Essays on a Frictional Labour Market with Inactive Workers

A thesis submitted
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by

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Dedications:

"This work is dedicated to my Grandmother Domenica."

Acknowledgments

Applying for the Ph.D. in Economics after a degree in Law and after passing the qualification examination to become Attorney was not exactly what I had dreamed to do when I was in my first year as undergraduate student at the University of Messina. People around me were surprised by my decision to progress with my studies in economics, while the satisfaction from my work as an Attorney was still amazing. However, as I have discovered during my undergraduate studies, when one starts to study economics there are only two possible roads: either studying economics for the rest of your life or forgetting the existence of economics in this life. I chose the first one, and now the path is set.

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Any remaining mistakes or omissions are my own sole responsibility.

Declaration

I hereby and formally declare that this work, entitled "*Essays on a Frictional Labour Market with Inactive Workers*", has been composed my myself; that it has not been accepted in any previous application for a degree; that the work of which it is a record has been done by myself; and that all verbatim extracts have been distinguished by quotation marks and the sources of my information have been fully and especially acknowledged.

Signed:

Antonio Parlavecchio

May 2017

SUMMARY

ESSAYS IN A FRICTIONAL LABOUR MARKET WITH INACTIVE WORKERS

In this Ph.D. thesis, I study the role of inactive workers (i.e., individuals classified by standard statistical measures in the labour market as non-participants or as out-of-labour force) in the context of a frictional labour market model. The theis is organised as follows.

In Chapter 1, I survey some of the most relevant contributions investigating the cyclical behaviour of the out-of-labour force variable and the main problems, which arise from its inclusion in the modern theoretical framework studying the dynamics of the labour market variables.

In Chapter 2, entitled "Do Out-of-Labour Force Workers Matter for the Cyclical Behaviour of the Labour Market Aggregates?", I develop a search and matching model with three labour market states, characterized by worker heterogeneity, endogenous separations and idiosyncratic home productivity shock, embedded into a standard DSGE (Dynamic Stochastic General Equilibrium) model. The goal of this study is to analyse the ability of such a model to replicate the observed large volatility of labour market variables such as vacancies, job-finding rate, labour market tightness and unemployment, that the standard search and matching model is not able to explain.[1] This framework is based on the empirical evidence regarding direct worker

[1] The standard search and matching model a' la Mortensen and Pissarides with exogenous separation, no search intensity and aggregate shock to total factor productivity is able to replicate usually one-tenth of the empirical volatility of labour market variables.

flows between all three labour market states. The focus is not only on the unemployment to employment flow, but also on the out-of-labour force to employment flow. The presence of these two channels is developed by a mechanism resembling that of labour market segmentation (workers belonging to the two groups, i.e. unemployment and out-of-labour force, cannot search for a job in the same market, but each group searches in his own sub-market). The crucial mechanism able to replicate large second moments for vacancies, job-finding rate and labour market tightness, together with consistent worker flows, is related to the presence of frictions related to home productivity. A new value of home productivity is drawn at the beginning of the period, but it is "full discovered" only at the end of the same periods. Thus, it affects the decisions of the agents when the search process is over. However, when the new value is "discovered", agents can choose to quit the job. Firms have knowledge of the new value of home productivity at the end of the period as well, and they know that agents with high draws of home productivity might separate from the job. Then, since some of the vacancies will be unmatched at the end of the period, because of the endogeneous separation process driven by high draws of home productivity for the workers, there is an incentive for firms to advertise a larger number of vacancies, and this creates large fluctuation in the labour-market tightness variable. On the other side, workers looking for a job will accept each job is offered them since they know that at the end of the period they might quit the job conditional to the new high draw of home productivity, and this creates large fluctuations in the variables job-finding rate. However, the presence of an additional margin, the out-of-labour force state, plays a crucial role as well. Indeed, working with three labour market states helps to re-calibrate the mass of workers for each labour market state and the dynamics they are involved in. In particular, the presence of inactive workers helps to re-determine the distribution of matches not only as an effect of a direct flow from unemployment to employment, but also the direct flow from out-of-labour force to employment, as it is observed in the data. The results show that this model is able to generate large volatilities of labour market variables, with values for vacancy, job-finding rate and vacancy-searchers ratio that are between 50 and 60 percent of their empirical counterparts, and the most relevant worker flows, especially the inactive to employment and the inactive to unemployment worker flows.

In Chapter 3, entitled "The Real Wage of Newly Hired Workers over the Business Cycle: When the Difference between Flows from Unemployment and Flows from Out-of-Labour Force Matters", I investigate the response of real wages to two aggregate cyclical indicators, i.e., the unemployment rate and the aggregate labour productivity, for different groups of workers, namely, job stayers, newly hired workers from unemployment, newly hired workers from out-of-labour force and job changers. The motivation for this exercise stems from the large debate on the empirical validity of the search and matching model. A basic search and matching model fails to replicate the large volatilities in unemployment, vacancies and job-finding rate. As a possible solution, researchers have focused on the role of wage and its rigidity. More precisely, following the work of Rudanko (2009), it has been suggested that hiring decision is the forward-looking variable and the number of jobs created depends on the wage to be paid to the newly hired workers. The presence of an acyclical real wage for new entrants into employment would represent the empirical cornerstone to support the empirical validity of the search model. However, models have been basically developed by assuming that the flow of new entrants into employment comes only from the unemployment state while empirical evidence shows the existence of worker transitions into employment from both unemployment and out-of-labour force (together with job to job transitions). Thus, the methodology used in these works results difficult to be supported. After reviewing evidence of these large flows, a model incorporating worker transitions in employment from both the unemployment state and the out-of-labour force state is estimated, using data from the Survey of Income and Program Participation (SIPP), a longitudinal nationally representative panel for the U.S. economy, over the period

1996-2013, and the results shed light on the cyclical behaviour of the real wage. Indeed, I find that the real wages of newly hired workers coming from unemployment are less procyclical than the real wages for newly hired workers coming from out-of-labour force. Introducing as an additional control variable the category of job to job changers does not affect qualitatively or quantitatively our findings, since the difference in the cyclical properties of the wages for the marginal workers from unemployment and out-of-labour force is maintained. These results could be explained in terms of the different compositional effects for the two groups of individuals. During periods of expansion of the economic activity, whilst workers joining employment from unemployment are more likely to be low-skilled workers and to find a low-paid job, the workers joining employment from out-of-labour force do not show the same compositional change. On the contrary, this last group, in the good times, consists of high-skilled workers that find a high-paid job and show a higher elasticity of real wage compared to that of newly hired workers from unemployment.

In Chapter 4, entitled "Labour Market Transitions and Wealth", I investigate the relationship between labour market transitions and wealth. More precisely, I estimate the impact of wealth on the “exit” margins, i.e., the probability for individuals to transition into the two non-employment states: unemployment and out-of-labour force. Researchers have shown that search and matching models including idiosyncratic home or market productivity shocks are able to replicate labour market transitions between employment and unemployment, but these models fail in explaining the flow from inactivity to employment and, at a smaller extent, the movements between inactivity and the other two labour market states. Furthermore, they are developed specifying preferences in linear terms, removing in this way any role for accumulated assets/savings in terms of consumption smoothing activity. This last point is particularly relevant in my analysis, given that flows into the non-employment states can be considered as the start of a new search activity but nothing is said as regards the resources used that can finance searching. My inquiry recognises that a crucial role can be attributed to wealth, in that process. A few papers have investigated whether wealth can finance active searching, i.e., searching while individuals are in the unemployment state, but no answer has been given to the question whether wealth can finance passive searching, i.e., searching while individuals are in the out-of-labour force state.[2] In this chapter, I try to provide an answer to this question, and more specifically, I test the presence of heterogeneity in the exit margin, between unemployed and out-of-labour force individuals. Using the transitory-permanent decomposition for the wealth effect, I find that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and the probability of transitioning to unemployment, while a permanent increase in wealth has a negative impact on both transition probabilities. However, I find that the quantitative effect is larger for the probability of transitioning into out-of-labour force compared to the probability of transitioning into unemployment. Thus, a temporary increase in wealth makes the individuals more likely to transition into out-of-labour force rather than in unemployment, while a permanent increase in wealth makes individuals less likely to transition into out-of-labour force.

[2] Statistical measurements basically differentiate active and passive searching according to the probability of the searcher to get potentially in contact with the employer. This is quite likely for active searchers, while the probability to observe this contact between the employer and the passive searchers is zero.

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CHAPTER 1:

INTRODUCTION

“*Given the frequency of movements between unemployment and not-in-labor-force, it is difficult to distinguish between these two states....these states are functionally indistinguishable*.”

Kim B. Clark and Lawrence H. Summers (1982, p.204 and 207)

“*Since anyone without a job and actively searching for one is classified as unemployed, the workers who move directly from out of labor force to employment are most likely the result of inadequate measuring,…*”

Barbara Petrongolo and Christopher A. Pissarides (2001, p.416)

During the decades the performance of the labour market in western countries has received renewed interest. Following the Great Recession, most of the developed countries have suffered a sharp contraction in their economic activity, with a substantial worsening in most of their labour market indicators. Researchers and policymakers have focused on the behaviour of the unemployment rate because of the cost that high unemployment levels generate for the individuals and the economy as a whole. Looking at the performance of the largest economy, i.e., the U.S., one observes a dramatic increase in the unemployment rate from 4.4 percent in December 2006 to 9.9 in December 2009, one of the largest values of unemployment in the post-war period and close to the highest peak of 10.8 percent reached in November 1982 (Figure 1.1). Despite the fact that the U.S. economy moved out of the recession in August 2009, the unemployment rate did not show a fast recovery to its pre-crisis level, even after the economic stimulus and the very drastic measures undertaken by the U.S. Government (i.e., the implementation of the Troubled Asset Relief Program (TARP) and the Recovery Act) and the Federal Reserve Board (i.e., the Fed Fund rates were cut from 5.25 percent in 2007 to a value between 0-0.25 percent in 2009, along with the implementation of the Quantitative Easing), took place. The ineffectiveness of these measures to reverting the labour market indicators back to their pre-recession values is manifested by the persistence of high levels of unemployment, around 10 percent, even one year later, in November 2010, more than five quarters after the end of the recession. It was only in August 2011 that a value for the unemployment rate reached 5 percent, i.e., the unemployment rate at the onset of the recession, with the measurements from the Bureau of Labor Statistics certifying a value of 5.1 percent, with a further fall to 4.5 percent in March 2017, almost seven years after the end of the recession.

A similar path has been observed for the other countries in the OECD. The performance of the labour market in these economies over the same period shows roughly the same dynamics. The OECD average unemployment has been heavily affected by the financial crisis, and a closer look at the data shows that the unemployment rate increased from 5.8 percent in December 2006 to 8.43 percent in December 2009, with a final value of 8.13 percent in December 2010. The recovery path for the OECD economies has displayed a similarly slow recovery process, as the U.S. labour market. Ineed, it is possible to observe values for the unemployment rate above 6 percent until the beginning of 2017.[3]

Looking at an additional relevant labour market indicator, namely the U.S. employment-to-population ratio (Figure 1.2), one can easily observe the scarring effect produced by the

[3] Some notable exceptions in terms of the unemployment rate in the OECD area are Greece, who started to experiment higher levels of unemployment from 2010, with values around 13 percent, and then moved to a value of 23 percent for the unemployment rate at the beginning of 2017, after a peak to 28 percent in September 2013, and Spain, who has experimented higher values for the unemployment rate since the beginning of 2009, with values around 16-17 percent, and moved to values of unemployment rate in the interval 20-25 percent in the period 2010-2016, to finally reaching 18 percent in 2017.

financial crisis.[4] Indeed, the employment-population ratio fell from a value of 63 percent in 2007 to that of 60 percent at the beginning of 2017, with a drop to values in the range 58-59 percent over the 2010-14 period. Disentangling the ratio by gender, it is observed that both men (Figure 1.3) and women (Figure 1.4) have suffered the consequences of the economic downturn, with the lowest values reached, during the recession, being roughly 9 percentage points below the pre-crisis levels of 2006. However, the employability conditions seem to be slightly more alleviated for women than for men, since the last statistical measures in 2017 show that the first group is only 2 percentage points far from the initial levels in 2006, against the 4 percentage points gap for men.

These figures have given rise to a large debate on the weak performance of the labour market. Unsurprisingly, this debate has been developed by analysing the behaviour of the unemployment rate as the key variable to be taken into account. Thus, large attention has been devoted to developing a setup involving the relationship between only two labour market states: employment and unemployment. In this sense one can justify the development of theoretical models explaining jobless recovery, i.e., the weak recovery of the labour market indicators, accompanied by the positive growth rates for the GDP, into the standard economic environment with only two labour market states.[5]

[4] The "scarring effect" is usually defined in terms of a negative long-term effect that individuals experiment in consequence of adverse events in their lives. In the literature, scarring effects have been related to poverty, i.e., the probability of experimenting longer periods of poverty is increased by the fact the individual is poor in one year (Cappellari and Jenkins, 2002), or with reference to unemployment, i.e., an individual who has been unemployed will be more likely to suffer from this negative experience in terms of future labour market outcomes (Arulampalam, 2001).

[5] Jobless recovery is not a new feature restricted to only the last recession. Indeed, as reported by Jaimovich and Siu (2012), this phenomenon has characterized the last three recessions of the U.S. economy (i.e., 1990-91, 2001 and 2007-09). However, after the Great Recession the combination of an extremely weak performance of the labour market with a recovery of the economic activity has motivated researchers to deeply investigate this issue. Shimer (2012) explains the presence of jobless recovery as a consequence of real wage rigidity in a context of search frictions in the labour market, Jaimovich and Siu (2012) offer an explanation of the jobless recovery related to the presence of technological changes and Mitman and Rabinovich (2014) suggest that the extension of unemployment benefits during recessions can provide an insightful view about the jobless recovery.

This is also the basic structure of the benchmark model currently used to address and analyse fluctuations in the labour market variables, the search and matching model, i.e., a model in which wedges to the creation of new matches between firms and workers are produced by the presence of search frictions, then generating flows between employment and unemployment. Thus, as clearly claimed by Veracierto (2008), "*such a model basically allows to be only employed or unemployed at any point in time*".

Little interest has been showed for the third labour market state: the out-of-labour force state (i.e., the inactivity state), despite representing a large fraction of the population in the developed countries, i.e., a figure around 30-40 percent.[6]

Following the very recent contributions of Shimer (2013) and Elsby, Hobjin and Sahin (2015), new evidence about the empirical relevance of flows between inactivity and the other two labour market states has been provided. Using microdata from the Current Population Survey (CPS), Mankart and Oikonomou (2017) find that the monthly gross flow from inactivity to employment is larger than the unemployment to employment gross flow, by a factor of 1.7. They find that 5 percent of the out-of-labour force workers transition each month into the employment state (and a figure around 3 percent transition into unemployment), while 3 percent of the individuals classified as employed transition into the out-of-labour force state, while the value for the transition unemployment to inactivity is much larger, a figure around 22 percent.

However, the relevance of worker flows between out-of-labour force and the other two labour market states has been largely neglected in the analysis of the dynamics of the labour market and this was also true for the study of the labour market recovery after the Great Recession.

[6] In the literature, individuals not belonging to the most investigated labour market states, i.e., the employment and unemployment states, are defined in different terms: inactive individuals, non-participants or out-of-labour force individuals. These definitions do not identify different characteristics or properties of the individuals collected in the not-in-labour force category. Thus, I will use these terms interchangeably in all the chapters of the PhD thesis.

Much of the distrust about results coming from any analysis grounded on a framework including the out-of-labour force state, as a relevant variable explaining the dynamics of the labour market, arises from the statistical classification of individuals, in the different labour market states, used by the Bureau of Labour Statistics. Indeed, while unemployment is defined as “an active searching condition related to one of the following activities: a) contacting an employer directly or having a job interview, b) sending out resumes or filling out applications, c) placing or answering advertisement, d) checking unions or professional registers”, out-of-labour force is defined as “the passive searching condition related generally, but not exclusively, to the following activities: a) attending a job training program or course, b) reading help-wanted ads”.

From this classification it follows that unemployed workers are considered as active individuals with a search activity that can potentially create a contact with the employer, while out-of-labour force workers are described as inactive individuals that do not work, and they are neither on layoffs (i.e., workers experimenting a temporary interruption in work) nor looking for a job. All these events prevent inactive workers from enjoying a positive probability of becoming employed.

Thus, individuals included in the inactivity state have been always considered under a twofold scenario. On the one hand, inactive individuals have been seen as a group of workers that does not display any direct impact on the labour market dynamics since this is developed around the reference framework with only the two standard labour market states, employment and unemployment. The out-of-labour force state has been basically considered as a residual category useful to determine only second-order effects for the employment state through the intermediate movement of its members in the unemployment state. In other words, it would play a role only in re-filling or re-absorbing unemployed workers over the business cycle.[7]

The motivation supporting such an approach stems from the assumption that the empirical evidence regarding worker flows from out-of-labour force to employment is a "statistical illusion". In other words, the inactivity to employment worker flow should take place through the "compulsory" intermediate transition into the unemployment state (Petrongolo and Pissarides, 2001). Thus, according to the proponents of this approach, there is no a direct flow from out-of-labour force to employment, but, instead, a movement from out-of-labour force to unemployment and, finally, to the employment state. To deal with this "misclassification" problem the concept of "time-aggregation bias" has been developed in the literature (Petrongolo and Pissarides, 2001), i.e., the failure of statistical measurements to capture the intra-monthly active searching.

On the other hand, it must be stressed how out-of-labour force workers have sometimes been seen as a group of workers that can be lumped together with the unemployed workers, bringing to the disappearance of any difference between the two states, with the former group aggregated with the latter one (Carneiro, Guimares and Portugal, 2012, and Haefke, Sonntag and Van Rens, 2013).

This PhD thesis aims at investigating the dynamics of the labour market, moving from a narrowed reference model with only two labour market states into a model with three labour

[7] Works discussing this approach are developed within a framework with endogenous labour force participation. These contributions investigate the ability of models incorporating this feature to explain the large business-cycle fluctuations of labour market variables. Examples are Garibaldi and Wasmer (2005), Haefke and Reiter (2006) , Veracierto (2008) and Ebell (2011). A shared feature of these studies is that they do not allow inactive workers to exert a job-finding activity (i.e., they do not allow inactive workers to move directly from the out-of-labour force state to employment). Finally, one must acknowledge the presence in the literature of contributions replicating the worker flows between all three labour market states, but not directly investigating the behavioural differences between out-of-labour force and unemployment. Examples are Kim (2008), Pries and Rogerson (2009), Moon (2011).

market states. Thus, the primary goal of the thesis is to contribute to the development of a framework describing the behaviour of the labour market variables consistent with the empirical evidence regarding worker flows, i.e., including the presence of the out-of-labour force state alongside with employment and unemployment. Then, by analysing the dynamics of the out-of-labour force in comparison with the other two labour market states, i.e., the employment and unemployment states, the main goal is to investigate whether out-of-labour force and unemployment are undifferentiated or distinctive labour market states.

The choice of making use of the search and matching framework to investigate the issue of inactive workers comes from the ability of this kind of set-up in dealing with equilibrium labour market participants in the different labour market states. A quite well understood feature of the standard real business cycle model is that this kind of model does not allow movements of workers from and into the out-of-labour force state. More precisely, the benchmark real business cycle model adopts the basic assumption of fixed labour force size, and given the baseline labour market structure of this model, i.e., a structure with only two states: employment and unemployment, this implies that there is no room for the out-of-labour force state. Furthermore, in this model holds the key assumption of frictionless markets, which implies the non-existence of equilibrium unemployment or inactivity.

On the contrary, the search and matching model allows for endogenous movements in the labour force size (i.e. the labour force size is not fixed). More precisely, the search and matching framework allows for unemployment and out-of-labour force fluctuations and consequently it creates room for agents' decisions involving worker flows between not only employment and unemployment, but from and to out-of-labour force as well. Thus, this model allows for a role for the inactivity state.

Compared to the standard real business cycle models, the presence of search frictions in labour market models substantially modifies the behaviour of a business cycle model since it leads to more than sufficient amplification and propagation in comparison with the data. Indeed, search and matching models are able to reproduce consistently second moments for variables such as labour force participation rate, out-of-labour force, inactive job-finding rate and wage of newly hired workers coming from the out-of-labour force state.

In theory, a different approach to the study of the behaviour of inactive workers could be developed, by using, for example, a framework with heterogeneous agents, just following the work of Lucas and Rapping (1969). In the model developed by these authors, worker flows between three labour market states could be rationalised in terms of optimal individual's labour supply response to movement in the prices (i.e., shocks to wages). However, previous empirical studies like Ham (1982) have clearly showed how non-employment spells could not be interpreted as optimal labour supply response.

Some empirical evidence, suggesting unemployment and out-of-labour force are not homogeneous states, comes from the work of Elsby, Hobjin and Sahin (2015). These authors describe the effect of the non-participation margin on the cyclical behaviour of unemployment during a recession. Based on U.S. data from the CPS, they show that using the benchmark framework with only worker flows between two states, i.e, employment and unemployment, is misleading in interpreting the volatility of the unemployment rate. Indeed, the presence of the unemployment to out-of-labour force and the out-of-labour force to unemployment flows account for one-third of the overall cyclicality in the unemployment rate, with a more substantial role for the former flow. Choi, Janiak and Villena-Roldan (2015) investigate the behaviour of transition probabilities between three labour market states using a life-cycle framework for the U.S. economy. They find that the behaviour of inactive workers plays a relevant role in shaping the low participation rate of older workers. However, and more interestingly, they find that a model with two labour market states, i.e., a model excluding the out-of-labour force state, cannot generate empirical transitions between employment and unemployment if inactive workers and unemployed workers are behaviourally different individuals, i.e., distinct behavioural equations govern transitions in and out of these labour market states. Indeed, abstracting from the inactivity state in replicating empirical worker flows would require flows between employment and unemployment through the out-of-labour force state (indirect flow) need to be equal to direct flows between these two states, implying what the authors call the “inactivity irrelevance condition”, a condition that might be satisfied only if inactive workers and unemployed workers are behaviourally not different groups of individuals. However, as said above, this is an assumption difficult to be supported. Furthermore, grouping together unemployed and out-of-labour force workers makes the model informationally inefficient regarding the behaviour of unemployed workers, given that the size of the inactivity state is much larger than that of the unemployment state, making the aggregate transition (i.e., the combination of out-of-labour force and unemployment) resembling that of the out-of-labour force.

To the best of my knowledge, the only study investigating the behaviour of out-of-labour force and unemployment states as different labour market states is Flinn and Heckman (1983). In their empirical analysis, they test the hypothesis of considering the distinction between transition from unemployment to employment and the transition from out-of-labour force to employment as not significant, and their results reject this hypothesis, i.e., there are significant differences between the two transition rates. This result brings the authors to argue that two different behavioural equations characterize the transitions from out-of-labour force to employment and from unemployment to employment. Hence, a three state labour market model cannot be reduced to a two state labour market model, aggregating unemployment and out-of-labour force into a single non-employment state. However, they conclude that “*unemployment is a state that facilitates the job search process*”, thus they interpret their findings still supporting the view that out-of-labour force is a labour market state, which is “subordinated” to the unemployment state, in describing the transition of individuals into the employment state.

The importance of testing this assumption, i.e., the hypothesis that out-of-labour force and unemployment are distinct labour market states, stems from the normative implications of this analysis. If the two labour market states are made up by the same kind of individuals, then it would make sense to assimilate them or to group them together in the non-employment group. However, if this assumption does not hold, then it is methodologically flawed to work with a homogeneous group of non-employed individuals so as to remove one group from the analysis of the dynamics of the labour market. The presence of heterogeneity between the unemployed and the inactive workers should lead to the implementation of more adequate macro-models, in order to explain the cyclical behaviour of labour market variables. Indeed, much of the analysis regarding the behaviour of the labour market variables using the search and matching model has been developed inside the theoretical framework with a representative agent model, but, if the two labour market states identify different individuals, it seems more appropriate to shift towards an approach using a heterogeneous agents model in dealing with this issue.

Therefore, a crucial point is to try and provide an answer to the following questions: is it crucial to distinguish between these two groups of workers and why? Whilst much of the recent research has analysed and developed models with heterogeneous agents, this has been done in terms of generating models able to reproduce the empirical cross-sectional distributions for variables such as wealth, reservation wages and hours worked, using a framework with *ex-post* individual heterogeneity, following the seminal paper of Krusell and Smith (1998), together with Huggett (1993) and Aiyagari (1994). My work is still interested in the presence of heterogeneity between agents, but the approach is developed looking at the existence of *ex-ante* heterogeneity as well. Then, I return back to the initial question: does this form of heterogeneity matter? To answer to this question, I rely on four studies that have faced different issues from the ones investigated in this paper, but whose conclusions reflect the substantial improvements that can be obtained through more realistic models in terms of comprehension and analysis of the economic behaviour of micro- and macro-aggregates.

Guvenen (2009) builds up an asset pricing model, with two different types of agents, and where a crucial role is played by the limited stock market participation and heterogeneity in the intertemporal elasticity of substitution (EIS), i.e. the response of growth rate of consumption to changes in the real interest rate. The rationale for such a model raises from the failure of previous macro-finance models to replicate both real business cycle and asset pricing facts. However, exploiting previous evidence provided by Mankiw and Zeldes (1991), regarding the more volatile consumption growth for stockholders, compared to that of non-stockholders, Guvenen (2009) studies the properties of a model with the presence of heterogeneous values for the EIS among these two groups of workers: stockholders and non-stockholders. In this setting, non-stockholders have a lower EIS compared to that of stockholders, as suggested by empirical studies using micro-level dataset (Vissing-Jorgensen, 2002). This heterogeneity in the EIS between stockholders and non-stockholders is crucial, in order to replicate empirical moments for the model. Indeed, it allows to explain the presence of a smooth consumption growth rate, with a large countercyclical equity premium. Due to the large value of EIS for stockholders, these agents can afford to insure non-stockholders, who demand for countercyclical consumption smoothing. However, they require a larger premium to bearing the burden of insuring non-stockholders and this implies a large equity premium, mirroring the high value empirically observed. On the other side, since they represent only a small fraction of the overall population, the large volatility of consumption for this group does not deeply affect the aggregate consumption volatility. Indeed, the latter mirrors the consumption volatility of the non-stockholders, who are the largest group in the economy. Thus, the presence of two groups of agents, and allowing for individual heterogeneity in the EIS between them, explain the volatility of aggregate variables, such as consumption and investment, and asset price facts, such as the equity premium puzzle. In contrast, the representative agent model is not able to replicate all of these facts.

Mankart and Oikonomou (2017) consider a model with search frictions in the labour market and incomplete financial markets, allowing for joint household search. In their model, the job search decision is no more the choice made by a household represented as a single-unit agent, but it is the result of a choice made jointly by the two individuals the household consists of, i.e., wife and husband. Joint search theory is usually built upon the idea that the search decision is the result of an interaction process between the members of the household. The authors take into account the failure of previous models to jointly explain the behaviour of the aggregate employment (procyclical), unemployment (countercyclical) and labour force participation (acyclical). They propose a model in which labour market outcomes are the result of a risk-sharing mechanism at the family level. Indeed, they assume that the aggregate unemployment risk can be self-insured at the family level, by adjustments at the labour supply from the other member of the household, who is not affected by the negative shock. However, this result is possible when the household is made up of two ex-ante heterogeneous individuals, in terms of different search technology, separation probability, value of leisure and potential earnings. The specification with ex-ante identical identical agents, i.e., the representative agent model, is not able to replicate the empirical moments, since the joint decision, at the household level, regarding the time they flow in and out-of-labour force in order to insure the household against unemployment risk, is not differentiated between agents.

Chang and Kim (2006) investigate the macro and micro differences in the labour supply elasticities as a function of the reservation wage and the wealth distribution. They study a model with incomplete financial markets and labour supply decisions, populated by a continuum of households, each of them consisting of two individuals, i.e., husband and wife, who have different market productivity. Results from this model show that the response of individuals, in terms of aggregate labour supply elasticity, is a value around one, which is larger than the standard micro-level estimates, but well below the values obtained in the representative agent model. Crucial to derive the more realistic aggregate labour supply elasticity is the cross-sectional distribution of the assets and reservation wages, a finding that the representative agent model cannot produce given the presence, in that case, of an environment with identical agents.

Jaimovich and Siu (2012) present a model accounting for both job polarization and jobless recovery. They show how a search and matching model with two groups of agents, differentiated in terms of skills, can capture both phenomena. Introducing high-skilled and medium-skilled workers to identify a distinction between cognitive and non-cognitive tasks performed by these workers, they illustrate how a negative aggregate productivity shock can bring about the disappearance of jobs for middle-skilled workers. Indeed, after the negative aggregate productivity shock occurs, the value of the match for high-skilled workers tends to increase compared to that of middle-skilled workers. This implies middle-skilled workers start to train themselves, in order to search for a job in the labour market segment for high-skilled workers, but when this happens the jobs for middle-skilled workers disappear and job polarization occurs. Furthermore, given the presence in the middle-skill jobs of low-productivity workers unable to transition into the high-skilled segment, the surplus in the matches, i.e., the rent obtained as difference between the value of a match and the value functions for unmatched individuals, related to those workers falls and consequently these jobs are subject to a higher rate of destruction. However, the transition of middle-skilled workers into the group of high-skilled workers brings about an increase in the output and a recovery of the economy. However, with a low job-finding rate for jobs related to routine tasks, jobless recovery occurs. Thus, the employment dynamics in this model are driven by the skill heterogeneity between workers.

Whether or not the framework with heterogeneous agents, e.g. Guvenen (2009), is relevant for our analysis can be understood when one thinks in terms of a representative versus a heterogeneous agent model, in an environment including both unemployed and out-of-labour force individuals. If new hires from unemployment show a different procyclicality of their wages compared to new hires from out-of-labour force, as it will be investigated in Chapter 3, and if the probability of transitioning into the inactivity state is different from the probability of transitioning into unemployment, as it will be investigated in Chapter 4, it can be thought of these two groups of individuals as belonging to distinctive labour market states. This would lead us to conclude that the representative unemployed individual might be different from the representative inactive worker. In that case, the current approach in the search and matching literature, using a model including only the representative unemployed individual would be methodologically inconsistent. A significant difference in the behaviour of the inactive and the unemployed workers would imply that any theoretical framework explaining the dynamics of the labour market should also include the representative inactive worker, as well. However, any aggregation between the representative unemployed and the representative inactive worker would represent a shift from the theoretical framework of the representative agent model to that of heterogeneous agents model.

The consequences of the presence of heterogeneity between unemployed and inactive workers are better explained if one thinks about the impact of this differentiation on the labour market variables. For example, in terms of job-finding rate, in the basic search and matching model, one takes into account only the representative unemployed individual. However, the empirical evidence on gross worker flows suggests that the job-finding rate is determined not only by unemployed workers looking for a job, but also by out-of-labour force workers. Cole and Rogerson (1999) was among the first to explicitly state the difficulties of replicating the empirical volatility for this variable without tracing back to the presence of flows into employment from out-of-labour force.

Furthermore, despite the fact that inactive workers fill positions advertised by the firms, it is not clear what is the mechanism behind the hiring process. In other words, it is not clear if vacancies are advertised for both unemployed and out-of-labour force workers, or whether there exist different criteria, such as sorting or ranking between them, which inform the decision of the firms. Assuming the extreme scenario of ranking, in a manner in which the majority of vacancies are posted only for unemployed workers, then the variable vacancy would be mainly driven by the unemployed group. However, the job-finding rate would be mainly driven by the out-of-labour force state given gross flow from out-of-labour force to employment is roughly twice as large as the gross flow from unemployment to employment. Then, the final stage of this process would be that the representative newly hired and the representative vacancy would be determined by two separate groups of workers, and the cyclical properties for the representative hired might be very different from those of the representative vacancy.

In terms of results, in Chapter 2 I show that a three labour market state model is able to generate large volatilities for key labour market variables and replicate the most relevant empirical worker flows.

Previous papers have investigated the business-cycle moments of a two-states frictional labour market model, but they have been unsuccessful in reproducing the large volatilities of key labour market variables such as vacancies, job-finding rate and unemployment. Different solutions have been proposed such as wage rigidities (Shimer, 2005), institutional factors (Hall, 2005), small rents (Hagedorn and Manovskii, 2008), asymmetric information on worker productivity (Kennan, 2010). However, some authors have examined the business cycle performance of models including as an additional feature the endogenous labour force participation, i.e., the model assumes participation to labour market is not fixed (restrict to employment and unemployment). Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Veracierto (2008) and Campolmi and Gnocchi (2016) are examples of this strand of research. However, the models of these authors do not allow for inactive workers to direct transition into employment, hence inactive workers cannot be part of the large group of job searchers and cannot fill a vacancy. Such models allow only to the group of unemployed workers to flow directly into employment after a successful searching period.

The benchmark model developed in Chapter 2 is able to replicate 50 percent of the empirical unemployment volatility, a result that constitutes a substantial improvement compared to the usual values (close to one-tenth the empirical analog) obtained by standard search model. The model is also able to generate large fluctuations for the job-finding rate, vacancies and vacancy-searchers ratio, with values that represent around 50-60 percent of their empirical counterparts. Moreover, the model performs well in replicating the empirical value for the Beveridge Curve, since the simulated value obtained is close to 70 percent of the empirical counterpart.

Furthermore, I am able to replicate the empirical values for the most relevant worker flows. Indeed, the model is successful in reproducing the out-of-labour force to employment flow, a statistical measure that previous papers have failed to match. The model is also able to explain 60 percent of the employment to unemployment worker flow, 70 percent of the unemployment to employment worker flow and 65 percent of the employment to out-of-labour force worker flow, even if the model shows some drawbacks in replicating the two worker flows between unemployment and out of labour force. In this case, the model overpredicts the flows by a factor close to 50 percent.

The reasonable performance of the model in replicating volatile second moments relies on two channels. The first channel is the existence of frictions in the "full discovery" of the new value of the idiosyncratic variable. Indeed, the model is specified such that the value for home productivity is “common knowledge” for all the agents only at the end of the period, even if the new draws occur at the beginning of the same. This implies that after a positive aggregate productivity shock, this is a good moment for firms to open new vacancies and for workers to accept jobs offered to them. Hence, new matches between firms and workers occur. However, some of these new matches are destroyed at the end of the current period, after workers have full knowledge of the new draws of home productivity, given that a high draw of h_t would bring the worker to quit the job. Since firms are forward-looking agents, they know a fraction of newly formed matches will be destroyed for the newly matched job-finders drawing high values of home productivity, and they will increase the number of vacancies posted on the market. This produces large fluctuations in vacancies, and it brings to large fluctuations for the other labour market variables as well. The second channel is the introduction of a third margin, i.e., the inactive workers. Indeed, it allows to redefine the mass and the flows of workers between the three labour market states.

In Chapter 3, I show that real wages for newly hired workers coming from out-of-labour force behave differently, over the cycle, from the real wages of newly hired workers coming from unemployment. I investigate the cyclical behaviour of real wages by estimating a wage equation in terms of the response to some aggregate cyclical indicators, specifically the unemployment rate and the aggregate labour productivity. In this exercise, I move one step forward compared to the standard empirical specifications of previous models. Indeed, prior studies, apart from the established interest in the standard categories of workers such as ongoing workers and job changers, have focused on either individuals classified as unemployed or individuals gathered into a large “black-box”, i.e., the non-employment state, to study the cyclical behaviour of real wages. I propose a new approach in investigating this relationship by disentangling the group of non-employment in the unemployed and the out-of-labour force workers and I estimate the cyclicality of real wages not only for individuals belonging to the unemployment state, but also for individuals classified as inactive workers.

