this empirical analysis for all the different groups of workers can be found in Table 2.3. This Table shows the estimated real hourly wage rates before and (1 quarter, 1, 2 to 4, and 5 years) after an involuntary job separation, for E-U-E flow, for E-E and for both flows. In addition, for each of the different flows (E-U-E, E-E and for both) we can see these estimates for all the separators and for that with college and non-college education. Note that, as I did in the previous section, the estimated real hourly wage rates before the displacement is taken as the average wages of the last 3 years before the separation[11]. The percentage drop of wages

[11] I use this method to avoid a possible downwards bias of the estimated losses due to the fact that a drop in wages 1 to 2 quarters before the displacement is observed in most of the cases.



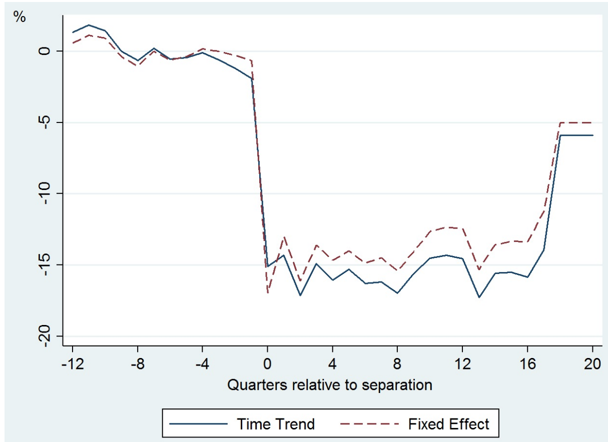
Data: (BHPS, 1990-2011)

Figure 2.8: Hourly wage losses for separators with a flow which includes an unemployment spell (E-U-E) (monthly earnings in pounds).

1 quarter, 1, 2 to 4, and 5 years after the separation can be seen in Table 2.2, and more specifically in the columns noted as "*Wages*".

Figure 2.8 shows the hourly real wage losses (in 2010 prices) for high tenured displaced workers with an unemployment flow after the involuntary separation. Second and third columns of Table A.10 (see Appendix A) show these estimation outputs with Driscoll-Kraay standard errors for the cases with and without time trends, respectively. I find that displaced workers who are included in this group are suffering from sustained and persistent wage losses following a separation. The estimated level of hourly wages before the displacement is on about 11 pounds and one year after the displacement 9.25 pounds. This result implies an immediate wage losses of about 1.75 pounds per hour 1 to 4 quarters after a separation, which can be translated to almost a 15% reduction in wages one year after the separation and are shown in Figure 2.9.

Note that the losses are 4 percentage points smaller than that of labour income and there is almost no growth until the fourth year following a separation. In the labour in-

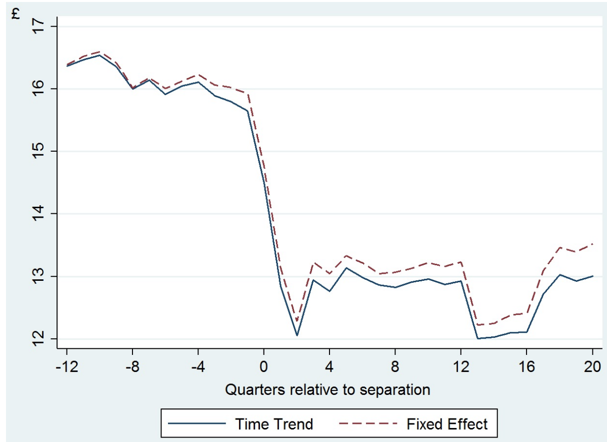


Data: (BHPS, 1990-2011)

Figure 2.9: Hourly wage losses in % terms for separators with a flow which includes an unemployment spell (E-U-E) (monthly earnings).

come case, we observe instead that the losses are decreasing 3 percentage points for the same period (from 18% to 15%). For this displaced group the above results can be interpreted as that only the hours of working are increasing during the first four years after a displacement. Five years after the separation, these losses are reduced to 5 percent, as they do in the labour income case. Moreover, again controlling for worker-specific time trends we observe that the losses are larger (see blue line in Figures 2.8 and 2.9). Thus, as Jacobson et al. (1993a) mention, these results do not come from the fact that employers systematically layoff employees with slower growth in hourly wages. Finally, we can see from the same figure that wages have a tendency to recover and after a decade may return to their expected level.

I also separate the sample into low and high type workers by the level of education and run the same estimations. Figures 2.10 and 2.11 show the expected real hourly wages for high tenured displaced workers with an unemployment flow after the involuntary separation, according to their education which can be either college and non college. In the Appendix A, the fourth and fifth columns of Table A.10 represent the estimation outputs of fixed-effect regressions with Driscoll-Kraay standard errors for the

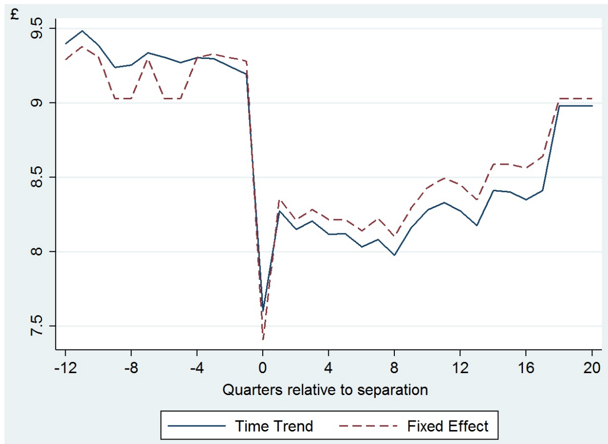


Data: (BHPS, 1990-2011)

Figure 2.10: Hourly wage losses for separators with a flow which includes an unemployment spell (E-U-E) for high educated workers (monthly earnings in pounds).

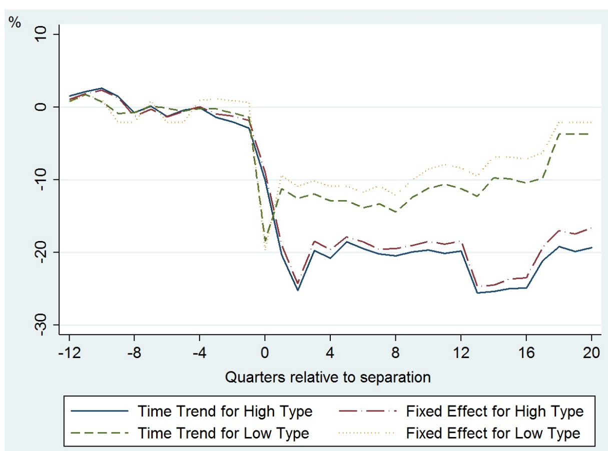
cases with and without time trends. From Figure 2.10 we observe that the estimated average hourly wages before the displacement for high educated workers is 16 pounds. In the first quarter after the separation is reduced by 4 pounds reaching a post-displacement level of about 12 pounds. One year after the separation the level of wages reach a 13 pounds per hour.

The blue and red lines of Figure 2.12 show that these losses represent a 25 and 20 percent difference from the pre-displacement level of income, 1 and 4 quarters after the separation, respectively. These losses in percentage terms are quite similar to the labour income case for the same group of workers. In the long run, these losses are slightly smaller but sustained from 20 to 25 percent which represents a level of hourly wage of about 12 to 13 pounds. So, in the long run wage losses are quite higher than that from the labour income case and there is no tendency to return to the their expected level after the 5th year of the separation. This means that increases in the hours of working should drive the upward trend of income for the same time period.



Data: (BHPS, 1990-2011)

Figure 2.11: Hourly wage losses for separators with a flow which includes an unemployment spell (E-U-E) for low educated workers (monthly earnings in pounds).



Data: (BHPS, 1990-2011)

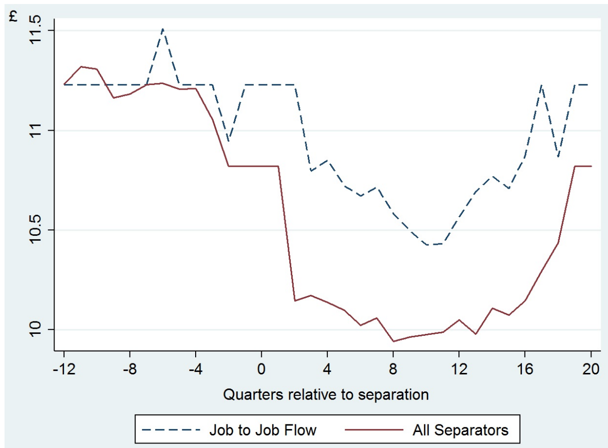
Figure 2.12: Hourly wage losses in % terms for separators with a flow which includes an unemployment spell (E-U-E) for high and low educated workers (monthly earnings).

On the other hand, wages of non college displaced workers are behaving quite differently from that of college educated workers who have experienced a displacement event. Figure 2.11 (see also in the Appendix A, sixth and seventh columns of Table A.10) shows that the estimated hourly wages before the displacement for low educated worker are 9.3 pounds and are reduced by about 1.7 pounds to 7.6 pounds one quarter after the separation. 1 year after the displacement, the losses are reduced only by 1.1 pounds reaching a level of 8.2 pounds.

In the green and yellow lines of Figure 2.12 we can observe that these losses represent an 18 and only 11 percent drop from the pre-displacement level of income, a quarter and a year after the separation, respectively. It is worth noting that as we can from these figures there is a large drop in the level of wages and income in the 1 year following a separation. Moreover, in the first quarter after a separation, the drop in wages (18%) is higher than that in the income case (15%), whereas 4 years after the separation it recovers faster (11% versus 16% percent). The interesting fact for this case is that in the long run, we can observe that these losses are also reduced to 3 percent which represents hourly wage losses of only 0.5 pounds.

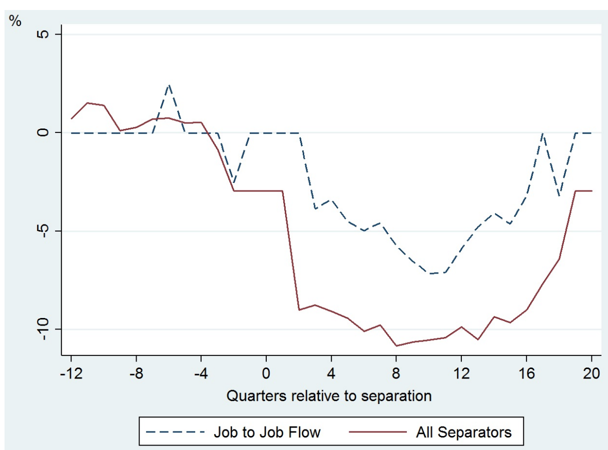
Furthermore, we can observe the differences between low and high educated workers in Figure 2.12 (percentage terms). From this figure we ca see that the wages for low type workers have almost return to their expected level after the 5th year of the displacement, driving the result that we observe in Figure 2.9. A final point is that 3 quarters before the displacement, the behaviour of wages for high and low type are almost the same. However, in the labour income case there is a larger income drop of high type workers in comparison to the income of low type, which is more stable. The reason should be that there is a reduction in the hours of working only for the group of high type workers before their displacement.

For the second group (E-E), as in the labour income case, the wage losses are very



Data: (BHPS, 1990-2011)

Figure 2.13: Hourly wage losses for separators with a job to job flow (E-E) and for all the separated workers (monthly earnings in pounds).



Data: (BHPS, 1990-2011)

Figure 2.14: Hourly wage losses in % terms for separators with a job to job flow (E-E) and for all the separated workers (monthly earnings).

small considering a job to job flow following an involuntary job separation. We can see that these estimated losses in Table A.11 (see Appendix A) and by the blue line of Figure 2.13 (estimates with a time trend)[12]. I find that the level of wages before the displacement for workers who had a job to job flow is on about 11.25 pounds and one year after the displacement is about 10.75 pounds (short run losses of only 0.5 pounds). These losses can be translated to a 4% reduction in wages one year after the separation and are shown by the blue line of Figure 2.14. As we can see from the same figures, these losses are becoming smaller in the long run and the wages 5 years after the separation have almost returned to their expected level.

Finally, for the third group, if we consider both separators who had a flow which includes an unemployment spell and also the displaced workers who had a job to job flow following an involuntary job separation, the losses, as expected, are quite bigger than that in the previous group. These estimated losses are presented in Table A.12 (see Appendix A) and by the red line of Figure 2.13[13]. Hourly wages before the displacement for all the displaced workers is about 11.25 pounds and one year after the displacement 10.2 pounds which implies short run wage losses of about 1 pound. These losses can be translated to almost 9% reduction in wages (which are larger by 1.5% from the income case) one year after the separation and are shown by the red line of Figure 2.14. As we can see from the same figure, these losses are becoming smaller in the long run and separators experience only a 2.5% wage losses after an involuntary job separation. So, we can conclude that and in this case, the wages 5 years after the separation have almost returned to their expected level.

[12]Note that the estimates without a time trend are showing that most of the dummy variables of D_{it}^{n} are statistical insignificant.

[13]Note that again these estimates are with a time trend. And in this case, estimates without a time trend are showing that most of the dummy variables of D_{it}^{n} are statistically insignificant.

2.5.2 Decomposition of Labour Income into Wages and Hours of Working

In the previous section I presented all the empirical estimations of fixed-effect regressions with Driscoll-Kraay standard errors. In this section, after decomposing changes in earning losses into changes in wages and in the hours of working, I present how much of the earning losses after a job separation are due to cuts in wages or due to reduction in hours of working. I carry out this analysis in an aggregate level by using descriptive statistics. Therefore, I follow the methodology described in section 4.2, and I run the two counterfactuals that enable me to find the earning losses which are purely driven by wage reductions, and also purely driven by changes in working hours.

In my analysis, I consider two different groups of displaced workers. Workers who found a job right after the involuntary separation and so they had a job to job flow (denoted as E-E), and workers who had an unemployed spell, in between jobs after they got displaced (denoted as E-U-E). I consider high-tenured workers who were continuously employed with the same employer at least 2 or 3 years before the separation (which I define as the pre-displacement tenure)[14]. Following Jacobson et al. (1993a) and Couch and Placzek (2010), I focus on these groups of workers since it is more likely for a worker who is attached to the labour market, and has accumulated substantial amounts of firm-specific human capital, to lose some of it and become less productive after he got displaced. The latter means that these losses should be reflected on their wages, as well. Furthermore, for the workers who had an unemployment spell within jobs (E-U-E), I also consider the duration of unemployement and observe if there are any differences between them. Due to data limitations, I choose the median of unemployed duration which is 3 months. I run the counterfactuals for all the displaced workers independently of their tenure, but the results where mixed since low tenured workers (which with high probability implies low earnings, as well) are more likely to get either equal or higher

[14]Note that the group of workers with at least 3 years of tenure, are also included in the group of workers who have at least 2 years of tenure.

earnings after the separation. So, I could not extract a definite conclusion about the role of wages and hours of working in the earning changes after their displacement.

It is worth mentioning that many papers find differences in the earning path after a displacement across education, age groups, unemployment duration and sex (see for instance, Farber (2005), Borland et al. (2002) and Addison and Portugal (1989)). I also run the same analysis across education (college or non-college), gender (female or male) and three different age groups (less than 30, from 30 to 50, and more than 50). Except from the past literature, the reason for my motivation of separating the sample into these subgroups is coming from the findings which are presented in Table 2.4. In this table we can observe the differences in the fractions of displaced workers with an E-E or an E-U-E flow after an involuntary job separation by sex, education and age groups, and also the average pre-displacement tenure depending on E-E or E-U-E flow after an involuntary job separation. College educated displaced workers with an E-E flow are 3.7% more from these with an E-U-E flow in comparison with non-college educated displaced workers. In addition, female displaced workers with an E-E flow are 6.5% more from these with an E-U-E flow in comparison to male displaced workers. Finally, displaced workers who are less than 30 years old with an E-E flow are 4.7% more from these with an E-U-E flow. Displaced workers who are more than 30 and less than 50 years old with an E-E flow are 2.6% less from these with an E-U-E flow, and displaced workers who are more than 50 years old with an E-E flow are 2.1% less from these with an E-U-E flow. In light of the above results, the contribution of wage cuts and the decreases in the hours of working on the earning losses after a displacement, should vary across education, sex, and age groups.

In Table 2.5, I present the earning losses following an involuntary separation 1, 4, 8 and 12 quarters after the displacement, and in Table 2.6 the contribution of wages and hours of working on earning losses after an involuntary separation, for different groups of workers. In the first part of the tables, the results for a job to job flow (E-E) following a separation are presented for 2 and 3 years of pre-displacement tenure, and also for

Table 2.4: Fraction of displaced workers depending on E-E or E-U-E flow after an involuntary job separation by sex, education and age groups, and average pre-displacement tenure depending on E-E or E-U-E flow after an involuntary job separation.

		E-E	E-U-E
Education	College	22.65	18.94
	Non-College	77.35	81.06
	Total	100	100
Sex	Female	39.81	33.27
	Male	60.19	66.73
	Total	100	100
Age Groups	<30	37.31	42.05
	30-50	44.87	42.22
	50>	17.82	15.73
	Total	100	100
Average Pre-displ Tenure (days)		827.42	761.74

workers who are in this group with college or non college education. The second part of this table represents the results for workers who had an unemployed spell in between jobs after they got displaced (E-U-E): for different pre-displacement tenure (more than 2 and more than 3 years), for workers with college or non college education, and finally for workers who were short unemployed (less than 3 months) and long unemployed (more that 3 months) following the separation.

Furthermore, in Tables A.13-A.48 (see Appendix A) for each quarter after the displacement, I present the contribution of wages and hours of working on earning losses after an involuntary separation, across different groups of workers. The first column of each table represents the quarters after the separation and the second the total earning differences (in percentage terms) between the pre-displacement and post-displacement level of earnings n quarters after the separation. The third and the fourth columns are the results from the counterfactual exercises.

Bearing in mind that in the first counterfactual, I keep the post-displacement level of wages equal to that in the pre-displacement period and calculate the potential earnings E_w^p by allowing hours of working to alter between the two periods. So, the differences between E_w^p and the pre-displacement earnings are purely driven by differences in the working hours, and the results are represented in column 3 (in percentage terms).

On the other hand, the second counterfactual is constructed by keeping the post-displacement working hours equal to that in the pre-displacement period. As I did before, I calculate the potential earnings E_h^p by allowing wages to alter freely between the two periods. With the same logic, the differences between E_h^p and the pre-displacement earnings are purely driven by wage cuts, and the results are represented in column 4. Finally, the most important results for this part, are illustrated in columns 5 and 6 which are the contribution of hours and wage differences on earning losses, respectively. These are the fractions of the columns 3 and 4 on column 2. Note that the positive sign in front of

Table 2.5: Earning losses (in percentage terms) of displaced workers after an involuntary job separation, by education, unemployment duration and pre-displacement tenure.

Quarters After Separation	1	4	8	12
E-E				
2> Years of Tenure	9.06	10.68	10.84	6.44
3> Years of Tenure	11.34	14.24	17.17	11.79
College				
2> Years of Tenure	-0.48	0.12	6.44	3.76
3> Years of Tenure	-1.31	-1.29	1.65	0.04
Non College				
2> Years of Tenure	18.92	22.72	18.16	11.58
3> Years of Tenure	23.64	30.66	25.73	18.38
E-U-E				
2> Years of Tenure	22.57	20.61	16.80	10.94
3> Years of Tenure	24.00	21.26	21.41	13.49
College				
2> Years of Tenure	35.90	22.56	2.77	4.20
3> Years of Tenure	42.84	32.24	33.69	19.46
Non College				
2> Years of Tenure	14.28	15.76	14.23	10.14
3> Years of Tenure	15.25	17.59	16.42	11.52
Short Unemployed				
2> Years of Tenure	22.57	16.49	6.33	3.37
3> Years of Tenure	24.00	16.78	8.46	2.77
Long Unemployed				
2> Years of Tenure	-	27.19	30.84	19.37
3> Years of Tenure	-	28.27	41.09	27.04

Table 2.6: Contribution of wages and hours of working on earning losses after a displacement (in percentage terms), by education, unemployment duration and pre-displacement tenure.

Quarters After Separation	1		4		8		12	
	Wages	Hours	Wages	Hours	Wages	Hours	Wages	Hours
E-E								
2> Years of Tenure	85.63	-14.68	89.46	-14.36	79.29	0.54	56.02	-3.51
3> Years of Tenure	90.25	-2.35	87.27	-0.54	86.03	6.68	79.04	2.85
College								
2> Years of Tenure	58.61	108.34	45.31	133.01	-81.94	-21.61	-7256.75	-4662.69
3> Years of Tenure	469.04	-329.62	484.57	-1468.33	73.99	-19.67	60.57	-86.88
Non College								
2> Years of Tenure	82.42	-6.66	85.41	-6.10	93.12	1.63	83.20	3.98
3> Years of Tenure	79.18	6.12	83.57	4.70	88.82	11.40	86.00	13.02
E-U-E								
2> Years of Tenure	81.25	9.15	87.67	-6.22	84.70	3.39	67.62	3.79
3> Years of Tenure	81.31	9.05	85.90	-5.00	85.87	2.63	70.76	-4.49
College								
2> Years of Tenure	110.19	2.82	164.41	-11.63	779.05	102.82	314.86	73.30
3> Years of Tenure	94.55	2.45	107.74	-6.17	90.41	11.70	98.02	4.48
Non College								
2> Years of Tenure	63.33	19.97	70.89	-4.10	78.07	-5.28	49.08	-9.96
3> Years of Tenure	62.75	20.32	71.58	-3.75	81.30	-8.28	50.70	-12.06
Short Unemployed								
2> Years of Tenure	81.25	9.15	93.04	2.56	98.23	-1.82	135.92	-65.53
3> Years of Tenure	81.31	9.05	94.16	-0.21	101.12	-3.14	152.90	-102.79
Long Unemployed								
2> Years of Tenure	-	-	82.00	-13.51	79.32	4.30	52.99	15.90
3> Years of Tenure	-	-	77.68	-8.81	78.82	3.77	57.55	6.66

the percentages implies earning losses and the negative earning gains (for instance from an increase of working hours between the pre-displacement and the post-displacement period).

In Tables A.13 and A.14 (see Appendix A), we can observe the decomposition of earning losses into wage cuts and changes in hours of working, for workers who had a job to job flow after the displacement, and also 2 or 3 years of pre-displacement tenure, respectively. In these two tables we can observe firstly that the drop in earnings for a job to job flow following a displacement is more severe for workers with more than 3 years pre-displacement tenure, than that with more than 2 years. This is an expected result since past literature such as Farber (2005) finds a very strong relationship between the pre-displacement tenure and the drop on earnings after a displacement. Earning losses after a displacement are larger for workers with high tenure in their previous job than that for workers with low tenure. I find that on average workers with at least 2 years of pre-displacement tenure experience a 9.7% earning losses in the first 3 years after an involuntary job separation (quarter 1 to 12) and 14.1% for that with 3 years of tenure. In the second year after the displacement (quarter 5 to 8), the earning losses are 11.3% for worker with at least 2 years of tenure and 16.2% for worker with at least 3 years. It is worth noting that for the first group the recovery starts 6 quarters after a displacement where the drop in earnings from the pre-displacement period are reduced from 11.3 to 10.9. On the other hand, earnings for workers with 3 years of tenure are starting to recover two years after the displacement (8th quarter) where the drop in earnings from the pre-displacement period are reduced from 17.2% to 15.1%[15].

Furthermore, we can observe that the total hours of working do not differ by much after the displacement from that before the displacement showing the crucial role of wage cuts on earning losses. In the first year after the separation on average the 88% of the drop in earnings for both groups of workers are purely driven by wage cuts, and total hours of working experience a small increase from the pre-displacement period.

[15] For the earning losses of specific quarters see also Table 2.5.

The contribution of wages on earnings are becoming 79.2% and 86% respectively in the second year after the separation. For the same period, only the 0.6% and 6.7% of the earning gap is purely driven by decreases in working hours[16].

For the workers who had an unemployment spell after the displacement and before finding a new job (an E-U-E flow), Tables A.29, A.30, A.31, A.32, A.33, and A.34 (see Appendix A) show the decomposition of earning losses into changes in working hours and reductions in wages, for different periods of tenure and unemployment duration. In these tables, we can see that there is a higher magnitude of about 1 to 3 percentage points in the drop of earnings for workers with at least 3 years of pre-displacement tenure, than that with 2 years. More specifically, Tables A.29 and A.30 (see Appendix A) refer to this group of workers who also had 2 and 3 years of pre-displacement tenure, respectively. We can observe that in the first year after a separation there is on average a 21% drop in earnings after a job separation. These losses are on average 8% larger from the losses in a job to job flow following an involuntary separation. In the second and third year the losses are decreased from 16.8 to 10.9 and from 21.4 to 13.5 percentage points, respectively, depending on the tenure. As we can see from these Tables, the drop in earnings which is purely driven by wage cuts is almost in the same magnitude as the actual drop in earnings after a job separation. More specifically, in the first and second year after the separation, on average 86 and 85 percent of the drop in earnings is purely due to wage cuts, again independently from the tenure. For this period, only on average the 2% of the earning gap is purely driven by decreases in working hours.

In tables A.31, A.32, A.33, and A.34 (see Appendix A), I present the exact same counterfactuals as before, but in this case for workers with different unemployment duration. Due to data limitation, I chose the median of the unemployment duration which

[16]For the contribution of wage cuts and hours of working on the earning losses after a displacement during a specific quarters see also Table 2.6. Note also that the sum of the pure effect of wages and hours of working on the drop in earnings is not equal to 100% because the decomposition does not take into account the residuals which can be interpreted as the interactions between wages and hours of working.

in this case is 3 months[17]. As expected, from these tables we can see that the magnitude of losses is larger for workers with more than three months of unemployment after a job separation than that with less (or equal) than 3 months. More specifically, these losses are from 17 to 23 percentage points larger for workers with longer unemployment duration, depending on their pre-displacement tenure. Also, we can observe that tenure also matters for the groups of workers with the same duration of unemployment. The losses for short unemployed displaced workers with 3 years of tenure are 2% larger from short unemployed displaced workers with 2 years of tenure. On the other hand, the losses for long unemployed displaced workers with 3 years of tenure are 7% larger from long unemployed displaced workers with 2 years of tenure.

It is worth mentioning that the results of this research are inline with Borland et al. (2002) and Addison and Portugal (1989) who find that workers with higher unemployment duration after a job separation experience larger pay cuts than the average.

A notable result which we can observe from the same tables is that the contribution of wages in the earning losses for the workers with short unemployment duration is on average from 35 to 40 percent higher (depending on tenure) from those workers with long duration of unemployment. More specifically, the contribution of cuts in wages on earning losses is 108% for short unemployed and only 70.5% for long unemployed[18]. These results show that the hours of working for the short unemployed are either stable or are increasing after the displacement (for that reason in most of their cases, there is

[17] I also separated the workers into those that were long term unemployed (more than 1 year), after the first job separation and those who had shorter duration of unemployment (less than a year). For the second group, there are not enough observations, which means that I could not extract a certain conclusion since the results are pretty ambiguous. But even with the available data, the earning losses for these two groups are also wage driven.

[18] When in percentage terms the contribution of wage cuts on earnings losses is more than 100%, it implies that the drop in wages is bigger than that of earnings (and so the contribution of wage cuts on the earning losses is higher than 100%). In these case, there is probably an increase of hours of working in the post-displacement period, instead of a decrease.

a negative sign for the losses due to hours of working, implying that the potential post-displacement earnings, keeping wages fixed and allowing hours of working to fluctuate, are actually higher that the pre-displacement earnings). So, the drop on earnings is almost 100% (or in some quarters even higher than 100%) purely driven by wage cuts.

Finally, it is worth noting that for the short run unemployed the recovery of earnings starts 1 year after a displacement where the drop in earnings from the pre-displacement period are reduced on average from 16.6 to 11 percent, independently from the tenure. On the other hand, the earnings for workers who were unemployed more than 3 months after the separation, are starting to recover two years after the displacement (7th and 8th quarter). In these quarters the drop in earnings from the pre-displacement period are reduced from 30.8% to 27.9% and from 41.1% to 37.6% for workers with 2 and 3 years of tenure, respectively.

2.5.2.1 Decomposition of Labour Income into Wages and Hours of Working across Education

In this part I perform the same analysis as above but across different educational levels (college and non-college educated workers). To analyse what is the contribution of wage cuts and reduction in the hours of working on earnings after a displacement across educational levels, I set up 4 subgroups which consist of displaced college and non-college workers who had either an E-E or an E-U-E flow and run the same counterfactuals as above. The results are presented in Tables 2.5 and 2.6.

It is worth mentioning that Farber (2005) finds that a displacement have a different effect on the displaced workers' post-displacement earnings across educational categories for the US labour market. More specifically, for the period 1981-91 he finds that low educated workers suffer larger earning losses than high educated workers. But after 2001 the effect has been reversed and high educated workers suffer larger losses than low educated workers. The latter findings are inline with the following results in this paper.

Tables A.15, A.16, A.17, and A.18 (which are in the Appendix A) show the earning losses after a job separation for each quarter, and the decomposition into wages and hours of working for high and low educated workers who had a job to job flow after the displacement and at least 2 and 3 years of tenure. A notable result is that on average high type workers do not face losses after a job to job separation and changes in earnings are driven both from changes in hours of working and in wages. For low type workers encounter a 22.7% and 30.7% earnings losses in the first year after the separation for our two groups, respectively. The losses are decreasing to 18.2% and 25.7%, in the second year after a separation for both groups and these losses are on average 85% driven from wage cuts.

Detailed results (for each quarter) of the counterfactual for the workers who had an unemployment spell after the displacement and before finding a new job (a E-U-E flow) and are either high or low educated are presented in Tables A.35, A.36, A.37, and A.38 (see Appendix A) which are referring to workers who belong to these groups of workers and also had 2 and 3 years of tenure.

More specifically, Tables A.35 and A.36 refer to displaced workers with at least 2 years of tenure with college and non-college education, respectively. As we can see from these tables, the results for high type workers are controversial with the ones on a job to job flow. There is a large drop in earnings for high type workers after a job separation which is on average 24% in the first year. But after the first year, the earnings are recovering fast and 3 years after the separation, are limited to 6%, with the tendency to reach the pre-displacement level of earnings. On the other hand, the short run losses for low type workers are less than that of high type (on average the losses are only 15.2% in the first year) but are decreased to about 10.1%, three years after the separation. The above results imply that the earnings of high type workers have a more severe short run effect (the drop is larger) than the low type, but their earnings are recovering faster than that of low type workers. Finally, another notable result is that the drop in earnings is almost purely driven from wage cuts for high type workers (more than 100%) and only 61% for low type workers.

On the other hand, for the above groups if we consider only the workers with more than 3 years of tenure, the results are different (see Table A.37). In the first year after the displacement there is a larger drop in earnings for high type workers after a job separation from the high type workers with 2 years of tenure. On average the losses for high type displaced worker with 3 years of tenure are about 34.7%. But after the first year, the earnings losses are sustained for this group of workers and do not recover (are on average 31.7%). The same is true for the earning recovery of low type workers with 3 years of tenure where the magnitude of losses is 15% smaller than that of high type (see Table A.38). As a final remark, we can see from the same table that the drop in earnings is almost 95% purely due to wage cuts for high type workers and only 66% for low type workers.

2.5.2.2 Decomposition of Labour Income into Wages and Hours of Working across Sex and different Age Groups

In this part I apply the same analysis as above, across sex and different age groups. To analyse what is the contribution of wage cuts and reduction in the hours of working on earnings after a displacement across sex I create 4 subgroups which are consisted by displaced females and males who had either an E-E or an E-U-E flow. Finally, to analyse what is the contribution of wage cuts and reduction in the hours of working on earnings after a displacement across age groups I create 6 subgroups which comprise displaced workers aged less than 30, between 30 and 50, and more than 50 who had either an E-E or an E-U-E flow.

It is worth mentioning that for Britain Borland et al. (2002) find that the earning losses for women who experience a displacement event is around twice that of men. The above results are inline with my findings for men and women with an E-U-E flow. Borland et al. (2002) also finds that older workers and those with higher unemployment duration after a job separation experience larger pay cuts than the average. Farber (2005) finds that the earning losses after a job separation are relatively large for older displaced workers since it is more likely that they have accumulated more specific human capital than younger worker before their displacement. The above results for age groups are in some cases inline with my findings but due to the small sample size, ambiguities could potentially be observed in my estimates.

Table 2.7 presents the earning losses following an involuntary separation 1, 4, 8 and 12 quarters after the displacement, and Table 2.8 the contribution of wages and hours of working on earning losses after an involuntary separation, across sex and different age groups. In the first part of the tables, the results for a job to job flow (E-E) following a separation are presented for 2 and 3 years of pre-displacement tenure, and also for workers who are either female or male, or are aged less than 30, between 30 and 50, and more than 50. The second part of this table represents the results for workers who had an unemployed spell, in between jobs after they got displaced (E-U-E) for 2 and 3 years of pre-displacement tenure, and who are either female or male, or are aged less than 30, between 30 and 50, and more than 50.

For each quarter, Tables A.19, A.20, A.21, and A.22 (see Appendix A) show the decomposition of earning losses into wage cuts and changes in hours of working, for female and male workers who had a job to job flow after the displacement, and also 2 or 3 years pre-displacement tenure. From these four tables we can observe firstly that female displaced workers who had a job to job flow after a displacement do not face any losses in their earnings; instead they experience small gains. The gains are higher for

Table 2.7: Earning losses (in percentage terms) of displaced workers after an involuntary job separation, by sex, age and pre-displacement tenure.

Quarters After Separation	1	4	8	12
E-E				
Female				
2> Years of Tenure	-1.39	-6.65	-4.15	-10.11
3> Years of Tenure	-0.14	-5.03	0.37	-6.15
Male				
2> Years of Tenure	13.86	19.29	16.64	13.99
3> Years of Tenure	16.56	23.79	23.19	19.85
Age Groups				
<30				
2> Years of Tenure	44.18	44.68	55.48	-20.18
3> Years of Tenure	74.05	74.72	92.20	-15.59
30−50				
2> Years of Tenure	-0.14	-0.55	-4.45	3.19
3> Years of Tenure	-0.62	-0.32	-2.76	7.66
50>				
2> Years of Tenure	13.29	21.68	25.33	21.45
3> Years of Tenure	13.42	24.28	29.11	24.21
E-U-E				
Female				
2> Years of Tenure	26.10	26.00	22.30	15.60
3> Years of Tenure	30.77	27.24	24.44	8.70
Male				
2> Years of Tenure	21.09	18.80	14.95	9.67
3> Years of Tenure	21.38	19.43	20.48	14.75
Age Groups				
<30				
2> Years of Tenure	12.67	-9.33	-4.09	-12.32
3> Years of Tenure	16.49	-9.57	-2.77	-15.04
30−50				
2> Years of Tenure	21.53	22.77	12.67	6.48
3> Years of Tenure	22.34	24.83	18.38	12.69
50>				
2> Years of Tenure	31.97	36.04	38.60	29.86
3> Years of Tenure	31.97	30.54	38.80	25.52

Table 2.8: Contribution of wages and hours of working on earning losses after a displacement (in percentage terms) of displaced workers after an involuntary job separation, by sex, age and pre-displacement tenure.

Quarters After Separation	1		4		8		12	
	Wages	Hours	Wages	Hours	Wages	Hours	Wages	Hours
E-E								
Female								
2> Years of Tenure	515.77	45.70	167.00	39.65	159.75	31.50	128.79	-5.68
3> Years of Tenure	5328.84	-2918.50	222.44	-28.98	-1398.67	1252.41	171.32	-78.85
Male								
2> Years of Tenure	109.02	-11.58	105.93	-5.70	87.34	3.01	80.46	-3.65
3> Years of Tenure	116.10	-11.48	105.38	-2.72	96.22	0.68	93.60	-5.85
Age Groups								
<30								
2> Years of Tenure	119.29	-14.70	95.61	-9.30	94.03	-0.13	100.82	12.67
3> Years of Tenure	112.06	-7.37	96.87	-6.54	88.68	1.43	83.74	24.82
30−50								
2> Years of Tenure	744.43	1921.66	33.78	575.50	146.27	22.77	-53.46	32.19
3> Years of Tenure	43.64	303.39	96.98	377.44	151.19	-11.30	33.56	32.47
50>								
2> Years of Tenure	55.04	42.32	74.46	21.32	91.59	7.70	103.42	-7.64
3> Years of Tenure	53.86	43.98	72.54	22.36	91.16	7.59	103.45	-7.08
E-U-E								
Female								
2> Years of Tenure	72.55	23.32	72.24	8.80	74.59	28.88	77.02	47.75
3> Years of Tenure	71.57	23.27	61.80	20.57	66.81	31.76	80.04	41.14
Male								
2> Years of Tenure	85.70	1.94	94.74	-13.24	89.59	-9.22	63.51	-14.89
3> Years of Tenure	86.53	1.06	96.45	-15.78	93.01	-7.42	75.55	-15.83
Age Groups								
<30								
2> Years of Tenure	73.94	11.81	87.31	61.02	231.75	-108.90	107.26	19.08
3> Years of Tenure	74.76	11.75	93.91	47.02	308.17	-176.13	85.88	36.81
30−50								
2> Years of Tenure	90.69	-2.16	110.42	-23.17	129.29	-40.58	125.38	-52.60
3> Years of Tenure	91.43	-2.91	107.63	-18.91	123.07	-30.18	111.20	-32.63
50>								
2> Years of Tenure	64.82	30.26	51.74	32.65	58.73	30.73	48.04	27.04
3> Years of Tenure	64.82	30.26	47.31	33.30	57.31	31.35	39.52	26.49

a displaced female worker with 2 years of tenure than that with 3 years of tenure. This is an expected result since in general displaced workers with 3 years of tenure have on average larger losses (or lower gains) than that with two years of tenure.

The drop in earnings for men with a job to job displacement are severe and larger for male workers with more than 3 years pre-displacement tenure, than that with more than 2 years. On average, workers with at least 2 years of pre-displacement tenure experience a 16.5% earning losses in the first 3 years after an involuntary job separation (quarters 1 to 12) and 21.6% for that with 3 years of tenure. In the second year after the displacement (quarter 5 to 8), the earning losses are 17.2% for worker with at least 2 years of tenure and 23% for worker with at least 3 years[19].

Furthermore, we can observe that total hours of working for male displaced workers are not differ much after the displacement from that before the displacement showing the crucial role of wage cuts on earning losses. In the first year after the separation on average the 111% of the drop in earnings are purely driven by wage cuts independently from the tenure, and total hours of working have a small increase from the pre-displacement period. In the second year after the separation the contribution of wages on earnings are becoming 96% and 99.8% for male worker with at least 2 and 3 years of tenure, respectively. For the same period, only the 2.8% and 0.9% of the earning gap is purely driven by decreases in working hours[20].

On the other hand, the drop in earnings for female workers who had an unemployment spell after the displacement and before finding a new job (an E-U-E flow) are higher than that of men. Detailed results (for each quarter) are represented in Tables A.39, A.40, A.41, and A.42 (see Appendix A) which refer to workers who are belonging to these groups of workers and also had 2 and 3 years of tenure.

[19]For the earning losses of specific quarters see also Table 2.7.

[20]For the contribution of wage cuts and hours of working on the earning losses after a displacement during a specific quarters see also Table 2.8.

More specifically, Tables A.39 and A.40 are referring to female and male workers with at least 2 years of tenure and as we can see the results for female workers are controversial with the ones on a job to job flow. There is a large drop in earnings for female workers after a job separation which is on average 26.8% in the first year whereas for men are smaller (19.2%). In the second year after the displacement the earning losses for female workers are 22.8% and for men 17.8%. Larger losses but in the same direction are observed for female and male workers with at least 3 years of tenure (see also Tables A.41 and A.42 in the Appendix A).

The results also show that the drop in earnings of female workers with at least 2 years of tenure are purely driven by 60.4% from cuts in wages and by 36.5% by reductions in hours of working, showing that hours of working play also a fundamental role in determining the earning losses after a displacement. The results are different for male displaced workers where the 81.5% of the earning losses are driven by wage cuts, and hours of working actually increase. Similar results are obtained for female and male workers with at least 3 years of tenure.

If I split the sample into three different age groups, the results are not always well determined because of the small sample size. Borland et al. (2002) also highlight the same problem of ambiguity on their results for workers who experience an involuntary or voluntary job separation across age groups. Note that, they are using the BHPS dataset for a shorter period of time than this research does.

For each quarter Tables A.23, A.24, A.25, A.26, A.27, and A.28 (see Appendix A) show the decomposition of earning losses into wage cuts and changes in hours of working, for workers belonging into three different age groups (less than thirty, more than thirty and less than fifty, and more than fifty) and who had a job to job flow after the displacement, with 2 or 3 years of pre-displacement tenure. The results from these groups of workers are mixed and not easily interpreted, as Borland et al. (2002) have noted as well. It should be expected that the drop on earnings will be higher for old workers, since they have accumulated a substantial amount of human capital before the displacement (see Borland et al. (2002) and Farber (2005)). In our case, there is a large drop on earnings for young displaced worker, middle aged workers are not suffering from any losses after a displacement, and old workers face smaller losses in their earnings. The first group of workers is behaving in an unexpected way due to the small sample size (only 20 observations) and due to the fact that I observe extreme values on this subsample (extreme drop on earnings after a displacement). The main finding from these groups of workers is that the earning losses for young workers are almost purely driven by wage cuts whereas in the first 2 years after the displacement of old workers the 78% is purely driven by wage cuts and the 20% from decreases in hours of working.

On the other hand, the drop on earnings for the three age groups of workers who had an unemployment spell after the displacement and before finding a new job (a E-U-E flow) are in most of the cases as expected from the past literature. Detailed results (for each quarter) are represented in Tables A.43, A.44, A.45, A.46, A.47, and A.48 (see Appendix A) which are referring to workers who belong to these groups of workers and also had 2 and 3 years of tenure. The drop on earnings are higher for old displaced workers (37% the first two years), quite smaller for middle aged (18%), and young workers almost do not suffer from any losses after a displacement. The main finding for these groups of workers is that the earning losses for middle aged workers are almost purely driven by wage cuts whereas in the first 2 years after the displacement of old workers the 53% is purely driven by wage cuts and the 31% from decreases in hours of working. As in the previous case, due to the small sample size the results for young workers are pretty ambiguous and not easily interpreted.

Note that in all the estimates I compare the pre-displacement earnings with the earnings of the post-displacement period. I am aware that these stylised facts do not show the difference between the post-displacement earnings and the potential earnings if the workers had not been displaced, as I did in the previous section where I estimate the panel with a fixed effect model (following Jacobson et al. (1993a) and Couch and Placzek (2010) methodology). Furthermore, I expect that the magnitude of these losses are 1 to 2 percent higher than that from the pre-displacement earnings, if I take into consideration that the growth rates of earnings and wages in a non-displaced group (continuously employed in the same firm) is on average 1% each year, which I do not account in the estimates of these counterfactuals.

2.6 Conclusion

There are many papers in the literature which investigate earning losses after an involuntary job displacement. The majority of these studies find that there are long-run losses in earnings after a displacement (see Jacobson et al. (1993a); Neal (1995); Couch and Placzek (2010)). These studies support the conclusion that earning losses after displacements for high tenured workers should be driven by losses in accumulated firm-specific human capital, since involuntary job separations make high tenured displaced workers less productive in their new jobs when compared to his production levels had he not been displaced. This latter implies that these losses should be reflected on their wages, as well. Nevertheless, in the literature, no further investigation regarding what drives these earning losses after job separations. The current paper, on the other hand, highlights this aspect that the literature ignores and quantifies the contribution of wage cuts and decreases in hours of working on earning losses after displacements.

More specifically, this chapter firstly documents what the earnings and wage losses are after an involuntary job separation at the individual level. Moreover, it measures what proportion of these losses are driven by (i) wage cuts and (ii) reductions in hours of work at the aggregate level. Jacobson et al. (1993a) highlight the importance of this kind of research, mentioning that a *"..lack of data prevent us from decomposing earnings losses into effects due to lower wages and reduced hours"*. Thus, the current research attempts to fill this gap in the literature and provides more insights into the driving forces behind the earning losses after an involuntary job separation.

In terms of results, I ran a fixed effect model with Driscoll-Kraay standard errors and found that high tenured workers who had an unemployment spell following an involuntary job separation experienced large and sustained income and wage losses during the post-displacement period. Furthermore, the losses are much smaller for displaced workers who had a job-to-job flow after their separation than for displaced workers who had an unemployment spell after their displacement and before finding a new job.

At the aggregate level, I decompose labour income into its two components: wages and hours of working. By decomposing labour income in this way, I can quantify the contributions of wage cuts and reductions in hours of working on earning losses after involuntary job displacements. After running counterfactual exercises, I found that, on average, 83 percent of the income losses for employees who had a job-to-job flow following an involuntary job separation are driven by wage cuts and that their hours of work did not fluctuate much. For workers who had an unemployment spell after their displacement, and before finding a new job, the drop in their earnings, which was purely driven by wage cuts, is almost 80 percent independently from their pre-displacement tenure. For this group, on average, only 2 percent of the earning gap was purely driven by decreases in working hours. It is worth noting that all of these results differ across pre-displacement tenure, education, unemployment duration, age, and sex.

More specifically, in most cases, the drop in earnings is higher for workers with more than 3 years of pre-displacement tenure from those with more than 2 years of pre-displacement tenure a finding which is consistent with the literature. College educated displaced workers do not face losses after a job-to-job separation and changes in earnings are driven by both changes in hours of working and in wages. For non-college educated displaced workers with a job-to-job flow, however, the results are different.

They encounter, on average, a 26% earnings loss in the first year after their separation. These losses for non-college workers are mainly wage driven. On the other hand, earnings for college educated displaced workers who had an unemployment spell after their displacement and before finding a new job suffer from a more severe short-run effect (the drop is larger after the displacement) than that of the non-college educated displaced workers, but their earnings recovered faster. Furthermore, the drop in earnings for college educated displaced workers is almost purely driven by wage cuts, whereas, for non-college educated displaced workers, the wage effect is smaller (i.e. between 60% and 80%).

Furthermore, female displaced workers who experienced a job-to-job flow after a displacement do not face any losses in their earnings but, rather, small gains. The drop in earnings for men with a job-to-job displacement were severe and large (on average 16.5% earning losses). These losses for male displaced workers were almost purely wage-driven. The results for female displaced workers who had an unemployment spell after a displacement and before finding a new job contradict those which had a job-to-job flow. There is a large drop in earnings for female workers after a job separation, which is on average 26.8% in the first year, whereas it is smaller for men (19.2%). In addition, the drop in the earnings of female workers is 60.4% purely driven by cuts in their wages and 36.5% by reductions in their working hours. For male displaced workers, on the other hand, 81.5% of their earning losses are driven by wage cuts, whereas their working hours do not fluctuate much after a displacement.

If one splits the sample into three different age groups, as Borland et al. (2002) have also noted, the results are not always well determined because of the small sample size. In this case, there is a large drop in earnings for young displaced worker who had a job-to-job flow, middle aged displaced workers did not suffer from any losses after a displacement, and old workers faced smaller losses in their earnings. The main finding is that the earning losses for young workers are almost purely driven by wage cuts, whereas, for old workers, 78% is purely driven by wage cuts and 20% by decreases in working hours. On the other hand, the drop in earnings for the three age groups of worker who experienced an unemployment spell after the displacement and before finding a new job are, in most cases, as expected from the past literature. The drop in earnings is higher for old displaced workers (on average 37%), quite smaller for middle aged workers (18%), and young workers almost do not suffer from any losses after their displacements. The main finding for these groups of worker is that the earning losses for middle aged workers are almost purely driven by wage cuts, whereas, for old workers, 53% is purely driven by wage cuts and 31% is driven by decreases in working hours.

It should be noted, however, that I am concerned that there might be a potential problem with the estimates reported in this chapter since the exogeneity condition of the event of an involuntary job separation might be challenged which could, in turn, bias my estimations. More specifically, I am concerned about any unobservable characteristics which vary across time and which can affect the performance of each individual worker. The latter implies that the likelihood of getting dismissed should be influenced as well. Due to the limitations of the data, it is difficult to find appropriate exclusion restrictions in the literature for job loss. Furthermore, due to the small sample size, the results in some cases might be ambiguous and not easily interpreted.

3

Can Job Displacements explain the UK's Productivity Puzzle?

3.1 Introduction

In the first quarter of 2008, the UK entered one of the deepest recessions in its modern history. During this crisis, real GDP and labour productivity (as output per hour worked) dropped by over 7%, with the UKs economy only starting to recover following the trough of the crisis in 2009Q2. After the trough, real GDP began to recover fast and finally reached its pre-crisis trend. Surprisingly, though, productivity did not follow the same path. More specifically, during the last 5 years, the UK experienced almost zero growth in labour productivity, following a 2.5% annual growth rate in the pre crisis period[1]. This zero growth in labour productivity is due to the fact that both employment

[1] See Figures B.3 and B.4 which are in the Appendix B.

and total hours worked are recovering faster than real GDP. This has been called the UK's productivity puzzle and recently has attracted the attention of many researchers who are trying to give plausible explanations to this puzzle (e.g. Blundell et al. (2014), Gregg et al. (2014), Oulton and Sebastia-Barriel (2013), Goodridge et al. (2013) and Barnett et al. (2014)[2]).

The aim of this chapter is to give more insight as to why output per hour worked did not catch up its pre-2008 trend. In particular, I study the possible role that involuntary job separations (or displacements) of high tenured workers had on post-2008 productivity; an aspect which the literature has ignored so far. Since, in the UK, during the current crisis, I observe that the fraction of displaced employed workers who had more than two years of tenure in their previous job, has increased by 50% and that their wages have decreased by about 16% relatively to that before the crisis, it becomes natural to ask to what extent these productivity losses for workers who have experienced a displacement event can explain the UK's productivity puzzle.

One possible reason why displacements should matter for productivity comes from Jacobson et al. (1993a)(among many others), who suggest that, after a job separation, the high tenured displaced workers lose some of their accumulated, firm-specific human capital. These individual human capital losses make these workers less productive in their new job vis-a-vis how they would have been if they had not been displaced. Intuitively, these human capital and productivity losses should be important at an aggregate level as well. Some evidence has been provided by Fujita and Ramey (2009) who find a negative correlation in productivity and cyclical changes in the job separation rate. Further motivation comes from the past literature, which studies the effect of compositional changes on the labour force and the role of human capital at the aggregate level. Acemoglu and Autor (2012) in their interesting review of the magnum opus (as they characterised it) of Goldin and Katz (2009), "*The Race between Education and Technology*", underline the fundamental role of human capital in determining the eco-

[2] See also: Martin (2011), Martin and Rowthorn (2012), Pessoa and Reenen (2013).

nomic growth of an economy (in their case, the USA). By running a careful accounting exercise, they measure that, on average, 15 percent of the USs economic growth is due to increases in human capital[3]. It is not very surprising that the empirical results of this chapter show that the displacements of high tenured workers (i.e. workers who had more than 2 years at the same job prior to the separation) can explain, on average, 27% of the post-crisis gap between actual productivity and potential productivity if productivity had followed the pre-2008 trend. Furthermore, 78 percent of this effect can be explained by job separations of college educated workers, with the remaining 22 percent being able to be explained by separations of non-college educated workers.

In the literature there are papers that built models based on the idea that, during a recession, there is a "cleansing" out effect of firms and workers which are less efficient and less productive, as well as a redirection of the economy into more efficient production arrangements[4]. This literature contrasts with my empirical findings from the UK economy. On the other hand, Barlevy (2002) points out that empirical evidence finds that job quality is pro-cyclical. The new jobs that are created during a recession have a higher probability of being temporary and low-paying. Furthermore, empirical evidence has shown that the new jobs that are created during recessions are more likely to have lower than the average productivity of a match between workers and employers during a more normal period. Bowlus (1993) and Davis et al. (1996) find that there is a higher probability of a job destruction for new jobs created during a recession than new jobs created during an expansion. The latter implies that firms during a recession are unlikely to keep the same short of production arrangements in the long run. In addition, Bowlus (1993) (in line with Bils (1985) and Shin (1994)) find that the new jobs that are created during a recession are generated from the lower wage pool of workers; some-

[3]Compositional changes are also important for business cycle fluctuations. Some empirical evidence are coming from Jaimovich and Siu (2009), who show that changes in the labour composition by age, affect the business cycle volatility (for the US and other G7 economies), and Mennuni (2013) who finds that age, gender and educational redistributions altered aggregate volatility (US: 1967-2013).

[4]See for instance Hall (1995, 2000), Mortensen and Pissarides (1994), Caballero and Hammour (1994); Caballero et al. (1996), Gomes et al. (2001), and Jaimovich and Siu (2012).

thing which implies that these workers are not that productive. The results of the current study that the displacements of college educated workers can explain the 21 percent of the UK's productivity puzzle, are in line with the above empirical evidence.