Previous works investigating the cyclical behavior of real wages have found a large procyclicality for the wage of newly hired workers, while a substantial lower cyclicality has been observed for the overall wages, a result suggesting real wages of job stayers are less responsive to the cycle. More in details, Haefke, Sonntag and Van Rens (2013), using data from Current Population Survey for the U.S. economy, show how the real wages of new hires is more sensitive than the real wages of ongoing workers to labour productivity shocks. They find percentage values for the elasticity of real wages for new hires in the interval 0.8-0.9, compared to values close to 0.2-0.3 for the elasticity of real wages for job stayers. Kudlyack (2014), who uses data from the National Longitudinal Survey of Youth for the U.S. economy, finds similar values to those in Haefke, Sonntag and Van Rens (2013).

Using data from the "Quadros de Pessoal", an employers/employees longitudinal dataset for the Portuguese economy, Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012) find that the real wages of newly hired workers, using the unemployment rate as the aggregate cyclical indicator, is strongly procyclical. Carneiro, Guimares and Portugal (2012) find a value for the semi-elasticity of real wage for marginal workers of 2.20 percentage points, while Martins, Solon and Thomas (2012) find a value of 1.60 percentage points, assuming a fall of one percentage point in the unemployment rate. Both values are larger than the semi-elasticity of wage for job stayers. When the aggregate labour productivity is taken into account as the reference cyclical indicator, Carneiro, Gumares and Portugal (2012) find a value for the elasticity of real wage close to 1.10 percentage points, while Martins, Solon and Thomas (2012) find a value close to 0.50 percentage points. Both values are larger than the analog value for the job stayers. On the contrary, Gertler, Huckfeldt and Trigari (2016) investigating the relationship between real wages and unemployment rate, using data from the Survey of Income and Program Participation (SIPP) over the period 1990-2012, for the U.S. economy, find that the strong procyclicality of real wages of newly hired workers coming from unemployment disappears when job to job movements are taken into account. Indeed, they find a value for the semi-elasticity of real wages equal to 0.155 percentage points, very close to 0.160 reported for job stayers, while the semi-elasticity of wages for job changers is equal to 1.90 percentage points.

However, the controversy in the literature between these two different approaches has been developed along a sharply stylized definition of the labour market, i.e., one with only two labour market states: employment and unemployment.

Using data for the U.S. economy, from the Survey of Income Participation Program, over the 1996-2013 period, I document the large presence of direct flows of workers from the out-of-labour force state to the employment state and I estimate a model where it is allowed for entry wages for marginal workers coming from both unemployment and out-of-labour force. I identify four different groups of workers: job stayers, newly hired workers from unemployment, newly hired workers from out-of-labour force and job changers, with this last group being defined as, respectively, (i) individuals making a job to job transition with a monthly break between consecutive spells of employment, and (ii) individuals making a job to job transition with weekly's (shorter than one month) break between consecutive periods in the employment state.

Estimating the model according the two different approaches used in the literature, i.e., the one proposed by Carneiro, Guimares and Portugal (2012), allowing for staggered wages (they assume wages are set one year in advance), which is labeled as CGP model, and the other one used by Gertler, Huckfeldt and Trigari (2016) that use higher-frequency data, which is labeled as GHT, I find, for the case with non-employed workers grouped together in one large "non-employment" state, a value for the semi-elasticity of real wage for job stayers and marginal workers close to 0.20 and 0.227 percentage points, when I use the GHT specification, and values of 1.452 and 1.704 percentage points, with the CGP specification. Then, the real wages for marginal workers are more procyclical compared to the wages for the job stayers. Introducing the distinction between marginal workers from unemployment and marginal workers coming from out-of-labour force, I find percentage values for the semi-elasticity of wages for marginal workers coming from unemployment and out-of-labour force, with the GHT specification, of 0.194 and 0.328 percentage points, compared to 0.204 for job stayers, and percentage values of 1.575 and 2.201, compared to 1.454 for job stayers, when the CGP model is used. This implies that there exists a substantial wedge between the two measures of the semi-elasticity of real wages for the new hires belonging to the two different groups, with the real wages for new hires coming from out-of-labour force more procyclical than the real wages for new hires coming from unemployment. When job changers are introduced in the model to control for the presence of individuals making job to job movements able to explain the large procyclicality of real wages of newly hired in the context of a "cyclical job-upgrading" environment, I find estimates of 0.317 percentage points for new hires from out-of-labour force and 0.194 percentage points for new hires from unemployment, when the GHT approach is used, and estimates of 2.222 and 1.610 percentage points for the semi-elasticity of real wage of new hires from, respectively, out-of-labour force and unemployment, when it is used the CGP model. Furthermore, it can be also observed that there is evidence of a larger procyclicality in the real wages of job changers, with values of 0.373 and 2.342 percentage points. To test the robustness of this empirical analysis, I repeat this exercise using the aggregate labour productivity as the cyclical indicator and I find that the elasticity of real wages of newly hired workers from unemployment is equal to 0.945 percentage points and for the newly hired workers coming from out-of-labour force is equal to 1.006 percentage points, for the GHT specification, while it is equal to 0.991 and 1.055 percentage points, respectively, for newly hired from unemployment and out-of-labour force, with the CGP model.

In Chapter 4, I show that wealth exerts a significant impact on the probability of transitioning in the non-employment states. More precisely, in this study I investigate how wealth can affect the “exit margin” for an individual in the labour market, i.e., the probability for individuals to transitioning into unemployment and out-of-labour force.

Researchers have shown that search and matching models including idiosyncratic home or market productivity shocks are able to replicate labour market transitions, but these models are usually developed in a framework with only two labour market states and with risk neutral agents. However, if one considers the transition into the non-employment states as the start of a new search activity, a not fully addressed question is: what can finance this search? In this sense a crucial role emerges for wealth. While a few papers (Bloemen and Stancanelli, 2001, and Algan, Chevron, Hairault and Langot, 2003) have examined whether wealth can finance active search, i.e., searching while individuals are in the unemployment state, no answer has been given to the question whether wealth can finance passive searching, i.e., searching while individuals are in the out-of-labour force state. In this work, I test the presence of heterogeneity in the exit margin, i.e., the existence of differences between the probability of transitioning into unemployment and the probability of transitioning into out-of-labour force. I develop this analysis by using the transitory-permanent decomposition wealth effect.

Using data from the Survey of Income Participation Program for the U.S. economy, over the period 1996-2013, I estimate the impact of wealth on the transition probabilities. I find that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and the probability of transitioning to unemployment, but values for the former transition probability are nearly twice as large as those for the latter. On the other side, I find that a permanent increase in wealth has a negative impact on both transition probabilities, with the coefficient for the transition probability to out-of-labour force much larger than that for the transition probability to unemployment. More precisely, I find that a transitory increase in individual wealth by $ 100,000 dollars increases by 50 percent the probability of transitioning to out-of-labour force and by 30 percent the probability of transitioning to unemployment. On the contrary, a permanent increase in individual wealth by $ 100,000 dollars decreases by 60 percent the probability of transitioning to out-of-labour force and by 40 percent the probability of transitioning to unemployment. Using as main regressor a broader definition of wealth (including all other forms of wealth reported in the dataset such as real estate property assets and life insurance policies) the estimates confirm that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and unemployment, while the sign is reversed for the permanent effect. However, coefficients are in this case roughly 50 percent lower than in the benchmark case.

Testing the robustness of our results by including in the model specification indicators of more illiquid forms of wealth such as home ownership, mortgaged home or other variables related to housing wealth, I find no substantial changes in the effect of wealth on the transition probabilities.

Controlling by gender, one can observe that a transitory increase in wealth makes males more likely to transitioning into out-of-labour force rather than in unemployment, while the effect is reversed for females, where an increase in wealth makes this group of individuals more likely to transitioning into unemployment. When it is considered the permanent effect of an increase in wealth, I find that males are less likely to transitioning into out-of-labour force than to unemployment and the same qualitative indication holds for females, even if the difference between the two coefficients is very small.

However, when I control for salary income, I find that estimates for the variable wealth confirm the standard qualitative results with the positive impact of a transitory increase in wealth on the probability of becoming inactive and unemployed, and a negative impact on the transition probabilities for the case of the permanent increase in wealth, but one can see that quantitatively the effect of wealth is now quite different from previous results. Indeed, I find that a transitory increase in wealth increases the probability to transitioning into out-of-labour force only by 20 percent, and the probability to transitioning into unemployment by roughly 12 percent. The values are negative and much lower for the permanent effect, 12 percent and 4 percent.

Similar results are reported when I control for both gender and salary income. Looking at the coefficients, I find that a temporary increase in wealth for males rises the probability of transitioning into out-of-labour force by 27 percent and that to transitioning into unemployment by 8 percent, while for females the values are 16 percent and 18 percent, respectively. Examining the effect of a permanent increase in wealth, I find in this case a fall in the probability of transitioning into the inactivity state by 18 percent compared to the value of 7 percent for unemployment for males, while the values are 7 percent and 5 percent for females.

Figure 1.1

Current Population Survey (CPS): Unemployment rate U.S

Figure 1.2

Current Population Survey (CPS): Employment-population ratio U.S

Figure 1.3

Current Population Survey (CPS): Employment-population ratio men U.S

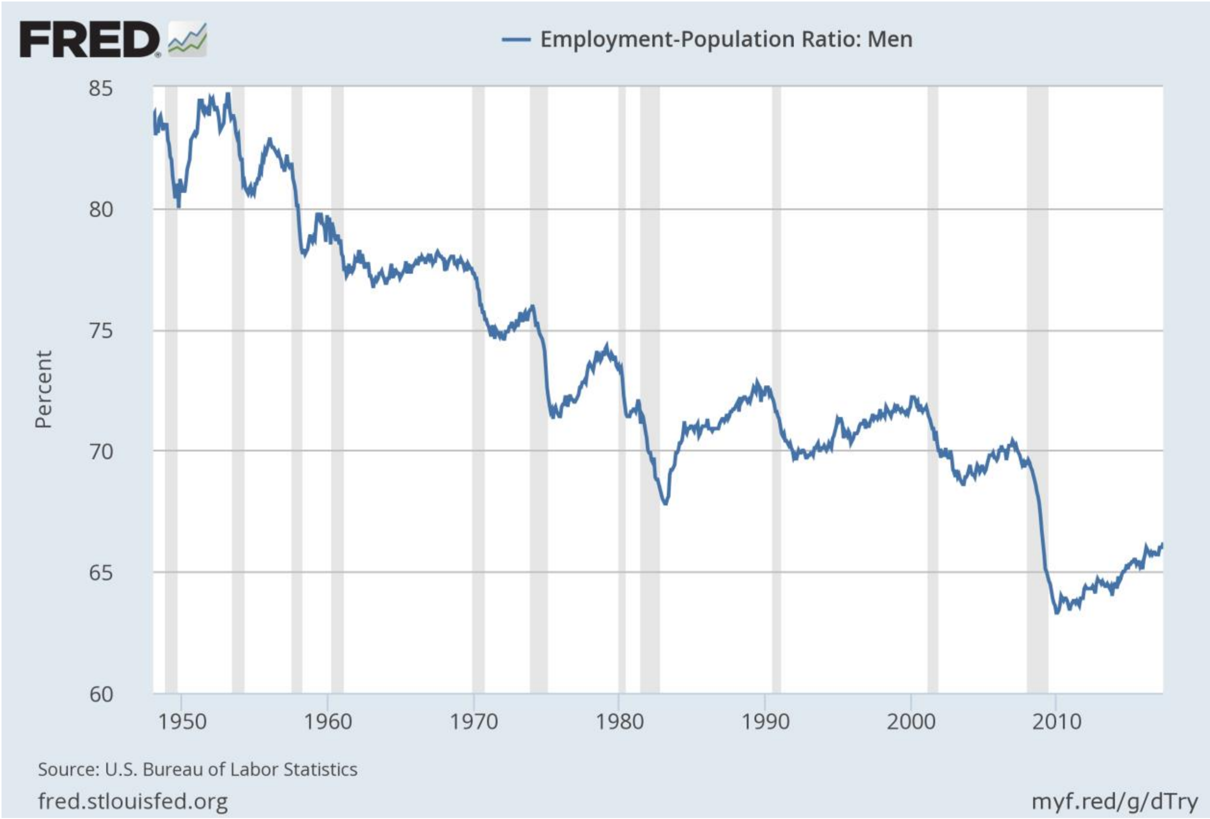
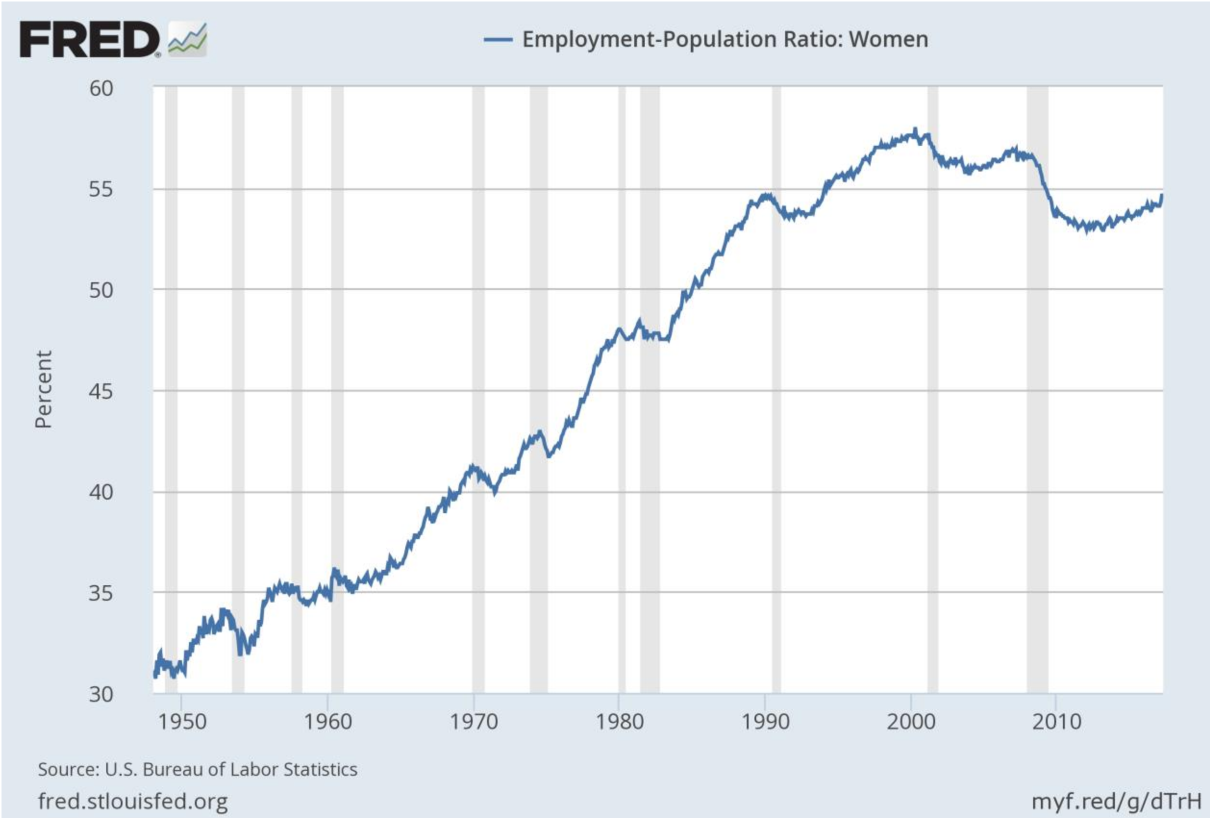


Figure 1.4

Current Population Survey (CPS): Employment-population ratio women U.S



Chapter 2:

DO OUT-OF-LABOUR FORCE WORKERS MATTER FOR THE CYCLICAL BEHAVIOUR OF THE LABOUR MARKET AGGREGATES?

Structure:

2.1 Introduction

In the last three decades, starting with the seminal papers of Merz (1995) and Andolfatto (1996), a growing body of the literature in labour economics has investigated the business-cycle moments of a standard dynamic stochastic general equilibrium model where the classical Walrasian labour market environment is substituted out by a frictional labour market, based on the search and matching model, as developed by Mortensen and Pissarides (1994). Results show how this approach has been initially successful in explaining a large set of macroeconomic aggregate facts, especially some labour market statistics that previous models have not been able to replicate. However, as Shimer (2005) and Costain and Reiter (2008) show in their papers, the empirical validity of this theoretical model is quite questionable when a basic search model, with exogenous separation rate and no intensity in search, is taken into account. Indeed, this framework does not fit quantitatively well with the cyclical fluctuations of labour market variables. The negative correlation between vacancies and unemployment (the so-called Beveridge curve) disappears and the volatility of labor market aggregates falls short of their empirical counterparts. This is particular true for the unemployment volatility, giving rise to the famous Shimer's puzzle. Several attempts have been since made to provide further support to the empirical validity of the search model, with different specifications of the model able, to a certain extent, to reproduce the empirical large volatilities of unemployment, vacancies and job-finding rate, together with a realistic negatively-sloped Beveridge curve. To solve this puzzle, that was in the spotlight of the recent search literature, researchers have focused on the behavior of aggregate real wages. Indeed, the standard search and matching model shows a substantial procyclicality of the aggregate real wages, while the equivalent in the data is almost acyclical. The strong procyclicality of the wage would operate as an instrument reducing the firms' incentive to increase the number of opening vacancies after a positive productivity shock, because it would be directed towards an increase in the wage and this would decrease the potential future profits of the firms and, consequently, their willingness to open new vacancies. To overcome these problems, a form of wage rigidity has been proposed as a possible solution (Shimer, 2004, Hall, 2005). However, this explanation basically relies on a definition of aggregate wage rigidity, which is not shared by most recent contributions on this topic. Rudanko (2009) investigates, in a directed search environment, the ability of a micro-founded rigid aggregate wage model to explain the volatility of unemployment, vacancies and their negative correlation. She micro-founds the aggregate wage rigidity by assuming both workers and firms engage in self-enforcing contracts (i.e., long-term wage contracts) and she finds that the resulting low volatility of aggregate wage is not able to explain any of these variables, suggesting to devote more attention to the wages of marginal workers, in the firm's hiring process, since this is the forward-looking variable firms are interested in when they choose to advertise new vacancies.

However, focusing on the newly hired workers' wage elasticity and its suggested rigidity, as the crucial variable able to explain this broad range of aggregate labour market facts, has come to be questioned in some recent contributions on the subject. In two independent papers, Pissarides (2009) and Haefke, Sonntag and Van Rens (2013) state that the wage of marginal workers is not rigid, but very sensitive to the aggregate productivity shock. While Pissarides (2009) presents his results by surveying the literature on the topic, Haefke, Sonntag and Van Rens (2013) empirically investigate the degree of elasticity of the wage of marginal workers and they find that this type of wage reacts strongly, usually with a value close to one, to labour productivity shocks, differently from the wage of ongoing workers, which is quite rigid. Kudlyack (2014) confirms these results. Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012) also show that there this empirical evidence supporting the assumption of the presence of elastic real wages for newly hired workers.[8]

According to this analysis, it seems that the wage of marginal workers is not the appropriate form of wage to be taken into account to explain the Shimer's puzzle, since its procyclicality comes at odds with the necessary large degree of rigidity required to replicate the data.[9]

Challenging this literature, focused on the rigidity of aggregate wage as a solution to the Shimer's puzzle, Hagedorn and Manovski (2008) show how it is possible to rationalize the cyclical volatility of labour market variables in an environment where wages are still flexible. Basically, they show that a model allowing for little rents from employment is successful in getting this result. Indeed, in this setting, workers receive a flow output from unemployment, reflecting the value of insurance, leisure and home production, which is roughly equivalent to 95 percent of their earnings when employed.[10] Then, small shocks to the value of new employment relationship translate into large percentage shocks to rents from employment that can yield large fluctuations in vacancies and unemployment.

However, this solution relying on a high constant level of opportunity cost of employment is not supported in the data. Chodorow-Reich and Karabarbounis (2016) show in their paper that the opportunity cost of employment (apart from being a value probably lower than what Hagedorn and Manovski (2008) propose) is not constant but procyclical, making the surplus

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[8] Both papers use the unemployment rate as main cyclical indicator, differently from Haefke, Sonntag and Van Rens (2013) that use the labour productivity as cyclical indicator.

[9] This view is challenged by Gertler, Huckfeldt and Trigari (2016). These authors, investigating empirically the procyclicality of real wages of marginal workers using data from the Survey of Income and Program Participation (SIPP), show that wages for the new hires are almost acyclical. They explain this result because of the presence of cyclical job-upgrading, i.e., the higher ages paid are the result of the improving quality of jobs offered in good times, and the presence of job changers, who are the workers enjoying mostly the successful match for these jobs.

[10] This value in Shimer (2005) and Gertler and Trigari (2009) is 40 percent, and in Hall (2005) a number around 70 percent of the employment's earnings.

relatively stable over the business cycle and eliminating any type of large fluctuation in vacancies and unemployment.

In this chapter, I test the ability of a modified Mortensen-Pissarides search and matching model to replicate the broad set of U.S. labour market statistics when a more realistic approach to the dynamics of labour market variables, in the form of heterogeneous workers and direct transitions between all the labour market states, is taken into account.

I modify the standard Mortensen-Pissarides model introducing the participation decision of non-employed in a different way from what the standard Mortensen-Pissarides model does. One common feature, in the line of research developed with search and matching models, has been to consider just workers in two labour market states: employment and unemployment, while little attention has been devoted to the third state: out-of-the-labor force, with some notable exceptions like Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Kim (2008), Veracierto (2008), Ebell (2011) and Campolmi and Gnocchi (2016). Indeed, the inactive participation margin, as suggested by some recent works (Barnichon and Figura, 2015, Elsby, Hobjin and Sahin, 2015), has to be taken into account if one wants a complete understanding of the dynamics of the labor market. Despite the out-of-labour force to unemployment transition rate is a modest figure around 2.8 percent, while the unemployment to employment rate of transition is a figure around 22 percent (Shimer, 2013, Elsby, Hobjin and Sahin, 2015), the gross flow from out-of-labour force to employment matters, since it would represent around 45 percent (according to Blanchard and Diamond, 1990) or 60 percent (according to Canon, Kudlyack and Reed, 2014, and Mankart and Oikonomou, 2017) of the overall gross flow of workers into employment. Abstracting from the out-of-labour force to employment flow would provide us with only a partial representation of the dynamics of the labour market.

The main finding of the chapter is that an otherwise standard Mortensen-Pissarides model featured by three labour market states, idiosyncratic home productivity and endogenous separation generates large volatility in vacancies, job-finding rate and labour market tightness and it is able to match the more relevant gross worker flows across the three labour market states: employment, unemployment and out-of-labour force.

Indeed, the answer of the model in terms of volatility of the key variables is enhanced by the presence of an additional margin in the characterization of the labour market framework, that is, the passive searchers margin.

To the best of our knowledge, this represents the first work successfully replicating empirical moments for the labour market variables and the worker flows. Previous attempts to produce this result have failed either in one way or the other (or both). The more evident failure of these models, in terms of reproducing worker flows, is about their ability to replicate the out-of-labour force to employment flow (see Garibaldi and Wasmer, 2005, Haefke and Reiter, 2006). As stated by Krusell, Mukoyama, Rogerson and Sahin (2012), "*one view in the literature is that a search and matching model with rigid wage formation and frictions that are entirely driven by productivity fluctuations can explain the date well. From the present perspective, such a model will likely be hard to square with labor market flows*".

The mechanism able to explain the cyclical behaviour of vacancies, job-finding rate and labour market tightness, together with worker flows, is related to the presence of frictions related to home productivity. It is assumed that the value of home productivity is drawn at the beginning of the period, but it affects the decisions of the agents when the search process is over, i.e., at the end of the period. In other words, "discovering" the new value of home productivity takes time. The presence of this friction in the adjustment of the information process for the idiosyncratic variable allows for a consistent answer in terms of number of vacancies posted in the markets by the firms, with direct effects on the job-finding rate and labour market tightness. After the aggregate and idiosyncratic productivity shocks take place, both firms and workers have knowledge of the aggregate shock, but they will discover the new value of the idiosyncratic home productivity only at the end of the period. However, as said above, this process takes time and it affects the decisions of agents only at the end of the period, when there is no further presence of search and matching activity. This implies that, on one side, firms know that with the "realisation" of the new draw of home productivity at the end of the period, a large number of workers matched in the current period could quit. Indeed, a fraction of vacancies posted this period will be still open next period, despite the match in the current period, because at the end of the current period, in the case of a new high draw of home productivity, some of the matches will be destroyed. This drives firms to advertise a large number of vacancies and it creates large fluctuations in the variable vacancy.

On the other side, workers looking for a job will accept each job is offered them since they know that at the end of the period they can quit the job conditional to the new high draw of home productivity. This drives workers to the begin of the period, to accept each job is offered them and to a large fluctuation in the job-finding rate.

However, the presence of an additional margin, the out-of-labour force state, plays a crucial role as well. Indeed, working with three labour market states helps to re-calibrate the mass of workers for each labour market state and the dynamics they are involved in. In particular, the presence of inactive workers helps to re-determine the distribution of matches not only as an effect of a direct flow from unemployment to employment, but also the direct flow from out-of-labour force to employment, as it is observed in the data.

This chapter proceeds as follows. The model is laid down in Section 2.1. In Section 2.2, it is introduced the matching model and the labour force classification. In Section 2.3, it is described the calibration strategy and perform a quantitative analysis. In Section 2.4, results are discussed. In Section 2.5, sensitivity analysis is performed of our findings is performed. Section 2.6 concludes.

2.2 The Model

2.2.1 Preferences and Technology

The model is in discrete time. It is a variant of the Mortensen and Pissarides (1994) matching model with both aggregate and idiosyncratic uncertainty, where the idiosyncratic variable refers to home productivity. It consists of a continuum of (homogeneous) firms and a continuum of workers. Workers and firms are both infinitely-lived and maximising agents. Workers have total mass equal to one and are assumed not to be pooled in the standard two labour market groups: unemployed and employed, but they are separated in three different groups: employed, active searchers and passive searchers.

This distinction comes down from a more realistic approach to labour market facts. Indeed, following the contribution of Jones and Riddel (1999) and Krusell, Mukoyama, Rogerson and Sahin (2016), it has been stressed how the empirical evidence supports the fact that there exist substantial and volatile flows of workers into the employment state not just from the unemployment state but also from what is called out-of-labour force state.

For example, Krusell, Mukoyama, Rogerson and Sahin (2016), investigating the behavior of gross worker flows using the matched Current Population Survey (CPS) data for the period 1968–2009, show a large movement of gross worker flows over the cycle.

[INSERT TABLE 2.1 ABOUT HERE]

Moreover, as stated by Canon, Kyudlack and Reed (2014), figures from Current Population Survey, for the period 2003-2014, show that the ratio of the two gross worker flows: out-of-labour force to employment and unemployment to employment, has been equal to 1.6, implying, on average, that the gross flow out-of-labour force to employment is much larger than the unemployment to employment gross flow.

Furthermore, using data from American Time Use Survey (ATUS), it is possible to infer the existence of a quite low but still positive searching activity carried out by the group of workers typically classified in the official statistics as out-of-labour force, i.e., agents not exerting any kind of active search effort in order to find a job.

Empirical data from ATUS, show that agents in the inactivity state spend in a searching activity around 40 seconds per day, much less than the time spent for the same activity by agents in the unemployment status, which is around 23 minutes per day, but pretty close to the time spent by agents in the employment status, which is around 52 seconds per day.

A suggested solution to rationalize these results comes from a careful reading of the questionnaire of Bureau of Labor Statistics (1994), which distinguishes between active and passive searching.[11] As stated in the structure of the section on the labour market conditions:

[11] The classification of individuals in the different labour market states, i.e., either unemployment or out-of-labour force, is obtained in the Current Population Survey by looking at the answer provided by each respondent in the interview, which usually takes place either the second or the third week of each month. In this occasion, it is asked to the respondent to report her employment status in the reference week. People are classified as unemployed if they do not have a job, have actively looked for work in the 4 weeks preceding the interview, and are currently available for work. Furthermore, workers expecting to be recalled from temporary layoff are counted as unemployed whether or not they have engaged in a specific job seeking activity. All persons who were not employed or unemployed during the brief reference period and hence not currently active for diverse reasons are classified as out-of-labour force. This category includes retired persons, students, those taking care of children or other family members, and others who are neither working nor seeking work. From this classification it follows that unemployed workers are considered as active individuals with a search activity that can potentially create a contact with the employer, while out-of-labour force are individuals who have no job and are neither on layoffs nor looking for one. All these events prevent inactive workers from enjoying a positive probability of becoming employed. Other studies investigating the business cycle properties of labour market models with search frictions are prone to pool together unemployed and out-of-labour force workers. Indeed, second moments for vacancies or job finding rate are computed assuming the existence of only one labour market state, i.e., unemployment, despite the fact information on both variables are used (e.g., empirical

“An active searching condition is related to one of the following activities: a) contacting an employer directly or having a job interview, b) sending out resumes or filling out applications, c) placing or answering advertisement, d) checking unions or professional registers”, while the passive searching condition is related generally, but not exclusively, to the following activities: “ a) attending a job training program or course, b) reading help-wanted ads”.

Whereas the first method of searching (i.e., active search) is the cornerstone of modern statistical methods to identify movements from unemployment to employment, less attention has been devoted to the second one (i.e., passive search). However, Montgomery (1991) shows that passive searching methods matter for the creation of labour market matches. Indeed, he reports in his work empirical evidence suggesting that 50 percent of all workers currently employed find jobs through non-active searching methods.

This evidence contradicts the idea that inactive workers have no direct access to the employment state, implying the existence of a form of searching activity for them as well.

Hence, the difference between unemployed agents and out-of-labour force agents relies on the different intensity in searching (quite significant for the agents in the former group, pretty low for those in the latter group). In order to accomplish with these empirical facts, it is introduced

flows into and out-of the inactivity state). However, this procedure used by other studies is not correct and it greatly affects the reliability of any investigation directed to test the empirical plausibility of the search model. Considering, for example, the models by Merz (1995) or Andolfatto (1996) that allow agents to search and enjoy leisure while they are unemployed but that restrict them to stay in the labour force. As it has been stressed by Veracierto (2008), if the main reason why agents become unemployed in those models is to enjoy leisure (i.e. if intertemporal substitution in leisure is the main factor driving employment fluctuations), a significant number of agents would want to leave the active labour force in order to enjoy even more leisure a transition into the inactivity state is allowed. Thus, most of the flows from employment to unemployment during a recession could end up being flows from employment to out-of-labour-force once the additional participation margin “inactivity” is included in the model, generating highly counterfactual behaviour. Lumping together unemployment and out-of-the-labor-force into a single non-employment state (as in Andolfatto, 1996) may hide similar problems. Thus, explaining together employment, unemployment and out-of-labour force dynamics is important to obtain a better understanding of the labour market dynamics.

the following classification for workers: employed, active searchers and passive searchers. In this way, it is possible to deal with a three state labour market model with search frictions.

2.2.2 The Agents

Workers have preferences defined by

$$E_0 \sum_{i=0}^{n} \beta_t \ \left(U\left(C_t^i\right) - g^i\right) \tag{1}$$

where $0<\beta<1$ is the discount factor, $U\left(C_t^i\right)$ is the utility from consumption that individuals obtain in the different labor market states, with *i* identifying, respectively, the employment state, *i*=*w*, the active searching state, *i*=*u*, and the passive searching state, *i*=*olf*. Let g^i be the participation cost (related to the activity of the workers and it is expressed in terms of the flow output from the different labour market states), while *E* is the expectational operator.

One can write:

$$g^i := \begin{cases} g^w & \text{if the worker is working} \\ g^u & \text{if the worker is searching actively} \\ g^{olf} & \text{if the worker is searching passively} \end{cases}$$

with $g^w > g^u > g^{olf}$.

The functional form of the utility function is specified as follows

$$U\left(C_t^i\right) = c_t^i \tag{2}$$

that is, there is linear utility in consumption, with

$$c_t^i := \begin{cases} c_t^w = \upsilon_t^w & \text{if the worker is working} \\ c_t^u = \upsilon_t^w & \text{if the worker is searching actively} \\ c_t^{olf} = \upsilon_t^w & \text{if the worker is searching passively} \end{cases}$$

where v_t^i is to be specified below.

It is also assumed that each worker is equipped with one unit of time to be consumed and the time constraint is defined as

$$1 = t^{n^i} + t^{h^i} + t^{s^i} + t^{l^i} \tag{3}$$

where, t^{n^i} is the time spent into the job, t^{h^i} is the time spent in home production, t^{s^i} is the time spent in the job search activity and t^{l^i} is the time spent in leisure.

Using data from the American Time Use Survey, it is assumed that:

1) t^{n^i} is the inelastic number of hours devoted to the working activity;

2) t^{h^i} is the inelastic number of hours devoted to home production, differing between employed, active searchers and passive searchers, with $t^{h^{olf}} > t^{h^u} > t^{h^w}$;

3) t^{s^i} is the inelastic number of hours devoted to searching activity, which is related just to active searchers and passive searchers, with $t^{s^{olf}} < t^{s^u}$, i.e., non-employed workers can decide to search actively or passively for a job, and this implies a different time consumption activity;

4) t^{l^i} is the inelastic number of hours devoted to leisure, with $t^{l^{olf}} > t^{l^u} > t^{l^w}$.

If everything is defined in terms of utility flows, I can write:

$$v_t^w = t^{n^w}\varpi_t + t^{h^w}h_t + t^{l^w}l_t \tag{4}$$

$$v_t^u = t^{s^u} + t^{h^u}h_t + t^{l^u}l_t \tag{5}$$

$$v_t^{olf} = t^{s^{olf}} + t^{h^{olf}}h_t + t^{l^{olf}}l_t \tag{6}$$

where ϖ_t is the hourly wage[12] and it will be determined in section 2.2.7. The risk-neutral identical entrepreneurs (or firms) have preferences defined by

$$E_0 \sum_{t=0}^{\infty} \beta^t \, c_t^E \tag{7}$$

where $0 < \beta < 1$ is the discount factor, c_t^E is consumption, which is equal to the profits, π_t, and E is the expectational operator. In a certain period a firm can be active or vacant. A vacant firm is one posting a vacant position and looking for a worker. An active firm is a firm matched with a worker and producing output, defined in terms of aggregate stochastic productivity process, z_t, that it is assumed is homogeneous for all workers. I set z_t to follow a Markov process (to be specified later on). The steady-states for the aggregate productivity and the home productivity levels are normalized to 1.

The number of vacancies posted in period t is given by v_t. Although firms can costlessly create those vacancies, each period of time they incur a recruiting cost k per vacancy posted.

2.2.3 *The Modified Matching Model*

The labour market features search frictions in the matching process between job searchers and vacancies posted by firms. Following Mumford and Smith (1999), who show that workers cannot be considered perfect substitutes in the search process, I assume that labor markets are segmented. This assumption can be justified in terms of a generalized form of directed search, making workers just searching in small segments of the labour market.

[12] In section 2.2.7, the wage is determined according to the Nash bargaining process, but I will deal with a definition of wage, denoted as ω_t, that assumes the individuals work all the hours devoted to the working activity.

Data from ATUS confirm that inactive workers are more likely to spend a large fraction of their time in the production of home goods, while unemployed devote a lower amount of time to this activity.

Then, it is reasonable to assume that individuals differ in their abilities to perform tasks related to home goods production. This implies that there exists a substantial level of heterogeneity between workers according to their different comparative advantage in terms of home productivity. Moreover, as it is showed in this study, this difference in home productivity is a long-lasting effect since it is related to the occurrence of the idiosyncratic productivity shock which is estimated to be quite persistent.

However, this information in terms of heterogeneous levels of home productivity is usually common knowledge and this means it is also shared by the firms.

Thus, it is possible to state that markets are segmented according to the different comparative advantage in home productivity. For each level of home productivity, i.e., unemployment and inactive labour market state, there is a continuum of workers with total mass equal to one, but each group of workers searches in its own segmented market.

In other words, this setup captures the idea that because of the differences in home productivity a worker can only match with vacancies opened in her segmented market.

Workers searching for a job, as explained above, are of two types: 1) active searchers, who show a higher level of search intensity and 2) passive searchers, who show a lower level of search intensity. In both cases, the search intensity is defined in terms of time (hours) spent for searching.

Firms post vacancies for the two different types of workers (i.e., active and passive searchers) in segmented markets.

The process by which workers and firms match with each other is described by a constant-returns-to-scale function of the number (measure) of vacancies and the number of job searchers of each type. Specifically, the number of matches, in each separated market, is determined by the aggregate matching function

$$m^i\left((s^i a_t), v_t^i\right) = \gamma^i {s^i}^{\alpha^i} a_t^{\alpha^i} {v_t^i}^{1-\alpha^i} \tag{8}$$

where a_t defines the job searchers (applicants), with a_t that can be either u if she is an active searcher or olf if she is a passive searcher, s^i defines the search intensity (which is defined in terms of time spent for searching and it is normalized to 1 for active searchers), v_t^i defines the vacancies posted by firms, γ^i denotes the matching efficiency parameter and α^i defines the elasticity of the matching function.

It follows from the constant-returns-to-scale assumption that the rate at which job searchers match with firms depends only on the ratio of vacancies to job searchers in each separated market,

$$\theta_t^i = \frac{v_t^i}{s^i a_t} \tag{9}$$

where θ_t^i is the tightness ratio. I let $f^i\left(\theta_t^i\right)$ denotes the job searchers' matching rate, where

$$f^u(\theta_t^u) = \frac{m^u(s^u u_t, v_t^u)}{s^u u_t} \tag{10}$$

and

$$f^{olf}\left(\theta_t^{olf}\right) = \frac{m^{olf}\left(s^{olf} olf_t, v_t^{olf}\right)}{s^{olf} olf_t} \tag{11}$$

I specify the firm's matching rate, $q^i\left(\theta_t^i\right)$, as follows

$$q^u(\theta_t^u) = \frac{m^u(s^u u_t, v_t^u)}{v_t^u} \tag{12}$$

and

$$q^{olf}\left(\theta_t^{olf}\right) = \frac{m^{olf}\left(s^{olf} olf_t, v_t^{olf}\right)}{v_t^{olf}} \tag{13}$$

2.2.4 <u>*The Timing*</u>

The timing of the events within a period is straightforward. At the beginning of the period, $t = 0$, workers are already in their own segmented sub-market. Consistent with the previous notation, I let employed be denoted as w_t, active searchers be denoted as u_t and passive searchers be denoted as olf_t.

At $t = 0$, the shocks (aggregate and idiosyncratic) occur and unmatched workers and entrepreneurs start to engage in the search and matching process.

However, it is assumed in the model that only the aggregate productivity shock, z_t, is common knowledge after its occurrence at $t = 0$, while the new value of home productivity, h_t, is fully "discovered", by both workers and firms, only at the end of the period, when the search process is over, despite the fact that the shock to home productivity occurs at the beginning of the period. Then, any decision of the workers related to the change in the value of h_t is feasible only at the end of the period and it involves only separations (i.e., movement from employment to either unemployment or inactivity state) and movements between the two non-employment states (i.e., transitions between unemployment and out-of-labour force). This is consistent with the idea there exist segmented markets (workers cannot search in different segments of the labour market in the same period).

Moreover, the importance of the draws of h_t for employed inddividuals, among the group of workers, is noticeable. Indeed, in the model, it is assumed that wages for ongoing workers are sticky, i.e., they are less elastic than the wages of newly hired workers, as it is confirmed by empirical research (Haefke, Sonntag and Van Rens, 2013, Carneiro, Guimares and Portugal, 2012, and, to a certain extent, Martins, Solon and Thomas, 2012; on the contrary Gertler, Huckfeldt and Trigari, 2016). More precisely, job stayers cannot to re-bargain their wages at the end of each period since the wage is just exogenously partly adjusted to the aggregate productivity shock. This implies that high draws of home productivity have no effects on wages already bargained. However, changes in home productivity can lead the employed workers to leave the employment status, in order to start to look for a job again but with a new, likely higher, level of home productivity, which can bring to a higher wage since the worker's outside option is higher. Hence, at the end of the period t, when the idiosyncratic shock to home productivity is common knowledge, workers can decide whether to remain into employment or separate, moving either into the active searching state or the passive searching state.

Thus, only a fraction of new matches survive at the end of period t, for them wages are bargained, but they start to produce only next period.

At the beginning of the period, $t = 0$, matches still alive from previous period are realized and after the aggregate productivity shock has occurred, these workers start to produce. Finally wages are paid.

Workers not matched with a firm, who discover the value of h_t at the end of the period, choose whether to continue to look for a job in the same labour market state in the next period, i.e., respectively active searching or passive searching, or switching labour market state (the active searchers (passive searchers) will move into a labour market state where they search passively (actively)).

2.2.5 The Equilibrium

The individual worker's and firm's problem can be formulated recursively. The state of the economy is described by the pair (z_t, h_t), where z_t is the stochastic aggregate productivity and h_t is the idiosyncratic home productivity. Fluctuations in technology are defined in terms of a discrete Markov process with transition matrix, Z, and elements represented by $\varsigma_{i,j} = prob(\varsigma' = \varsigma_j | \varsigma = \varsigma_i)$. Home productivity, h_t, is heterogeneous and stochastic. It is defined in terms of a discrete Markov process with transition matrix, Q, and elements represented by $\varphi_{l,m} = prob(\varphi' = \varphi_l | \varphi = \varphi_m)$. Let $W(z,h)$ denote the value function of an employed worker, $U(z,h)$ the value function of a worker actively searching for a job, $OLF(z,h)$ the value function of a worker passively searching for a job. Let $\mathbb{E}$ be the expectational operator with respect to the aggregate productivity state. The idiosyncratic home productivity level, h_t, is assumed to evolve stochastically over time according to a Poisson process at rate λ, i.e., next period's idiosyncratic productivity level will be equal to the current period's idiosyncratic home productivity level with probability rate 1-λ, while, with probability λ, next period's home productivity level will be switching to a new value. In the case the home productivity level switches to a new value, this will be drawn randomly according to the c.d.f. G(h) defined over the support $h \epsilon [h^{min}, h^{max}]$. The value functions can be defined as follows:[13]

$$W(z, h_{-1}) = v^{w}(z, h_{-1}) + \beta \mathbb{E}\lambda \int_{h^{min}}^{h^{max}} max[W(z', h), U(z', h), OLF(z', h)] dG(h) \tag{14}$$

$$\begin{aligned} U(z, h_{-1}) &= b^{u} + v^{u}(h_{-1}) \\ &+ \beta \left\{ f^{u}\big(\theta^{u}(z)\big) \mathbb{E}\lambda \int_{h^{min}}^{h^{max}} [W(z', h)] dG(h) \right. \\ &\left. + \Big(1 - f^{u}\big(\theta^{u}(z)\big)\Big) \mathbb{E}\lambda \int_{h^{min}}^{h^{max}} [\Lambda(z', h)] dG(h) \right\} \end{aligned} \tag{15}$$

$$\begin{aligned} OLF(z, h_{-1}) &= v^{olf}(h_{-1}) \\ &+ \beta \left\{ f^{olf}\left(\theta^{olf}(z)\right) \mathbb{E}\lambda \int_{h^{min}}^{h^{max}} [W(z', h)] dG(h) \right. \\ &\left. + \left(1 - f^{olf}\left(\theta^{olf}(z)\right)\right) \mathbb{E}\lambda \int_{h^{min}}^{h^{max}} [\Lambda(z', h)] dG(h) \right\} \end{aligned} \tag{16}$$

with $\Lambda(z, h) = max[U(z, h), OLF(z, h)]$.

Moreover, I denote $f^{u}\big(\theta^{u}(z)\big)$ as the job-finding probability for an active searcher and $f^{olf}\left(\theta^{olf}(z)\right)$ as the job-finding probability for a passive searcher.

The interpretation of the value function for the employed is quite standard. The equity value of employment is equal to the utility flow and the capital gain or loss from the re-optimization

[13] The value function for the worker is specified in very general terms in this section, but it will be recast in terms of notation when it will deal with the determination of surplus in each segmented sub-market.

after the shocks. The employed worker can choose whether to leave the employment state, after the realization of h_t. She can separate either in active searching or in passive searching.

The interpretation of the value functions for an active and a passive searchers is as follows. It is stated that the equity value of being an active searcher/passive searcher is equal to the utility flow (i.e., $b^U + v^u(h_{-1})$ and $v^{olf}(h_{-1})$, respectively, for active searcher and passive searcher, where b^U represents the unemployment benefit) and the potential capital gain deriving from finding a job, with the movement in the employment state. The active (passive) searcher can also choose either to move into passive searching (active searching), or to remain in the same state if she does not match with a firm. Put simply, both active and passive searchers face, with different job-finding probabilities, the chance to find a job and moving into the employment state with next period's value function $W(z', h)$. With probabilities $\left(1 - f^u\left(\theta^u(z)\right)\right)$ and $\left(1 - f^{olf}\left(\theta^{olf}(z)\right)\right)$, the job-finding activity is not successful and they can decide whether searching actively, $U(z', h)$, or passively, $OLF(z', h)$, next period, according to the value of h_t following the shock to home productivity.

Finally, the equilibrium condition defining the threshold value that brings workers to choose between remaining into the employment state or moving into a searching state is written as follows

$$W(z, h^*) = \Lambda(z, h^*) \tag{17}$$

and the equilibrium condition defining the threshold value that brings workers to choose between moving into active searching state or passive searching state is

$$U(z, h^{**}) = OLF(z, h^{**}) \tag{18}$$

When a value of h_t below the threshold value h^* is drawn, the employed worker will choose to stay in the employment state, while for values above h^* she will leave the employment state (endogenous separation).

When h_t is above (below) the threshold value h^{**}, the active (passive) searcher will choose to leave her own labor market state to move into the passive searching state (active searching state), while the passive (active) searcher will remain in her own labour market state.

The discussion on these equilibrium conditions in terms of effects on worker flows will be developed further in section 2.2.8

2.2.6 <u>Introducting Firms</u>

Since, I assume there exist separate markets for the different groups of workers, the choices of vacancies and wages in the labour market for a group are independent of the choices and the outcomes for the other group. The segmentation of markets implies that there are some firms posting in the sub-market for active searchers and other firms posting in the sub-market for passive searchers.

The value functions for a filled position in the sub-market for active searchers and passive searchers are, respectively, given by

$$J^U(z, h_{-1}) = z_t - \omega_t^i(z, h_{-1}) + \beta\mathbb{E}\lambda\int_{h^{min}}^{h^{max}} J^U(z', h)dG(h) \tag{19}$$

and

$$J^{OLF}(z, h_{-1}) = z_t - \omega_t^i(z, h_{-1}) + \beta\mathbb{E}\lambda\int_{h^{min}}^{h^{max}} J^{OLF}(z', h)dG(h) \tag{20}$$

where $z_t - \omega_t^i(z, h_{-1})$, with $i = u, olf$, is the net flow of profit from the filled position, and the remaining terms are the discounted expected values of the matches in the two different sub-markets, conditional to the draw of new value of home productivity.

The equilibrium number of job vacancies is determined by the free-entry conditions, which state that vacancies earn zero profits:

$$k = \beta q^u\big(\theta^u(z)\big)\mathbb{E}\lambda\int_{h^{min}}^{h^{max}} J^U(z', h)dG(h) \tag{21}$$

and

$$k = \beta q^{olf}\left(\theta^{olf}(z)\right)\mathbb{E}\lambda\int_{h^{min}}^{h^{max}} J^{OLF}(z', h)dG(h) \tag{22}$$

where k is the job posting cost, and $q^u\big(\theta^u(z)\big)$ and $q^{olf}\left(\theta^{olf}(z)\right)$ are the job-filling rates for active and passive searchers.

2.2.7 *The Wage Determination and Surplus*

When it is described how wages are determined, it is necessary to distinguish between the wage of existing workers and the wage of newly hired workers. As it has been showed in the literature (Carneiro, Guimares and Portugal, 2012, and Martins, Solon and Thomas, 2012, Haefke, Sonntag and Van Rens, 2013), the wage of newly hired workers is more elastic than the wage of existing workers.[14]

[14] In the empirical papers on this topic, when the aggregate cyclical indicator is represented by the aggregate labour productivity, the elasticity of wages of existing workers is a value close to 0.3 percentage points, while the elasticity of wages of newly hired workers presents values in the interval 0.8-0.9 percentage points for Heafke, Sonntag and Van Rens (2013), using U.S. data from the Current Population Survey. Carneiro, Guimares and Portugal (2012), using a large dataset for the Portuguese economy, the “Quadros de Pessoal”, find values close to 1 for the job stayers and equal to 0.059 percentage points for the incremental effect. Martins, Solon and Thomas (2012), using the same Portuguese dataset, find values that confirm the results in Carneiro, Gumares and Portugal (2012), with a very small incremental effect for the new hires and an overall value for the elasticity of wages close to 0.55 percentage points, When one takes into account the unemployment rate as a cyclical indicator, it is found that the semi-elasticity of wages of existing workers is a value between 1.60 in Martins, Solon and Thomas (2012) and 2.20 percentage points in Carneiro, Guimares and Portugal (2012).

In this chapter, it is assumed that the wage of job stayers, ω^{js} is determined using the formulation popularized by Blanchard and Gali (2010), i.e.,

$$\omega^{js}(z, h_{-1}) = \omega^{nhw}(z, h_{-1})z^{\tau} \tag{23}$$

Where ω^{nhw} is the average wage for newly hired workers and τ is a parameter with a value lower than one. This implies the wage of job stayers is more rigid than the one for newly hired. The wage for newly hired workers, $\omega^{nhw^i}(z, h_{-1})$, with $i = u, olf$, is determined by a generalized Nash bargaining solution that can be written as

$$\omega^{nhw^i}(z, h_{-1}) = argmax\left(W^i(z, h_{-1}) - I(z, h_{-1})\right)^{\psi} J^i(z, h_{-1})^{1-\psi} \tag{24}$$

with $i = U, OLF$ and where ψ is the worker's bargaining power (it is assumed the same value for all agents and sub-markets) and $I(z, h_{-1})$ is the threat point, which is represented by either $U(z, h_{-1})$ *or* $OLF(z, h_{-1})$. The wage is derived by assuming that a fixed fraction of the surplus accrues to the worker and the firm. The total match surplus is shared in accordance with the above Nash solution. A worker earns wages in the current period and in the subsequent periods if the match survives, but after the first period, the wage is determined exogenously, because she becomes an ongoing worker.

Finally, let $S^U(z, h_{-1})$ and $S^{OLF}(z, h_{-1})$ denote the match surplus between a worker and a firm in each sub-market. The match surplus is defined to be the sum of the payoffs of the worker and the firm:

However, the semi-elasticity of wages of newly hired workers is equal to 2.70 percentage points in the latter paper and to 1.80 percentage points in the former. A different sets of results are provided by Gertler, Huckfeldt and Trigari (2016). These authors, using data from the Survey of Income and Program Participation, a longitudinal dataset for the U.S. economy, show that the semi-elasticity of wage for job stayers is close to 0.16 percentage points, while the incremental effect can be either a positive or negative value, according to the different specification of the model, but not significant.

$$S^U(z, h_{-1}) = W^U(z, h_{-1}) - U(z, h_{-1}) + J^U(z, h_{-1}) \tag{25}$$

and

$$S^{OLF}(z, h_{-1}) = W^{OLF}(z, h_{-1}) - OLF(z, h_{-1}) + J^{OLF}(z, h_{-1}) \tag{26}$$

2.2.8 The Worker Flows

Working with a three labour market state model allows us to compute values for all the empirical gross worker flows. Workers in the employment state can decide to separate only at the end of the period t, after the new idiosyncratic value of home productivity is fully discovered.[15] However, the worker can choose to move either in active searching or in passive searching. It is assumed that a threshold value, h^*, determines the decision rule of the workers, i.e., the choice between quitting the job because they prefer to search again to obtain a higher wage and remaining in the same job. More precisely, the threshold value h^* comes from the condition

$$W(z, h^*) = \Lambda(z, h^*) \tag{27}$$

and it is to be interpreted in the standard way:

-if $h < h^*$ the worker will remain in the employment state;

-if $h > h^*$ the worker will separate.

This implies that the separation rate for workers moving into active searching is given by

[15] In theory separations can be determined by the decisions of the firms, but the model parameters are assumed such that this case does not arise in our model.

$$SR_t^{EU} = \frac{EU_t}{m_t} \tag{28}$$

and the separation rate for workers moving into passive searching is given by

$$SR_t^{EOLF} = \frac{EOLF_t}{m_t} \tag{29}$$

where m_t is the overall number of matches, EU_t is the employment to unemployment worker flow and $EOLF_t$ is the employment to out-of-labour force worker flow.

To determine the employment to unemployment and the employment to out-of-labour force worker flows, since the model is defined in terms of endogenous separation, one needs to take into account the distribution of h across the existing matches. Assuming that the surplus for the workers, is strictly decreasing in h, there exists a value h^*, such that the match is destroyed when the draw of h is greater than h^*, as explained in the section above. Since $G(h)$ is the c.d.f. for all values of h, which is assumed identical and independently distributed, the employment to unemployment worker flow and the employment to out-of-labour force worker flow are defined as follows:

$$EU_t = \lambda G(h) m_t \tag{30}$$

for $h \epsilon [h^*, h^{**})$, where h^{**} is the threshold value that determines the choice of agents to move between the unemployment state and the out-of-labour force state, as it will be further discussed below, and

$$EOLF_t = \lambda G(h) m_t \tag{31}$$

for $h \epsilon [h^{**}, h^{max}]$.

Furthermore, our model introduces the possibility to have flows between active searching state and passive searching state. This happens because it is also allowed non-employed workers to change labour market state at the end of the period after a new draw of h. This is determined by the following threshold value, h^{**}, which determines the choice of both active and passive searchers between the different labour market states in which starting to search for a job next period.

The threshold is determined by the condition

$$U(z, h^{**}) = OLF(z, h^{**}) \tag{32}$$

and its interpretation is basically the following:

-if $h < h^{**}$ the active searcher will remain in her own state and the passive searcher will move into the active searching state;

-if $h > h^{**}$ the passive worker will remain in her own state and the active searcher will move into the labour market state representing passive searching.

Thus, it is constructed the unemployment to out-of-labour force, $UOLF_t$, and the out-of-labour force to unemployment, $OLFU_t$, worker flows. I can write

$$UOLF_t = \lambda G(h) u_t \tag{33}$$

for $h \epsilon [h^{**}, h^{max}]$, and

$$OLFU_t = \lambda G(h) olf_t \tag{34}$$

for $h \epsilon [h^{*}, h^{**})$. Lastly, it is possible to measure the job-finding rate and the number of new hires related to the unemployment to employment, UE_t, and the out-of-labour force to employment, $OLFE_t$, worker flows.

I can write

$$JFR_t^{UE} = \frac{\gamma^u {s^u}^{\alpha^u} u_t^{\alpha^u} {v_t^u}^{1-\alpha^u}}{s^u u_t} \tag{35}$$

and

$$JFR_t^{OLFE} = \frac{\gamma^{olf} {s^{olf}}^{\alpha^{olf}} olf_t^{\alpha^{olf}} {v_t^{olf}}^{1-\alpha^{olf}}}{s^{olf} olf_t} \tag{36}$$

which are the two matching functions related to the two segmented markets. Finally the flows of new hires are measured by the following worker flows

$$UE_t = m_t^u u_t \tag{37}$$

and

$$OLFE_t = m_t^{olf} olf_t \tag{38}$$

2.3 Simulation and calibration

2.3.1 *The Solution Method*

To solve the model I use the free-entry condition and the equations for surplus together with the equations describing the aggregate and idiosyncratic laws of motion. The aggregate stochastic productivity, z_t, is a Markov process. I assume a 21-state process, whose vector of values, ς, and probability transition matrix, Z, is chosen to approximate an AR(1) process with autocorrelation, $\rho(z)$, and standard deviation, $\sigma(z)$. The Tauchen's method is used to represent it. The idiosyncratic home productivity process, $h(t)$, is approximated by a 140-state Markov process, with vector of values, φ, and transition matrix Q.

The model is solved numerically using value function iteration given the saddlepoint stability property of the matching model. Indeed, since the left side of the surplus equation is increasing in θ_t, whereas the right side is decreasing in the same variable, because of the decrease in the surplus value when θ_t increases, there is a unique θ_t that solves the equation. Once I solve for θ_t, the surplus functions are solved. The model is simulated for 1,000 months. All monthly series are logged and HP detrended using a smoothing parameter of 129,000 as suggested by Ravn and Uhlig (2002). I replicate the simulations 1,000 times, and despite each series consists of 1000 observations, I discard the first 674 observations and I use only the last 336 (corresponding to the data from I/1976 to XII/2004) to compute the standard moments: mean, standard deviations and autocorrelations. Reported statistics are averages over 1,000 simulations.

2.3.2 The Calibration

To simulate and solve the model, I will use values for the parameters that are standard in the literature. However, this will not be possible for all parameters because the model developed in this chapter considers three and not only two labour market states. Finding empirical evidence to provide suitable values for parameters as regards the passive searching state is not an easy task.

The baseline calibration is presented in Table 2.2. The period length is one month, which is different from the frequency used in the literature, i.e., the weekly frequency (e.g., Hagedorn and Manovski, 2008), but it allows to get a perfect fit with the frequency concerning worker flows.

Four parameters are calibrated following what are the standard assumptions in the literature. I set the discount factor, β, equal to 0.9967, which is consistent with the annual interest rate of 4 percent. The process for aggregate productivity is obtained from a 21-state Markov process, $\varsigma_{i,j} = prob(\varsigma' = \varsigma_j | \varsigma = \varsigma_i)$, which approximates an AR(1) process $\ln z_{t+1} = \rho_z \ln z_t + \epsilon^z$, with $\epsilon^z \sim N(0, \sigma^2_{\epsilon^z})$. Consistent with the values used in the Real Business cycle literature, I set the persistence of technological process, ρ_z, equal to 0.97 and the standard deviation of the innovation process, σ_z, equal to 0.0077 (Bils, Chang and Kim, 2012). Unfortunately, the calibration of the idiosyncratic home productivity is quite challenging because there are not empirical measures of the dispersion of home productivity. The solution is to consider this variable like a measure of "relative productivity" since, in the reality, what one should try to measure is the difference between market productivity and home productivity. I assume that the idiosyncratic shock evolves according to a 140-state Markov process $\varphi_{l,m} = prob\ (\varphi' = \varphi_l | \varphi = \varphi_m)$ that approximates an AR(1) process $\ln h_{t+1} = \rho_h \ln h_t + \xi^h$, with $\xi^h \sim N\left(0, \sigma^2_{\xi^h}\right)$. I set the persistence parameter, ρ_h, equal to 0.9895, and the standard deviation of the innovation process, σ_h, equal to 0.227. The high value set for the persistence and the volatility of home productivity shock are derived from the results reported by Topel and Ward (1992), with estimates reporting a high persistence for the individual wages and earnings, with the standard deviation in the annual growth rate in earnings being equal to 19 percent.

The steady state productivity level for aggregate and idiosyncratic process is normalized to one. The flow cost of posting a vacancy k, is equal to 17 percent of monthly productivity. This is the value suggested by Fujita and Ramey (2012), based on survey evidence on employer recruitment behaviour.

To calibrate the values of the matching function, I use the Cobb-Douglas matching technology as proposed by Shimer (2005). However, the fact I have segmented markets implies I have two matching functions, i.e, $m^i(s^i a_t, v^i_t) = \gamma^i {s^i}^{\alpha^i} a_t^{\alpha^i} {v_t^i}^{1-\alpha^i}$. I normalize to one the value of the efficiency parameter of the matching function, γ, while the elasticity parameter of the matching function, α, is set equals to 0.5 for both matching functions. The same value, 0.5, is used for the workers' bargaining power, ψ, as it is the common value used in the literature on search and matching with the exception of Hagedorn and Manovskii (2008).

The unemployment benefit b^U is set equal to 0.041 based on Chodorow-Reich and Karabarbounis (2016). The real wage flexibility parameter, τ, is set equal to 0.3 following Haefke, Sonntag and Van Rens (2013).

As concerns the values for the participation costs for all the three groups of workers, since there is no supporting empirical evidence about these variables, I choose then such that the model replicates the observed employment, unemployment and out-of-labour force rates.

Data about the time spent in working, home production, searching and leisure activities is derived by ATUS dataset.

[INSERT TABLE 2.2 ABOUT HERE]

2.4 Results

Results of the baseline calibration are presented in the tables below, while findings from the sensitive analysis will be presented in next section. Table 2.3 reports monthly US data (1976-2004) for labour market tightness, unemployment, vacancies and job-finding rate as well as the correlation between unemployment and vacancies, i.e., the so-called Beveridge Curve, and the other labour market variables. Statistical facts are taken using data from the Bureau of Labour Survey (BLS). They are defined in logs as deviations from an Hodrick-Prescott trend with smoothing parameter 129,000.

[INSERT TABLE 2.3 ABOUT HERE]

In what follows, I will first discuss the results produced by the baseline model for the active searchers and the passive searchers, and then I will show how results from aggregation can be compared with findings from prior models.

Tables 2.4 and 2.5 report the findings of the simulated model for the two segmented markets, while Table 2.6 presents the findings when I aggregate the two segmented markets. The results of the monthly calibration have not been aggregated to a quarterly frequency, so that they can be compared to the usual empirical monthly values for the labour market variables and the worker flows.

[INSERT TABLE 2.4 ABOUT HERE]

Looking at the results in Table 2.4, where it is considered only the segmented sub-market for active searchers, i.e., the unemployed, one can observe that the model for this group of individuals replicates well a large part of the empirical volatility for the labour market variables. The reasonable performance of the model in generating volatile second moments relies on two channels. The first, and more relevant in terms of impact on the creation of vacancies, is the existence of frictions in the "full discovery" of the value of the idiosyncratic variable after the occurrence of the shock. More precisely, the home productivity shock occurs at the beginning of the reference period, but its value is fully "realised" by the agents only at the end of the same period. This implies that when there is a positive aggregate productivity shock, i.e., there is an expansion of the economic activity, it is a good moment for firms to open new vacancies and for workers to accept jobs offered to them. Hence, firms and workers form new matches. However, the survival of these matches, at the end of the period, is subject to the new draws of home productivity. With a high draw, workers matched in the current period are likely to quit their jobs and search again next period. Indeed, the higher value for the idiosyncratic home productivity brings about an increase in the worker's outside option. Since firms are forward-looking agents, they know a fraction of newly formed matches will be destroyed at the end of each period, then they are more likely to increase the number of vacancies posted on the market. However, the workers are also forward-looking agents and after a positive aggregate productivity shock, they know it is a good moment to form a match, since they do not have information on the new idiosyncratic value of home productivity until the end of the period. Moreover, even in the case of a high draw, they will be able, when the new value of home productivity is common knowledge, to quit the job and search for a better match next period. All this dynamics produces large fluctuations in vacancies and, to a certain extent, in the job-finding rate and labour market tightness as well.

Looking at the results, I mainly focus on the cyclical behaviour of the key labour market variables. In particular, it can be observed that the volatility of unemployment is equal to 4.122. Despite being below its empirical value, it is a much larger figure compared to the values reported in the previous papers using the standard Mortensen-Pissarides model. Indeed, the baseline search model usually generates too little volatility for the unemployment variable (Shimer, 2005, and Costain and Reiter, 2008), roughly a value around one-tenth of the empirical counterpart. The particular specification of the present model, incorporating variability in the separation rate and transitions between unemployment and out-of-labour force, helps in increasing the volatility of unemployment (while in the literature, one finds a constant exogenous separation rate, with a counterfactual absence of volatility in the separation rate). The volatility of the labor market tightness ratio and job-finding rate is for both around 50 percent of the analog value in the U.S. data, while the value for vacancy observed in the simulation is roughly 60 percent of its empirical counterpart. Observing the correlation values between vacancies and labor market tightness with unemployment, one can see that the values fall short of their empirical analogs. The model's correlation between unemployment and vacancies is -0.632 compared to -0.89 in the data, while the correlation between labour market tightness and unemployment is equal to 70 percent of its empirical value. It could be argued, given the calibration strategy used in this chapter, that the mildly weak performance of the model is direct evidence of the inability of unemployed workers' rents to generate enough impact on aggregate labour statistics, but this conclusion does not hold in this model since it allows for endogenous separation rate (a result that holds particularly for high-wage workers as highlighted by Mueller (2017)).

Results for the model with the group of passive searchers, i.e., the out-of-labour force individuals, are reported in Table 2.5.

[INSERT TABLE 2.5 ABOUT HERE]

The figures in Table 2.5 are quite challenging to be interpreted since statistical measures for labour market variables in a search model are usually interpreted in relation with the unemployment state and not with reference to the out-of-labour force state. Thus, a comparison will be made using the values generated for the scenario with unemployed. Overall, the model seems to work well since it is able to produce a volatility for out-of-labour force, a value of 0.231 , which is close to 0.3, i.e., its empirical value. The variables labour market tightness, job-finding rate and vacancy show also a remarkable volatility, with values, respectively, around 65 percent, 80 percent and 75 percent of the simulated analogs found for the unemployed group in Table 2.4.

Looking at aggregated model, the results show a substantially higher level of cyclical volatility for the variables compared to the volatilities resulting in previous studies based on standard search and matching models. The findings in Table 2.6 show that the cyclical fluctuations in vacancies, job-finding rate and labor market tightness represent around the 50 percent of the empirical counterparts. These results support the assumption that including the passive searchers margin plays an important role in generating results that can resemble empirical moments.

[INSERT TABLE 2.6 ABOUT HERE]

Table 2.7 reports the empirical and simulated values for worker flows. It can be observed that the model does a good job in replicating the out-of-labour force to employment worker flow, a statistic previous papers have failed to match. This is a crucial result since the present model does not necessarily address this issue. Indeed, the inclusion of the passive searchers just produces a chance for these individuals to find a job, but the searching activity of passive searchers is calibrated on data from ATUS and the value of time devoted to searching by passive searchers in the survey is pretty low compared to that observed for active searchers, implying a lower intensity in searching and a lower successful likelihood rate in finding a job, even in the presence of segmented labour markets. The model is decent in terms of reproducing the employment to unemployment and the employment to out-of-labour force worker flows. While the model explains 60 percent of the former, it is also able to explain 65 percent of the latter. The specification of the model, allowing for endogenous separation, plays a key role in generating realistic monthly worker flows compared to the results reported in the literature in the case of the presence of only exogenous separations. However, in order to obtain a better match one could probably introduce, together with endogenous separation, a slight form of exogenous separation like in Fujita and Ramey (2012). Furthermore, the model grossly overpredicts the flows from unemployment to out-of-labour force and from out-of-labour force to unemployment. They are roughly twice as large as the ones found in the data. The value for the former flow is equal to 0.199, while it is 0.122 in the data, and for the latter flow, it can be observed a value of 0.039 compared to 0.021 in the data. Finally, the unemployment to employment worker flow is roughly 70 percent of its empirical counterpart. These results seem to support the idea that the temporary fluctuations in home productivity drive the flows between these two labor market states. A larger magnitude in the aggregate productivity shock would probably improve the model, by bringing active and passive searchers to larger movements into the employment state instead of moving backward and forward between these two labor market states, following the new draws for the idiosyncratic variable.

[INSERT TABLE 2.7 ABOUT HERE]

2.5 Sensitivity Analysis

In this section, I test the robustness of the model by introducing a calibration for the bargaining power and workers' surplus from a new match that resembles that proposed by Hagedorn and Manovski (2008). The exercise that is proposed is similar to that used in their study by Fujita and Ramey (2012).

2.5.1 A New Calibration: Comparison with the Hagedorn and Manovski (2008) model

The goal in this sub-section is to test the implications for this model to introduce a calibration similar to that proposed in their work by Hagedorn and Manovski (2008). As it has been showed by these authors, the Shimer's puzzle can be rationalized and the volatilities for the labour market variables are replicated when one allows for a different calibration of the search and matching model from the standard set-up proposed in the literature. Especially, introducing a high replacement rate (a value close to 90 percent, quite different from the values usually used in he majority of the contributions on this issue, that are included in the range 40-70 percent) and a small workers' bargaining power (below 5 percent) produces realistic results for the relevant moments and correlations.

The basic strategy is to follow Hagedorn and Manovski (2008) by calibrating the value of the replacement rate and workers' bargaining power in order to match the elasticity of wages to the aggregate productivity shock and the steady-state wage-productivity ratio. Indeed, the authors aim at producing an elasticity of wages that is lower than that produced by the search models with a standard calibration.

Results presented in Table 2.8 show that adopting a calibration a' la Hagerdon and Manovski (2008) produces substantially more volatile moments. This effect can be attributed to the fact that, following a positive aggregate productivity shock, individuals are less willing to separate since the workers' outside option declines compared to the value of the match.

However, the model presents little improvements in terms of responses of worker flows. Indeed, the worker flows show a lower responsiveness to the TFP shock due to the fact that the incentive provided to the workers in terms of higher productivity and, consequently, the lower value for the workers' outside option, brings about a drop in the rate of separations for the workers.

[INSERT TABLE 2.9 ABOUT HERE]

2.6 Conclusions

The objective of this chapter is to investigate the ability of a three state frictional labour market model to replicate both the empirical labour market volatilities and worker flows. I present a model where workers heterogeneity in terms of idiosyncratic home productivity and direct worker flows between the three labour market states play a key role. When I simulate the baseline model, I obtain results showing a large volatility for labour market variables such as unemployment rate, vacancy and labour market tightness, compared to their values in the standard search model, and more realistic worker flows. Indeed, the simulated second moments can replicate between 50 and 60 percent of their empirical analogs and the model is also able to perform quite well along the replication of the other worker flows, especially the out-of-labour force to employment worker flow, a statistical value that previous models have struggled to replicate.

These result crucially depends on three assumptions. The presence of frictions in the adjustment of the information process regarding the idiosyncratic variable, the role played of out-of-labour force as an extra participation margin and the inclusion of endogenous separations.

In particular, the introduction of the third labour market state, i.e., the passive searchers margin, is a clear enhancement in modelling search and matching models, since it explicitly allows to address the recurrent drawback of search models in generating direct worker flows from inactivity to employment.

Furthermore, allowing for endogenous separation not only helps to replicate the empirical cyclicality of the separation rate, but it also affects the volatilities of vacancies, labor market tightness and job-finding rate.

When a calibration a' la Hagedorn and Manovskii (2008) is introduced, together with the two standard features of the baseline model, i.e.e, endogenous separations and passive searchers margin, the second moments of all the variables above mentioned show greater values compared to those in the baseline model, but the performance of the model in terms of replicating worker flows is less satisfying since the rate of separation experience a substantial drops due to the increasing value of the match compared to the workers' outside option.