For the analysis, I use the British Household Panel Survey (BHPS) data set from 1991 to 2011. I also extract data on aggregate level from the Office for National Statistics (ONS). In order to measure for quarterly labour productivity, I use actual quarterly data related to output, the number of workers, and the total hours worked from the ONS; then, I divide the countrys GDP over the total hours worked. For the BHPS dataset, I group workers according to some individual characteristics (college and non college educated workers who can be either displaced or non-displaced; I label them as being *displaced* or *non-displaced*)[5]. After that, I construct and estimate a production function of total output as a function of displaced and non-displaced workers.

Following Acemoglu (2002b, 2003, 2002a)), this research takes *production* to be a constant elasticity of substitution (CES) function. Then, I estimate the parameters of this production function based on the real UK data that I have accrued. At this point, it should be mentioned that the basic assumption of this chapter is perfect competition. This implies that, at the macro-level, the average real wage of workers who are in a particular group is equal to their average marginal productivity. Some supportive empirical evidence for this assumption come from Blundell et al. (2014), where they find a positive correlation between labour productivity (as gross value added per hour worked) and average real hourly wages for the UK economy, at a regional level[6]. Finally, I run counterfactuals exercises which enable one to highlight the effect of job separations on the aggregate productivity of the UK economy.

[5]Non-displaced is a worker who is continuously employed and did not experienced a displacement event.

[6]More supportive evidence about this assumption at a firm level for the UK economy is coming from Crawford (2013).

More specifically, in order to account for the effect of job separations of high tenured workers (more than 2 years in the same job prior to the separation) on the aggregate productivity of the UK economy during the recent economic crisis, I run the following accounting counterfactual exercise (Counterfactual 1): by using the previously CES production function, I measure the level of aggregate productivity that would have been if a displaced worker was as productive as a non-displaced one. The findings show that productivity during the 2008 crisis would have been 2.49% higher than the actual one, which explains 26% of the gap between actual and potential productivity had the crisis not occurred.

The above result, however, is subject to either an upward or a downward bias. The upwards bias can come if the displaced worker before the displacement was not as productive as a non-displaced one. There is a probability that some workers were low productive in their previous job and, thus, had a higher probability to get displaced. Furthermore, during the crisis, it might have been the case that highly productive workers who gained high wages, got displaced and that, in their next job, they experienced severe earning losses. This means that the workers which got displaced during the crisis might actually be more productive than the non-displaced ones, implying a downward bias in the estimates from this counterfactual.

To overcome this potential upwards or downwards bias, I ran another counterfactual exercise under the condition that the workers who experienced an involuntary job separation were as productive as they used to be before their first displacement (Counterfactual 2). In terms of results, the aggregate labour productivity during the crisis would have been increased on average by 2.36 percentage points from the actual one, thereby explaining, on average, 36.7% of this puzzle if productivity had followed the path of its pre-2008 trend. One critique regarding this counterfactual is that it can be upwards or downwards biased as well. This can happen since, for some workers, the displacement might have occurred before, during, or after the start of the crisis. Therefore, the wage in the previous job of this displaced worker may or may not have been affected by the crisis.

Thus, in order to handle the potential bias abovementioned, I run alternative exercises which I argue are more robust on the effect of job displacements on labour productivity during the 2008 crisis (Counterfactuals 3 to 7). The general idea behind running these counterfactuals is that they account for post-2008 labour productivity under the condition that the average productivity of the displaced workers and/or their fraction during the crisis were equal to that which occurred at the beginning of the crisis (2007Q4)[7]. Someone can think about these counterfactuals as follows: what would the post-2008 productivity have been if the economy during that period had been at its potential (with no crisis) but the average wage of displaced workers and/or their fraction over employment were equal with the actual post-crisis levels and not with the ones that they had at the beginning of the crisis.

More specifically, in Counterfactual 3, I set the average pre-crisis level of the real hourly wage rates for the displaced group as the values for the period during the crisis. With this exercise, I am able to measure how much of the total productivity losses could be accounted for by changes in productivity (or in average wages) of the displaced workers during the crisis. The results show that productivity after the crisis would have been from 1.1 to 3.67 percentage points larger than the actual labour productivity, thereby explaining, on average, 27 percent of the UK's productivity puzzle. In addition, I quantify the contribution of the displaced workers who are either high or low educated separately as well in order to better explain the productivity puzzle (Counterfactuals 4 and 5). The results show that the job displacements of college educated workers explain, on average, 21.1 percent of this puzzle. This means that the 78 percent of the overall effect of displacements on the puzzle is due to wage losses which occurred on college educated workers. The remaining 22 percent of the overall effect of displacements on the puzzle can be explained by the drop in wages of non-college educated workers (Counterfactual

[7]Note that under perfect competition the average productivity of the displaced group is assumed to be approximately equal to the average wage of the displaced group.

5).

It is worth noting that this research relies heavily on the theory of specific human capital and productivity losses after a displacement. In other words, it assumes that the real wage rate of the displaced group equals its average marginal productivity before and after the displacement. There are other theories of costly job displacement, however, which criticise the above assumption. In the third section, I briefly analyse the human capital theory and the main alternative theories which can refute my results. The main theories which criticise the assumption of perfect competition are theories based on job matching, theories of backloaded compensation, rents, theories based on revelation of information, and, finally, intra-household reallocation and health-related theories.

Furthermore, I am interested in accounting for the effect that the 50% increase in the fraction of displaced workers during the crisis had on productivity. For that reason, I ran Counterfactual 6 by setting the post-crisis fraction of displaced workers to being equal with the pre-crisis fraction. This accounting exercise gives between 0.13 and 1.2 percentage points of increase in the aggregate productivity, given that there was no change in the fraction of displaced workers after the crisis from that before. I find the changes in the fractions of displaced workers can be explain, on average, 7.4% of this puzzle.

Finally, I measure how much the UK's productivity puzzle can be explained from the drop in wages in both the displaced and the non-displaced group during the crisis. I run an alternative counterfactual exercise (Counterfactual 8) where I set the average post-crisis level of the real wage rates of both the displaced and the non-displaced groups as being equal with those before the beginning of the crisis. The results show that productivity after the crisis would have been from 1.06 to 2.75 percentage points larger than the actual one, thereby explaining 18 percent of the UK's productivity puzzle. Furthermore, the results show that the drop in wages of both college educated displaced and non-displaced workers can explain 17.8 percent of this puzzle (Counterfactual 9), which is 99 percent of the overall effect of the wage drop in both groups in the puzzle. The remaining 1 percent can be explained by the drop in wages of non-college educated displaced and non-displaced workers (Counterfactual 10).

In the next section, I present the literature review and, in section 3, I present the theories on costly job displacement. In section 4, I describe the household and aggregate data that are used to tackle the abovementioned questions of this chapter. The theoretical model used for the UK economy is introduced in section 5. Then, in section 6, the main empirical findings of this chapter are presented. Finally, in the last section, I conclude the chapter.

3.2 Literature Review

This research attempts to make a contribution to the growing literature on the UK's productivity puzzle. It aims to provide more insights and highlight the role of displacements on post-crisis productivity. In the literature there are many papers which attempt to explain this puzzle. For instance, Blundell et al. (2014) find that aggregate labour productivity should have been affected by the increase in the labour supply and by flexible wages. They conclude that the reduction in wages (which implies a reduction in labour productivity) cannot be explained by compositional changes in the labour force. These studies do not, however, focus on any compositional changes to the displaced and non-displaced groups; something which might have affected labour productivity. Gregg et al. (2014) find that, in recent years, real wages have been much more sensitive to negative shocks than in previous recessions.

Moreover, Pessoa and Reenen (2013) argue that, since real wages dropped during the crisis, a labour-capital substitution exists which has made the UK economy less productive. They find that capital shallowing explains the 68% of the puzzle. On the other hand, there are other papers such as Martin and Rowthorn (2012) and Martin (2011), which suggest that compositional changes in the labour force in favour of low-skilled workers and less productive sectors account for 33% of the puzzle. Goodridge et al. (2014) challenge the capital shallowing and the supply-side hypotheses and argue that this puzzle is, actually, a TFP puzzle, claiming that that would explain 33% of the UK's productivity puzzle. Furthermore, Oulton and Sebastia-Barriel (2013) argue that the recession and the financial crisis have caused permanent damage on the aggregate productivity of the UK. They find that the banking crises have decreased the short-run growth of labour productivity by around 0.65% each year, as well as the long-run level by around 1%.

Perhaps surprisingly, though, the literature does not consider displacements as being a factor which has the potentiality of explaining part of the UK's productivity puzzle. I argue that involuntary job separations should have played a role in determining post-crisis productivity since, in the UK, during the current crisis, they have increased by 56% in comparison with that which occurred before 2008[8]. Moreover, during the crisis, the average wage of high educated workers decreased by 27.6% and that of low educated workers by 4.4% in comparison with what occurred before the beginning of the crisis, creating an overall 16% decrease in the average wage of the displaced group.

[8]Note that for instance in the US a productivity puzzle is not observed since after the recession both GDP and output per hour worked recovered strongly (see Hughes and Saleheen (2012) and Oulton and Sebastia-Barriel (2013), among others). Furthermore, involuntary job separations increased only by 23% in comparison with the UK where the effect was almost 2 and a half times larger. So, since in the UK we observe zero growth in productivity, it makes stronger the argument that the UK productivity puzzle may related with displacements. For more details about the data, see Table B.4 and Figures B.5 and B.6 which are the total number of involuntary job separations (as a % of employees) across time and their annual percentage difference. The data in the US are taken from the US. Bureau of Labour Statistics, retrieved from Federal Reserve Bank of St. Louis (https://research.stlouisfed.org/fred2/series/JTULDR/), and the data for the UK from the Office for National Statistics, retrieved from Nomis (https://www.nomisweb.co.uk/published/stories/story.asp?id=17).

Furthermore, there are many papers which suggest that a displaced worker will become less productive in the new job as he would have been if not displaced. More specifically, previous studies of job displacements at a micro level have extracted very interesting empirical results. Jacobson et al. (1993a) in their influential paper *Earnings Losses of Displaced Workers*, find a 40% short-run and 25% long-run earning losses for high tenured workers who experience a mass layoff event (Pennsylvania state: 1975-1985)[9]. They conclude that this *"lost attribute might be some form of specific human capital"*. Many other papers arrive at the same conclusion; i.e. that there are firm-specific human capital losses due to job separation (Kletzer (1989, 1998), Neal (1995), Carrington (1993), and more recently, Couch and Placzek (2010))[10].

Jung and Kuhn (2012) go one step further and separate the earning losses which occur after a job separation into three components. These components are the *selection effect*, the *extensive margin effect* and the *wage loss effect*. *Selection effect* which cause an upward bias can account the 30% of the estimated earning losses. 20% is due to the fact that worker, after their first involuntary job separation, have higher probability to experience a displacement event again in the future. The remaining 50% is due to gaining lower wage in the new job. Furthermore, they conduct an interesting decomposition of the last effect. They find that 85% of the wage losses are due to losses in firm-specific human capital and that the remaining 15% are due to losses in worker-specific human capital. In this paper, I can argue that my measures do not suffer from the *extensive margin effect*. This should be the case since I measure the post- and pre-displacement levels of wages, earnings, working hours, etc., for workers who have only experienced their first job separation. By eliminating this effect, I can ensure that the larger component of earning losses referred to in this research is due to the *wage loss effect*. This is due to

[9]"*WARN* defines a *mass layoff* as a reduction in labour force that: (A) is not the result of a plant closing; and (B) results in an employment loss at the single site of employment during any 30-day period for (i) at least 33 percent of the employees (excluding any part-time employees); and (ii) at least 50 employees (excluding any part-time employees); or (iii) at least 500 employees (excluding any part-time employees)". See also McKittrick and Schnairsohn (2008).

[10]For more details about this literature see also Abowd et al. (2009).

some short of losses in the specific human capital after the involuntary job separation. In the literature, however, there is a gap between translating the individual productivity losses due to displacements, into their aggregate effects, which this chapter attempts to cover.

Further motivation about a primary focus on the UK economy comes from three papers which estimate earning losses after a job separation at the individual level. Their results encourage me to investigate the aggregate effect that displacements have on the UK's labour productivity. All these studies confirm the general findings of Jacobson et al. (1993a); i.e. that there are productivity losses after job separations. The first paper that motivates me is Borland et al. (2002). According to their findings, on average, there is a 2 to 14 percent penalty in wages observed after a separation (1991-1996). Larger losses are, thus, estimated between workers who had a period of non-employment after displacement. The second one is coming from Hijzen et al. (2010). They observe 18 to 35 percent losses in earnings from workers that lost their jobs due to a firm closure and only 14 to 25 percent losses from a mass layoff event (1994-2003). I present more recent stylised facts in chapter 1. In particular, I give more insides about the separation effect on earnings, for the UK between 1991 and 2011. I estimated that, on average, high tenured employees experience 18% short-run and 12% long-run earning losses after an involuntary job separation. The short-run losses are larger for college educated workers than for those with no college education. Nevertheless, earnings of college educated workers are recovering quicker. Moreover, at an aggregate level, the earning losses which accrued after a job separation were 86% driven by wage cuts[11]. These results may imply that, and for the UK economy, individual productivity losses occurred after a displacement. Furthermore, these losses should vary across high and low educated workers. The above findings drive this research to further investigate about any aggregate effect of displacements on the UK's productivity during the 2008 recession.

[11] I decompose earnings losses into wage cuts and working hours decreases.

3.3 Theories on Costly Job Displacement

This research relies heavily on the theory of specific human capital and productivity losses after a displacement. More specifically, it assumes that the real wage rate of the displaced group is equal to its average marginal productivity. Therefore, in the case of a displacement which, according to the theory, is largely due to bad luck, productivity losses (driven by human capital losses) are equal to the average wage losses of the displaced group. There are other theories which criticise the abovementioned assumption. I focus on the main ones, which are theories based on job matching, theories of backloaded compensation, rents, theories based on the revelation of information, and, finally, the intra-household reallocation and health-related theories. In this part, I briefly analyse the human capital theory and all other alternative theories which can criticise my results[12].

3.3.1 Specific Human Capital Theories

Specific human capital theories with relation to the concept of job separation rely on the idea that each worker has a component of skill which is only productive in its current work. Becker (1962), Mincer (1962), and Oi (1962), all built up the first models on specific human capital theory. These models are the most commonly used in the literature, and support that this component of skill which is only productive in the current job of an employee is developed in virtue of tenure, either from learning-by-doing on the job or from job training; nevertheless, those skills are often lost after a job separation. Specific human capital losses after a displacement make the worker less productive in the new job when compared to how he would be had his job not been displaced.

In particular, from the perspectives of the firm specific human capital theory, it is easy

[12]For more details about the literature see Carrington (2015).

to understand the reasoning behind why the displaced worker will experience losses in earnings after an involuntary job separation. A worker who is working in a firm builds up a stock of human capital that is specific to the particular firm's demand conditions for goods and services. The rental price of those firm-specific skills which are developed by the worker are also tied to the firm's demand conditions and will perhaps become equal to zero in the case of a firm closure, a mass layoff event, or a random redundancy. Therefore, the remaining human capital for the displaced worker will only be general (accumulated through education and experience). The latter implies that this lost component of firm-specific skills will drive earning losses after a displacement and will be dependent on pre-displacement job tenure. According to the current research, which relies on the firm-specific human capital theory, the productivity losses which are incurred after a displacement should be equal to the wage losses that this worker would have experienced after an involuntary job separation. The prediction of these models is that workers with low job tenure will experience lower losses after a displacement. This is the main reason that these theories are more concentrated on "high tenured" workers who have accumulated in their previous jobs a substantial amount of firm-specific human capital, which will be lost after the displacement. This research follows the same reasoning.

There are other models on specific human capital theory which do not deviate by much from the firm-specific human capital theory. These theories are based on human capital which is industries specific (Carrington (1993), Fallick (1993), occupation specific (Shaw (1984), and Neal (1995)), and locales specific (Howland and Peterson (1988)). According to these theories, workers develop specific skills in virtue of their tenure either from learning-by-doing on the job or from formal training. It is worth noting, however, that these models imply earning losses after a displacement only in the case of a mismatch (the new job is not in the same occupation or industry as the previous job). Finally, one basic critique of these specific human capital theories is that they cannot explain possible increases in earnings after a displacement.

3.3.2 Job Matching Theories

In the literature, there are alternative theories which criticise the traditional specific human capital theory. Specific human capital theories cannot explain why, after a displacement, some displaced workers experience increases in their earnings at their new workplace.

The job matching model developed by Jovanovic (1979) tries to answer this crucial question. Jovanovic (1979) proposes that, in matchings between firms and workers, there exists a different productivity component which is unique to each particular matching. That productivity component could be a distinguishing quality or characteristic, a particular skill, or a capacity which endures specific conditions, which is more valuable at particular firms and not at others. The job matching model deviates from the human capital theory by assuming that this component is fixed and that it can be transferred to other similar jobs (or other "good" matchings). Job tenure can potentially reveal information about the quality of a matching between a worker and a firm. From the worker's perspective, if he learns that the matching is not good, then, with very high probability, he or she will quit and find a better matching at his or her new job.

The predictions made by job matching theory regarding workers' earnings after an involuntary job separation is very similar to the one proposed by the human capital theory. More specifically, it supports the hypothesis that long tenured displaced workers experience earning losses after a displacement because, on average, the quality of the matching after a displacement was lower from that at their previous job (i.e. before the displacement). The latter occurs since, according to this theory, the worker has to start the job-matching process over again and investigate the quality of each new job opportunity which, on average, will be lower than the previous one. More specifically, the model suggests that workers with high levels of experience will suffer larger earnings and wage losses after an involuntary job separation. The reason for this is because those workers had the time to discover whether their current job is a "good" match or not.

Otherwise, if the matching was “bad”, then with high probability, the “bad” matched workers would have quit their jobs and would have attempted to find a “better” quality match. Some empirical evidence supports this theory and are coming from Krolikowski (2015) who is using the PSID dataset. It is worth mentioning that the implications of the job matching theory are also in line with the current research.

On the other hand, a worker who experiences an involuntary job separation might find a better match at a new job vis-a-vis their previous one. The result of being a better match to ones new job should also be reflected as an increase (instead of a decrease) on their earnings and wages. For instance, Neal (1999) finds that young workers at the beginning of their careers are more flexible to changes in occupation and industry with the purpose of finding a better match. For these workers, it is more unlikely that their jobs will be a relatively “good” match. For that reason, a displacement will be less costly for them. As discussed above, in the traditional models of specific human capital, an increase in earnings cannot occur after an involuntary separation.

The latter implication of this theory suggests that my results should suffer from an upwards bias. According to this implication of job matching theory, since the previous job of the displaced worker was a relatively “worst” match in comparison with its current job (after the displacement), the worker should have been less productive in its previous job than his real wage rate. As a result, my assumption that the marginal product of labour is equal to the real wage before and after a displacement does not hold for those workers who have found a better match after a displacement.

Finally, it should be mentioned that both theories of firm-specific human capital and firm-specific matching implicitly assume that the skills that are developed on the job by the worker are tight to a particular firm’s demand conditions for goods and services. Lazear (2009), on the other hand, points out that some of the skills accumulated at one job are valued by other jobs as well. As a result, after a displacement, it should not be the case that all the amount of the skills which were accumulated at the previous job will become lost.

3.3.3 Backloaded Compensation Theories

Other theories that can explain the strong link between the earnings of workers and their firms rose to prominence during the 70s from the development of models of adverse selection and moral hazards. Spence (1973), for instance, found that the level of education, job experience, race, sex and other characteristics can be used as sorting mechanisms from firms during the hiring process, the giving out of promotions, etc. Salop and Salop (1976) use these ideas and also the idea (which is derived from the specific human capital and job matching theories) that a worker with a long tenure at a firm will gain a higher wage and will have a lower probability of quitting from their job. One version of their model was developed under the idea that the firm has strong incentives for attracting workers who are less likely to quit from their jobs. The firms desire to attract more stable workers, since they have to pay some training cost for new hired workers which will be lost in the case of a worker will quit. One can think it as firms will lose a return to their investment from training a worker who in a later stage will quit. Since preferences of quitting vary across workers then, according to this model, the firm might offer a wage lower to that of marginal productivity to a new worker and, at a later stage (when this worker will become high tenured), a wage higher than that of marginal productivity. The latter imply that the wage-tenure profile will be steeper than that for average productivity. Someone can thing this idea as, by doing so, the firm is able to indirectly force newly hired workers to post an upfront bond which will be repaid by the firm at a later stage with a wage that will be higher than that which is commensurate for their actual productivity. In this way, workers will have less incentives for quitting.

In the agency models developed by Lazear (1979, 1981), which have a similar mechanism to that of Salop and Salop (1976), firms are worried about the moral hazards of their workers. If firms offer a wage very close to that commensurate with a workers marginal product, then workers have little incentive to avoid shirking in the form of negligence, theft, or other forms that are difficult to be monitored. According to these models, the latter will occur since it will be easy for those workers to find a job at another similar firm. So, the punishment from getting caught will have a very small effect on them. Lazear highlights that the implicit bond that is generated by wage-tenure profiles provides strong incentives for employees to avoid shrinking. In the cases of firing, which is caused from shrinking, the workers will lose part or all of their bonds.

It is worth noting that the current research assumes that workers, on average, always receive a wage which is equal to their average productivity before and after a displacement. Therefore, according to the models described above, my results might have an upwards or downwards bias depending on the tenure of the workers and how much steeper their wage-tenure profiles will be than average productivity. Furthermore, the descriptive statistics of this chapter show that the average pre displacement wages of the displaced workers were lower than that of non-displaced workers. The latter may imply that there was a source of adverse selection in the sense that the displaced workers before their displacement were less productive than the average non displaced and for that reason they experienced an involuntary job separation. Due to data limitations I cannot control for possible adverse selection in my estimates.

Another implication of these types of agency models is that long-tenured workers will receive higher wages in their current firm than elsewhere and that these wages will not necessarily be equal to their marginal productivity. Indeed, it is more likely that these workers will be less productive than what would be commensurate for the wage they are currently receiving. If employees will move from long-term jobs to new jobs, it seems unlikely that any direct social cost will be incurred since these displaced workers in their new jobs will be receiving a wage which is commensurate to their marginal productivity. So, according to this implication of the models, the results of the current research might be upwards biased under the imposing assumption that those workers on average will always receive a wage which is commensurate to their average productivity before and after their displacement.

Backloaded compensation theories similar to human capital and job matching theories propose that worker productivity or firm costs are tied to increases in wage (tenure or experience) profiles and that it is this that makes job separations so costly. One may criticise these theories for assuming that workers will maximise their discounted stream of utility (or, according to some simplified models, their earnings). There exists some empirical evidences which do not support this assumption and which have found that workers might be more attracted to increasing their earning profiles, both across and within jobs[13].

3.3.4 Theories on Rents

Theories on rent suggest that part of the profits which come from firms might be distributed among the employees (see, for instance, Blanchflower et al. (1996)). This implies that workers will gain wages exceeding that which is commensurate to their marginal product. Hildreth and Oswald (1997), among others, argue that the same might be true for unionised, heavily regulated, or particularly profitable firms. These rents are different from the human capital or agency theories, which are considered as ex-post quasi-rents. More specifically, human capital theory considers rents as returns on investment, and agency theory regards them as a kind of incentive mechanism. Rents theories, on the other hand, understand the rents given by particular firms more as a random process. As a result, during a recession, those workers who received rents and will get displaced, with a high probability will lose those rents. Similarly, theories on efficiency wages (see Carl Shapiro (1984)) arrive at the same conclusion (i.e. that some employees receive a higher wage than if their current jobs were to be eliminated), implying that these workers are paid more than that which is commensurate to their

[13] See for instance Loewenstein and Sicherman (1991) and Loewenstein and Prelec (1993).

marginal product.

According to rents theories, there are two types of model: in the first one, all firms pay rents or efficiency wages; whereas, in the second one, there are some firms that pay rents or efficiency wages and some others that do not. More specifically, in the first type of models, workers were lucky to have a job in rent-paying firms. All the others did not have a job and were unemployed. A job separation in this type of model is costly because the displaced worker will remain unemployed until he finds a job in another firm which will also offer rents or efficiency wages. In the second type of models, displacements will be costly for the displaced workers only from rent-paying firms, whereas a job separation is not costly from a firm which does not pay rents or efficiency wages. So, the average cost of a displacement should depend on the number of rent-paying and non-rent-paying firms. Finally, a critique of this type of models states that they do not have any mechanism which will lead to any correlation between job tenure and earning losses after a displacement.

It is worth noting that, according to the theories on rents, my estimates can either be upwards or downwards biased. This potential bias depends on the magnitude of the rents or efficiency wages which the displaced worker might have before and after the displacement. For instance, if a worker gains efficiency wages before the displacement and is not paid any after the displacement, then my results will be upwards biased. The latter will occurred since, before the displacement, the marginal productivity of that worker is lower than that expected from the commensurate wage. In my estimates, the drop in wages - which, according to this paper, equals the individual productivity (from the assumption of perfect competition) - will include the component of the efficiency wage. So, the efficiency wage prior to the separation will be included in the estimation of the productivity losses. In this case, my estimates will be subject to an upwards bias. With the same reasoning, if a worker receives efficiency wages after the displacement and did not receive any before the displacement, then my results will be affected by a downwards bias.

3.3.5 Revelation of Information Theories

The revelation of information theories are based on the idea that employers gather private information about their employees performance. For instance, an employer who knows that a potential worker was displaced from his previous job, that might provide them with information about that worker's actual productivity at that job. The potential employer might assume that the wage of that potential worker at his previous job was actually higher than a wage that would be commensurate to the average marginal productivity of a worker working at that firm and is similar in terms of observable characteristics to that displaced worker. The latter implies that future employers might lower their expectations for the productivity of a displaced worker (in other words, they will treat that worker as if he had been fired for a cause).

Gibbons and Katz (1991) apply those ideas in their wide known "lemons" model. They develop a model where firms with partial layoffs (or redundancies) dismiss the less productive workers, whereas, in firms which are closing, they cannot distinguish between the good and bad workers and dismiss all of them. In light of the previously described features of the model, potential employers might assume that displaced workers at firms which had partial layoffs are less productive than those displaced workers coming from firms which have shut down. In other words, potential employers will hire displaced workers from firms which had partial layoffs only at lower wages from the one that the displaced workers had received in their previous jobs. On the other hand, potential employers will not make any conjectures about displaced workers from firm closures since all of the workers at that firm were dismissed irrespective of their skills (or lack thereof). A critique of the above model is that empirical evidence does not consistently show that earning losses are higher for displaced workers from partial layoffs than that accrued by displaced workers from firm closures.

Furthermore, there are more reasons that a sharp distinction between partial layoffs and layoffs from firm closures are not so important - even if one accepts that a partial layoff is a bad signal for displaced workers. Troske (1996) points out that there are signals that the firm might fail way before they actually do and that workers can understand that something is not going well. Thus, the workers who are less attached to the failing plant and who know of other plants that are offering wages near to their current ones have a higher probability of leaving before their company actually fails. On the other hand, workers who stay with the failing company until the very end might not have the same option of finding work elsewhere. In addition, differences in current wages between workers might be due to the accumulation of firm-specific human capital or just because some workers are paid more than what their marginal product justifies them to receive (rents, efficiency wages, etc.). Workers who receive very high wages have a higher probability of either getting fired or experiencing a wage cut if the company they are working for is close to failing, whereas this is not the case for only moderately overpaid employees. The implication is that the claim that the workers displaced from firm closures are actually the least productive ones is not justified. The latter findings can justify why for the current research is not important to distinguish between displaced workers from partial layoffs or from layoffs as a result of firm closures.

It is worth mentioning that, according to the revelation of information theories, my estimates are liable to an upwards bias. This can occur if workers in the jobs prior to their displacements gave their employers a wrong signal about their productivity and, ergo, received wages which were higher than that which was commensurate for their actual marginal product rate. As a result of the wrong signals that they gave to their employers, in a later stage they were fired. As a result, in their new job, these workers started receiving a wage which was commensurate to their actual marginal productivity rate. On the other hand, it might be the case that, after a displacement, the employer underestimated the productivity of a worker who lost his previous job. Thus, it will lead this employer to give that worker a wage which is lower than that which is commensurate to its actual productivity rate. The latter can, therefore, potentially create a downward bias on my estimates.

3.3.6 Intra-household Reallocation and Health Related Theories

The primary focus of most of the previous models is on the individual displaced worker and not on their household. In most cases, a displaced worker is a member of a household. Therefore, it will be useful to examine the effects of a displacement from the perspective of household utility and budgeting maximisation. Risk sharing and intra-household consumption models propose that a displacement event which befalls a member of a household is more likely to cause an increase in the working hours of the other members of that same household. There are papers in the literature (e.g. Lundberg (1985)) which highlight the "added worker effect" which occurs when a spouse enters the labour market after the other member of the household experiences an involuntary job separation. In some cases, the earnings of a displaced worker will not recover if the spouse continues to work in the long-run. This can occur if the spouse's increased labour income decreases the labour supply of the displaced worker or if it affects the displaced workers decision to choose lower paying jobs. The latter decision implies that the displaced worker will find a low paid and low productive job, even if his actual productivity is higher than is commensurate to his current wage. This effect, thus, might cause a downward bias in my estimates. Finally, health-related theories suggest that an involuntary job separation might affect the health of the displaced worker or that they might be affected by other psychological impacts which will, in turn, decrease his productivity in his new job.

3.4 Data

The data that is used in this chapter were obtained from two main sources: household and aggregate data. For the purpose of constructing employment and earning histories in a panel form, the British Household Panel Survey (BHPS) was used. BHPS is a long panel with quite rich data on working histories, labour and non-labour income, wages, hours of working, individual and job characteristics, as well as macroeconomic and local market indicators. Individuals can be followed at most for 20 years, starting from the end of 1990 to the end of 2011 (waves 1-20). It is the first analysis which can measure flows in and out of unemployment for the period until 2011, including the current economic crisis. In order to make the sample representative of Great Britain (excluding Scotland), this analysis uses longitudinal weights. For the employment histories, I have improved upon, not only the methodology used by Smith (2011) but also the earning histories used by Smith (2013) (in the same papers, there is a more detailed description of the data).

I improved upon the construction of the dataset by gaining 15% more information than Smith in her papers (Smith (2011), Smith (2013)). For data inconsistencies, Smith follows the reconciliation method introduced by Paull (2002). This research improves upon that methodology in the following ways: a) It does not follow the method for overlapping spells as Smith does; Paull (2002) describes his method as follows: "The start date for the second spell in overlapping spells was set to the end date of the first spell. If the spells had the same start date or the first spell began after the second, the second spell is dropped." (Appendix B, point C). For instance, if an individual states that he was employed for the whole period in one wave (i.e. wave A) and has the same job in the subsequent wave (i.e. wave B), then clearly the spell in wave B overlaps with that in wave A. This happens because, in both of them, the individual has to state when he started his current job. The same occurs for individuals who are currently unemployed or out of the labour force. By deleting the spell in wave A, as Smith does, very important information about the growth in earnings, wages, hours of working, benefits, etc., over time (i.e. from wave to wave) is lost. This can be a critique, especially for the paper Smith (2013), where she makes estimations on earnings, wages, and hours of working without taking into consideration a possible growth in these variables over time (or over waves). Smith has less than 132,000 spells, whereas this paper, by following point A, constructs more than 243,000 spells for the first 18 waves, with an overall amount of almost 270,000 spells. These spells are converted into a monthly panel for each individual of at most 256 months. 32,869 individuals created a rich dataset with a sum total of 4,436,077 monthly spells. b) This research gains 15% more information by applying the following: from subsequent waves (for instance, from waves A & B), the employment history of an individual in his last spell of wave A should always be the same as the first spell of wave B, as soon as the individual's employment status does not change. So, the lost information on hours of working, wages, etc., which were not reported if an individual changes his or her employment status within wave B (this information is reported only in the last spell of each wave but not in the previous spells of this wave), can be regained by using the complete information of the last spell from wave A. Note that all of the above data are individually and seasonally adjusted by using the Census Bureau's X12 programme.

Furthermore, a demanding goal was to link the data obtained from the BHPS with that of the Understanding Societys, which is the continuation of the original sample for waves 19 and 20. In that attempt, unfortunately, quite important information for this research was lost from the construction of the new survey. In the new survey, the Understanding Societys data has complete information for the last spell of each wave but, disappointingly, does not contain information on earnings, benefits, industrial and occupation classifications for the spells within a wave. For instance, if a worker changes his or her employment status four times during a single year (within the same wave), complete information regarding their earnings, etc., is only provided at the last spell and offers limited information for all the other spells. One issue which could potentially influence the results of this research is the classification of college and non-college educated workers. In the original BHPS dataset, there is a variable which uses the International Standard Classification of Education (ISCED) as a measurement. Unfortunately, in the Understanding Societys dataset, there is no direct variable for that distinction; furthermore, in the Appendix B, it is explained how an education variable is generated.

Another issue which can legitimately be raised is why this chapter does not use the Labour Force Survey (LFS), which is a larger dataset than BHPS. The reason that the BHPS is used is that, unlike LFS, the BHPS portrays employment histories better and more holistically. In the survey, it asks the exact date of any employment flows into employment (E), unemployment (U), and out of the labour force (O) within a wave. Furthermore, it can follows the same individual across time without imposing any restrictions in the length of the time period that this individual will be interviewed. So, there is a complete history of each individual for at most 20 years. On the other hand, in the LFS, only a quarter of information about employment status (i.e. the employment status at the time of the interview) for, at most, 5 subsequent quarters is provided. It is, thus, obvious that a long-run estimation of the earnings after a displacement (5 years after) is impossible to be generated using the LFS.

An alternative source of data for the UK economy is the *"New Earnings Survey"*, the *"Inter-Departmental Business Register"*, and the *"Annual Business Inquiry"*, all of which Hijzen et al. (2010) use for their analysis of the effect of mass layoffs on earnings at the individual level. The problem with these three sources of data is that I cannot use them for my analysis since they do not allow one to aggregate them and find, for example, what the fraction of displaced workers over employment for the whole UK economy is - something which I am easily able to do with the BHPS dataset.

Finally, for aggregate UK data, the main sources are the *"Office for National Statistics"* (ONS) and the *"Organisation for Economic Co-operation and Development"* (OECD). For the calibration of the first exercise and in order to transform all of the data from the BHPS into real terms, monthly prices as an index (Consumer Price Index, or CPI) with a base year of 2010 are used from the OECD[14]. The gross domestic product (GDP), on a quarterly basis, is extracted from the ONS. From the UKs *"Quarterly Labour Force Survey"* (QLFS), I extracted quarterly estimates of the total labour force at the aggregate level. Finally, the total weekly hours worked were on a monthly basis, and derived from the LFS; I then transformed those estimates to reflect their quarterly equivalents. Thereby, the aggregate labour productivity is equal to gross domestic product per hour worked. Note that all of the above data are also seasonally adjusted.

Table 3.1: Average hourly wage rate for displaced and non-displaced workers across time.

	High Type			Low Type		
Period	Non-displ	Displaced		Non-displ	Displaced	
		Post-displac	Pre-displac		Post-displac	Pre-displac
1992-2011	14.31	11.45	12.38	9.5	8.57	8.85
2007	15.61	13.16	12.45	10.41	9.97	9.94
2008	15.62	13.62	14.32	10.34	9.53	9.96
2009-2011	14.81	10.21	14.76	9.96	9.83	10.35

In terms of descriptive statistics for high tenured workers (i.e. more than 2 years in the same job), we can observe from Table 3.1 that the average wage of college educated non-displaced workers are, on average, 2.45 pounds more than that of college educated displaced workers after their first displacement and almost 1.9 before they were displaced. For non-college educated workers, the difference is smaller. The average wage of low educated non-displaced workers are, on average, only 1 pound more than that of displaced workers after their first displacement and almost 0.65 pounds before they were displaced. The drop in wages for: I) high type non-displaced workers during the crisis from the time period before the crisis (2008Q1, which is the base quarter that

[14]The ONS provides the CPI index with a base year 2005, but the OECD transform it to 2010 prices. All the other aggregate data (GDP, Productivity) from LFS are in 2010 prices, so the index from the OECD is preferred.

this chapter uses) is 4.4%; II) high type displaced workers is 27.6%; III) low type non-displaced workers is 5.4%; and IV) low type displaced workers is 4.4%. Therefore, on average, the drop in wages of displaced workers overall is 16%. The above results suggest that the high type displaced workers experienced the most severe losses in their wages during the crisis.

Table 3.2: Average total weekly hours for displaced and non-displaced workers across time.

	High Type		Low Type	
Period	Non-displ	Displaced	Non-displ	Displaced
1992-2011	36.57	38.37	36.69	37.99
2007	35.66	39.9	36.55	37.75
2008	36.26	38.26	36.4	36.42
2009-2011	36.2	36.32	35.7	35.83

Table 3.2 shows the average total weekly hours worked by high and low type displaced and non-displaced workers. In this table, we can observe that displaced workers, on average, are working from 1 to 1.8 hours more than that of non-displaced workers. During the crisis, however, it seems that there are no differences between them and that both groups are working almost the same amount of hours every week.

Finally, Table 3.3 shows the fraction of high and low type displaced and non-displaced workers over employment across time. From this table, we can observe that the 32% of the employed workers are non-displaced and that 2.4% are workers who have experienced at least one displacement event. Remarkably, the fraction of displaced workers increased during the crisis by 50% from the base quarter (2008Q1). More specifically, during the crisis, the fraction of high type displaced workers increased by 34%, whereas the fraction of low type displaced workers increased by 59.5%.

Table 3.3: Average fractions of displaced and non-displaced workers over employment across time.

	High Type		Low Type	
Period	Non-displ	Displaced	Non-displ	Displaced
1992-2011	12.55	0.72	19.28	1.67
2007	9.61	0.67	13.12	1.18
2008	8.15	0.68	11.75	1.11
2009-2011	5.2	0.86	8.93	1.78

3.5 The Model

This section describes the theoretical model that is used for running the counterfactual accounting exercises. I introduce a production function with constant elasticity of substitution (CES) between two types of workers - high (college) and low (non-college) educated - who are imperfect substitutes. I make the separation of the sample into high and low type since, in my previous findings (see Giannarakis (2015)), after a job displacement, a different recovery path of earnings and wages between college and non-college workers is observed. The earnings and wages of high type displaced workers have more severe losses after the displacement than that of low type displaced workers and do not recover as much as they do in the case of the low educated workers. Moreover, a general CES production function is preferred instead of a Cobb-Douglas because the elasticity of substitution between high and low type workers can be estimated from the data[15]. High and low educated workers supply labour inelastically at time t. In addition, there is an extensive literature which investigates how investment in general human capital (mainly in education) creates wage differentials which are driven from

[15] If the estimated elasticity of substitution between college and non college workers is equal to one, then the production function is Cobb-Douglas with fixed shares paid to each factor. With imperfect substitutability there is a better understanding of how relative prices affect skills. In the case of perfect substitution, the wages of each type of workers would always move together up to a multiplicative constant (reflecting relative efficiency units) so skill premia would not exist.

differences in productivity between college and non-college workers (Becker (1962); Becker and Chiswick (1966); Mincer (1958, 1962); and Willis (1987)). That literature has motivated me further to make this distinction between high and low educated workers.

In this CES production function, a heterogeneity across high and low type workers is introduced. So, let us assume that college and non-college workers consist of two different groups of workers: non-displaced and displaced. Non-displaced workers (which we can consider as a control group) are workers who were always working at the same job or had a job-to-job flow, with the reason for their changing their job not being that the company made a redundancy or the worker got sacked. On the other hand, the displacement group consists of workers who experienced at least one involuntary job separation (i.e. displacement event) in their employment history. For this group, the reason for leaving their job was that the company made a redundancy or the worker got sacked. Therefore, overall, there are four different groups of workers: high and low non-displaced workers (H_1; L_1) and high and low displaced workers (H_2; L_2).

This chapter assumes that displaced and non-displaced workers (who can either be a high or low type) are perfect substitutes since the input (job) of the two different groups of workers (displaced and non-displaced) is the same. For instance, a position for a university lecturer (high type) can be filled either by a non-displaced or by a displaced university lecturer (high type) such that $H = H_1 + H_2$; or, in more general form, $H = H_1 + \gamma_2 H_2$ (with γ_1 to be normalised to one). Therefore, it means that one group of workers can be substituted by the other at a constant rate. The low type worker equivalent is: $L = L_1 + \gamma_2^{'} L_2$.

Following Acemoglu (2002b), who uses and extends a large literature introduced by Krusell et al. (2000), the production function takes the CES form (considering capital in the residual, *Z*) as follows:

$$Y_t = Z_t[(1-\alpha_t)(A_{Lt}L_t)^\rho + \alpha_t(A_{Ht}H_t)^\rho]^{\frac{1}{\rho}} \quad (3.5.1)$$

where H_t and L_t are the total hours worked by the high and low skilled workers, respectively, at each time *t* (quarter), $\alpha_t = \frac{E_{Ht}}{E_t}$ (see also Appendix B), is the share of income that high type workers receive; and $1-\alpha_t = \frac{E_{Lt}}{E_t}$ (with E_H and E_L being the total earnings of the high and low type workers, respectively, and $E = E_H + E_L$). Z_t is the residual which includes capital, total fctor productivity (TFP), the rest of the workers that are not displaced or non-displaced, and other factors that might be missing[16]. $A_{Ht}; A_{Lt}$ signifies the skill augmenting parameters and $\sigma \equiv 1/(1-\rho)$ is the elasticity of substitution between skilled and unskilled workers (who are either displaced or non-displaced), $\rho \leq 1$.

To estimate the parameters of the above CES, this research uses weighted averages of quarterly estimates on wages, number of workers, hours of working, and earnings, taken from the BHPS dataset. For instance, $\frac{E_{Ht}}{E_t} \equiv \frac{e_{ht}}{e_t}$ and $\frac{E_{Lt}}{E_t} \equiv \frac{e_{lt}}{e_t}$, where e_h and e_l are the total earnings of high and low type workers at aggregate level, and $e = e_h + e_l$ are the total earnings of both types of workers, all taken from the BHPS dataset. Note that, in this part, upper cases refer to the aggregate data from the UK economy, whereas lower cases refer to estimates from the BHPS dataset (except $\gamma; \alpha; \rho$, and σ which still refer to the population).

This research makes two basic assumptions. The economy is in equilibrium and in a perfectly competitive world (where the average marginal product of labour is equal to the average real hourly wage rate, $MPL = w/p$). Furthermore, as was mentioned above, non-displaced and displaced workers which are high type (H_{1t} and H_{2t}) are as-

[16]Note that workers that cannot be justified neither as displaced nor as non-displaced are these that could have a flow such as $O \rightarrow U \rightarrow E$ or $E \rightarrow O \rightarrow U \rightarrow E$ or any other possible combination that does not satisfy the definition of displaced and non-displaced worker (where *E* is employed, *U* is unemployed, and *O* is out of the labour force).

sumed to be perfect substitutes and equal to:

$$H_t = H_{1t} + \gamma_{2t} H_{2t}, \text{ where } \gamma_{2t} = \frac{\sum_{i=1}^{N_{H_{2t}}} \gamma_{2it}}{N_{H_{2t}}} \tag{3.5.2}$$

with γ_{2t} being the skill premium between displaced and non-displaced workers who are high type, and $N_{H_{2t}}$ to be the number of high type displaced workers in the UK economy for each period of time. Equivalently for low type:

$$L_t = L_{1t} + \gamma_2^{'} L_{2t}, \text{ where } \gamma_{2t}^{'} = \frac{\sum_{i=1}^{N_{L_{2t}}} \gamma_{2it}^{'}}{N_{L_{2t}}} \tag{3.5.3}$$

with $\gamma_{2t}^{'}$ being the skill premium between the displaced and non-displaced workers who are of a low type, and $N_{L_{2t}}$ being the number of low type displaced workers in the UK economy for each period of time. Since H_t and L_t are the total hours worked by high and low type workers, I use the estimates from the BHPS dataset as an approximation for determining them. So, the total hours worked for all the high type non-displaced worker in the population can be calculated as the number of high type non-displaced workers multiplied by their relevant average hours of working:

$$H_{1t} = (N_{H_{1t}})(\overline{H}_{1t}) \tag{3.5.4}$$

where N_{H_1} and $\overline{H}_1$ are the number of non-displaced high type workers and their relevant average hours of working, respectively, both in the population. Since I did not have measurements of N_{H_1} and $\overline{H}_1$ in the population, this research takes approximations from the BHPS dataset as follows: the aggregate hours worked in the population from all the high type non-displaced workers for every period *t* can be approximated as the fraction of displaced workers who are in the BHPS dataset ($n_{h_{1t}}/n_t$) multiplied by the whole labour force of the UK economy (this product represents an approximation of the number of high type non-displaced workers who are in the population) multiplied by their relevant average hours of working (which is, itself, estimated from the BHPS dataset). Thus, we have:

$$(N_{H_{1t}})(\overline{H}_{1t}) \equiv \frac{n_{h_{1t}}}{n_t} N_t(\overline{h}_{1t}) \tag{3.5.5}$$

with n_{h_1} and $\overline{h}_1$ being the number of non-displaced high type workers and their relevant average hours of working, respectively, and n being the total employment or the total number of workers (all of which are taken from the BHPS dataset), and N being the total employment of the UK economy (aggregate number of workers taken from the ONS).

Equivalently, the aggregate hours of working for high type displaced (H_{2t}), low type non-displaced (L_{1t}), and low type displaced (L_{2t}) workers are:

$$\begin{aligned} H_{2t} &= (N_{H_{2t}})(\overline{H}_{2t}) \equiv \frac{n_{h_{2t}}}{n_t} N_t(\overline{h}_{2t}) \\ L_{1t} &= (N_{L_{1t}})(\overline{L}_{1t}) \equiv \frac{n_{l_{1t}}}{n_t} N_t(\bar{l}_{1t}) \\ L_{2t} &= (N_{L_{2t}})(\overline{L}_{2t}) \equiv \frac{n_{l_{2t}}}{n_t} N_t(\bar{l}_{2t}) \end{aligned} \tag{3.5.6}$$

In the above CES production function (equation 3.5.1), however, the unknown parameters which need to be determined for each *t* (quarter) are $\gamma_2; \gamma_2^{'}; \rho; Z; A_H$, and A_L. In order to determine γ_2 and $\gamma_2^{'}$, I solved the profit maximisation problem with respect to H_i and L_i (with $i = 1,2$), assuming that prices (P) are exogenous determined and that perfect competition holds (time subscripts are dropped where possible)[17]:

$$\max_{H_i,L_i}\{\pi\} = \max_{H_i,L_i}\{TR - TC = PY - C_{lab}\} =$$
$$\max_{H_i,L_i}\{PZ[(1-\alpha)(A_L L)^{\rho} + \alpha(A_H H)^{\rho}]^{\frac{1}{\rho}} - (W_{H_1}H_1 + W_{H_2}H_2 + W_{L_1}L_1 + W_{L_2}L_2)\} \quad (3.5.7)$$

where π are the profits; C_{lab} is the labour cost (I drop other possible types of cost which are irrelevant to the maximisation problem); W_{H_i} and W_{L_i} are the average wages of the group of workers *i* ($i = 1,2$ are for the non-displaced and the displaced groups of worker, respectively); and $W_{H_i}H_i, W_{L_i}L_i$ is the labour cost of each group of workers.

The first order conditions in respect to H_i, L_i give[18]:

For the skilled workers, $\frac{W_{H_2}}{W_{H_1}} = \gamma_2$, and for the unskilled workers $\frac{W_{L_2}}{W_{L_1}} = \gamma_2^{'}$[19]. Since again there are no estimates of these wages in the population, I will use an approxi-

[17] The case where makes the profit maximization problem (PMP) not to be the most suitable methodology that can be applied, is when a firm (or a sector, a whole economy, a country etc.) is not a price taker. In that case, one should apply a cost minimization problem. Furthermore, *"when the production set exhibits nondecreasing returns to scale, the value function and optimizing vectors of the cost minimization problem, which keeps the level of outputs fixed, are better behaved than the profit function and the supply correspondence of the PMP"* (see Mas-Colell et al. (1995), page 139). In our case, the CES production function exhibits constant returns to scale and a perfect competitive world is assumed. So, the PMP is more suitable for this analysis.

[18] See Appendix B for more analytical solution.

[19] For the displaced group, I tried to introduce more heterogeneity by creating three displaced subgroups according to the duration of unemployment (long, short or a job to job flow following an involuntary separation). One basic problem of the BHPS dataset is the small number of observations, especially for

mation by using estimates from the BHPS dataset as follows: $\gamma_2 = \frac{W_{H_2}}{W_{H_1}} \equiv \frac{w_{H_2}}{w_{H_1}}$ and $\gamma_2^{'} = \frac{W_{L_2}}{W_{L_1}} \equiv \frac{w_{L_2}}{w_{L_1}}$, where w_{H_1} and w_{H_2} are the average hourly wage rates estimates of high type non-displaced and displaced workers, respectively and w_{L_1} and w_{L_2} are the average hourly wage rates estimates of low type non-displaced and displaced workers, respectively (all of which were taken from the BHPS dataset).

After defining γ_2 and $\gamma_2^{'}$, from the CES the remaining unknown parameters are $\rho; Z; A_H$, and A_L.

In order to estimate ρ, I follow the well-established methodology developed by Katz and Murphy (1992) and Acemoglu (2002b)[20]. The remaining unknowns are the following three: $Z; A_H$, and A_L. Nevertheless, the skill premium between high and low type non-displaced workers ω is equal to:

$$\omega_t = \frac{W_{H_{1t}}}{W_{L_{1t}}} = \frac{\alpha_t}{1-\alpha_t}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\rho}\left(\frac{H_{1t}+\gamma_{2t}H_{2t}}{L_{1t}+\gamma_{2t}^{'}L_{2t}}\right)^{\rho-1} \tag{3.5.8}$$

This can be used as the first equation[21]. The second equation will be the function for the aggregate labour productivity $Prod_t$, which involves the CES production function as followed:

the high type displaced workers, which make the estimates for these subgroups, pretty ambiguous. But in the Appendix B, I extend the model accordingly.

[20]The method and the empirical estimation of ρ is introduced in the Appendix B.

[21]This equation can be derived by dividing the equations B.2.11 over B.2.13, which are in the Appendix B, and is also used in the next section for defining the elasticity of substitution between high and low type workers.

$$Prod_t = \frac{Y_t}{Hours_t} = \frac{Z_t[(1-\alpha_t)(A_{Lt}(L_{1t}+\gamma_{2t}^{'}L_{2t}))^{\rho}+\alpha_t(A_{Ht}(H_{1t}+\gamma_{2t}H_{2t}))^{\rho}]^{\frac{1}{\rho}}}{Hours_t} \quad (3.5.9)$$

Where $Hours_t$ are the aggregate hours worked in a quarter from all the workers in the economy (estimates derived from ONS), and $Prod_t$ is the fraction of the quarterly Real GDP (Y_t) of the economy over $Hours_t$. Finally, from the above system of two equations there are three unknowns $A_H; A_L$ and Z[22]. Since the above identification problem exists, I use a normalisation by setting A_H equal to 1.

Finally, after this normalization, from 3.5.8 and 3.5.9 there is a system of two equations with two unknowns Z and A_L, which is the following:

$$Prod_t = \frac{Y_t}{Hours_t} = \frac{Z_t[(1-\alpha_t)(A_{Lt}(L_{1t}+\gamma_{2t}^{'}L_{2t}))^{\rho}+\alpha_t((H_{1t}+\gamma_{2t}H_{2t}))^{\rho}]^{\frac{1}{\rho}}}{Hours_t} \quad (3.5.10)$$

and, by solving 3.5.8 for A_L:

$$A_{Lt}^{\rho} = \frac{\alpha_t}{1-\alpha_t}\frac{W_{L_{1t}}}{W_{H_{1t}}}\left(\frac{H_{1t}+\gamma_{2t}H_{2t}}{L_{1t}+\gamma_{2t}^{'}L_{2t}}\right)^{\rho-1} \quad (3.5.11)$$

This system can be solved and quarterly estimates of Z and A_L can be extracted.

After adjusting the CES using real UK data, I am able to run the counterfactual accounting exercises. In section 5, and for each particular counterfactual exercise, there

[22] In fact, from the beginning of the maximization problem there is this identification problem since there are 5 unknowns (γ_2; $\gamma_2^{'}$; A_H; A_L, and Z) and from the FOC's we can get 4 equations and we also have the production function itself. In the Appendix B I prove that the production function is a linear combination of the four other equations, which means that actually there are 4 equations and 5 unknowns.

is an analytical description of which variables I change in the adjusted CES in order to evaluate the amount of productivity after the crisis.