Despite the good performance of the model, it can be observed how a more realistic approach would also need to take into account the role played by the firms, which is not covered in the present work. Incorporating the firm's side into the model (e.g., allowing for separations driven by job-specific productivity shock) would enrich the dynamics of the behaviour of agents in matching and separation, providing more accurate results in terms of movements between the labour market states.

Table 2.1

Krusell, Mukoyama, Rogerson and Sahin (2016) estimates of Cyclical properties of Unemployment rate, Labour Force Participation rate and Gross Worker Flows

	U	LFP	E-U	E-OLF	U-E	U-OLF	OLF-E	OLF-U
std(x)	7.6	.21	5.4	2.0	4.9	3.8	2.7	4.0
corrcoef (x,y)	-.87	.46	-.82	.33	.78	.78	.64	-.70
correcoef (x,x(-1))	.92	.72	.73	.20	.84	.73	.41	.75

Notes: Quarterly average values of monthly series for the U.S. economy over the period 1978-2009. Std(x): standard deviation of the variable X; corrcoef(x,y): correlation between the variable X and the GDP; corrcoef(x,x(-1)): correlation between X(t) and X(t-1). All series are logged and HP filtered. The variable U indicates the unemployment rate, the variable LFP indicates the labour force participation rate, the variable E indicates the employment and the variable OLF indicates the out-of-labour force.

Table 2.2

Calibration

Parameters	Description	Value
β	Discount factor	0.9967
α	Matching function elasticity	0.5
ψ	Workers' bargaining power	0.5
γ	Matching function efficiency	1
b^u	Unemployment benefit	0.041
κ	Cost of posting a vacancy	0.17
ρ_z	Persistence of the technological shock	0.95
σ_z	Volatility of the technological shock	0.0077
ρ_h	Persistence of the idiosyncratic shock	0.9895
σ_h	Volatility of the idiosyncratic shock	0.227
τ	Real wage flexibility	0.3
g^w	Participation cost for Employed	0.942
g^u	Participation cost for Unemployed	0.211
g^{olf}	Participation cost for OLF	0.043
l^i	Leisure value	1

Data from American Time Use Survey (ATUS) 2003-2009

Parameters	Description	Value (minutes per day)
t^{h^w}	Time spent in home production for employed	119
t^{h^u}	Time spent in home production for unemployed	154
$t^{h^{olf}}$	Time spent in home production for inactive individuals	178
t^{s^u}	Time spent in searching for unemployed	23
$t^{s^{olf}}$	Time spent in searching for inactive individuals	0.37

Table 2.3: Summary Statistics

Monthly US data: Sample period 1976:I-2005:IV						
	Unemployment	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Std. Dev.	9.6	0.294	10.1	19.1	7.72	0.0077
Monthly Autocorrelation	0.936	0.776	0.940	0.941	0.926	0.794
Correlation matrix	*Unemployment*	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Unemployment	1	0.621	-0.894	-0.971	-0.949	-0.234
Out of labour force		1	-0.622	-0.554	-0.432	-0.177
Vacancies			1	0.975	0.897	0.329
Labour market tightness				1	0.948	0.302
Job finding rate					1	0.294
Labour productivity						1

Notes: Seasonally adjusted unemployment rate, u, and out-of-labour force rate, olf, are constructed by using the monthly official BLS unemployment rate and out-of-labour force rate from the Current Population Survey (CPS); vacancies are obtained through the seasonally adjusted help-wanted advertising index constructed by the Conference Board; the labour productivity is defined as the monthly average output per worker, which is the seasonally adjusted real average output per worker constructed by using the index constructed by Macroeconomic Advisers. The Index has been developed from National Income and Production Account (NIPA) data. The series are deflated by using a GDP deflator index developed by Macroeconomic Advisers and transformed in per-capita terms by dividing the real term series by CPS total population series. Job-finding rates are obtained using data for the monthly worker flows from the Current Population Survey for the U.S. economy over the period 1976-2005. The values for the variables are reported in logs and de-trended using HP-filter, with smoothing parameter 129,000 as suggested by Ravn and Uhlig (2002).

Table 2.4

Simulated moments for the Unemployment segmented market

	Unemployment	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Std. Dev.	4.122	5.982	8.148	3.711	0.0077
Monthly Autocorrelation	0.903	0.934	0.922	0.929	0.794
Correlation matrix	*Unemployment*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Unemployment	1	-0.632	-0.723	-0.695	-0.645
Vacancies		1	0.911	0.889	0.884
Labour market tightness			1	0.886	0.899
Job finding rate				1	0.765
Labour productivity					1

Notes: Comments in Table 2.3 apply.

Table 2.5

Simulated moments for the segmented market with Out of Labour Force

	Out of labour force	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Std. Dev.	0.231	4.809	5.134	3.112	0.0077
Monthly Autocorrelation	0.912	0.904	0.872	0.894	0.794
Correlation matrix	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Out of labour force	1	-0.412	-0.523	-0.491	-0.459
Vacancies		1	0.782	0.811	0.778
Labour market tightness			1	0.807	0.724
Job finding rate				1	0.699
Labour productivity					1

Notes: Comments in Table 2.3 apply.

Table 2.6

Simulated moments for the Aggregate model

	Unemployment	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Std. Dev.	4.122	0.231	5.398	6.334	3.442	0.0077
Monthly Autocorrelation	0.903	0.912	0.904	0.872	0.894	0.794
Correlation matrix	*Unemployment*	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Unemp+OLF	-	-	-0.595	-0.643	-0.612	-0.545
Vacancies			1	0.842	0.781	0.811
Labour market tightness				1	0.814	0.824
Job finding rate					1	0.709
Labour productivity						1

Notes: Comments in Table 2.3 apply.

Table 2.7

U.S. monthly worker flows data: 1976:I-2005:IV			
	E	**U**	**OLF**
E	0.971	0.011	0.018
U	0.166	0.712	0.122
OLF	0.037	0.021	0.942

Monthly worker flows simulated results			
	E	**U**	**OLF**
E	0.981	0.007	0.012
U	0.111	0.685	0.199
OLF	0.031	0.039	0.927

Notes: Data for the monthly worker flows are from the Current Population Survey for the U.S. economy over the period 1976-2005. The variable **U** indicates the unemployment rate, the variable **E** indicates the employment and the variable **OLF** indicates the out-of-labour force.

Table 2.8

Re-calibrating the model using Hagedorn and Manovskii (2008) approach

	Unemployment	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Std. Dev.	5.618	0.271	5.698	6.734	3.502	0.0077
Monthly Autocorrelation	0.911	0.902	0.910	0.902	0.890	0.794
Correlation matrix	*Unemployment*	*Out of labour force*	*Vacancies*	*Labour market tightness*	*Job finding rate*	*Labour productivity*
Unemp+OLF	-	-	-0.782	-0.801	-0.738	-0.672
Vacancies			1	0.882	0.811	0.855
Labour market tightness				1	0.837	0.868
Job finding rate					1	0.749
Labour productivity						1

Notes: Comments in Table 2.3 apply.

Monthly worker flows using Hagedorn and Manovskii (2008) approach

	E	**U**	**OLF**
E	0.986	0.004	0.010
U	0.104	0.727	0.169
OLF	0.029	0.029	0.942

Notes: Comments in Table 2.7 apply.

CHAPTER 3:

REAL WAGES OF NEWLY HIRED WORKERS OVER THE BUSINESS CYCLE: WHEN THE DIFFERENCE BETWEEN FLOWS FROM UNEMPLOYMENT AND FLOWS FROM OUT-OF-LABOUR FORCE MATTERS

Structure:

3.1 Background and Literature Review

The business cycle moments of the real wages have been attracting the interest of the researchers since the 1930s. The first investigations on the cyclical behaviour of the real wages of existing workers date back to the works of Dunlop (1938) and Keynes (1939), followed by the contributions later on of Lucas (1977) and Mankiw (1989), who have tried to shed light on this issue. However, results have not been conclusive. While Keynes (1939) supported the view of countercyclical real wages, empirical evidence provided by Dunlop (1938) showed that real wages are procyclical. The other studies mentioned above have found that the real wages can be described as weakly procyclical (and often statistically not significant). The main reason why these studies have raised critiques lies in the nature of the data used for the analysis, basically aggregated time-series data. Indeed, the use of aggregate data has been rising concerns since it implies that, on average, the composition of the workforce does not change over the business cycle.

Only with the development of micro-level datasets researchers have been allowed to investigate the issue from this different perspective. Bils (1985) and Solon, Barsky and Parker (1994) are the most prominent studies taking into account the key role played by workforce compositional changes over the business cycle on the fluctuations of real wages. Indeed, if hirings or layoffs are not independent outcomes from the type of workers that experiment these events (e.g., during expansions low-skilled workers might represent a disproportionate part of employed workers, producing a downward bias in the cyclicality of the real wages and vice versa, as showed by Barsky, Solon and Parker (1994)), then the presence of compositional changes would generate a bias in the estimation of the aggregate real wage (i.e., it is faced the problem of composition bias). While the results in Bils (1985) have supported the idea of a significant rigidity of real wages of existing workers (with the presence of a higher elasticity for the real wage of job changers, since the estimates show that a fall of one percentage point in the unemployment rate would produce an increase in the wage of job changers of 3.5-4 percentage points), in Solon, Barsky and Parker (1994) the authors have reported evidence of procyclical real wages even among the job stayers, with the individual's real wage growth increasing by more than one percentage point when unemployment rate falls by one percentage point.

A set of additional results can be found in the works of Barlevy (2001) and, Devereaux and Hart (2006), who investigate the behaviour of real wages for job changers. Their findings show that the real wages of job changers are much more flexible than the real wages of job stayers.

The interest for the cyclical behaviour of real wages has seen a further resurgence in the very recent years, with the seminal contributions of Pissarides (2009) and Haefke, Sonntag and Van Rens (2013), followed by the works of Carneiro, Guimares and Portugal (2012), Martins, Solon and Thomas (2012), Kudlyack (2014) and Gertler, Huckfeldt and Trigari (2016). However, differently from the studies in the past decades, that were developed following an approach focused on the behaviour of real wages of ongoing workers and job changers, these latest set of papers have devoted much more attention to the behaviour of real wages of newly hired workers. The rationale giving rise to this new strand in the literature rests on the debate surrounding the empirical validity of the search and matching model (e.g., Mortensen and Pissarides, 1994). Following the contributions of Shimer (2005) and Costain and Reiter (2008), it has been showed that the standard search and matching model with Nash bargaining wage process is unable to replicate the empirical volatilities of unemployment, vacancies and job-finding rate.[16] Introducing a form of aggregate real wages rigidity in the wage bargaining

[16] Studies trying to provide a solution to this puzzle are countless. The works cited represent the seminal papers dealing with this issue, but substantial contributions have been provided for, and it is an incomplete list yet, by Cole and Rogerson (1999), Hall (2005), Hall and Milgrom (2008), Hagedorn and Manovskii (2008), Gertler and Trigari (2009), Kennan (2010), Gertler, Huckfeldt and Trigari (2016).

process appears to be a reasonable (the empirical values about volatility of real wages are lower than those obtained in the standard search models with wages determined through Nash bargaining process) and plausible (the search model with a form of real wages rigidity does a good job in making the simulated volatilities of all key labour market variables consistent with their empirical counterparts) solution to put an end to this controversy. However, as pointed out by Haefke, Sonntag and Van Rens (2013), "*in a frictional labour market the forward-looking variable is the job creation and the amount of jobs that are created depends on the expected net present value of real wages over the entire duration of the newly created jobs*". This implies that what really matters in the search and matching model is not the behaviour (*rectius*: rigidity) of aggregate real wages, but the behaviour (*rectius*: rigidity) of the real wages of newly hired workers coming from the unemployment state.[17] This is the relevant variable able to provide an answer to the unemployment volatility puzzle.

Pissarides (2009) is the first author arguing on the empirical validity of the canonical search and matching model as affected by the newly hired workers' wages. He summarizes microeconometric evidence about the cyclicality of real wages of newly hired workers as opposed to cyclical behaviour of the real wages of the job stayers, since it is the cyclicality of the real wages in the individual new matches the key variable able to explain the large empirical volatilities in the search and matching model. Results from studies on wage behaviour, according to Pissarides, clearly show that wages of job stayers are less procyclical than wages of overall workers, thus suggesting the presence of a relevant form of wage elasticity in the new jobs.

[17] Rudanko (2009) using a directed search model with long-term labour contracts shows that the presence of a rigid aggregate real wages is not able to improve considerably the performance of the search model in terms of volatilities of unemployment, labour market tightness and job-finding rate. Then, she also argues that the variable one should pointing to in order to replicate empirical moments for unemployment, vacancies and job-finding rate is the hiring real wage.

Results from Haefke, Sonntag and Van Rens (2013), who use data from the Current Population Survey (CPS), show how the real wages of new hires is more sensitive than the real wages of ongoing workers to labour productivity shocks. Their findings show a value close to one as regards the elasticity of real wages for new hires, compared to values close to 0.2-0.3 for the elasticity of real wages for job stayers. These results are confirmed by Kudlyack (2014), who uses data from the National Longitudinal Survey of Youth (NLSY). Furthermore, Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012), both using the same employers/employees longitudinal dataset regarding Portugal economy, the Quadros de Pessoal, find that the real wages of newly hired workers, using the unemployment rate as the aggregate cycle indicator, is strongly procyclical, confirming the results in Haefke, Sonntag and Van Rens (2013).[18]

All together, the crucial aspect in these studies is that the standard assumption validating the search and matching model, i.e., the rigidity of real wages of new hires, is no more retainable.[19]

Nevertheless, a different conclusion is suggested by Gertler, Huckfeldt and Trigari (2016), who investigate the relationship between real wages and unemployment rate, using data from the Survey of Income and Program Participation (SIPP) for the U.S. economy. These authors find no signs of a strong procyclicality of real wages of new hires coming from the unemployment state. Their findings are based on two inter-related set of arguments: 1) the empirical evidence

[18] It has to be mentioned as the results, in these two studies, about the elasticity of real wages of ongoing workers are not concordant. While findings in Carneiro, Guimares and Portugal (2012) suggest that the real wages of ongoing workers are quite elastic but less procyclical than the real wages of new hires, results in Martins, Solon and Thomas (2012) suggest that real wages of job stayers are almost as much procyclical as the real wages of new hires.

[19] A subtler issue is: what is the required level of rigidity of real wages able to replicate the empirical volatilities for the labour market variables? Martins, Solon and Thomas (2012) and Haefke, Sonntag and Van Rens (2013) discuss this issue in their papers.

about "cyclical job-upgrading" in worker/employer matches and 2) the role played by workers making job to job transitions.

Indeed, Gertler, Huckfeldt and Trigari (2016) are able to disentangle the unemployment to employment transition from the employment to employment transition,[20] showing that the strong procyclicality of real wages of newly hired workers coming from unemployment disappears when job to job movements are taken into account as well. The procyclical behaviour of real wages is magnified by the change in the real wages of job changers, but it dramatically decreases when it is considered only the group of unemployed workers moving into employment. According to Gertler, Huckfeldt and Trigari (2016), the procyclical real wages of newly hired workers observed in the previous investigations is due to the presence of cyclical job-upgrading, with the substantial higher elasticity of real wages to be intertwined to the high wages paid to the workers making job to job transitions, as pointed out by Topel and Ward (1992) and Barlevy (2001). In other words, it would happen that in good times employed workers, with bad jobs accepted in bad times, look for better, high-paying jobs and they move into these new jobs when they are found, producing the substantial procyclicality of real wages, while unemployed workers tend to accept each job is offered them when they try to transition into the employment state, an event that occurs with a larger probability in good times. This implies it is the group of low-skilled unemployed individuals the one more likely to transitioning into the employment state. Thus, the procyclicality of the real wages of the new hires from unemployment is quite modest, given the large proportion into this group of low-skilled workers.

[20] The authors make use of data from real hour wages paid over time, identifying job changers as individuals earning different wages in two consecutive periods.

Looking at the dynamics of real wages from this perspective, it comes to light that the effect produced from the job to job transitions, together with the change in the quality (upgrading) of the jobs offered in the labour market, is to magnify the procyclicality of the real wages for newly hired workers. This result clearly affects the empirical validity of the standard search and matching model, because the variable researchers are interested in is the elasticity of the real wages of newly hired workers coming from the unemployment state and not the elasticity of the real wages of workers making job to job transitions.

However, it is worth noting as the controversy in the literature between these two different approaches has been developed along a sharply stylized definition of the labour market. Works dealing with the search and matching model have dismissed any complication in the way they have traced out the economic structure of their models, embracing the basic assumption popularizing the relevance of only two labour market states, employment and unemployment, and assuming all new hires come from the unemployment state,[21] crossing out the empirical classification of workers in three different labour market states: employment, unemployment and out-of-labour force, a classification recognizing an autonomous role to out-of-labour force, and wiping out the relevance, as suggested by the empirical evidence, of the transitions of individuals between the out-of-labour force state and the other two labour market states.[22]

Recent literature has stressed the importance of considering the dynamics of the worker flows between the three labour market states. Shimer (2013) and Elsby, Hobjin and Sahin (2015) clearly show that, despite the prominent role played by the unemployment to employment flow, the flow out-of-labour force to employment is definitely crucial in order to get a better

[21] Some papers, like Carneiro, Guimares and Portugal (2012), have proposed a different solution, lumping together all workers becoming new hires into the general group non-employment, i.e., a group including both unemployed and inactive workers.

[22] Conan, Kudlyack and Reed (2012), using CPS data, show that, in levels, the flow out-of-labour force to employment is roughly twice as large as the flow unemployment to employment.

understanding of the business cycle facts. For example, Elsby, Hobjin and Sahin (2015) show that using the benchmark framework with only worker flows between two states, that is, employment and unemployment, is misleading in interpreting the volatility of the unemployment rate. Indeed, the presence of the unemployment to out-of-labour force and the out-of-labour force to unemployment flows account for one-third of the overall cyclicality in the unemployment rate, with a more substantial role for the former flow.

Nevertheless, the view proposed by these two works, despite being potentially more informative about the dynamics of the labour market, has not been consistently reiterated in the literature, where the majority still makes use of a conservative approach based on a framework with only two labour market states.

All together, the empirical evidence described above shows that a large group of individuals, the out-of-labour force workers, consistently moves directly into the employment state each month, and this labour market transition produces not second-order effects. However, this straight movement is either ignored or swallowed up into the large locked black box called “newly hired workers”, which is usually identified as a category absorbing individuals from the unemployment state.

If the new hires are to be considered as individuals with the same preferences, tastes and behaviour, differences between new hires coming from unemployment and new hires coming from out-of-labour force could be ruled out. However, if new hires coming from out-of-labour force are a heterogeneous group compared to new hires coming from unemployment, then the current exercise of researchers, pointed to lumping together all workers moving into the employment status in the undifferentiated state called non-employment, is methodologically flawed.

Investigating the cyclicality of the real wages of newly hired workers coming from both out-of-labour and unemployment, not only put more discipline on the subject *per se,* but it also adds more evidence to the debate on the representative versus heterogeneous agents model, providing further support for the development of a valid model able to explain macroeconomic facts.

In this study, I argue that the standard interpretation of the new hires as a homogeneous group of workers has to be rejected because the individuals moving from the non-employment state to the employment state show a substantial degree of heterogeneity in terms of cyclical responsiveness of real wages. Using data from the Survey of Income Program Participation, for the period 1996-2013, I find results confirming findings from previous studies, as concerns the semi-elasticity of real wages. The real wages for newly hired coming from non-employment are more procyclical than the real wages of job stayers. However, these results hold only in a setting with staggered wages. Indeed, following the standard approach in the literature suggesting that wages are set between six months and one year in advance, I find estimates of real wages at lower frequency are values larger than one, accommodating the presence of elastic real wages. On the contrary, using measures of wages at higher frequencies imply that a change in the unemployment rate shows a substantial lower effect on the procyclicality of the real wages. However, and most remarkable for the investigation I carry on in this study, I find that the real wages of newly hired workers coming from unemployment are less procyclical than the real wages of newly hired workers coming from out-of-labour force and this result is robust to different specifications of the model. Including job changers, in the model, produces results highlighting the higher procyclicality of real wages for job changers, even if at a lower magnitude compared to values in Gertler, Huckfeldt and Trigari (2016) and Barlevy (2001), but it does not affect the difference in the semi-elasticity of real wages for the two groups of new hires. Furthermore, when I take into account the effect on real wages of a change in the aggregate labour productivity (an alternative aggregate cyclical indicator), I obtain estimates confirming previous results as regards the heterogeneity in the elasticity of real wages between new hires from out-of-labour force and new hires from unemployment.

The chapter is developed as follows. Section 3.2 presents the dataset with the description of data. In Section 3.3, I discuss the empirical methodology used to investigate the relationship between wages and the cyclical indicators for different groups of workers and results are reported from the sensitivity analysis I perform. In Section 3.4, I test the robustness of my results. In Section 3.5, I examine the empirical relevance of the newly hired workers from out-of-labour force. Section 3.6 concludes.

3.2 The Dataset

3.2.1 The Survey of Income and Program Participation (SIPP)

The data used to investigate the behaviour of real wages stems from the Survey of Income and Program Participation (SIPP), which is administered by the U.S. Census Bureau.

The SIPP is a nationally representative longitudinal survey based on a stratified multi-stage random sample. The sample consists of civilian, non-institutionalized U.S. households. The interview process is conducted on each member of the household,[23] who is at least 15 years old, and the individuals who live with them. Information is nevertheless collected for all the individuals who live in the households without any limitation in terms of age.

More precisely, the SIPP can described as a collection of panels going through 1984 to 2008. The initial panels started each year since 1984 and they roughly covered a period of 32 months.

[23] Individuals are followed in the panel even in the case that they move to a different address.

This structure produced the existence of overlap panels since a new panel was drawn at the beginning of each year (usually February), while the other panels drew in the previous years were run at the same moment. Each panel included a sample of around 12,000 households and roughly 30,000 individuals.

This general structure and methodology of the SIPP faced a large change in the 1996. New panels starting in 1996 show an increase in the sample size (households that are regularly interviewed in each wave have moved from 21,823 units in the 1993 panel to 40,188 units in the 1996 panel, and finally to 52,031 units in the 2008 panel), an increase in the average length of the panels (the 1996 panel runs for 12 waves, the 2001 panel runs for 9 waves, the 2004 panel runs for 12 waves and the 2008 panel runs for 16 waves. This implies that the last four panels cover roughly a period between thirty-six and sixty months) and the drop of the overlapping panel structure (each panel starts after the previous one has been completed).

In this study, I use only data coming from the panels after the change in 1995, i.e.: 1996-2001-2004 and 2008.

The structure of the SIPP panels is as such: in each panel all the sampled individuals included into a household are interviewed every four months. The SIPP divides each panel into four sub-samples and each sub-sample is referred to as a rotation group. These four rotation groups enter the SIPP survey at different points in time.[24] Respondents provide information about their lives during the previous four months, which are referred to as the reference months.[25]

[24] For example, for the 2008 SIPP panel, the entry months for these rotation groups are, respectively, May, June, July and August 2008, respectively.

[25] This implies that the collection of information is made retrospectively, a feature that helps to somewhat overcome the problem of left-censoring. The information provided for the four months is thus contained in what is called a reference wave.

The information relevant for the investigation I carry out in this study is collected in the SIPP module called core wave files.[26]

The core module files are run each four months and they provide information on individuals' labour market history (e.g., labour market state, occupation, industry, class of workers, etc.), earnings/income, demographic characteristics (e.g., age, gender, race, marital status, education), participation to public programs supporting household income (such as Social Security and Food Stamps) and other additional variables.[27]

Information on the labour market state the individuals belong to is collected at a higher frequency, usually weekly or monthly, compared to other datasets. However, for some variables information is collected for one month and then the value is reported for the other three months forming a wave.

The advantages of the SIPP over similar data sources such as the Panel Study of Income Dynamics (PSID), National Longitudinal Survey of Youth (NYLS) and British Household Panel Survey (BHPS) is that the questionnaires collect a broader range of information concerning labour market history (at a higher frequency), it contains a larger sample interviewed each panel compared to the other two datasets, and there is evidence of a very low presence of attrition and measurement errors.

[26] For the sake of completeness it must be reported how the SIPP offers a second type of files called topical module files collecting information on aspects related, broadly, to the following categories: assets and liabilities, well-being expenses, material hardship measures, fertility history, medical expenses, retirement plan, children support, welfare reforms, disability statistics and other minor variables, and a third type of file as well, the longitudinal research file, which contains information on all the waves of a panel.

[27] Regarding labour market data, information on occupation, industry, employer identification, starting and ending date for the job, up to two main jobs, is collected as well.

3.2.2 <u>Sample and Descriptive Statistics</u>

A description of the characteristics of the sample, in terms of the main variables, is provided in Table 3.1. The sample includes all individuals in the SIPP with age above 15 and below 65. Individuals with mental and physical disabilities, retired, in armed forces, running one or more business and working in the non-private sector are removed from the sample.[28] In order to correct for outliers and top-coding I remove from the sample the 1 percent of top and bottom observations. Table 3.1 reports mean and the standard deviation for variables related to individual demographic characteristics such as gender, ethnicity, marital status together with education. More precisely, the summary statistics presented in Table 3.1 are obtained for the model including job stayers, new hires from unemployment, new hires from out-of-labour force and the group of job changers, defined as the individuals with an intra-monthly job to job transition detected by the presence of either a weekly spell of non-employment or a change in the starting date of the job between two consecutive periods in the employment state. Summary statistics for the job stayers are provided in column 1. Columns 2 and 3 report the descriptive statistics for newly hired workers from unemployment and newly hired from out-of-labour force. Columns 4 reports statistics for job changers.

This is the benchmark case investigated in this chapter. However, I also estimate the model with different specifications of the groups of workers. This implies the construction of the variables described above can show quantitative differences. For this reason I provide in Appendix C, Table 3.2, 3.3 and 3.4, the summary statistics for three alternatives scenarios: 1) the case with only job stayers and newly hired workers from a large group called non-employment; 2) the case with job stayers, newly hired from unemployment and newly hired

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[28] The sample selection procedure specified above produces the drop of 678,708 observations for the 1996 panel, 442,891 observations for the 2001 panel, 620,637 observations for the 2004 panel and 616,620 observations for the 2008 panel.

from out-of-labour force; 3) the case with job stayers, newly hired workers from unemployment, newly hired workers from out-of-labour force and job changers, with this last group defined as individuals making a job to job movement with one month's spell of non-employment between two consecutive periods into employment.

As showed by Fujita and Moscarini (2013), there is clear evidence in the SIPP of the presence of recalls. Even if summary statistics for this group of individuals are not reported in Tables 3.1 and 3.4 (the model specifications taking into account this additional group of workers are only those whose results are reported in these two tables), I find an overall value of 24,740 recalls spanned in the 1996-2013 period for the benchmark case including job stayers, new hires from unemployment, new hires from out-of-labour force and job changers.[29] The procedure bringing to the construction of the category recalls is described in Appendix A.

On average, the summary statistics show a slightly prevalence of men in all the groups but newly hired workers from inactivity, with the highest value reported for the case of newly hired workers from unemployment, close to 60 percent. Individuals transitioning from out-of-labour force to employment are those with the lowest value for age, roughly 30 years, and this makes the individuals from this group, on average, five years younger than the newly hired from unemployment. Job changers (not experimenting one month's break in their employment history) are the second younger group of individuals with, on average, 31 years. Labour market experience presents large variations between the different groups. Indeed, as it could be expected, the lowest value is registered for the out-of-labour force group (9 years), while the highest value is for the ongoing workers (17 years) followed by the newly hired from the unemployment state (14 years). The value for this group is even larger than that of job changers.

[29] Values of recalls are spread over the four panel. It is possible to identify 6,940 recalls in the 1996 panel, 4,760 recalls in the 2001 panel, 6,252 recalls in the 2004 panel and 6,788 recalls in the 2008 panel.

As regards the variable marital status, one can observe that the new hires from out-of-labour force are largely single individuals, while ongoing workers are largely involved into a stable relationship within a household. Indeed, the statistics show that 60 percent of the members of the former group are single against a value of 33 percent for the job stayers. However, individuals making job to job transitions are also more likely to be singles, with a value close to 50 percent. It is interesting to notice the higher likelihood to be single is a feature shared by the new hired from unemployment as well, with a value close to 45 percent.

One can also observe how, on average, the largest proportion of each group is made by whites, with values above 80 percent. Finally, I find that the job stayers are the group with the largest level of highly educated individuals (16 percent for the education level: University). However, the newly hired from out-of-labour force also consist of a large fraction of highly educated individuals, with values for the two highest educational levels, i.e. university and less than university, around to 47 percent, while the newly hired workers from unemployment result as the less educated, with a value for education at the two highest level around to 42 percent. Furthermore, the value for the lowest level of education is similar between all the three groups of new hires (job changers are also included in this case), around 20 percent, while it is below 15 percent for the ongoing workers. Finally, one can observe how the (hourly) real wage is higher for job stayers than for the individuals in other groups as it is expected.

In Table 3.5, Appendix C, I also report the summary statistics for the two raw groups of unemployed and out-of-labour force. This exercise is performed in order to highlight potential differences in terms of demographic characteristics between the two groups. Clearly, the unemployed and inactive workers included in this descriptive analysis are only those that experiment, at least one time, a movement into employment. Looking at the values for the case where it is taken into account only the unemployed and out-of-labour force male groups, it can be observed how the values for labour market experience and age are larger for the unemployed compared to the inactive individuals. The unemployed result also more educated than the out-of-labour force since only 24 percent of all members of the former group have less than high school education, while the value is 40 percent for inactive workers. Differences are less evident when the female groups are taken into account. In this case, the gap for labour market experience is smaller and there is no substantial difference in terms of high level of education (i.e., university and less than university). Panel B reports values for the different age groups. Columns (1) and (2) present statistics for the case of young workers, i.e. individuals in the aging 16-24. In this case, statistics for labour market experience and education are not very informative. Values are very similar. When one considers workers in their prime age, it is possible to observe that out-of-labour force individuals result more highly educated (56 percent) than unemployed individuals (50 percent). Finally, in Panel C, it is showed that unemployed are made up of a larger proportion of skilled individuals (25 percent) compared to inactive workers (19 percent) and that unemployed show a large presence in industry sectors such as construction and manufacturing compared to out-of-labour force workers (24 percent vs 14 percent), while inactive workers are largely present in services (e.g., food services and accommodation and retail trade) compared to unemployed (41 percent vs 30 percent).

[INSERT TABLE 3.1 ABOUT HERE]

Table 3.6 dicusses the correlation between the variables. One can see that wages and demographic variables show the standard correlations with the variables representing the four different groups of workers populating the labour market. Wages are positively correlated with both age and labour market experience and education for the highest level (i.e., university), while they are negatively correlated with the marital status single. Furthermore, one can observe there is a positive correlation between real wage and the category job stayers, while the correlation is small and negative between the real wage and the categories job changers and newly hired workers (either from unemployment or out-of-labour force).

[INSERT TABLE 3.6 ABOUT HERE]

3.3 Empirical methodology

3.3.1 *The Standard Approach: The Sensitivity of Real Wages of Newly Hired Workers coming from the Non-Employment Group*

The model that will be used to study the response of individual real wages to changes in aggregate conditions is a wage equation, similar to the econometric specification proposed by Bils (1985).

The baseline equation is

$$\log(\omega_{it}) = \chi_i + \boldsymbol{x}'_{\boldsymbol{it}}\beta_1 + \gamma^u u_t + \gamma_\varphi^{ne}\iota + \gamma_\psi^{ne}\iota u_t + e_{it} \quad (1)$$

where ω_{it} is the real hourly wage of individual i at time t, χ_i is an individual fixed effect, x_{it} is a vector including time-varying individual level characteristics such as marital status, labour market experience and its square, and education, u_t is the cyclical aggregate indicator (in this case, the unemployment rate), ι is a dummy variable equals to one if the worker is a newly hired and zero otherwise and e_{it} is a zero-mean random term with constant variance.[30]

The key parameters are γ^u, γ_φ^{ne} and γ_ψ^{ne}. While γ^u can be interpreted as the semi-elasticity of real wages with respect to the unemployment rate, γ_ψ^{ne} can be interpreted as the extra differential in the semi-elasticity of the real wages with respect to the unemployment rate for new hires and, finally, γ_φ^{ne} is to be interpreted as capturing the change in the labour market state for newly hired workers, i.e., the movement from non-employment to employment. One can consider the sum of the two coefficients, γ^u and γ_ψ^{ne}, as expressing the overall semi-elasticity of the real wages with respect to the unemployment rate for new hires.

[30] The model estimated in all sections includes also a dummy variable for the year and state.

Results from previous studies show there exists a negative relationship between real wages of newly hired workers and unemployment rate, with the values for the semi-elasticity of real wages close or larger than one,[31] while the same relationship for all workers is less elastic,[32] indicating the presence of a lower procyclicality in the real wages of ongoing workers, since the larger proportion of job stayers in the overall working population compared to the small amount of newly hired workers.

I proceed by estimating the above equation using data from the Survey of Income and Program Participation. The advantage of the SIPP dataset on the widespread employers/employees datasets, such as the one used by Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012), the "Quadros de Pessoal", is given by the suitable property of the SIPP to record the labour market state the newly hired workers are coming from. Indeed, in the matched employers/employees datasets there is no detailed information about the labour market history of the newly hired workers before their inclusion in the dataset and this implies that this kind of dataset cannot properly address the issue I investigate in this study.[33]

Moreover, a further advantage of the SIPP is also the fact that the questions concerning the labour market state each individual finds herself in different periods of time is associated with an answer that provides information at a very high frequency. Indeed, individuals are usually observed in the labour market state at a weekly and monthly frequency.

[31] The procyclical behaviour of real wages for newly hired workers, when the aggregate indicator is the aggregate labour productivity, has been showed by Haefke, Sonntag and Van Rens (2013).

[32] An important exception, as it has been previously mentioned, is Martins, Solon and Thomas (2012), where there is no evidence of a significant difference in the procyclicality of real wages of both groups of workers.

[33] More precisely, the employers/employees dataset can collect information for the job changers, since these workers were already registered in a match with a firm, but they do not provide in-depth details on new hires coming from non-employment history.

I propose a monthly estimation since, as said above, the high frequency nature of the records in the dataset allows for wages and employment status to be both measured at monthly frequency.

The transition in the employment state is measured as follows: I consider a newly hired worker as an individual with a tenure of four consecutive months after a spell of non-employment, as in Gertler, Huckfeldt and Trigari (2016). In this section, I do not differentiate for the non-employment state the newly hired workers are coming from (either unemployment or out-of-labour force), but I lump together unemployed workers and out-of-labour force workers into the same group, the so-called non-employment group (I will deal with this issue, i.e., the construction of the two different groups of new hires next section).

Finally, some points about the identification of the category newly hired workers, the construction of the wage variable, i.e., the dependent variable, and the structure by which data on this last variable are collected in the SIPP must be discussed. The last two points are discussed below, while the procedure to construct the newly hired worker variable is discussed in the Appendix B.

As regards the construction of the variable wage, three different aspects deserve a more in-depth analysis.

Firstly, since it is generally stated that wages are set between six months and one year in advance, this implies that there is a lagged relationship between real wages and unemployment rate. I deal with this problem by using both lags. I define as CGP model the case where I use the aggregate cyclical indicator with one year lag, since this time specification is that used by Carneiro, Guimares and Portugal (2012) to estimate their model. On the contrary, I define as GHT model the case where I use an aggregate cyclical indicator with a six months lag, because this time specification resembles (even if it is not perfectly similar) that used by Gertler, Heckfeldt and Trigari (2016).

Secondly, wages are either directly defined in terms of hourly pay rate by using SIPP data[34] or I define them in the same terms using information on monthly job-specific earnings and job-specific hours worked. Indeed, the SIPP does not collect values for the variable defining the hourly wage paid in a wave for all four months it consists of, but the value is collected just once and then reported for the other three months. This implies that in a wave it is observed for all four months the same value for the hourly wage paid. On the contrary, the SIPP provides information on the gross monthly wage paid to the workers each month.[35] Unfortunately, the SIPP does not provide information on the number of hours worked in each of the four months that makes a wave, but information on the overall worked monthly hours is obtained through the variable EJBHRS that usually collects information on hours worked each week, but only for one month, and then this value is reported for the other three months included in the reference wave.[36] Then there exists a reliable information only for one month, which implies that one could not use it together with information on the gross monthly paid wage to get an hourly wage paid for all four months of a wave. Thus, to settle this issue I follow Gertler, Huckfeldt and Trigari (2016) that propose to estimate the model on the hourly wage reported in the fourth month.[37] I set the wages for all the months into a wave equal to that obtained through the interview process. This implies an artificial level of rigidity for the wage at the

[34] This information is identified in the SIPP through the variable TPYRATE1 and TPYRATE2, since the SIPP collects information up to two main jobs. The variable TPYRATE, in general, reports values for the regular hourly pay rate.

[35] This information is identified in the SIPP through the variable TPMSUM1 and TPMSUM2, since the SIPP collects information up to two main jobs. The variable TPMSUM, in general, reports values for monthly gross pay before deductions.

[36] The variable EJBHRS1 and EJBHRS2 report values for hours worked per week at the main and second job.

[37] The hourly wage in the fourth month is the value obtained either through the variable TPYRATE or through the use of the variables TPMSUM and EJBHRS, with this last variable multiplied by 4.3 (number of weeks in a month) to make it a consistent information at monthly level.

intra-wave level. However, if I want to test the model using a consistent measure for wage, it can be observed that using the value reported for the wage in the fourth month is a more reliable option than just relying on all the values reported at the beginning of the employment history, where it can be expected that the wage for a newly hired workers is quite volatile and it takes time to get settled. I think that four months is a period of time that can be considered a good approximation of this process.

Furthermore, I do not expect that wages of newly hired workers can initially benefit from overtime pay or further benefits that can substantially affect it, thus I have reasons to believe the correction method proposed should approximate quite well the dynamics of the true wage, i.e., I believe that four months is not a period of time in which it is reasonable to observe large fluctuations due to permanent changes in the level of wages paid.

A different matter is whether this procedure can fit well with the dynamic of the wage for ongoing workers. In this last case, it could be possible to observe intra-wave changes due to permanent changes in the status of the workers, but I still believe the above procedure can work even in this case given the short period of time (four months) taken into account. Finally, the problem of the effects of this "artificial" wage rigidity does not rise in the case I deal with job changers since, as it will be discussed later on, since for that case I will implement a correction procedure strategy allowing to differentiate the wage of the job changers in the reference wave, in order to capture its elasticity.

The other point it is needed to be discussed here concerns the "seam bias" effect. The structure of the SIPP is such that information are retrospectively collected every four months. Then, it happens that changes in variables, for example new occupation or differentials in wages, are often observed to the seam rather than between the four months of a wave. This phenomenon is quite pervasive for the SIPP and it is well-documented. However, in the present investigation

I am able to deal with labour market transitions at the monthly level and changes in wages at the monthly level for job changers are also constructed. Thus, results should not be seriously affected by this problem.

I estimate this relationship by using the fixed effects estimator.[38] Since the results from the two different estimators show no substantial differences, I will discuss in this work the findings obtained by using the fixed-effects estimator. Indeed, the standard approach in the literature, as regards the use of these two different estimators, i.e., the fixed-effects estimator and the first-difference estimator, is based on the analysis of the different properties of the error term. A low serial correlation of the error term is a result that favours the use of the fixed-effects estimator. Since this is the case in the present study, I will focus mainly on the results obtained by using this estimator.

The overall number of observations in the dataset are 2,504,475, with 2,490,645 individuals identified as job stayers and the overall number of observations for newly hired workers from non-employment is 14,120.[39] Real wages are obtained by deflating wages for the monthly Price and Consumption Expenditure (PCE) Index and, are finally, expressed in logs. The unemployment rate is measured by using data from the Current Population Survey for civilian non-institutional workers in U.S. aged 16-64, including both men and women.

[INSERT TABLE 3.8 ABOUT HERE]

[38] The model is estimated with the first-difference estimator as a robustness check. Results are not significantly different from those obtained with the fixed-effects estimator.

[39] See Table 3.7. I do not consider recalls or job changers in this first exercise. The estimations include the state dummy variable with the reference category state1 (Arizona). However, results are not reported in the table, but are available upon request. The reference category for gender, race, marital status, education and year are, respectively, male, white, single, university, 1997 and 2011. The variable education is defined from the lowest level to the highest as 1) less than high school, 2) high school, 3) less than university. The variable marital status defined for married includes both cases with and without the spouse in the household.

From the results showed in Table 3.8, one can observe that, dealing with the two different time specifications for the wage setting process, it is possible to explain the different results produced in the literature (procyclical real wages for Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012) *contra* acyclical real wages for Gertler, Huckfeldt and Trigari (2016)). Estimates from the GHT model are roughly similar to those found by Gertler, Huckfeldt and Trigari (2016). Indeed, I find a percentage value of -0.202 as regards the semi-elasticity of real wages of job stayers and of -0.227 percentage points for the semi-elasticity of the real wage of marginal workers, compared to the estimates of -0.160 and -0.155 found by Gertler, Huckfeldt and Trigari (2016).

Thus, confronting our findings with those in Gertler, Huckfeldt and Trigari (2016), which is the most straightforward comparison study because of the spirit of their work is the closest to this study, I can speculate that the difference is likely to be due to the different length of the sample investigated and to the different methodology used in this chapter. In fact, their results are obtained on a dataset spanning from 1990 to 2014, while the dataset used in this work spans from 1996 to 2013. Furthermore, they define as job stayers only those workers receiving a wage and as new hires those workers who receive a wage after a period without any employment payment, while I define the ongoing workers as workers, but new hires, who are recorded as having a job, and new hires as workers moving from a labour market state different from employment straight on the employment state.[40]

On the other hand, when I use the CGP model, results are close to those in Carneiro, Guimares and Portugal (2012) and Martins, Solon and Thomas (2012), since I obtain a percentage value for the semi-elasticity of real wages of job stayers equal to -1.452, but I also observe the

[40] Moreover, I consider both men and women in the sample used in this work and in the aging range 16-64, while Gertler, Huckfeldt and Trigari (2016) consider only men in a smaller aging period (i.e., 20-64).

presence of a procyclical incremental effect for the wage of new hires, which brings about an overall value of -1.704 percentage points, compared to -2.20 found in Carneiro, Guimares and Portugal (2012) and -1.8 found in Martins, Solon and Thomas (2012).[41] These results confirm the presence of a more procyclical real wages for new hires, even if some differences still persist compared to estimates from other works.

One question is thus left on the table: how can one justify the difference in the values for the semi-elasticity of wages with the two different specifications for the explanatory variable? As implicitly suggested by Gertler, Huckfeldt and Trigari (2016), it seems that the different data-frequency used in the estimations (yearly data for Carneiro, Guimares and Portugal, 2012, and Martins, Solon and Thomas, 2012, but a higher data-frequency for Gertler, Huckfeldt and Trigari, 2016) can rationalize this puzzle. Indeed, one can speculate there is evidence of staggered wages and the higher elasticity found in the case of one year lag, compared with the case of six months lag, tends to reinforce the idea that at a lower frequencies a larger fraction of wage contracts adjust for the changes in the prices and this produces a higher elasticity of wages.

3.3.2 A New Approach: The Sensitivity of Real Wages of Newly Hired Workers coming from Unemployment and Newly Hired Workers coming from Out-of-Labour Force

While a lot of interest has been showed for the sensitivity of real wages of newly hired workers to changes in the aggregate cyclical indicator, a more detailed analysis on what a newly hired worker is has been dismissed by researchers. Reviewing the literature on the subject, one can observe a certain degree of heterogeneity in the way authors have approached the matter.

[41] This value in Martins, Solon and Thomas (2012) is not clearly specified, but it can be inferred by the broad explanation provided by the authors about the non significant difference between the two values for the two elasticities.

Carneiro, Guimares and Portugal (2012) define the new hires as workers coming from non-employment, with less than twelve months of tenure in their job. They characterize this category lumping together individuals coming from unemployment, out-of-labour force, public and business sector. Martins, Solon and Thomas (2012) define the category as those workers with no more than four months of tenure with the firm. However, they connect this criteria with a sample selection that is based on the "port-of-entry" jobs strategy, i.e., they select a set of jobs in which firms are observed over time to hire new workers. Moreover, they impose some constraints on the size of these firms in terms of workers employed, and on the category of workers, lumping together workers with the "same job" into eight categories. Haefke, Sonntag and Van Rens (2013) define new hires as those individuals with at least one out of three previous months, before observing their current wage (i.e., being registered as employed), spent into unemployment. However, they allow for job to job transitions in the way they define newly hired workers. Gertler, Huckfeldt and Trigari (2016) consider only men and define the new hires as those individuals, who are in the first four months of their tenure on a job, coming from a period of unemployment, but they introduce some different time intervals in order to control for job to job transitions.

It is clear that the current research has focused mainly on the unemployment state as the reference labour market state and this is consistent with the framework used by Shimer (2005) to describe the unemployment volatility puzzle. However, it must be stressed that the flow into employment cannot be reduced to the movements from unemployment to employment only. A much richer dynamics is present and it involves direct flows into employment from both unemployment and out-of-labour force. As observed by Krusell, Mukoyama, Rogerson and

Sahin (2016) the out-of-labour force to employment flow is an order of magnitude greater than the unemployment to employment flow, when measured in levels.[42]

If the purpose of empirical evidence is to put more discipline on the matter, this means that neither considering newly hired workers as a homogeneous group of workers coming from the locked box "non-employment" nor assuming that only those workers coming from unemployment are to be considered as newly hired workers is the correct approach. In this section, I disentangle the large group of new hires from non-employment in the two groups: newly hired workers coming from unemployment and newly hired workers coming from out-of-labour force.

The contribution of this study is mainly directed to shed light on the cyclicality behaviour of the real wages of newly hired workers, conditional to the labour market state the workers are coming from. However, this work also aims at adding more evidence to the debate on the representative versus heterogeneous agent(s) model. Remarkable differences in the responsiveness of real wages for newly hired workers coming from different labour market states would imply substantial divergences in the behaviour of the individuals belonging to these two groups supporting the need for heterogeneous agents model in order to explain the dynamics of the labour market variables.

To study the response of individual real wages to changes in aggregate conditions when one consider flows from both unemployment and out-of-labour force into employment, I still make use of a wage equation specified as follows:

[42] Canon, Kudlyack and Reed (2012) confirm these results for the period 2002-2012. They also show that the ratio out-of-labour force to employment over unemployment to employment is strongly procyclical.

$$\log(\omega_{it}) = \chi_i + \boldsymbol{x}'_{it}\beta_1 + \gamma^u u_t + \gamma_{\psi}^{u,e} \iota u_t + \gamma_{\psi}^{olf,e} \iota u_t + \gamma_{\varphi}^{u,e} \iota + \gamma_{\varphi}^{olf,e} \iota + e_{it} \tag{2}$$

The change in the structure of the standard equation just takes into account the possibility newly hired workers can come from different labour market states, not only from the unemployment state.

Following the notation introduced in equation (1), I have the new parameters for the newly hired workers from unemployment, $\gamma_{\psi}{}^{u,e}$ and $\gamma_{\varphi}{}^{u,e}$, and the newly hired workers from out-of-labour force, $\gamma_{\psi}{}^{olf,e}$ and $\gamma_{\varphi}{}^{olf,e}$. More precisely, the parameters $\gamma_{\psi}{}^{u,e}$ and $\gamma_{\psi}{}^{olf,e}$ can be interpreted as the extra differentials in the semi-elasticity of real wages with respect to unemployment for new hires coming from, respectively, unemployment and out-of-labour force, while the parameters $\gamma_{\varphi}{}^{u,e}$ and $\gamma_{\varphi}{}^{olf,e}$ can be interpreted as the change in the state for newly hired workers, i.e., the movements from unemployed to employed and from out-of-labour force to employment.

As in the previous section, I define a worker either as a newly hired workers from unemployment or as a newly hired workers from out-of-labour force according to the different labour market state the worker is coming from and conditional to the fact the worker has experimented at least a period of tenure on the job of four (consecutive) months.

A crucial issue for the current investigation is that related to the presence of individuals moving backward and forward between unemployment and out-of-labour force before finding a job. In this case, I need a criteria to identify the relevant labour market state the newly hired workers are coming from. The approach followed in this study is to consider only the labour market state the individual is registered at in the last period (i.e., last month) before finding a job.[43]

I present the results in Table 3.10. In this case, the dataset includes 10,300 observations for new hires coming from unemployment and 3,820 observations for new hires coming from out-of-labour force, while the number of observations for job stayers are 2,490,645.[44]

[INSERT TABLE 3.10 ABOUT HERE]

Results for the semi-elasticity of real wages for job stayers and for new hires are not significantly different from those reported in previous works.

Using the GHT specification, I obtain a percentage value for the semi-elasticity of wages for job stayers of -0.204 and a percentage value of -1.454 when I use the CGP model, which are both pretty similar to the set of results I obtained with the previous model specification.

However, the most striking fact consists in the significant difference in the behaviour of real wages for new hires coming from unemployment and new hires coming from out-of-labour force. One can, indeed, observe that the semi-elasticities of real wages for new hires coming from out-of-labour force and unemployment, when I use the GHT specification, are equal to -0.328 and to -0.194 percentage points, respectively, while with the CGP specification, the semi-elasticity of real wages for new hires coming from unemployment is equal to -1.573 and that for new hires from out-of-labour force is equal to -2.201 percentage points.[45]

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[43] Results from a model with the alternative scenario, i.e., removing from the sample the individuals transitioning between the two non-employment groups before finding a job, are not significantly different from those reported in Table 3.10.

[44] See Table 3.9 for a detailed description of the different groups of workers, when it is distinguished between job stayers, new hires coming from unemployment and new hires coming from out-of-labour force.

[45] The coefficient for the incremental effect of the semi-elasticity of real wage for new hires from out-of-labour force is significant at the 1%, while the coefficient for the incremental effect of the semi-elasticity of real wage

This implies that there exists a substantial wedge between the two measures of the semi-elasticity of real wages for the new hires belonging to the two different groups, with the real wages for new hires coming from out-of-labour force more procyclical than the real wages for new hires coming from unemployment.

Interpreting these last results is crucial, because they show the presence of heterogeneity between the two groups of new hires. One could argue that, in good times, as described by several papers in the literature (e.g., Bils, 1985, and Solon, Barsky and Parker, 1994) individuals transitioning from the unemployment state to the employment state are the low-quality ones, because in periods of expansion of the economic activity, these workers search for a job and they are more likely to find it (i.e., the probability to find a job for low-skilled workers is higher in good times rather than in bad times) and filling a substantial amount of vacancies (compositional workforce bias). The wage for these workers shows a lower degree of procyclicality, since it is likely to reflect a low-quality of the same jobs, thus resulting in "low-paying jobs". How can one rationalize the presence of a more elastic real wage for new hires coming from out-of-labour force compared to new hires coming from unemployment? In this case, it might be inferred that in bad times the individuals in the out-of-labour force state entering the employment state are the low-quality ones, because in downturns this is the group of inactive individuals that starts to search for a job in order to smooth consumption at the household level. In other words, in bad times, when the marginal value of income is high, the out-of-labour force workforce looking for a job is made up of low-skilled workers, who find and accept a job, in an attempt to insure the household against the consumption risk (which is higher in recession than in boom). On the other side, when there is an economic expansion, there is a large participation of high-quality out-of-labour force workers since their probability

for newly hired worker from unemployment is not significant. The coefficient for the semi-elasticity of real wage for job stayers is significant at the 1%.

of finding a better paid job is higher and this explains the possibility for new hires from out-of-labour force to get a more procyclical wage.

The different composition of workforces as regards new hires from unemployment and new hires from out-of-labour force is a further feature that sharply hinder the reduction of the newly hired workers from the two different non-employment states to just one category. It is interesting to notice that the presence of high-quality inactive workers in booms tends to reinforce the procyclical effect of real wages since it counterbalances the negative effect produced by the compositional shift in the unemployed group towards low-skilled workers.

3.3.3 *An Extension of the New Approach: The Introduction of the Job Changers*

Despite the strong focus in this chapter on the differentiation between new hires coming from unemployment and new hires coming from out-of-labour force, it has to be taken into account the fact that a recent literature (Gertler, Huckfeldt and Trigari, 2016) has emphasized the role played by the job changers as the variable able to capture a very large part of the procyclicality behaviour of the real wage observed in the previous estimates. Whilst past papers have considered the new hires as workers coming from a "broad" unemployment state, and consequently looking at their wages as the relevant variable to be taken into account in order to explain the unemployment volatility puzzle, Gertler, Huckfeldt and Trigari (2016) have challenged this methodological approach. More precisely, these authors argue that the substantial cyclicality of real wages for new hires coming from unemployment disappears when job to job transitions are included in the model. The rationale for this approach stems from the fact it appears that job changers is the group of workers who experiments the benefits of a cyclical job-upgrading. Following results provided by Topel and Ward (1992), and Barlevy (2001), they find evidence of a strong procyclicality of real wages for job changers, with values for their semi-elasticity of real wage higher than those observed for the real wage of new hires coming from unemployment by roughly a factor of ten.

Although this group of workers does not provide any direct indication to identify or affect the distinction between the two groups of workers of interest for us, i.e., new hires coming from unemployment and new hires coming from out-of-labour force, it is nevertheless significant to make the model informationally more efficient. In this sense, including the job changers into another group would produce biased estimations and excluding them from the model would produce a significant misspecification of the same.

To address these concerns, I re-estimate the model as defined in the previous section but with the inclusion of job changers.

However, measuring job to job transitions is both methodologically and analytically challenging. Regarding the former point, one can observe that it is often not clear who the job changers are. Broadly speaking, job changers could be described as either workers that make an infra-monthly transition from one job to another, such that they do not experiment any non-employment spell in the transition between these two different jobs, or as workers that transition from one job to another spending a relatively small spell as non-employed. Indeed, by looking at the empirical evidence, it is possible to observe the presence of institutional and legal frictions that can produce a spell of non-employment in the transition between the previous and the new job.

For the purpose of this chapter, I develop a model dealing with both specifications.[46] To be more precise, I construct the category job changers by assuming this group is made up of,

[46] Haefke, Sonntag and Van Rens (2013) have suggested that the two groups of potential job changers could represent different groups of workers, with different preferences and characteristics. Hence, it makes sense to

alternatively, a) workers making infra-monthly job to job transitions without observing any non-employment spell (*E'E'* job changers), b) workers making infra-monthly job to job transitions but with at least one week's non-employment spell (and no more than three weeks' non-employment spell), i.e., there are individuals that are registered as employed in two consecutive months but with the presence of a short spell of non-employment in between (*EE* job changers), and c) workers who make a job to job transitions with one month's non-employment spell in the job change process (*E∄E* job changers), hence I look at individuals who have not been registered as employed in two consecutive months.

While the category job changers as defined by letter c) is not difficult to be constructed, since it can be considered like a special case of the category newly hired workers with only one month's spell of non-employment, substantial problems rise as regards the reliability of the information provided by the data sets in order to identify job changers, with reference to the letter a) and b). Usually data sets are not very efficient in identifying and reporting job to job transitions at high frequency. However, the particular structure of the SIPP makes it also possible to identify these two categories of job changers. I construct the category job changers as defined by letter b) using the variable RWKESR, which identifies the labour market state individual belongs to at weekly frequency. Hence, the category *EE* job changers is obtained by looking at the presence of at least one week's spell of non-employment (and no more than three weeks' spell of non-employment) for individuals being reported as employed in two consecutive months.

As regards the construction of the category *E'E'* job changers as defined by letter a), fortunately, the SIPP provides a rich set of variables that can help in this regards. Information regarding job

propose both specifications to address this heterogeneity issue between these two groups of potential job changers.

changers can be obtained through three different variables: EENO,[47] ESTLEMP,[48] TSJDATE.[49] While the first variable identifies the Job ID of the employer, i.e., the number uniquely linking the worker to the employer, the second variable identifies the continuation of the job with the same employer as reported in the first interview in the panel, and the third variable identifies the starting date of a job.

However, both the first and second variable present some shortcomings. The variable ESTLEMP only registers the continuation of a job with last employer, as identified at the beginning of each panel, and in this sense is not useful in identifying job changes that usually happen at higher frequency. The variable EENO, which could do a better job given its presence in all the waves, presents the drawback to register changes in the Job ID number (hence, it identifies changes in the employment relationship, with the movement of the worker from one employer to another one) for one month and this value is then reported in the other three months of the reference wave. Hence, changes can be "reasonably" observed only at the "seam" between two consecutive waves. This makes quite difficult to identify intra-wave changes. To overcome these drawbacks, I make use of the variable TSJDATE that can help to identify the possible job to job transitions.

Thus, I can construct the category of workers making infra-monthly transitions without observing any non-employment spell (*E'E'* job changers) whether an individual is registered in

[47] The variable EENO contains a 2-digits code that uniquely identifies the employer for each worker (the job ID code). Every time there is a match between a worker and an employer, a job ID code uniquely identifying the employer matched in the working relationship with the worker and it is registered in the variable EENO. Information on job ID is reported up to two jobs. Hence, in the dataset one finds EENO1 and EENO2. However, for the purpose of this study, I am only interested in the main job. This means that when I refer to the variable EENO, or also to other variables that identify characteristics up to the two main jobs, I will use only information coming from the first one.

[48] The variable ESTLEMP provides information as regards the continuation of the job with the same employer as registered in the first interview in the panel.

[49] The variable TSJDATE provides information as regards the starting date of a job in the format YYYY:MM:DD.

the two consecutive months as an employed, and the starting date of the job is different between the two months.

I proceed by estimating both specifications for job changers using alternative models, but I gather together the cases defined under letter a) and b) in only one category. When one considers job changers as individual with one month's break in their employment history, the number of observations for new hires coming from unemployment, out-of-labour force and job changers amount respectively to 3,547 and 1,531 and 2,014. Dealing with the group of job changers as individuals with one week's break or a change in the job between two consecutive periods into employment identified by a change in the starting date of the job, I end up with 5,244 new hires from unemployment, 1,848 new hires from out-of-labour force and 12,539 job changers.[50]

The wage equation is now specified as follows:

$$\log(\omega_{it}) = \chi_i + \boldsymbol{x}_{it}'\beta_1 + \gamma^u u_t + \gamma_\psi^{u,e} \iota u_t + \gamma_\psi^{olf,e} \iota u_t + \gamma_\varphi^{u,e} \iota + \gamma_\varphi^{olf,e} \iota + \gamma_\psi^{e,e} \iota u_t + \gamma_\varphi^{e,e} \iota + e_{it} \quad (3)$$

The only difference with respect to the previous specification is the inclusion of the terms to identify job changers. More precisely, the introduction of the parameters, $\gamma_\psi^{e,e}$ and $\gamma_\varphi^{e,e}$, where the first term defines the extra differential in the semi-elasticity of real wages with respect to unemployment for job changers and the second term defines the change in the status of newly hired workers, i.e., the job to job transition.

The results in Table 3.13, when I deal with the specification of job changers as workers “without” a monthly spell of non-employment between two consecutive periods into the

[50] See Table 3.11 and 3.12 for a detailed description of the different groups of workers, when it is distinguished between ongoing workers, new hires coming from unemployment, new hires coming from out-of-labour force and job changers using the appropriate definitions.

employment state, show that the real wage for job stayers is roughly as much cyclical as the real wage for new hires from unemployment and less procyclical than the real wages for new hires coming from out-of-labour force. Indeed, I find estimates of -0.317 percentage points for new hires from out-of-labour force and -0.194 percentage points for new hires from unemployment, when I test the model using the GHT approach, and estimates of -2.222 and -1.610 percentage points for the semi-elasticity of real wage of new hires from, respectively, out-of-labour force and unemployment, when I use the CGP specification. Furthermore, one can also observe that there is evidence of a larger procyclicality in the real wage of job changers. Usually, a one-point increase in the unemployment rate leads to a fall of the real wages for job changers of -0.373 and of -2.341 percentage points, according to the different specification used. Both values confirm the evidence of higher real wage cyclicality for the job changers as found in Gertler, Huckfeldt and Trigari (2016) and in prior works like Barlevy (2001).[51]

When I use the second definition of job changers, i.e., the one defining as job changers the workers who experiment a monthly spell of non-employment between two periods into the employment status, I find that the real wages of job changers show only a slightly lower change, with values roughly equal to -0.344 and -2.291 percentage points. Nevertheless, the real wage of new hires from out-of-labour force is still more procyclical than that of new hires from unemployment.

[INSERT TABLE 3.13 ABOUT HERE]

[51] The coefficient for the incremental effect of the semi-elasticity of real wage for new hires from out-of-labour force is significant at the 5%, while the coefficient for the incremental effect of the semi-elasticity of real wage for newly hired worker from unemployment is not significant. The coefficient for the incremental effect of the semi-elasticity of real wage for job changers and the coefficient for the semi-elasticity of real wage for job stayers are both significant at the 1%.

3.3.4 A Sensitivity Test for the New Approach: The Response of Real Wages to Labour Productivity

An alternative approach focusing on a different aggregate cyclical indicator, in order to further test the validity of previous observed results, is proposed in this section. I estimate the elasticity of the real wage for new hires with respect to the aggregate labour productivity. The idea is to compare these results with the findings in Haefke, Sonntag and Van Rens (2013), even if these authors use a different methodology and dataset from ours.

I adopt, as a measure for the aggregate labour productivity, the monthly Gross Domestic Product (GDP) for U.S. in the non-farm private sector.[52]

Results are reported in the Table 3.14. One can observe that, using the GHT specification, a one-point percentage increase in the aggregate labour productivity raises the real wages for job stayers by 0.887 percentage points, and by 0.941 percentage points when I use the CGP specification. However, when one points to the values for the incremental effect of real wages I have that the additional effect for newly hired workers coming from unemployment is a value close to zero, while it is a positive value for new hires coming from out-of-labour force, confirming the basic intuition of our previous results, i.e., the heterogeneity in the cyclicality of real wages for the two groups of newly hired workers.

[52] Data for the GDP of the U.S. are not usually available at monthly frequency, but only at quarterly frequency. This makes any attempt to measure the monthly elasticity of real wages for new hires quite challenging. In order to provide robust results from this test, I use data describing the monthly series of GDP in the private sector for U.S., using the index constructed by Macroeconomic Advisers. The Index has been developed using data from National Income and Production Account (NIPA). The series are deflated by using the Price Consumption Expenditure (PCE) Index, transformed in per-capita terms by dividing the real term series by the CPS total population series, and finally are logged and de-trended using the HP-filter, with smoothing parameter 129,000, as suggested by Ravn and Uhlig (2002).

Indeed, findings reported in Table 3.14[53] show that the elasticity of real wages of newly hired workers from unemployment is equal to 0.945 and for the newly hired workers coming from out-of-labour force is equal to 1.006, for the GHT specification, while it is equal to 0.991 and 1.055 for, respectively, newly hired workers from unemployment and out-of-labour force, with the CGP model. However, even in this case, when it is used as a cyclical indicator the aggregate labour productivity it can be seen how the job changers represent the group with a more procyclical wage. Indeed, I obtain the following findings, according to the different model specification: 1.013 and 1.118.[54]

Comparing these results to those in Haefke, Sonntag and Van Rens (2013), where the elasticity for newly hired workers is a value around 0.8-0.9, one can observe that the estimates from the present model are slightly higher. However, it should be noticed how Haefke, Sonntag and Van Rens (2013) use a different procedure to identify the group of new hires, impose some restrictions about the sample investigated (the employable prime age sample is dropped) and employ a different estimation methodology. As an interesting point, I find that results in this study are very close to the findings obtained in Carneiro, Guimares and Portugal (2012), where the authors report a value for the elasticity of real wages for newly hired workers equal to 1.06.

[INSERT TABLE 3.14 ABOUT HERE]

[53] Table 3.14 shows only estimates from the model defined by equation (3) and with job changers identified as workers making a job to job transition without a monthly spell of non-employment, since results from the FE and the FD estimator with job changers identified as individuals with one month's break are not significant different.

[54] The coefficient for the incremental effect of the semi-elasticity of real wage for new hires from out-of-labour force is significant at the 10%, while the coefficient for the incremental effect of the semi-elasticity of real wage for newly hired worker from unemployment and job changers is not significant. The coefficient for the semi-elasticity of real wage job stayers is significant at the 1%.

3.4 Assessment of the Empirical Evidence of New Hires from Out-of-Labour Force

A true concern in this investigation is represented by the rationalisation of the very large flow of individuals from out-of-labour force to employment using the economic theory. What could the economic theory tell us in order to explain the observed transitions of workers between out-of-labour force and employment?

Several studies, such as Garibaldi and Wasmer (2005), emphasize the relevance of the time-aggregation procedure as a feature that should inform the movements from inactivity to employment. The out-of-labour force to employment worker flow is, in other words, a statistical illusion. In reality, according to this view, individuals tend to make a “compulsory” transition from inactivity to unemployment before finding a job, but this movement is not spotted in the standard statistical models dealing with the measurement of worker flows because of the small interval of time that characterizes this transition, compared to the monthly statistical survey used to measure worker flows.

However, the unique structure of the SIPP in terms of data collection procedure comes to our aid allowing to overcome this critique since it permits to identify the labour market state each individual belongs to in very small time intervals. Indeed, as explained in the previous sections, the SIPP records the labour market state individuals are registered to at different frequencies, and among them, it uses weekly frequencies as well. This implies I am able to identify worker flows between out-of-labour force and employment at a very high frequency. Thus, even if the investigation is based on a monthly estimation, it has been provided for a correction procedure that restricts the identification of newly hired workers from out-of-labour force making use of the weekly values to identify the labour market state the individuals belong to. Moreover, even if results are not reported in this work, I have further restricted this benchmark criteria and I have controlled for all the individuals that do not show any weekly movement into unemployment from the inactivity state before transitioning into the employment state, in order to make the estimates more robust. Results still confirm the presence of a large number of individuals transitioning directly from out-of-labour force to employment.[55]

Supported by the empirical evidence described above, how can one justify the presence of such a large group of newly hired workes from out-of-labour force? What might the economic theory tell us about this large flow? It seems quite obvious to try to think how in everyday's life individuals into the inactivity state can find a job. Statistical methods tend to define the inactive workers as those who are neither looking for a job nor on layoff. More precisely, the Current Population Survey, which is the main reference for the official measurement involving most of the labour market variables, defines the out-of-labour force workers as those individuals searching passively for a job. Such activity implies, for example, the attendance of a job training program or course, or merely reading about job openings that are posted in newspapers or on the Internet. In other words the passive methods of job search do not possess the potential to connect job finding workers with potential employers.[56] Moreover, the results from the use of time in the American Time Use Survey shows that the time devoted to passive search is positive, even if it is quite lower compared to the time devoted to the same activity by unemployed individuals yet. Thus, the question still needs to be answered.

I believe that the more fruitful approach lies in linking the presence of large outflows from inactivity to employment with that strand of the literature focusing on the role of social

[55] Results obtained through the estimation of a model with this further restriction in terms of identification of the newly hired workers from out-of-labour force are not significantly different from those obtained using the benchmark model in this chapter.

[56] In contrast, the CPS defines as active searching the following activities: Contacting an employer directly or having a job interview, contacting a public employment agency, contacting a private employment agency, contacting friends or relatives, contacting a school or university employment center, submitting resumes or filling out applications, placing or answering job advertisements, checking union or professional registers.

networks in labour markets. The seminal papers of Montgomery (1991), Granovetter (1995) and, more recently, Kramarz and Skans (2014), are all contributions dealing with the role of social networks in determining labour market outcomes in developed economies.

The theory behind this approach is focused on highlighting the role played by social structures, i.e., using Montgomery's (1991) words: "*the pattern of social ties between individuals*", in shaping labour market outcomes. Montgomery (1991) in his work reports how previous studies have shown that roughly 50 percent of all the matches between workers and firms are created through a process involving generally the participation of friends and relatives. The presence of the informal hiring channel is not a feature neglected to economists. The role of friends and relatives as a source of information to find a job or the use of employee referrals have been extensively examined as search methods used by applicants. However, the point needs a further clarification. Indeed, the CPS considers contacting friends and relatives as an active searching method. Nevertheless, it makes sense to consider the fact that social networks are not necessarily assumed to play a passive role in the job seeker-social network relationship as regards the hiring channel. Social networks are social structures where the individuals interact each other and they play the role to let people stay connected in an environment where the concentration of information is determined as a by-product of social ties. In this sense, social networks might be considered as an environment where information determing labour market outcomes is free and is shared by all the participants, without the need of paying any specific cost or involving the implementation of any specific "active" action to obtain the same.

Kramarz and Skans (2014) investigate the effects of social networks on youth labour market entry distinguishing between strong ties and weak ties.[57] They find that the presence of strong

[57] The difference between strong and weak ties stems from the presence or not of a family link. In the first case, the parents are the agents of the match for the son/daughter and they offer and receive information from and to the son/daughter that help to determine a positive labour market outcome. In the latter case, family does not

ties brings to a large impact on the graduate's job-finding success, especially in the presence of weak positions, i.e., individuals with low education or in a period of high unemployment. Kramarz and Skans (2014) find that the presence of strong ties produces an increase of roughly 10 percentage points in the probability of a low-educated individual to work in a specific plant.

Caliendo, Schmidl and Uhlendorff (2010) find that individuals with larger networks show a preference for informal search methods than formal search methods, where the latter method is more related to the idea of active searching, while the first one is defined in terms of searching through friends and relatives. Even if their analysis is focused on search methods for unemployed, the authors find surprisingly a strong effect in terms of substitution of the formal passive search with searching through social networks, with an increase in one point of the social network indicators to produce a fall of 4-5 percentage points in the use of passive search. This result tends to confirm the linkage between passive search and informal channels in job searching through social networks. Indeed, the two options are considered as very close substitute in the probability of getting a job offer.

Thus theory and empirical analysis seem to support the idea that passive searching can also come by searching through social networks. In this sense, it does justice to the possibility people can experience a poor performance in terms of search intensity, but still they can be successful to find a job when a scenario with an informal approach to job searching, like the one with social networks, is taken into account.

play this role, but a different set of variables like environment, location, and other minor variables is taken into account.

3.5 Conclusions

The objective of this study is to measure the sensitivity of the real wages for different groups of workers: job stayers, newly hired workers coming from unemployment, newly hired workers coming from out-of-labour force and job changers. Thus, I use a model allowing for direct transitions between labour market states. When I estimate the baseline model, with all newly hired workers aggregated into a single workforce, the so-called non-employment group, I obtain results for the semi-elasticity of wages for job stayers that are close to those found in earlier studies, but the semi-elasticity of wages for newly hired workes is somewhat slightly lower in contrast with the results found in previous papers like Carneiro, Guimares and Portugal (2012) or Martins, Solon and Thomas (2012).