At this point, from the model, it should be noticed that aggregate productivity does not depend, per se, only upon the level of wages of each type of worker but on their relative wages to the other type. In this model, a change in the skill premium between high and low type workers who are non-displaced or a change in the skill premium between displaced and non-displaced workers (γ's) can alter aggregate productivity. For instance, a decrease in the inequality between low and high type workers who are non-displaced, which will also imply an increase in their skill premium ($\frac{W_{L_1}}{W_{H_1}}$), overall will increase the productivity of the economy, and the vice versa[23]. So, wage cuts will not necessarily lead to a decrease in labour productivity. The behaviour of aggregate productivity depends on the magnitude of these cuts in wages over both types of worker.

Furthermore, it should be mentioned that I use a structural approach in order to estimate the contribution of displacements on explaining the UK's productivity puzzle since a rough computation of the fact based on the hours worked by displaced workers multiplied by their average wage drop can probably be misleading. A rough computation using a linear production function in the form of $Y_t = Z_t * (L_{1t}w_{1t} + L_{2t}w_{2t} + H_{1t}w_{1t} + H_{2t}w_{2t})$ does not take into account possible general equilibrium effects, nor does it take into account the link between wages, the supply of skills and demand due to technological progress (see Acemoglu (2002b)).

It should also be noticed that, if someone uses a linear function for the purpose of estimating the contribution that displaced workers have had on the UK's productivity puzzle, they have to implicitly assume that College and Non-College educated workers are perfect substitutes. Perfect substitution between high and low educated workers will

[23] An increase in the inequality between low and high type workers will decrease the skill premium between low and high and so overall, aggregate productivity will decrease.

imply an elasticity of substitution of $\sigma \rightarrow \infty$ (or $\rho = 1$). Therefore, the wage premium between high and low types of worker (see, for instance 3.5.8) will not depend upon the supply of labour but only upon the labour augmenting parameters of the model, which is an unrealistic scenario. Empirical evidence extracted from this research shows that the elasticity of substitution is approximately equal to 3 and not close to infinity, as the perfect substitutability implies. Independently from that, I ran a sensitivity analysis for the different values of ρ (see the "Empirical Results" section). The results which were generated were rather robust, except that the case of the high and low types of worker (who are either displaced or non-displaced) are *Leontief*. So, even though perfect substitution does not seem to influence the results of this paper, someone cannot implicitly assume that $\rho = 1$ and base the entire analysis of this chapter on the perfect substitutability between high and low types of worker.

Finally, it is worth noting the linear technologies of labour for the several groups, which implies that the marginal productivity of labour (MPL) is constant, omit the complementarity of the different groups and the fact that the *MPL*s are downward slopping. These features imply that the wage is a combination of productivity parameters and of labour inputs. My counterfactuals are more conservative exercises because, other things being equal, when labour is reduced, wages are increased. So, in my exercise, the wages are endogenous in the counterfactuals in which the workers are reshuffled. For this reason, a rough computation can potentially generate different results from my counterfactuals. This fact motivated me to use a general CES production function - which became the standard methodology as is endorsed by a large literature including Acemoglu (2002b) - and test whether there are any significant differences in the results for the various values of ρ.

3.6 Counterfactual Exercises

3.6.1 Introduction

This section describes and presents the results of the counterfactual accounting exercises. Recall that the target of this chapter is to determine how much of the UK's productivity puzzle can be explained by displacements. As mentioned before, the puzzle for the UK economy is that, after the crisis, output per hour worked did not follow its pre-crisis trend, as GDP did, and experienced almost zero growth. After running careful counterfactual exercises, the main findings are that the displacements of high tenured workers (i.e. who had worked for more than 2 years at the same job prior to the separation) can explain, on average, 27 percent of the gap between actual post-2008 labour productivity and the one if productivity had followed the path of its potential level in the absence of a crisis (i.e. if post-2008 productivity had followed the pre-2008 trend). A notable result is also that 78 percent of the effect that the displacements had on the puzzle can be explained by productivity (and wage) losses in the college educated displaced workers. The remaining 22 percent is due to losses in the displaced workers who are non-college educated.

The first step of analysing the data is to adjust the production function over the total hours worked (see equation 3.5.9 which represents aggregate productivity as output per hour worked), on the actual quarterly data of the UK's labour productivity taken from the ONS. I proceed as follows: from the BHPS dataset, I create two different groups of worker. The first group is consisted of workers who were continuously working and who had never been displaced throughout their employment history (let us consider this group as the control group), and the second is consisted of all the workers who experienced at least one involuntary job separation (or displacement event).

For the displaced group, I focus only on their post-displacement period and follow the displaced worker for, at most, three years after the displacement[24]. I do that since, in the previous chapter, for the same dataset and during the same time period, after a displacement, I estimate significant earning losses which are wage driven. From the data, however, it cannot be extracted a clear loss of earnings that is due to wage losses for some groups after the third year of their first displacement. Thus, the idea is that a displacement which occurred, for instance, in 1997Q4, created a significant loss in specific human capital, thereby making the worker less productive, until 2000Q4. This means that, in estimating the average wage for the displaced group in 1998Q2, I included the wage of this displaced worker and all of the other workers who were displaced at most 3 years before that quarter (i.e. 1995Q2).

Following the methodology described above, I create a pool of displaced workers. Someone can regard the displaced worker after their first involuntary job separation as being scarred (see Ruhm (1991) for more details about the definition of scarred workers due to job displacements). The rest of the employment history of the displaced worker is included in the residual Z. I also distinguished between workers who had received a college education and those who had not since, from previous estimates, I have observed that the recovery path of high type displaced workers differs from the recovery path of low type displaced workers. So, overall there are 4 different groups of workers: college and non-college educated who are either displaced or non-displaced.

For these four groups of worker, I extract quarterly estimates of average wages, earnings, hours of working, and number of workers, all of which are taken from the BHPS. From the ONS, quarterly data of the real GDP, the total hours worked (denoted in this chapter as $Hours_t$), and the total employment for the UK economy are used. To find the output per hour worked, I divide the Real GDP with total hours worked and use this as an estimate for the quarterly aggregate labour productivity (denoted as $Prod_t$). With these aggregate data, and after estimating the elasticity of substitution between high and

[24]For instance, one counterfactual is to account the aggregate productivity if their post-displacement wages where equal with that before the displacement.

low types or workers σ (which I assume that is fixed over time) from the BHPS dataset (see Appendix B), I am able to solve for every quarter the system of two equations with two unknowns A_L and Z (see equations 3.5.8 and 3.5.10) described in section 2, and obtain quarterly estimates of them. Since there are quarterly estimates for all of the models parameters, the adjusted production function over total hours worked takes the following form:

$$Prod_t = \frac{\widehat{Y}_t}{Hours_t} = \frac{\widehat{Z}_t \left[(1-\widehat{\alpha}_t)(\widehat{A}_{L_t}(\widehat{L}_{1t}+\widehat{\gamma}'_{2t}\widehat{L}_{2t}))^{\widehat{\rho}} + \widehat{\alpha}_t(\widehat{H}_{1t}+\widehat{\gamma}_{2t}\widehat{H}_{2t})^{\widehat{\rho}}\right]^{\frac{1}{\widehat{\rho}}}}{Hours_t} \tag{3.6.1}$$

Where the hats symbolise that the variables are estimated from the BHPS dataset and from the solution of equations 3.5.8 and 3.5.10 (i.e. for A_L and Z) for each quarter of time.

Therefore, the quarterly estimates for A_L and Z fit the data exactly[25]. This absolute match is demonstrated in Figure 3.1, which is the calibration of the model. As can be observed, the estimated productivity from the adjusted model is a perfect match with the actual data since this is the design of the calibration.

By changing the parameters for equation 3.6.1, I can run the counterfactual accounting exercises in order to find whether displacements can explain part of the UK's productivity puzzle. Nevertheless, it is important to provide more insights about this puzzle. From the first two columns of Table B.5 (see Appendix B), the aggregate productivity for the UK reached its peak during the fourth quarter of 2007 or, for simplicity, in 2008Q1 since I followed the methodology introduced by Blundell et al. (2014). The

[25]Note that from the maximization problem, I can extract quarterly estimates of γ's as: $\gamma_{2t} \equiv \frac{w_{H_{2t}}}{w_{H_{1t}}}$, and $\gamma'_{2t} \equiv \frac{w_{L_{2t}}}{w_{L_{1t}}}$.

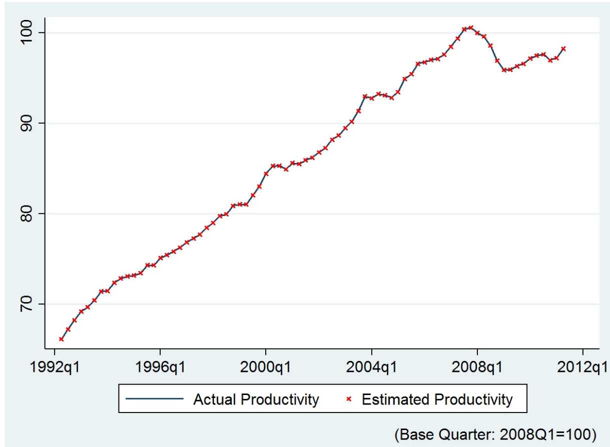


Figure 3.1: Calibration of the CES Production Function to Actual UK data in Labour Productivity.

first quarter of 2009 therefore marks the trough of the productivity during the current economic crisis, as well as at the beginning of the recovery. The difference between the peak to trough of the actual productivity is 4.1 percent. At the trough, there is a 6.74 percent difference from its estimated potential productivity if the financial crisis had not occurred (see in the Appendix B how I estimated the pre-crisis trend of productivity). Therefore, this chapter highlights how much of this productivity gap can be explained by displacements. It does this by running careful counterfactual accounting exercises.

More specifically, in order to account for how much of the puzzle can be explained by displacements, I follow Blundell et al. (2014) by comparing the estimated post-2008 productivity to each of the counterfactuals, with that if the productivity had followed the path of the pre-2008 trend. Furthermore, I also compare the estimated post-2008 productivity from the counterfactuals with the one that assumes that the productivity had followed the path of two past recessions in the UK (1979Q4 and 1990Q2). One issue is that, since the BHPS dataset goes back to 1991, for these two recessions, there is not enough actual data on the average wage of displaced workers and on their fraction over employment in order to make a broader comparison between that and the current recession. Therefore, for these cases, I can only find the upper bound of how much displacements can explain the productivity puzzle if the actual post-2008 productivity had followed the path of these two recessions.

Let us examine the UKs productivity puzzle in terms of magnitude. Columns 2-4 of Table 3.4 show the productivity gap between the two past recessions (1979Q4 and 1990Q2) and the pre-2008 trend with the actual post-2008 productivity, *n* quarters after the start of the recessions. So, for instance, 8 quarters (or 2 years) after the start of the 1979Q4 and 2008Q1 crises, the implied productivity gap between them was 8%. Furthermore, three years after the start of the 2008Q1 recession (i.e. 12 quarters), productivity was 9% below its potential one had productivity followed the pre-2008 trend, 13,4% had it followed the path of the 1990Q2 crisis, and 12% had it followed the 1979Q4 crisis. So, overall, the gap between the 2008 and: I) 1979 crisis is between 4.4 and 12.9 percentage points; II) 1990 crisis is between 4.4 and 13.5 percentage points; and III) pre-2008 trend is between 5.1 and 8.5 percentage points. Note that all the counterfactuals provided below refer to high tenured workers (i.e. they have had more than 2 years in the same job).

3.6.2 Counterfactuals 1 and 2

Having quantified the puzzle, I can now describe the first counterfactual accounting exercise (Counterfactual 1). In this counterfactual, I find what the productivity in the UK would have been had all the displaced workers after their first involuntary job separation been as productive as the average non-displaced worker. Thus, given the above adjusted CES, in this exercise, I calculate for the productivity in the UK (denoted as $Prod_t^{\bullet}$) if there were any job separations (and any human capital losses from displacements) in the economy and if the displaced workers were equally productive as the non-displaced ones. Note that the implication of the equal productivity between displaced and non-

Table 3.4: Implied Productivity Gap between recessions.

	1979q4	1990q2	Pre-2008q1 Trend
Quarter	2008q1	2008q1	2008q1
3	4.4	4.4	5.1
4	4.7	6.5	6.6
5	6.4	7.6	7.0
6	6.9	8.2	7.1
7	7.5	8.9	7.3
8	8.0	8.8	7.2
9	8.7	10.1	7.4
10	9.5	11.2	7.7
11	10.8	13.0	8.8
12	12.0	13.4	9.0
13	12.9	13.5	8.5

displaced workers is that, on average, they have an equal level of real hourly wage rates. Recall that in this paper, the average real hourly wages reflect average individual labour productivity since the basic assumption that I impose is that the economy, on a macro-level, is under perfect competition.

So, for the period from 1990 to 2011, I use the quarterly estimations of $\rho; Z; A_L$, and $A_H = 1$ (which were described previously) and I account for the aggregate labour productivity of the UK economy under the condition that the skill premiums between the displaced and the non-displaced workers (for both high and low educated workers) are equal to one. This means that $\gamma_2 \equiv \frac{w_{H_2}}{w_{H_1}} = 1$, that $\gamma_2^{'} \equiv \frac{w_{L_2}}{w_{L_1}} = 1$, and that the productivity for this counterfactual is equal to:

$$Prod_t^{\bullet} = \frac{\widehat{Z}_t \left[(1-\widehat{\alpha}_t)(\widehat{A}_{L_t}(\widehat{L}_{1t}+\widehat{L}_{2t}))^{\widehat{\rho}} + \widehat{\alpha}_t(\widehat{H}_{1t}+\widehat{H}_{2t})^{\widehat{\rho}} \right]^{\frac{1}{\widehat{\rho}}}}{Hours_t} \tag{3.6.2}$$

The green line in Figure 3.2 represents the accounted productivity from the first counterfactual exercise. From this counterfactual, we can observe that, if the displaced workers were as productive as the non-displaced ones, then, on average, their pre-crisis productivity (1992-2007) would have been 0.94 percentage points more than the actual one. For the period after the trough of the crisis (2009Q1), productivity would have been, on average, 2.1 percentage points more than the actual one, which is, on average, 1.16 percentage points larger than that which was evidenced during the pre-crisis period. These results show that, on average, 27.9 percent of the UK's productivity puzzle can be explained by this counterfactual[26].

[26]See Table B.4 which is in the Appendix B for more details about the results. A detailed explanation of equivalent tables is in the next part (Counterfactuals 2 and 3).

One may note, however, that this counterfactual reflects a basic problem of selection towards low productive workers that cannot be controlled for. More specifically, it might be the case that low productive workers have a higher probability of getting fired, which implies that, in their previous job, they were not equally productive with the workers in the non-displaced group. So, there might be an upward bias in this counterfactual exercise and the actual effect of displacements on the UK's productivity is smaller than the estimates of this counterfactual. Controversially, during the crisis, it might have been the case that high productive workers who gain high wages got displaced and that, in their next job, they experienced severe earning losses. The latter could have occurred since, during periods of crisis, firms always tend to decrease their labour cost. Thus, their response to the crisis might have been to layoff some high-skilled workers and replace them with lower-skilled workers in order to reduce the cost of labour. Barlevy (2002) points out that empirical evidence suggest that during recessions a "sullying" effect is observed and a redirection of the economy from highly paid workers (which can imply that these workers are more productive, as well) to lower paid workers. This means that the workers which got displaced during the crisis might have actually been more productive than the non-displaced ones, implying a downward bias on the estimates of this counterfactual. Furthermore, counterfactual 1 assumes that there were no involuntary job separations in the labour market - something which is unrealistic in the real world. So, the results from this exercise have been affected either by an upwards or a downwards bias.

By partially controlling the potential bias in the estimates described above, a different counterfactual is proposed. I ran a more careful exercise that takes into account the productivity in the UK (denoted as $Prod_t^*$) had there been no job separations in the labour market and the displaced workers were as productive as they used to be before their first displacement (Counterfactual 2). Since average wages reflect average individual productivity (due to the assumption of perfect competition), this means that, for each worker, I set the post-displacement real hourly wage rate to be equal with the one before the displacement.

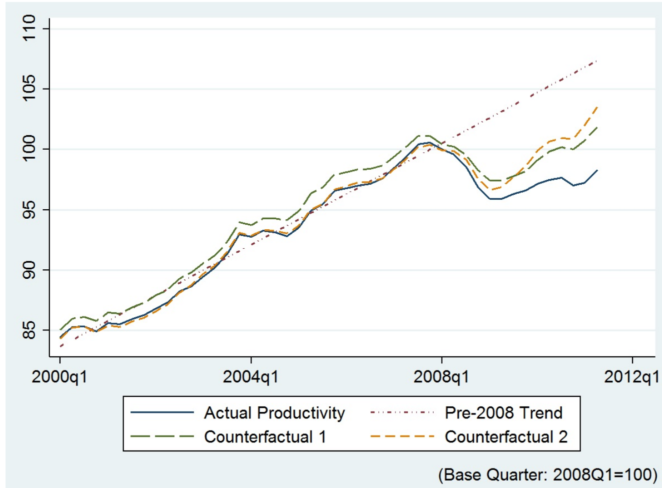


Figure 3.2: Actual and Labour Productivity from counterfactuals 1 and 2.

More specifically, I account for aggregate productivity ($Prod^*$) under the condition that $\gamma_2 = \widetilde{\gamma}_2 \equiv \frac{\widetilde{w}_{H_2}}{w_{H_1}}$ and $\gamma_2^{'} = \widetilde{\gamma}_2^{'} \equiv \frac{\widetilde{w}_{L_2}}{w_{L_1}}$, where $\widetilde{w}_{H_2}$ and $\widetilde{w}_{L_2}$ are the average real wages of the displaced group (for high and low type) had the level of the hourly wage for each displaced worker been equal with the one that this worker had before its first displacement. Therefore, $\widetilde{\gamma}_2$ is the skill premium between high type displaced to non-displaced workers by assuming that the displaced workers were as productive as they used to be, before their first displacement, with $\widetilde{\gamma}_2^{'}$ being defined exactly the same way for low type workers. This means that, for this counterfactual, I can account productivity (and compare these quarterly measurements with the actual aggregate productivity) from the following function:

$$Prod_t^* = \frac{\widehat{Y}_t}{Hours_t} = \frac{\widehat{Z}_t\left[(1-\widehat{\alpha}_t)(\widehat{A}_{L_t}(\widehat{L}_{1t}+\widetilde{\gamma}_{2t}^{'}\widehat{L}_{2t}))^{\widehat{\rho}} + \widehat{\alpha}_t(\widehat{H}_{1t}+\widetilde{\gamma}_{2t}\widehat{H}_{2t})^{\widehat{\rho}}\right]^{\frac{1}{\widehat{\rho}}}}{Hours_t} \tag{3.6.3}$$

In Figure 3.2 we can observe the actual (blue line) and the accounted productivity of this counterfactual (yellow line). This figure covers the period from 2000 until 2011 and the yellow line shows the aggregate productivity had the displaced workers after their first displacement been as productive as they used to be before the displacement. Note that, after 2010, this estimated productivity overcomes the one from the first counterfactual (green line), implying that, during the crisis, it seems that high type workers who were more productive than the average non-displaced workers lost their jobs. For that reason, the effect on productivity from the second counterfactual can be considered to be higher than that from the first.

From this counterfactual, we can observe that the productivity during the crisis would have increased, on average, by 2.36 percentage points from the actual one and that, for the period before the crisis, productivity would have been increased, on average, by only 0.16 percentage points. These results can be interpreted as that displacements indeed explaining part of the UK's productivity puzzle.

In terms of magnitude, we can examine columns 2 through 4 in Table 3.5. This table shows the implied gap between the estimated post-2008 productivity under the condition that the displaced workers were as productive as they used to be before their first displacement (Counterfactual 2), both in terms of the past two recessions (1979Q4 and 1990Q2) and in terms of the pre-2008 trend. Comparing this table with the actual gaps presented in Table 3.4, we can observe the following: two years after the beginning of the 2008 crisis (quarter 8), the gap between the actual post-2008 productivity and the one had productivity followed its pre-2008 trend is 7.2 percentage points. For the same time period, the implied gap between the accounted post-2008 productivity from this counterfactual and the one had productivity followed its pre-2008 trend would have been 4.6 percentage points (which indicates a reduction of 2.6 percentage points), thereby explaining 36.3% of this gap[27]. So, for the entire period after the trough of the crisis (2009Q1), displacements from this counterfactual can explain, on average, 31.8%

[27] See in quarter 8, fourth and seventh columns of Table 3.5.

of the gap based on the pre-2008 trend.

If one wanted to find the upper bound of how much displacements can explain the gap between the actual post-2008 productivity and the one had productivity followed the path of the two past recessions, we simply conduct the same analysis as above. So, two years after the beginning of the 2008 crisis, the implied gap from the 1990Q2 crisis would have been 2.5 percentage points less than the actual one (from 8.8% to 6.3%), thereby explaining, at most, 29.1% of this gap (see the third and sixth columns of Table 3.5); finally, the implied gap from the 1979Q4 crisis would have been 2.6 percentage points less than the actual one (from 8% to 5.4%), thereby explaining, at most, 32.5% of this gap (see the second and fifth columns of the same table). So, in columns 5 and 6 of Table 3.5, we can observe that, for each quarter, the upper bound of how much the UK's productivity puzzle can be explained by displacements had productivity followed the path of the two past recessions. On average, then, displacements from this counterfactual can explain, at most, 26.8% of the gap from the 1979Q4 recession and 23.1% of the gap from the 1990Q2 recession.

3.6.3 Counterfactuals 3 to 5

One potential problem that can arise from the previous counterfactual is that, for the displaced workers during the post-crisis period, the displacement may have occurred before, during or after the drop of both the UK's GDP and labour productivity which was observed from 2008Q1 to 2009Q2. Therefore, the wage that a displaced worker received at their previous job may or may not have been affected by the crisis. This can create a potential over- or under-estimation of productivity losses due to the fact that job separations occurred throughout the crisis.

To overcome this bias, I ran an alternative counterfactual which I argue is more ro-

Table 3.5: Implied productivity gap (in %) between recessions and counterfactual 2, and percentage of the gap which is explained by counterfactual 2.

	Implied Gap: Reces.-Counter. 2			Gap to be explained by Counter. 2		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.7	3.8	4.4	15.4	15.4	13.3
4	4.0	5.8	5.8	15.3	10.9	10.8
5	5.4	6.6	6.1	14.6	12.1	13.2
6	5.6	6.9	5.7	19.5	16.1	19.0
7	5.6	7.0	5.4	25.6	21.4	26.5
8	5.4	6.3	4.6	32.5	29.1	36.3
9	5.8	7.1	4.4	34.1	29.2	40.9
10	6.4	8.3	4.6	32.0	26.5	40.2
11	7.2	9.5	5.1	33.3	27.0	42.0
12	7.7	9.1	4.5	36.2	31.9	50.1
13	8.3	8.8	3.6	36.2	34.6	57.9

bust with regards to the effect that the crisis had on labour productivity (Counterfactual 3). This counterfactual accounts for the post-crisis productivity had the average productivity of the displaced group after 2008 been equal with the average productivity (or average wage) that this group had before the beginning of the crisis. It should be mentioned that, due to the assumption of perfect competition, the average productivity of the displaced group is approximately equal to the average wage of this group. Someone might think about the counterfactual as follows: what would have been the post-2008 productivity had the economy during that period been at its potential level (with no crisis) but the average wage of displaced workers was equal to the actual post-crisis level and not with the one that they had had at the beginning of the crisis. Note that this counterfactual relaxes both of the above counterfactuals assumptions that there were no involuntary job separations in the labour market.

In particular, for this counterfactual, I set the average post-crisis level of real wage rates of the displaced group (which under perfect competition reflects the average productivity for each worker who belongs to this group) to be equal with that before the beginning of the crisis (2008Q1). With this exercise I can account the post-crisis aggregate labour productivity ($Prod^{**}$) if the wages of displaced workers (and their productivity) have not been affected by the crisis. Thus, in the counterfactual I set $\gamma_2 = \check{\gamma}_2 = \check{w}_{H_2}/w_{H_1}$ and $\gamma_2^{'} = \check{\gamma}_2^{'} = \check{w}_{L_2}/w_{L_1}$, where $\check{w}_{H_2}$ and $\check{w}_{L_2}$ are the average wages of high and low type displaced workers before the beginning of the crisis (2008Q1), respectively, and I account productivity as:

In particular, for this counterfactual, I set the average post-crisis level of real wage rates of the displaced group (which, under perfect competition, reflects the average productivity of each worker who belongs to this group) to be equal with that before the beginning of the crisis (2008Q1). With this exercise, I am able to account the post-2008 aggregate labour productivity ($Prod^{**}$) had the wages of the displaced workers (and their productivity) not been affected by the crisis. Thus, in the counterfactual, I set $\gamma_2 = \check{\gamma}_2 = \check{w}_{H_2}/w_{H_1}$ and $\gamma_2^{'} = \check{\gamma}_2^{'} = \check{w}_{L_2}/w_{L_1}$, where $\check{w}_{H_2}$ and $\check{w}_{L_2}$ are the average wages of high and low type displaced workers before the beginning of the crisis (2008Q1), respectively. I account the productivity as follows:

$$Prod_t^{**} = \frac{\widehat{Z}_t \left[(1-\widehat{\alpha}_t)(\widehat{A}_{L_t}(\widehat{L}_{1t} + \check{\gamma}_{2t}'\widehat{L}_{2t}))^{\widehat{\rho}} + \widehat{\alpha}_t(\widehat{H}_{1t} + \check{\gamma}_{2t}\widehat{H}_{2t})^{\widehat{\rho}}\right]^{\frac{1}{\widehat{\rho}}}}{Hours_t} \quad (3.6.4)$$

Therefore, the difference between the actual and this estimated productivity is purely driven by differences in the average wages of the displaced workers between the periods before and after the crisis. In Figures B.7 and B.8 (See Appendix B), the wages of the four groups of worker can be observed. Furthermore, Figures B.9 and B.10 (Appendix B) represent the skill premium between the displaced and non-displaced workers who are either of a high or low type ($\frac{w_{H_1}}{w_{H_2}}$ and $\frac{w_{L_1}}{w_{L_2}}$) over time. In these Figures, we can observe the evolution of $\gamma's$ over time where, during the 2008-crisis, the skill premium between the displaced and non-displaced workers (who can either be of a high or low type) decreased - especially for the high type. For that reason, someone should expect an increase in the potential aggregate productivity after the crisis had the post-2008 average wages for the displaced group been equal with those before 2008. This expected increase can be discerned in Figure 3.3. The green line in this figure shows the potential productivity under this counterfactual exercise (Counterfactual 3).

In terms of results, as was expected, one can observe in Table B.7 (which is in Appendix B) that the potential productivity would have been from 1.1 to 3.67 percentage points larger than the current one. Furthermore, from the same table, one can discern that the difference between the peak (2007Q4 or, for simplicity, 2008Q1, since I am following the methodology of Blundell et al. (2014)) and trough (2009Q1) of the actual productivity derived from this counterfactual is 1.06 percentage points (95.9 versus 96.96, respectively). The same is true for the difference between the potential productivity in the absence of the crisis in 2009Q1: potential productivity is 6.74 percentage

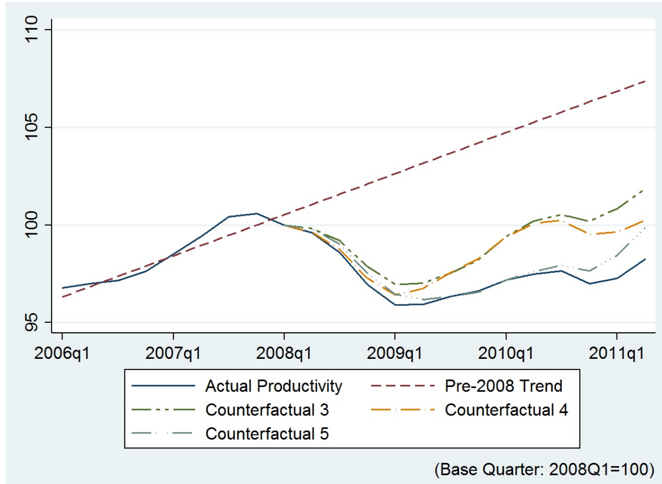


Figure 3.3: Real and Potential Labour Productivity: Wages Case.

points higher than the actual productivity (102.64 versus 95.9, respectively) and 5.68 percentage points from the productivity had, during this quarter, the level of real wages of the displaced workers were equal to those before the crisis (102.64 versus 96.96, respectively). The above results show that the changes in the average wages of the displaced group during the crisis play a role in explaining part of the UK's productivity puzzle.

More specifically, from Figure 3.4 and Table 3.6 we can observe that the gap between the post-2008 productivity (this was estimated by using the pre-2008 estimates of the average wages of displaced workers) and the pre-2008 trend is between 4.2 and 5.1 percentage points, thereby explaining 27 percent of the productivity gap[28].

[28]Note that in Figure 3.4 the series 1979Q1 is the output per hour worked after the 1979Q1 crisis normalised to 100 at the labelled quarter. The same holds for the 1990Q2 and 2008Q1. The series Pre-2008 Trend is the estimated trend (see Appendix B) before the 2008 crisis, the series Counterfactual 3 and 8 are the post-2008 productivity from these counterfactual and are both normalised to 100 at the 2008Q1 quarter.

Table 3.6: Implied productivity gap (in %) between recessions and counterfactual 3, and percentage of the gap which is explained by counterfactual 3.

	Implied Gap: Reces.-Counter. 3			Gap to be explained by Counter. 3		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.5	3.5	4.2	21.0	20.9	18.1
4	3.7	5.5	5.5	22.2	15.9	15.7
5	5.3	6.5	6.0	16.7	13.9	15.1
6	5.8	7.1	5.9	16.8	13.9	16.4
7	6.0	7.4	5.8	20.2	16.9	21.0
8	5.9	6.7	5.1	26.7	23.9	29.8
9	6.2	7.6	4.8	29.1	24.9	34.9
10	6.8	8.6	5.0	28.2	23.3	35.4
11	7.9	10.2	5.8	27.2	22.0	34.3
12	8.8	10.2	5.6	26.9	23.8	37.3
13	9.7	10.3	5.1	24.7	23.6	39.5

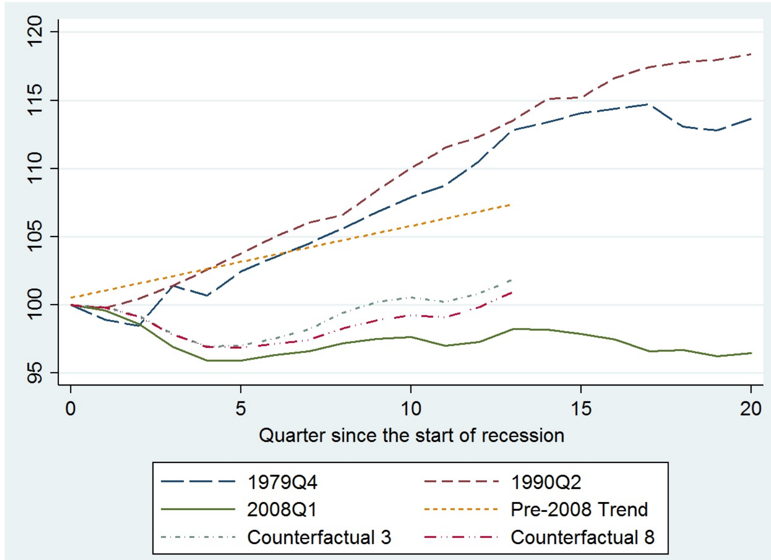


Figure 3.4: Changes to Real Output per Hour by UK Recession.

Furthermore, if we want to find the upper bound of how much displacements can explain the UK productivity puzzle, then one can compare this counterfactual with what would have happened had the actual post-2008 productivity levels followed the path of the two previous recessions. In order to do this, I follow the same logic as above. In this way, we observe that the gap between the post-2008 productivity (by using the pre-2008 estimates of the average wages of displaced workers) and: I) the 1979 post-crisis is between 3.5 and 9.7 percentage points which thereby explains, at most, 23.6 percent of the productivity gap; and II) the 1990 post-crisis is between 3.5 and 10.3 percentage points, thereby explaining, at most, 20.3 percent of the productivity gap.

So, after running different counterfactual exercises and partially controlling for possible bias in the estimations, we can conclude that displacements do in fact explain more than one fourth of the UK's productivity puzzle (i.e. 27%).

Moreover, I quantify the contribution of the displaced workers who are either college or non-college educated separately in order to explain the productivity puzzle. In order to capture the effect of a drop in wages in college educated workers during the crisis, I ran Counterfactual 4. In this counterfactual, I only set the post-2008 average hourly wage rate of college educated workers to be equal with the one before the beginning of the crisis (2008Q1); furthermore, I allow the average wage of non-college educated displaced workers to fluctuate freely during the crisis. The effect on productivity can be seen in the yellow line of Figure 3.3; and from Table B.8 (which is in Appendix B). From this figure we can observe that the post-2008 productivity under this counterfactual would have been from 0.53 to 2.03 percentage points higher than the actual one. So, on average, the drop in wages of high type displaced workers can explain 21.1% of the UK's productivity puzzle. Since the overall wage drop of the displaced group can explain 27% of this puzzle (Counterfactual 3), that means that 21.1/27, or more than the 78% of this effect, can be explained by the drop in wages of high type workers[29]. This result seems to be inline with Barlevy (2002) who points out that empirical evidence suggest that during recessions a "sullying" effect is observed and a redirection of the economy from highly paid workers (which can imply that these workers are more productive, as well) to lower paid workers.

Equivalently, in order to capturing the effect of the drop in wages of non-college educated displaced workers during the crisis, I ran Counterfactual 5. In this Counterfactual, I set the post-2008 average wage rate of non-college educated displaced workers to be equal with the one before the beginning of the crisis (2008Q1) and allow the average wage of college educated displaced workers to fluctuate freely during the crisis. The effect on productivity can be seen in the grey line of Figure 3.3; and, in Table B.10 (which is in the Appendix B). From this figure we can observe that the post-2008 productivity under this counterfactual would have been from 0.57 to 1.62 percentage points higher than the actual one which, in turn, explains only 5.9% of the UK's productivity puzzle. This result implies that 5.9/27, or 22%, of the overall effect of the drop in wages

[29] For more details about the effect of high type on the puzzle see Table B.9 which is in the Appendix B.

for the displaced group can be explained by the drop in wages of non-college educated displaced workers[30].

Finally, it should be mentioned that, from Figure 3.3, we can see that the implied gap between counterfactual productivity and actual productivity is widening as the recovery continues from post-2008 until late 2010; afterwards, though, it seems to have a parallel path. The main reason for this should be because the drop in the real hourly wage rates of the displaced workers is widening as the recovery continues post-2008[31]. The drop in the level of wages in 2009Q1 from that in 2008Q1 was 10.9%, whereas the drop in the level of wages in 2010Q1 and 2011Q1 from that in 2008Q1 was 14.8% and 22.9%, respectively. Between 2010Q3 and 2011Q2, however, the wage drop stabilised at 19.4%. Maybe this is the reason why, after late 2010, counterfactual productivity and actual productivity seem to share a parallel path.

Furthermore, this widening drop in wages of displaced workers seems to be driven by the large drop in wages of college educated displaced workers. The drop in wages of college educated displaced workers in 2009Q1, 2010Q1, and 2011Q1 was 12.1%, 30.5%, and 33.7%, respectively, from the average wages of this group in 2008Q1. On the other hand, the drop in wages of non-college educated displaced workers in 2009Q1 was 11.5%. In 2010Q1, they were almost fully recovered to the 2008Q1 level, but in 2011Q1, it dropped again to 9% in comparison with the 2008Q1 level. The drop in wages is possibly linked to productivity losses after a displacement, labour supply and demand forces which determine wages, possible mismatches (workers found their new job in another sector or occupation from the one that they were displaced from), and the duration of unemployment for the displaced workers after the displacement and before

---

[30] For more details about the effect of low type on the puzzle see Table B.11 which is in the Appendix B.

[31] From Counterfactuals 6 and 7 we see that displaced rates explain a small part of the productivity puzzle and is not the main reason that the implied gap between counterfactual productivity and actual productivity is widening as the recovery continues post 2008.

finding a new job. Due to data limitations, I could not check the strength of the second and third reason; but, in Figure B.13 (see Appendix B), we can observe that the average unemployment duration (in months) after an involuntary separation increased by 49% in 2010Q1 in comparison to the trough of the crisis (2009Q1), which is from 2.1 to 3.2 months, and by 106% in 2011Q1 (4.4 months). It should also be noted that the duration of unemployment after late 2010 seems to be decreasing, which might be linked to the fact that, during the same period, the wage drop stabilised at 19.4% and both the counterfactual productivity and actual productivity seem to share a parallel path.

3.6.4 Counterfactuals 6 and 7

According to the data, during the crisis, one can also observe, on average, a 50% increase in the fraction of the displaced group over employed. The following exercise aims to highlight the effect of the increase in displacement rates on the post-crisis productivity (Counterfactual 6). So, in this counterfactual, I account for post-2008 productivity by setting the post-crisis fraction of displaced workers over employment for both high (n_{h_2}/n) and low type (n_{l_2}/n) workers to being equal with the amounts before the crisis[32].

More specifically, I set $n_{h_2}/n = \overline{n}_{h_2}/\overline{n}$, and $n_{l_2}/n = \overline{n}_{l_2}/\overline{n}$. Note that the bar signs symbolise the fractions of displaced workers over employment in 2008Q1 and that those fractions under the current counterfactual remain fixed for the period after the crisis. Furthermore, I adjust accordingly the fractions n_{h_1}/n and n_{l_1}/n, which are the fractions of high and low type non-displaced workers over employment, to the new sample sizes in each quarter, by setting $n_{h_1}/n = \widetilde{n}_{h_1}/\widetilde{n}$, and $n_{l_1}/n = \widetilde{n}_{l_1}/\widetilde{n}$. In this case, the

[32]Someone can think this counterfactual as followed: what would have been the post-2008 productivity if the economy during that period was in its potential level (with no crisis) but the fraction of displaced workers over employment was equal with the actual post-crisis level and not with the one that they had in the beginning of the crisis.

tilde sign symbolises the post-crisis adjusted fractions of the non-displaced group to the new sample sizes[33]. Figures B.11 and B.12 in the Appendix B show these fractions over time. Finally, in this counterfactual, the total hours worked for each group of workers in the population $H_1; H_2; L_1$, and L_2 will change after the crisis to $\breve{H}_1; \breve{H}_2; \breve{L}_1$, and $\breve{L}_2$, where:

$$\begin{aligned}
\breve{H}_{1t} &\equiv \frac{\widetilde{n}_{h_{1t}}}{\widetilde{n}_t} N_t(h_{h_{1t}}) \\
\breve{H}_{2t} &\equiv \frac{\overline{n}_{h_{2t}}}{\overline{n}} N_t(h_{h_{2t}}) \\
\breve{L}_{1t} &\equiv \frac{\widetilde{n}_{l_{1t}}}{\widetilde{n}_t} N_t(h_{l_{1t}}) \\
\breve{L}_{2t} &\equiv \frac{\overline{n}_{l_{2t}}}{\overline{n}} N_t(h_{l_{2t}})
\end{aligned} \tag{3.6.5}$$

I account the post-crisis productivity for this counterfactual ($Prod_t^{***}$) as:

$$Prod_t^{***} = \frac{\widehat{Z}_t \left[(1-\widehat{\alpha}_t)(\widehat{A}_{L_t}(\breve{L}_{1t} + \widehat{\gamma}'_{2t}\breve{L}_{2t}))^{\widehat{\rho}} + \widehat{\alpha}_t(\breve{H}_{1t} + \widehat{\gamma}_{2t}\breve{H}_{2t})^{\widehat{\rho}}\right]^{\frac{1}{\widehat{\rho}}}}{Hours_t} \tag{3.6.6}$$

$Prod_t^{***}$ accounts for post-crisis productivity by using the pre-crisis fractions for displaced workers. Thus, after the beginning of the crisis, the difference between the actual and the counterfactual productivity is purely driven by differences in the displacement rates between the pre- and post-crisis periods. In terms of results, we can observe from

[33] Since I keep fixed the post-crisis fractions of displaced workers and equal with that before the beginning of the crisis, this implies that the post-crisis sample size will change and for that reason I have to adjust accordingly the fractions of the non-displaced group.

the yellow line of Figure 3.5 the post-crisis productivity had the displaced workers (as a fraction of employment) during the crisis been equal to the level that they had been before the beginning of the crisis. So, the productivity from this counterfactual would have been between 0.13 and 1.2 percentage points (and, on average, 0.7 percentage points) more than the actual post-2008 productivity (see Table B.12 in Appendix B).

Furthermore, the difference between the peak (2008Q1) and trough (2009Q1) of the actual productivity with the post-crisis productivity from this counterfactual is 0.13 percentage points. Finally, in 2009Q1, the potential productivity in the absence of the crisis is 7.02 percentage points higher than the actual productivity (102.64 versus 95.90) and 6.88 percentage points from the productivity if, at this quarter, the displacement rates were equal with those before the crisis (102.64 versus 96.03). From these results, one can also conclude that displacement rates played a role on the UK's productivity puzzle but is smaller in magnitude than the wage case.

More specifically, column 4 of Table 3.7 depicts the implied gap between the estimated post-2008 productivity under this counterfactual (Counterfactual 6) and that of the pre-2008 trend. In the same table, column 7 shows how much of the UK's productivity puzzle can be explained purely by the increase in the fraction of the displaced group during the crisis. As one can discern from this table, displacement rates can explain, on average, 7.4% of the gap based on the pre-2008 trend.

In addition, if we want to find the upper bound of how much displacement rates can explain the gap between the actual post-2008 productivity and the one had productivity followed the path of the two past recessions, we follow the same logic as above. Columns 2 and 3 of Table 3.7 show the implied gap between the estimated post-2008 productivity under this counterfactual (Counterfactual 6) with the two past recessions (1979Q4 and 1990Q2) and the pre-2008 trend. In the same table, Columns 5 and 6 show the upper bound of how much of the UK's productivity puzzle can be explained purely

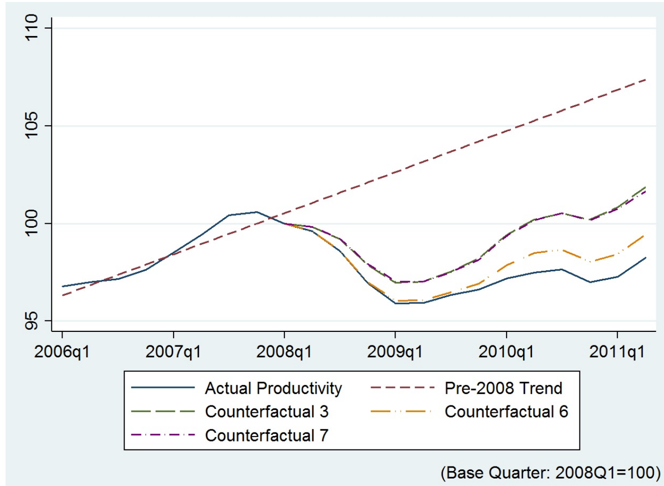


Figure 3.5: Real and Potential Labour Productivity: Counterfactuals 6 and 7.

by the increase in the fraction of the displaced group during the crisis. As one can see from this table, displacement rates can explain, on average, at most 6% of the gap from the 1979Q4 recession and 5.2% of the gap from the 1990Q2 recession.

The model also allows one to test what the overall effect that the wage drop in the displaced group and the increase in the displacement rates (Counterfactual 7) had on the post-2008 aggregate productivity of the UK economy. In the purple line of Figure 3.5 (noted as Counterfactual 7), one can discern this effect. Moreover, from Table B.13 (see Appendix B) and Table 3.8 one can conclude that the overall effect of displacements and wage drops is almost exactly the same (on average, 26.7%) as in the third counterfactual (i.e. the wage case). Someone could expect that the overall effect from both forces should be higher than the effect from solely the drop in wages of the displaced workers (Counterfactual 3). Below I argue why that is not the case in this counterfactual.

In the displacement rate case (Counterfactual 6), the parts of the production function which change during the crisis are as follows: $\breve{L}_{1t} + \widehat{\gamma}'_{2t}\breve{L}_{2t}$ and $\breve{H}_{1t} + \widehat{\gamma}_{2t}\breve{H}_{2t}$. So, after

Table 3.7: Implied productivity gap (in %) between recessions and counterfactual 6, and percentage of the gap which is explained by counterfactual 6.

	Implied Gap: Reces.-Counter. 6			Gap to be explained by Counter. 6		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	4.4	4.4	5.0	1.4	1.4	1.2
4	4.6	6.4	6.4	2.6	1.9	1.9
5	6.2	7.4	6.9	2.3	1.9	2.1
6	6.8	8.1	7.0	1.8	1.5	1.8
7	7.3	8.6	7.0	3.8	3.2	4.0
8	7.3	8.2	6.6	8.1	7.3	9.1
9	7.8	9.1	6.5	10.6	9.0	12.7
10	8.6	10.3	6.8	9.8	8.1	12.4
11	9.9	12.1	7.8	8.9	7.2	11.2
12	11.0	12.4	7.9	8.8	7.8	12.2
13	11.9	12.4	7.4	8.1	7.7	13.0

running Counterfactual 6, during the post-crisis period, H_1 and L_1 will increase slightly because of the necessary resizing of the data described above. On the other hand, under Counterfactual 6, H_2 and L_2 decrease slightly in the post-2008 period since I set the fraction of displaced workers equal to the fraction that they were in 2008Q1. These fractions are lower than the actual ones in the post-2008 period since there are more displaced workers after the crisis[34]. So, in the displacement rate case, the effect is slightly positive, increasing the potential post-crisis productivity. In the wage case, however, the post-crisis productivity is increasing vis-a-vis the actual ones. This means that, if we combine both the displacement rates and the wage effect, the $\check{\gamma}'_{2t}\breve{L}_{2t}$ and $\check{\gamma}_{2t}\breve{H}_{2t}$ will not increase as much as they do in the wage case. This is the reason why productivity under Counterfactual 7 is not higher from that which occurred under Counterfactual 3 (in this case, for instance, they almost coincide).

3.6.5 Counterfactuals 8 to 10

Finally, in order to measure how much of the UK's productivity puzzle can be explained from the drop in wages in both the displaced and the non-displaced groups during the crisis, I ran an alternative counterfactual exercise (Counterfactual 8). In this counterfactual, I set the average post-crisis level of real wage rates of both the displaced and the non-displaced groups to be equal with those before the beginning of the crisis (2008Q1). So, in B.14 (which is in the Appendix B) and in Figure 3.6, one can observe the effect that this Counterfactual (yellow line) has is quite smaller than that from Counterfactual 3 (green line). More specifically, the potential productivity would have been from 1.06 to 2.75 percentage points larger than the actual one, whereas the Counterfactual 3 is from 1.1 to 3.67 percentage points.

Furthermore, from the same table, we can see that the difference between the peak and the trough of the actual productivity and that from this counterfactual is 1.02 per-

[34]Note that in Counterfactual 6 γ's are fluctuate freely during the crisis.

Table 3.8: Implied productivity gap (in %) between recessions and counterfactual 7, and percentage of the gap which is explained by counterfactual 7.

	Implied Gap: Reces.-Counter. 7			Gap to be explained by Counter. 7		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.4	3.4	4.1	22.3	22.2	19.3
4	3.6	5.4	5.5	23.6	16.9	16.7
5	5.3	6.5	5.9	16.9	14.0	15.2
6	5.8	7.1	6.0	16.2	13.4	15.8
7	6.1	7.5	5.8	19.3	16.2	20.0
8	5.9	6.8	5.1	26.0	23.2	29.0
9	6.2	7.6	4.8	28.8	24.7	34.6
10	6.8	8.6	5.0	28.1	23.3	35.3
11	7.9	10.2	5.8	27.0	21.8	34.0
12	8.9	10.3	5.7	26.2	23.1	36.4
13	9.9	10.5	5.3	23.4	22.3	37.4

centage points (95.9 versus 96.92, respectively) which is again smaller than that in the wage case (1.06 percentage points). The same is true for the difference between the potential productivity in the absence of the crisis in 2009Q1: potential productivity is 6.74 percentage points more than actual productivity (102.64 versus 95.9, respectively), 5.64 percentage points more from the productivity if at this quarter, the level of real wages of displaced and non-displaced workers were equal with that before the crisis (102.64 versus 96.92, respectively), and 5.68 percentage points under Counterfactual 3.

In terms of magnitude, from Table 3.9, we can observe that, by running this counterfactual, the gap between the pre-2008 trend and post-2008 productivity is between 4.2 to 6 percentage points, thereby explaining 18 percent of this productivity gap. So, on average, the drop in wages in both groups during the crisis can explain almost the one fifth of the UK's productivity puzzle.

If we want to find the upper bound of how much displacements (under this counterfactual) can explain the UKs productivity puzzle had the actual post-2008 productivity followed the path of the two past recessions, then we can observe Table 3.9 again, where the gap between post-2008 productivity (by using pre-2008 estimates of the average wages of the displaced and non-displaced workers) and: I) the 1979 post-crisis is from 3.5 to 10.5 percentage points, which thereby explains, at most and on average, the 16% of this productivity gap; and II) the 1990 post-crisis is from 3.6 to 11.1 percentage points, thereby explaining, at most, 13.8% of this productivity gap.

Equivalently - as in Counterfactuals 4 and 5 - I can isolate the effect of the wage drop during the crisis of only the high educated displaced and non-displaced workers and only the low educated displaced and non-displaced workers. For the purpose of capturing the effect of the drop in wages of high type workers during the crisis, I ran Counterfactual 9. In this counterfactual, I set only the post-2008 average wage rate of high type displaced and non-displaced workers to be equal with the one before the beginning of the crisis (2008Q1) and allow the average wage of the low type displaced and non-displaced workers to fluctuate freely during the crisis. The effect on productivity can be seen by the grey line of Figure 3.6 and Table B.15 (see Appendix B). One can observe that the post-2008 productivity under this counterfactual would have been from 0.7 to 1.26 percentage points higher than the actual one. So, on average, the drop in wages of high type displaced and non-displaced workers can explain 17.8% of the UK's productivity puzzle. Since the overall wage drop of the displaced and non-displaced groups can explain 18% of this puzzle (Counterfactual 8), that means that 17.8/18, or 99%, of this effect can be explained by the drop in wages of high type workers[35]. So, in comparison to Counterfactual 3, almost all the part of the puzzle which is explained by the drop in wages in both displaced and non-displaced groups (18%), can actually be explained by the drop in wages of the college educated workers who belong in those groups. This seems to be a stronger result (from counterfactual 4) which is inline with Barlevy (2002) who points out that empirical evidence suggest that during recessions a "sullying" effect is observed and a redirection of the economy from highly paid workers (which can imply that these workers are more productive, as well) to lower paid workers.

In order to confirm the above result, I ran Counterfactual 10, where I set the post-2008 average wage rate of low type displaced and non-displaced workers to be equal with the one before the beginning of the crisis (2008Q1); furthermore, I also allow the average wage of high type workers to fluctuate freely during the crisis. The effect on productivity can be seen by the red line of Figure 3.6 and Table B.17 (see Appendix B). We can observe that the post-2008 productivity under this counterfactual would have been between 0.36 and 1.48 percentage points higher than the actual one. So, on average, the drop in wages of low type displaced and non-displaced workers can explain only 0.2% of the UK's productivity puzzle, which means that only 1% of the overall effect of the drop in wages for the displaced and non-displaced group can be explained by the drop in wages of non-college educated workers[36].

[35]For more details about the effect of high type on the puzzle see Table B.16 which is in the Appendix B.

[36]For more details about the effect of low type on the puzzle see Table B.18 which is in the Appendix

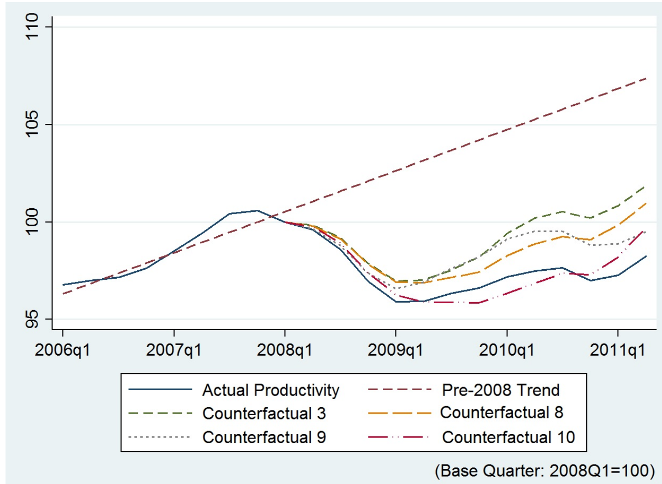


Figure 3.6: Real and Potential Labour Productivity: Counterfactuals 8, 9 and 10.

3.6.6 Sensitivity Analysis

Finally, in order to test if the estimated ρ from the previous part plays any role in determining the results, I ran a sensitivity analysis by using different values of ρ (including extreme values) and repeating the counterfactual exercises again. Except of the estimated ρ from the BHPS (0,25), I pick other, including extreme values, such as: I) 0.29, which is the estimated ρ from Katz and Murphy (1992); II) 0.44, which is the estimated ρ from Acemoglu (2002b); III) 1, where high and low type workers are *perfect substitutes*; IV) 0.11, where the production function is close to a *Cobb-Douglas*; and, finally V) -10, in the extreme case where the production function is close to a *Leontief*.

Graphs 3.7 and 3.8 are the sensitivity analyses for Counterfactuals 3 and 8, respectively. In these graphs, we can observe that, besides the unlikely case that high and low

B.

Table 3.9: Implied productivity gap (in %) between recessions and counterfactual 8, and percentage of the gap which is explained by counterfactual 8.

	Implied Gap: Reces.-Counter. 8			Gap to be explained by Counter. 8		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.5	3.6	4.2	19.8	19.7	17.1
4	3.7	5.5	5.6	21.3	15.2	15.1
5	5.4	6.7	6.1	14.5	12.0	13.1
6	6.1	7.5	6.3	11.3	9.4	11.0
7	6.8	8.1	6.5	10.4	8.7	10.8
8	7.0	7.8	6.2	13.0	11.7	14.6
9	7.4	8.8	6.1	14.8	12.7	17.8
10	8.0	9.8	6.2	15.7	13.0	19.7
11	8.9	11.2	6.8	17.8	14.4	22.5
12	9.7	11.1	6.6	19.4	17.1	26.9
13	10.5	11.1	6.0	18.5	17.7	29.7

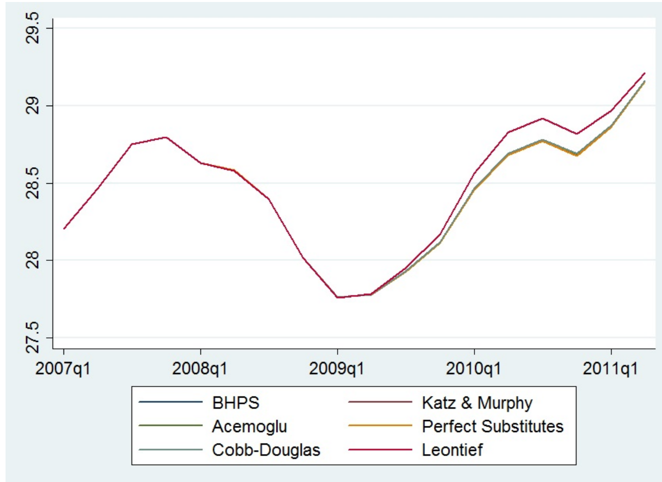


Figure 3.7: Sensitivity analysis of the counterfactual exercise 3, where "BHPS" notes the estimated ρ from the BHPS dataset.

type workers (who are either displaced or non-displaced) are *Leontief*, the estimated productivity of the counterfactuals do not change if someone uses different values of ρ. This sensitivity analysis makes the results of this chapter robust independently from the estimates of the elasticity of substitution between high and low educated workers. Furthermore, it is worth noting that case III, where high and low type workers are *perfect substitutes*, implies that the results from a rough computation of the fact based on the hours worked by displaced workers multiplied by their average wage drops will not be significantly different from the results of the counterfactuals by using the general CES production function.

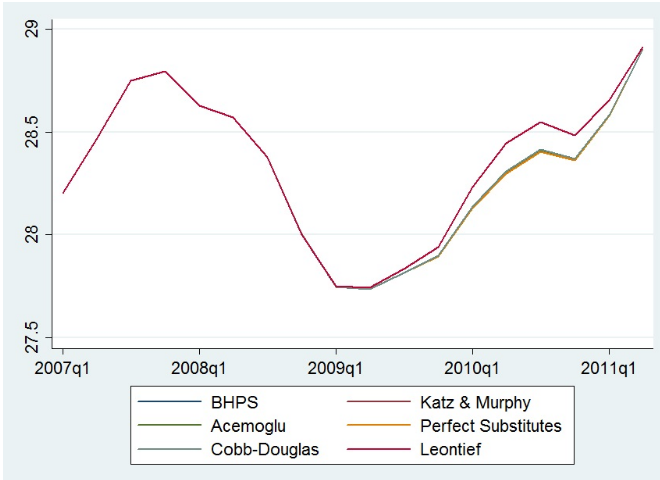


Figure 3.8: Sensitivity analysis of the counterfactual exercise 8, where “BHPS” notes the estimated ρ from the BHPS dataset.

3.7 Conclusion

In the UK after the deep recession of 2008, labour productivity showed poor performance and and did not follow the recovery of the labour market and the real GDP. This is called the UK’s productivity puzzle. The puzzle is well known in the literature and many researchers are trying to give a plausible explanation for what the facts were which created this puzzle while also recommending policies which will solve it. In this paper, I focus on highlighting the role of involuntary job separations on the UK’s post-2008 labour productivity (as output per hour worked). Job displacements have been investigated at the micro-level, where the findings from previous papers suggest that there are individual productivity losses after involuntary job separations. The aggregate effect of displacements, however, is an aspect which the literature has ignored so far. Therefore, this chapter attempts to fill in this gap by translating the individual productivity losses due to the displacements of high tenured workers (more than 2 years in the same job prior to the separation) into their aggregate effect on labour productivity. I focus on the

UK's labour productivity in the post-2008 crisis since I observed a 50 percent increase in the fraction of displaced workers with a 16 percent decrease in their average wages.

In order to tackle this question and define how much the UK's productivity puzzle can be explained by displacements, I ran counterfactual accounting exercises. In the counterfactual exercise which is the most unbiased from the others, I account that the post-2008 labour productivity that would have been the case had the post-crisis average individual productivity of displaced workers been equal with the one that they had before the crisis. Note that, in this paper, I assume perfect competition at the macro-level where the individual average productivity of the displaced workers can be approximated to their average wage rates. The results show that, on average, 27 percent of the productivity gap between the actual and the potential productivity, in the absence of a crisis, can be explained by the displacements of high tenured workers. Therefore, involuntary job separations, on average, can explain more than one fourth of the UK's productivity puzzle.

Furthermore, I quantified the contribution of the displaced workers who are either college or non-college educated separately in order to explain this puzzle. The results show that college educated displaced workers can explain 21.1 percent of the UK's productivity puzzle. This means that 78 percent of the overall effect of displacements on this puzzle are due to productivity (and wage) losses from college educated displaced workers. The remaining 22 percent of the overall effect of displacements on the puzzle can be explained by the drop in wages of non-college educated workers.

In order to check for robustness of the estimates, I ran alternative counterfactual exercises, arguing that the results were likely to suffer from either an upwards or a downwards bias. The counterfactual exercise described above, however, seems to have underestimated the role of displacements on post-crisis productivity. This should be the case since I did not account for possible post-crisis trends that the wages of the displaced workers would have had had the crisis not occurred. So, overall, I can conclude that the aggregate effect of displacements should not be ignored since one can, in fact, explain part of the UK's productivity puzzle in light of those displacements.

4

Investigating matchings in the labour market through formal and informal channels: The UK case.

4.1 Introduction

There is an extensive literature which studies labour market outcomes by means of referrals and social networks. Rees (1966) is one of the first researchers who argues that there might be a preference towards informal job matching methods from both the unemployed, who are searching for jobs, and employers. Granovetter (1995) highlights the importance of referrals on the labour market, finding that 56% of male white-collar workers in a Boston suburb use referrals to find their current job. For the US, Holzer (1987c) finds that more than 85% of unemployed and new workers use personal contacts in order to search for jobs. On the other hand, in the UK, my estimates from the "Quarterly Labour Force Survey" (QLFS) for the years between 2001 and 2015 are quite lower than that obtained from the US. Across 6 different channels of searching for jobs, referrals are used only by about 54% of unemployed persons. Furthermore, as a labour outcome, 26% of new workers found their current job through referrals. So, in this paper, I empirically investigate what is the matching efficiency across different channels of search and highlight the role of referrals on the UK's labour market.

Since there is a lower fraction of job seekers and workers who are using informal channels while looking for a job in the UK than in the US, in this paper, I estimate whether there are any significant differences in the efficiencies between matchings through referrals and matchings through formal channels. Therefore, the broader question that this chapter attempts to answer is whether referrals in the UK have the highest matching efficiency. To my knowledge, this is the first research which estimates matching efficiencies through different channels of search. I focus on the UK economy, and I follow the standard methodology which is used in the literature (see, for instance, Galenianos (2014) and Sahin et al. (2014)), but I also introduce an alternative estimation which handles possible endogeneity issues in the estimations better. By using the "Quarterly Labour Force Survey" (QLFS) and the "Vacancy Survey" datasets for the years between 2001 and 2015, I tackle these broader questions by estimating a matching function where both the workers and the firms can meet through several channels. In all the estimations, I find that referrals have the highest matching efficiency. The channel "Job Advertisement" has the second highest matching efficiency and "Direct Applications" have the third highest matching efficiency. The channel "Private employment agency or business", on the other hand, has a low matching efficiency. Finally, the searching channel with the lowest matching efficiency is "Jobcenter, Jobmarket, etc.".

In the literature, there are papers which estimate the matching functions at an aggregate level, but also across industries and occupations. The majority of the past papers estimate matching functions in the form of a Cobb-Douglas. For instance, Barnichon and Figura (2015, 2011) estimate an aggregate matching function in the form of a Cobb-Douglas for the US economy and find that the aggregate matching efficiency across time to be between 0.7 and 1.1. Davis et al. (2013) also estimate Cobb-Douglas matching functions with a common elasticity (as I do) and industry-specific efficiency parameters, finding variation in the matching efficiencies across industries for the US (data from JOLTS for 2001-2011). Galenianos (2014) estimates a Cobb-Douglas matching function across sectors of the US economy and finds that the matching efficiency across industries varies from 0.78 to 1.89, depending on the sector[1]. Sahin et al. (2014) investigate mismatches in the US labour market and, by using data on hires from the JOLTS database, estimate industry-specific matching efficiencies to be between 0.76 and 1.71 before the crisis and between 0.7 and 1.87 after the crisis. In addition, by using data on hires from CPS, they estimate industry-specific matching efficiencies between 0.33 and 0.5 before and after the crisis. Furthermore, they estimate occupation-specific matching efficiencies between 0.32 and 0.58 before the crisis, and between 0.33 and 0.63 after the crisis. Sahin et al. (2014) impose matching functions in the form of a Cobb-Douglas, as Galenianos (2014) does, since they estimate the elasticity of substitution for a general CES matching function to be statistically close to 1.

Patterson et al. (2013) also investigate mismatches in the UK labour market by using data from the "Vacancy Survey", the "Jobcentre Plus Vacancy Statistics" and "Labour Force Survey". They follow the methodology introduced by Sahin et al. (2014), and estimate sectoral matching efficiencies from between 0.43 and 0.66 for the pre-crisis period and between 0.4 and 0.57 for the post-crisis period. It is worth noting that also Patterson et al. (2013) impose a Cobb-Douglas matching function[2].

According to my knowledge, however, the current research is the only one which investigates the aggregate matching efficiency of both formal and informal searching channels in the labour market. This researchs primary focus is the UK economy. I fol-

[1] Galenianos (2014) uses monthly data from 2001 to 2011 of industry-specific unemployed taken from the CPS, and of hires and industry-specific vacancies taken from JOLTS.

[2] More studies on estimation of aggregate matching functions can be found in Petrongolo and Pissarides (2001).

low Galenianos (2014) and Sahin et al. (2014) in estimating the matching efficiencies across different search channels by assuming that the matching functions are in the form of a Cobb-Douglas. For the purpose of estimating the matching efficiencies across channels, I follow the standard methodology that is used in the literature. On the other hand, Borowczyk-Martins et al. (2013) argue that this estimation methodology (i.e. of matching functions) could suffer from possible endogeneity biases stemming from the search behaviours of both job seekers and employers. For that reason, I introduce an alternative methodology which can reduce this potential bias. Finally, I also follow Sahin et al. (2014), who suggest that one should model the matching efficiency dynamics through structural breaks and time-varying polynomials in order to handle this potential bias in the estimates. According to Sahin et al. (2014) and Borowczyk-Martins et al. (2013), the latter methodology is more robust to endogeneity issues compared to all of the other methodologies. The estimates of the matching efficiencies from these three different methodologies are quite similar, and the ranking of the matching efficiencies across channels is the same independently from the methodology that I used. Overall, the empirical results suggest that the matching efficiency of the channel “Referrals” is the highest one, with “Job Advertisement” being the second highest. “Jobcenter, Jobmarket, etc.” on the other hand, is the searching channel with the lowest matching efficiency.

It worth mentioning that, in the QLFS data, the job seekers state their main channel of search, as well as all of the channels that they use, while searching for a job. Thus, one issue that can be raised is which information should be used in order to measure workers’ search efforts. For that reason, I use in the estimations three different methods for measuring the search effort of each worker. These are as follows: in method one, I use only the main channel as the worker’s search effort. In method 2, each unemployed person has one unit of time, which is split equally across every method of search. And, finally, in method 3, one unit of time for each worker is split by 50% to the main method, with the other 50% being split equally across every method of search, including the main method.

As for the methods of estimation, firstly I run a time series estimation at the aggregate level and for matches disaggregated by channels. The results show that it is reasonable to assume a common elasticity of the matching function (noted as η) across channels. Therefore, I restrict the model and assume that the elasticity of the matching function is the same for all channels. Then, I run a panel analysis across channels and introduce dummy variables which can be interpreted as the average matching efficiency by channel (this is similar to a fixed effect estimation). It is worth noting that the estimates of this research are lower from Galenianos (2014) but very close to Sahin et al. (2014), who both estimate sectoral matching efficiencies for the US economy. The above estimates are also very close those found by Patterson et al. (2013), who estimate sectoral matching efficiencies in the UK.

In terms of results for the panel estimation of the standard methodology, the matching efficiency of referrals for the three different methods of measuring the worker's search effort (s_{it}) is between 0.52 and 0.59. The second most efficient channel is "Job Advertisements", where the estimated matching efficiency is between 0.38 and 0.41. The channel "Direct Applications" has the third highest matching efficiency. The estimated matching efficiency for this channel is approximately equal to 0.35. "Private employment agency or business" has a low matching efficiency (approximately equal to 0.26). The lowest matching efficiency is observed for "Jobcenter, Jobmarket, etc." at between 0.13 and 0.15. Finally, the channel "Through some other way" display a matching efficiency approximately equal to 0.33. It is worth noting the estimated matching efficiencies of each channel by estimating the panel as being quite similar to the estimated efficiencies for each channel by applying a time series analysis. In particular, the panel estimations are slightly higher from that of the time series estimations, but the ranking of the matching efficiencies across channels is the same independently from the method of measuring, (s_{it}).

For the alternative methodology (again for the panel), the estimates of the matching efficiency across the different channels are lower than that from the standard methodology, but the ranking is the same. More specifically, the matching efficiency of referrals with the three different methods of measuring the search effort is between 0.44 and 0.5, being the highest across channels in all of the estimates. The second most efficient channel is job advertisements, where the estimated matching efficiencies for the three different methods of measuring s_{it} is approximated between 0.37 and 0.39. The channel "Direct Applications" has, as in the previous case, the third highest matching efficiency and which is approximately equal to 0.3. The channel "Private employment agency or business" has a low matching efficiency (between 0.2 and 0.21); and the channel with the lowest efficiency is "Jobcenter, Jobmarket, etc." (between 0.12 and 0.13). Finally, the channel "Through some other way" has a matching efficiency of between 0.25 and 0.27. It is worth noting that the estimated matching efficiencies of each channel from the panel are quite similar to the estimated efficiencies for each channel (which is obtained by using a time series analysis). In particular, the panel estimations are slightly higher from that of the time series estimations; nevertheless, though, the ranking of the matching efficiencies across channel is the same.

For the third methodology, following Sahin et al. (2014), I model the matching efficiency dynamics through structural breaks and time-varying polynomials in order to handle a potential bias in the estimates. The data shows that, in 2008, one can observe a structural break (i.e. at the beginning of the 2008 crisis). From this estimation process, one can discern that the matching efficiencies across the channels before 2008 (i.e. the structural break) are higher than that from the standard and alternative methodologies, whereas the matching efficiencies across channels after 2008 are, in some cases, lower than that obtained by the standard and alternative methodologies. Furthermore, the ranking of the matching efficiencies is the same with that in all of the previous methodologies.

More specifically, in terms of results, the matching efficiency of referrals is the highest across channels and equal between 0.57 and 0.69 before the 2008 crisis, and between 0.49 and 0.62 after the crisis, implying an average drop of 15%. The second most efficient channel is “Job Advertisements”, where the estimated matching efficiency is between 0.39 and 0.41 before the crisis, and between 0.3 and 0.32 after the crisis, implying an average drop of 22%. The channel “Direct Applications” has the third highest matching efficiency, which is between 0.33 and 0.39 before the crisis, and between 0.33 and 0.36 after the crisis, implying an average drop of 6% across the three different methods of measuring the s_{it}. “Private employment agency or business” has the fourth highest matching efficiency and is equal to between 0.32 and 0.34 before the crisis, and between 0.25 and 0.29 after the crisis, implying an average drop of 20%. The lowest matching efficiency is observed again for “Jobcenter, Jobmarket, etc.” at between 0.14 and 0.17 before the crisis, and between 0.12 and 0.14 after the crisis, implying an average 14% drop across the three different methods of measuring the s_{it}. Finally, the channel “Through some other way” has a matching efficiency between 0.35 and 0.39 before and after 2008 (almost no effect from the crisis). It is worth noting that the highest drop in the matching efficiency for the period post-2008 from that pre-2008 is observed in the channels “Job Advertisements” and “Private employment agency or business”. A smaller drop is observed in the channels “Referrals” and “Jobcenter, Jobmarket, etc”. Finally being almost no drop detected in the channels “Direct Applications” and “Through some other way”.

In the next section, I present the literature that examines the roles of friends, relatives and networks on the labour market. In section 3, I present the matching functions to be estimated. In section 4, I describe the household and vacancy data that are used to tackle the questions raised by this research. The empirical results of the time series estimations at the aggregate level and for matches disaggregated by channels are presented in section 5.1. Furthermore, the results of the panel estimations for the standard methodology, the alternative methodology, and the methodology with structural breaks and time-varying polynomials are presented in section 5.2. Then, in the final sixth section, I present the conclusions extracted by this chapter.

4.2 Literature Review

There are many papers in the literature that examine the role of friends, relatives and networks in the labour market. For instance in the US, Holzer (1987c) finds that the 85% of the unemployed workers used personal contacts among other methods while searching for a job and the 87% of new workers found their current job through referrals (data from National Longitudinal Survey of Youth for the years 1981-1982). By using survey data, Lin et al. (1981) obtain that the 59% of the workers found their current job from referrals (Albany, New York). Similar results are coming from Bridges and Villemez (1986) who use employed survey data in the Chicago SMSA (1981). Elliott (1999) finds that the 77% of unemployed (aged between 21 and 64) use referrals as one of their searching channel (data from Multi-City Study of Urban Inequality which includes the metropolitan areas of Atlanta, Boston, Detroit and Los Angeles and this paper considers only low educated workers). Corcoran et al. (1980) use data from the Panel Study of Income Dynamics and find that more than 50% of all workers found their current job through referrals. Furthermore, 24 studies surveyed by Bewley (1999) brings this number from 30 to 60 percent.

Similar results as that in the US are extracted internationally. Wahba and Zenou (2005) obtain the following results: about one third of the Egyptian workers find their current job through personal contacts and 52% of the job seekers use this channel while searching for a job (Labour Market Survey for the year 1998). Alon (1997) also finds high fraction of unemployed who are using referrals as a searching method in Israel whereas Addison and Portugal (1989) by using the Labour Force Survey find a smaller usage of friends and relatives in the Portuguese labour market (about 25 percent). Pellizzari (2010) is inline with Addison and Portugal (1989) and finds that only between 25 to 40 percent of the employed find their current job by using personal contacts in 14 European countries (data from the European Community Household Panel for the years 1994 to 1999). Finally, Gregg et al. (2014) use the UK's Labour Force Survey for the year 1992 and report that the 70% of unemployed use referrals while searching for a job. The latter estimates are about 15% smaller than my estimates for the period of 2000−2015[3].

From the firm side, many papers have documented the extensive usage of personal contacts by employers while recruiting potential workers for a job vacancy. For instance, Marsden and Gorman (2001) use data from the National Organizations Survey and find that from 37 to 53 percent of employers advertise new job vacancies through the personal network of their current employees. Holzer (1987a) uses data from the Employment Opportunity Pilot Project, and he finds that 36% of the firms use personal network during the recruitment process for hiring new workers. Data from Chicago-area surveys of firms show that personal network of employees are used by 65 to 88 percent of their current employers during the hiring period (see Neckerman and Kirschenman (1991) and Miller and Rosenbaum (1997)). Finally, Fernandez et al. (2000) and Fernandez and Castilla (2001) find that referrals is extensively used as a hiring method[4].

The usage of referrals as a searching channel for a job also varies across different demographic groups. For instance, since there is a higher probability for low educated and low income workers to lose their job, as Elsby et al. (2010) document, these groups of workers are using referrals more intensively while searching for a job (see also Kuzubas (2010)). On the other hand, Pellizzari (2010) proposes that the higher usage of friends, relatives and personal contacts from low type job seekers might be due to differential adverse selection and due to problems in signaling across different occupations and education levels. There are many other papers that find a higher usage of networks for low type job seekers[5]. Elliott (1999) obtains that referrals are used significantly more intensively by unemployed from high poverty neighborhoods than those who reside in

[3]For more details about the literature on referrals until 2011 see Topa (2011)

[4]Both studies (Fernandez et al. (2000) and Fernandez and Castilla (2001)) use data from the Phone Customer Services Representative for the years between 1995 to 1996. These are data of hires for entry level jobs at a large phone center within a global financial services institution.

[5]See for instance Datcher (1983), Ornstein (1976), Corcoran et al. (1980) and Marx and Leicht (1992).

low poverty neighborhoods. The latter job seekers have higher probability to use formal hiring channels than informal. For Atlanta, Green et al. (1995) find that low income unemployed have a higher probability to use personal contacts for finding a job than that of a high income. There is also evidence that job seekers in blue-collar occupations are more likely to use referrals than the job seekers in white-collar occupations (see for instance Corcoran et al. (1980) and Rees and Shultz (1970)).

Furthermore, some papers investigate the gender differences in the usage of referrals by job seekers, where the results are mixed. Some of them find that men are more likely to use friends, relatives and networks while searching for a job than women job seekers (Corcoran et al. (1980), Bortnick and Ports (1992), Bradshaw (1973), Ports (1993)). On the other hand, there are findings that are controversial to the above results and suggest that women job seekers use more informal methods than men (Moore (1990) and Marsden and Campbell (1990) among others). Furthermore, there are studies which find that young job seekers with little or no experience have higher probability to use friends and relatives as a searching method (Corcoran et al. (1980), Marsden and Hurlbert (1988), Wegener (1991)). However, there are other papers which support that there are no significant differences in the usage of informal methods between age groups (see Hilaski (1971) and Falcon (1995))[6].

In terms of labour outcomes, there are several studies which find that personal contacts increase the job finding rate of employees. Topa (2001) using Census data for the city of Chicago (1980 and 1990) finds that a one standard deviation increase in neighborhood employment raises job finding rate from 0.6 to 1.3 percent and these results are stronger for low educated workers. By using confidential longitudinal data from the 1979 National Longitudinal Survey of Youth (NLSY), Weinberg et al. (2004) find that a one standard deviation increase in neighborhood employment increases the annual total

[6]There is also an extensive literature on the differences in the usage of formal and informal channels by job seekers across different racial and ethnic groups such as: Corcoran et al. (1980), Datcher (1983, 2006), Green et al. (1999), Holzer (1987b), Marx and Leicht (1992) and Korenman and Turner (1996).

hours worked by 9.5 percent. Bayer et al. (2008) using the US Census of population for the Boston metropolitan area (1990) arrive to the following result: a one standard deviation increase in potential personal contacts increase labour income from 2% to 3.7% and total weekly hours from 0.3 to 1.8 hours for men and labour force participation from 0.8% to 3.6% for women.

Granovetter (1995) argues that weak ties offer better information to job seekers about perspective jobs and also higher wage outcome than strong ties. Moreover, Montgomery (1991) finds that weak ties increase the reservation wage of an employee. Schmutte (2015) obtains that for job seekers a significant amount of job offers are received through referrals. He finds also that for non-native workers the magnitude of the effect of personal contacts on the quality of the job is almost two times stronger than that from natives, and that non-native workers are more likely to use social networks to find a work[7]. Conley and Topa (2007) use the same data sources as Schmutte (2015) and extract that the average wage premium in a worker's network has a positive effect on the wage premia of an individual worker who is part of this network. Additionally, they find that referrals generate the 10% of the offers for a job to potential workers. For the UK labour market, Cappellari and Tatsiramos (2010) find that one additional employed friend increases the job finding rate by 3.7% and the wages by 5% (British Household Panel Survey from 1992 to 2003).

4.3 Matching Function Specification

In this section, I describe the strategy that this chapter follows for deriving indexes which will measure the size of the efficiency of matches through different search channels. I use three different methodologies in the estimates. The first one is standard in

[7]Data from Longitudinal Employer Household Dynamics Program of the US Census Bureau linked to data on workers Census blocks of residence from the Statistical Administrative Records System.

the literature (titled "Standard Methodology") but I also propose an alternative way to estimate matching functions which I argue that handles better possible endogeneity issues (titled "Alternative Methodology"). Finally, for handling further potential bias in the estimates, I follow Sahin et al. (2014) and model the matching efficiency dynamics through structural breaks and time-varying polynomials.

In the first one, I follow the standard methodology introduced by Pissarides (2000) and Galenianos (2014)[8]. So, I consider a market where v vacancies and u unemployed workers are searching for each other. A worker and a firm might meet through one of I channels. Each unemployed worker has a unit of time which he allocates across these channels. I assume that a vacancy searches through all channels simultaneously (this is due to data limitations and is discussed below). An additional assumption that this chapter does is that the flow of matches through channel i is given by the Cobb-Douglas function[9]:

$$m_{it}(v_t, u_{it}) = M_t \mu_i {v_t}^{\eta} (s_{it} u_t)^{1-\eta} \tag{4.3.1}$$

where M_t is the aggregate matching efficiency, μ_i is channel i's matching efficiency, and $\eta \in (0.1)$ is the elasticity of the matching function. In this chapter the elasticity of the matching function is assumed to be constant across channels. Finally, s_{it} is the search effort that unemployed workers put on searching through channel i. In the next section, I describe the methods of estimating s_{it}.

[8]For the specification of the matching functions see also Petrongolo and Pissarides (2001)

[9]Pissarides and Petrongolo (2001) find that a representation of a matching function in the form of a Cobb-Douglas performs reasonable well.

So, the overall flow of matches is given by:

$$m(v_t,u_t) = \sum_{i=1}^{I} m_i(v_t,u_t)$$
$$= M_t {v_t}^{\eta} {u_t}^{1-\eta} \sum_{i=1}^{I} \mu_i {s_{it}}^{1-\eta} \qquad (4.3.2)$$

Notice that firms' differential search effort is subsumed into μ_i: if $\tilde{\mu}_i$ is the fundamental matching efficiency and s_i^F is firms' search effort, then $\mu_i = \tilde{\mu}_i (s_i^E)^{\eta}$.

If we take natural logarithms in both sides of 4.3.1 we can estimate the matching function at the aggregate level as:

$$\ln(\frac{m_t}{u_t}) = \ln(M_t) + \eta \ln(\frac{v_t}{u_t}) + \epsilon_t \qquad (4.3.3)$$

and if we take natural logarithms in both sides of 4.3.2 we can estimate the matching functions at the level of each matching channel as:

$$\ln(\frac{m_{it}}{s_{it}u_t}) = \ln(M_t) + \ln(\mu_i) + \eta \ln(\frac{v_t}{s_{it}u_t}) + \epsilon_{it} \qquad (4.3.4)$$

It should be noticed that the above matching functions do not account for employer behaviour, which means that employer behaviour and channel efficiency are jointly identified. The latter can potentially create a bias in the estimates. As mentioned above, lack of data on which channel of search employers are using for filling a vacancy forced to impose this restriction to the model. Further bias can arise since in the matching functions it is assumed that a job can arrive only from one channel and is not allowed for duplicates (for instance a job can arrive from a combination of formal and informal channels). In the labour market, a worker could found a job through a formal channel (direct application) but it can be actually a referral and these particular cases are excluded from the matching function.

It should also be highlighted that the matching functions do not reflect the optimal behaviour of the job seekers. In particular, this means that the empirical approach is designed to measure only equilibrium outcomes and not to test a particular mechanism or suggest a labour market policy since for instance the use of referrals is endogenous; only individuals who seem to merit a referral will get one.

On the other hand, to get a sense of the extent to which job finding probabilities through formal or informal channels can be taken "structurally", it would be interesting to compare them with job finding probabilities in other countries where referrals are used more or less than in the UK, and see if these probabilities are different from the estimates of the current research.

With the above matching function specification and the assumptions that imply, I run my estimates and present the results in section 4 (the subsections titled "Standard Methodology").

The issue is that with Equations (4.3.1) and (4.3.2) the exogeneity conditions required for consistency ($E(\ln(\frac{v}{u})_t\epsilon_t) = 0$ for Equation (4.3.1) and $E\left(\ln(\frac{v_t}{s_{it}u_t})\epsilon_{it}\right) = 0$ for Equation (4.3.2)) can be violated. For instance, the second condition is violated because the search effort s_{it} might depend on the residual ϵ_{it}. To handle this potential problem I introduce the "Alternative Methodology" which is the following:

$$\begin{aligned} m_{it}(v_t, u_t) &= \Phi_{it} M_t \mu_i v_t^{\eta} (s_{it} u_t)^{1-\eta} \Leftrightarrow \\ \frac{m_{it}(v_t, u_t)}{u_t} &= \Phi_{it} M_t \mu_i (\frac{v_t}{u_t})^{\eta} s_{it}^{1-\eta} \end{aligned} \tag{4.3.5}$$

Where Φ_{it} is an idiosyncratic shock. If we take natural logarithms in both sides of 4.3.5 we have:

$$\begin{aligned}\ln(\frac{m_{it}(v_t,u_t)}{u_t}) &= \ln M_t + \ln \mu_i + \eta \ln \frac{v_t}{u_t} + (1-\eta)\ln s_{it} + \ln \Phi_{it} \Leftrightarrow \\ \ln(\frac{m_{it}(v_t,u_t)}{u_t}) &= \ln M_t + \ln \mu_i + \eta \ln \frac{v_t}{u_t} + (1-\eta)\ln s_{it} + \varepsilon_{it}\end{aligned}$$

where $\varepsilon_{it} = \ln \Phi_{it}$

This means that the exogeneity condition is now $E\left(\ln(\frac{v_t}{u_t})\varepsilon_{it}\right) = 0, \forall i$. In principles, a big shock (ε_{it}), could change v_t and u_t, as Borowczyk-Martins et al. (2013) also point out. But those are aggregate variables, while ε_{it} is an idiosyncratic shock to one channel of searching only. So, it should have a smaller aggregate effect on v_t/u_t. This is easy to defend given the assumption that $\sum_i s_{it} = 1$ and also that there is an aggregate effect $\ln(M_t)$, so that $\sum_i \epsilon_{it} = 0$.

Thus, with the above matching function specification, I run my estimates and present the results in section 4 (the the subsections titled “Alternative Methodology”).

On the other hand, Borowczyk-Martins et al. (2013) argue that this estimation methodology of the matching functions should suffer from possible endogeneity bias coming from the search behaviour of both job seekers and employers. Borowczyk-Martins et al. (2013) state that this bias can be occurred since the job vacancies which are posted by employers might be affected by random shocks to the unobserved matching efficiency. So, even idiosyncratic shocks to one channel might affect aggregate variables. Borowczyk-Martins et al. (2013) recognise that mainly big, low frequency movements (or shocks) in the matching efficiency can create a bias in the OLS estimations. These shocks are observable in the data, such as the deep recession in the UK economy started in 2008. A way to deal with this bias, as Borowczyk-Martins et al. (2013) and Sahin et al. (2014) suggest, is to model the matching efficiency dynamics through structural breaks and time-varying polynomials[10]. According to Sahin et al. (2014) and Borowczyk-Martins et al. (2013) the latter methodology is more robust to endogeneity issues, from all the other methodologies.

So, at the channel level, I am interested in the aggregate movements of the matching efficiency to be orthogonal with the channel-specific component of the matching efficiency. I follow the methodology proposed by Sahin et al. (2014) and at the channel level I estimate the following model by running a panel regression:

$$\ln(\frac{m_{it}(v_t, u_{it})}{s_{it}u_t}) \quad = \quad \ln(M_t) + \delta' QTT_t + \gamma_{\{t<2008\}} \ln \mu_i^{pre} + \gamma_{\{t\geq 2008\}} \ln \mu_i^{post} + \eta \ln \frac{v_t}{s_{it}u_t} + \varepsilon_{it}$$

Where the vector QTT_t consists of two elements which are for the quadratic time trend, $\gamma_{\{t<2008\}}$ is an indicator for the period before the crisis and is used for absorbing channel-specific shifts in the matching efficiency. Finally, μ_i^{pre} represents the matching efficiency of channel *i* before the crisis and μ_i^{post} the matching efficiency of channel *i* after the crisis.

4.4 Data and Descriptive Evidence

For the analysis, I use data from two different sources. The first one is the UK "Quarterly Labour Force Survey" (QLFS) and the second one is the UK "Vacancy Survey". The QLFS is a large scale household survey in quarterly basis, which is conducted by

[10]It is worth noting that Borowczyk-Martins et al. (2013) highlight that the estimates of the matching efficiencies from a matching function which exhibits constant returns to scale with structural breaks and time-varying polynomials are very close to their GMM estimations.

the Office for National Statistics (ONS) under the Department for Education and Employment. It covers a period of time from the quarter April-June 1992 to January-March 2015 and it includes a wide information on labour market and other related topics[11]. The QLFS interviews the participants at most for five consecutive quarters, making the survey a rotating quarterly panel across time. One advantage of this data set is that it covers the tail end of the 1991 recession and all the 2008 one, interviewing about 59,000 households and 138,000 individuals every quarter. The design and the sample size makes the QLFS the most suitable data set that can be used for the purpose of this study[12].

For the estimations of the matching functions, the interesting part of the Labour Force Survey is the structure of the questionnaire which allows to distinguish matchings through formal and informal channels. For instance, in the survey if respondents are working in the same job for at most one year from the time of the interview, they are asked to provide information on which channel they used to find that job. The exact question is "Did you get the work that you were doing/were away from in the week ending Sunday [date] through..". In that question the respondents can be either employees or working in a government scheme (self-employed are not included in this question) and the possible channels that they have used to find their current job are the followings: 1. Replying to a job advertisement, 2. Through a jobcentre/jobmarket or training and employment agency office, 3. A careers office, 4. A jobclub, 5 A private employment agency or business, 6 Through hearing from someone who worked there, 7. A direct application, and finally 8. Through some other way[13]. In the quarterly measurements, I considered only the workers who found their job within the quarter that they were in-

[11]Note that in the "QLFS" there was a measurement issue about the months that are included in each quarter. Until May 2006, the "QLFS" was running on seasonal quarters (March to May, June to August, September to November, and December to February) and afterwards on calendar basis (January to March, April to June, July to September, and October to December) but recently ONS has fixed the problem by providing only data in calendar basis.

[12]All the information about the description of the QLFS and the description of the variables that this chapter uses see the LFS User Guide and the Questionnaires provided in ONS

[13]Until 1994Q4 the option "through a Jobclub" was not available in the questionnaire, so in the data we had to reassign the options for that variable and make the order to be the same with that after 1994Q4.

terviewed. So, for instance in 2005Q1 if a worker who got interviewed in 2005Q1 find his current job through channel i in the quarter 2005Q1, then this worker is considered in the sample. I can do this distinction since in the QLFS there is information about the starting date of the current job.

On the other hand, there is the same type of question for respondents who are seeking for a job. The respondents can be either unemployed or working in unpaid job and are seeking to work as employees[14] or employees who are seeking for different or additional paid work[15]. In the questionnaire, the respondents who are seeking for a job have to define firstly all the different channels that they are using to find a job and also the main channel of searching. Depending on which group the job seekers are included, the respondents can choose between the following channels of searching: 1. Visit a Jobcentre/Jobmarket or Training and Employment Agency Office, 2. Visit a Careers Office, 3. Visit a Jobclub, 4. Have their name on the books of a private employment agency, 5. Advertise for jobs in newspapers, journals or on the internet, 6. Answer advertisements in newspapers, journals or on the internet, 7. Study situations vacant columns in newspapers, journals or on the internet, 8. Apply directly to employers, 9. Ask friends, relatives, colleagues or trade unions about jobs, 10. Wait for the results of an application for a job, 11. Look for premises or equipment for a job, 12. Seek any kind of permit to be able to do a job, 13. Try to get a loan or other financial backing for a job or business, and finally, 14. Do anything else to find work.

More specifically, the exact question is "In the four weeks ending Sunday the [date], did you do any of these things..". This question and a question about the main channel of searching for a job is asked in three different groups of job seekers: I. Respondents

[14]The respondents who are currently unemployed or do any unpaid job have to answer yes in the question if at any time during a month or a week before the interview was taken, they were looking for any kind of paid job.

[15]The respondents have to answer yes in the question if they are looking for a different or additional paid job or a business one week before the interview was taken.

who are seeking to work or will be working as employees or seeking place on government scheme in 4 weeks before the reference week, II. Respondents who are seeking to work or will be working as self employees and finally, III. They are indifferent between working as employed or self employed. The respondents who are eligible to answer these questions and are in the first group (seeking to become employed), can choose between the (previously defined) channels 1 to 10 and also the 14, whereas respondents who are in the second group (seeking to become self employed) can choose only between the channels 5, 6, and 11 to 14. Finally, for the third group (indifferent between employed or self employed) they can choose between all the possible channels (1 to 14)[16]. Since in the QLFS self-employed are not included in the sample of new workers who are asked which search channel they used to find their current, and also they do not have the channels 1 to 4 and 7 to 10 as possible options, I exclude all the unemployed who are searching to work as self-employed from our sample.

One issue that can be raised is which information shall I use as the measure of worker's search effort, since the job seekers state their main channel of search and also all the channels that they used while searching for a job. For that reason, I use in the estimations three different methods for measuring the search effort of each worker. These methods are the following: In the first one, I use only the main channel as the worker's search effort. In the second method, each unemployed has one unit of time, which is split equally across every method of search, and finally in the third method one unit of time for each worker is split by 50% to the main method, and the other 50% is split equally across every method of search, including the main method.

As previously mentioned, for workers who are in the same job for at most one year, there are 8 different channels of finding that job. On the other hand, for job seekers who are either looking to work as employees or there are indifferent between working

[16]Until 1994Q2, for all the above variables the option "visit a Careers office" was not available in the questionnaire, so we had to reassign the options for that variables and make them to have the same order with that after 1994Q2.

as employed or self-employed, there are 11 different channels of searching. So, I have to align the 8 channels of finding a job with the 11 channels of searching for a job. Firstly I drop the search channel "Wait for the results of an application for a job", since the job seeker who is using this channel is not actually searching for a job. In most of the cases there is a direct link between channels of searching with channels of finding a job[17]. There is only one case, where there is not a direct link between channels for job finders and job seekers. In this case, I align the first channel of finding a job, which is "Replying to a job advertisement" with the following channels of searching: "Advertise for jobs in newspapers, journals or on the internet", "Answer advertisements in newspapers, journals or on the internet", and "Study situations vacant columns in newspapers, journals or on the internet". I align them together since they all involve job advertisements. Finally, for the purpose of this study, I individually seasonally adjust all the data from QLFS by using the Census Bureau's X12 program.

The second source that I am using for the analysis is the British "Vacancy Survey" (for more information about this survey see Machin (2003)). The Vacancy Survey is conducted by ONS in monthly basis from June 2001Q2 until 2015Q1 approaching on average 6000 enterprises, and the data represent the stock of vacancies (rather than the flow of new vacancies) in the whole UK economy (total number of job vacancies)[18]. The one quarter of the sample consists of a random selection of large firms and the remaining three quarters by a random selection of smaller businesses. Both of them remain in the sample for five or nine consecutive quarters (depending on the size) and for these businesses the response is compulsory under the Statistics of Trade Act. ONS Vacancy

[17]For instance, I align the job finders through a JobCentre/Jobmarket or Training and Employment Agency Office with the job seekers through the same channel. The job finders through a Job Club with the job seekers through a job club, etc.

[18]The only other information about vacancies which covers the whole UK economy is coming from records of vacancies notified to Job Centres by employers. ONS highlights that these estimates provide possibly less than a half of all vacancies, because employers are not obliged to notify the Job Centers for available vacancies. On the other hand, the Vacancy Survey, which is a business based survey has a more thorough coverage of the UK economy (see also Machin (2003)).

Survey respondents are asked to enter (via their telephone keypad) their current number of vacancies, defined as positions that are newly created, unoccupied or available in the near future, where the employer is actively trying to fill the position and the position is available to people outside the organisation. The statistics and further information about total vacancies and total unemployed can be found in the site of ONS. Only the Great Britain is covered in this survey (Northern Ireland is excluded), but figures are grossed up to provide estimates for the whole United Kingdom. This survey covers the whole UK economy apart from sector A, which is the agriculture, forestry and fishing (about the 1.73% of the whole economy in terms of workforce). For that reason, from the dataset, I exclude new workers that are in sector A (which are the 1.49% of the sample). Furthermore, I also exclude all the new workers who are included in the QLFS and they found their job outside from the country of the UK. From the same source (ONS), I also extract total number of unemployed per quarter. These data are constructed by ONS from LFS. Both vacancy and unemployment data are seasonally adjusted.

Since I described the data sources that are used in this paper, now I can give some descriptive evidence about the usage of different channels of searching for unemployed and new workers. In Table 4.1 which refers to the period 2001 to 2015, we can observe summary statistics of the unemployed, who used all possible channels while searching for a job as employed or are indifferent between working as employed or self-employed, and for the three different methods of measuring the search effort. Note that for the rest of the chapter when I am referring to unemployed, I exclude these job seeker who are searching for a job as self-employed. Furthermore, recall that in the first method, I use only the main channel as the worker's search effort. In the second method, each unemployed has one unit of time, which is split equally across every method of search, and finally in the third method one unit of time for each worker is split by 50% to the main method, and the other 50% is split equally across every method of search, including the main method. From this table we can observe that the channel "Study situations vacant columns in newspapers, journals or on the internet" is used as a main channel by almost the 41 percent of unemployed (see second column of Table 4.1). If each unemployed has one unit of time, which is split equally across every method of search (method 2) then this channel is used from the 25 percent of unemployed (third column) and the 33 percent with method 3 (column 4). Finally, more than the 81 percent among all unemployed use this channel as one among all the others (column 5). Furthermore, more than the 24 percent of unemployed use the channel "Visit a Jobcentre/Jobmarket or Training and Employment Agency Office" as the main channel of searching for the job. With the second method, the usage of this channel decreases to 17 percent and with the third method is on average more than 20.7 percent. Finally, more than the 57 percent among all unemployed use this channel as one among all the others. A remarkable statistic is that on average only the 7.2 percent of job seekers are using friends and relatives as a main method of searching for a job. With the second method of measuring search effort this number goes to 14.8 percent and with the third to 11 percent. Moreover, more than the 54 percent of unemployed use referrals as one of their methods of searching for a job.

As previously mentioned, from the questionnaires of QLFS there are 10 different channels that job seekers can choose as one of their search channels. On the other hand, there are only 8 channels that new workers may have used as their channel of finding a job. For that reason, I aggregate them and create 8 channels of finding a job. For that reason, I aligned these 8 channels to the 8 channels of searching for a job. Table 4.2 shows summary statistics for the fraction of the eight possible channels that new workers have used when they found their current job. Moreover, this table shows summary statistics for all the possible channels that unemployed have used while searching for a job as employed or are indifferent between working as employed or self-employed, and for the three different methods of measuring the search effort. Finally, since the channels "Careers Office" and "Jobclub" are on average less than 2.5 percent, I include them in the channel "Other Channel". Therefore, there are only 6 different channels of search.

In Table 4.3 we can observe summary statistics for our 6 channels of finding and searching for a job (for the three different methods of measuring the search effort in the case of job seekers). Moreover, the relevant graphs for the 6 channels that have been

Table 4.1: Averages of the fraction of unemployment who are searching for a job through different channels over all the possible searching channels that they have used (%) for the three different methods of measuring the search effort, and unemployed who are searching for a job through different channels among all unemployed (last column) for the years 2001-2015.

Channels	Method 1	Method 2	Method 3	All unemp.
Jobcentre/Jobmarket	24.42	17.02	20.74	57.13
Careers Office	0.90	2.28	1.59	10.53
Jobclub	0.52	1.18	0.86	5.88
Priv. empl. ag.	3.87	5.66	4.76	24.05
Advert. jobs in newsp	1.15	2.47	1.82	10.30
Answer adv. jobs in newsp	8.04	13.60	10.81	56.05
Study sit. for a job	40.92	25.42	33.19	81.44
Apply dir. to empl.	10.67	15.13	12.85	54.14
Referrals	7.21	14.77	10.99	54.12
Other	2.32	2.47	2.39	6.94
Total	100	100	100	-

Table 4.2: Averages of the fraction of unemployment who are searching for a job through different channels over all the three different methods of measuring the total search effort, and averages of new workers who found their current job within the quarter through different channels, among those who found their current job within the quarter (%): 8 Channels.

		Job Searchers		
Channels	Job Finders	Method 1	Method 2	Method 3
Advert	26.63	50.11	41.49	45.82
JobCenter	8.00	24.42	17.02	20.74
Careers Off.	0.52	0.90	2.28	1.59
Jobclub	0.09	0.52	1.18	0.86
Priv. Empl.	10.01	3.87	5.66	4.76
Referrals	25.94	7.21	14.77	10.99
Direct Appl.	16.81	10.67	15.13	12.85
Other	12.00	2.30	2.47	2.39
Total	100	100	100	100

used for searching and finding a job (again for the three different methods of measuring the search effort in the case of job seekers) are presented in Figure 4.1. In the first column of this table, the 6 different channels are presented. The second column illustrates the averages of the fraction of new workers who found their current job within the quarter through different channels, among those who found their current job within the quarter. This averages are for the years 2001 to 2015 (see also blue line in Figure 4.1 for a graphical representation across time). The third column of Table 4.3 demonstrates the averages of the fraction of unemployment who are searching to work as employed or are indifferent between working as employed or self-employed and used a specific channel of searching among all the unemployed who are willing to work as employed or are indifferent between working as employed and self-employed, by using the first method of measuring the total search effort (see also maroon dash line in Figure 4.1). The fourth column shows the same fractions as above by using the second method of measuring the total search effort (see also green dash dot line in Figure 4.1). Finally, the fifth column illustrates again the same fractions as above by using the third method of measuring the total search effort (see also yellow long dash line in Figure 4.1).

From these statistics we observe that in the UK the most important channels that are used for finding a job by new workers (who found their current job within the quarter), are through job advertisements (26.6%) and from friends or relatives (25.9%). The 16.8% of the new worker found their current job through a direct application to the employer, the 10% through a private employment agency or business, the 8% through a jobcenter/jobmarket or training and employment agency office, and finally the 12.6% through some other way.

From Figure 4.1 we can observe that there is a structural break in 2008, which is the beginning of the 2008 crisis. In the same figure we can observe also that the channel "Through advertisement" has been used by almost 5% more during the crisis from the period before. The usage of referrals has been increase by almost 5% from the beginning of the 2008 crisis but after 2011 it decreased by around 7 percent. Direct applications to

Table 4.3: Averages of the fraction of unemployment who are searching for a job through different channels over all the three different methods of measuring the total search effort, and averages of new workers who found their current job within the quarter through different channels, among those who found their current job within the quarter (%): 6 Channels.

		Job Searchers		
Channels	Job Finders	Method 1	Method 2	Method 3
Advert	26.63	50.11	41.49	45.82
JobCenter	8.00	24.42	17.02	20.74
Priv. Empl.	10.01	3.87	5.66	4.76
Referrals	25.94	7.21	14.77	10.99
Direct Appl.	16.81	10.67	15.13	12.85
Other	12.61	3.72	5.93	4.84
Total	100	100	100	100

Figure 4.1: Fraction of unemployment who are searching for a job through different channels over all the three different methods of measuring the total search effort, and fraction of new workers who found their current job within the quarter through different channels, among those who found their current job within the quarter (blue line is for new workers, maroon dash line is for method 1, green dash dot line is for method 2, and yellow long dash line is for method 3).

employers are almost stable from 15 to 20 percent and the usage of private employment agencies by new workers is also stable between 8 and 10 percent. Finally the usage of jobcenters, jobmarkets etc is between 5 and 10 percent.

On the other hand, individuals who are unemployed are using as a main search methods job advertisements by 50% (if we measure the search effort with Method 1), 41.5% if we measure the search effort with Method 2 and 45.8% with Method 3. 24.4% of the job seekers are using as a main method jobcenters, jobmarkets etc., 17% if we measure the search effort with Method 2 and 20.7% with Method 3. The 10.7% of the unemployed apply directly to employers if we measure the search effort with Method 1, 15.1% with Method 2 and 12.9% with Method 3. The usage of referrals is low, where the 7.2% of the unemployed are using this channel as a main method of search, 14.8% if we measure the search effort with Method 2 and 11% with Method 3. Finally, the 3.9% of the job seekers are using private employment agencies as their main method of search, 5.7% if we measure the search effort with Method 2 and 4.8% with Method 3.

Furthermore, as we can see from Figure 4.1, individuals that are unemployed are searching through job advertisements more intensively during the crisis, independently from the method of measuring the search effort. A big drop during the crisis is observed in the usage of jobcenters, jobmarkets etc. by job seekers. There is also a drop in the fraction of unemployed who apply directly to employers in the post-2008 period. Finally, the usage of referrals and private employment agencies seem to be unaffected by the crisis and are pretty stable.

From the above summary statistics we can conclude that only almost the 11% of the unemployed, are using referrals as one of their channels of searching. But the 25.9% (more than the double) among new workers found their current job within the quarter from friends and relatives. This descriptive statistic shows how much important are the informal channels for finding a job and that unemployed are not using this channel of searching as much as they do for other channels (mainly, job advertisements and jobcenters, jobmarkets etc.). We can also observe that even though on average the 41.5% of the channels of searching among unemployed, are though job advertisements (method 2), only the 26.7% (among recently employed) finds a job through this channel (which is almost the half). Furthermore, the 17% of unemployed are searching for a job through jobcenters, jobmarkets etc. but only the 8% among all the recently job finders, used this channel of searching. On the other hand, the 5.7% of unemployed are using private employment agencies while searching for a job but the 10% among recently employed, found their current job though that channel (almost the double). Finally, for direct applications the usage from new workers and job seekers are pretty similar (16.8% versus 15.1%).

4.5 Empirical Results

In this section I present estimates of the matching functions for the UK economy. These estimates are not only in aggregate level, but also in channel of search level. Following Galenianos (2014), Song et al. (2012), and Sahin et al. (2014), I am using two different methods of estimation. Firstly, a time series estimation at the aggregate level and for matches disaggregated by channels. I run OLS estimations for our standard model and for the alternative one, to test if the elasticity of the matching functions (η) can be assumed to be equal across channels. The results show that this is a reasonable assumption. Note that the alternative methodology is applied for handling possible endogeneity issues (see also Borowczyk-Martins et al. (2013)). Subsequently, I also run a panel regression for the standard and the alternative methodology. I also model the matching efficiency dynamics through structural breaks and time-varying polynomials proposed by Sahin et al. (2014).

As it is mentioned above, one issue that can be raised is which information shall I use as the measurement of workers' search effort. This can be problematic since the job seekers state their main channel of search and also all the channels that are using while searching for a job. For that reason, in the estimations I use three different methods for measuring the search effort of each worker. In method one, I use only the main channel as the workers' search effort. In method 2, each unemployed has one unit of time, which is split equally across every method of search, and finally in method 3 one unit of time for each worker is split by 50% to the main method, and the other 50% is split equally across every method of search, including the main method. Below I present and analyse the estimation outputs from the time series and the panel data. It is notable that the average matching efficiency of "Referrals" is the highest among all the channels of searching.