However, when I introduce the out-of-labour force, as a separated labour market state from unemployment, using empirical evidence about the out-of-labour force to employment flow, I can confirm real wage for newly hired workers coming from unemployment is more procyclical than the real wage of job stayers, but the real wage for newly hired workers coming from out-of-labour force are more procyclical than the real wage of new hires from unemployment.

Following the critique formulated by Gertler, Huckfeldt and Trigari (2016), I also take into account the possibility of cyclical job-upgrading introducing job to job transitions in our model, using different specifications to make this exercise more robust. I find that the semi-elasticity of real wage for job changers is larger than that of new hires from unemployment and new hires from out-of-labour force. But the difference between the semi-elasticity of real wages for new hires from unemployment and the real wage for new hires from out-of-labour force still persists and it is significant.

Finally, I also find evidence of the larger values for the elasticity of the real wages for the newly hired workers coming from out-of-labour force compared to that of newly hired from unemployment, when I use the aggregate labour productivity as cyclical indicator.

These findings bring us back to the initial question asked in Section 3.1, i.e., whether the Mortensen-Pissarides model with only two labour market states (employment and unemployment) is a good picture of the dynamics of the labour market. Additionally, a further question set in this work needs to be answered: can the representative agent model be considered as a good fit for replicating the labour market dynamics yet or it is the heterogeneous agents model a more appropriate setup to study the behaviour of labour market facts?

The results showed in this study seem to clearly reject a positive answer to both questions. The standard Mortensen-Pissarides model with only two labour market states tends to misspecify the empirical analysis of labour market dynamics because of the exclusion of out-of-labour force workers and their direct transition into the employment state. Moreover, the representative agent model does not seem to be a good fit for describing the labour market facts.

In particular, results from the full-specified model in Table 3.13, as regards the sensitivity of the real wages to unemployment rate, make it clear that the real wage for newly hired workers coming from unemployment is less procyclical than that for newly hired workers coming from out-of-labour force. These findings, highlighting the existence of a relevant form of heterogeneity between new hires coming from unemployment and new hires coming from out-of-labour force, are ultimately confirmed when I use the labour productivity as the cyclical indicator to test the robustness of these results.

To conclude, what implications from this investigation can be drawn for the unemployment volatility puzzle? Unfortunately, it is quite hard to provide a final word. Indeed, the empirical presence of the unemployment volatility puzzle should be tested making use of a three-state labour market model with heterogeneous agents. Computational difficulties and the lack of a clear model specifying the hiring criteria used by firms in filling vacancies with different workers (i.e., sorting between unemployed and inactive workers or segmentation between the two groups or else?) do not ensure a consistent analysis of the Shimer's puzzle.

In Chapter 2 of this PhD thesis, it is considered the above framework with heterogeneous agents and direct flows between the three labour market states, using the segmented labour markets hypotheses, i.e., unemployed and inactive workers search for a job in segmented and separated sub-markets. I find that such a model can explain a large part of the volatility of labour market variables without necessarily relying on the presence of a rigid real wage for new hires. However, further research on this issue is largely hoped for to shed more light on this crucial feature affecting the validity of the search and matching model.

Table 3.1

Summary Statistics: Job stayers, Newly hired workers from Unemployment and Out-of-labour force and Job Changers[a]

	Job stayers	**NHW UE**	**NHW OLFE**	**Job Changers[a]**
# Observations	*2,478,106*	*5,244*	*1,848*	*12,539*
	(1)	(2)	(3)	(4)
Sex: Male	51.88%	57.49%	46.21%	54.32%
	[0.50]	[0.50]	[0.50]	[0.54]
Age	36.77	32.90	28.02	31.03
	[12.35]	[12.03]	[11.11]	[11.69]
Labour market experience	17.32	13.96	9.03	11.95
	[12.33]	[12.07]	[10.92]	[11.53]
Marital status: Married	52.02%	40.56%	31.81%	38.21%
	[0 .50]	[0.49]	[0.46]	[0.48]
-“-: Widowed/separated/divorced	14.66%	14.51%	8.54%	13.53%
	[0.35]	[0.35]	[0.28]	[0.34]
-“-: Single	33.30%	44.92%	59.63%	48.25%
	[0.47]	[0.50]	[0.49]	[0.50]
Ethnic group: White	83.35%	83.73%	84.90%	83.72%
	[0.37]	[0.37]	[0.36]	[0.37]
-“-: Black	11.00%	11.76%	9.68%	10.74%
	[0.31]	[0.12]	[0.29]	[0.31]
-“-: Asian	2.09%	1.33%	1.67%	1.91%
	[0.14]	[0.11]	[0.13]	[0.14]
-“-: Other	3.54%	3.16%	3.73%	3.61%
	[0.18]	[0.17]	[0.19]	[0.19]
Education: University	16.03%	8.21%	10.01%	11.47%
	[0.37]	[0.27]	[0.30]	[0.32]
-“-: Less than University	36.06%	34.17%	37.33%	35.34%
	[0.48]	[0.47]	[0.48]	[0.48]
-“-: High School	33.32%	38.08%	32.09%	33.85%
	[0.47]	[0.48]	[0.47]	0[.47]
-“-: Less than high school	14.58%	19.52%	20.56%	19.32%
	[0.35]	[0.40]	[0.40]	[0.39]
(Hourly) Real wage[a]	8.21	6.84	6.22	6.82
	[0.51]	[0.45]	[0.46]	[0.48]

Notes: Averages and standard deviations for selected variables from SIPP 1996-2013. The variables included in the summary statistics are usually observed in each panel, and each panel runs between 36 and 60 months. The real wage is computed in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate its nominal value. The variable NHW UE indicates the newly hired workers coming from the unemployment state, the variable NHW OLFE indicates the newly hired workers coming from the out-of-labour force state, the variable Job Changers[a] indicates the group of individuals with a weekly non-employment spell between two consecutive monthly spells of employment or the presence of a new starting date for the present job, and the variable Job stayers indicates ongoing workers. The variable real wage[a] indicates a correction procedure takes place in order to impute the correct wage to job changers with a weekly break in their employment spell. Given that the variable reporting the hourly wage is obtained for the last month in a wave and then the values are reported for all other months in the reference wave, I impute for all individual making a job to job transition the wage reported in the last month of the previous reference wave.

Table 3.6

Correlation matrix

	Log(Real wages)	Log(Real wages[a])	Sex: Male	Age	Labour market experience	Marital status: Single	Race: White	Education: Universiy	Education: Less than university	Education: High school	Job stayers	New hired UE	New hired OLFE	Job Changers
Log(Real wages)	1													
Log(Real wages[a])	0.99*	1												
Sex: Male	0.18*	0.18*	1											
Age	0.32*	0.32*	-0.02*	1										
Labour market experience	0.26*	0.26*	-0.02*	0.98*	1									
Marital status: Single	-0.30*	-0.30*	0.06*	-0.61*	-0.59*	1								
Race: White	0.08*	0.08*	0.04*	0.02*	-0.01*	-0.09*	1							
Education: Universiy	0.27*	0.27*	-0.02*	0.10*	-0.01*	-0.07*	0.02*	1						
Education: Less than university	0.05*	0.05*	-0.05*	0.03*	-0.02*	-0.02*	0.01	-0.31*	1					
Education: High school	-0.09*	-0.09*	0.03*	0.05*	0.08*	-0.05*	-0.01*	-0.29*	-0.50*	1				
Job stayers	0.04*	0.04*	-0.01*	0.05*	0.04*	-0.03*	-0.01*	0.01*	0.00*	-0.01	1			
New hired UE	-0.02*	-0.02*	0.01*	-0.01*	-0.01*	0.01*	0.00	-0.01*	0.01*	0.01*	-0.44*	1		
New hired OLFE	-0.02*	-0.02*	-0.01*	-0.02*	-0.02*	0.02*	0.00	-0.01*	0.01*	-0.01*	-0.26*	-0.01*	1	
Job Changers	-0.03*	-0.03*	0.01*	-0.04*	-0.04*	0.03*	0.00	-0.01*	0.01*	0.01*	-0.85*	0.52*	0.16*	1

Notes: Correlations for selected variables from SIPP 1996-2013. The variables included in the summary statistics are usually observed in each panel, and each panel runs between 36 and 60 months. The real wage is computed in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate its nominal value. The variable New hired UE indicates the newly hired workers coming from the unemployment state, the variable New hired OLFE indicates the newly hired workers coming from the out-of-labour force state, the variable Job Changers indicates the group of individuals making a job to job transition that experiments a weekly spell of non-employment between two consecutive periods in the employment state or a different starting date for a job between two consecutive periods into employment, and the variable Job stayers indicates ongoing workers. The variable Real wages[a] indicates a correction procedure takes place in order to impute the correct wage to job changers with no break in their employment spell. Values for this variable are taken in logs.

Table 3.7

Job stayers and Newly hired workers from Non-employment

Year	Job Stayers	New Hires
1996	205,215	637
1997	199,674	1,427
1998	190,344	1,413
1999	177,667	1,152
2000	36,783	-
2001	171,237	743
2002	150,617	1,231
2003	147,907	683
2004	196,593	754
2005	183,859	1,407
2006	127,408	788
2007	62,713	340
2008	82,889	31
2009	133,745	868
2010	123,476	818
2011	115,859	759
2012	108,896	720
2013	70,759	349

Notes: Values are computed using variables from SIPP 1996-2013. The variable New Hires indicates the newly hired workers coming from a large non-employment (NE) state, the variable Job stayers indicates ongoing workers.

Table 3.8

Sensitivity of Real Wage to Unemployment Rate with Job stayers and Newly hired from Non-employment

Dependent Variable: Log hourly real wage		
	(γ^{u})	(γ_{ψ}^{ne})
Estimation method	Job stayers	Incremental effect New Hires
Fixed-Effects estimator with six-month lag in unemployment rate	-0.202*** [0.0028]	-0.025 [0.026]
Fixed-Effects estimator with one-year lag in unemployment rate	-1.452*** [0.0140]	-0.252 [0.163]
First-Difference estimator with six-month lag in unemployment rate	-0.182*** [0.0023]	-0.141 [0.030]
First-Difference estimator with one-year lag in unemployment rate	-1.211*** [0.0132]	-0.149 [0.147]
#Observations	*2,490,645*	*14,120*

Notes: The number of observations are reported for the Fixed-effects estimator. The wage is computed in real terms using the Price Consumption Expenditure Index (PCE) as deflator for nominal values at 1995 prices. Values are in dollars. (i) The duration of the non-employment spell is in the monthly interval [1,9] for all the cases. *** indicates a significant level of 1 percent. ** indicates a significant level of 5 percent. * indicates a significant level of 10 percent. Robust standard errors are in brackets and are clustered at the individual level.

Table 3.9

Job stayers, Newly hired workers from Unemployment and Out-of-labour force

Year	Job Stayers	New Hires UE	New Hires OLFE
1996	205,215	484	153
1997	199,674	1,041	386
1998	190,342	993	422
1999	177,666	756	397
2000	36,783	-	-
2001	171,235	523	222
2002	150,615	838	395
2003	147,906	498	186
2004	196,592	525	230
2005	183,855	977	434
2006	127,407	594	195
2007	62,713	239	101
2008	82,889	27	4
2009	133,744	724	145
2010	123,476	647	171
2011	115,859	606	153
2012	108,896	568	152
2013	70,759	269	80

Notes: Values are computed using variables from SIPP 1996-2013. The variable New Hires UE indicates the newly hired workers coming from the unemployment state, the variable New Hires OLFE indicates the newly hired workers coming from the out-of-labour force state and the variable Job stayers indicates ongoing workers.

Table 3.10

Sensitivity of Real Wage to Unemployment Rate with Job stayers, New hired from unemployment and New hired from Out-of-labour force

Dependent Variable: Log hourly real wage			
	(γ^{u})	($\gamma_{\psi}^{u,e}$)	($\gamma_{\psi}^{olf,e}$)
Estimation method	Job stayers	Incremental effect New Hires from Unemployment	Incremental effect New Hires from OLF
Fixed-Effects estimator with six-month lag in unemployment rate	-0.204*** [0.0024]	0.010 [0.026]	-0.124*** [0.027]
Fixed-Effects estimator with one-year lag in unemployment rate	-1.452*** [0.0140]	-0.121 [0.183]	-0.747*** [0.163]
First-Difference estimator with six-month lag in unemployment rate	-0.192*** [0.0025]	0.003 [0.024]	-0.109*** [0.022]
First-Difference estimator with one-year lag in unemployment rate	-1.242*** [0.0138]	-0.102 [0.153]	-0.411*** [0.159]
#Observations	*2,490,645*	*10,300*	*3,820*

Notes: The number of observations are reported for the Fixed-effects estimator. The wage is computed in real terms using the Price Consumption Expenditure Index (PCE) as deflator for nominal values at 1995 prices. Values are in dollars. (i) The duration of the non-employment spell is in the monthly interval [1,9] for all the cases. *** indicates a significant level of 1 percent. ** indicates a significant level of 5 percent. * indicates a significant level of 10 percent. Robust standard errors are in brackets and are clustered at the individual level.

Table 3.11

Job stayers, Newly hired workers from Unemployment and Out-of-labour force and Job Changers[a]

Year	Job Stayers	New Hires UE	New Hires OLFE	Job Changers[a]
1996	203,574	242	76	1,960
1997	198,457	570	209	1,865
1998	189,314	524	234	1,685
1999	176,617	439	202	1,561
2000	36,674	-	-	109
2001	170,040	256	101	1,583
2002	150,110	415	167	1,158
2003	147,482	265	65	778
2004	195,227	231	117	1,772
2005	183,027	514	219	1,507
2006	126,807	324	103	962
2007	62,444	122	47	440
2008	82,256	13	2	649
2009	133,301	320	66	926
2010	123,193	301	78	722
2011	115,512	289	65	752
2012	108,551	282	60	723
2013	70,516	137	37	418

Notes: Values are computed using variables from SIPP 1996-2013. The variable New Hires UE indicates the newly hired workers coming from the unemployment state, the variable New Hires OLFE indicates the newly hired workers coming from the out-of-labour force state, the variable Job Changers[a] indicates the group of job changers that does not experiment a transition between two consecutive periods in the employment state (i.e. individuals without a monthly break between two consecutive periods into the employment state) and the variable Job stayers indicates ongoing workers.

Table 3.12

Job stayers, Newly hired workers from Unemployment and Out-of-labour force and Job Changers[b]

Year	Job Stayers	New Hires UE	New Hires OLFE	Job Changers [b]
1996	205,534	118	56	144
1997	200,322	385	172	222
1998	190,999	358	199	201
1999	178,178	318	178	145
2000	36,783	-	-	-
2001	171,623	141	80	136
2002	151,266	298	147	137
2003	148,260	183	60	87
2004	196,999	126	89	133
2005	184,533	340	184	209
2006	127,769	228	78	121
2007	62,884	88	37	44
2008	82,905	1	-	14
2009	134,227	220	52	114
2010	123,915	223	64	92
2011	116,264	215	57	82
2012	109,274	199	46	97
2013	70,934	106	32	36

Notes: Values are computed using variables from SIPP 1996-2013. The variable New Hires UE indicates the newly hired workers coming from the unemployment state, the variable New Hires OLFE indicates the newly hired workers coming from the out-of-labour force state, the variable Job Changers[b] indicates the group of job changers that does experiment a non-employment spell (i.e., a monthly break) between two consecutive periods into the employment state and the variable Job stayers indicates ongoing workers.

Table 3.13

Sensitivity of Real Wage to Unemployment Rate with Job stayers, New hired from Unemployment, New hired from Out-of-labour force and Job Changers

Dependent Variable: Log hourly real wage

Estimation method	(γ^{u}) Job stayers	($\gamma_{\psi}^{u,e}$) Incremental effect New Hires from Unemployment	($\gamma_{\psi}^{olf,e}$) Incremental effect New Hires from OLF	($\gamma_{\psi}^{e,e}$) Increment Incremental effect Job changers[a]
Fixed-Effects estimator with six-month lag in unemployment rate	-0.205*** [0.0024]	0.011 [0.034]	-0.112** [0.057]	-0.168*** [0.027]
Fixed-Effects estimator with one-year lag in unemployment rate	-1.501*** [0.0159]	-0.109 [0.180]	-0.721** [0.353]	-0.841*** [0.132]
First-Difference estimator with six-month lag in unemployment rate	-0.190*** [0.0023]	0.009 [0.021]	-0.089** [0.051]	-0.133*** [0.019]
First-Difference estimator with one-year lag in unemployment rate	-1.394*** [0.0129]	-0.089 [0.104]	-0.583* [0.318]	-0.696*** [0.119]
#Observations	*2,478,106*	*5,244*	*1,848*	*12,539*

	(γ^{u}) Job stayers	($\gamma_{\psi}^{u,e}$) Incremental effect New Hires from Unemployment	($\gamma_{\psi}^{olf,e}$) Incremental effect New Hires from OLF	($\gamma_{\psi}^{e,e}$) Incremental effect Job changers[b]
Fixed-Effects estimator with six-month lag in unemployment rate	-0.201*** [0.0023]	0.029 [0.036]	-0.118** [0.052]	-0.143*** [0.047]
Fixed-Effects estimator with one-year lag in unemployment rate	-1.501*** [0.0150]	-0.229 [0.233]	-0.751** [0.345]	-0.790** [0.386]
First-Difference estimator with six-month lag in unemployment rate	-0.194*** [0.0023]	0.025 [0.034]	-0.103** [0.050]	-0.113*** [0.042]
First-Difference estimator with one-year lag in unemployment rate	-1.339*** [0.0129]	-0.114 [0.214]	-0.511** [0.326]	-0.568* [0.328]
#Observations	*2,488,631*	*3,547*	*1,531*	*2,014*

Notes: Notes Table 3.9 hold. Furthermore, the superscript (a) for job changers denotes the individuals with one week's break in their employment history or individuals making job-to-job transitions into one month since the starting date of a job is posterior with respect to that indicated in the prior month. The superscript (b) for job changers denotes the individuals with one month's break in their employment history

Table 3.14

Sensitivity of Real Wage to Labour Productivity with Job stayers, New hired from Unemployment, New hired from Out-of-labour force and Job Changers

Dependent Variable: Log hourly real wage

	(γ^{u})	($\gamma_{\psi}^{u,e}$)	($\gamma_{\psi}^{olf,e}$)	($\gamma_{\psi}^{e,e}$)
Estimation method	Job stayers	Incremental effect New Hires from Unemployment	Incremental effect New Hires from OLF	Incremental effect Job changers[a]
Fixed-Effects estimator with six-month lag in the GDP	0.887*** [0.0462]	0.058 [0.0413]	0.119* [0.0662]	0.126 [0.264]
Fixed-Effects estimator with one-year lag in the GDP	0.931*** [0.0483]	0.060 [0.0432]	0.124* [0.0695]	0.187 [0.278]
First-Difference estimator with six-month lag in the GDP	0.842*** [0.0401]	0.053 [0.0404]	0.105* [0.0555]	0.113 [0.236]
First-Difference estimator with one-year lag in the GDP	0.930*** [0.0453]	0.057 [0.0406]	0.114* [0.0602]	0.154 [0.236]
#Observations	*2,478,106*	*5,244*	*1,848*	*12,539*

Notes: The number of observations are reported for the Fixed-effects estimator. The wage is computed in real terms using the Price Consumption Expenditure Index (PCE) as deflator for nominal values at 1995 prices. Values are in dollars. (i) The duration of the non-employment spell is in the monthly interval [1,9] for all the cases. The superscript (a) for job changers denotes the individuals with one week's break in their employment history or individuals making job-to-job transitions into one month since the starting date of a job is posterior with respect to that indicated in the prior month. *** indicates a significant level of 1 percent. ** indicates a significant level of 5 percent. * indicates a significant level of 10 percent. Robust standard errors are in brackets and are clustered at the individual level.

Appendix A: Construction of the category Recall

Fujita and Moscarini (2013) show in their paper that in the dynamics concerning worker transitions, a key role is played by "recalls". The notion of recalls refers to the case where workers have previously separated from their last employer/job, but they are finally recalled by the same employer/for the same job. Usually these workers are identified as individuals that are on temporary layoff. According to the definition provided by the CPS, laid off individuals are either workers who have been provided with a date for returning to the job or workers expecting to return to the same job by six months.

Based on some evidence provided by data sets like SIPP, CPS and Quarterly Workforce Indicators (QWI), Fujita and Moscarini (2013) show that recalls are quite pervasive in the U.S. economy. The authors state that 40 percent of all the cases of temporary layoffs end up with a recall, and this value is even higher for individuals who do not move into out-of-labour force after the separation but remain in the unemployment state. Moreover, Fujita and Moscarini (2013) also show that recalls are not only related to workers on temporary layoff, but they are also observed for individuals who have separated from previous job and have spent a long period of time in the non-employment state (individuals who result with a separation period longer than six months and without the provision of any date for a possible return to the same job). In their calculations, Fujita and Moscarini (2013) show that 20 percent of overall recalls can be attributed to these "permanently separated" individuals.

However, identifying recalls in the SIPP is not an easy task. Information about a potential recall might be obtained using the variable EENO. When there is a break in a spell of employment (i.e., the break in the spell of employment creates two consecutive employment spells spaced out by a spell of non-employment), if the job ID code registered in the second spell of employment is kept the same as the one in the first spell, this would imply that there is not a new employer for the worker, but it is just a recall from the last one.[58]

Luckily, the SIPP uses a particular procedure for assigning or keeping the job ID value. Indeed, if the individual presents a spell of non-employment that does not cover an entire wave, i.e., the individual is not in the non-employment status for the consecutive four months composing a wave,[59] the job ID does not change if the individual has returned to work for the same last employer/job.[60] Hence, it is possible to infer about the presence or not of recalls just looking at the value for the variable EENO. However, if the individual spends a spell of non-employment covering the entire wave, the SIPP procedure provides for automatically assigning a new job ID even if the worker returns to the previous job with the same employer, apart from the case when the worker is on temporary layoff, since in this last case the existence of a full wave spent into non-employment does not produce any change in the job ID.

This mismeasurement issue can be fixed in the SIPP panels for the period before the 1996 panel. Indeed, to obtain consistent job IDs a procedure using administrative data concerning the employer can be implemented and correct job IDs are derived.[61] Unfortunately, the same procedure is not feasible for the panels after 1996. This implies that there is no consistency in the job ID codes for post-1996 observations. As a direct effect of this problem in reporting the correct job ID, it might be possible to end up with large misclassifications. Indeed, changes

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58 However, this value is obtained only for one month in a wave and then it is reported for the other three months in the four-month wave. This means that the job ID does not change over the months grouped in a reference wave. Hence, it is not possible, in principle, to classify the case of individuals experimenting in the same wave two consecutive periods of employment (E) and non-employment (NE), such as NE-E-NE-E, as recalls. Thus, the only change in its value, in principle, is observable at the "seam" between different waves.

59 The SIPP still keeps track of the job ID in the case the spells of non-employment are even longer than four months, but they are not concentrated in an entire wave.

60 The job ID changes, of course, whether the individual moves into a new job/new employer.

61 For the panels 1990-1991-1992-1993, using additional data on firms coming from administrative records, it is possible to overcome the problem of new assignment of job ID with the same employer by imputing the correct job ID code for each worker. Stinson (2003) provides a clear explanation of the procedure to be followed.

over time in the job ID would be usually recorded as new hires, while they are recalls finally.[62] In other words, the effect of this mismeasurement is the underestimation of the number of recalls in the post-1996 panels.

Fujita and Moscarini (2013) propose to solve this problem by using an imputation procedure, based on the sample 1990-1993, which gives the possibility to correct the values of the job ID.

The results seem to be consistent in terms of comparability of recall rates before and after 1996. However, this procedure is based on a small sample for a very short period of time (a period with only a mild recession) compared to the 1996-2013 period, where the US economy faced two substantial downturns such as the dotcom bust and the Great Recession.

Since the investigation in this chapter is based on the post 1996 sample, I fully bear the burden to produce the correct job ID code for the variable EENO.

Following the procedure used by Gertler, Huckfeldt and Trigari (2016), in order to detect the cases of recalls, I exploit the unique feature of the SIPP to collect a large set of information on the labour market history of the workers. More precisely, I make use of the information on the job starting date (i.e., I make use of the variable TSJDATE).[63] Facing the problem of identifying recalls, I use the following procedure:

1) In the case there is a break in the spell of employment that does not cover an entire wave there is no assignment of a new job ID to the worker for the potential new employer. The job ID is retained. Thus, I make use of the variable EENO. If the value for the variable EENO does

[62] It is also possible that recalls are classified as job to job transitions instead of new hires, if one allows for the alternative definition of job changers, i.e., the one considering a worker experimenting a job to job transition as someone that spends a spell of one month in the non-employment status, in between 2 consecutive months in employment.

[63] Even in this case, I use only the variables TSJDATE1 identifies the main (first) job.

not change when the spell of employment presents an interval with some months spent in unemployment or out-of-labour force, then it means there is a recall.[64]

2) In the case ther is a break in the spell of employment that covers an entire wave, a new job ID is assigned to the worker. To identify the presence of recalls, I use the variable TSJDATE. If the date in the variable TSJDATE, for the first period in employment after the spell of non-employment, either corresponds to the date describing the starting date of the job with the former employer before the separation or it is prior to the date at which the worker appears to make the employment to non-employment movement, then it can be inferred that the transition E-NE-E can be considered as a recall. Indeed, in this case the presence of a different value for the variable EENO together with the presence of a starting date for the new job (TSJDATE) that is prior to the reference month the new job has started, does not bring to classify the individual as a new hired.

[64] The only exception to this rule might come from the presence of a different value for the variable TSJDATE compared to the date registered before the individual started her spell into non-employment. In this case it might be assumed that the worker has made a transition from the former employer to a new one. However, I do stick to the initial criteria relying on the variable EENO.

Appendix B: Construction of the category Newly Hired Workers

As regards the procedure followed in this chapter to identify newly hired workers, it consists of labelling as such all the individuals that, after a spell of non-employment,[65] spend at least four consecutive months in the employment state. To construct this variable I could in principle adopt a procedure that basically makes use of the information obtained through the variable RMESR, which identifies, at a monthly frequency, the labour market state an individual belongs to. More precisely, this variable recodes at the monthly level the weekly employment status of each individual. It takes values ranging from 1, defining a worker with a job the entire month and working all weeks, to 8, defining a worker with no job all month, who never looked for a job or was on layoff in the same period.

Thus, I could construct the category newly hired workers by looking at individuals that for four consecutive months take values 1 or 2 in the variable RMESR.

However, the variable RMESR does not specify "uniquely" the labour market state. Indeed, the variable RMESR, together with values 1 and 2, that define an individual as employed, values 6 and 7, that define an individual as an unemployed and value 8, that defines an individual as out-of-labour force worker, can also take values 3, 4 and 5, that define the cases where individuals spend only a fraction of monthly time into employment (respectively, from 1 to 4 weeks due to layoff, from 2 to 4 weeks with no time spent looking for a job or on layoff, from 2 to 4 weeks

[65] I deal with different time specifications for the spell of non-employment, in a range between one and nine monthly spells. This interval is chosen since it is usually assumed that a period of non-employment larger than nine months is related to long-term non-employment and as such identifying individuals subject to different incentives and withdifferent preferences. However, estimates from a larger interval do not show significant differences from the results obtained in this study.

with time spent on layoff or looking for a job). Thus, it is possible to have workers classified at weekly level in different labour market states in the same month.

Moreover, the identification in the SIPP of the labour market state the individual belongs to using the variable RMESR is not fully consistent with the definition of the analog in the Current Population Survey, which is the official reference source in providing the labour market statistics. The classification of individuals in the different labour market states in the CPS is achieved by looking at the answer of each respondent in the interview which is usually made the week including the 12th of each month. In this occasion, it is asked to the respondent to report her employment status in the reference week.

Thus, the time structure of the interviewing process in the CPS implies that the relevant labour market state is defined by looking at the value obtained in either the second or the third week of each month.

An additional issue, arising from the methodological difference between SIPP and CPS, for the registration of the information regarding the identification of the individual’s labour market state, is that related to the measurement of the unemployment rate. It can be observed that the unemployment rate is officially obtained through data from CPS, but due to the different labour market force classification of the individuals in the two surveys, it derives that the unemployment rate computed by CPS might be different from that computed by SIPP.

In order to overcome these problems and to make the labour market classification in the SIPP consistent with that in the CPS, a correction procedure is implemented.

In theory, my procedure could be structured such that one would end up with identifying the labour market state for the individuals in the SIPP, relying only on the individuals’ weekly records. This solution is feasible with the SIPP by using the variable RWKESR. This variable reports recoded values for the employment status for each week: RWKESR1, RWKESR2, RWKESR3, RWKESR4, and, according to the length of the month, sometimes RWKESR5. Thus, it provides information, at a weekly frequency, as regards the labour market state the individual belongs to. This is not the approach followed in this chapter. However, I still make use of the weekly information on the labour market state the individual is classified at to identify the labour market state the individuals belong to. Thus, the information collected in the variable RWKESR is somewhat crucial since information contained in the variable RMESR does not always allow us to uniquely identifying the monthly labour market state the individual is classified at.

To perform this adjustment procedure I drift apart from a full abidance to the values reported in the variable RMESR. Precisely, I adjust the labour market status, as defined in the variable RMESR, according to the value registered in the reference week (second or third week of each month, as it holds for the CPS) using the variable RWKESR.[66]

This is not an issue for the cases RMESR =1 or RMESR =2 because these values are linked to the event that the individuals spend the full month into employment. Nor it is the case for RMESR = 6 or RMESR =7 or RMESR =8, because I refer to events identifying individuals spending all their time into a non-employment state. The problem rises, as explained above, for the cases RMESR = 3, RMESR = 4 and RMESR = 5. Indeed, in these latter cases, individuals are registered at a weekly level in different labour market states. In order to provide a “unique” labour market state classification, I look at the values for RWKESR in the CPS reference week and I assign the value RMESR=1 (employment) if RWSWRK = 1 or 2, and RMESR=6 (unemployment) if RWKESR = 3 or 4 (despite the presence of some weeks in a month with a

[66] This allows us to estimate the model consistently with the aggregate cyclical variable I use for our empirical investigation, i.e, the unemployment rate derived from CPS.

job, but not in the CPS reference week). Finally, in the case in the CPS reference week one finds a value for RWKESR = 5, I can classify the individual as out-of-labour force or RMESR=8, if the individual is reporting to have been not looking for a job or on layoff the previous 4 weeks, because to be classified as out-of-labour force the CPS requires the individual must spend four consecutive weeks without looking for a job or on layoff. In the case the individual has spent one of the previous weeks looking for a job or on layoff or working in a job, as it is the case for a value of RMESR included in the range 3-5, then the individual cannot be classified as included in the out-of-labour force state, but as an unemployed (i.e., RMESR=6).

Appendix C: Additional Tables

Table 3.2

Summary Statistics: Job stayers and Newly hired workers from Non-employment

	Job stayers	**NHW NE**
# Observations	*2,490,645*	*14,120*
	(1)	(2)
Sex: Male	51.91%	53.86%
	[0.49]	[0.49]
Age	36.74	31.42
	[12.35]	[11.89]
Labour market experience	17.30	12.48
	[12.33]	[11.90]
Marital status: Married	51.95%	38.25%
	[0.49]	[0.48]
-“-: Widowed/separated/divorced	14.66%	12.19%
	[0.35]	[0.32]
-“-: Single	33.37%	49.55%
	[0.47]	[0.49]
Ethnic group: White	83.36%	83.00%
	[0.37]	[0.37]
-“-: Black	11.00%	11.65%
	[0.31]	[0.32]
-“-: Asian	2.08%	1.65%
	[0.14]	[0.12]
-“-: Other	3.54%	3.69%
	[0.18]	[0.18]
Education: University	16.01%	8.91%
	[0.36]	[0.28]
-“-: Less than University	36.05%	35.60%
	[0.48]	[0.47]
-“-: High School	33.32%	35.51%
	[0.47]	[0.47]
-“-: Less than high school	14.60%	19.96%
	[0.35]	[0.39]
(Hourly) Real wage	8.21	6.65
	[0.50]	[0.45]

Notes: Averages and standard deviations for selected variables from SIPP 1996-2013. The variables included in the summary statistics are usually observed in each panel, and each panel runs between 36 and 60 months. The real wage is computed in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate its nominal value. The variable NHW NE indicates the newly hired workers coming from a large non-employment (NE) state, the variable Job stayers indicates ongoing workers.

Table 3.3
Summary Statistics: Job stayers, Newly hired workers from Unemployment and Out-of-labour force

	Job stayers	**NHW UE**	**NHW OLFE**
# Observations	*2,490,645*	*10,300*	*3,820*
	(1)	(2)	(3)
Sex: Male	51.90%	56.98%	45.47%
	[0.49]	[0.49]	[0.49]
Age	36.74	32.57	28.29
	[12.35]	[12.04]	[10.89]
Labour market experience	17.30	13.66	9.29
	[12.33]	[12.07]	[10.79]
Marital status: Married	51.95%	40.19%	32.93%
	[0.49]	[0.49]	[0.47]
-“-: Widowed/separated/divorced	14.66%	13.53%	8.57%
	[0.35]	[0.34]	[0.28]
-“-: Single	33.37%	46.27%	58.49%
	[0.47]	[0.49]	[0.49]
Ethnic group: White	83.36%	83.23%	82.38%
	[0.37]	[0.37]	[0.38]
-“-: Black	11.00%	11.76%	11.34%
	[0.31]	[0.32]	[0.31]
-“-: Asian	2.08%	1.53%	1.96%
	[0.14]	[0.12]	[0.13]
-“-: Other	3.54%	3.46%	4.31%
	[0.18]	[0.18]	[0.20]
Education: University	16.01%	8.34%	10.42%
	[0.36]	[0.27]	[0.30]
-“-: Less than University	36.05%	34.90%	37.42%
	[0.48]	[0.47]	[0.48]
-“-: High School	33.32%	36.79%	32.07%
	[0.47]	[0.48]	[0.46]
-“-: Less than high school	14.60%	19.96%	20.07%
	[0.35]	[0.39]	[0.40]
(Hourly) Real wage	8.21	6.83	6.23
	[0.50]	[0.45]	[0.45]

Notes: Averages and standard deviations for selected variables from SIPP 1996-2013. The variables included in the summary statistics are usually observed in each panel, and each panel runs between 36 and 60 months. The real wage is computed in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate its nominal value. The variable NHW UE indicates the newly hired workers coming from the unemployment state, the variable NHW OLFE indicates the newly hired workers coming from the out-of-labour force state and the variable Job stayers indicates ongoing workers.