4.5.1 Time Series Estimations

4.5.1.1 Standard Method

I start the empirical analysis with OLS estimations at the aggregate level and for matches disaggregated by channels. In this part, I estimate our standard model with and without a quadratic time trend for the three different methods of measuring the search effort s_i. Recall that the models that I am estimating are the following (7 different estimations):

$$\ln(\frac{m_t}{u_t}) = \ln(M_t) + \eta \ln(\frac{v_t}{u_t}) + \epsilon_t \qquad (4.5.1)$$

and

$$\ln(\frac{m_{it}}{s_{it}u_t}) = \ln(M_t) + \ln(\mu_i) + \eta_i \ln(\frac{v_t}{s_{it}u_t}) + \epsilon_{it} \qquad (4.5.2)$$

The first model is in aggregate level and the second for matches disaggregated by channels. In tables C.1, C.3, C.5, and C.2, C.4, C.6 which are in the Appendix C, we can see the OLS time series estimations of the matching functions with and without time trend, for each of the three methods of measuring the s_i, respectively. In these estimations we can observe that the elasticity of the matching functions across channels for method 1 are between 0.59-0.88, including time trends and 0.68-0.97 without, for method 2 are between 0.56-0.9, including time trends and 0.75-1.07 without, and for method 3 are between 0.58-0.84, including time trends and 0.72-1.06 without. Note that for instance the elasticity of the aggregate matching function of method 1 (0.76) represents that a one percent increase in the tightness of the labour market $\theta = v/u$, will increase the job finding rate m/u by 7.6 percent. These estimated elasticities are quite close to each other, suggesting that it is reasonable to assume a common elasticity of the matching function across channels.

As we can see from the same tables, the coefficients of the estimation of the aggregate matching function tend to be higher (especially the constant) than those disaggregated by channel of search, probably for the reason that aggregation induces some measurement error (see also Berman (1997) for measurement error of the estimation of the aggregate matching function). Furthermore, there are small negative trends and the constants for each channel of searching are also negative. Following Berman (1997) we can interpret the constant, which is the logarithm of the matching efficiency for each channel, as the probability that a given *u*, *v* pair will match each other through channel *i* in the third quarter of 2007, when $v = 1$, $u = 1$. In this quarter according to our dataset the quarterly time trend is equal to zero ($t = 0$). So, the estimated constant is negative because its exponent should be less than one. It is worth noting that all our estimated matching functions suffer from strong positive serial correlation of the error term.

Furthermore, the estimates of the matching efficiencies across channels are presented in Tables 4.4 and 4.5. In these tables we can see that the estimated matching efficiency of "Referrals" is equal to 0.55 (estimations with a time trend) and is the highest among all the channels of searching. This supports my special interest in matching efficiency of informal channels of searching or finding a job. Furthermore, the channel "Job Ad-

Table 4.4: Matching Efficiency Estimations of OLS with a quadratic time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	-0.161	0.851				
Advert	-1.151	0.316	-1.129	0.323	-1.141	0.319
JobCenter	-2.236	0.107	-2.048	0.129	-2.154	0.116
Priv. Empl.	-1.750	0.174	-1.841	0.159	-1.803	0.165
Referrals	-0.598	0.550	-0.839	0.432	-0.744	0.475
Direct Appl.	-1.181	0.307	-1.271	0.281	-1.230	0.292
Other	-1.076	0.341	-1.331	0.264	-1.225	0.294

Table 4.5: Matching Efficiency Estimations of OLS without a time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	0.063	1.065				
Advert	-1.124	0.325	-1.182	0.307	-1.122	0.326
JobCenter	-2.295	0.101	-2.354	0.095	-2.284	0.102
Priv. Empl.	-2.045	0.129	-2.285	0.102	-2.212	0.109
Referrals	-0.874	0.417	-1.138	0.320	-1.025	0.359
Direct Appl.	-1.313	0.269	-1.504	0.222	-1.393	0.248
Other	-1.191	0.304	-1.528	0.217	-1.363	0.256

vertisement" has the second highest matching efficiency which is equal to 0.32 (estimations with a time trend). "Direct Applications" have the third highest matching efficiency (0.31) which is very close to the matching efficiency of "Job Advertisement". The channel "Private employment agency or business" has a low matching efficiency (0.17) and finally the search channel with the lowest matching efficiency is the "Jobcenter, Jobmarket, etc (0.11). It is worth noting that the channel "Through some other way" has matching efficiency equal to 0.32. Note that the estimates of matching efficiencies through referrals for the UK economy is quite smaller than that in the US (see for instance Galenianos (2014), Berman (1997), etc.)

4.5.1.2 Alternative Method

As I described above, for possible endogeneity issues I estimate the following alternative model for each of the six different channels:

$$\ln(\frac{m_{it}(v_t,u_t)}{u_t}) = \ln M_t + \ln \mu_i + \eta_i \ln \frac{v_t}{u_t} + (1-\eta_i)\ln s_{it} + \varepsilon_{it}$$

where $\varepsilon_{it} = \ln \Phi_{it}$. For this alternative model, I impose in the estimates an elasticity η_i for the $\ln \frac{v_t}{u_t}$ and $1-\eta_i$ for the $\ln s_{it}$ and run the estimations with and without a quadratic time trend.

Recall that the exogeneity condition is now $E\left(\ln(\frac{v_t}{u_t})\varepsilon_{it}\right) = 0, \forall i$. This implies that a big shock (ε_{it}), could potentially change the aggregate variables v_t and u_t. But on the other hand, ε_{it} is an idiosyncratic shock to one channel of search only, so this shock should not have a relevant aggregate effect on v_t/u_t. This is easy to defend since I assumed that $\sum_i s_{it} = 1$ and that there is an aggregate effect $\ln(M_t)$, so that $\sum_i \epsilon_{it} = 0$.

Since I argue that this alternative model can handle better possible endogeneity issues, I can estimate it with the following procedure. In this alternative model I run two OLS estimations for each channel, one with and one without a time trend (in total 36 or 2 times 6 times 3 since I have 6 search channels and three different methodologies).

Tables C.7 to C.12 (see Appendix C) report the estimated output for this model, with a quadratic time trend and without a quadratic time trend, for our three different methods of measuring the s_{it}. The estimated elasticity of the matching functions with this approach are quite higher from that in the previous case since, as mentioned above, in the estimations I impose an elasticity η_i for the $\ln \frac{v_t}{u_t}$ and $1 - \eta_i$ for the $\ln s_{it}$. In particular, the estimated elasticity of the matching function with a quadratic time trend is approximately from 0.7 to 0.9 across the three different methods of measuring the search effort. This implies that the estimated coefficient of the natural logarithm of search effort is approximately from 0.1 to 0.3 (since from the structure of the model it is imposed to be equal to $1 - \eta_i$). Note that for instance the estimated elasticity of the matching function with a quadratic time trend of method 1 for the channel "Job Advertisement" (0.9) represents that a one percent increase in the fraction $\theta = v/s_i u$ will increase the job finding rate for the channel "Job Advertisement" ($m/s_i u$) by 9 percent. Again, these estimated elasticities are quite close to one another, suggesting that it is reasonable to assume a common elasticity of the matching functions across channels, even if we use the alternative method.

Tables 4.10 and 4.11 report, as in the previous section, the estimates of the matching efficiencies across channels by applying OLS regressions for each channel of search, one with and one without a time trend (in columns two, four and six is in logarithmic terms for each method of measuring the s_{it} and in columns three, five and seven is in absolute terms). From this tables we can observe that the matching efficiencies across channels are lower than that from the standard methodology but the ranking is the same. Furthermore, for the alternative model the results are the same with those from applying the standard methodology for estimating the matching functions: the average matching efficiency of "Referrals" is the highest among all the channels of searching.

Table 4.6: Matching Efficiency Estimations of OLS for the alternative model with a quadratic time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	-0.161	0.851	-0.161	0.851	-0.161	0.851
Advert	-1.184	0.306	-1.171	0.310	-1.178	0.308
JobCenter	-2.422	0.089	-2.307	0.100	-2.373	0.093
Priv. Empl.	-1.892	0.151	-1.936	0.144	-1.918	0.147
Referrals	-0.881	0.414	-1.035	0.355	-0.973	0.378
Direct Appl.	-1.377	0.252	-1.423	0.241	-1.402	0.246
Other	-1.493	0.225	-1.621	0.198	-1.568	0.208

More specifically, in terms of results Table 4.6 show the matching efficiency for each channel by estimating the model with a quadratic time trend for the three different methods of measuring the s_{it}. From this table we can observe that the matching efficiency of referrals with the first method of measuring the s_{it} is 0.41, with the second method 0.36, with the third method 0.38, and is the highest across channels. The second most efficient channel is “Job Advertisements” where the estimated matching efficiency is approximately equal to 0.31 for the three methods of measuring the s_{it}. The channel “Direct Applications” has the third highest matching efficiency, as it did in the previous section, with an estimated matching efficiency approximately equal to 0.25. “Private employment agency or business” has a low matching efficiency (0.15 with the first method, 0.14 with the second method, and 0.15 with the third method) but the lowest matching efficiency is observed and in this case for the Jobcenter, Jobmarket, etc (0.09 with the first method, 0.1 with the second method, and 0.09 with the third method). The channel “Through some other way” has matching efficiency equal to: 0.23 with the first method, 0.2 with the second method, and 0.21 with the third method. Finally the results are in a similar direction if we exclude the time trend (see Table 4.7 and Table 4.7 which

Table 4.7: Matching Efficiency Estimations of OLS without a time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	0.063	1.065	0.063	1.065	0.063	1.065
Advert	-1.255	0.285	-1.253	0.286	-1.254	0.285
JobCenter	-2.474	0.084	-2.455	0.086	-2.463	0.085
Priv. Empl.	-2.294	0.101	-2.282	0.102	-2.293	0.101
Referrals	-1.208	0.299	-1.262	0.283	-1.246	0.288
Direct Appl.	-1.635	0.195	-1.678	0.187	-1.661	0.190
Other	-1.745	0.175	-1.849	0.157	-1.808	0.164

is in the Appendix C).

4.5.2 Panel Estimations

4.5.2.1 Standard Method

In the previous section we observed that the OLS regressions in the time series analysis suggest that the estimations of the elasticity of the matching functions are quite similar across channels. So, in this section I restrict the model and assume that the elasticity of the matching function is the same for all the channels. I estimate a panel including all the channels of search and estimate my model including dummy variables for each channels of search (similar to a fixed effect estimation). The estimated coefficient of each dummy variable gives the estimates of the matching efficiency by channel. Recall that the model to be estimated is the following:

$$\ln(\frac{m_{it}}{s_{it}u_t}) \quad = \quad \ln(M_t) + \ln(\mu_i) + \eta \ln\left(\frac{v_t}{s_{it}u_t}\right) + e_{it} \qquad (4.5.3)$$

Tables C.13 and C.14 (see Appendix C) report the estimated output for this model, with a quadratic time trend and without a quadratic time trend, for our three different methods of measuring the s_{it}. The estimated elasticity of the matching function with a quadratic time trend is 0.76 with the first method, 0.74 with the second method, and 0.74 with the third method. The estimated η without a time trend is 0.87 for the first method, 0.91 with the second method, and 0.89 with the third method. Note that for instance the estimated elasticity of the matching function with a quadratic time trend of method 1 (0.76) represents that a one percent increase in the fraction $\theta = v/s_i u$ will increase the job finding rate for each channel of searching $m/s_i u$ by 7.6 percent.

Tables 4.8 and 4.9 report the estimates of the matching efficiencies across channels by using dummy variables for each channels of search (in columns two, four and six is in logarithmic terms for each method of measuring the s_{it} and in columns three, five and seven is in absolute terms). At the bottom of these tables the estimated elasticity of the matching function for each method is presented[19].

More specifically, in terms of results Table 4.8 show the matching efficiency across channels by estimating the panel with a quadratic time trend for the three different methods of measuring the s_{it}. From this table we can observe that the matching efficiency of referrals with the first method of measuring the s_{it} is 0.59, with the second method 0.52, with the third method 0.55, and is the highest across channels. The second most efficient channel is “Job Advertisements” where the estimated matching efficiency is equal to: 0.38 with the first method, 0.41 with the second method, and 0.4 with the third method. The channel “Direct Applications” has the third highest matching efficiency

[19]It is worth noting that in all the tables that represent the estimates of the matching efficiencies across channels, I assume that for each channel of search the aggregate matching efficiency is equal with that M_t which is estimated from the aggregate OLS in 4.5.1 (with and without time trend, respectively).

Table 4.8: Matching Efficiency Estimations of the Panel with a quadratic time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	-0.161	0.851	-0.161	0.851	-0.161	0.851
Advert	-0.967	0.380	-0.889	0.411	-0.926	0.396
JobCenter	-2.015	0.133	-1.883	0.152	-1.943	0.143
Priv. Empl.	-1.337	0.263	-1.370	0.254	-1.331	0.264
Referrals	-0.530	0.588	-0.657	0.518	-0.590	0.554
Direct Appl.	-1.043	0.352	-1.080	0.340	-1.048	0.351
Other	-1.099	0.333	-1.148	0.317	-1.103	0.332
η	0.757		0.742		0.739	

Table 4.9: Matching Efficiency Estimations of the Panel with no time trend for the three different methods.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	0.063	1.065	0.063	1.065	0.063	1.065
Advert	-1.296	0.274	-1.258	0.284	-1.274	0.280
JobCenter	-2.426	0.088	-2.406	0.090	-2.415	0.089
Priv. Empl.	-1.955	0.142	-2.083	0.125	-2.032	0.131
Referrals	-1.078	0.340	-1.204	0.300	-1.160	0.314
Direct Appl.	-1.546	0.213	-1.623	0.197	-1.593	0.203
Other	-1.719	0.179	-1.853	0.157	-1.800	0.165
η	0.869		0.914		0.895	

as it did in the previous section (time series estimations). The estimated matching efficiency for this channel is 0.35 with the first method, 0.34 with the second method, and 0.35 with the third method. “Private employment agency or business” has a low matching efficiency (0.26 with the first method, 0.25 with the second method, and 0.26 with the third method) but the lowest matching efficiency is observed and in this case for the Jobcenter, Jobmarket, etc (0.13 with the first method, 0.15 with the second method, and 0.14 with the third method). The channel “Through some other way” has matching efficiency equal to: 0.33 with the first method, 0.32 with the second method, and 0.33 with the third method. It is worth mentioning that the estimated matching efficiencies of each channel by estimating the panel, are quite similar with the estimated efficiencies for each channel by using a time series analysis. In particular, the panel estimations are slightly higher from that of the time series estimations, but the ranking of the matching efficiencies across channel is the same.

Table 4.9 shows the matching efficiency across channels by estimating the panel without a quadratic time trend for the three different methods of measuring the s_{it}. From this table we can observe that the matching efficiency across channels without including a time trend are quite lower from the estimated model which includes a time trend. In particular, the matching efficiency of referrals with the first method of measuring the s_{it} is 0.34, with the second method 0.3, with the third method 0.31, and is the highest across channels. The second most efficient channel is “Job Advertisements” where the estimated matching efficiency is equal to: 0.27 with the first method, 0.28 with the second method, and 0.28 with the third method. The channel “Direct Applications” has the third highest matching efficiency which is 0.21 with the first method, and 0.2 with the second and third method. “Private employment agency or business” has a low matching efficiency (0.14 with the first method, 0.12 with the second method, and 0.13 with the third method) but the lowest matching efficiency is observed and in this case for the Jobcenter, Jobmarket, etc (almost 0.09 for all the methods of measuring the s_{it}). The channel “Through some other way” has matching efficiency equal to: 0.18 with the first method, 0.16 with the second method, and 0.17 with the third method.

Finally, it should be pointed out that and in this case the estimated matching efficiencies of each channel by estimating the panel are quite similar to the estimated efficiencies for each channel by using a time series analysis. More specifically, the panel estimations are slightly higher from that of the time series estimations, but the ranking of the matching efficiencies across channels is the same.

On the other hand, as stated before, Borowczyk-Martins et al. (2013) argue that this estimation methodology of the matching functions should suffer from possible endogeneity bias coming from the search behaviour of both job seekers and employers. Borowczyk-Martins et al. (2013) state that this bias may occur since the job vacancies which are posted by employers might be affected by random shocks to the unobserved matching efficiency. So, even idiosyncratic shocks to one channel might affect aggregate variables. They propose a GMM estimation by imposing an ARMA structure in the matching function and they do the estimations by using time series data from JOLTS. The issue, as stated by the authors, is that this methodology cannot be applied in a panel structure without imposing matching efficiency to be constant across channel. This is the reason that I used the alternative methodology and also followed Sahin et al. (2014) who suggest to model the matching efficiency dynamics through structural breaks and time-varying polynomials.

In this section a way to handle from the above endogeneity issue is also to apply an instrumental variable estimation. I use 2 lags of the labour market tightness as instruments since random shocks in time *t* should not affect the labour market tightness in time *t-1* and *t-2*. The estimation outputs for the three methods of measuring the s_{it} are presented in Tables C.21 and C.22 and the estimated matching efficiencies in Tables C.19 and C.20 for the case with and without a quadratic time trend, respectively. The estimations of the matching efficiencies across channels with IV, are very similar to the estimations of this section (slightly larger in most of the cases for the model with quadratic time trend). The latter suggests that the possible bias in the estimates should not be large. Finally, the ranking of the matching efficiencies across channels is the same.

Overall, the panel estimations, as in the time series case, are suggesting that the matching efficiency of the channel “Referrals” is the highest one, with “Job Advertisement” to be the second highest independently from the method of measuring s_{it}. “Job-center, Jobmarket, etc.” is the searching channel with the lowest matching efficiency.

4.5.2.2 Alternative Method

As I described previously, for possible endogeneity issues I estimate the alternative model by using the same panel and the same strategy as above. So, in this subsection I estimate the following model:

$$\ln(\frac{m_{it}(v_t, u_t)}{u_t}) = \ln M_t + \ln \mu_i + \eta \ln \frac{v_t}{u_t} + (1 - \eta) \ln s_{it} + \varepsilon_{it}$$

where $\varepsilon_{it} = \ln \Phi_{it}$

For this alternative model, I impose in the estimates an elasticity η for the $\ln \frac{v_t}{u_t}$ and $1 - \eta$ for the $\ln s_{it}$ and run the estimations with and without a quadratic time trend.

Recall again that the exogeneity condition is $E\left(\ln(\frac{v_t}{u_t})\varepsilon_{it}\right) = 0, \forall i$ which implies that a big shock (ε_{it}), could change the aggregate variables v_t and u_t. But ε_{it} is an idiosyncratic shock to one channel of searching only. The latter means that this shock should not have a relevant aggregate effect on v_t/u_t, reducing possible bias in the estimates.

Tables C.15 and C.16 (see Appendix C) report the estimated output for this model, with a quadratic time trend and without a quadratic time trend, for our three different methods of measuring the s_{it}. The estimated elasticity of the matching functions with this approach is quite higher from that in the previous case since, as mentioned above; I impose in the estimations an elasticity η for the $\ln \frac{v_t}{u_t}$ and $1 - \eta$ for the $\ln s_{it}$. In particular, the estimated elasticity of the matching function with a quadratic time trend is approximately equal to 0.83 across the three different methods of measuring the search effort. This implies that the estimated coefficient of the natural logarithm of search effort is approximately 0.17, since from the structure of the model it is imposed to be equal to $1 - \eta$. Furthermore, the estimated η without a time trend is 0.94 for the first method, 0.96 with the second method, and 0.95 with the third method. Note that for instance the estimated elasticity of the matching function with a quadratic time trend of method 1 (0.83) represents that a one percent increase in the fraction $\theta = v/s_i u$ will increase the job finding rate for each channel of searching $m/s_i u$ by 8.3 percent.

Tables 4.10 and 4.11 report, as in the previous section, the estimates of the matching efficiencies across channels by using dummy variables for each channels of search (in columns two, four and six is in logarithmic terms for each method of measuring the s_{it} and in columns three, five and seven is in absolute terms). At the bottom of these tables the estimated elasticity of the matching function for each method is presented. From these Tables we can observe that the matching efficiencies across channels are lower than that from the standard methodology but the ranking is the same.

More specifically, in terms of results Table 4.10 show the matching efficiency across channels by estimating the panel for the alternative model with a quadratic time trend for the three different methods of measuring the search effort (s_{it}). From this table we can observe that the matching efficiency of referrals with the first method of measuring the s_{it} is 0.5, with the second method 0.44, with the third method 0.47, and is the highest across channels. The second most efficient channel is “Job Advertisements” where the estimated matching efficiency is equal to: 0.37 with the first method, 0.39 with the

Table 4.10: Matching Efficiency Estimations of the Panel with a quadratic time trend for the three different methods: Alternative Estimation.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	-0.161	0.851	-0.161	0.851	-0.161	0.851
Advert	-1.005	0.366	-0.951	0.386	-0.977	0.376
JobCenter	-2.104	0.122	-2.026	0.132	-2.064	0.127
Priv. Empl.	-1.558	0.211	-1.613	0.199	-1.581	0.206
Referrals	-0.706	0.493	-0.813	0.443	-0.766	0.465
Direct Appl.	-1.191	0.304	-1.234	0.291	-1.210	0.298
Other	-1.321	0.267	-1.387	0.250	-1.351	0.259
η	0.828		0.832		0.827	

Table 4.11: Matching Efficiency Estimations of the Panel with a quadratic time trend for the three different methods: Alternative Estimation.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	0.063	1.065	0.063	1.065	0.063	1.065
Advert	-1.299	0.273	-1.271	0.281	-1.283	0.277
JobCenter	-2.480	0.084	-2.457	0.086	-2.467	0.085
Priv. Empl.	-2.139	0.118	-2.181	0.113	-2.165	0.115
Referrals	-1.216	0.296	-1.262	0.283	-1.246	0.288
Direct Appl.	-1.657	0.191	-1.680	0.186	-1.671	0.188
Other	-1.904	0.149	-1.949	0.142	-1.932	0.145
η	0.939		0.957		0.950	

second method, and 0.38 with the third method. The channel "Direct Applications" has the third highest matching efficiency as it did in the previous section (time series estimations). The estimated matching efficiency for this channel is approximately equal to 0.3 across the three different methods of measuring the s_{it}. "Private employment agency or business" has a low matching efficiency (0.21 with the first method, 0.2 with the second method, and 0.21 with the third method) but the lowest matching efficiency is observed and in this case for the Jobcenter, Jobmarket, etc (0.12 with the first method, 0.13 with the second method, and 0.13 with the third method). The channel "Through some other way" has matching efficiency equal to: 0.27 with the first method, 0.25 with the second method, and 0.26 with the third method. It is worth noting that the estimated matching efficiencies of each channel by estimating the panel are quite similar to the estimated efficiencies for each channel by using a time series analysis. In particular, the panel estimations are slightly higher from that of the time series estimations, but the ranking of the matching efficiencies across channel is the same. Finally, the empirical results for the matching efficiencies are in a similar direction if we exclude the time trend (see Table 4.11, and Table C.16 which is in the Appendix C)

Overall, the panel estimations with the alternative model suggest that the matching efficiency of the channel "Referrals" is the highest one and "Job Advertisement" have the second highest matching efficiency. Finally, "Jobcenter, Jobmarket, etc." is the search channel with the lowest matching efficiency. In addition, the ranking of the channels according to their matching efficiencies is the same with the one in the standard methodology.

It is worth noting that with this methodology I attempt to decrease the potential bias coming from satisfying the exogeneity condition of this model which is $E\left(\ln(\frac{v_t}{u_t})\varepsilon_{it}\right) = 0, \forall i$. But I cannot fully eliminate a short of bias from the effect of an idiosyncratic shock (ε_{it}) in channel *i* on the aggregate variables v_t and u_t. A way to deal with this potential bias as Sahin et al. (2014) suggest is to model the matching efficiency dynamics through structural breaks and time-varying polynomials. The results from this estimation methodology are presented in the next section.

4.5.2.3 Method with structural breaks and time-varying polynomials

In this section, I present the results of matching efficiencies across channel by estimating a model with structural breaks and time-varying polynomials, which is proposed by Borowczyk-Martins et al. (2013) and Sahin et al. (2014) for handling possible endogeneity issues. From Figure 4.1 we can observe that there is a structural break in 2008, which is the beginning of the 2008 crisis. Thus, after replicating the methodology followed by Sahin et al. (2014) in estimating matching efficiencies by sector in the US labour market, I follow the same strategy in estimating matching efficiencies for each search channel in the UK labour market[20]. According to Sahin et al. (2014) and Borowczyk-Martins et al. (2013) the latter methodology is more robust to possible endogeneity issues from all the other methodologies.

Recall that at the channel level, I am interested in the aggregate movements of the matching efficiency to be orthogonal with the channel-specific component of the matching efficiency. So, for the three methods of measuring the search effort, I estimate the following model by running a panel regression:

$$\ln\left(\frac{m_{it}(v_t, u_{it})}{s_{it}u_t}\right) = \delta' QTT_t + \ln(M_t) + \gamma_{\{t<2008\}} \ln \mu_i^{pre} + \gamma_{\{t\geq 2008\}} \ln \mu_i^{post} + \eta \ln \frac{v_t}{s_{it}u_t} + \varepsilon_{it}$$

Where the vector QTT_t is consists of two elements which are for the quadratic time trend, $\gamma_{\{t<2008\}}$ is an indicator for the period before the crisis and is used for absorbing channel-specific shifts in the matching efficiency. Finally, μ_i^{pre} represent the matching

[20]Panel data and codes of the estimations of matching efficiencies across sectors by Sahin et al. (2014) are publicly available in the American Economic Association.

efficiency of channel *i* before the crisis and μ_i^{post} the matching efficiency of channel *i* after the crisis. As I did in the previous sections, I estimate the above specified model with and without time trend.

Tables C.17 and C.18 (see Appendix C) report the estimated output for this model, with a quadratic time trend and without a quadratic time trend, for our three different methods of measuring the s_{it}. The estimated elasticity of the matching functions with this approach are quite lower from that in the previous cases since, as mentioned above, I model the matching efficiency dynamics through structural breaks and time-varying polynomials. In particular, the estimated elasticity of the matching function with a quadratic time trend is approximately equal to 0.65 with the first method of measuring the search effort and 0.64 for the second and third method. Furthermore, the estimated η without a time trend is approximately equal to 0.68 for the first and second method, and 0.67 with the third method. Note that for instance, the estimated elasticity of the matching function with a quadratic time trend of method 1 (0.65) represents that a one percent increase in the fraction $\theta = v/s_i u$ will increase the job finding rate for each channel of searching $m/s_i u$ by 6.5 percent.

Tables 4.12 and 4.13 report, as in the previous sections, the estimates of the matching efficiencies across channels by estimating a model with structural breaks and time-varying polynomials (estimates are in absolute terms). At the bottom of these tables the estimated elasticity of the matching function for each method is documented. From these tables, we can observe that the matching efficiencies across channels before 2008 (the structural break) are higher than that from the standard and the alternative methodology, whereas the matching efficiencies across channels after 2008 are in some cases lower than that from the standard and alternative methodology. Furthermore, the ranking of the matching efficiencies is the same with that in the previous sections.

More specifically, in terms of results, Table 4.12 show the matching efficiency across

Table 4.12: Matching Efficiency Estimations of the model with structural breaks and time-varying polynomials for the three methods of measuring the search effort.

	Method 1		Method 2		Method 3	
Channel	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}
Advertis	0.394	0.296	0.413	0.342	0.404	0.317
Job Cent	0.139	0.121	0.166	0.139	0.152	0.130
Priv Empl	0.336	0.287	0.323	0.249	0.337	0.270
Referrals	0.690	0.615	0.570	0.485	0.626	0.537
Direct Appl	0.385	0.363	0.359	0.329	0.376	0.347
Other	0.394	0.397	0.354	0.353	0.379	0.377
η	0.651		0.642		0.637	

Table 4.13: Matching Efficiency Estimations of the model with structural breaks and without time-varying polynomials for the three methods of measuring the search effort.

	Method 1		Method 2		Method 3	
Channel	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}
Advertis	0.287	0.213	0.295	0.233	0.291	0.220
Job Cent	0.100	0.084	0.115	0.091	0.107	0.088
Priv Empl	0.230	0.191	0.215	0.157	0.226	0.174
Referrals	0.479	0.416	0.392	0.317	0.432	0.356
Direct Appl	0.270	0.249	0.248	0.215	0.261	0.231
Other	0.268	0.264	0.236	0.223	0.255	0.243
η	0.678		0.678		0.668	

channels of the model with structural breaks and time-varying polynomials by estimating the panel with a quadratic time trend for the three different methods of measuring the s_{it}. From this table, we can observe that the matching efficiency of referrals is the highest across channels, where: with the first method of measuring the s_{it}, equal to 0.69 before 2008 and 0.62 after 2008 implying an 11% drop, with the second method 0.57 before 2008 and 0.49 after 2008 implying a 15% drop, and with the third method 0.63 before 2008 and 0.54 after 2008 implying a 14% drop. The second most efficient channel is "Job Advertisements" where the estimated matching efficiency is equal to: 0.39 before 2008 and 0.3 after 2008 with the first method implying a 25% drop, with the second method 0.41 before 2008 and 0.32 after 2008 implying a 17% drop, and with the third method 0.4 before 2008 and 0.32 after 2008 implying a 22% drop. The channel "Direct Applications" has the third highest matching efficiency and equal to 0.39 before 2008 and 0.36 after 2008 with the first method, 0.36 before 2008 and 0.33 after 2008 with the second method, and with the third method 0.38 before 2008 and 0.35 after 2008, implying an average 6% drop across the three different methods of measuring the s_{it}. "Private employment agency or business" has the fourth highest matching efficiency and equal to 0.34 before 2008 and 0.29 after 2008 with the first method, implying a 15% drop, with the second method 0.32 before 2008 and 0.25 after 2008 implying a 24% drop, and with the third method 0.34 before 2008 and 0.27 after 2008, implying a 20% drop. The lowest matching efficiency is observed again for the Jobcenter, Jobmarket, etc (with the first method 0.14 before 2008 and 0.12 after 2008, with the second method 0.17 before 2008 and 0.14 after 2008, and with the third method 0.15 before 2008 and 0.13 after 2008, implying an average 14% drop across the three different methods of measuring the s_{it}). The channel "Through some other way" has matching efficiency equal to: 0.39 before and after 2008 with the first method, 0.35 before and after 2008 with the second method, and 0.38 before and after 2008 with the third method. It is worth noting that the highest drop in the matching efficiency for the period after the 2008 with that before 2008 is observed in channels "Job Advertisements" and "Private employment agency or business". A smaller drop is observed in the channels "Referrals" and "Jobcenter, Jobmarket, etc", and almost no drop is observed in the channels "Direct Applications" and "Through some other way". Finally, the results are in a similar direction if we exclude the time trend (see Table 4.13 and Table C.18 which is in the Appendix C).

As in the “Standard Methodology” and in this section a way to deal with possible endogeneity issues from low frequency shocks is to apply an instrumental variable estimation. I use 2 lags of the labour market tightness as instruments, since random shocks in time *t* should not affect the labour market tightness in time *t-1* and *t-2*. The estimation outputs for the three methods of measuring the s_{it} are presented in Tables C.23 and C.24 and the estimated matching efficiencies in Tables C.25 and C.26 for the case with and without a quadratic time trend, respectively. The estimations of the matching efficiencies across channels with IV, are very similar to the estimations of this section (slightly larger in most of the cases for the model with quadratic time trend). The latter suggests that the possible bias in the estimates should not be large. Finally, the ranking of the matching efficiencies across channels is the same, independently from the method of estimating the matching functions.

In conclusion, time series and panel regressions produce similar results. More specifically, we can conclude that firstly “Referrals” and secondly “Job Advertisement” have the highest matching efficiencies. These results are robust across different estimation methodologies and motivate my initial focus on informal matching channels. Furthermore, it worth mentioning that the estimates of this research are lower from Galenianos (2014) but very close to Sahin et al. (2014), who both estimate sectoral matching efficiencies for the US economy. The above estimates are also very close those found by Patterson et al. (2013), who estimate sectoral matching efficiencies in the UK economy.

4.6 Conclusion

The aim of this chapter is to estimate the matching efficiencies of both the informal and formal channels of searching for jobs in the UK labour market. I focus on the UK's labour market since referrals are used only by about 54% and 26% of the unemployed and new workers, respectively, in that country, whereas, in the US, there are many studies which find higher usage of this channel. For instance, Holzer (1987c) finds that more than 85% of both the unemployed and new workers in the US use personal contact as a search method. So, in this paper, I empirically investigate what the matching efficiency across the different channels of searching for a job are and highlight the role of referrals on the UK's labour market. To my knowledge, this is the first research which attempts to estimate matching efficiencies through different channels of searching for a job. The primary focus is the UKs economy, and I follow the standard methodology which is used in the literature (see, for instance, Galenianos (2014)). In addition, I introduce an alternative estimation which handles possible endogeneity issues in the estimations of the matching functions better (these issues are also highlighted by Borowczyk-Martins et al. (2013)). Following Sahin et al. (2014), I handle these possible endogeneity issues by introducing in the matching function structural breaks and time-varying polynomials.

For the estimations of the matching function, I use the "Quarterly Labour Force Survey" (QLFS) and the "Vacancy Survey" datasets for the years 2001 to 2015. In all of the estimates, I find that, in the UK's labour market, referrals have the highest matching efficiency. Moreover, I determined that the channel "Job Advertisement" has the second highest matching efficiency and that "Direct Applications" have the third highest matching efficiency. The channel "Private employment agency or business" has a low matching efficiency, with the "Jobcenter, Jobmarket, etc." channel having the lowest matching efficiency. Furthermore, the estimates of the matching efficiencies across channels from the methodology introduced by Sahin et al. (2014) are higher than that from the standard and alternative methodologies used in this paper, but all the estimates point towards the same direction in terms of ranking for efficiency across channels.

Possible extensions of this chapter could be made. For instance, one could introduce more heterogeneity in the model across different groups of worker. This heterogeneity in the model could provide different matching efficiencies across the different education or income groups, genders, sectors of work, size of firm, ethnic groups, natives vis-a-vis immigrants, etc. For instance, there are papers which argue that low educated and low income workers may use friends, relatives and networks more intensively while searching for a job (see, for instance, studies conducted in the US by Corcoran et al. (1980), Pellizzari (2010) and Elliott (1999)). Another possible extension could be to estimate matching efficiencies across different age groups, especially since some literature suggests that it is more probable that young job seekers with little or no experience will use their friends and relatives as a potential job-searching method (see Corcoran et al. (1980) and Marsden and Gorman (2001)). Other papers investigate gender differences in the usage of referrals by job seekers[21] or differences in the usage of formal and informal channels by the unemployed across different racial and ethnic groups[22].

From the results of this paper, we can observe that there are different job finding probabilities using different channels of searching for jobs. Informal channels (referrals) have the highest job finding probabilities, with the second highest being the channel "Job Advertisement". Another possible extension motivated by the findings of the current chapter is determining what the other labour outcomes of the matches between employers and employees are through informal and formal channels. Someone can investigate the role of referrals and formal channels on future wages, future hours of working (full-time versus part-time jobs and their relationship with a specific channel), the sector and occupation of the previous and the new job, possible migration decisions, the type of job and its relationship with education, and the relationship between the usage of specific channels of searching for jobs and possible mismatches. Furthermore,

[21]See Corcoran et al. (1980), Ports (1993) Moore (1990) and Marsden and Campbell (1990) among others.

[22]See Corcoran et al. (1980), Datcher (1983, 2006), Green et al. (1999), and Holzer (1987b)

if the usage of formal or informal channels creates “good” quality matches in terms of productivity, duration of employment in the same job, the growth rate of wages for workers who found a job from a specific channel of search, and possible higher probabilities of an involuntary job separation from matches that occurred from a specific channel. Moreover, someone can investigate possible differences in labour outcomes between the period before and after the 2008 crisis. Finally, a further extension of this research can focus on investigating the relationship between the prevalence of formal and informal channels of job-searching and the aggregate matching efficiency of the UK’s labour market.

5

Conclusion

In this Ph.D. thesis I explore important topics on the area of applied labour economics with a primary focus on the UK economy. In the first two chapters, I investigate issues on job separations and in the third chapter, I investigate issues on how firms and job seekers match in the labour market. In particular, the first chapter investigates the effect of involuntary job separations on earnings and on wages. Furthermore, I quantify, what is the contribution of wage cuts and of reduction in hours of working, on earning losses followed an involuntary job separation. In the second chapter, I am accounting how much of the UK's productivity puzzle can be explained by involuntary job separations. Finally, in the third chapter, I investigate the efficiency of matchings from formal and informal channels between firms and workers, in the UK's labour market.

These broader topics in labour economics are arising from a growing literature which investigates in depth job flows and unemployment dynamics (see for instance **?**). These papers are exploring the role of inflows and outflows from unemployment (or from employment) and investigate the mechanisms that drives them. This literature gives the motivation of the current Ph.D. thesis to do a deeper investigation on job finding and separation issues such as on involuntary job separations and on the hiring methods between firms and workers.

More specifically, in the first chapter of this Ph.D. thesis, I estimate the labour outcomes of an involuntary job separation on income and on wages. Furthermore, I measure the contribution of the driving forces which led to the drop in earnings after a displacement. These driving forces are the wages and the hours of working. In the literature, there are many papers in the literature which investigate earning losses after an involuntary job displacement. The majority of these studies find that there are long-run losses in earnings after a displacement (see Jacobson et al. (1993a); Neal (1995); Couch and Placzek (2010)). These studies support the conclusion that earning losses after displacements for high tenured workers should be driven by losses in accumulated firm-specific human capital, since involuntary job separations make high tenured displaced workers less productive in their new jobs when compared to his production levels had he not been displaced. This latter implies that these losses should be reflected on their wages, as well. Nevertheless, in the literature, no further investigation regarding what drives these earning losses after job separations. This chapter, on the other hand, highlights this aspect that the literature ignores and quantifies the contribution of wage cuts and decreases in hours of working on earning losses after displacements.

In particular, this chapter firstly documents what the earnings and wage losses are after an involuntary job separation at the individual level. Moreover, it measures what proportion of these losses are driven by (i) wage cuts and (ii) reductions in hours of work at the aggregate level. Jacobson et al. (1993a) highlight the importance of this kind of research, mentioning that a *"..lack of data prevent us from decomposing earnings losses into effects due to lower wages and reduced hours"*. Thus, the current research attempts to fill this gap in the literature and provides more insights into the driving forces behind the earning losses after an involuntary job separation.

In terms of results, I ran a fixed effect model with Driscoll-Kraay standard errors and found that high tenured workers who had an unemployment spell following an involuntary job separation experienced large and sustained income and wage losses during the post-displacement period. Furthermore, the losses are much smaller for displaced workers who had a job-to-job flow after their separation than for displaced workers who had an unemployment spell after their displacement and before finding a new job.

At the aggregate level, I decompose labour income into its two components: wages and hours of working. By decomposing labour income in this way, I can quantify the contributions of wage cuts and reductions in hours of working on earning losses after involuntary job displacements. After running counterfactual exercises, I found that, on average, 83 percent of the income losses for employees who had a job-to-job flow following an involuntary job separation are driven by wage cuts and that their hours of work did not fluctuate much. For workers who had an unemployment spell after their displacement, and before finding a new job, the drop in their earnings, which was purely driven by wage cuts, is almost 80 percent independently from their pre-displacement tenure. For this group, on average, only 2 percent of the earning gap was purely driven by decreases in working hours. It is worth to note that all of these results differ across pre-displacement tenure, education, unemployment duration, age, and sex.

More specifically, in most cases, the drop in earnings is higher for workers with more than 3 years of pre-displacement tenure from those with more than 2 years of pre-displacement tenure a finding which is consistent with the literature. College educated displaced workers do not face losses after a job-to-job separation and changes in earnings are driven by both changes in hours of working and in wages. For non-college educated displaced workers with a job-to-job flow, however, the results are different. They encounter, on average, a 26% earnings loss in the first year after their separation.

These losses for non-college workers are mainly wage driven. On the other hand, earnings for college educated displaced workers who had an unemployment spell after their displacement and before finding a new job suffer from a more severe short-run effect (the drop is larger after the displacement) than that of the non-college educated displaced workers, but their earnings recovered faster. Furthermore, the drop in earnings for college educated displaced workers is almost purely driven by wage cuts, whereas, for non-college educated displaced workers, the wage effect is smaller (i.e. between 60% and 80%).

Furthermore, female displaced workers who experienced a job-to-job flow after a displacement do not face any losses in their earnings but, rather, small gains. The drop in earnings for men with a job-to-job displacement were severe and large (on average 16.5% earning losses). These losses for male displaced workers were almost purely wage-driven. The results for female displaced workers who had an unemployment spell after a displacement and before finding a new job contradict those which had a job-to-job flow. There is a large drop in earnings for female workers after a job separation, which is on average 26.8% in the first year, whereas it is smaller for men (19.2%). In addition, the drop in the earnings of female workers is 60.4% purely driven by cuts in their wages and 36.5% by reductions in their working hours. For male displaced workers, on the other hand, 81.5% of their earning losses are driven by wage cuts, whereas their working hours do not fluctuate much after a displacement.

If one splits the sample into three different age groups, as Borland et al. (2002) have also noted, the results are not always well determined because of the small sample size. In this case, there is a large drop in earnings for young displaced worker who had a job-to-job flow, middle aged displaced workers did not suffer from any losses after a displacement, and old workers faced smaller losses in their earnings. The main finding is that the earning losses for young workers are almost purely driven by wage cuts, whereas, for old workers, 78% is purely driven by wage cuts and 20% by decreases in working hours. On the other hand, the drop in earnings for the three age groups of worker who experienced an unemployment spell after the displacement and before finding a new job are, in most cases, as expected from the past literature. The drop in earnings is higher for old displaced workers (on average 37%), quite smaller for middle aged workers (18%), and young workers almost do not suffer from any losses after their displacements. The main finding for these groups of worker is that the earning losses for middle aged workers are almost purely driven by wage cuts, whereas, for old workers, 53% is purely driven by wage cuts and 31% is driven by decreases in working hours.

It should be noted, however, that I am concerned that there might be a potential problem with the estimates reported in this chapter since the exogeneity condition of the event of an involuntary job separation might be challenged which could, in turn, bias my estimations. More specifically, I am concerned about any unobservable characteristics which vary across time and which can affect the performance of each individual worker. The latter implies that the likelihood of getting dismissed should be influenced as well. Due to the limitations of the data, it is difficult to find appropriate exclusion restrictions in the literature for job loss. Furthermore, due to the small sample size, the results in some cases might be ambiguous and not easily interpreted.

In the second chapter of this Ph.D. thesis, I investigate how much of the UK's productivity puzzle can be explained by displacements. This is an important aspect since in the UK after the deep recession of 2008, labour productivity showed poor performance and and did not follow the recovery of the labour market and the real GDP. This is called the UK's productivity puzzle. The puzzle is well known in the literature and many researchers are trying to give a plausible explanation for what the facts were which created this puzzle while also recommending policies which will solve it. In this paper, I focus on highlighting the role of involuntary job separations on the UK's post-2008 labour productivity (as output per hour worked). Job displacements have been investigated at the micro-level, where the findings from previous papers suggest that there are individual productivity losses after involuntary job separations. The aggregate effect of displacements, however, is an aspect which the literature has ignored so far. Therefore, this chapter attempts to fill in this gap by translating the individual productivity losses due to the displacements of high tenured workers (more than 2 years in the same job prior to the separation) into their aggregate effect on labour productivity. I focus on the UK's labour productivity in the post-2008 crisis since I observed a 50 percent increase in the fraction of displaced workers with a 16 percent decrease in their average wages.

In order to tackle this question and define how much the UK's productivity puzzle can be explained by displacements, I ran counterfactual accounting exercises. In the counterfactual exercise which is the most unbiased from the others, I account that the post-2008 labour productivity that would have been the case had the post-crisis average individual productivity of displaced workers been equal with the one that they had before the crisis. Note that, in this paper, I assume perfect competition at the macro-level where the individual average productivity of the displaced workers can be approximated to their average wage rates. The results show that, on average, 27 percent of the productivity gap between the actual and the potential productivity, in the absence of a crisis, can be explained by the displacements of high tenured workers. Therefore, involuntary job separations, on average, can explain more than one fourth of the UK's productivity puzzle.

Furthermore, I quantified the contribution of the displaced workers who are either college or non-college educated separately in order to explain this puzzle. The results show that college educated displaced workers can explain 21.1 percent of the UK's productivity puzzle. This means that 78 percent of the overall effect of displacements on this puzzle are due to productivity (and wage) losses from college educated displaced workers. The remaining 22 percent of the overall effect of displacements on the puzzle can be explained by the drop in wages of non-college educated workers.

In order to check for robustness of the estimates, I ran alternative counterfactual exercises, arguing that the results were likely to suffer from either an upwards or a downwards bias. The counterfactual exercise described above, however, seems to have underestimated the role of displacements on post-crisis productivity. This should be the case since I did not account for possible post-crisis trends that the wages of the displaced workers would have had had the crisis not occurred. So, overall, I can conclude that the aggregate effect of displacements should not be ignored since one can, in fact, explain part of the UK's productivity puzzle in light of those displacements.

Finally, in the last chapter of this Ph.D. thesis, I investigate the hiring methods that are used in the UK labour market. In particular, the aim of this chapter is to estimate the matching efficiencies of both the informal and formal channels of searching for jobs in the UK labour market. I focus on the UK's labour market since referrals are used only by about 54% and 26% of the unemployed and new workers, respectively, in that country, whereas, in the US, there are many studies which find higher usage of this channel. For instance, Holzer (1987c) finds that more than 85% of both the unemployed and new workers in the US use personal contact as a search method. So, in this paper, I empirically investigate what the matching efficiency across the different channels of searching for a job are and highlight the role of referrals on the UK's labour market. To my knowledge, this is the first paper which attempts to estimate matching efficiencies through different channels of searching for a job. The primary focus is the UKs economy, and I follow the standard methodology which is used in the literature (see, for instance, Galenianos (2014)). In addition, I introduce an alternative estimation which handles possible endogeneity issues in the estimations of the matching functions better (these issues are also highlighted by Borowczyk-Martins et al. (2013)). Following Sahin et al. (2014), I handle these possible endogeneity issues by introducing in the matching function structural breaks and time-varying polynomials.

For the estimations of the matching function, I use the "Quarterly Labour Force Survey" (QLFS) and the "Vacancy Survey" datasets for the years 2001 to 2015. In all of the estimates, I find that, in the UK's labour market, referrals have the highest matching efficiency. Moreover, I determined that the channel "Job Advertisement" has the second highest matching efficiency and that “Direct Applications” have the third highest matching efficiency. The channel “Private employment agency or business” has a low matching efficiency, with the “Jobcenter, Jobmarket, etc.” channel having the lowest matching efficiency. Furthermore, the estimates of the matching efficiencies across channels from the methodology introduced by Sahin et al. (2014) are higher than that from the standard and alternative methodologies used in this paper, but all the estimates point towards the same direction in terms of ranking for efficiency across channels.

Possible extensions of this chapter could be made. For instance, one could introduce more heterogeneity in the model across different groups of worker. This heterogeneity in the model could provide different matching efficiencies across the different education or income groups, genders, sectors of work, size of firm, ethnic groups, natives vis-a-vis immigrants, etc. For instance, there are papers which argue that low educated and low income workers may use friends, relatives and networks more intensively while searching for a job (see, for instance, studies conducted in the US by Corcoran et al. (1980), Pellizzari (2010) and Elliott (1999)). Another possible extension could be to estimate matching efficiencies across different age groups, especially since some literature suggests that it is more probable that young job seekers with little or no experience will use their friends and relatives as a potential job-searching method (see Corcoran et al. (1980) and Marsden and Gorman (2001)). Other papers investigate gender differences in the usage of referrals by job seekers[1] or differences in the usage of formal and informal channels by the unemployed across different racial and ethnic groups[2].

From the results of this paper, we can observe that there are different job finding probabilities using different channels of searching for jobs. Informal channels (referrals) have the highest job finding probabilities, with the second highest being the channel “Job Advertisement”. Another possible extension motivated by the findings of the

[1] See Corcoran et al. (1980), Ports (1993) Moore (1990) and Marsden and Campbell (1990) among others.

[2] See Corcoran et al. (1980), Datcher (1983, 2006), Green et al. (1999), and Holzer (1987b)

current chapter is determining what the other labour outcomes of the matches between employers and employees are through informal and formal channels. Someone can investigate the role of referrals and formal channels on future wages, future hours of working (full-time versus part-time jobs and their relationship with a specific channel), the sector and occupation of the previous and the new job, possible migration decisions, the type of job and its relationship with education, and the relationship between the usage of specific channels of searching for jobs and possible mismatches. Furthermore, if the usage of formal or informal channels creates "good" quality matches in terms of productivity, duration of employment in the same job, the growth rate of wages for workers who found a job from a specific channel of search, and possible higher probabilities of an involuntary job separation from matches that occurred from a specific channel. Moreover, someone can investigate possible differences in labour outcomes between the period before and after the 2008 crisis. Finally, a further extension of this research can focus on investigating the relationship between the prevalence of formal and informal channels of job-searching and the aggregate matching efficiency of the UK's labour market.

References

Abowd, J. M., McKinney, K. L., and Vilhuber, L. (2009). The Link between Human Capital, Mass Layoffs, and Firm Deaths. In *Producer Dynamics: New Evidence from Micro Data*, NBER Chapters, pages 447–472. National Bureau of Economic Research, Inc.

Acemoglu, D. (2002a). Directed Technical Change. *Review of Economic Studies*, 69(4):781–809.

Acemoglu, D. (2002b). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, 40(1):7–72.

Acemoglu, D. (2003). Patterns of Skill Premia. *Review of Economic Studies*, 70(2):199–230.

Acemoglu, D. and Autor, D. (2011). *Skills, Tasks and Technologies: Implications for Employment and Earnings*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.

Acemoglu, D. and Autor, D. (2012). What Does Human Capital Do? A Review of

Goldin and Katz's The Race between Education and Technology. *Journal of Economic Literature*, 50(2):426–63.

Addison, J. T. and Portugal, P. (1989). Job Displacement, Relative Wage Changes, and Duration of Unemployment. *Journal of Labor Economics*, 7(3):281–302.

Alon, S. (1997). Job search, gender, and the quality of employment in israel. *Research in social stratification and mobility : the official journal of the ISA RC28 on Social Stratification and Mobility*, 15:133–149.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in us wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2):300–323.

Balestra, S. and Backes-Gellner, U. (2012). When a Door Closes a Window Opens? Investigating the Effects of Involuntary Separations. Economics of Education Working Paper Series 0072, University of Zurich, Institute for Strategy and Business Economics (ISU).

Barlevy, G. (2002). The sullying effect of recessions. *The Review of Economic Studies*, 69(1):65–96.

Barnett, A., Batten, S., Chiu, A., and Franklin, J. (2014). The uk productivity puzzle'. *Bank of England Quarterly Bulletin 2014Q2*.

Barnichon, R. and Figura, A. (2011). What drives matching efficiency? a tale of composition and dispersion. Technical report.

Barnichon, R. and Figura, A. (2015). Labor Market Heterogeneity and the Aggregate Matching Function. *American Economic Journal: Macroeconomics*, 7(4):222–49.

Bayer, P., Ross, S. L., and Topa, G. (2008). Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy*, 116(6):1150–1196.

Becker, G. S. (1962). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education*. University of Chicago Press.

Becker, G. S. and Chiswick, B. R. (1966). Education and the distribution of earnings. *The American Economic Review*, 56(1/2):pp. 358–369.

Berman, E. (1997). Help Wanted, Job Needed: Estimates of a Matching Function from Employment Service Data. *Journal of Labor Economics*, 15(1):S251–92.

Bewley, T. F. (1999). *Why wages don't fall during a recession / Truman F. Bewley*. Harvared University Press Cambridge, MA.

Bils, M. J. (1985). Real wages over the business cycle: evidence from panel data. *Journal of Political Economy*, 93(4):666–689.

Blanchflower, D. G., Oswald, A. J., and Sanfey, P. (1996). Wages, Profits, and Rent-Sharing. *The Quarterly Journal of Economics*, 111(1):227–251.

Blundell, R., Crawford, C., and Jin, W. (2014). What can wages and employment tell us about the uk's productivity puzzle? *The Economic Journal*, 124(576):377–407.

Borland, J., Gregg, P., Knight, J., and Wadsworth, J. (2002). *They Get Knocked Down, Do They Get Up Again? Displaced Workers in Britain and Australia*. Michigan, Upjohn Institute.

Borowczyk-Martins, D., Jolivet, G., and Postel-Vinay, F. (2013). Accounting For Endogeneity in Matching Function Estimation. *Review of Economic Dynamics*, 16(3):440–451.

Bortnick, S. M. and Ports, M. H. (1992). Job search methods and results: Tracking the unemployed, 1991. *Monthly Labor Review*, 115:29.

Bowlus, A. (1993). Job match quality over the business cycle. *in H. Bunzel, P. Jensen and N. Westergard-Neilsen (eds.), Panel Data and Labour Market Dynamics, (Amsterdam: North Holland)*, pages 21–41.

Bradshaw, T. F. (1973). Jobseeking methods used by unemployed workers. *Monthly Labor Review*, 96(2):pp. 35–40.

Bridges, W. P. and Villemez, W. J. (1986). Informal hiring and income in the labor market. *American Sociological Review*, 51(4):pp. 574–582.

Caballero, R. J. and Hammour, M. L. (1994). The cleansing effect of recessions. *The American Economic Review*, pages 1350–1368.

Caballero, R. J., Hammour, M. L., et al. (1996). On the timing and efficiency of creative destruction. *The Quarterly Journal of Economics*, 111(3):805–852.

Cameron, A. and Triverdi, P. (2005). *Microeconometrics Methods and Applications*. Cambridge University Press.

Cameron, A. and Triverdi, P. (2010). *Microeconometrics Using Stata*. StataCorp LP.

Cappellari, L. and Tatsiramos, K. (2010). Friends' Networks and Job Finding Rates. Technical report.

Card, D. and Lemieux, T. (2001). Can Falling Supply Explain The Rising Return To College For Younger Men? A Cohort-Based Analysis. *The Quarterly Journal of Economics*, 116(2):705–746.

Carl Shapiro, J. E. S. (1984). Equilibrium unemployment as a worker discipline device. *The American Economic Review*, 74(3):433–444.

Carneiro, P. and Lee, S. (2011). Trends in Quality-Adjusted Skill Premia in the United States, 1960-2000. *American Economic Review*, 101(6):2309–49.

Carrington, W. J. (1993). Wage Losses for Displaced Workers: Is It Really the Firm That Matters? *Journal of Human Resources*, 28(3):435–462.

Carrington, W. J. (2015). Do We Know Why Earnings Fall with Job Displacement? Working Paper: 2015-01. Working papers, Congressional Budget Office.

Chan, S. and Stevens, A. H. (1999). Employment and Retirement Following a Late Career Job Loss. Departmental Working Papers 199903, Rutgers University, Department of Economics.

Chan, S. and Stevens, A. H. (2004). How Does Job Loss Affect the Timing of Retirement? *The B.E. Journal of Economic Analysis & Policy*, 3(1):1–26.

Conley, T. G. and Topa, G. (2007). Estimating dynamic local interactions models. *Journal of Econometrics*, 140(1):282–303.

Corcoran, M., Datcher, L., and Duncan, G. (1980). Information and influence networks in labor markets. *Five thousand American families: Patterns of economic progress*, 8(S 1):37.

Couch, K. A. (1998). Late life job displacement. *Gerontologist*, 38(1):7–17.

Couch, K. A. and Placzek, D. W. (2010). Earnings Losses of Displaced Workers Revisited. *American Economic Review*, 100(1):572–89.

Crawford, R. (2013). The effect of the financial crisis on the retirement plans of older workers in England. *Economics Letters*, 121(2):156–159.

Datcher, L. (1983). The Impact of Informal Networks of Quit Behavior. *The Review of Economics and Statistics*, 65(3):491–95.

Datcher, L. (2006). Some Contacts Are More Equal than Others: Informal Networks, Job Tenure, and Wages. *Journal of Labor Economics*, 24(2):299–318.

Davis, S. J., Faberman, R. J., and Haltiwanger, J. C. (2013). The Establishment-Level Behavior of Vacancies and Hiring. *The Quarterly Journal of Economics*, 128(2):581–622.

Davis, S. J., Haltiwanger, J., and Schuh, S. (1996). Job creation and job destruction.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4):549–560.

Eliason, M. and Storrie, D. (2006). Lasting or Latent Scars? Swedish Evidence on the Long-Term Effects of Job Displacement. *Journal of Labor Economics*, 24(4):831–856.

Elliott, J. R. (1999). Social isolation and labor market insulation: Network and neighborhood effects on less-educated urban workers. *The Sociological Quarterly*, 40(2):pp. 199–216.

Elsby, M. W. L., Hobijn, B., and Sahin, A. (2010). The Labor Market in the Great Recession. *Brookings Papers on Economic Activity*, 41(1 (Spring):1–69.

Enders, W. (2010). *Applied econometric time series*. Wiley series in probability and statistics. Wiley, Hoboken, NJ, 3. ed. edition.

Falcon, L. M. (1995). Social networks and employment for latinos, blacks, and whites. *New England Journal of Public Policy*, 11(1):4.

Fallick, B. C. (1993). The Industrial Mobility of Displaced Workers. *Journal of Labor Economics*, 11(2):302–23.

Farber, H. S. (2005). What do we know about job loss in the United States? evidence from the displaced workers survey, 1984-2004. *Economic Perspectives*, (Q II):13–28.

Fernandez, R. M. and Castilla, E. J. (2001). How much is that network worth? social capital in employee referral networks. *Social Capital: Theory and Research*, pages 85–104.

Fernandez, R. M., Castilla, E. J., and Moore, P. (2000). Social capital at work: Networks and employment at a phone center. *American journal of sociology*, pages 1288–1356.

Fujita, S. and Ramey, G. (2009). The Cyclicality Of Separation And Job Finding Rates. *International Economic Review*, 50(2):415–430.

Galenianos, M. (2014). Hiring through referrals. *Journal of Economic Theory*, 152(C):304–323.

Giannarakis, P. (2015). Are earning losses after involuntary seperations wage driven: The uk case. *Working Paper*.

Gibbons, R. and Katz, L. F. (1991). Layoffs and Lemons. *Journal of Labor Economics*, 9(4):351–80.

Goldin, C. D. and Katz, L. F. (2009). *The race between education and technology*. Harvard University Press.

Gomes, J., Greenwood, J., and Rebelo, S. (2001). Equilibrium unemployment. *Journal of Monetary Economics*, 48(1):109–152.

Goodridge, P., Haskel, J., and Wallis, G. (2013). Can Intangible Investment Explain the UK Productivity Puzzle? *National Institute Economic Review*, 224(1):R48–R58.

Goodridge, P., Haskel, J., and Wallis, G. (2014). The UK productivity puzzle is a TFP puzzle: current data and future predictions. Working Papers 18381, Imperial College, London, Imperial College Business School.

Granovetter, M. S. (1995). *Getting a job : a study of contacts and careers*. University of Chicago Press, Chicago.

Green, G. P., Tigges, L. M., and Browne, I. (1995). Social resources, job search, and poverty in atlanta. *Research in Community Sociology*, 5:161–182.

Green, G. P., Tigges, L. M., and Diaz, D. (1999). Racial and ethnic differences in job-search strategies in atlanta, boston, and los angeles. *Social Science Quarterly*, 80(2):pp. 263–278.

Gregg, P., Machin, S., and FernndezSalgado, M. (2014). Real Wages and Unemployment in the Big Squeeze. *Economic Journal*, 0(576):408–432.

Hall, R. (1995). Lost jobs. *Brookings Papers on Economic Activity*, 26(1, 25th Anniversary Issue):221–274.

Hall, R. E. (2000). Reorganization. In *Carnegie-Rochester Conference Series on Public Policy*, volume 52, pages 1–22. Elsevier.

Hijzen, A., Upward, R., and Wright, P. W. (2010). The Income Losses of Displaced Workers. *Journal of Human Resources*, 45(1).

Hilaski, H. J. (1971). How poverty area residents look for work. *Monthly Labor Review*, 94(3):pp. 41–45.

Hildreth, A. K. G. and Oswald, A. J. (1997). Rent-Sharing and Wages: Evidence from Company and Establishment Panels. *Journal of Labor Economics*, 15(2):318–37.

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, 7(3):281–312(32).

Holzer, H. J. (1987a). *Hiring Procedures in the Firm: Their Economic Determinants and Outcomes*. Number no. 2185 in Hiring procedures in the firm: their economic determinants and outcomes. National Bureau of Economic Research.

Holzer, H. J. (1987b). Informal job search and black youth unemployment. *The American Economic Review*, 77(3):pp. 446–452.

Holzer, H. J. (1987c). Job search by employed and unemployed youth. *Industrial and Labor Relations Review*, 40(4):601–611.

Howland, M. and Peterson, G. E. (1988). Labor market conditions and the reemployment of displaced workers. *Industrial & Labor Relations Review*, 42(1):109–122.

Hughes, A. and Saleheen, J. (2012). UK labour productivity since the onset of the crisis an international and historical perspective. *Bank of England Quarterly Bulletin*, 52(2):138–146.

Huttunen, K., Men, J., and Salvanes, K. G. (2011). How Destructive Is Creative Destruction? Effects Of Job Loss On Job Mobility, Withdrawal And Income. *Journal of the European Economic Association*, 9(5):840–870.

Ichino, A., Schwerdt, G., Winter-Ebmer, R., and Ichino, A. (2013). Too Old to Work, Too Young to Retire? NRN working papers 2013-09, The Austrian Center for Labor Economics and the Analysis of the Welfare State, Johannes Kepler University Linz, Austria.

Jacobson, L., LaLonde, R., and G. Sullivan, D. (2005). Estimating the returns to community college schooling for displaced workers. *Journal of Econometrics*, 125(1-2):271–304.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993a). Earnings Losses of Displaced Workers. *American Economic Review*, 83(4):685–709.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993b). *The Costs of Worker*

Dislocation. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Jaimovich, N. and Siu, H. E. (2009). The Young, the Old, and the Restless: Demographics and Business Cycle Volatility. *American Economic Review*, 99(3):804–26.

Jaimovich, N. and Siu, H. E. (2012). The Trend is the Cycle: Job Polarization and Jobless Recoveries. NBER Working Papers 18334, National Bureau of Economic Research, Inc.

Jovanovic, B. (1979). Job matching and the theory of turnover. *The Journal of Political Economy*, pages 972–990.

Jung, P. and Kuhn, M. (2012). Earnings losses and labor mobility over the lifecycle. IZA Discussion Papers 6835, Institute for the Study of Labor (IZA).

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Kletzer, L. G. (1989). Returns to Seniority after Permanent Job Loss. *American Economic Review*, 79(3):536–43.

Kletzer, L. G. (1998). Job Displacement. *Journal of Economic Perspectives*, 12(1):115–136.

Kletzer, L. G. and Fairlie, R. W. (2003). The long-term costs of job displacement for young adult workers. *Industrial and Labor Relations Review*, 56(4):682–698.

Korenman, S. and Turner, S. C. (1996). Employment contacts and minority-white wage differences. *Industrial Relations: A Journal of Economy and Society*, 35(1):106–122.

Krolikowski, P. (2015). Job Ladders and Earnings of Displaced Workers. Working paper, Federal Reserve Bank of Cleveland.

Krusell, P., Ohanian, L. E., Ros-Rull, J.-V., and Violante, G. L. (2000). Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68(5):1029–1054.

Kuhn, P. J., editor (2002). *Losing Work, Moving On: International Perspectives on Worker Displacement*. Number lwmo in Books from Upjohn Press. W.E. Upjohn Institute for Employment Research.

Kuttner, K. N. (1994). Estimating Potential Output as a Latent Variable. *Journal of Business & Economic Statistics*, 12(3):361–68.

Kuzubas, T. U. (2010). Endogenous Social Networks in the Labor Market. Technical report.

Lazear, E. P. (1979). Why is there mandatory retirement? *Journal of Political Economy*, 87(6):1261–1284.

Lazear, E. P. (1981). Agency, earnings profiles, productivity, and hours restrictions. *The American Economic Review*, 71(4):606–620.

Lazear, E. P. (2009). Firm-Specific Human Capital: A Skill-Weights Approach. *Journal of Political Economy*, 117(5):914–940.

Lin, N., Ensel, W. M., and Vaughn, J. C. (1981). Social resources and strength of ties: Structural factors in occupational status attainment. *American Sociological Review*, 46(4):pp. 393–405.

Loewenstein, G. F. and Prelec, D. (1993). Preferences for sequences of outcomes. *Psychological review*, 100(1):91.

Loewenstein, G. F. and Sicherman, N. (1991). Do Workers Prefer Increasing Wage Profiles? *Journal of Labor Economics*, 9(1):67–84.

Lundberg, S. (1985). The added worker effect. *Journal of Labor Economics*, 3(1):11–37.

Machin, A. (2003). The vacancy survey: a new series of national statistics. *Labour Market Trends*, 111(7):349–362.

Manacorda, M., Manning, A., and Wadsworth, J. (2010). The Impact of Immigration on the Structure of Wages: Theory and Evidence from Britain. CEPR Discussion

Papers 7888, C.E.P.R. Discussion Papers.

Marsden, P. V. and Campbell, K. E. (1990). Recruitment and selection processes: The organizational side of job searches. *Social mobility and social structure*, pages 59–79.

Marsden, P. V. and Gorman, E. H. (2001). Interpersonal ties, social capital, and employer staffing practices. *Social capital: Theory and research*, pages 105–26.

Marsden, P. V. and Hurlbert, J. S. (1988). Social resources and mobility outcomes: A replication and extension. *Social Forces*, 66(4):pp. 1038–1059.

Martin, B. (2011). Is the british economy supply constrained? a critique of productivity pessimism. *Centre for Business Research, University of Cambridge*.

Martin, B. and Rowthorn, R. (2012). Is the british economy supply constrained ii? a renewed critique of productivity pessimism. *Centre for Business Research, University of Cambridge*.

Marx, J. and Leicht, K. T. (1992). Formality of recruitment to 229 jobs - variations by race, sex and job characteristics. *Sociology and Social Research*, 76:190–196.

Mas-Colell, A., Whinston, M., and Green, J. (1995). *Microeconomic Theory*. Oxford student edition. Oxford University Press.

McKittrick, N. V. and Schnairsohn, E. L. (2008). Competing Definitions of Mass Layoffs Under the WARN Act. *Law Journal Newsletters, Employment Law Strategist*.

Mennuni, A. (2013). Labor force composition and aggregate fluctuations. *EUI Working Paper*.

Miller, S. R. and Rosenbaum, J. E. (1997). Hiring in a hobbesian world: Social infrastructure and employers' use of information. *Work and Occupations*, 24.

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy*, 66:281.

Mincer, J. (1962). On-the-job training: Costs, returns, and some implications. *Journal of Political Economy*, 70(5):pp. 50–79.

Monks, J. and Pizer, S. D. (1998). Trends in voluntary and involuntary job turnover. *Industrial Relations: A Journal of Economy and Society*, 37(4):440–459.

Montgomery, J. D. (1991). Social Networks and Labor-Market Outcomes: Toward an Economic Analysis. *American Economic Review*, 81(5):1407–18.

Moore, G. (1990). Structural determinants of men's and women's personal networks. *American sociological review*, pages 726–735.

Mortensen, D. T. and Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3):397–415.

Neal, D. (1995). Industry-Specific Human Capital: Evidence from Displaced Workers. *Journal of Labor Economics*, 13(4):653–77.

Neal, D. (1999). The Complexity of Job Mobility among Young Men. *Journal of Labor Economics*, 17(2):237–61.

Neckerman, K. M. and Kirschenman, J. (1991). Hiring strategies, racial bias, and inner-city workers. *Social Problems*, 38(4):pp. 433–447.

Oi, W. Y. (1962). Labor as a quasi-fixed factor. *The Journal of Political Economy*, pages 538–555.

Ornstein, M. D. (1976). *Entry into the American labor force*. Quantitative studies in social relations. Academic Press, New York.

Oulton, N. and Sebastia-Barriel, M. (2013). Long and short-term effects of the financial crisis on labour productivity, capital and output. Bank of England working papers 470, Bank of England.

Patterson, C., Sahin, A., Topa, G., and Violante, G. L. (2013). Mismatch unemployment in the uk. Technical report, mimeo, Federal Reserve Bank of New York.

Paull, G. (2002). Biases in the reporting of labour market dynamics. IFS Working Papers W02/10, Institute for Fiscal Studies.

Pellizzari, M. (2010). Do Friends and Relatives Really Help in Getting a Good Job?

Industrial and Labor Relations Review, 63(3):494–510.

Pessoa, J. P. and Reenen, J. V. (2013). The UK Productivity and Jobs Puzzle: Does the Answer Lie in Labour Market Flexibility? CEP Special Papers 31, Centre for Economic Performance, LSE.

Petrongolo, B. and Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, 39(2):390–431.

Pissarides, C. A. (2000). *Equilibrium Unemployment Theory, 2nd Edition*, volume 1 of *MIT Press Books*. The MIT Press.

Pissarides, C. A. and Petrongolo, B. (2001). Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature*, 39(2):390–431.

Polsky, D. (1999). Changing consequences of job separation in the united states. *Industrial and Labor Relations Review*, 52(4):pp. 565–580.

Ports, M. H. (1993). Trends in job search methods, 1970-92. *Monthly Labor Review*, 116(10):63–67.

Rees, A. (1966). Information networks in labor markets. *The American Economic Review*, 56(1/2):pp. 559–566.

Rees, A. and Shultz, G. P. (1970). *Workers and wages in an urban labor market*. University of Chicago Press Chicago.

Ruhm, C. J. (1991). Are Workers Permanently Scarred by Job Displacements? *American Economic Review*, 81(1):319–24.

Sahin, A., Song, J., Topa, G., and Violante, G. L. (2014). Mismatch Unemployment. *American Economic Review*, 104(11):3529–64.

Salop, J. and Salop, S. C. (1976). Self-selection and turnover in the labor market. Technical report.

Schmutte, I. M. (2015). Job Referral Networks and the Determination of Earnings in Local Labor Markets. *Journal of Labor Economics*, 33(1):1 – 32.

Schneider, S. L. and Kogan, I. (2008). The international standard classification of education 1997: Challenges in the application to national data and the implementation in cross-national surveys. *The International Standard Classification of Education (ISCED-97). An evaluation of content and criterion validity for*, 15.

Shaw, K. L. (1984). A formulation of the earnings function using the concept of occupational investment. *Journal of Human Resources*, pages 319–340.

Shin, D. (1994). Cyclicality of real wages among young men. *Economics Letters*, 46(2):137–142.

Smith, J. C. (2011). The Ins and Outs of UK Unemployment. *Economic Journal*, 121(552):402–444.

Smith, J. C. (2013). Pay Growth, Fairness and Job Satisfaction: Implications for Nominal and Real Wage Rigidity. Technical report.

Song, J., Topa, G., Violante, G., and Sahin, A. (2012). Measuring Mismatch in the US Labor Market. Technical report.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, 87(3):355–374.

Stevens, A. H. (1997). Persistent Effects of Job Displacement: The Importance of Multiple Job Losses. *Journal of Labor Economics*, 15(1):165–88.

Topa, G. (2001). Social Interactions, Local Spillovers and Unemployment. *Review of Economic Studies*, 68(2):261–95.

Topa, G. (2011). Chapter 22 - labor markets and referrals. volume 1 of *Handbook of Social Economics*, pages 1193 – 1221. North-Holland.

Topel, R. (1990). Specific capital and unemployment: Measuring the costs and consequences of job loss. *Carnegie-Rochester Conference Series on Public Policy*, 33(1):181–214.

Troske, K. R. (1996). The dynamic adjustment process of firm entry and exit in manufacturing and finance, insurance, and real estate. *The Journal of Law & Economics*, 39(2):705–735.

Wahba, J. and Zenou, Y. (2005). Density, social networks and job search methods: Theory and application to Egypt. *Journal of Development Economics*, 78(2):443–473.

Wegener, B. (1991). Job mobility and social ties: Social resources, prior job, and status attainment. *American Sociological Review*, 56(1):pp. 60–71.

Weinberg, B. A., Reagan, P. B., and Yankow, J. J. (2004). Do Neighborhoods Affect Hours Worked? Evidence from Longitudinal Data. *Journal of Labor Economics*, 22(4):891–924.

Willis, R. J. (1987). Wage determinants: A survey and reinterpretation of human capital earnings functions. In Ashenfelter, O. and Layard, R., editors, *Handbook of Labor Economics*, volume 1 of *Handbook of Labor Economics*, chapter 10, pages 525–602. Elsevier.

APPENDIX A

Appendix to Chapter 2

A.1

Empirical Analysis: Fixed effect model with the Driscoll-Kraay standard errors

In this section I present the empirical strategy of analysing the data from BHPS data set. The British Household Panel Survey is a rich data set which includes annual information of employment history for each surveyor. Individuals declare the beginning and the ending of their employment status. Thus, I can have information for the exact dates of each event. Taking that into consideration, I construct a monthly panel of 10000 individuals with up to 7 million spells. The basic issue is that for each spell, the wage does not change over time (since the individual declares that is employed). So, there is a high volume of serial correlation in the data and the actual information may be overstated because "NT correlated observations have less information than NT independent observations" (Cameron and Triverdi (2005)). Although most empirical studies now provide standard error estimates that are heteroskedasticity and autocorrelation consistent, cross-sectional or spatial dependence is still largely ignored. However, assuming that the disturbances of a panel model are cross-sectionally independent is often inappropriate (Cameron and Triverdi (2010)).

Another issue with the BHPS dataset is that it is a long unbalanced panel starting from 1990 until 2011 so standard Panel-data estimation methods for short panels might not be unbiased or efficient (Cameron and Triverdi (2010)). Hoechle (2007) highlights that the coefficients which are estimated from standard panel estimators such as random or fixed effect estimators, pooled ordinary least-squares (OLS) estimations are consistent (but inefficient) if the unobservable common factors are uncorrelated with the explanatory variables. However, there is a bias in the estimates of standard errors from commonly applied covariance matrix estimation techniques such as OLS, White and Rogers or clustered standard errors. Thus statistical inference based on such standard errors are not valid (Hoechle (2007)).

On the other hand, Driscoll and Kraay (1998) proposes an alternative estimation of a covariance matrix which is nonparametric and can be applied only to balanced panels. This estimator can produce standard errors that are heteroskedasticity and autocorrelation consistent and also robust to general forms of spatial and temporal dependence. Hoechle (2007) is an extension of Driscoll and Kraay (1998) covariance matrix estimator specifically to be applied on unbalanced panels for estimating a pooled OLS and a Fixed Effect regression. He uses an adjusted estimator from Driscoll and Kraay (1998) in medium and large scale (microeconometric) panels and tests the estimator's finite sample performance by running Monte Carlo simulations. These simulations show that it should not be ignored a spatial correlation in panel regressions since it can lead to excessively optimistic (anti-conservative) standard error estimates regardless of whether a panel is balanced. Furthermore, the small sample properties are much better than those of the alternative covariance estimators when cross-sectional dependence is present, despite the fact that Driscoll and Kraay standard errors turn to be slightly optimistic. In our case, the BHPS dataset is a long and unbalanced panel, thus the above standard errors estimator seems to be the most appropriate one to be used.

Finally, following Cameron and Triverdi (2010) I compare three different estimation methods for our $N * T$ observations with T to be the number of panels and N the number of individuals. One for finite panels (sort) with infinity number of individuals ($T \nrightarrow \infty$, $N \rightarrow \infty$) where I run a robust estimate of the variance-covariance matrix (VCE) in a fixed effect estimation. One for long panels with finite number of individuals ($N \nrightarrow \infty$, $T \rightarrow \infty$) where I run a Feasible Generalised Least Square estimation (FGLS) and finally for our case where I have an unbalanced long panel with infinity number of individuals ($N \rightarrow \infty$, $T \rightarrow \infty$) I run a Fixed-effect regression with Driscoll-Kraay standard errors. The results are presented in the next section.

A.2

Table A.1: Estimation Outputs for Models 1-3 (All Separators): Real Labour Income

Variables	Real Weekly Income		
	Model 1	Model 2	Model 3
Age	48.27***	35.00***	48.27***
	(0.40)	(0.36)	(0.91)
Age squared/100	-40.15***	-39.39***	-40.15***
	(0.40)	(0.43)	(0.94)
Time	-0.50***	0.12***	-0.50***
	(0.01)	(0.01)	(0.04)
3 years prior displacement	23.77***	12.89	23.77***
	(3.41)	(8.94)	(3.48)
2 years prior displacement	25.93***	12.33	25.93***
	(3.29)	(8.21)	(3.65)
1 years prior displacement	24.85***	9.94	24.85***
	(4.08)	(7.90)	(4.06)
1 years after displacement	-30.28***	-33.68***	-30.28***
	(4.70)	(9.75)	(4.80)
2 years after displacement	-35.35***	-35.86***	-35.35***
	(4.68)	(10.13)	(4.92)
3 years after displacement	-27.40***	-26.21*	-27.40***
	(4.90)	(10.74)	(5.23)
4 years after displacement	-26.63***	-24.54*	-26.63***
	(6.08)	(11.29)	(6.46)
5 years after displacement	-12.32	-7.48	-12.32
	(7.48)	(12.07)	(7.58)
Constand	-858.75***	-316.88***	-858.75***
	(10.76)	(7.14)	(24.64)
N	214857	214857	214857
r2	0.07		
F	597.55		281.34
ll	-1.42e+06	-1.53e+06	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Estimation Outputs for Models 1-3 (Job to Job Flow, E-E): Real Labour Income

Variables	Real Weekly Income		
	Model 1	Model 2	Model 3
Age	46.82***	35.17***	46.82***
	(0.53)	(0.52)	(0.80)
Age squared/100	-37.94***	-39.41***	-37.94***
	(0.53)	(0.64)	(0.79)
Time	-0.40***	0.17***	-0.40***
	(0.02)	(0.01)	(0.04)
3 years prior displacement	15.97***	-0.24	15.97***
	(4.22)	(11.84)	(4.02)
2 years prior displacement	17.82***	1.76	17.82***
	(4.06)	(10.93)	(4.17)
1 years prior displacement	12.29**	-4.19	12.29***
	(3.86)	(10.63)	(3.67)
1 years after displacement	-17.97**	-16.55	-17.97**
	(6.22)	(13.80)	(5.79)
2 years after displacement	-23.70***	-16.46	-23.70***
	(6.24)	(14.44)	(5.86)
3 years after displacement	-19.74**	-11.48	-19.74**
	(6.42)	(15.48)	(6.43)
4 years after displacement	-15.33	-8.42	-15.33*
	(7.88)	(16.34)	(7.56)
5 years after displacement	-11.30	-0.07	-11.30
	(7.47)	(17.81)	(7.86)
Constand	-834.34***	-319.72***	-834.34***
	(14.43)	(10.36)	(24.69)
N	121683	121683	121683
r2	0.07		
F	422.79		308.26
ll	-814563.79	-870371.60	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Estimation Outputs for Models 1-3 (Flow which includes an unemployment spell, E-U-E): Real Labour Income

Variables	Real Weekly Income		
	Model 1	Model 2	Model 3
Age	49.35***	34.46***	49.35***
	(0.61)	(0.48)	(1.39)
Age squared/100	-41.85***	-38.98***	-41.85***
	(0.60)	(0.57)	(1.52)
Time	-0.63***	0.07***	-0.63***
	(0.02)	(0.01)	(0.05)
3 years prior displacement	36.64***	34.13*	36.64***
	(5.73)	(13.62)	(6.11)
2 years prior displacement	37.75***	28.19*	37.75***
	(5.53)	(12.41)	(5.55)
1 years prior displacement	41.65***	30.09*	41.65***
	(8.48)	(11.74)	(8.03)
1 years after displacement	-46.95***	-56.60***	-46.95***
	(7.05)	(13.52)	(7.25)
2 years after displacement	-51.43***	-60.92***	-51.43***
	(6.97)	(13.93)	(7.59)
3 years after displacement	-38.24***	-44.59**	-38.24***
	(7.42)	(14.56)	(8.20)
4 years after displacement	-41.68***	-44.31**	-41.68***
	(9.25)	(15.25)	(10.39)
5 years after displacement	-15.01	-16.45	-15.01
	(13.05)	(15.96)	(12.50)
Constand	-874.80***	-305.34***	-874.80***
	(16.22)	(9.69)	(35.31)
N	93174	93174	93174
r2	0.09		
F	241.67		158.49
ll	-602049.31	-654847.34	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Estimation Outputs for Models 1-3 (all separators): Real Hourly Wages

Variables	Real Hourly Wages		
	Model 1	Model 2	Model 3
Age	1.13***	0.82***	1.13***
	(0.01)	(0.01)	(0.03)
Age squared/100	-0.81***	-0.91***	-0.81***
	(0.01)	(0.01)	(0.03)
Time	-0.02***	0.00***	-0.02***
	(0.00)	(0.00)	(0.00)
3 years prior displacement	0.56***	0.53	0.56***
	(0.12)	(0.28)	(0.12)
2 years prior displacement	0.55***	0.40	0.55***
	(0.11)	(0.25)	(0.12)
1 years prior displacement	0.54***	0.36	0.54***
	(0.10)	(0.25)	(0.11)
1 years after displacement	-0.68***	-0.70*	-0.68***
	(0.15)	(0.29)	(0.14)
2 years after displacement	-0.92***	-1.01***	-0.92***
	(0.13)	(0.29)	(0.14)
3 years after displacement	-0.87***	-0.94**	-0.87***
	(0.15)	(0.31)	(0.17)
4 years after displacement	-0.75***	-0.86**	-0.75***
	(0.16)	(0.33)	(0.18)
5 years after displacement	-0.20	-0.11	-0.20
	(0.28)	(0.35)	(0.28)
Constand	-21.49***	-6.42***	-21.49***
	(0.42)	(0.22)	(0.70)
N	166007	166007	166007
r2	0.06		
F	562.62		189.96
ll	-503654.61	-578552.41	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Estimation Outputs for Models 1-3 (Job to Job Flow, E-E): Real Hourly Wages

Variables	Real Hourly Wages		
	Model 1	Model 2	Model 3
Age	1.23***	0.88***	1.23***
	(0.02)	(0.02)	(0.03)
Age squared/100	-0.87***	-0.99***	-0.87***
	(0.01)	(0.02)	(0.02)
Time	-0.02***	0.01***	-0.02***
	(0.00)	(0.00)	(0.00)
3 years prior displacement	0.35*	0.18	0.35*
	(0.16)	(0.40)	(0.15)
2 years prior displacement	0.44**	0.13	0.44**
	(0.14)	(0.37)	(0.14)
1 years prior displacement	0.38**	0.07	0.38**
	(0.14)	(0.36)	(0.14)
1 years after displacement	-0.42	-0.27	-0.42*
	(0.21)	(0.42)	(0.21)
2 years after displacement	-0.70***	-0.59	-0.70***
	(0.19)	(0.43)	(0.19)
3 years after displacement	-0.79***	-0.81	-0.79**
	(0.21)	(0.46)	(0.25)
4 years after displacement	-0.49*	-0.42	-0.49*
	(0.20)	(0.49)	(0.20)
5 years after displacement	-0.05	0.23	-0.05
	(0.43)	(0.53)	(0.40)
Constand	-24.03***	-7.15***	-24.03***
	(0.64)	(0.34)	(0.82)
N	92061	92061	92061
r2	0.05		
F	359.05		185.36
ll	-295395.07	-329568.98	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: Estimation Outputs for Models 1-3 (Flow which includes an unemployment spell, E-U-E): Real Hourly Wages

Variables	Real Hourly Wages		
	Model 1	Model 2	Model 3
Age	1.01***	0.74***	1.01***
	(0.02)	(0.01)	(0.04)
Age squared/100	-0.73***	-0.81***	-0.73***
	(0.01)	(0.02)	(0.04)
Time	-0.02***	0.00***	-0.02***
	(0.00)	(0.00)	(0.00)
3 years prior displacement	0.89***	0.98**	0.89***
	(0.16)	(0.38)	(0.16)
2 years prior displacement	0.72***	0.70*	0.72***
	(0.17)	(0.34)	(0.18)
1 years prior displacement	0.74***	0.66*	0.74***
	(0.15)	(0.32)	(0.15)
1 years after displacement	-1.08***	-1.33***	-1.08***
	(0.21)	(0.37)	(0.20)
2 years after displacement	-1.25***	-1.62***	-1.25***
	(0.18)	(0.38)	(0.20)
3 years after displacement	-1.02***	-1.19**	-1.02***
	(0.20)	(0.39)	(0.23)
4 years after displacement	-1.11***	-1.45***	-1.11***
	(0.25)	(0.41)	(0.31)
5 years after displacement	-0.40	-0.54	-0.40
	(0.34)	(0.43)	(0.35)
Constand	-18.17***	-5.43***	-18.17***
	(0.46)	(0.28)	(1.09)
N	73946	73946	73946
r2	0.09		
F	215.02		111.11
ll	-196831.24	-246207.93	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Estimation outputs of real labour income for separators with a flow which includes an unemployment spell (E-U-E): with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.36***		0.37***		0.29***	
	(0.03)		(0.05)		(0.03)	
3 years prior displacement	34.63***	30.59***	60.22***	54.89**	22.70***	19.20**
	(6.52)	(6.92)	(16.10)	(17.13)	(6.06)	(6.18)
2 years prior displacement	32.23***	29.08***	65.68***	62.00***	19.86***	17.25***
	(6.04)	(6.48)	(17.18)	(18.07)	(4.67)	(4.86)
1 years prior displacement	36.26***	34.73***	69.16***	67.27***	24.58*	23.33*
	(8.60)	(8.83)	(15.44)	(15.91)	(10.38)	(10.43)
1 years after displacement	-46.49***	-42.69***	-61.66**	-60.27**	-41.08***	-37.61***
	(7.69)	(7.62)	(21.21)	(21.31)	(6.18)	(6.25)
2 years after displacement	-46.99***	-42.34***	-57.93**	-56.69**	-42.25***	-37.89***
	(7.99)	(8.15)	(21.12)	(20.83)	(6.60)	(6.93)
3 years after displacement	-33.79***	-27.75**	-40.50	-37.42	-31.11***	-25.71***
	(8.51)	(8.71)	(23.67)	(23.57)	(6.74)	(7.01)
4 years after displacement	-38.29***	-30.80**	-73.58*	-69.82*	-25.56***	-18.80**
	(10.57)	(10.40)	(30.43)	(29.70)	(6.53)	(6.63)
5 years after displacement	-12.25	-2.41	-40.77	-34.11	-1.55	7.02
	(12.85)	(13.03)	(28.56)	(28.14)	(14.29)	(14.42)
Constand	400.83***	400.22***	537.35***	539.55***	353.12***	351.90***
	(1.75)	(3.02)	(3.03)	(4.16)	(1.47)	(2.42)
N	93174	93174	24062	24062	69112	69112
F	37.31	16.04	10.88	6.87	37.69	15.20
Standard errors in parentheses						
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table A.8: Estimation outputs of real labour income for separators with a job to flow: with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.64***		1.21***		0.33***	
	(0.03)		(0.04)		(0.03)	
3 years prior displacement	8.72*	4.57	20.94*	10.45	2.79	0.89
	(4.18)	(4.48)	(9.84)	(10.71)	(4.10)	(4.27)
2 years prior displacement	8.41	8.74	15.50	14.15	4.81	5.04
	(4.52)	(4.48)	(10.54)	(10.80)	(4.46)	(4.42)
1 years prior displacement	1.92	8.52*	4.72	16.00	0.83	4.14
	(3.90)	(3.80)	(10.32)	(10.25)	(3.59)	(3.57)
1 years after displacement	-14.09*	-0.10	0.51	24.98	-21.53***	-14.77*
	(6.04)	(6.17)	(14.34)	(15.13)	(6.24)	(6.13)
2 years after displacement	-18.65**	-0.63	-10.52	20.48	-21.53***	-12.47*
	(6.06)	(6.32)	(13.91)	(13.78)	(6.23)	(6.24)
3 years after displacement	-11.88	9.88	-11.55	24.67	-11.32*	-0.29
	(6.77)	(7.47)	(15.85)	(16.91)	(5.28)	(5.59)
4 years after displacement	-7.32	18.56*	-4.06	40.92	-8.26	4.84
	(7.98)	(8.72)	(20.17)	(20.94)	(6.92)	(6.92)
5 years after displacement	-5.13	23.58**	5.96	53.38**	-6.86	8.08
	(7.67)	(8.40)	(18.32)	(19.18)	(8.07)	(8.38)
Constand	418.09***	404.86***	576.10***	555.30***	348.12***	341.01***
	(1.90)	(4.42)	(2.57)	(8.21)	(1.93)	(2.55)
N	122063	122117	36515	36515	85548	85602
F	25.20	4.52	56.61	3.32	6.31	1.81
Standard errors in parentheses						
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table A.9: Estimation outputs of real labour income for all displaced: with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.51***		0.87***		0.31***	
	(0.03)		(0.04)		(0.03)	
3 years prior displacement	18.55***	14.28***	34.85***	25.51*	10.53**	7.97*
	(3.74)	(4.01)	(8.90)	(10.08)	(3.60)	(3.66)
2 years prior displacement	18.13***	16.55***	34.58***	30.89**	10.85**	9.88**
	(4.03)	(4.18)	(9.81)	(10.60)	(3.44)	(3.47)
1 years prior displacement	16.62***	18.93***	31.16***	34.77***	10.62*	11.96*
	(4.36)	(4.43)	(9.28)	(9.70)	(4.73)	(4.75)
1 years after displacement	-27.96***	-19.36***	-20.67	-8.59	-30.84***	-25.68***
	(5.10)	(4.98)	(12.37)	(13.00)	(4.86)	(4.78)
2 years after displacement	-30.63***	-19.77***	-25.60*	-11.03	-31.40***	-24.67***
	(5.05)	(5.04)	(12.21)	(12.19)	(4.44)	(4.52)
3 years after displacement	-21.13***	-7.85	-19.96	-1.70	-20.95***	-12.76**
	(5.47)	(5.81)	(14.57)	(15.20)	(3.97)	(4.16)
4 years after displacement	-20.81**	-4.86	-28.55	-6.01	-16.76***	-6.89
	(6.78)	(6.95)	(18.26)	(18.32)	(4.49)	(4.58)
5 years after displacement	-7.84	10.73	-12.71	13.10	-4.17	7.48
	(7.85)	(7.96)	(16.50)	(16.28)	(8.42)	(8.20)
Constand	409.19***	402.85***	556.07***	549.04***	350.19***	345.88***
	(1.68)	(3.75)	(2.46)	(6.26)	(1.51)	(2.44)
N	215237	215291	60577	60577	154660	154714
F	60.90	9.30	51.16	3.77	28.90	7.10
Standard errors in parentheses						
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table A.10: Estimation outputs of real hourly wage for separators with a flow which includes an unemployment spell (E-U-E): with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.01***		0.02***		0.01***	
	(0.00)		(0.00)		(0.00)	
3 years prior displacement	0.80***	0.62***	1.87***	1.63**	0.42**	0.26
	(0.16)	(0.17)	(0.48)	(0.49)	(0.15)	(0.15)
2 years prior displacement	0.58**	0.44*	1.51**	1.25*	0.28	0.17
	(0.18)	(0.19)	(0.49)	(0.52)	(0.15)	(0.15)
1 years prior displacement	0.64***	0.57**	1.61***	1.47***	0.33*	0.28
	(0.16)	(0.17)	(0.42)	(0.43)	(0.15)	(0.16)
1 years after displacement	-1.12***	-1.06***	-1.74*	-1.73*	-0.86***	-0.81***
	(0.21)	(0.22)	(0.70)	(0.72)	(0.17)	(0.17)
2 years after displacement	-1.22***	-1.15***	-1.67**	-1.70**	-1.00***	-0.93***
	(0.20)	(0.20)	(0.59)	(0.58)	(0.14)	(0.15)
3 years after displacement	-0.95***	-0.82***	-1.57*	-1.54*	-0.70***	-0.58**
	(0.23)	(0.24)	(0.62)	(0.62)	(0.19)	(0.20)
4 years after displacement	-1.09***	-0.92**	-2.40**	-2.36**	-0.63**	-0.47*
	(0.31)	(0.31)	(0.86)	(0.85)	(0.20)	(0.20)
5 years after displacement	-0.40	-0.11	-1.50	-1.25	-0.01	0.24
	(0.36)	(0.36)	(0.80)	(0.80)	(0.37)	(0.38)
Constand	10.35***	10.45***	14.49***	14.76***	8.97***	9.03***
	(0.05)	(0.09)	(0.13)	(0.16)	(0.03)	(0.07)
N	73946	73946	18353	18353	55593	55593
F	30.72	14.81	19.73	11.00	31.50	8.97
Standard errors in parentheses						
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table A.11: Estimation outputs of real hourly wage for separators with a job to flow: with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.02***		0.03***		0.01***	
	(0.00)		(0.00)		(0.00)	
3 years prior displacement	0.15	-0.10	0.47	-0.10	0.04	-0.09
	(0.15)	(0.17)	(0.36)	(0.42)	(0.17)	(0.18)
2 years prior displacement	0.20	0.05	0.56	0.19	0.07	-0.02
	(0.15)	(0.16)	(0.35)	(0.39)	(0.15)	(0.15)
1 years prior displacement	0.20	0.19	0.50	0.44	0.09	0.09
	(0.14)	(0.15)	(0.34)	(0.37)	(0.14)	(0.14)
1 years after displacement	-0.38	-0.03	0.14	0.69	-0.60**	-0.41*
	(0.22)	(0.22)	(0.54)	(0.56)	(0.20)	(0.19)
2 years after displacement	-0.65**	-0.21	-0.76	-0.04	-0.58**	-0.33
	(0.20)	(0.19)	(0.45)	(0.42)	(0.21)	(0.20)
3 years after displacement	-0.66**	-0.14	-1.02	-0.15	-0.46*	-0.17
	(0.25)	(0.26)	(0.58)	(0.61)	(0.21)	(0.22)
4 years after displacement	-0.36	0.30	0.03	1.18*	-0.51*	-0.14
	(0.21)	(0.21)	(0.45)	(0.46)	(0.21)	(0.20)
5 years after displacement	0.04	0.74	0.93	2.07	-0.29	0.12
	(0.41)	(0.41)	(1.25)	(1.23)	(0.24)	(0.24)
Constand	11.22***	11.03***	15.59***	15.35***	9.28***	9.16***
	(0.04)	(0.12)	(0.05)	(0.22)	(0.05)	(0.08)
N	92061	92091	27871	27871	64190	64220
F	22.32	1.07	68.94	1.23	7.10	1.31
Standard errors in parentheses						
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table A.12: Estimation outputs of real hourly wage for all displaced: with and without time trend and for high or low educated workers.

	All		High		Low	
	Time Trend	Fixed Effect	Time Trend	Fixed Effect	Time Trend	Fixed Effect
Time	0.01***		0.03***		0.01***	
	(0.00)		(0.00)		(0.00)	
3 years prior displacement	0.41***	0.19	0.93**	0.48	0.21	0.07
	(0.12)	(0.13)	(0.29)	(0.33)	(0.12)	(0.12)
2 years prior displacement	0.36**	0.21	0.93**	0.58	0.16	0.06
	(0.12)	(0.13)	(0.31)	(0.34)	(0.11)	(0.11)
1 years prior displacement	0.39***	0.35**	0.95***	0.83**	0.19	0.17
	(0.12)	(0.12)	(0.28)	(0.30)	(0.11)	(0.11)
1 years after displacement	-0.68***	-0.48**	-0.48	-0.19	-0.73***	-0.60***
	(0.15)	(0.15)	(0.40)	(0.42)	(0.13)	(0.13)
2 years after displacement	-0.88***	-0.63***	-1.03**	-0.69	-0.78***	-0.61***
	(0.14)	(0.14)	(0.36)	(0.35)	(0.13)	(0.12)
3 years after displacement	-0.77***	-0.45*	-1.17**	-0.73	-0.58***	-0.36*
	(0.17)	(0.18)	(0.44)	(0.46)	(0.14)	(0.15)
4 years after displacement	-0.68***	-0.27	-0.88	-0.30	-0.57***	-0.30*
	(0.19)	(0.19)	(0.47)	(0.48)	(0.14)	(0.14)
5 years after displacement	-0.16	0.33	-0.08	0.64	-0.15	0.18
	(0.29)	(0.29)	(0.85)	(0.84)	(0.22)	(0.22)
Constand	10.81***	10.77***	15.06***	15.12***	9.14***	9.10***
	(0.04)	(0.11)	(0.06)	(0.19)	(0.04)	(0.07)
N	166007	166037	46224	46224	119783	119813
F	29.92	4.97	37.09	1.45	23.29	6.61
Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

A.3

Table A.13: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with more than 2 years of tenure prior separation (job to job flow).

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	9.06	-1.33	7.76	-14.68	85.63
2	10.24	-2.59	10.36	-25.24	101.17
3	9.72	-1.54	8.75	-15.87	89.94
4	10.68	-1.53	9.56	-14.36	89.46
5	10.64	0.06	8.65	0.61	81.32
6	11.33	0.96	8.32	8.49	73.41
7	10.86	0.77	8.03	7.11	73.94
8	10.84	0.06	8.59	0.54	79.29
9	9.12	-0.24	7.53	-2.62	82.55
10	8.95	0.08	7.38	0.91	82.40
11	8.50	0.56	5.71	6.63	67.14
12	6.44	-0.23	3.61	-3.51	56.02

Table A.14: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with more than 3 years of tenure prior separation (job to job flow).

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	11.34	-0.27	10.24	-2.35	90.25
2	12.10	-1.23	11.64	-10.16	96.21
3	12.48	-0.25	11.04	-1.98	88.44
4	14.24	-0.08	12.43	-0.54	87.27
5	15.15	0.92	13.06	6.07	86.23
6	16.19	1.51	13.50	9.31	83.34
7	16.66	1.79	13.53	10.77	81.19
8	17.17	1.15	14.77	6.68	86.03
9	15.11	0.86	13.54	5.68	89.61
10	13.96	1.07	12.41	7.66	88.88
11	13.75	1.33	11.24	9.68	81.76
12	11.79	0.34	9.32	2.85	79.04

Table A.15: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for non-college educated workers with 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	18.92	-1.26	15.59	-6.66	82.42
2	21.28	-2.24	19.24	-10.52	90.41
3	23.41	-1.47	20.10	-6.30	85.89
4	22.72	-1.39	19.41	-6.10	85.41
5	21.06	1.37	15.54	6.50	73.81
6	19.66	1.22	15.61	6.21	79.39
7	16.89	-0.15	15.01	-0.86	88.89
8	18.16	0.30	16.91	1.63	93.12
9	15.78	0.30	14.88	1.88	94.31
10	13.54	1.37	11.48	10.10	84.79
11	12.00	0.55	10.34	4.57	86.11
12	11.58	0.46	9.63	3.98	83.20

Table A.16: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for college educated workers with 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-1.31	-1.42	-0.77	108.34	58.61
2	-0.86	-3.01	1.11	351.55	-129.22
3	-3.15	-1.63	-2.33	51.59	73.91
4	-1.29	-1.72	-0.58	133.01	45.31
5	0.38	-1.44	1.47	-376.76	383.77
6	2.37	0.64	0.36	26.93	15.08
7	3.29	1.86	-0.26	56.52	-7.91
8	1.65	-0.36	-1.35	-21.61	-81.94
9	1.35	-1.00	-0.88	-73.51	-64.63
10	3.53	-1.59	2.54	-45.18	72.00
11	3.95	0.58	-0.18	14.79	-4.59
12	0.04	-1.97	-3.06	-4662.69	-7256.75

Table A.17: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for non-college educated workers with 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	23.64	1.45	18.72	6.12	79.18
2	25.26	0.40	21.86	1.59	86.56
3	29.82	0.86	25.54	2.89	85.63
4	30.66	1.44	25.62	4.70	83.57
5	30.75	3.42	24.25	11.12	78.86
6	27.24	3.06	21.77	11.22	79.92
7	23.05	2.08	19.43	9.01	84.30
8	25.73	2.93	22.85	11.40	88.82
9	23.44	3.11	20.87	13.27	89.05
10	19.56	4.02	15.80	20.53	80.78
11	19.13	2.56	16.56	13.35	86.55
12	18.38	2.39	15.81	13.02	86.00

Table A.18: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for college educated workers with 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-0.48	-2.24	1.57	469.04	-329.62
2	0.19	-3.01	1.96	-1602.42	1042.79
3	-2.05	-1.45	-1.58	70.91	77.29
4	0.12	-1.73	0.57	-1468.33	484.57
5	1.43	-1.77	2.60	-123.70	181.05
6	4.59	-0.41	4.43	-8.83	96.50
7	8.32	1.28	5.95	15.42	71.57
8	6.44	-1.27	4.77	-19.67	73.99
9	5.73	-2.03	5.22	-35.40	91.13
10	7.53	-2.55	8.44	-33.83	112.16
11	6.95	-0.36	4.53	-5.12	65.16
12	3.76	-3.26	2.27	-86.88	60.57

Table A.19: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for female workers with more than 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-1.39	-0.63	-7.15	45.70	515.77
2	-2.23	-2.39	-7.26	107.19	325.70
3	-4.88	-2.38	-9.07	48.74	185.96
4	-6.65	-2.63	-11.10	39.65	167.00
5	-7.16	-1.74	-11.74	24.33	163.91
6	-1.14	0.80	-7.02	-69.68	614.91
7	-2.38	-0.22	-6.97	9.13	293.07
8	-4.15	-1.31	-6.63	31.50	159.75
9	-7.33	-1.69	-8.54	23.04	116.47
10	-9.11	-1.29	-10.14	14.12	111.26
11	-8.59	-1.18	-10.50	13.78	122.26
12	-10.11	0.57	-13.02	-5.68	128.79

Table A.20: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for male workers with more than 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	13.86	-1.60	15.11	-11.58	109.02
2	15.81	-2.66	18.87	-16.83	119.38
3	16.59	-1.22	17.59	-7.35	106.00
4	19.29	-1.10	20.43	-5.70	105.93
5	18.97	0.74	18.67	3.91	98.39
6	16.80	1.02	15.38	6.10	91.55
7	16.39	1.12	14.50	6.85	88.47
8	16.64	0.50	14.53	3.01	87.34
9	16.46	0.29	14.68	1.73	89.18
10	17.12	0.57	15.26	3.34	89.13
11	15.83	1.17	12.61	7.38	79.65
12	13.99	-0.51	11.26	-3.65	80.46

Table A.21: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for female workers with more than 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-0.14	4.19	-7.65	-2918.50	5328.84
2	-1.11	2.31	-8.23	-207.28	738.99
3	-3.72	1.78	-9.50	-47.78	255.01
4	-5.03	1.46	-11.19	-28.98	222.44
5	-4.89	3.02	-11.40	-61.67	233.12
6	2.99	5.11	-5.83	170.85	-194.61
7	1.00	4.37	-6.55	436.32	-653.62
8	0.37	4.69	-5.23	1252.41	-1398.67
9	-3.87	3.74	-7.37	-96.60	190.40
10	-6.77	3.14	-9.55	-46.33	141.03
11	-6.08	3.45	-9.60	-56.75	157.85
12	-6.15	4.85	-10.54	-78.85	171.32

Table A.22: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for male workers with more than 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	16.56	-1.90	19.23	-11.48	116.10
2	17.89	-2.47	21.30	-13.80	119.03
3	20.00	-0.98	21.28	-4.90	106.42
4	23.79	-0.65	25.07	-2.72	105.38
5	24.21	0.21	25.01	0.88	103.31
6	21.69	0.30	22.34	1.37	102.99
7	23.00	0.96	22.26	4.19	96.79
8	23.19	0.16	22.31	0.68	96.22
9	23.36	-0.08	22.94	-0.35	98.20
10	23.38	0.38	22.63	1.62	96.78
11	22.16	0.66	20.28	2.97	91.54
12	19.85	-1.16	18.58	-5.85	93.60

Table A.23: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are less than 30 years old with more than 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	44.18	-6.49	52.71	-14.70	119.29
2	35.96	-7.84	42.64	-21.81	118.57
3	41.60	-5.95	43.61	-14.29	104.82
4	44.68	-4.15	42.72	-9.30	95.61
5	43.29	2.62	35.98	6.06	83.11
6	49.50	1.11	44.20	2.24	89.30
7	54.71	-0.55	54.45	-1.00	99.53
8	55.48	-0.07	52.17	-0.13	94.03
9	58.04	0.89	52.00	1.53	89.61
10	51.31	-0.52	49.13	-1.02	95.74
11	-17.37	-2.21	-17.29	12.72	99.53
12	-20.18	-2.56	-20.35	12.67	100.82

Table A.24: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 30 and less than 50 years old with more than 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-0.14	-2.62	-1.02	1921.66	744.43
2	1.72	-3.49	2.28	-203.69	133.05
3	0.73	-2.38	0.50	-325.38	69.01
4	-0.55	-3.15	-0.19	575.50	33.78
5	-2.45	-2.13	-2.85	87.00	116.58
6	0.82	0.09	-1.83	11.52	-222.12
7	0.34	0.85	-3.12	249.11	-912.84
8	-4.45	-1.01	-6.51	22.77	146.27
9	-6.43	-1.40	-7.87	21.78	122.50
10	-6.29	-0.54	-8.24	8.60	130.85
11	5.69	0.73	1.50	12.92	26.32
12	3.19	1.03	-1.71	32.19	-53.46

Table A.25: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 50 years old with more than 2 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	13.29	5.62	7.31	42.32	55.04
2	18.30	4.03	13.76	22.04	75.19
3	15.66	4.01	11.15	25.60	71.23
4	21.68	4.62	16.14	21.32	74.46
5	26.33	3.08	22.05	11.68	83.74
6	19.51	2.69	16.50	13.81	84.60
7	16.54	1.41	14.92	8.55	90.25
8	25.33	1.95	23.20	7.70	91.59
9	21.95	1.05	21.52	4.78	98.06
10	19.65	1.26	19.27	6.42	98.07
11	22.99	0.93	22.22	4.05	96.64
12	21.45	-1.64	22.18	-7.64	103.42

Table A.26: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are less than 30 years old with more than 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	74.05	-5.46	82.98	-7.37	112.06
2	56.27	-6.69	61.57	-11.89	109.43
3	64.36	-6.27	67.60	-9.74	105.03
4	74.72	-4.89	72.38	-6.54	96.87
5	68.54	0.97	61.48	1.42	89.70
6	71.21	1.39	62.54	1.95	87.82
7	77.70	0.94	70.99	1.21	91.37
8	92.20	1.32	81.76	1.43	88.68
9	96.99	2.50	82.27	2.58	84.83
10	88.74	0.54	81.93	0.61	92.32
11	-14.51	-3.11	-12.60	21.43	86.88
12	-15.59	-3.87	-13.06	24.82	83.74

Table A.27: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 30 and less than 50 years old with more than 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	-0.62	-1.87	-0.27	303.39	43.64
2	0.89	-2.20	1.44	-247.78	161.98
3	0.82	-0.65	0.36	-78.69	43.76
4	-0.32	-1.20	-0.31	377.44	96.98
5	-1.43	-0.69	-1.69	48.14	118.42
6	2.87	0.50	1.48	17.44	51.42
7	3.36	1.93	0.49	57.31	14.46
8	-2.76	0.31	-4.18	-11.30	151.19
9	-4.98	-0.03	-5.68	0.58	113.96
10	-5.71	0.91	-7.13	-15.90	124.70
11	10.38	2.11	6.28	20.33	60.50
12	7.66	2.49	2.57	32.47	33.56

Table A.28: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 50 years old with more than 3 years of tenure prior separation (job to job flow).