Table 3.4

Summary Statistics: Job stayers, Newly hired workers from Unemployment and Out-of-labour force and Job Changers[b]

	Job stayers	**NHW UE**	**NHW OLFE**	**Job Changers[b]**
# Observations	*2,488,631*	*3,547*	*1,531*	*2,014*
	(1)	(2)	(3)	(4)
Sex: Male	51.90	57.65	45.46	56.00
	[0.50]	[0.50]	[0.50]	[0.50]
Age	36.73	33.04	27.94	31.93
	[12.36]	[12.11]	[11.05]	[11.89]
Labour market experience	17.28	14.18	8.99	12.85
	[12.34]	[2.14]	[10.92]	[11.88]
Marital status: Married	51.92	39.36	31.16	41.81
	[0.50]	[0.49]	[0.46]	[0.49]
-“-: Widowed/separated/divorced	14.66	14.38	8.55	13.80
	[0.35]	[0.35]	[0.28]	[0.34]
-“-: Single	33.42	46.26	60.29	44.39
	[0.47]	[0.50]	[0.49]	[0.50]
Ethnic group: White	83.36	83.22	85.24	84.55
	[0.37]	[0.37]	[0.35]	[0.36]
-“-: Black	11.00	12.07	9.73	10.87
	[0.31]	[0.32]	[0.30]	[0.31]
-“-: Asian	2.09	1.58	1.56	1.04
	[0.14]	[0.12]	[0.12]	[0.10]
-“-: Other	3.55	3.13	3.46	3.52
	[0.18]	[0.17]	[0.18]	[0.18]
Education: University	15.99	7.89	9.27	9.63
	[0.37]	[0.27]	[0.29]	[0.29]
-“-: Less than University	36.05	33.60	38.27	34.95
	[0.48]	[0.47]	[0.49]	[0.48]
-“-: High School	33.33	37.92	32.13	37.39
	[0.47]	[0.48]	[0.47]	[0.48]
-“-: Less than high school	14.62	20.58	20.31	18.02
	[0.35]	[0.40]	[0.40]	[0.38]
(Hourly) Real wage[a]	8.21	6.81	6.22	7.07
	[0.51]	[0.45]	[0.45]	[0.48]

Notes: Averages and standard deviations for selected variables from SIPP 1996-2013. The variables included in the summary statistics are usually observed in each panel, and each panel runs between 36 and 60 months. The real wage is computed in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate its nominal value. The variable NHW UE indicates the newly hired workers coming from the unemployment state, the variable NHW OLFE indicates the newly hired workers coming from the out-of-labour force state, the variable Job Changers[b] indicates the group of individuals that does experiment a monthly spell of unemployment between two consecutive periods into the employment state, and the variable Job stayers indicates ongoing workers. The variable real wage[a] indicates a correction procedure takes place in order to impute the correct wage to job changers with one month’s break in their employment spell. Given that the variable reporting the hourly wage is obtained for the last month in a wave and then the values are reported for all other months in the reference wave, I impute for all individual making a job to job transition the wage reported in the last month of the previous reference wave.

Table 3.5

Summary statistics for unemployed and out-of-labour force individuals

Panel A: Mean values for unemployed and out-of-labour force workers for different gender groups				
	U	**OLF**	**U**	**OLF**
# Observations	*123,328*	*186,926*	*107,309*	*343,859*
	(1)	(2)	(3)	(4)
Age	33.26	23.25	33.73	29.34
Labour market experience	14.31	5.02	14.64	10.50
Marital status: married	35.46%	12.96%	36.61%	47.00%
-"-: Widowed/separated/divorced	11.78%	4.03%	18.71%	6.93%
-"-: Single	52.75%	83.00%	44.67%	46.07%
Ethnic group: White	77.64%	77.89%	72.53%	79.36%
-"-: Black	15.22%	13.47%	20.40%	12.60%
-"-: Asian	2.87%	3.12%	3.07%	3.56%
-"-: Other	4.26%	5.51%	4.00%	4.48%
Education: University	12.89%	8.08%	14.20%	14.74%
-"-: Less than University	28.71%	28.10%	32.65%	31.12%
-"-: High school	34.72%	22.97%	31.15%	25.85%
-"-: Less than high school	23.66%	40.83%	22.00%	28.28%

Panel B: Mean values for unemployed and out-of-labour force workers for different age groups				
	U	**OLF**	**U**	**OLF**
# Observations	*75,738*	*294,161*	*154,899*	*236,624*
	(1)	(2)	(3)	(4)
Sex: Male	55.90%	47.79%	52.28%	19.59%
Age	19.86	18.84	40.14	37.59
Labour market experience	1.65	0.99	20.74	17.98
Marital status: married	8.03%	6.64%	49.66%	70.27%
-"-: Widowed/separated/divorced	2.09%	1.14%	21.32%	11.83%
-"-: Single	89.88%	92.20%	29.00%	17.89%
Ethnic group: White	74.83%	77.66%	75.48%	80.31%
-"-: Black	18.71%	14.36%	17.10%	11.10%
-"-: Asian	2.49%	2.96%	3.19%	3.96%
-"-: Other	3.96%	5.01%	4.22%	4.62%
Education: University	4.46%	3.71%	17.92%	23.20%
-"-: Less than University	25.13%	27.93%	33.19%	32.70%
-"-: High school	35.79%	22.02%	31.72%	28.35%
-"-: Less than high school	34.61%	46.34%	17.15%	15.75%

Panel C: Mean values for unemployed and out-of-labour force workers for different occupation and industry groups				
	U	**OLF**	**U**	**OLF**
# Observations	*105,899*	*75,706*	*106,121*	*75,809*
	(1)	(2)	(3)	(4)
Occup.: Skilled non-manual	11.09%	10.68%	-	-
-"-: Skilled manual	14.07%	8.09%	-	-
-"-: Unskilled non-manual	26.95%	33.69%	-	-
-"-: Unskilled manual	47.88%	47.53%	-	-
Industry: Agric., Forest., Fish.	-	-	2.62%	2.08%
-"-: Mining	-	-	0.42%	0.26%
-"-: Utilities	-	-	0.26%	0.19%
-"-: Construction	-	-	11.96%	6.00%
-"-: Manufacturing	-	-	12.57%	8.20%
-"-: Wholesale Trade	-	-	2.89%	2.38%
-"-: Retail Trade	-	-	15.88%	20.66%

Table 3.5 continued in next page

Table 3.5 continued from last page

-"-: Transport. & Warehous.	-	-	3.53%	2.04%
-"-: Information	-	-	2.45%	2.40%
-"-: Finance and Insurance	-	-	2.78%	2.86%
-"-: Real Estate and Rental	-	-	1.39%	1.49%
-"-: Prof., Scient. & Techn.	-	-	4.24%	4.15%
-"-: Mgmt of Companies	-	-	0.01%	0.15%
-"-: Admin & Mgmt Waste Services	-	-	10.05%	6.98%
-"-: Educational Services	-	-	1.57%	2.56%
-"-: Health Care and Assist.	-	-	6.65%	8.27%
-"-: Arts & Entertainment	-	-	2.29%	3.98%
-"-: Accomm. & Food Serv.	-	-	14.26%	20.59%
-"-: Other Services	-	-	3.89%	4.60%
-"-: Public Administration	-	-	0.21%	0.27%

Notes: Averages from SIPP 1996-2013. Panel A reports values for unemployed and out-of-labour force workers for different gender groups. Column (1) and (2) refer to male gender, while columns (3) and (4) refer to female gender. Panel B reports values for unemployed and out-of-labour force workers for different age groups. Column (1) and (2) refer to age below or equal to 24 years, while columns (3) and (4) refer to group of individuals aging 25-64. Panel C reports values for unemployed and out-of-labour force workers for different occupations and industries. Column (1) and (2) refer to occupations, while column (3) and (4) refer to industry.

CHAPTER 4:

WEALTH AND LABOUR MARKET TRANSITIONS

<u>Structure</u>:

4.1 Introduction

Over the last decade, following the rise of the Shimer's puzzle (2005),[67] several studies have been actively contributing to the debate on the ability of the search and matching model to replicate the empirical moments of the labour market variables such as vacancy, job-finding rate and unemployment.[68] However, less attention has been devoted to the dynamics of the labour market transitions. Indeed, the most relevant works in this field have focused on replicating empirical worker flows by embedding either a home productivity idiosyncratic shock (e.g., Garibaldi and Wasmer, 2005, Haefke and Reiter, 2006) or a market productivity idiosyncratic shock (e.g., Pries and Rogerson, 2009) into a frictional labour market model.[69] Nevertheless, results have not been very satisfactory, especially when a framework with three labour market states: employment, unemployment and out of labour force, is taken into account. In this direction, models have struggled in replicating quantitatively the worker flows between inactivity and the other labour market states.

Furthermore, these investigations have been carried out by using very parsimonious models, which entail little room for any additional variable to substantially contribute to the explanation of the empirical worker flows. In this sense, wealth and its role in the individuals' choice

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[67] The Shimer's puzzle is usually defined in terms of the failure of a standard search and matching model, à la Mortensen and Pissarides, to replicate the empirical volatilities for the unemployment rate and other labour market-related variables such as vacancies, labour market tightness and job finding rate. In details, following a labour productivity shock, the baseline search model lacks an amplification mechanism able to reproduce the observed second moments in the variables above mentioned. Shimer (2005) identifies the large volatility of real wage as the crucial variable explaining the poor performance of such models. With Nash bargaining process, wages are flexible to labour productivity shock and this implies that wages capture a large part of the productivity shock, leaving firms unwilling to advertise new vacancies. This effect reduces both volatilities of vacancies, job-finding rate and labour market tightness, together with little changes in the unemployment rate.

[68] The literature on the unemployment volatility puzzle is very extensive. After the seminal papers of Shimer (2005), and Costain and Reiter (2008), a very incomplete list of notably contributions includes Hall (2005), Hagedorn and Manovski (2008), Hall and Milgrom (2008), Pissarides (2009) and Kennan (2010). All of these studies have focused on data from the U.S. economy.

[69] A partially different approach is followed by Krusell, Mukoyama, Rogerson and Sahin (2016), who build up a model to replicate the gross worker flows using both standard labour supply features and search frictions.

concerning labour market transitions have been largely neglected. The research in this field has primarily focused on an environment where agents have preferences defined in terms of linear utility and are income maximization, but this specification implies that there is no room for precautionary saving since there are no risk aversion motives. Thus, little progress has been observed regarding the analysis of the role of wealth in affecting the worker flows between the three labour market states.

Broadly speaking, developing a labour market transition model using the standard search and matching theory implies that the movements from the employment state to the non-employment states need to be seen as a new searching process following a separation between workers and firms. Moreover, transitions between unemployment and inactivity, the two non-employment states, should be considered as changes in the search intensity. Indeed, data from the American Time Use Survey (ATUS) show that agents from both groups devote a positive amount of time to searching.[70] In both cases, the search activity of the individuals suggests an important role for time. It takes time for the firms searching for the worker who represents a desirable fit for the vacancy that has been advertised and it takes time for the workers to find a suitable job and being hired. Thus, if searching is a process which requires time and (monetary) resources, a reasonable question is: how is searching financed? A quite obvious answer would be that individuals in the unemployment state can rely on public transfers from the government, especially in the form of unemployment benefits. However, any monetary support is typically for a limited amount of time and is subject to a large variability in its amount. Individuals in the out-of-labour force state face an even worse situation, since they do not typically enjoy such monetary support from the government.[71] Thus, abstracting from a careful investigation of the

[70] Data from ATUS show that unemployed individuals tend to spend around 23 minutes per day in their search activity, while out of labour force individuals show a lower propensity to search, with less than one minute per day devoted to this activity.

[71] The literature has not adequately discussed, at the moment, the realistic possibility for individuals to finance searching in the non-employment state via a risk-sharing mechanism at the household level, which could

role of individual wealth in describing the dynamics of labour market transitions might be a reasonable assumption in a set-up like the one proposed by the standard search and matching model, in which the primary focus is on the non-employment to employment transition (i.e., the hiring activity), since this is usually considered as a process in which individuals accept each job that is offered to them and the key variable is the choice of the firm.[72] However, this assumption does not hold in the opposite scenario, the one in which it is investigated the worker flows from the employment to the non-employment states, or even between the non-employment states. In such cases, it is reasonable to think of wealth like a key feature that can affect the decisions made by individuals in their choices about their transitions between labour market states.[73]

Furthermore, a major drawback of a few previous contributions on the relationship between wealth and labour market transition, has been the strong focus on a framework in which only two labour market states are identified: employment and unemployment. Empirically, the role of wealth has usually been captured in terms of the decision of workers regarding the transition from employment to unemployment and in terms of unemployment duration. In this direction, for example, Algan, Cheron, Hairault and Langot (2003) show that (i) workers with a higher level of wealth have a higher probability to quit the job and move from employment to

involve a role for the partner's income, or via financial support from parents. This issue will be empirically investigated in this study.

72 Bloemen and Stancanelli (2001) have proposed a different approach to this issue still using the search and matching model. Indeed, they have studied how wealth can affect the reservation wages, the unemployment duration and the job acceptance rate, conditional on the job offer made by the firm. In this sense, workers are given the opportunity to accept or refuse a received job offer, whose probability is characterized in terms of a stochastic wage-offer distribution. They find that wealth affects positively the reservation wage and the unemployment duration and negatively affects the probability of transition into employment. In this study, I do not follow this approach, but I embrace the original version of the search and matching model assuming all workers are job-finders and they are willing to accept every job that is offered to them. This is based upon the standard condition that the value function of being employed is larger or equal to the value function of being unemployed.

73 Some scattered attempts to moving to a deeper investigation of the interaction between the choice of agents in terms of labour market transitions and their wealth level have been proposed, but substantially disregarded. Relevant contributions are those by Danforth (1979), Blundell, Magnac and Meghir (1997), Bloemen and Stancanelli (2001), Bloemen (2002) and Algan, Cheron, Hairault and Langot (2003).

unemployment and (ii) workers with a higher level of wealth have a higher probability to remain in the state of unemployment.

Thus, the main issue investigated in the previous studies was related to the possibility of using wealth to finance spells of active searching (i.e., unemployment).[74] Surprisingly, an analysis related to the possibility of using asset holdings to finance searching when individuals transition into the out-of-labour force state has not been carried out, and in this sense no answer has been provided to the question: does wealth finance spells of passive searching (i.e., out-of-labour force)? Indeed, if wealth plays the role to finance searching, it would make sense to observe, in the case of a positive idiosyncratic shock to individual wealth, a movement from employment to out-of-labour force rather than from employment to unemployment, because rational wealthy agents would face a loosening job-searching constraint.[75]

Moreover, it would be also expected that any change in the level of wealth should be perceived as an incentive for the workers, when non-employed, to optimally re-formulate their searching decisions. For example, in the case of negative (positive) idiosyncratic shock to wealth, it would be expected individuals formulate their rational decisions to increase (decrease) their search intensity and in this way moving from out-of-labour force (unemployment) to unemployment (out-of-labour force). Thus, the wealth variable would play a role not only in the decisions of agents to move from employment to non-employment, but also in their decisions to move

[74] The only exceptions to this standard framework are Blundell, Magnac and Meghir (1997), who propose a theoretical formal model investigating the relationship between savings and labour market transition with the presence of a third labour market state, and Krusell, Mukoyama, Rogerson and Sahin (2016), who investigate the role of search and wage frictions in order to replicate the gross worker flows between all labour market states.

[75] In different terms, it can be stated that, assuming individuals choose optimally between the search activity and leisure, and considering both variables as normal goods, it should be observed that a higher level of wealth might work as an incentive for agents to enjoy an even larger fraction of their time in leisure when their wealth experiences a large positive change after an idiosyncratic shock. In this case, it is claimed that the substitution effect is smaller than the income effect, i.e., following an increase in wealth, agents are more willing to move into passive searching activity rather than into active searching activity, and thus enjoying a large fraction of time devoted to leisure.

between unemployment and out-of-labour force. In fact, while this is an often ignored fact, the two worker flows, i.e., the unemployment to out-of-labour force flow and the out-of-labour force to unemployment flow, are quite volatile and persistent.

An appropriate investigation of these issues requires an adequate theoretical context and, in this sense, it seems that the search and matching model would provide a substantial and reliable model for this analysis. However, one of the most recurrent observations in the search literature points out to the irrelevance of the distinction between unemployment and out-of-labour force, since the out-of-labour force state is seen as essentially playing a subordinate role to the unemployment state in the dynamics of the worker flows.[76]

However, as suggested in Chapter 3of this thesis, this assumption is not correct. For example, based on data from the Survey of Income and Programme Participation (SIPP), in Chapter 3 it has been investigated the cyclical behaviour of real wages for new hires coming from either unemployment or out-of-labour force and it has been found evidence of the existence of a substantial flow of newly hired workers moving directly from out-of-labour force, and not only from unemployment, into employment, thus questioning the insignificance of the out-of-labour force state. Furthermore, it has been found that the real wage of newly hired from out-of-labour force shows a different cyclicality compared to the real wage of newly hired from unemployment. This result is robust to different specifications of the model. This implies the

[76] An example of this view is the usual statement regarding the possibility to have transitions from inactivity to employment only by a movement through the unemployment state, discarding the possibility for a direct flow from out-of-labour force to employment. An exception to this view is represented in the literature by some papers (e.g., Garibaldi and Wasmer, 2005) in which the issue of the presence of worker flows into employment from these two different groups, unemployment and out-of-labour force, is tackled by considering individuals who are not looking for a job (and as such they are considered as out-of-labour force), but are ready to accept one if an offer comes to them, as a slacked labour market attached group. They are defined as discouraged workers and they are lumped together with the unemployed individuals.

existence of a certain degree of heterogeneity between unemployed and out-of-labour force individuals moving into employment.

Another critique concerning the consistency of any investigation linked to the relationship between wealth and worker flows is that related to the relevance of the wealth variable in affecting the labour market transitions, since the distribution of wealth in the developed countries is dramatically skewed.[77] Thus, it can be claimed that a very large part of the overall population in the developed countries does not hold a positive level of wealth (Chetty, 2008). As a logical consequence, it is expected that wealth cannot play a relevant role in labour market transitions, especially for people spending a large fraction of their time in either the unemployment or the out-of-labour force state, since it is reasonable to argue that the individuals in these two latter labour market states would make up the bulk of the unwealthy people. Hence, any study examining the relationship between labour market transitions and wealth would be questionable. However, contrary to this remark, empirical evidence produced in this study shows that this critique is inaccurate. Indeed, a substantial fraction of individuals spending time into unemployment and/or out-of-labour force hold significant amounts of wealth that can reasonably play a role in their decisions as concern labour market transitions. Based on data from the sample used for our investigation, one can see that individuals moving into out-of-labour force have a level of liquid wealth (e.g., bonds, stocks and other liquid wealth assets) that is just 15 percent lower than that of individuals moving into unemployment. When

[77] Using the data from Saez and Zucman (2014) for the U.S. wealth distribution in 2012, one can see that the bottom 90 percent of households hold a total net wealth of 23 percent. The next 9 percent of households own 35 percent of total net wealth and the top 1 percent of households hold 22 percent of total net wealth, i.e., roughly the same amount held by the bottom 90 percent. The same pattern holds for other developed countries. Moreover, using Registry data from the Norway's Household Income Statistics (an accurate dataset avoiding or minimising non-response, attrition and measurement errors) it is observed that the bottom 90 percent of households own slightly less than 50 percent of the total net wealth, with the bottom 10 percent holding more than half of the overall net wealth. Looking at the wealthiest households at the top 1 percent of the wealth distribution in the U.S., it is shown that households in the last percentile hold 22 percent of the overall net wealth. This figure is replicated by the data for Norway with the top 1 percent households holding 21 percent of the total net wealth.

one considers a more aggregated wealth value, one can observe how the wealth level for individuals moving into out-of-labour force is roughly equal to that of individuals moving into unemployment.

The findings in this chapter show that wealth exerts a statistically significant impact on the individuals' probability of transitioning to out-of-labour force or unemployment. This result holds even when different specifications for the wealth variable are used. Moreover, these results are robust to a rich series of different controls. Building upon the transitory-permanent decomposition of wealth effect, I am able to identify a significant positive effect of a transitory increase in wealth on the probability to transitioning to out-of-labour force and unemployment, while the impact on the transition probabilities is negative when I deal with a permanent increase in wealth.

A possible explanation for the positive transitory effect of wealth, as resulting from the willingness of the individuals to transition in the non-employment states (i.e. starting a search activity), can be found in the fact that the change in wealth is temporary and it does not affect the consumption profile. Thus, the increase in wealth, in this case, can be considered as a buffer stock useful to look for a better job that can guarantee individuals transitioning in the non-employment states a higher wage profile, a feature present in the empirical evidence on the life-cycle paths of wage dynamics, and consequently satisfying the permanent income hypothesis. Hence, a transitory increase in wealth can bring individuals to start a new search in order to exploit labour market opportunities allowing for higher future wage profiles.

On the other side, the negative permanent effect of an increase in wealth on the transition probabilities could be explained by the fact that the increase in wealth would play the role of a close substitute to the labour income flow. In this sense, the permanent increase in wealth disincentives individuals from starting a new search in order to find a high-paying job since it allows for a permanent effect on consumption. Thus, it makes sense to observe a drop in the transition probabilities of individuals, as regards the movements into out-of-labour force and unemployment, since one can assume it is operating a sort of “income effect”.

However, the estimated impact of wealth is larger for the probability of transitioning to out-of-labour force rather than for the probability to transitioning to the unemployment state. Indeed, a well-established result across the different model specifications is that a temporary increase of $ 100,000 dollars in wealth leads, on average, to an increase of 50 percent in the probability of transitioning to out-of-labour force, but it increases the probability of becoming unemployed only by 30 percent. On the other hand, a permanent increase in wealth decreases the probability to transitioning into out-of-labour force by roughly 50 percent, and that to unemployment by 30 percent.

Thus, these findings reveal the presence of differences in the behaviour of agents when their transition into the non-employment states, i.e., the “exit margin”, is examined.

Therefore, one can argue that the currently developments of theoretical models not including the presence of the out-of-labour force workers or lumping them together with unemployed workers into a large non-employment state are at odds with the empirical findings found in this study.

The reminder of the chapter is structured as follows. Section 4.2 provides a review of the literature. Section 4.3 discusses the empirical strategy used to estimate the model. Section 4.4 describes the dataset and provides descriptive statistics. Section 4.5 presents and discusses results. Section 4.6 develops some sensitivity analysis. Finally Section 4.7 concludes.

4.2 Background and Hypotheses

The literature on labour market transitions is quite widespread. Classical references such as Blanchard and Diamond (1990) and Mortensen (1994) come along with more recent advancements on this matter like Garibaldi and Wasmer (2005), Pries and Rogerson (2009), Krusell, Mukoyama, Rogerson and Sahin (2016). At the same time, the concept of wealth has attracted the interest of scholars with reference to its role in enhancing entrepreneurship or the transition into self-employment.[78] Surprisingly, the researchers have devoted little attention to the relationship between worker flows and wealth, with just a limited number of studies directly dealing with this matter.

The seminal paper, regarding the relationship between wealth and labour market transitions, is by Danforth (1979). The author investigates the job search activity in an environment in which agents are allowed to make decisions conditional to the level of asset holdings. He shows that there is a negative correlation between asset holdings and the job acceptance rate, i.e., a higher level of wealth would result in a lower acceptance probability. However, the presence of decreasing absolute risk aversion and the individual maximization as a function of consumption are crucial assumptions in the choice of agents between labour market states.

Blundell, Magnac and Meghir (1997) investigate the relationship between savings and labour market transitions in a discrete dynamic model of expected life time utility maximization, in which the utility does not depend only on consumption but also on labour market transition as well. They introduce a job offer as a random process and allow for risk of layoff. Under the

[78] On entrepreneurship, see Hurst and Lusardi (2004), Cagetti and De Nardi (2006), Hvide and Panos (2014), and Sauer and Wilson (2016), and on self-employment, see Lindh and Ohlsson (1998), Carrasco (1999) and Zissimopoulos and Karoly (2007).

assumption that leisure is a normal good, they derive a negative relationship between wealth and the probability of staying or becoming employed.

Algan, Cheron, Hairault and Langot (2003) show that, in an environment with only two labour market states, i.e., employment and unemployment, wealth plays a substantial role in determining the employment to unemployment labour market transition and the unemployment duration. Indeed, the authors find that the probability of a voluntarily movement from employment to unemployment increases with the level of wealth and that wealthier unemployed individuals show a longer unemployment duration.

Using data from the Dutch Socio-Economic panel (SEP), Bloemen and Stancanelli (2001) empirically investigate the relationship between financial wealth, reservation wage, and labour market transitions, namely between employment and unemployment. Based on the job search model put forward by Danforth (1979), they specify a simultaneous equations model with a wealth equation, an employment transition equation and a reservation wage equation, and show that financial wealth has a significant positive effect on the reservation wage. Moreover, a higher reservation wage produces a lower employment probability, even if this effect is quite small.

Finally, Bloemen (2002) analyses the relationship between savings and the employment probability and his results confirm the existence of a negative relationship between these two variables.

4.3 Empirical Strategy

In order to investigate the relationship between wealth and movements into non-employment labour market states, transition probabilities are estimated. I use a random-effects probit model to estimate the probability of transitioning to out-of-labour force (at time $t+1$) from either employment or unemployment (at time *t*) and the probability of transitioning to unemployment (at time *t+1*) from either employment and out-of-labour force (at time *t*).

In general terms, a standard probit model to estimate this relationship could be written as follows:

$$y_{it} = 1[y_{it}^{*} = x_{it}'\beta + u_{it}] \tag{2}$$

$$with\ i = 1,2,\dots,N;\ \ t = 1,2,\dots,T$$

with

$$y_{it} = 1 \quad if \quad y_{it}^{*} > 0 \tag{3}$$

$$y_{it} = 0 \quad otherwise$$

where *i* is the individual index and *t* is the time index. Let the observed dependent variable y_{it} be defined as a binary variable taking value one if the individual *i* makes a transition to out-of-labour force, between time *t* and *t+1*, from either employment or unemployment, or to unemployment, between time *t* and *t+1*, from either employment or out-of-labour force, and zero otherwise. Let *1[.]* be the indicator variable. Let y_{it}^{*} be the latent variable (the unobservable individual probability of transitioning to a non-employment state, at time *t+1*). The latent variable is assumed to be linear in the observed, x_{it} , and unobserved, u_{it} , variables, with β to be interpreted as a vector of coefficients associated with the vector of the explanatory variables. Let u_{it} denote the error term with standard normal distribution u_{it} ~N (0, σ_u^2), i.e., with mean zero[79] and constant finite variance, $\sigma_u^2 < \infty$.

[79] It is assumed strict exogeneity for the error term, $E(u_{it} | X_{it})=0$, i.e., the error term is stochastically independent from the regressors for all *i* and *t*.

Given the panel structure of our dataset, labour market transitions can be observed for the time period $t=1,2,...,T_{i-1}$, since the presence of an unbalanced panel.

However, the presence of individual-specific effects has implications for the binary choice model that it is used. Indeed, individual-specific effects are usually specified either as fixed parameters (fixed-effects model) or as random error components, independently and identically distributed over time (random-effects model). While unobserved heterogeneity specified with fixed effects model is a suitable procedure since it allows the individual effects to be correlated with the independent variables, it also incurs in the incidental parameter problem.[80]

Thus, the random-effects model seems more appropriate for a large sample with many individuals having few observations over time.[81]

Hence, in this investigation I make use of the random-effects model, with both observed and unobserved individual-specific effects, given the relatively short average length of each panel (approximately 4 years).

The unobserved variable is then decomposed to a time-invariant and a time-variant variable

$$u_{it} = \gamma_i + \varepsilon_{it} \tag{4}$$

and the equation is written as follows:

[80] I.e., the maximum likelihood estimation is inconsistent. See Verbeek (2007).

[81] It is known that the random-effects model, differently from the fixed-effects model, requires the extra condition of specifying a functional distribution of the unobserved individual heterogeneity. Moreover, it requires the assumption of zero correlation (independence) between the random error components and the explanatory variables (but this is something that must hold for the regular error terms as well) and that the correlation of the combined residuals over time (via the random effects) is the same for all the individuals. However, the random-effects estimator is more efficient than the fixed-effects estimator when the distributional assumptions about the parameters in the model are satisfied. The random-effects model contrarily to the fixed-effects model allows to estimate time-invariant characteristic variables that can play a role in the analysis such as gender or race.

$$y^*_{it} = x'_{it}\beta + \gamma_i + \varepsilon_{it} \tag{5}$$

$$with\ \ i = 1,2,..,N;\ \ t = 1,2,..,T$$

where γ_i is the vector of unobserved time-invariant individual-specific random effect and ε_{it} is the time-variant unobservable term (i.e., the shock), which is independently and identically normal distributed, ε_{it} ~ N IID $(0, \sigma^2_\varepsilon)$ and the ε_{it} are independent of the x_{it} for all *i* and *t*. The binary decision is then consistent with the following equation:

$$y_{it} = 1(x'_{it}\beta + \gamma_i + \varepsilon_{it}) \quad if \quad y^*_{it} > 0 \tag{6}$$

$$y_{it} = 0 \ \ otherwise$$

It is assumed that, γ_i~N IID $(0, \sigma^2_\gamma)$, and that there is independence between unobserved individual effects and the observable covariates, x_{it}, and between unobservable individual effects and the idiosyncratic random effect, ε_{it}. Finally, the correlation of the composite error term, $\gamma_i + \varepsilon_{it}$, is given by *corr* (u_{it}, u_{is}), i.e., $\rho = \frac{\sigma^2_\gamma}{(\sigma^2_\gamma + \sigma^2_\varepsilon)}$, for $t,s=1,2,..T$ and $t \neq s$, which represents the proportion of the overall error variance explained by the the individual effect.

However, as described above, incorporating unobserved individual-specific effects requires two main assumptions being satisfied: 1) independence of individual heterogeneity with the covariates and 2) strict exogeneity of the error term, conditional on the individual heterogeneity component.

The failure of just one of the two assumptions produces inconsistently estimated coefficients (i.e., the estimated coefficients will pick up some of the effects of the unobservable random error term, ε_{it}).

In order to remove this problem, I follow the approach popularized by Mundlak (1981) and Chamberlain (1984), which allows for a correlated random-effects probit model. Thus, I allow for the correlation between individual unobserved effects and the observable time-varying regressors.

Following Mundlak (1981), I formulate the dependence between x_{it} and γ_i by assuming that the time-invariant individual unobserved effects are a linear function of the average of all time-variant covariates, that is:

$$\gamma_i = \bar{x}_i'\theta + \alpha_i \tag{7}$$

where $\bar{x}_i'$ denotes the time average of the vector $x_{it} = \left(x_{ilt,\dots,}x_{iMt}\right)'$ containing the *M* elements of x_{it} describing the time-varying covariates for the individual *i* over time *t*, and with α_i~N IID (0, σ_α^2) and independent of the x_{it} and the ε_{it} for all *i*,*t*.

Thus, eq.(5) can be rewritten as

$$y_{it}^* = x'_{it}\beta + \bar{x}_i'\theta + \alpha_i + \varepsilon_{it} \tag{8}$$

4.4 The Data

4.4.1 The Survey of Income and Program Participation (SIPP)

The data used for the analysis in this chapter stems from the Survey of Income and Program Participation (SIPP), which is maintained by the U.S. Census Bureau. The SIPP is a longitudinal survey of household that are interviewed every four months. Its longitudinal design allows to keep track of all the individuals into the household and to collect information, on each member of the household, related to a large set of variables.

The SIPP consists of a collection of panels and each panel consists of a new random sample. Within each panel, all the sampled individuals are interviewed every four months. The SIPP divides each panel into four sub-samples and each sub-sample is referred to as a rotation group. These four rotation groups enter the SIPP survey at different points in time.[82] Respondents provide information about their lives during the previous four months, which are referred to as the reference months.[83]

The SIPP collects information using two different modules: the core wave files and the topical module files.[84]

The core module files are run each four months and they provide information on employment status, earnings/income, demographic characteristics, participation to public programs supporting household's income and other additional variables.[85]

Information on the labour market state the individuals belong to is collected at a higher frequency, usually weekly or monthly, compared to other datasets. However, for some variables information is collected for one month and then the value is reported for the other three months forming a wave.

Topical module files contain extra questions that are asked for each reference wave (four-month period) to the same respondent. Information collected in the topical module files is related, broadly, to the following categories: assets and liabilities, well-being expenses, material hardship measures, fertility history, medical expenses, retirement plan, children support, welfare reforms, disability statistics and other minor variables. However, these are variables for

[82] For example, for the 2008 SIPP panel, the entry months for these rotation groups are, respectively, May, June, July and August 2008, respectively.

[83] This implies that the collection of information is made retrospectively, a feature that helps to somewhat overcome the problem of left-censoring. The information provided for the four months is thus contained in what is called a reference wave.

[84] For the sake of completeness, it must be reported how the SIPP offers a third type of file as well, the longitudinal research file, which contains information on all the waves of a panel.

[85] Regarding labour market data, information on occupation, industry, employer identification, starting and ending date for the job, up to two main jobs, is collected as well.

which the values are not collected subsequently in all the waves. Indeed, topics vary across waves. Hence, the values are collected at a lower frequency, usually yearly, i.e., every three waves, and for only one out of four months in a wave.

The advantage of the SIPP over similar data sources, such as the Panel Study of Income Dynamics (PSID), National Longitudinal Survey of Youth (NYLS) and British Household Panel Survey (BHPS), is that the questionnaires collect a broader range of information concerning labour market history and asset holdings.

The primary focus of our investigation is on the Assets and Liabilities topical module file, since it provides information on the balance sheet of observed units. The Assets and Liabilities topical module file is particularly well-suited for studying the effects of wealth on labour market transitions, because the objective of this study is to investigate the relationship between the "individual" labour market transitions and the "individual" wealth and the Asset and Liabilities topical module collects very reliable information on assets/wealth and liabilities at the individual level.[86]

The topical module files contain information on liquid assets such as shares, stocks, bonds, saving accounts, pension plans such as IRA, 401 k and KEOG, together with information on more illiquid assets such as real estate property, business equity and life insurance policies. Information is also collected on household liabilities with data on mortgages, financial debt, credit cards debt and loans related to the ownership of vehicles and businesses.

[86] Information on assets and liabilities is collected at the household level as well. However, for variables reporting assets and liabilities owned jointly by the married couple, the SIPP provides individual values by dividing the overall value by two and then imputing to each individual her own fraction. For the other variables not involved in such imputation procedure, in order to exploit them for the investigation I carry out in this chapter, I follow the same procedure used by SIPP and specified above, but with a further correction. The values of the variables at the household level will be recast at the individual level by dividing the overall value by the number of individuals that are potentially involved in the ownership of the asset, who are once again the two married persons if this is the case, or the single individual if there is no presence of a marriage.

For the investigation in this study, I focus on the period 1996-2012 because the structure of the SIPP panels has incurred in a major change after the review of the collection process, which took place in 1995. The original design for administrating SIPP provided for a set of continuous panels, running for three years, with a new panel starting each year and a sample of roughly 20,000 households interviewed. Post 1996 panels exhibit a larger and increasing sample.[87] Moreover, the design of the panels has moved towards a structure avoiding any kind of overlapping, which was an underlying feature of the previous panels. After the change in 1996, the new structure of the SIPP provides for the start of a new panel after the end of the previous one. Furthermore, the panels are spanning a longer period of time and this implies the increase of person-months observations.

Regarding the Assets and Liabilities topical module files, the interviews were initially planned to be conducted in the third, the sixth, the ninth and the twelfth wave for each panel. Nevertheless, only the 1996 panel was successfully fully completed, while in the 2001 panel the last wave (the twelfth wave) is missing. In the 2004 panel only data for the first two waves were collected, i.e., the third and the sixth, because of a lack of funding. In the 2008 panel, data have been only collected in the fourth, seventh and tenth wave.[88]

Hence, from 1996 to 2013, there are four panels: 1996, 2001, 2004 and 2008, and I use data from 12 waves: 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2008, 2009, 2010 and 2011.