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	13.42	5.90	7.23	43.98	53.86
2	18.47	4.31	13.68	23.36	74.07
3	17.25	4.46	12.18	25.84	70.61
4	24.28	5.43	17.61	22.36	72.54
5	30.89	3.79	25.37	12.27	82.12
6	23.32	3.39	19.31	14.55	82.80
7	20.69	2.05	18.20	9.93	88.00
8	29.11	2.21	26.53	7.59	91.16
9	25.29	1.27	24.60	5.02	97.27
10	22.91	1.49	22.29	6.50	97.29
11	25.91	0.96	25.07	3.71	96.78
12	24.21	-1.71	25.04	-7.08	103.45

Table A.29: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	22.57	2.06	18.34	9.15	81.25
2	21.10	-2.62	19.34	-12.39	91.65
3	20.27	-0.69	16.41	-3.42	80.97
4	20.61	-1.28	18.06	-6.22	87.67
5	18.52	0.37	15.38	2.02	83.01
6	18.14	0.12	15.33	0.67	84.51
7	18.98	2.24	14.51	11.82	76.46
8	16.80	0.57	14.23	3.39	84.70
9	16.13	1.24	11.61	7.72	71.97
10	14.72	1.26	9.96	8.55	67.67
11	11.43	1.16	7.32	10.14	64.02
12	10.94	0.41	7.40	3.79	67.62

Table A.30: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	24.00	2.17	19.51	9.05	81.31
2	22.85	-2.12	20.71	-9.26	90.64
3	20.14	-0.28	15.81	-1.37	78.49
4	21.26	-1.06	18.27	-5.00	85.90
5	21.07	0.13	17.76	0.63	84.25
6	23.46	0.75	20.34	3.19	86.68
7	23.10	2.38	18.22	10.31	78.88
8	21.41	0.56	18.38	2.63	85.87
9	21.22	1.07	16.28	5.06	76.72
10	19.58	1.26	14.09	6.42	71.95
11	15.08	0.04	10.76	0.29	71.38
12	13.49	-0.61	9.54	-4.49	70.76

Table A.31: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 2 years of tenure prior separation and up to 3 months unemployed after separation.

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	22.57	2.06	18.34	9.15	81.25
2	17.87	0.62	15.31	3.46	85.69
3	15.70	1.19	13.74	7.55	87.50
4	16.49	0.42	15.34	2.56	93.04
5	10.89	-0.90	10.97	-8.24	100.70
6	10.55	-1.11	11.58	-10.56	109.83
7	10.83	0.57	10.32	5.29	95.35
8	6.33	-0.12	6.21	-1.82	98.23
9	6.14	-0.84	6.59	-13.64	107.42
10	5.42	-0.36	5.59	-6.56	103.10
11	0.86	-2.31	1.97	-268.74	229.22
12	3.37	-2.21	4.58	-65.53	135.92

Table A.32: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 3 years of tenure prior separation and up to 3 months unemployed after separation.

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	24.00	2.17	19.51	9.05	81.31
2	19.21	0.87	16.21	4.55	84.38
3	15.52	0.80	13.67	5.13	88.08
4	16.78	-0.03	15.80	-0.21	94.16
5	11.39	-1.14	11.60	-10.04	101.82
6	11.91	-1.52	13.41	-12.75	112.67
7	12.36	0.53	11.91	4.29	96.38
8	8.46	-0.27	8.56	-3.14	101.12
9	8.62	-1.31	9.51	-15.18	110.34
10	7.64	-0.61	7.94	-7.94	103.96
11	2.95	-2.75	4.34	-92.96	146.90
12	2.77	-2.85	4.24	-102.79	152.90

Table A.33: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 2 years of tenure prior separation and more than 3 months unemployed after separation.

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	.	.	.	.	.
2	31.07	-10.58	32.13	-34.05	103.43
3	29.94	-4.05	21.81	-13.54	72.83
4	27.19	-3.67	22.29	-13.51	82.00
5	28.97	1.91	21.03	6.60	72.61
6	28.82	1.66	20.20	5.74	70.10
7	29.39	4.13	19.47	14.07	66.26
8	30.84	1.33	24.46	4.30	79.32
9	27.90	3.37	16.99	12.07	60.89
10	25.07	2.82	14.41	11.25	57.46
11	23.63	4.66	12.89	19.70	54.56
12	19.37	3.08	10.27	15.90	52.99

Table A.34: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers with 3 years of tenure prior separation and more than 3 months unemployed after separation.

Quarters After Separation	Earnings Losses Total	Due to h	Due to w	Contribution Hours	Wages
1	.	.	.	.	.
2	33.76	-9.29	34.64	-27.52	102.59
3	29.76	-2.20	20.00	-7.41	67.18
4	28.27	-2.49	21.96	-8.81	77.68
5	35.61	1.76	26.36	4.93	74.00
6	41.38	3.68	30.08	8.89	72.69
7	38.43	4.61	26.48	12.01	68.91
8	41.09	1.55	32.39	3.77	78.82
9	37.62	3.64	24.16	9.69	64.23
10	34.23	3.16	20.86	9.23	60.93
11	30.48	3.01	18.05	9.87	59.21
12	27.04	1.80	15.56	6.66	57.55

Table A.35: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for college educated workers with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	35.90	1.01	39.56	2.82	110.19
2	19.25	-2.28	34.12	-11.83	177.24
3	19.63	-1.58	32.37	-8.03	164.93
4	22.56	-2.62	37.10	-11.63	164.41
5	12.87	5.77	25.46	44.82	197.81
6	2.46	2.41	21.07	97.99	855.03
7	2.48	5.90	21.35	237.51	859.40
8	2.77	2.85	21.59	102.82	779.05
9	7.57	2.70	23.12	35.64	305.39
10	6.64	2.67	22.66	40.25	341.44
11	6.98	3.47	20.12	49.64	288.09
12	4.20	3.08	13.24	73.30	314.86

Table A.36: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for non-college educated workers with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	13.29	2.71	8.38	20.40	63.04
2	14.97	-2.81	11.99	-18.80	80.04
3	14.69	-0.18	8.89	-1.22	60.49
4	15.18	-0.63	10.75	-4.15	70.84
5	13.05	-2.37	10.49	-18.12	80.37
6	16.02	-1.08	12.44	-6.72	77.69
7	15.67	0.30	11.00	1.92	70.23
8	13.27	-0.73	10.29	-5.51	77.50
9	11.50	0.37	5.50	3.19	47.86
10	10.13	0.43	3.55	4.27	35.07
11	6.56	-0.17	0.88	-2.64	13.46
12	9.43	-0.98	4.46	-10.42	47.33

Table A.37: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for college educated workers with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	42.84	1.05	40.50	2.45	94.55
2	34.60	-0.59	34.75	-1.71	100.44
3	29.03	-0.27	28.96	-0.94	99.75
4	32.24	-1.99	34.73	-6.17	107.74
5	36.42	6.37	30.53	17.49	83.85
6	33.53	5.21	30.86	15.53	92.02
7	34.92	7.60	29.44	21.77	84.32
8	33.69	3.94	30.46	11.70	90.41
9	35.09	3.58	32.57	10.21	92.80
10	33.47	3.64	31.80	10.87	95.00
11	26.96	1.47	26.86	5.44	99.65
12	19.46	0.87	19.08	4.48	98.02

Table A.38: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for non-college educated workers with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	15.25	3.10	9.57	20.32	62.75
2	17.48	-3.16	14.14	-18.07	80.91
3	16.46	-0.29	10.08	-1.75	61.26
4	17.59	-0.66	12.59	-3.75	71.58
5	15.59	-2.87	13.13	-18.43	84.21
6	19.80	-1.62	16.32	-8.19	82.43
7	18.81	-0.26	13.96	-1.41	74.21
8	16.42	-1.36	13.35	-8.28	81.30
9	15.11	-0.42	8.90	-2.80	58.94
10	13.58	-0.12	6.28	-0.85	46.27
11	9.94	-0.79	3.67	-7.98	36.95
12	11.52	-1.39	5.84	-12.06	50.70

Table A.39: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for female workers with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	26.10	6.09	18.93	23.32	72.55
2	29.01	2.92	22.31	10.07	76.89
3	25.91	1.94	18.80	7.48	72.57
4	26.00	2.29	18.78	8.80	72.24
5	25.43	7.10	16.50	27.91	64.89
6	17.30	2.27	11.22	13.13	64.87
7	22.48	4.92	15.96	21.87	71.01
8	22.30	6.44	16.64	28.88	74.59
9	21.71	6.80	16.06	31.30	73.99
10	21.38	6.25	16.32	29.25	76.33
11	8.12	7.26	4.67	89.50	57.50
12	15.60	7.45	12.01	47.75	77.02

Table A.40: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for male workers with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	21.09	0.41	18.08	1.94	85.70
2	18.74	-4.29	18.41	-22.88	98.23
3	18.24	-1.67	15.52	-9.13	85.09
4	18.80	-2.49	17.81	-13.24	94.74
5	16.32	-1.75	14.99	-10.71	91.87
6	18.41	-0.54	16.69	-2.93	90.69
7	17.83	1.36	14.02	7.61	78.67
8	14.95	-1.38	13.39	-9.22	89.59
9	14.51	-0.34	10.31	-2.36	71.01
10	12.84	-0.16	8.17	-1.27	63.60
11	12.41	-0.44	8.09	-3.53	65.22
12	9.67	-1.44	6.14	-14.89	63.51

Table A.41: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for female workers with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	30.77	7.16	22.03	23.27	71.57
2	33.41	6.55	24.21	19.60	72.45
3	25.60	5.63	15.84	21.99	61.87
4	27.24	5.60	16.84	20.57	61.80
5	20.62	7.83	10.43	37.99	50.57
6	21.01	6.27	12.45	29.84	59.25
7	19.40	5.68	12.14	29.28	62.59
8	24.44	7.76	16.33	31.76	66.81
9	24.52	8.38	16.11	34.17	65.67
10	23.60	8.06	15.77	34.14	66.83
11	8.90	6.77	3.92	76.03	44.04
12	8.70	6.96	3.58	80.04	41.14

Table A.42: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for male workers with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	21.38	0.23	18.50	1.06	86.53
2	19.91	-4.52	19.67	-22.69	98.78
3	18.32	-2.21	15.80	-12.04	86.21
4	19.43	-3.07	18.74	-15.78	96.45
5	21.21	-1.91	20.09	-9.03	94.71
6	24.18	-0.72	22.79	-2.98	94.26
7	24.22	1.46	20.12	6.02	83.06
8	20.48	-1.52	19.04	-7.42	93.01
9	20.37	-0.70	16.32	-3.43	80.13
10	18.57	-0.39	13.65	-2.09	73.53
11	16.71	-1.48	12.59	-8.87	75.34
12	14.75	-2.33	11.15	-15.83	75.55

Table A.43: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are less than 30 years old with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	12.67	1.50	9.37	11.81	73.94
2	5.08	0.10	1.09	2.02	21.36
3	-2.35	-5.44	-1.80	231.33	76.64
4	-9.33	-5.70	-8.15	61.02	87.31
5	-5.39	-3.88	-5.42	72.02	100.49
6	0.26	2.21	-4.05	841.25	-1539.60
7	1.60	2.41	-3.37	150.45	-210.69
8	-4.09	4.46	-9.48	-108.90	231.75
9	-5.64	6.30	-13.28	-111.67	235.37
10	-7.25	4.53	-13.30	-62.52	183.41
11	-16.73	1.59	-20.74	-9.49	123.96
12	-12.32	-2.35	-13.22	19.08	107.26

Table A.44: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 30 and less than 50 years old with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	21.53	-0.47	19.53	-2.16	90.69
2	19.92	-6.78	21.91	-34.06	110.00
3	19.92	-4.79	21.35	-24.03	107.18
4	22.77	-5.28	25.15	-23.17	110.42
5	16.91	-4.19	19.84	-24.79	117.30
6	14.23	-5.19	17.72	-36.50	124.54
7	16.66	-3.25	18.19	-19.50	109.15
8	12.67	-5.14	16.38	-40.58	129.29
9	13.24	-3.57	15.57	-26.95	117.54
10	12.40	-3.06	12.95	-24.68	104.41
11	6.59	-3.50	8.51	-53.19	129.13
12	6.48	-3.41	8.13	-52.60	125.38

Table A.45: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 50 years old with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	31.97	9.67	20.72	30.26	64.82
2	39.26	10.35	26.31	26.36	67.01
3	39.23	14.66	16.76	37.37	42.74
4	36.04	11.77	18.65	32.65	51.74
5	38.79	13.55	18.77	34.95	48.39
6	37.69	12.09	20.09	32.07	53.31
7	35.37	15.73	17.12	44.49	48.41
8	38.60	11.86	22.67	30.73	58.73
9	33.57	9.00	16.90	26.81	50.33
10	29.93	8.54	15.21	28.54	50.83
11	33.42	8.56	17.74	25.60	53.07
12	29.86	8.07	14.34	27.04	48.04

Table A.46: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are less than 30 years old with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	16.49	1.94	12.33	11.75	74.76
2	7.03	-0.59	3.71	-8.39	52.81
3	-2.75	-3.58	-2.94	130.21	107.12
4	-9.57	-4.50	-8.99	47.02	93.91
5	-8.44	-3.69	-8.92	43.67	105.67
6	0.82	4.54	-5.04	556.51	-617.05
7	-0.10	6.15	-7.62	-5947.34	7365.28
8	-2.77	4.88	-8.53	-176.13	308.17
9	-0.50	5.44	-7.43	-1097.25	1498.78
10	-2.66	3.16	-7.24	-118.56	272.06
11	-13.63	-0.67	-15.76	4.89	115.62
12	-15.04	-5.54	-12.92	36.81	85.88

Table A.47: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 30 and less than 50 years old with 3 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	22.34	-0.65	20.43	-2.91	91.43
2	21.11	-6.27	22.70	-29.72	107.55
3	20.93	-4.20	22.06	-20.05	105.39
4	24.83	-4.69	26.72	-18.91	107.63
5	21.37	-5.05	25.56	-23.64	119.63
6	21.36	-4.91	26.12	-22.97	122.28
7	22.75	-4.06	25.73	-17.86	113.09
8	18.38	-5.55	22.62	-30.18	123.07
9	19.31	-3.89	22.01	-20.16	113.98
10	18.57	-3.12	18.56	-16.82	99.95
11	12.00	-4.34	13.74	-36.16	114.47
12	12.69	-4.14	14.12	-32.63	111.20

Table A.48: Decomposition of Earnings Losses into Wages Cuts and Changes in Hours of Working for workers who are more than 50 years old with 2 years of tenure prior separation and an unemployment spell after separation.

Quarters After	Earnings Losses			Contribution	
Separation	Total	Due to h	Due to w	Hours	Wages
1	31.97	9.67	20.72	30.26	64.82
2	40.06	10.87	26.41	27.14	65.94
3	33.39	13.39	11.94	40.09	35.76
4	30.54	10.17	14.45	33.30	47.31
5	36.58	13.54	16.52	37.02	45.17
6	38.44	12.48	20.19	32.46	52.53
7	35.33	16.46	16.25	46.58	46.00
8	38.80	12.16	22.23	31.35	57.31
9	33.88	8.88	16.66	26.22	49.17
10	29.76	8.54	14.64	28.70	49.20
11	30.45	6.75	15.63	22.16	51.35
12	25.52	6.76	10.09	26.49	39.52

A.4

Data Issues:

In Understanding Society data set, if the highest qualification reported in the current wave is named as ”Degree” that implies either first degree (BSc) or higher degree (MPhil/PhD) for the ISCED classification (variables `w_nhigual_dv` for new qualifications and `w_higual_dv` for considering fed forward information from previous waves). We clarify if the level of education is first degree or higher degree by using a second variable, which states the highest educational qualification reported in this wave (variable `w_nqfhigh_dv`) or the highest educational qualification considering fed forward information from previous waves (variables `w_qfhigh_dv` or `w_qfhigh`). On the other hand, if the highest qualification reported is ”Other higher degree”, then this aligns with the post secondary non-tertiary education in ISCED classification. The ”A-level etc” aligns with the higher secondary and middle vocational education (3a). ”GCSE etc” allligns with low secondary vocational educational (3c), ”other qualification” aligns with low secondary education an finally ”No qualification” with Primary or non defined (in this paper is one group). Also for missing values in education we do the following reasonable assumption. If the individual has missing value in the level of education but we have this information in the previous spell and also is not currently student, then we assume that he has the same level of education as the one that he had in the previous spell. By following this rule, we gain 4% more information than before.

APPENDIX B

Appendix to Chapter 3

B.1

Forecasting the Pre-crisis Trend of Aggregate Productivity:

I will analyze the methodology that is used to estimate the pre-2008 productivity trend (or potentially productivity) if the 2008 recession has not been occurred. As we can see in Figure B.1, aggregate productivity until the end of 2007 has an upwards trend. So, for forecasting the potential productivity with the absence of the recession I follow the forecasting method which is described in Enders (2010) and I measure the productivity gap as in Kuttner (1994). I estimate an AR(1) process with a time trend and an intercept by using a standard OLS. The formation of this AR(1) process is the following:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 t + \varepsilon_t \tag{B.1.1}$$

Where the estimated α_0, α_1, and α_2 are used to forecast the future values of productivity after 2008 if the recession will not have been occurred. We use the below model to do the forecasting:

$$\hat{y}_{t+1} = \hat{\alpha}_0 + \hat{\alpha}_1 y_t + \hat{\alpha}_2 t \tag{B.1.2}$$

In Table B.1 we can see the estimation output of the AR(1) process for the actual productivity before the 2008 crisis. All the estimated coefficients are statistically significant in 1% level. The productivity gap is the percentage difference between potential and actual productivity. In Figure B.1 we can see the estimated productivity gap which is caused from the 2008 crisis. In 2009 the potential productivity would have been 5% more than the actual one and in 2010 this gap has been doubled to 10% with an upwards behaviour. These results are in line with Oulton and Sebastia-Barriel (2013).

Table B.1: Estimation of an AR(1) with an intercept and a time trend for the period before 2008

	Variables	Productivity
AR(1)	0.741***	
	(0.084)	
time trend	0.151***	
	(0.003)	
Constand	25.011***	
	(0.06)	
N	62	
r2	0.998	
F	16489.28	
DW	1.549	

Standard errors in parentheses

Source: BHPS

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

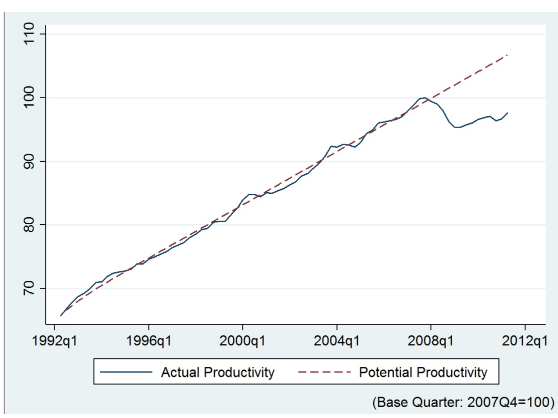


Figure B.1: Estimated Productivity Gap with the absence of the 2008 crisis (with base quarter 2007Q4).

B.2

I do the below maximization problem:

$$\underset{H_i,L_i}{max}\{\pi = TR - TC = PY - C_{lab}\} =$$
$$\underset{H_i,L_i}{max}\{PZ[(1-\alpha)(A_L L)^\rho + \alpha(A_H H)^\rho]^{\frac{1}{\rho}} - (W_{H_1}H_1 + W_{H_2}H_2 + W_{L_1}L_1 + W_{L_2}L_2)\} \tag{B.2.1}$$

Where W_{H_i}, W_{L_i} to be the average wages of the group of workers *i* ($i = 1, 2$ for non displaced and displaced groups of workers, respectively) and $W_{H_i}H_i, W_{L_i}L_i$ to be the labour cost of each type of worker and prices P are exogenous determined.

The first order conditions in respect to H_i, L_i will give:

For the skilled workers.

$$\frac{\partial\pi}{\partial H_1} = 0 \Leftrightarrow W_{H_1} = PZ\frac{1}{\rho}[M]^{(\frac{1}{\rho}-1)}\rho(H_1 + \gamma_2 H_2)^{\rho-1}\alpha A_H^\rho \tag{B.2.2}$$

$$\frac{\partial\pi}{\partial H_2} = 0 \Leftrightarrow W_{H_2} = PZ\frac{1}{\rho}[M]^{(\frac{1}{\rho}-1)}\rho(H_1 + \gamma_2 H_2)^{\rho-1}\gamma_2\alpha A_H^\rho \tag{B.2.3}$$

With

$$M = \alpha A_H^\rho(H_1 + \gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho(L_1 + \gamma_2^{'} L_2)^\rho$$

So, $\frac{W_{H_2}}{W_{H_1}} = \gamma_2$

Similarly from the FOC's for L_i we have:

$$\frac{\partial \pi}{\partial L_1} = 0 \Leftrightarrow W_{L_1} = PZ\frac{1}{\rho}[M]^{(\frac{1}{\rho}-1)}\rho(L_1 + \gamma_2^{'}L_2)^{\rho-1}(1-\alpha)A_L^{\rho} \quad \text{(B.2.4)}$$

and

$$\frac{\partial \pi}{\partial L_2} = 0 \Leftrightarrow W_{L_2} = PZ\frac{1}{\rho}[M]^{(\frac{1}{\rho}-1)}\rho(L_1 + \gamma_2^{'}L_2)^{\rho-1}(1-\alpha)A_L^{\rho}\gamma_2^{'} \quad \text{(B.2.5)}$$

So $\frac{W_{L_2}}{W_{L_1}} = \gamma_2^{'}$

Introducing in the model three different displacement subgroups:

The first order conditions of the maximization problem 3.5.7 in respect to H_i, L_i gives

For the skilled workers: $\frac{W_{H_2}}{W_{H_1}} = \gamma_2$ and we have that:

$$\gamma_2 H_2 = \frac{W_{H_2}}{W_{H_1}} H_2 = \frac{\frac{\sum_{i=1}^{3} W_{H_{2i}}}{3}}{W_{H_1}} H_2 = \frac{\sum_{i=1}^{3} \gamma_{2i}}{3} H_2 \tag{B.2.6}$$

Since under a perfect competitive world we have: $\gamma_{2i} = \frac{W_{H_{2i}}}{W_{H_1}}$

In this case there are three different displacement groups (it can be extended to many): the displacement group H_I which is the high type displaced workers who had a job to job flow after the displacement, H_{II} which is the high type displaced workers who after the displacement had a short unemployment spell (less than a year) and H_{III} which is the high type displaced workers who after the displacement had a long unemployment spell (more than a year).

So, $\gamma_{21} = \frac{W_{H_{21}}}{W_{H_1}}$ is the skill premium between H_I and H_1, with $W_{H_{11}}$ the average wage of that displaced group, $\gamma_{22} = \frac{W_{H_{22}}}{W_{H_1}}$ is the skill premium between H_{II} and H_1, with $W_{H_{12}}$ the average wage of the second displaced group, and finally $\gamma_{23} = \frac{W_{H_{23}}}{W_{H_1}}$ is the skill premium between H_{III} and H_1, with $W_{H_{13}}$ the average wage of the third displaced group.

So since $\gamma_2 = \frac{\sum_{i=1}^{3} \gamma_{2i}}{3} = \frac{\sum_{i=1}^{3} \frac{W_{H_{2i}}}{W_{H_1}}}{3}$ we can take as approximation the estimations from the BHPS data set by setting:

$$\sum_{i=1}^{3}\frac{W_{H_{2i}}}{W_{H_1}} \equiv \sum_{i=1}^{3}\frac{w_{h_{2i}}}{w_{h_1}} \tag{B.2.7}$$

As it is mentioned above, one basic problem of the BHPS dataset is the small number of observations, especially for the three displacement groups, which make our estimates pretty ambiguous. For that reason I am forced to approximate the B.2.10 as:

$$\frac{\sum_{i=1}^{3}\frac{w_{h_{2it}}}{w_{h_{1t}}}}{3} \equiv \frac{w_{h_{2t}}}{w_{h_{1t}}} \tag{B.2.8}$$

Similarly from the FOC's for L_i there are: $\frac{W_{L_2}}{W_{L_1}} = \gamma_2^{'}$ and equivalently:

$$\gamma_2^{'} L_2 = \frac{W_{L_2}}{W_{L_1}} L_2 = \frac{\frac{\sum_{i=1}^{3} W_{L_{2i}}}{3}}{W_{L_1}} L_2 = \frac{\sum_{i=1}^{3}\gamma_{2i}^{'}}{3} L_2 \tag{B.2.9}$$

For low type workers we have the same three different displacement groups with that of the high type where we can get:

$\gamma_2^{'} = \frac{\sum_{i=1}^{3}\gamma_{2i}^{'}}{3} = \frac{\sum_{i=1}^{3}\frac{W_{L_{2i}}}{W_{L_1}}}{3}$ and we can get again the estimations as approximation from the BHPS data set by setting:

$$\frac{\sum_{i=1}^{3}\frac{W_{L_{2i}}}{W_{L_1}}}{3} \equiv \frac{\sum_{i=1}^{3}\frac{w_{l_{2i}}}{w_{l_1}}}{3} \equiv \frac{w_{l_2}}{w_{l_1}} \tag{B.2.10}$$

Identification Problem:

In our model and after empirically estimating σ, we have five unknown parameters which are: γ_2, $\gamma_2^{'}$, A_H, A_L, and Z. From the FOC's we can get 4 equations and with the production function itself, we can have in total five, which are the following (ignoring prices):

$$W_{H_1} = Z[\alpha A_H^{\rho}(H_1 + \gamma_2 H_2)^{\rho} + (1-\alpha)A_L^{\rho}(L_1 + \gamma_2^{'} L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(H_1 + \gamma_2 H_2)^{\rho-1}\alpha A_H^{\rho} \tag{B.2.11}$$

$$W_{H_2} = Z[\alpha A_H^{\rho}(H_1 + \gamma_2 H_2)^{\rho} + (1-\alpha)A_L^{\rho}(L_1 + \gamma_2^{'} L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(H_1 + \gamma_2 H_2)^{\rho-1}\gamma_2\alpha A_H^{\rho} \tag{B.2.12}$$

$$W_{L_1} = Z[\alpha A_H^{\rho}(H_1 + \gamma_2 H_2)^{\rho} + (1-\alpha)A_L^{\rho}(L_1 + \gamma_2^{'} L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(L_1 + \gamma_2^{'} L_2)^{\rho-1}(1-\alpha)A_L^{\rho} \tag{B.2.13}$$

$$W_{L_2} = Z[\alpha A_H^{\rho}(H_1 + \gamma_2 H_2)^{\rho} + (1-\alpha)A_L^{\rho}(L_1 + \gamma_2^{'} L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(L_1 + \gamma_2^{'} L_2)^{\rho-1}(1-\alpha)A_L^{\rho}\gamma_2^{'} \tag{B.2.14}$$

and

$$Y = Z[\alpha A_H^{\rho}(H_1 + \gamma_2 H_2)^{\rho} + (1-\alpha)A_L^{\rho}(L_1 + \gamma_2^{'} L_2)^{\rho}]^{\frac{1}{\rho}} \tag{B.2.15}$$

Where $\frac{W_{H_2}}{W_{H_1}} = \gamma_2 \Leftrightarrow W_{H_2} = \gamma_2 W_{H_1}$ and $\frac{W_{L_2}}{W_{L_1}} = \gamma_2^{'} \Leftrightarrow W_{L_2} = \gamma_2^{'} W_{L_1}$

I will prove that the production function is a linear combination of the four other equations. We know that output is equal to:

$$Y = MPL_{H_1}H_1 + MPL_{H_2}H_2 + MPL_{L_1}L_1 + MPL_{L_2}H_2 \tag{B.2.16}$$

Where under the assumption of perfect competition it will become:

$$Y = W_{H_1}H_1 + W_{H_2}H_2 + W_{L_1}L_1 + W_{L_2}H_2 \tag{B.2.17}$$

This is true because:

$$\begin{aligned}
&W_{H_1}H_1 + W_{H_2}H_2 \Leftrightarrow W_{H_1}H_1 + \gamma_2 W_{H_1}H_2 = W_{H_1}(H_1 + \gamma_2 H_2) = \\
&Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)}(H_1 + \gamma_2 H_2)^{\rho-1}\alpha A_H^\rho (H_1 + \gamma_2 H_2) = \\
&Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)}(H_1 + \gamma_2 H_2)^{\rho}\alpha A_H^\rho
\end{aligned} \tag{B.2.18}$$

and

$$\begin{aligned}
&W_{L_1}L_1 + W_{L_2}L_2 \Leftrightarrow W_{L_1}L_1 + \gamma_2^{'} W_{L_1}L_2 = W_{L_1}(L_1 + \gamma_2^{'} L_2) = \\
&Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)}(L_1 + \gamma_2^{'} H_2)^{\rho-1}(1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2) = \\
&Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)}(L_1 + \gamma_2^{'} L_2)^{\rho}(1-\alpha) A_L^\rho
\end{aligned} \tag{B.2.19}$$

So, substituting B.2.18 and B.2.19 in B.2.17, we get:

$$Y = Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{\frac{1}{\rho}-1} \\ ([\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]) \tag{B.2.20}$$

Ending up to the original CES production function:

$$Y = Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{\frac{1}{\rho}} \tag{B.2.21}$$

From the above prof we can conclude that the production function is a linear combination of the 4 equations which I get from the FOC's, and the system is underidentified since there are actually 4 equations and 5 unknowns. For that reason I normalize $A_H = 1$.

Identifying share of income that high (s_H) and low (s_L) type receives:

If we assume that ρ is very close to zero then the share of income that high type receives is equal to:

$$\begin{aligned} s_H &= \frac{W_{H_1} H_1 + W_{H_2} H_2}{Y} \overset{B.2.18}{=} \\ &= \frac{Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)} (L_1 + \gamma_2^{'} L_2)^\rho (1-\alpha) A_L^\rho}{Z[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]^{\frac{1}{\rho}}} = \\ &= \frac{(H_1 + \gamma_2 H_2)^\rho \alpha A_H^\rho}{[\alpha A_H^\rho (H_1 + \gamma_2 H_2)^\rho + (1-\alpha) A_L^\rho (L_1 + \gamma_2^{'} L_2)^\rho]} \overset{\rho \to 0}{=} \alpha \end{aligned} \tag{B.2.22}$$

and the share of income that low type receives is equal to:

$$
\begin{aligned}
s_L &= \frac{W_{L_1}L_1 + W_{L_2}L_2}{Y} \overset{B.2.19}{=} \\
&= \frac{Z[\alpha A_H^\rho (H_1+\gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1+\gamma_2^{'} L_2)^\rho]^{(\frac{1}{\rho}-1)}(L_1+\gamma_2^{'} L_2)^\rho (1-\alpha)A_L^\rho}{Z[\alpha A_H^\rho (H_1+\gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1+\gamma_2^{'} L_2)^\rho]^{\frac{1}{\rho}}} = \\
&= \frac{(L_1+\gamma_2^{'} L_2)^\rho (1-\alpha)A_L^\rho}{[\alpha A_H^\rho (H_1+\gamma_2 H_2)^\rho + (1-\alpha)A_L^\rho (L_1+\gamma_2^{'} L_2)^\rho]} \overset{\rho\to 0}{=} 1-\alpha
\end{aligned}
\tag{B.2.23}
$$

B.3

Estimation of the Elasticity of Substitution between College and non-College Workers:

The first step for running the counterfactual exercises is to estimate the elasticity of substitution between the high and low educated workers (college and non-college education) σ for the UK economy. Number of authors have empirically estimated the elasticity of substitution between high and low type workers by education, such as Card and Lemieux (2001), Acemoglu (2002b), Autor et al. (2008), Manacorda et al. (2010), Acemoglu and Autor (2011), Carneiro and Lee (2011), but all of them base their estimation on Katz-Murphy model, which is introduced by Katz and Murphy (1992). This paper follows the standard approach by Katz and Murphy (1992) and Acemoglu (2002b), by using the CES production function 3.5.1, which is:

$$Y_t = Z_t[(1-\alpha_t)(A_{Lt}(L_{1t}+\gamma_2^{'}L_{2t}))^{\rho}+\alpha_t(A_{Ht}(H_{1t}+\gamma_2 H_{2t}))^{\rho}]^{\frac{1}{\rho}} \quad \text{(B.3.1)}$$

From the profit maximization problem of 3.5.7, the following equations can be extracted:

$$W_{H_1} = Z[\alpha A_H^{\rho}(H_1+\gamma_2 H_2)^{\rho}+(1-\alpha)A_L^{\rho}(L_1+\gamma_2^{'}L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(H_1+\gamma_2 H_2)^{\rho-1}\alpha A_H^{\rho} \quad \text{(B.3.2)}$$

$$W_{L_1} = Z[\alpha A_H^{\rho}(H_1+\gamma_2 H_2)^{\rho}+(1-\alpha)A_L^{\rho}(L_1+\gamma_2^{'}L_2)^{\rho}]^{(\frac{1}{\rho}-1)}(L_1+\gamma_2^{'}L_2)^{\rho-1}(1-\alpha)A_L^{\rho} \quad \text{(B.3.3)}$$

So, dividing (B.3.2) with (B.3.3), the skill premium ω between high and low type workers who are non-displaced, is equal to (dropping the time subscripts):

$$\omega = \frac{W_{H_1}}{W_{L_1}} = \frac{\alpha}{1-\alpha}\left(\frac{A_H}{A_L}\right)^{\rho}\left(\frac{H_1+\gamma_2 H_2}{L_1+\gamma_2' L_2}\right)^{\rho-1} \tag{B.3.4}$$

(with $\sigma \equiv 1/(1-\rho)$)

By using logs, the B.3.4 becomes:

$$\ln\omega = \ln(\frac{\alpha}{1-\alpha}) + \frac{\sigma-1}{\sigma}\ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\ln\left(\frac{H_1+\gamma_2 H_2}{L_1+\gamma_2' L_2}\right) \tag{B.3.5}$$

As it is mentioned above, this paper uses the same baseline as in Katz-Murphy model assuming that σ is fixed, and that the A's, the *H, L* (which are the supplies of high and low type workers) and also their wage ratio, vary over time (quarter). In the BHPS dataset, I can observe supplies and also estimate the wage premium. So, the unknowns are σ and the $\frac{A_H}{A_L}$. But following the Katz-Murphy model, I can transform B.3.5 by parameterising the $\ln\left(\frac{H}{L}\right)$ (which formulates the labour demand shifts of high and low type workers) as $\alpha_o + \alpha_1 t + \epsilon_t$, and then substitute this transformation, on B.3.5. Finally, we can get (with the time subscripts):

$$\ln\omega_t = \beta_o + \beta_1 t + \beta_2 \ln\left(\frac{H_{1t}+\gamma_{2t} H_{2t}}{L_{1t}+\gamma_{2t}' L_{2t}}\right) + e_t \tag{B.3.6}$$

where *t* is a linear function of time. In estimating this equation, $\beta_o = \ln(\frac{\alpha}{1-\alpha}) + \frac{\sigma-1}{\sigma}\alpha_0$, $\beta_1 = \frac{\sigma-1}{\sigma}\alpha_1$ gives the time trend on $\frac{\sigma-1}{\sigma}\ln\left(\frac{A_H}{A_L}\right)$, and $\beta_2 = -\frac{1}{\sigma}$ can give an estimate of the elasticity of substitution.

With this process, I estimate σ by running a simple OLS with a time trend (I use quadratic time trend which fits better the data in this case than a linear time trend), as Katz and Murphy did for the US economy (1939-1996). For the skill premium between high and low educated workers, they used the relative supply of college equivalent workers as I do in this estimation[1]. The above OLS estimation in the UK economy for the period 1991Q1 to 2011Q4 yields:

$$\ln\omega_t = \underset{(0.001)}{0.001t} - \underset{(0.001)}{0.003t^2} - \underset{(0.078)}{0.331}\ln\left(\frac{H_{1t} + \gamma_{2t}H_{2t}}{L_{1t} + \gamma'_{2t}L_{2t}}\right) + constant \quad \text{(B.3.7)}$$

where the R^2 is equal to 0.4, which means that this estimation can explain the data reasonably well. From the above estimation, it is implied an elasticity of substitution between high and low type workers (which can be either displaced or non-displaced) of about 3.02, which is larger from both estimates of Katz and Murphy (1992) (1.4) and Acemoglu (2002b) (1.79). In this estimation, 77 aggregate measurements are used and all the above data are individual seasonally adjusted by using the Census Bureau's

[1]For creating the measures of $\frac{H}{L}$, Katz and Murphy use the relative supply of college equivalent workers, where they measure a weighted average of $\frac{H}{L}$ from four different educational groups: college graduates, some college, high school graduates, and high school dropouts. Following the British educational system, we consider as *college graduates* all the workers who have an International Standard Classification of Education (ISCED) higher than 4, *some college* all the workes with ISCED equal to 4, *high school* graduates are workers with ISCED equal to 3, and finally *high school dropouts* with ISCED less than 3. Since in this case I have $(H_{1t} + \gamma_{2t}H_{2t})/(L_{1t} + \gamma'_{2t}L_{2t})$, this weighted average is defined as college graduates + 0.29 x some college - 0.05 x high school dropouts for non-displaced plus γ_2 times college graduates + 0.29 x some college - 0.05 x high school dropouts for displaced divided by high school graduates + 0.69 x some college + 0.93 x high school dropouts for non-displaced plus γ'_2 times high school graduates + 0.69 x some college + 0.93 x high school dropouts.

X12 program. It should be mentioned that there is a significant serial correlation in the college premium and also possible endogeneity issues that for the purpose of this paper, I do not investigate further. The same problems has been raised also in previous attempts of estimating σ (see Katz and Murphy (1992) and Acemoglu (2002b)). For checking if the results in the analysis are robust, I run some sensitivity analysis for different values of σ (including extreme values) where it is observed that the findings do not alter. I present this analysis at the end of the "Counterfactual Exercises" section.

B.4

Table B.2: Rates of leaving main job on involuntary basis (as a percentage of employees), Q2 of each year, 2000-2011, in the United Kingdom and the United States.

Year	UK	% Change	US	% Change
2001	1.2		1.3	
2002	1.2	0.0	1.3	0.0
2003	1.1	-8.3	1.4	7.7
2004	1.0	-9.1	1.3	-7.1
2005	0.9	-10.0	1.3	0.0
2006	1.0	11.1	1.2	-7.7
2007	0.9	-10.0	1.2	0.0
2008	0.9	0.0	1.3	8.3
2009	1.4	55.6	1.6	23.1
2010	0.9	-35.7	1.3	-18.8
2011	1.0	11.1	1.2	-7.7

Source: US. Bureau of Labor Statistics, Layoffs and Discharges: Total Nonfarm [JTULDR], retrieved from FRED, Federal Reserve Bank of St. Louis, for the US, and Office for National Statistics, ONS, retrieved from Nomis, for the UK (both series are non seasonally adjusted).

Table B.3: Rates of leaving main job on involuntary basis (as a percentage of employees), Q2 of each year, 2000-2011, in the United Kingdom and the United States.

Year	UK	% Change	US	% Change
2001	1.2		1.3	
2002	1.2	0.0	1.3	0.0
2003	1.1	-8.3	1.4	7.7
2004	1.0	-9.1	1.3	-7.1
2005	0.9	-10.0	1.3	0.0
2006	1.0	11.1	1.2	-7.7
2007	0.9	-10.0	1.2	0.0
2008	0.9	0.0	1.3	8.3
2009	1.4	55.6	1.6	23.1
2010	0.9	-35.7	1.3	-18.8
2011	1.0	11.1	1.2	-7.7

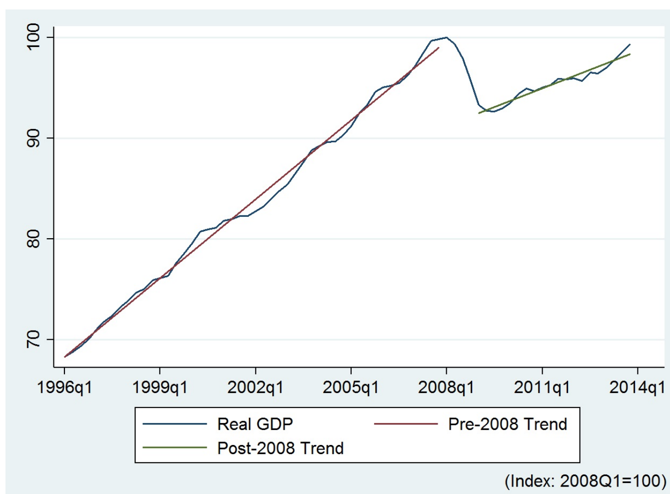


Figure B.2: Real GDP in the UK.

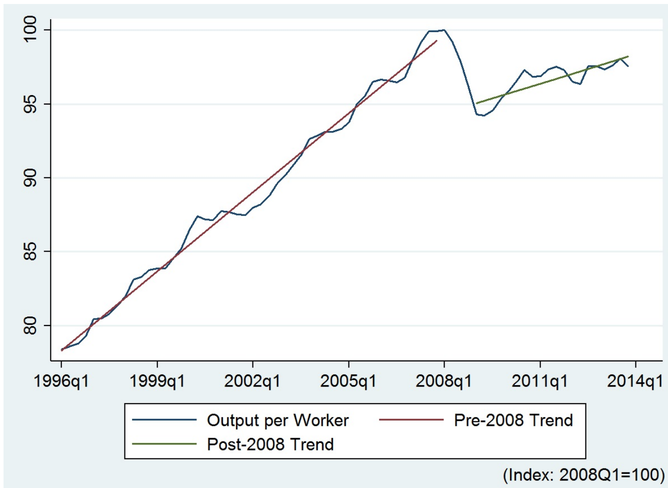


Figure B.3: Output per Worker in the UK.

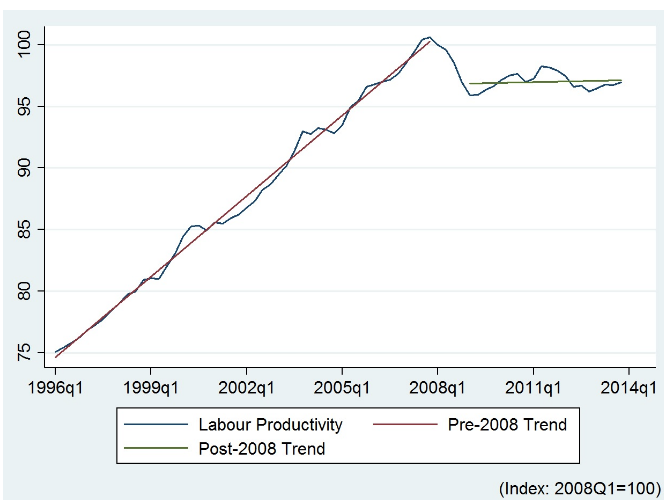


Figure B.4: Output per hour worked in the UK.

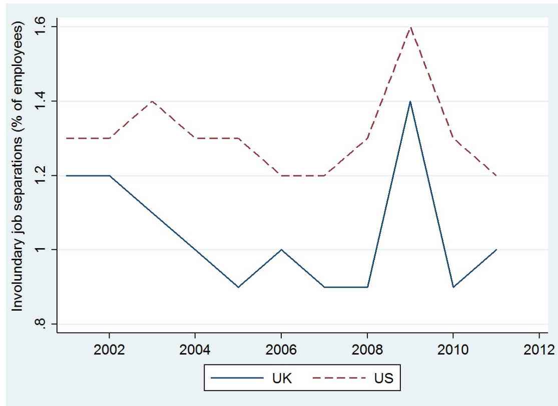


Figure B.5: Rates of leaving main job on involuntary basis (as a percentage of employees), Q2 of each year, 2000-2011, in the United Kingdom and the United States.

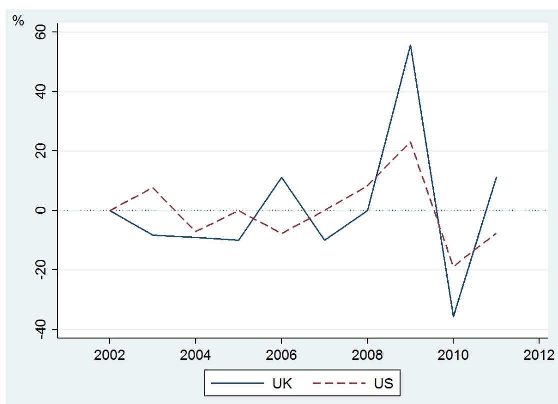


Figure B.6: Annual percentage differences between the rates of leaving main job on involuntary basis (as a percentage of employees), Q2 of each year, 2000-2011, in the United Kingdom and the United States.

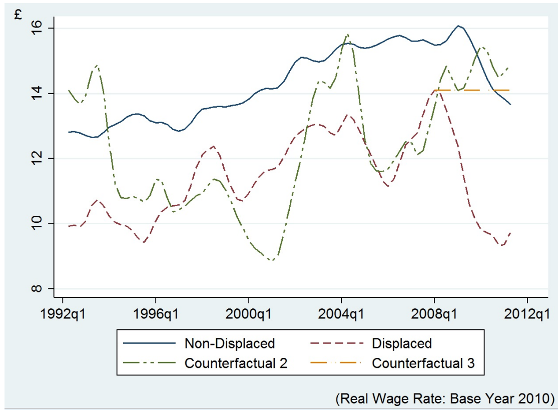


Figure B.7: Real Wage Rates between non-displaced and displaced worker who are high type workers over time (in 2010 Prices).

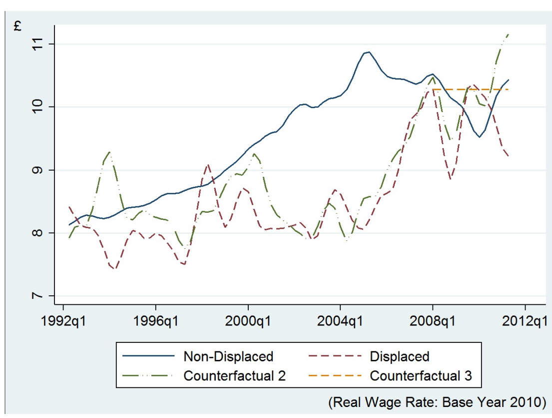


Figure B.8: Real Wage Rates between non-displaced and displaced worker who are low type workers over time (in 2010 Prices).

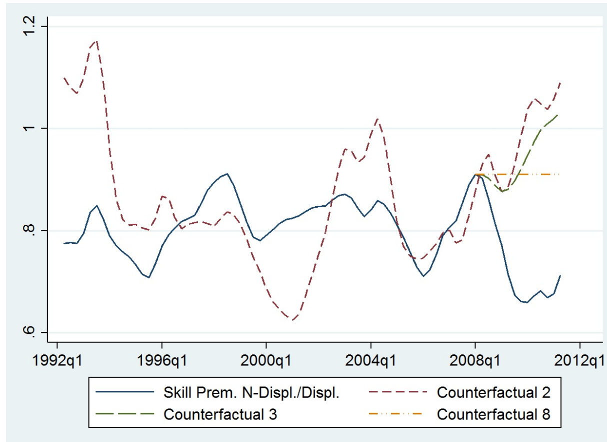


Figure B.9: Skill premium between high type non-displaced and displaced worker over time.

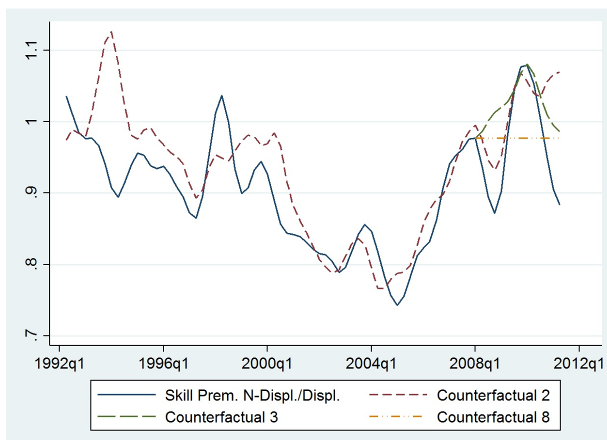


Figure B.10: Skill premium between low type non-displaced and displaced worker over time.

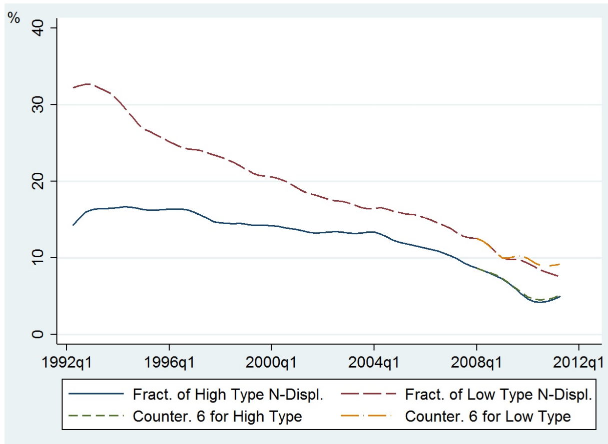


Figure B.11: Fraction of High and Low Type non displaced workers (H1, L1) over Employment.

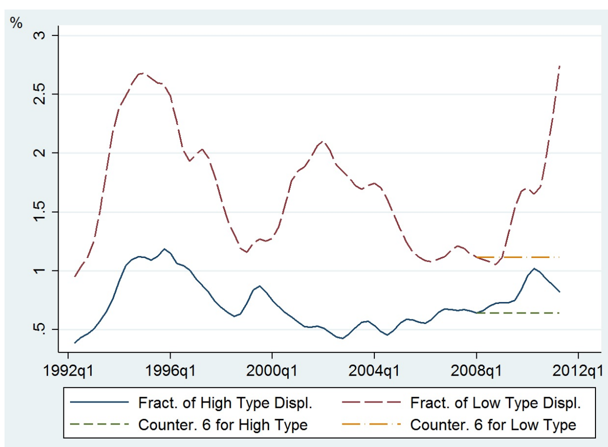


Figure B.12: Fraction of High and Low Type displaced workers (H1, L1) over Employment.

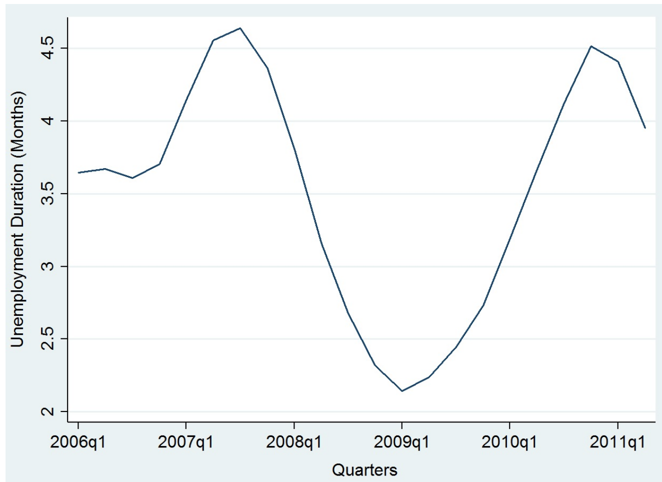


Figure B.13: Unemployment Duration of Displaced workers (in months).

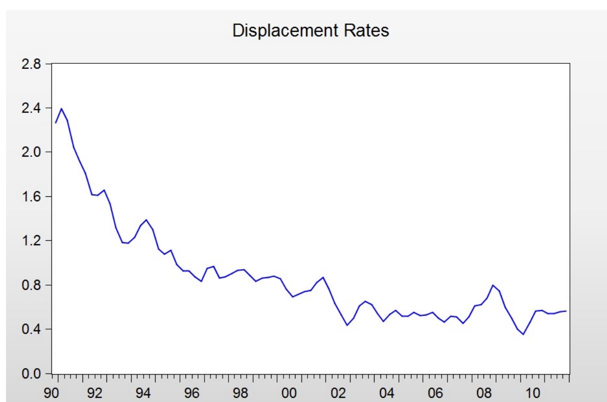


Figure B.14: Displacement Rates from the BHPS data set.

Table B.4: Implied productivity gap (in %) between recessions and counterfactual 1, and percentage of the gap which is explained by counterfactual 2, n quarters after the start of the recession.

	Implied Gap: Reces.-Counter. 1			Gap to be explained by Counter. 1		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.0	3.1	3.7	31.1	31.0	26.8
4	3.2	5.0	5.0	32.5	23.3	23.1
5	4.9	6.1	5.5	23.3	19.4	21.0
6	5.5	6.9	5.7	20.2	16.7	19.7
7	6.0	7.4	5.8	19.8	16.6	20.6
8	6.1	7.0	5.3	23.4	20.9	26.1
9	6.5	7.9	5.2	25.0	21.4	30.0
10	7.1	8.9	5.3	24.9	20.6	31.3
11	8.0	10.3	5.9	25.7	20.8	32.4
12	8.8	10.3	5.7	26.4	23.3	36.6
13	9.7	10.3	5.1	24.9	23.7	39.8

Table B.5: Actual, Potential and Productivity from counterfactual 1 during the post-crisis period (2008Q1=100).

	Product.			% Differ.		
Quarter	Actual	Potential	Count. 1	Actual Count. 1	Actual Potential	Potential Count. 1
2008Q1	100.00	100.53	100.43	0.43	0.53	0.10
2008Q2	99.61	101.06	100.25	0.64	1.45	0.81
2008Q3	98.58	101.58	99.60	1.04	3.05	1.99
2008Q4	96.93	102.11	98.32	1.44	5.35	3.86
2009Q1	95.90	102.64	97.46	1.62	7.02	5.31
2009Q2	95.93	103.16	97.45	1.59	7.54	5.86
2009Q3	96.34	103.69	97.79	1.50	7.63	6.03
2009Q4	96.62	104.22	98.18	1.62	7.86	6.15
2010Q1	97.18	104.74	99.15	2.03	7.79	5.64
2010Q2	97.49	105.27	99.83	2.39	7.98	5.45
2010Q3	97.64	105.80	100.20	2.61	8.35	5.59
2010Q4	96.99	106.32	100.01	3.11	9.62	6.31
2011Q1	97.26	106.85	100.77	3.61	9.86	6.04
2011Q2	98.25	107.38	101.88	3.69	9.29	5.39

Table B.6: Actual, Potential and Productivity from counterfactual 2 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 2	Actual Count. 2	Actual Potential	Potential Count. 2
2008Q1	100.00	100.53	99.95	-0.05	0.53	0.58
2008Q2	99.61	101.06	99.87	0.26	1.45	1.19
2008Q3	98.58	101.58	99.17	0.60	3.05	2.44
2008Q4	96.93	102.11	97.62	0.71	5.35	4.60
2009Q1	95.90	102.64	96.63	0.76	7.02	6.21
2009Q2	95.93	103.16	96.88	0.99	7.54	6.48
2009Q3	96.34	103.69	97.74	1.45	7.63	6.09
2009Q4	96.62	104.22	98.63	2.09	7.86	5.66
2010Q1	97.18	104.74	99.92	2.83	7.79	4.83
2010Q2	97.49	105.27	100.67	3.26	7.98	4.57
2010Q3	97.64	105.80	100.93	3.36	8.35	4.83
2010Q4	96.99	106.32	100.92	4.04	9.62	5.36
2011Q1	97.26	106.85	102.07	4.94	9.86	4.69
2011Q2	98.25	107.38	103.53	5.37	9.29	3.71

Table B.7: Actual, Potential and Productivity from counterfactual 3 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 3	Actual Count. 3	Actual Potential	Potential Count. 3
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.83	0.22	1.45	1.23
2008Q3	98.58	101.58	99.19	0.62	3.05	2.41
2008Q4	96.93	102.11	97.86	0.97	5.35	4.34
2009Q1	95.90	102.64	96.96	1.10	7.02	5.85
2009Q2	95.93	103.16	97.02	1.14	7.54	6.33
2009Q3	96.34	103.69	97.55	1.25	7.63	6.30
2009Q4	96.62	104.22	98.21	1.65	7.86	6.11
2010Q1	97.18	104.74	99.43	2.32	7.79	5.34
2010Q2	97.49	105.27	100.20	2.78	7.98	5.06
2010Q3	97.64	105.80	100.53	2.96	8.35	5.24
2010Q4	96.99	106.32	100.20	3.30	9.62	6.11
2011Q1	97.26	106.85	100.84	3.68	9.86	5.96
2011Q2	98.25	107.38	101.86	3.67	9.29	5.42

Table B.8: Actual, Potential and Productivity from counterfactual 4 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 4	Actual Count. 4	Actual Potential	Potential Count. 4
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.64	0.03	1.45	1.42
2008Q3	98.58	101.58	98.75	0.17	3.05	2.87
2008Q4	96.93	102.11	97.26	0.35	5.35	4.98
2009Q1	95.90	102.64	96.41	0.53	7.02	6.46
2009Q2	95.93	103.16	96.76	0.86	7.54	6.62
2009Q3	96.34	103.69	97.56	1.26	7.63	6.29
2009Q4	96.62	104.22	98.28	1.72	7.86	6.04
2010Q1	97.18	104.74	99.41	2.30	7.79	5.36
2010Q2	97.49	105.27	100.08	2.65	7.98	5.18
2010Q3	97.64	105.80	100.24	2.65	8.35	5.55
2010Q4	96.99	106.32	99.53	2.61	9.62	6.82
2011Q1	97.26	106.85	99.63	2.44	9.86	7.25
2011Q2	98.25	107.38	100.25	2.03	9.29	7.11

Table B.9: Implied productivity gap (in %) between recessions and counterfactual 4, and percentage of the gap which is explained by counterfactual 4, n quarters after the start of the recession.

	Implied Gap: Reces.-Counter. 4			Gap to be explained by Counter. 4		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	4.1	4.1	4.7	7.5	7.5	6.5
4	4.2	6.0	6.1	10.7	7.6	7.6
5	5.6	6.8	6.2	12.7	10.6	11.5
6	5.8	7.1	5.9	16.9	14.0	16.5
7	6.0	7.3	5.7	21.1	17.6	21.9
8	5.9	6.7	5.1	26.5	23.7	29.6
9	6.3	7.7	4.9	27.7	23.8	33.3
10	7.1	8.9	5.3	25.3	21.0	31.8
11	8.5	10.8	6.4	21.6	17.5	27.2
12	9.9	11.3	6.8	17.8	15.7	24.7
13	11.2	11.7	6.6	13.7	13.0	21.8

Table B.10: Actual, Potential and Productivity from counterfactual 5 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 5	Actual Count. 5	Actual Potential	Potential Count. 5
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.80	0.19	1.45	1.26
2008Q3	98.58	101.58	99.02	0.45	3.05	2.59
2008Q4	96.93	102.11	97.53	0.62	5.35	4.70
2009Q1	95.90	102.64	96.45	0.57	7.02	6.41
2009Q2	95.93	103.16	96.19	0.27	7.54	7.25
2009Q3	96.34	103.69	96.33	-0.01	7.63	7.64
2009Q4	96.62	104.22	96.55	-0.07	7.86	7.94
2010Q1	97.18	104.74	97.19	0.02	7.79	7.77
2010Q2	97.49	105.27	97.61	0.12	7.98	7.84
2010Q3	97.64	105.80	97.93	0.30	8.35	8.03
2010Q4	96.99	106.32	97.65	0.68	9.62	8.88
2011Q1	97.26	106.85	98.45	1.22	9.86	8.54
2011Q2	98.25	107.38	99.84	1.62	9.29	7.55

Table B.11: Implied productivity gap (in %) between recessions and counterfactual 5, and percentage of the gap which is explained by counterfactual 5quarters, n quarters after the start of the recession.

	Implied Gap: Reces.-Counter. 5			Gap to be explained by Counter. 5		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	3.8	3.8	4.5	13.4	13.4	11.6
4	4.2	6.0	6.0	11.5	8.2	8.1
5	6.1	7.3	6.8	4.0	3.3	3.6
6	6.9	8.2	7.1	-0.1	-0.1	-0.1
7	7.6	8.9	7.4	-0.8	-0.7	-0.9
8	8.0	8.8	7.2	0.2	0.2	0.2
9	8.6	9.9	7.3	1.3	1.1	1.5
10	9.2	11.0	7.4	2.8	2.3	3.5
11	10.2	12.4	8.2	5.6	4.5	7.0
12	10.9	12.4	7.9	8.9	7.9	12.4
13	11.5	12.1	7.0	10.9	10.4	17.4

Table B.12: Actual, Potential and Productivity from counterfactual 6 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
				Actual	Actual	Potential
Quarter	Actual	Potential	Count. 6	Count. 6	Potential	Count. 6
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.61	0.00	1.45	1.46
2008Q3	98.58	101.58	98.59	0.02	3.05	3.03
2008Q4	96.93	102.11	96.99	0.07	5.35	5.28
2009Q1	95.90	102.64	96.03	0.13	7.02	6.88
2009Q2	95.93	103.16	96.08	0.16	7.54	7.37
2009Q3	96.34	103.69	96.48	0.14	7.63	7.48
2009Q4	96.62	104.22	96.92	0.31	7.86	7.53
2010Q1	97.18	104.74	97.86	0.71	7.79	7.03
2010Q2	97.49	105.27	98.48	1.01	7.98	6.90
2010Q3	97.64	105.80	98.65	1.03	8.35	7.24
2010Q4	96.99	106.32	98.04	1.07	9.62	8.45
2011Q1	97.26	106.85	98.43	1.21	9.86	8.55
2011Q2	98.25	107.38	99.44	1.20	9.29	7.99

Table B.13: Actual, Potential and Productivity from counterfactual 7 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 7	Actual Count. 7	Actual Potential	Potential Count. 7
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.83	0.22	1.45	1.23
2008Q3	98.58	101.58	99.21	0.64	3.05	2.39
2008Q4	96.93	102.11	97.93	1.03	5.35	4.27
2009Q1	95.90	102.64	97.03	1.17	7.02	5.78
2009Q2	95.93	103.16	97.03	1.15	7.54	6.32
2009Q3	96.34	103.69	97.50	1.21	7.63	6.34
2009Q4	96.62	104.22	98.14	1.58	7.86	6.19
2010Q1	97.18	104.74	99.37	2.26	7.79	5.41
2010Q2	97.49	105.27	100.18	2.76	7.98	5.08
2010Q3	97.64	105.80	100.52	2.95	8.35	5.25
2010Q4	96.99	106.32	100.17	3.27	9.62	6.14
2011Q1	97.26	106.85	100.75	3.58	9.86	6.06
2011Q2	98.25	107.38	101.66	3.47	9.29	5.62

Table B.14: Actual, Potential and Productivity from counterfactual 8 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 8	Actual Count. 8	Actual Potential	Potential Count. 8
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.80	0.19	1.45	1.26
2008Q3	98.58	101.58	99.13	0.56	3.05	2.48
2008Q4	96.93	102.11	97.81	0.91	5.35	4.39
2009Q1	95.90	102.64	96.92	1.06	7.02	5.90
2009Q2	95.93	103.16	96.87	0.98	7.54	6.49
2009Q3	96.34	103.69	97.15	0.84	7.63	6.73
2009Q4	96.62	104.22	97.44	0.85	7.86	6.96
2010Q1	97.18	104.74	98.28	1.13	7.79	6.58
2010Q2	97.49	105.27	98.88	1.42	7.98	6.46
2010Q3	97.64	105.80	99.25	1.65	8.35	6.59
2010Q4	96.99	106.32	99.09	2.16	9.62	7.30
2011Q1	97.26	106.85	99.84	2.65	9.86	7.02
2011Q2	98.25	107.38	100.96	2.75	9.29	6.36

Table B.15: Actual, Potential and Productivity from counterfactual 9 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 9	Actual Count. 9	Actual Potential	Potential Count. 9
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.64	0.03	1.45	1.42
2008Q3	98.58	101.58	98.78	0.21	3.05	2.83
2008Q4	96.93	102.11	97.36	0.45	5.35	4.87
2009Q1	95.90	102.64	96.57	0.70	7.02	6.28
2009Q2	95.93	103.16	96.91	1.02	7.54	6.46
2009Q3	96.34	103.69	97.63	1.33	7.63	6.21
2009Q4	96.62	104.22	98.22	1.65	7.86	6.11
2010Q1	97.18	104.74	99.13	2.01	7.79	5.67
2010Q2	97.49	105.27	99.53	2.09	7.98	5.76
2010Q3	97.64	105.80	99.53	1.93	8.35	6.30
2010Q4	96.99	106.32	98.80	1.86	9.62	7.61
2011Q1	97.26	106.85	98.88	1.67	9.86	8.06
2011Q2	98.25	107.38	99.49	1.26	9.29	7.92

Table B.16: Implied productivity gap (in %) between recessions and counterfactual 9, and percentage of the gap which is explained by counterfactual 9, n quarters after the start of the recession.

	Implied Gap: Reces.-Counter. 9			Gap to be explained by Counter. 9		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	4.0	4.0	4.6	9.8	9.7	8.4
4	4.1	5.9	5.9	14.0	10.0	9.9
5	5.4	6.6	6.1	15.0	12.4	13.5
6	5.7	7.0	5.8	17.9	14.8	17.5
7	6.0	7.4	5.8	20.2	16.9	21.0
8	6.2	7.0	5.4	23.1	20.7	25.8
9	6.8	8.2	5.4	21.9	18.7	26.2
10	7.7	9.5	5.9	18.4	15.2	23.1
11	9.2	11.4	7.1	15.4	12.4	19.4
12	10.6	12.0	7.5	12.2	10.8	16.9
13	11.8	12.4	7.3	8.5	8.1	13.6

Table B.17: Actual, Potential and Productivity from counterfactual 10 during the post-crisis period (2008Q1=100).

	Productiv.			% Differ.		
Quarter	Actual	Potential	Count. 10	Actual Count. 10	Actual Potential	Potential Count. 10
2008Q1	100.00	100.53	100.00	0.00	0.53	0.53
2008Q2	99.61	101.06	99.77	0.16	1.45	1.29
2008Q3	98.58	101.58	98.92	0.35	3.05	2.69
2008Q4	96.93	102.11	97.37	0.46	5.35	4.87
2009Q1	95.90	102.64	96.25	0.36	7.02	6.63
2009Q2	95.93	103.16	95.90	-0.03	7.54	7.58
2009Q3	96.34	103.69	95.87	-0.49	7.63	8.15
2009Q4	96.62	104.22	95.85	-0.79	7.86	8.73
2010Q1	97.18	104.74	96.34	-0.86	7.79	8.72
2010Q2	97.49	105.27	96.85	-0.66	7.98	8.70
2010Q3	97.64	105.80	97.37	-0.28	8.35	8.65
2010Q4	96.99	106.32	97.28	0.29	9.62	9.30
2011Q1	97.26	106.85	98.20	0.97	9.86	8.81
2011Q2	98.25	107.38	99.70	1.48	9.29	7.70

Table B.18: Implied productivity gap (in %) between recessions and counterfactual 10, and percentage of the gap which is explained by counterfactual 10, n quarters after the start of the recession.

	Implied Gap: Reces.-Counter. 10			Gap to be explained by Counter. 10		
Quarter	1979q4	1990q2	Pre-2008q1 Trend	1979q4	1990q2	Pre-2008q1 Trend
3	4.0	4.0	4.6	10.0	9.9	8.6
4	4.4	6.2	6.2	7.3	5.2	5.1
5	6.4	7.6	7.0	-0.5	-0.4	-0.4
6	7.4	8.7	7.5	-6.5	-5.4	-6.4
7	8.3	9.6	8.0	-9.7	-8.1	-10.1
8	8.8	9.6	8.0	-9.9	-8.9	-11.0
9	9.3	10.6	8.0	-6.9	-5.9	-8.3
10	9.7	11.5	8.0	-2.6	-2.2	-3.3
11	10.6	12.8	8.5	2.4	2.0	3.1
12	11.2	12.6	8.1	7.1	6.3	9.8
13	11.6	12.2	7.1	9.9	9.5	15.9

B.5

Data Issues:

In the Understanding Society data set, if the highest qualification reported in the current wave is named as ”Degree” that implies either first degree (BSc) or higher degree (MPhil/PhD) for the ISCED classification (variables `w_nhigual_dv` for new qualifications and `w_higual_dv` for considering fed forward information from previous waves). I clarify if the level of education is first degree or higher degree by using a second variable, which states the highest educational qualification reported in this wave (variable `w_nqfhigh_dv`) or the highest educational qualification considering fed forward information from previous waves (variables `w_qfhigh_dv` or `w_qfhigh`). On the other hand, if the highest qualification reported is ”Other higher degree”, then this aligns with the post secondary non-tertiary education in ISCED classification. The ”A-level etc” aligns with the higher secondary and middle vocational education (3a). ”GCSE etc” allligns with low secondary vocational educational (3c), ”other qualification” aligns with low secondary education an finally ”No qualification” with Primary or non defined (in this paper is one group). Also, for missing values in education I do the following reasonable assumption. If the individual has missing value in the level of education but there is this information in the previous spell and also is not currently student, then I assume that he has the same level of education as the one that he had in the previous spell. By following this rule, I gain 4% more information than before.

APPENDIX C

Appendix to Chapter 4

C.1

Table C.1: OLS Estimations of Matching Functions with a time trend: Method 1.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.84***					
		(0.04)					
η_2			0.59***				
			(0.05)				
η_3				0.88***			
				(0.05)			
η_4					0.69***		
					(0.04)		
η_5						0.74***	
						(0.05)	
η_6							0.65***
							(0.05)
Time	-0.01***	-0.01***	-0.01***	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.31***	-2.40***	-1.91***	-0.76***	-1.34***	-1.24***
	(0.04)	(0.02)	(0.02)	(0.10)	(0.05)	(0.05)	(0.11)
N	53	53	53	53	53	53	53
r2	0.98	0.98	0.90	0.90	0.94	0.91	0.88
F	721.26	823.73	146.68	152.30	241.69	172.24	118.68
ll	81.94	67.51	50.82	61.75	74.35	71.04	67.27

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: OLS Estimations of Matching Functions without a time trend: Method 1.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.96***					
		(0.03)					
η_2			0.84***				
			(0.07)				
η_3				0.97***			
				(0.06)			
η_4					0.81***		
					(0.04)		
η_5						0.77***	
						(0.03)	
η_6							0.68***
							(0.04)
Constant	0.06*	-1.19***	-2.36***	-2.11***	-0.94***	-1.38***	-1.25***
	(0.04)	(0.02)	(0.03)	(0.13)	(0.06)	(0.04)	(0.08)
N	53	53	53	53	53	53	53
r2	0.95	0.96	0.73	0.83	0.87	0.91	0.86
F	1077.01	1183.04	139.18	240.63	355.27	505.51	319.77
ll	63.03	47.53	24.73	46.09	56.21	69.54	63.87

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: OLS Estimations of Matching Functions with a time trend: Method 2.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.83***					
		(0.04)					
η_2			0.56***				
			(0.05)				
η_3				0.90***			
				(0.04)			
η_4					0.70***		
					(0.03)		
η_5						0.76***	
						(0.04)	
η_6							0.70***
							(0.04)
Time	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***	-0.00**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.29***	-2.21***	-2.00***	-1.00***	-1.43***	-1.49***
	(0.04)	(0.02)	(0.03)	(0.07)	(0.03)	(0.03)	(0.07)
N	53	53	53	53	53	53	53
r2	0.98	0.97	0.93	0.96	0.97	0.96	0.94
F	721.26	519.37	223.47	447.98	587.02	349.62	259.69
ll	81.94	66.87	51.94	61.40	76.54	72.35	69.42

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: OLS Estimations of Matching Functions without a time trend: Method 2.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.95***					
		(0.03)					
η_2			0.93***				
			(0.07)				
η_3				1.07***			
				(0.04)			
η_4					0.91***		
					(0.04)		
η_5						0.83***	
						(0.03)	
η_6							0.75***
							(0.03)
Constant	0.06*	-1.18***	-2.35***	-2.28***	-1.14***	-1.50***	-1.53***
	(0.04)	(0.02)	(0.04)	(0.06)	(0.03)	(0.02)	(0.05)
N	53	53	53	53	53	53	53
r2	0.95	0.94	0.80	0.94	0.93	0.94	0.92
F	1077.01	753.35	199.45	822.92	675.21	845.61	602.47
ll	63.03	47.46	22.92	47.98	51.27	65.93	62.09

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: OLS Estimations of Matching Functions with a time trend: Method 3.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.84***					
		(0.04)					
η_2			0.58***				
			(0.05)				
η_3				0.89***			
				(0.05)			
η_4					0.70***		
					(0.03)		
η_5						0.75***	
						(0.04)	
η_6							0.68***
							(0.05)
Time	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00*	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.30***	-2.32***	-1.96***	-0.90***	-1.39***	-1.39***
	(0.04)	(0.02)	(0.02)	(0.09)	(0.04)	(0.04)	(0.08)
N	53	53	53	53	53	53	53
r2	0.98	0.98	0.91	0.95	0.96	0.94	0.93
F	721.26	675.62	167.92	301.59	445.92	261.98	203.33
ll	81.94	67.23	51.34	61.54	75.78	71.79	69.68

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: OLS Estimations of Matching Functions without a time trend: Method 3.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.96***					
		(0.03)					
η_2			0.88***				
			(0.07)				
η_3				1.06***			
				(0.05)			
η_4					0.89***		
					(0.04)		
η_5						0.81***	
						(0.03)	
η_6							0.72***
							(0.03)
Constant	0.06*	-1.18***	-2.35***	-2.28***	-1.09***	-1.46***	-1.43***
	(0.04)	(0.02)	(0.03)	(0.09)	(0.04)	(0.03)	(0.06)
N	53	53	53	53	53	53	53
r2	0.95	0.95	0.75	0.91	0.91	0.93	0.91
F	1077.01	975.38	152.38	520.45	546.54	681.47	493.95
ll	63.03	47.51	23.78	46.91	52.40	67.26	63.58

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: OLS Estimations of Matching Functions with a quarterly time trend for the alternative model: Method 1.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.90***					
		(0.03)					
$1-\eta_1$		0.10***					
		(0.03)					
η_2			0.72***				
			(0.04)				
$1-\eta_2$			0.28***				
			(0.04)				
η_3				0.92***			
				(0.03)			
$1-\eta_3$				0.08**			
				(0.03)			
η_4					0.79***		
					(0.02)		
$1-\eta_4$					0.21***		
					(0.02)		
η_5						0.85***	
						(0.03)	
$1-\eta_5$						0.15***	
						(0.03)	
η_6							0.79***
							(0.03)
$1-\eta_6$							0.21***
							(0.03)
Time	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***	-0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.35***	-2.58***	-2.05***	-1.04***	-1.54***	-1.65***
	(0.04)	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)	(0.05)
N	53	53	53	53	53	53	53
r2	0.98						
F	721.26	.	.	.	.	.	.
ll	81.94	65.84	50.36	61.49	74.00	69.93	67.08

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: OLS Estimations of Matching Functions without a quarterly time trend for the alternative model: Method 1.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.98***					
		(0.02)					
$1-\eta_1$		0.02					
		(0.02)					
η_2			0.95***				
			(0.04)				
$1-\eta_2$			0.05				
			(0.04)				
η_3				1.05***			
				(0.03)			
$1-\eta_3$				-0.05			
				(0.03)			
η_4					0.93***		
					(0.03)		
$1-\eta_4$					0.07***		
					(0.03)		
η_5						0.88***	
						(0.02)	
$1-\eta_5$						0.12***	
						(0.02)	
η_6							0.83***
							(0.02)
$1-\eta_6$							0.17***
							(0.02)
Constant	0.06*	-1.19***	-2.41***	-2.23***	-1.15***	-1.57***	-1.68***
	(0.04)	(0.03)	(0.03)	(0.05)	(0.02)	(0.01)	(0.03)
N	53	53	53	53	53	53	53
r2	0.95						
F	1077.01	.	.	.	.	.	.
ll	63.03	47.22	22.96	47.13	51.63	65.66	62.28

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: OLS Estimations of Matching Functions with a quarterly time trend for the alternative model: Method 2.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.90***					
		(0.03)					
$1-\eta_1$		0.10***					
		(0.03)					
η_2			0.71***				
			(0.04)				
$1-\eta_2$			0.29***				
			(0.04)				
η_3				0.93***			
				(0.03)			
$1-\eta_3$				0.07**			
				(0.03)			
η_4					0.80***		
					(0.02)		
$1-\eta_4$					0.20***		
					(0.02)		
η_5						0.85***	
						(0.03)	
$1-\eta_5$						0.15***	
						(0.03)	
η_6							0.81***
							(0.03)
$1-\eta_6$							0.19***
							(0.03)
Time	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.33***	-2.47***	-2.10***	-1.20***	-1.58***	-1.78***
	(0.04)	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)
N	53	53	53	53	53	53	53
r2	0.98						
F	721.26	.	.	.	.	.	.
ll	81.94	65.36	51.20	61.22	75.31	70.71	68.15

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: OLS Estimations of Matching Functions without a quarterly time trend for the alternative model: Method 2.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.98***					
		(0.02)					
$1-\eta_1$		0.02					
		(0.02)					
η_2			0.98***				
			(0.04)				
$1-\eta_2$			0.02				
			(0.04)				
η_3				1.06***			
				(0.02)			
$1-\eta_3$				-0.06**			
				(0.02)			
η_4					0.96***		
					(0.02)		
$1-\eta_4$					0.04*		
					(0.02)		
η_5						0.91***	
						(0.02)	
$1-\eta_5$						0.09***	
						(0.02)	
η_6							0.85***
							(0.02)
$1-\eta_6$							0.15***
							(0.02)
Constant	0.06*	-1.19***	-2.39***	-2.22***	-1.20***	-1.61***	-1.79***
	(0.04)	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)
N	53	53	53	53	53	53	53
r2	0.95						
F	1077.01	.	.	.	.	.	.
ll	63.03	47.14	22.48	49.11	49.98	63.71	61.26

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.11: OLS Estimations of Matching Functions with a quarterly time trend for the alternative model: Method 3.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.76***						
	(0.03)						
η_1		0.90***					
		(0.03)					
$1-\eta\_1$		0.10***					
		(0.03)					
η_2			0.72***				
			(0.04)				
$1-\eta\_2$			0.28***				
			(0.04)				
η_3				0.93***			
				(0.03)			
$1-\eta\_3$				0.07**			
				(0.03)			
η_4					0.80***		
					(0.02)		
$1-\eta\_4$					0.20***		
					(0.02)		
η_5						0.85***	
						(0.03)	
$1-\eta\_5$						0.15***	
						(0.03)	
η_6							0.80***
							(0.03)
$1-\eta\_6$							0.20***
							(0.03)
Time	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***	0.00	0.00	-0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.16***	-1.34***	-2.53***	-2.08***	-1.13***	-1.56***	-1.73***
	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)	(0.01)	(0.04)
N	53	53	53	53	53	53	53
r2	0.98						
F	721.26	.	.	.	.	.	.
ll	81.94	65.62	50.72	61.31	74.83	70.33	68.34

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: OLS Estimations of Matching Functions without a quarterly time trend for the alternative model: Method 3.

	Aggregate	Job Adv	Jobcent	Priv	Refer	Appl	Other
η	0.92***						
	(0.03)						
η_1		0.98***					
		(0.02)					
$1-\eta_1$		0.02					
		(0.02)					
η_2			0.97***				
			(0.04)				
$1-\eta_2$			0.03				
			(0.04)				
η_3				1.06***			
				(0.03)			
$1-\eta_3$				-0.06**			
				(0.03)			
η_4					0.95***		
					(0.02)		
$1-\eta_4$					0.05**		
					(0.02)		
η_5						0.90***	
						(0.02)	
$1-\eta_5$						0.10***	
						(0.02)	
η_6							0.84***
							(0.02)
$1-\eta_6$							0.16***
							(0.02)
Constant	0.06*	-1.19***	-2.40***	-2.23***	-1.18***	-1.60***	-1.74***
	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)
N	53	53	53	53	53	53	53
r2	0.95						
F	1077.01	.	.	.	.	.	.
ll	63.03	47.19	22.69	48.42	50.41	64.34	62.07

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.2

Table C.13: Panel Estimations of Matching Function with a quadratic time trend for the three methods of measuring the search effort.

	Method 1	Method 2	Method 3
η_1	0.76***		
	(0.02)		
η_2		0.74***	
		(0.03)	
η_3			0.74***
			(0.03)
Advertis	-1.13***	-1.05***	-1.09***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.18***	-2.04***	-2.10***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.50***	-1.53***	-1.49***
	(0.06)	(0.06)	(0.06)
Referrals	-0.69***	-0.82***	-0.75***
	(0.05)	(0.04)	(0.04)
Direct Appl	-1.20***	-1.24***	-1.21***
	(0.04)	(0.04)	(0.04)
Other	-1.26***	-1.31***	-1.26***
	(0.06)	(0.06)	(0.06)
Time	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
N	318	318	318
r2	0.99	0.99	0.99
F	4711.41	5240.43	4875.03
ll	308.85	306.87	311.28

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Panel Estimations of Matching Function without a quadratic time trend for the three methods of measuring the search effort.

	Method 1	Method 2	Method 3
η_1	0.87***		
	(0.02)		
η_2		0.91***	
		(0.02)	
η_3			0.89***
			(0.02)
Advertis	-1.23***	-1.19***	-1.21***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.36***	-2.34***	-2.35***
	(0.02)	(0.02)	(0.02)
Priv Empl	-1.89***	-2.02***	-1.97***
	(0.04)	(0.03)	(0.03)
Referrals	-1.01***	-1.14***	-1.10***
	(0.03)	(0.02)	(0.02)
Direct Appl	-1.48***	-1.56***	-1.53***
	(0.02)	(0.02)	(0.02)
Other	-1.66***	-1.79***	-1.74***
	(0.04)	(0.03)	(0.03)
N	318	318	318
r2	0.99	0.99	0.99
F	5256.62	5728.65	5599.56
ll	266.01	255.19	259.65

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.15: Panel Estimations of Matching Function with a quadratic time trend for the three methods of measuring the search effort: Alternative model.

	Method 1	Method 2	Method 3
η_i	0.83***	0.83***	0.83***
	(0.02)	(0.02)	(0.02)
$1-\eta_1$	0.17***		
	(0.02)		
$1-\eta_2$		0.17***	
		(0.02)	
$1-\eta_3$			0.17***
			(0.02)
Advertis	-1.17***	-1.11***	-1.14***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.27***	-2.19***	-2.22***
	(0.03)	(0.03)	(0.03)
Priv Empl	-1.72***	-1.77***	-1.74***
	(0.04)	(0.04)	(0.04)
Referrals	-0.87***	-0.97***	-0.93***
	(0.03)	(0.03)	(0.03)
Direct Appl	-1.35***	-1.39***	-1.37***
	(0.03)	(0.03)	(0.03)
Other	-1.48***	-1.55***	-1.51***
	(0.05)	(0.04)	(0.04)
Time	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
N	318	318	318
r2			
F	10243.57	12768.52	11615.39
ll	308.04	302.20	306.46

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.16: Panel Estimations of Matching Function without a quadratic time trend for the three methods of measuring the search effort: Alternative model.

	Method 1	Method 2	Method 3
η_i	0.94***	0.96***	0.95***
	(0.01)	(0.01)	(0.01)
$1-\eta_1$	0.06***		
	(0.01)		
$1-\eta_2$		0.04***	
		(0.01)	
$1-\eta_3$			0.05***
			(0.01)
Advertis	-1.24***	-1.21***	-1.22***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.42***	-2.39***	-2.40***
	(0.02)	(0.02)	(0.02)
Priv Empl	-2.08***	-2.12***	-2.10***
	(0.02)	(0.02)	(0.02)
Referrals	-1.15***	-1.20***	-1.18***
	(0.01)	(0.01)	(0.01)
Direct A l	-1.59***	-1.62***	-1.61***
	(0.01)	(0.01)	(0.01)
Other	-1.84***	-1.89***	-1.87***
	(0.02)	(0.02)	(0.02)
N	318	318	318
r2			
F	12306.58	13391.49	13001.92
ll	256.46	251.20	253.32

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.17: Panel Estimations of Matching Function with a structural break and a quadratic time trend for the three methods of measuring the search effort.

	Method 1	Method 2	Method 3
η_1	0.65***		
	(0.03)		
η_2		0.64***	
		(0.03)	
η_3			0.64***
			(0.03)
Time	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Pre 2008			
Advertis	-1.09***	-1.04***	-1.07***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.13***	-1.95***	-2.05***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.25***	-1.29***	-1.25***
	(0.06)	(0.06)	(0.06)
Referrals	-0.53***	-0.72***	-0.63***
	(0.05)	(0.04)	(0.04)
Direct Appl	-1.12***	-1.18***	-1.14***
	(0.04)	(0.04)	(0.04)
Other	-1.09***	-1.20***	-1.13***
	(0.06)	(0.06)	(0.06)
Post 2008			
Advertis× post	-0.29***	-0.19***	-0.24***
	(0.03)	(0.03)	(0.03)
Job Cent× post	-0.14***	-0.18***	-0.15***
	(0.04)	(0.04)	(0.04)
Priv Emp× post	-0.16***	-0.26***	-0.22***
	(0.03)	(0.04)	(0.03)
Referral× post	-0.12***	-0.16***	-0.15***
	(0.03)	(0.03)	(0.03)
Direct Appl× post	-0.06**	-0.09***	-0.08***
	(0.03)	(0.03)	(0.03)
Other× post	0.01	-0.00	-0.00
	(0.03)	(0.03)	(0.03)
N	318	318	318
r2	1.00	1.00	1.00
F	4948.89	4305.22	4335.33
ll	359.91	360.16	364.25

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.18: Panel Estimations of Matching Function with a structural break and without a quadratic time trend for the three methods of measuring the search effort.

	Method 1	Method 2	Method 3
η_1	0.68***		
	(0.03)		
η_2		0.68***	
		(0.03)	
η_3			0.67***
			(0.03)
Pre 2008			
Advertis	-1.19***	-1.16***	-1.17***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.24***	-2.10***	-2.17***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.41***	-1.48***	-1.42***
	(0.06)	(0.06)	(0.06)
Referrals	-0.67***	-0.87***	-0.78***
	(0.04)	(0.03)	(0.04)
Direct Appl	-1.25***	-1.33***	-1.28***
	(0.03)	(0.03)	(0.03)
Other	-1.25***	-1.38***	-1.30***
	(0.06)	(0.06)	(0.06)
Post 2008			
Advertis× post	-0.30***	-0.24***	-0.28***
	(0.03)	(0.03)	(0.03)
Job Cent× post	-0.17***	-0.23***	-0.20***
	(0.04)	(0.04)	(0.04)
Priv Emp× post	-0.19***	-0.31***	-0.27***
	(0.02)	(0.03)	(0.03)
Referral× post	-0.14***	-0.21***	-0.19***
	(0.02)	(0.03)	(0.02)
Direct Appl× post	-0.08***	-0.14***	-0.12***
	(0.02)	(0.02)	(0.02)
Other× post	-0.01	-0.06**	-0.04*
	(0.02)	(0.03)	(0.02)
N	318	318	318
r2	0.99	0.99	0.99
F	4047.19	4433.81	4013.48
ll	332.28	326.87	332.51

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.19: Panel Estimations of Matching Function with a quadratic time trend for the three methods of measuring the search effort by using an AR(2) as instrument.

	Method 1	Method 2	Method 3
η_1	0.75***		
	(0.02)		
η_2		0.74***	
		(0.03)	
η_3			0.73***
			(0.02)
Advertis	-1.12***	-1.03***	-1.07***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.17***	-2.03***	-2.09***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.46***	-1.50***	-1.46***
	(0.06)	(0.06)	(0.06)
Referrals	-0.66***	-0.80***	-0.73***
	(0.05)	(0.04)	(0.04)
Direct Appl	-1.17***	-1.21***	-1.18***
	(0.04)	(0.04)	(0.04)
Other	-1.22***	-1.28***	-1.23***
	(0.06)	(0.06)	(0.06)
Time	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
N	306	306	306
r2			
F			
ll			

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.20: Panel Estimations of Matching Function without a quadratic time trend for the three methods of measuring the search effort by using an AR(2) as instrument.

	Method 1	Method 2	Method 3
η_1	0.86***		
	(0.02)		
η_2		0.90***	
		(0.02)	
η_3			0.88***
			(0.02)
Advertis	-1.24***	-1.20***	-1.22***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.37***	-2.35***	-2.36***
	(0.02)	(0.02)	(0.02)
Priv Empl	-1.87***	-2.00***	-1.95***
	(0.04)	(0.03)	(0.03)
Referrals	-1.00***	-1.14***	-1.09***
	(0.03)	(0.02)	(0.02)
Direct A l	-1.47***	-1.55***	-1.52***
	(0.02)	(0.01)	(0.02)
Other	-1.63***	-1.77***	-1.72***
	(0.04)	(0.03)	(0.03)
N	306	306	306
r2			
F			
ll			

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.21: Matching Efficiency Estimations of the Panel with a quadratic time trend for the three different methods by using an AR(2) as IV.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	-0.161	0.851	-0.161	0.851	-0.161	0.851
Advert	-0.958	0.384	-0.873	0.418	-0.913	0.401
JobCenter	-2.006	0.135	-1.871	0.154	-1.931	0.145
Priv. Empl.	-1.300	0.273	-1.343	0.261	-1.299	0.273
Referrals	-0.500	0.607	-0.636	0.530	-0.565	0.569
Direct Appl.	-1.011	0.364	-1.052	0.349	-1.017	0.362
Other	-1.060	0.346	-1.118	0.327	-1.069	0.343
η	0.747		0.735		0.732	

Table C.22: Matching Efficiency Estimations of the Panel with no time trend for the three different methods by using an AR(2) as IV.

	Method 1		Method 2		Method 3	
Channels	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$	$\ln(\hat{\mu}_i)$	$\hat{\mu}_i$
Aggregate	0.063	1.065	0.063	1.065	0.063	1.065
Advert	-1.307	0.271	-1.265	0.282	-1.283	0.277
JobCenter	-2.436	0.087	-2.412	0.090	-2.424	0.089
Priv. Empl.	-1.932	0.145	-2.066	0.127	-2.013	0.134
Referrals	-1.063	0.345	-1.200	0.301	-1.151	0.316
Direct Appl.	-1.530	0.216	-1.611	0.200	-1.579	0.206
Other	-1.694	0.184	-1.834	0.160	-1.779	0.169
η	0.857		0.902		0.882	

Table C.23: Panel Estimations of Matching Function with a structural break and a quadratic time trend for the three methods of measuring the search effort by using an AR(2) as instrument.

	Method 1	Method 2	Method 3
η_1	0.65***		
	(0.03)		
η_2		0.64***	
		(0.03)	
η_3			0.64***
			(0.03)
Time	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Time-Sq	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Pre 2008			
Advertis	-1.09***	-1.04***	-1.06***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.14***	-1.97***	-2.06***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.23***	-1.29***	-1.24***
	(0.06)	(0.06)	(0.06)
Referrals	-0.52***	-0.72***	-0.62***
	(0.05)	(0.04)	(0.04)
Direct Appl	-1.10***	-1.17***	-1.12***
	(0.04)	(0.04)	(0.04)
Other	-1.08***	-1.20***	-1.13***
	(0.06)	(0.06)	(0.06)
Post 2008			
Advertis× post	-0.29***	-0.19***	-0.24***
	(0.03)	(0.03)	(0.03)
Job Cent× post	-0.12***	-0.16***	-0.14***
	(0.03)	(0.04)	(0.03)
Priv Emp× post	-0.16***	-0.26***	-0.22***
	(0.03)	(0.03)	(0.03)
Referral× post	-0.12***	-0.16***	-0.15***
	(0.02)	(0.03)	(0.03)
Direct Appl× post	-0.07***	-0.10***	-0.09***
	(0.02)	(0.03)	(0.03)
Other× post	0.01	0.00	-0.00
	(0.03)	(0.03)	(0.03)
N	306	306	306
r2			
F			
ll			

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.24: Panel Estimations of Matching Function with a structural break and without a quadratic time trend for the three methods of measuring the search effort by using an AR(2) as instrument.

	Method 1	Method 2	Method 3
η_1	0.67***		
	(0.03)		
η_2		0.67***	
		(0.03)	
η_3			0.67***
			(0.03)
Pre 2008			
Advertis	-1.19***	-1.16***	-1.18***
	(0.02)	(0.02)	(0.02)
Job Cent	-2.26***	-2.12***	-2.19***
	(0.03)	(0.04)	(0.03)
Priv Empl	-1.40***	-1.47***	-1.42***
	(0.06)	(0.06)	(0.06)
Referrals	-0.67***	-0.88***	-0.78***
	(0.04)	(0.03)	(0.04)
Direct Appl	-1.24***	-1.32***	-1.27***
	(0.03)	(0.03)	(0.03)
Other	-1.25***	-1.38***	-1.30***
	(0.06)	(0.05)	(0.06)
Post 2008			
Advertis× post	-0.30***	-0.23***	-0.27***
	(0.03)	(0.03)	(0.03)
Job Cent× post	-0.15***	-0.21***	-0.18***
	(0.04)	(0.04)	(0.04)
Priv Emp× post	-0.19***	-0.31***	-0.26***
	(0.02)	(0.03)	(0.03)
Referral× post	-0.14***	-0.21***	-0.19***
	(0.02)	(0.03)	(0.02)
Direct Appl× post	-0.09***	-0.15***	-0.13***
	(0.02)	(0.02)	(0.02)
Other× post	-0.01	-0.05**	-0.04*
	(0.02)	(0.03)	(0.02)
N	306	306	306
r2			
F			
ll			

Standard errors in parentheses

Source: Quarterly Labour Force Survey

* p¡0.1, ** p¡0.05, *** p¡0.01

Table C.25: Matching Efficiency Estimations of the model with structural breaks and time-varying polynomials for the three methods of measuring the search effort by using an AR(2) as IV.

	Method 1		Method 2		Method 3	
Channel	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}
Advertis	0.396	0.298	0.416	0.345	0.407	0.319
Job Cent	0.138	0.122	0.164	0.140	0.150	0.131
Priv Empl	0.343	0.292	0.324	0.250	0.340	0.272
Referrals	0.700	0.622	0.572	0.488	0.630	0.541
Direct Appl	0.392	0.367	0.364	0.331	0.382	0.350
Other	0.400	0.403	0.354	0.354	0.381	0.380
η	0.647		0.644		0.637	

Table C.26: Matching Efficiency Estimations of the model with structural breaks without time-varying polynomials for the three methods of measuring the search effort.

	Method 1		Method 2		Method 3	
Channel	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}	μ_i^{pre}	μ_i^{post}
Advertis	0.285	0.212	0.294	0.232	0.289	0.220
Job Cent	0.098	0.085	0.113	0.091	0.105	0.088
Priv Empl	0.232	0.193	0.215	0.158	0.227	0.174
Referrals	0.482	0.419	0.391	0.317	0.431	0.356
Direct Appl	0.273	0.250	0.250	0.216	0.263	0.231
Other	0.270	0.267	0.235	0.224	0.255	0.245
η	0.673		0.675		0.665	

C.3

In Figure C.1 we can see the correlations between the five most important channels for finding a job, after using the Hodrick-Prescott filter with smoothing parameter 1600 in each time series, which are through advertisement, jobcenter/jobmarket, private employment agency, referrals, direct application and other channels. In Table C.27 we can see the correlations between all available channels after 2000. From these tables, we can observe that the higher correlations which are statistical significant are between job centers and direct application by -0.49, Referrals with advertisements by -0.45 and referrals with direct applications with -0.41. Negative correlation between these variables seems an expected result since they are all add up to 100. So, an increase of one variable will imply on average a decrease of another variable. Table C.1 shows the actual data in logarithmic terms and the logarithm of its time series' trend, after applying the Hodrick-Prescott filter. We can observe that during the current crisis, job finding through advertisements and through jobcenter/jobmarkets etc. decrease from their trend, whereas finding job through private employment agency, Careers Office and Jobclub increase instead. Referrals seem to be unaffected during the crisis.

Table C.27: Correlations between different channels of finding a job after 2000 (detrended).

	Advert	JobCen.	Car. Off	JobCl.	Priv. Em.	Refer.	Dir. Appl.	Oth.
Advert	1							
JobCenter	-0.15	1						
Career Off	-0.25*	0.02	1					
JobClub	-0.07	-0.06	-0.05	1				
Priv. Empl.	-0.47*	-0.19	-0.2	0.16	1			
Referrals	-0.45*	0.01	-0.14	-0.03	0.11	1		
Direct Appl.	-0.08	-0.32*	0.39*	0.01	-0.15	-0.52*	1	
Other	-0.27*	0.18	0.12	-0.04	-0.14	0.13	-0.36*	1

* $p < 0.1$

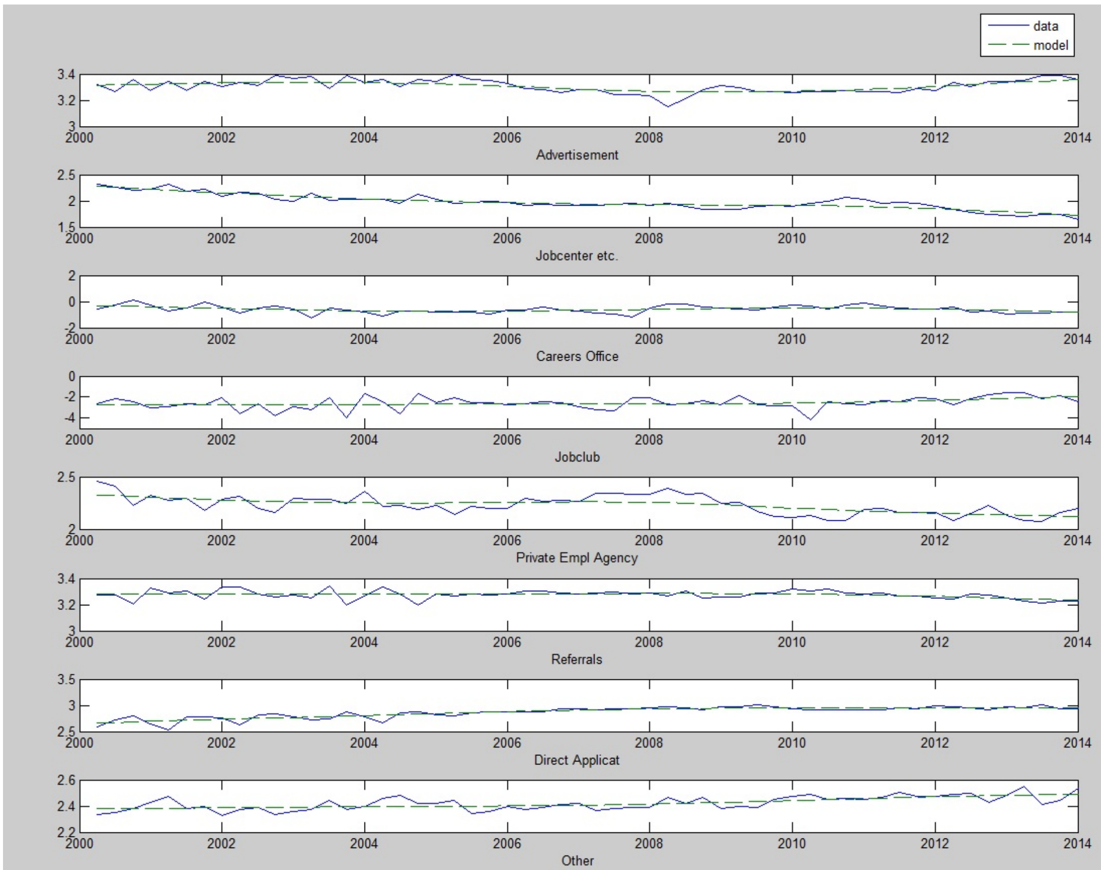


Figure C.1: Actual data with their trend components in logarithmic terms applying the HodrickPrescott filter from 2000-2014.

C.4

Data Issues:

In the QLFS dataset there is not a one variable for education since the levels of education changed over time. To create a common variable for educational level we used the variable higuald from 2002Q2-2003Q4, higual4d from 2004Q1-2005Q1, higual5d from 2005Q2-2007Q4, higual8d from 2008Q1-2010Q4, higul11d from 2011Q1-2014Q4, and higul15d for 2015Q1. These variables classify the different levels of education into 6 broader groups which can be seen in Table C.28. For instance the levels of education for the period from 2011Q1-2014Q4 can be seen in Tables C.30 and C.31. From these Tables, the levels of education 1-9 are included in the group 1 “Degree or equivalent” which contains National Vocational Qualification (NQF) Level 4 and above, 10-26 are included in the group 2 “Higher education” (NQF Levels 3& 4), 27-46 are included in the group 3 “GCE, A-level or equivalent” (NQF Level 3), 47-57 are included in the group 4 “GCSE grades $A^{*} - C$ or equivalent” (NQF Level 2), 58-78 are included in the group 5 “Other qualifications”(Below NQF Level 2), and 79 is included in the group 6 “No qualification”. These level of education can slightly change over time. For more details about any changes see the “Labour Force Survey User Guide” volumes 1-5: Details of LFS variables[1].

[1]See also Schneider and Kogan (2008) for a connection between these classifications and the 1997 International Standard Classification of Education (ISCED-97).

Table C.28: Broader educational groups for The UK according to LFS.

Number	Educ. Groups
1	Degree or equivalent
2	Higher education
3	GCE, A-level or equivalent
4	GCSE grades A*-C or equivalent
5	Other qualifications
6	No qualification

Table C.29: Educational groups for The UK according to LFS (2011 Classification).

Number	Level of Education (2011 Classification)
1	Higher degree
2	NVQ level 5
4	Level 8 Certificate
5	Level 7 Diploma
7	Level 8 Award
8	First degree/foundation degree
9	Other degree
10	NVQ level 4
11	Level 6 Diploma
12	Level 6 Certificate
14	Diploma in higher education
15	Level 5 Diploma
16	Level 5 Certificate
18	HNC/HND/BTEC higher etc
19	Teaching further education
20	Teaching secondary education
21	Teaching primary education
22	Teaching foundation stage
23	Teaching level not stated
24	Nursing etc
25	RSA higher diploma
26	Other higher education below degree
27	Level 4 Diploma
28	Level 4 Certificate
29	Level 5 Award
30	NVQ level 3

Table C.30: Educational groups for The UK according to LFS continue (2011 Classification).

Number	Level of Education (2011 Classification)
31	Advanced/Progression (14-19) Diploma
32	Level 3 Diploma
33	Advanced Welsh Baccalaureate
34	International Baccalaureate
35	GNVQ/GSVQ advanced
36	A-level or equivalent
37	RSA advanced diploma
38	OND/ONC/BTEC/SCOTVEC National etc
39	City & Guilds Advanced Craft/Part 1
40	Scottish 6 year certificate/CSYS
41	SCE higher or equivalent
42	Access qualifications
43	AS-level or equivalent
44	Trade apprenticeship
45	Level 3 Certificate
46	Level 4 Award
47	NVQ level 2 or equivalent
49	GNVQ/GSVQ intermediate
50	RSA diploma
51	City & Guilds Craft/Part 2
52	BTEC/SCOTVEC First or General diploma e
53	Higher (14-19) Diploma
54	Level 2 Diploma
55	Level 2 Certificate
56	O-level, GCSE grade A*-C or equivalent
57	Level 3 Award
58	NVQ level 1 or equivalent
60	GNVQ/GSVQ foundation level

Table C.31: Educational groups for The UK according to LFS continue (2011 Classification).

Number	Level of Education (2011 Classification)
61	Foundation (14-19) Diploma
62	Level 1 Diploma
63	CSE below grade 1, GCSE below grade C
64	BTEC/SCOTVEC First or General certifica
65	SCOTVEC modules
66	RSA other
67	City & Guilds foundation/Part 1
68	Level 1 Certificate
69	Level 2 Award
70	YT/YTP certificate
71	Key skills qualification
72	Basic skills qualification
73	Entry level qualification
75	Entry level Certificate
76	Level 1 Award
77	Entry level Award
78	Other qualification
79	No qualifications
80	D/K