The sample selection procedure adopted in the study restricts the final sample to individuals between the age of 18 and 65, and that are not included in one of the following categories: 1)

[87] The sample interviewed has steadily increased from 40,183 households in the 1996 panel to 52,013 households in the 2008 panel.

[88] While most of the households included in the first wave of the Asset and Liabilities topical module file are re-interviewed in the other waves of the same panel, as being part of the same representative randomly drawn sample, a few households were not observed in the subsequent sample. The number is quite small and this should not affect our results. Moreover, I take into account only individuals present in all the topical waves for each panel.

disabled individuals, 2) individuals with health problems, 3) individuals in armed force, 4) retired individuals, 5) individuals that are owners of one or more businesses and 6) individuals working in other than the private non-charitable and not family managed firms sector. All individuals in the sample are observed in all the waves for each panel in which they are included. This implies that individuals, with missing values in one or more waves of the panel they belong to, are dropped.

Employed individuals are identified using the methodology of the Current Population Survey (CPS). This means all individuals who report to be in the employment status in the week including the 12th day of each month are considered employed. Unemployed individuals are defined as those not working during the week of the interview. Out-of-labour force workers (i.e., inactive workers) are those neither having a job nor reporting being on layoff or looking for one during the week of the interview and during the past three weeks. All variables are expressed in levels, but age, labour market experience, household size, wage and spouse's wage are defined in log terms.

The quality of wealth data in the Asset and Liabilities topical module file has been under scrutiny, by researchers and data-users as government organizations, for a long time. The reason for this in-depth analysis of the SIPP data concerning individuals and households' wealth stems from the specific goal of the survey itself. The SIPP dataset has been constructed in order to study the implementation of the participation to social programs. This makes the low-income (and usually low-wealth) individuals as the natural target of the program. However, oversampling low-income households may produce discrepancies in the representativeness of the wealth data in the SIPP compared to the population wealth. In this sense, the analysis of wealth data has usually been carried out by using data from the Survey of Consumer Finances (SCF), which offers a more detailed micro-level information about households' wealth holdings and presents the interesting characteristic to oversampling high-income households that enhances the representativeness of the right tail of the distribution of wealth.

However, the investigations on the quality of SIPP wealth data conducted by, firstly, Czajka, Jacobson and Cody (2003) and, secondly, by Eggleston and Klee (2015), comparing wealth estimates in SIPP and SCF, show that the level and distribution of wealth in the SIPP replicates quite well that of SCF.[89] Czajka, Jacobson and Cody (2003) study the wealth estimates for Wave 9 of the 1996 SIPP panel and compare the results to the estimates for SCF for the same period.[90] They find that SIPP estimates of aggregate net worth, aggregate assets and aggregate debts are 75 percent, 80 percent and 101 percent of their SCF analogs. Comparisons show that the SIPP data represent well the debt categories, together with 401 k and thrift accounts, and real estate values related to primary home.

Eggleston and Klee (2015) replicate the same investigation using the 2008 SIPP panel, concerning the period September and December 2010 and compare it with the analog from SCF. This analysis followed the previous study of Czajka, Jacobson and Cody (2003) in order to evaluate the implementation of a set of suggestions formulated by the authors devoted to get a better representativeness of the SIPP wealth data.

New results show that the median net worth for SIPP is now about 84 percent of the SCF estimate, the mean of aggregate wealth in SIPP being 75 percent of the SCF and the SIPP estimate of the 75th percentile being 87 percent of the SCF counterpart. Finally, Eggleston and

89 This result is evident for the study of Eggleston and Klee (2015), while it holds only for the group excluding the wealthiest households for the study of Czajka, Jacobson and Cody (2003). This last group is defined in these studies as being represented by households with a level of wealth above two million dollars. The proportion of this group in SCF to the same group in SIPP is equal to 2.66, since in SIPP it is reported 550 unweighted high wealth households against 1,082 in the SCF sample, upon 6,942 and 33,795 households interviewed in, respectively, the SCF and SIPP. The difference between the two results is due to the implementation of some measures suggested by Czajka, Jacobson and Cody (2003) after their study to improve the reliability of data from wealthiest households.

90 Precisely, the studies refer to the period between the end of 1998 and the beginning of 1999.

Klee (2015) find the SIPP estimate of asset mean is 89 percent of the SCF analog, while there is an estimate close to 100 percent for the debt average for both datasets. These results show a dramatic improvement in the representativeness of the SIPP wealth data since they refer to the full sample, i.e., the sample including the wealthiest group.[91]

4.4.2 *Sample Descriptive Statistics*

A description of the characteristics of the sample in terms of the main variables is provided in Table 4.1. As discussed in the previous section, the sample includes all individuals in the SIPP with age above 18 and below 65. However, I drop all the observations related to individuals with mental and physical disabilities, retired, in armed forces, running one or more business and working in the public sector or charitable organizations.[92] I also drop all the observations for individuals that are not present in the relevant waves of the topical module for each panel. To be more precise, there is not a balanced panel since the number of individuals vary among the panels, but it is required that individuals observed in each panel do not have any break in their records. Panel A of Table 4.1 reports individual characteristics related to demographics, labour market status, education, and other variables. Panel B of Table 4.1 exhibits summary statistics for financial variables, e.g. asset holdings and liabilities, total income and salary income. While in Panel A the table displays the mean for these non-financial variables,[93] Panel B reports both the mean and standard deviations for the financial variables.

[91] Furthermore, Eggleston and Klee (2015) suggest that existing discrepancies in the estimates between SIPP and SCF might stem from differences in question text wording. Indeed, it seems that the difference between SIPP and SCF ownership rates for some assets and liabilities stems from the larger list of examples of that class of assets and liabilities produced in the SCF compared to that in the SIPP. Moreover, the authors find evidence that small differences in the wording produce large variability in the answers, with the final outcome affecting the estimates of assets and liabilities.

[92] With this sample selection procedure I drop 124,666 observations.

[93] Tables including standard deviations for the demographic variables are available from the author upon request.

In Table 4.1 are reported summary statistics for the pooled sample, the individuals who transition into out-of-labour force and the individuals who transition into unemployment in column 1, column 2 and column 3, respectively. Then in column 4 are reported averages for the sample of individuals who do not show any labour force movement. The t-statistics (with asterisks denoting significance levels) are provided in columns 5, 6 and 7, comparing across distinct sub-samples.

The statistics presented in Table 4.1 indicate that in the pooled sample the distribution between employed, unemployed and out-of-labour force workers shows a large proportion of the employed (75 percent of the overall sample) with respect to out-of-labour force workers (only 20 percent), compared to their empirical values (roughly 60 percent for unemployed and 35 percent for out-of-labour force agents). Moreover, part-time workers are more likely to transition out-of-labour force rather than to unemployment (40 percent and 26.10 percent).

On average, the summary statistics also show that individuals transitioning into out-of-labour force, compared to those transitioning into unemployment, are younger (31 years old in the first case and 33 years old in the second one) and more likely to be females (66 percent vs 50 percent). As it might be expected, individuals who transition into unemployment have a higher labour market experience (14 years vs 11 years).[94] As regards the variable race, one can see that the blacks are the group of individuals more likely to transitioning into unemployment and less likely to transitioning into out-of-labour force. On average, individuals with higher education levels are more likely to transitioning into out-of-labour force rather than into unemployment, with people having less than high school education representing the 22.5 percent of individuals

[94] Labour market experience is measured using age minus six years related to the pre-school period and minus the time spent in schooling.

moving into unemployment against the 18.70 percent of individuals with less than high school transitioning into out-of-labour force.

In Panel B of Table 4.1 are reported the summary statistics for the financial variables. One can firstly observe that individuals not making any labour market transition result with the highest values for liquid and illiquid financial assets, wages and income. Looking at the individuals making a labour market transition, it can be observed that individuals transitioning into unemployment have larger wealth values compared to those transitioning into out-of-labour force, with a value for liquid assets (stocks, shares, bonds, and other liquid wealth variables) which is roughly 20 percent higher. The same result holds for the individual's wage, with individuals transitioning into unemployment displaying a wage which is 30 percent larger than that of the individuals transitioning into out-of-labour force. Interestingly, partner's wage is larger for the latter group than for the former one. However, the overall level of wealth for the two groups of individuals does not show a significant difference. This result is due to the rebalancing role of the illiquid assets.

[INSERT TABLE 4.1 ABOUT HERE]

Table 4.2 presents the correlation matrix for the key variables of interest. Unsurprisingly, one can see that the correlations between the two different forms of wealth (*liquid wealth* and *total wealth*) and all other variables are very similar, with the largest differences observed in the correlation with the variable single for the marital status (-0.14 for liquid wealth and -0.24 for total wealth) and household size (-0.03 for liquid wealth and -0.11 for total wealth). Furthemore, it is found that wealth is positively correlated with the highest education level (i.e., university), even if the coefficient is not significant, and significantly and negatively correlated with the two lowest levels of the same variable. Among the other variables, one can observe how age, labour market experience and household income are strongly positively correlated with wealth and all significant. This outcome is somewhat expected since wealth tends to increase with a longer duration of the employment relationship and/or over the life-cycle of an individual. However, the largest positive correlation is found between wealth and wage, with values for the two types of wealth of 0.42 and 0.46 (while the correlation between wealth and spouse's wage is still positive and significant, but with a value around 0.10), suggesting that changes in individual's wage are largely mirrored by changes in wealth in the same direction. Finally, it can be noted how the correlation is positive between wealth and the no transition variable, while it is negative for the other two transition variables (i.e., transition into inactivity and into unemployment), even if the correlation coefficients are low.

[INSERT TABLE 4.2 ABOUT HERE]

4.4.3 Definition of Wealth

Given the goal of this chapter to study the relationship between wealth and labour market transitions, a preliminary question to be addressed is that concerning the definition of wealth to be used. In principle, the relevant wealth variable for our investigation should include any type of accumulated savings that can be used to finance consumption (i.e., search activity). However, it has been often claimed that wealth can be differentiated in terms of liquidity and risk, and it has been remarked that not all the forms of wealth can be gathered together in order to construct a general variable wealth. Real estate property, life insurance or business equity play a different role from bonds, shares, saving accounts in the decision of agents. Algan, Cheron, Hairault and Langot (2003) empirically show that only the most liquid form of wealth plays a role in the choice of agents to transition from employment to unemployment. Bloemen and Stancanelli (2001) show that only liquid form of wealth affects the decision of individuals to accept a job offer. Thus, this empirical evidence points out to sustain a narrowed definition of wealth to be identified as precautionary savings.

In other words, wealth should be identified as precautionary saving that allows workers to move between labour market states without large fluctuations in consumption (i.e., allowing search activity).[95] Thus, I deal with definition of wealth that includes the most liquid wealth aggregates such as savings accounts, shares, bonds and stocks.

4.4.4 *Definition of the Dependent Variable*

The SIPP provides information at a very high frequency on whether an individual can be classified as employed or in a non-employment state, i.e., either unemployed or inactive. The individuals are considered as employed if they are recoded at the monthly level in the employment state. I use the variable RMESR, that identifies, at a monthly frequency, the labour market state for each individual included in the dataset. It takes values ranging from 1, defining a worker with a job the entire month and working all weeks, to 8, defining a worker with no job all month, who never looked for a job or was on layoff in the same period

Thus, I can classify workers as employed, if they take values 1 or 2 in the variable RMESR, as unemployed, if they take values 6 and 7, and finally as inactive, if they take value 8.

However, the variable RMESR does not specify "uniquely" the labour market state. Indeed, this variable can also take values 3, 4 and 5, that define the cases where individuals spend only a fraction of monthly time into employment (respectively, from 1 to 4 weeks due to layoff, from 2 to 4 weeks with no time spent looking for a job or on layoff, from 2 to 4 weeks with time spent on layoff or looking for a job). Thus, it is possible to have workers classified at weekly level in different labour market states in the same month.

[95] Algan, Cheron, Hairault and Langot (2003) concentrate on assets truly used as a buffer stock against idiosyncratic labour market risks. According to the authors, these assets should increase with employment spells, as workers are willing to hedge against future income risks, and should decrease with unemployment spells.

To overcome this problem and to make the classification of individuals in different labour market states fully consistent with the definition of the analogs in the Current Population Survey, I look at the value taken by the variable RMESR on the week including the 12th of each month, as explained in section 4.4.1.

Through this information collected in the dataset, I am able to construct the two transition probabilities: the probability of transitioning to unemployment and the probability of transitioning to out-of-labour force, since in this work I am interested in examining the “exit margin”.

In theory, two possible approaches can be followed in the construction of the dependent variable. Either considering only the transition from employment to the two non-employment states or a broader definition including the overall transition into each of the two non-employment states from the two left labour market states, i.e., the transition of individuals from employment and unemployment to out-of-labour force and the transition of individuals from employment and out-of-labour force to unemployment.

I follow, in this study, the specification embraced by the second definition.

Furthermore, it is needed to clarify the time dimension of the dependent variable. In this respect, I define the transition probability according to the following criteria: an individual is denoted as entering the unemployment state (out-of-labour force state) whether she is employed or unemployed (employed or inactive) during the current period and inactive (unemployed) in the subsequent period.

As it can be observed from the summary statistics, the sample presents 7,063 observations for the transition into out-of-labour force and 5,271 observations for the transition into unemployment.

Since the pooled sample consists of 276,686 observations, the transitions into out-of-labour force represent roughly 3 percent of full sample, while the transitions into unemployment represent 2 percent of the full sample.

4.5 Results

Results reported for different specifications of the model are obtained using the random-effects probit estimator with Mundlak terms. I produce marginal effects coefficient estimates (level and averages effects) for the explanatory variables.[96] Furthermore, I also provide the permanent effect coefficients obtained through a test on the estimated joint effects of the mean and level terms of the variables.[97]

Besides the wealth variable, the baseline estimation contains binary variables for gender, race (3), marital status (3), education (3), year (10), U.S. states (50), along with variables expressed in logs such as age, labour market experience and household size,[98] and in column (5) and (6), the initial labour market state as well.

The dependent variables are, respectively, the probability of transitioning into out-of-labour force (OLF_{t+1}) and the probability of transitioning into unemployment (U_{t+1}). Columns (1) and (2) report estimates for the transition probabilities with *liquid wealth* as the main regressor. Columns (3) and (4) report estimates for the transition probabilities with *total wealth* as the main regressor. Using *liquid wealth* as the main regressor, in column (5) are reported estimates for the probability of becoming out-of-labour force, conditional on transitioning from

[96] The marginal effects compute the probability of a positive outcome assuming that the random effect is zero.

[97] More precisely the joint effect is estimated by imposing the condition of strict equality in the linear constraint on the difference between each separated Mundlak term and level variable. Following Panos, Pouliakas and Zangelidis (2014), I obtain the coefficients and standard errors of the permanent effects using a test for the linear constraint under the hypothesis that the summation of the mean and level terms of the variables are equal to zero (e.g., $\gamma_{wealth} + \vartheta_{wealth} = 0$).

[98] In different model specifications, I also include and express in log terms the wage and spouse's wage.

unemployment, with employment as the reference category, while in column (6) are reported estimates for the probability of becoming unemployment, conditional on transitioning from out-of-labour force, still using employment as the reference category.[99]

In Table 4.3, columns (1) and (2), are reported the coefficients obtained using the benchmark definition of wealth, as the main regressor. Indeed, as explained in Section 4.3, since I am investigating how wealth can affect the "exit margin" in the labour market transition probabilities, it makes sense to assume that using the variable wealth, defined as the summation of all liquid and illiquid assets, would not represent the more appropriate definition for the explanatory variable in our analysis. I then rely on a definition of wealth closely related to the concept of precautionary saving, as the relevant form of wealth that can finance searching. Thus, I use as main regressor a definition of wealth denoting the sum of market values for IRA accounts, KEOGH[100] accounts, 401k, 403k and thrift plans, face value of U.S. saving bonds, estimates of non-interest checking accounts and interest accounts, amount of bonds/U.S. securities and net value of vehicles. Hence, I define this variable as "liquid wealth" since it represents the largest aggregated form of liquid wealth in the SIPP.[101]

[99] The estimation procedure includes the state dummy variable with the reference category state1 (Arizona). However, the coefficients for the state dummy variables are not reported in the tables, but are available upon request. The reference category for gender, race, marital status, education and year are, respectively, male, white, single, university, 1997 and 2011. The variable education is defined from the lowest level to the highest as 1) less than high school, 2) high school, 3) less than university. The variable marital status defined for married people includes both cases with and without the spouse in the household.

[100] The KEOGH is an employer-funded, tax-deferred retirement plan designed for unincorporated businesses or self-employed people.

[101] Despite being denoted only as liquid wealth, it must be stressed how the value is defined in net terms, i.e., it is computed as net of "liquid" debts.

However, to compare results through different specifications of the wealth variable, I also introduce a more illiquid wealth variable as the main regressor (i.e., the variable total wealth[102]) in the columns (3) and (4), and I express it as the summation of liquid and illiquid wealth.

[INSERT TABLE 4.3 ABOUT HERE]

Results in Table 4.3, columns (1) and (2), show that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and the probability of transitioning to unemployment. However, the magnitude of the coefficients for the two transition probabilities is quite different, with the former value being twice as large as the latter.

One can also observe that the level effect for females is negative in column (1) but positive in column (2), making this group of individuals, compared to men, less likely to make a transition into out-of-labour force and more likely to move into unemployment. The level effect for age and labour market experience shows a negative sign. This makes less likely the probability to transitioning into the two non-employment states. This result might be interpreted as confirming the standard view seeing employed with a temporary increase in job experience as individuals more attached to their labour market state and non-employed as individuals less likely to re-adjust their inter-temporal choice between leisure and searching. However, the sign for labour market experience becomes positive when one considers the permanent effect. This last effect could be interpreted in the context of growing earnings linked to experience. A permanent change in labour market experience should bring the individuals, having gained a higher level of skills, to look for a higher wage. In this sense, one would expect to see individuals experiencing a spell of search in their labour market history, making them more likely to move either in the unemployment or in the out-of-labour force state, to look for a better and high-

[102] The variable total wealth is also defined in net terms.

paying job. Finally, while the transitory effect for household size is negative, suggesting individuals living in households with "new arrivals" tend to be less likely to transitioning into the non-employment states, one finds that the temporary effects for education are positive and decreasing with the increase in the levels (i.e., years) of education, with the value for the transition probability to out-of-labour force larger than those for transitioning to unemployment. The permanent effect for education shows the same sign, but values are smaller.

Interestingly, it must be noted how the permanent effect of an increase in wealth on both transition probabilities is negative, with the coefficient for the transition probability to out-of-labour force much larger than that for the transition probability to unemployment.

Using the values for the marginal effects together with the predicted probability values of labour market transitions (which are computed for each individual and then averaged over all individuals), that are equal to 0.0255 for the transition probability into out-of-labour force and to 0.019 for the transition probability into unemployment, one can see that a transitory increase in individual wealth by $ 100,000 dollars increases by 50 percent the probability of transitioning to out-of-labour force and by 30 percent the probability of transitioning to unemployment. On the contrary, a permanent increase in individual wealth by $ 100,000 dollars decreases by 60 percent the probability of transitioning to out-of-labour force and by 40 percent the probability of transitioning to unemployment.

In columns (3) and (4) a broader definition of wealth (including all other forms of wealth reported in the dataset such as real estate property assets, life insurance policies and equity business) is used. Looking at the values for the controls, one can see that females are still, compared to males, more likely to make a transition into unemployment and less likely to transitioning into out-of-labour force. The signs for age, labour market experience, household size and education are not significantly different from those reported in columns (1) and (2).

Furthermore, the estimates confirm that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and unemployment, while the sign is reversed for the permanent effect. However, coefficients are now lower than in the case with *liquid wealth* as main regressor.

Using the values for the marginal effects together with the predicted probability values of labour market transitions, it is found that a transitory increase in individual wealth would increase the probability of transitioning to unemployment by 18 percent and the probability of transitioning to out-of-labour force by 16 percent, while a permanent increase in wealth decreases by 21 percent the former and by 19 percent the latter transition probability.

Finally, in columns (5) and (6), it can be observed that using as main regressor the benchmark definition of wealth, together with the inclusion of the current labour market states as further controls in the estimation of the model, produces results in line with those obtained in columns (1) and (2).

An interesting feature in this estimation is the different set of results obtained from the transitory-permanent decomposition. Indeed, it can be observed a positive impact of a transitory increase in wealth in the transition probabilities, while the sign is negative when the effect of a permanent increase in the same variable is taken into account. Rationalizing this difference in the signs of the marginal effects (estimated and computed) is quite challenging, but it would make sense to interpret the decision of the individuals to start a new search, when there is a transitory increase in wealth (positive sign for the coefficient of transition probability in unemployment and out-of-labour force), as a mechanism related to the empirical evidence on the life-cycle wage dynamics.

More specifically, one may think of individuals as making transitions into the non-employment state (i.e., starting a new search) when they look for a better job that can guarantee them a higher wage profile over their life-cycle period. Hence, a transitory increase in wealth does not play any role in terms of providing a permanent higher level of labour income since it does not represent a permanent change. However, it can allow people to start a a new search (i.e, financing a new search) in order to exploit opportunities present in the labour market and in this way to match with a high-paying job (a feature reflected in the empirical path of the individual's life-cycle wage dynamics). In this sense, it is also possible to rationalize the negative impact of a permanent increase in wealth on the transition probabilities. Indeed, wealth could play the role of a close substitute of labour income flows. More precisely, the permanent increase in wealth relaxes the need for a new search for the worker in order to find a job allowing for smoothing the life-cycle consumption profile. Then, the resulting low willingness of individuals to quit the present job to start a new search.

While this explanation is quite intuitive, more challenging is to rationalize the higher positive value for the probability of transitioning into out-of-labour force (around 60 percent) compared to the probability of transitioning into unemployment (around 40 percent) when the case of a transitory increase in wealth is taken into account. The same issue raises also for the case with a permanent shock to wealth, where it is more likely to observe a transition into unemployment rather than into out-of-labour force.

However, it is possible to rationalize even these effects using the above mentioned approach based on the concepts of life-cycle wage dynamics and consumption smoothing.

Indeed, the presence of a transitory shock to wealth makes individuals more willing to search for a new high-paying job. Nevertheless, a movement into unemployment (rather than into out-of-labour force) would make this event less likely because unemployment is a labour market state that is considered populated by more employment attached individuals, i.e., the unemployment state allows for individuals to enjoy a higher probability to find a job in a shorter period of time. Basically, following a transitory wealth shock, workers transitioning into unemployment would be going to return soon into the employment state and receive a wage quite similar to their last one, since labour market conditions do not dramatically change in short period of times. Thus, the choice of individuals to transitioning into the out-of-labour force state makes it evident the desire for a higher-paying job that normally requires a long search and changes in labour market conditions.

The same argument holds in the case of a permanent shock to wealth. In this event, it is likely for individuals showing a preference for a movement into unemployment rather than into out-of-labour force in order to find a new job shortly. Indeed, agents such may want to return on the previous consumption path after the permanent shock (or they are less willing to spend time looking for a high-paying job if inactive workers) since new higher levels of consumption are guaranteed by the permanent increase in wealth, without relying on looking for a better paid job.

While the above explanation can work well when one refers to transitions between employment and non-employment states, it might be questioned when the additional flows unemployment to out-of-labour force and out-of-labour force to unemployment are also considered. Does the previous explanation fit with the empirical results for the transition probabilities for these two additional margins?

It can be claimed that the larger value for the probability of transitioning from unemployment to out-of-labour force compared to the one for the probability of transitioning from out-of-labour force to unemployment might be still rationalized using the same arguments. Indeed, it is possible to state that the transitory increase in wealth relaxes the intensity of the search activity for individuals. Then, what is observed in the estimates is the prevailing of the movement from unemployment to out-of-labour force rather than the one from out-of-labour force to unemployment.

In Table 4.4 are reported the results for the model with three different but insightful specifications for the wealth variable. Precisely, while the results in Table 4.3 are obtained through what can be defined as the benchmark "linear" model in wealth, in Table 4.4, columns (1) and (2), are reported results using a "non-linear" model, expressed as a fifth-order polynomial in wealth.[103] In columns (3) and (4) I report results using the wealth percentiles as the main regressor and, finally, in columns (5) and (6) I present results from a model with wealth expressed in logs and with a dummy variable controlling for not strictly positive wealth values.

[INSERT TABLE 4.4 ABOUT HERE]

As expected, it is found that the values for all the control variables show no significant differences from those in Table 4.3. Thus, I point to analyse the impact of wealth on the transition probabilities. Results from the model specification including the fifth order polynomial term are not significantly different from those reported in the benchmark case using a linear term in wealth as main regressor. However, it must be highlighted that the wealth parameters estimated are all significant only for the probability of transitioning into unemployment, while only the coefficient defining the linear relationship between wealth and transition probabilities is significant in column (1). Results in columns (3) and (4) show that a

[103] Testing the relationship between wealth and labout market transitions by introducing a fifth order polynomial in wealth follows from the recent contribution of Lusardi and Hurst (2004) showing that a higher order polynomial in wealth can capture well the relationship between wealth and the probability of becoming entrepreneur. This result would stem from the observation that wealth data include a very large fraction of individuals concentrated in the tails of its distribution, i.e., a large number of individuals, holding very negligible or very large amounts of wealth, are concentrated in the tails. Strictly speaking, it can be argued that Hurst and Lusardi's work and the present one are investigating two different relationships. Thus, the use of the fifth order polynomial should be taken into account with some degrees of freedom. However, I still believe this exercise is worth to be performed for comparative reasons.

transitory increase in wealth makes individuals more likely to transitioning to the non-employment states. More specifically moving upward in each percentile makes individuals more likely to transitioning into out-of-labour force and unemployment by 0.39 percent and 0.52 percent, respectively. The effect is reversed for the permanent effect, with values of -1.18 percent for the former and -1.58 percent for the latter. The impact of an increase in wealth on the transition probabilities is smoother for the case where the wealth variable is expressed in logs, but the signs are not different from those discussed for the other specifications.

4.6 Robustness Analysis

Previous results were obtained based on a definition of wealth strictly related to the idea of precautionary saving. In this section, I still stick to this assumption, but in the model are introduced some further controls to check the robustness of the results. Firstly, one might think different indicators of more illiquid forms of wealth can still affect the agents' choice of transitioning between labour market states. A remarkable advantage of the SIPP is that this survey contains very detailed information on assets and debts related to real estate property, especially primary home. Thus, a baseline model including as additional controls home ownership, mortgage debts and other rental properties is estimated. Whether individuals are able or not to borrow money against accumulated housing wealth, identified by these variables, to financing search can be regarded as a controversial issue. However, empirical evidence seems to support this hypothesis, especially for the U.S. economy, where housing property appears to play the role of an alternative source of income used to finance consumption.

Case, Quigly and Shiller (2005), using a panel of developed countries (U.S. and OECD countries) find that the housing wealth effect is larger than the stock market wealth effect. In their estimates a 1 percentage point increase in housing wealth increases consumption by roughly 11 percentage points. Bostic, Gabriel and Painter (2009), using a matched sample of household data from the Survey of Consumer Finance and the Consumer Expenditure Survey, find that the estimated elasticity of consumption spending with respect to housing wealth is in the range 0.06-0.08 over the 1989-2001 period, while for financial wealth is close to 0.02.[104]

From results reported in Table 4.5, it can be observed how a transitory increase in home ownership and mortgages makes individuals more likely to transitioning into both unemployment and out-of-labour force. However, the permanent effect of these variables on the transition probabilities is generally negative, with the only exception of the positive values for home ownership as regards the transition probability into out-of-labour force.

Looking at the estimates for wealth, one can find that there are not substantial changes from results obtained in the benchmark case. Thus individuals are more likely to transitioning into out-of-labour force and unemployed after a transitory increase in wealth and less likely to transitioning into out-of-labour force and unemployed after a permanent increase in wealth.

Hence, controlling for the variables related to housing wealth shows there are not substantial differences in the impact of wealth on the transition probabilities.

[INSERT TABLE 4.5 ABOUT HERE]

Table 4.6 reports results for a model including the labour income flows.

More precisely, personal wage and households' income, together with government transfers and parental support, are used as further controls. The inclusion of household's income in the model specification should account for the potential role this variable can play as a source of additional

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[104] It must be stressed that the results reported above are not conclusive on the relevance of the housing wealth in terms of impact on consumption. Indeed, it has been observed how the relationship between housing wealth and consumption should be interpreted not as a causal link since housing wealth could not be purely exogenous. Thus, what is basically observed might be only a comovement between housing wealth and consumption, reflected by common factors driving both variables.

income at the household level, since household income could be seen as a tool providing a risk-sharing mechanism against labour income fluctuations and consequently allowing for labour market transitions. The same role can be avowed to government transfers and parental support.

Findings for households' income are provided in columns (1) and (2), and estimates for the variable wage are included in columns (3) to (6), with the presence in the last two columns of estimates for government transfers and parental support as well.

The marginal effects for the controls show that a transitory increase in households' income and own individuals wage makes agents more likely to transitioning into inactivity and unemployment, while the effect is reversed for the case of a permanent increase in these variables. The interpretation of these effects follows the basic discussion in section 4.3. It appears that a transitory increase in variables reflecting a rise in the income flow, such as households' income, is an incentive for individuals to start a new search, while a permanent increase produces a sort of "income effect" for the individual, who is now less willing to search again for a new job.

As concerns the role of government transfers one can observe that a transitory increase is significant only for the probability to transitioning into out-of-labour force, while a permanent increase exerts a negative impact for the probability to transitioning into out-of-labour force and a positive impact for that into unemployment.

Estimates reported for the variable wealth confirm the standard qualitative results with the positive impact of a transitory increase in wealth on the probability of becoming inactive and unemployed, and a negative impact for the case of the permanent increase in wealth.

However, it can be seen that quantitatively the effect of wealth is now quite different from previous results. Indeed, I find in columns (3) to (6) that a transitory increase in wealth increases the probability to transitioning into out-of-labour force only by 20 percent, and the probability to transitioning into unemployment by roughly 12 percent. The values are negative and much lower for the permanent effect, i.e., 12 percent and 4 percent.

A possible explanation for the striking divergence in the values of the transition probabilities found in this section can be linked to the role of the labour income variable in the searching choice of individuals`. A more detailed discussion on this point will be presented in the Conclusions.

[INSERT TABLE 4.6 ABOUT HERE]

Table 4.7 reports, in columns (1) and (2), results for a model including as a further control the partner's wage (together with individual’s own wage, home ownership and mortgages). Then, in columns (3) to (6) I control for gender. The differentiation by gender is proposed as a further robustness check since in the literature on labour economics it has often been assumed that females are a slacked labour market attached group, representing individuals making labour market transitions driven by particular reasons. Attanasio, Low and Sanchez-Marcos (2005) investigate the role of female labour supply as an insurance mechanism against idiosyncratic labour income risks within the household. They find mixed results on this relationship. However, there is still some consensus that the female labour market participation would be driven by increasing individual’s labour income uncertainty at the household level and consequently the female labour supply would be affected by other forms of risk-sharing mechanism or insurance policies such as unemployment benefits or other public insurance substitutes. Hence, it would make sense to investigate only the role of males in the relationship between wealth and labour market transition probabilities.[105]

Looking at the estimates, one can observe that the marginal effects for wage are all significant and similar to those reported in Table 4.6, while the marginal effect for spouse's wage is small and often not significant. Examining the transitory and the permanent effects for wealth, only mildly higher values are found compared to those in Table 4.6 (where the model specification includes wage as a control variable), but still significantly lower than those obtained with the benchmark model in Table 4.3. Taking into account the linear predicted transition probabilities differentiated by gender, it can be observed that wealth has a larger level effect for males than females when we consider the probability of transitioning into out-of-labour force, while the effect is smaller and not significant for the transition into unemployment. When the permanent effect of wealth is examined, it is found that female are less likely to transitioning into the two non-employment states compared to males.

[INSERT TABLE 4.7 ABOUT HERE]

As a final robustness check, occupation and industry variables are used as controls, together wih part-time working activity and union membership. So far, I have assumed a large homogeneity in the characteristics of individuals when they transition into out-of-labour force or unemployment. However, this can be the product of a selection bias across the workers. That is, the transition probabilities can be affected by the occupation or the industry sector. If some occupations or industries are more prone to changes in the business cycle, labour market conditions can deteriorate for these occupations/industries and producing a rise in the transition

[105] A further widespread claim is that stressing the importance to investigate only males' transition probabilities because of the low number of females making labour market transitions in available data. However, this is not the case in our sample, where females' labour market transitions are quite large.

probabilities of individuals linked to them. I investigate the role of these variables in a model with a more detailed classification of occupations and industries by making use for the first variable of the SOC90 (3-digits code) classification system for occupations and for the latter of the NAICS97 (3-digits code) classification code for industry. As concerns the use of the SOC90 system, it is well-known the fact that the occupational system using the three-digit Census code has been modified over time. In particular, in the period 1979-2015 it has faced four major changes. Furthermore, it has to be stressed how the adjustments in the occupational codes have been carried out in a period of high technology transformation. This has produced obvious implications in terms of missing data (some occupations have disappeared over time) with the usual problem of relying on the imputation procedure.[106] The same problems are present for the NAICS97 system.

Table 4.8 reports estimates. Columns (1) and (2) provide results for the case with part-time as additional control, columns (3) and (4) include union membership, while estimates in columns (5) and (6) are related to a model including three dummy variables to control for occupation and twenty dummy variables to control for the industry sector.

It can be observed a positive level effect for both part-time and union membership, while the permanent effect is negative. For the three variables related to the occupation category, the level effect shows that individuals working in the each of the three categories are, compared to the reference category, less likely to transitioning to unemployed, while the coefficients for the transitioning probability to out-of-labour force are not significant. However, looking at the permanent effect, one can observe that the sign is positive for the transition probability into out-of-labour force as regards unskilled non-manual and manual, while the coefficients are not

[106] A possible alternative to the three-digit code would be the two-digit code. However, this procedure code groups together distinct occupation. Moreover, the SIPP adopts the three-digit occupation classification.

significant for the transition into unemployment, apart from the unskilled manual, which is positive.

The results for the effects of wealth on the transition probabilities do not show significant differences compared to previous findings. The model with the three variables defining the occupation variable (i.e., skilled manual, unskilled non-manual and unskilled manual, with skilled non-manual use as the reference category) replicates previous results as concerns the impact of a transitory and permanent increase in wealth.

[INSERT TABLE 4.8 ABOUT HERE]

4.7 Conclusions

This chapter investigates the impact of wealth on the probability to transitioning either into out-of-labour force or unemployment. The analysis is carried out making use of longitudinal data from the Survey of Income and Program Participation, for the U.S. economy, over the period 1996-2013. To the best of my knowledge this is the first study trying to investigate this relationship making use of information collected in the SIPP. Indeed, previous studies have either focused only on a framework with two labour market states (employment and unemployment) or addressed the issue without developing any empirical analysis.

In performing this exercise, I take advantage of the special features of the SIPP. This Survey, composed by a very large sample (more than 50,000 households per panel), is able to provide quite accurately information as concerns assets and liabilities at the individual level, together with high-frequency collected information on the labour market history of individuals.

The results in this chapter show that wealth exerts a statistically significant impact on the probability of transitioning to out-of-labour force or unemployment for all the different specifications of the wealth variable and it is still robust to a rich series of different controls. More precisely, building upon the transitory-permanent decomposition of wealth effect, I am able to identify a significant positive effect of a transitory increase in wealth on the probability to transitioning to out-of-labour force and unemployment, while a negative statistically significant effect on the transition probabilities is observed for the case with a permanent increase in wealth.

The positive transitory effect of wealth could be explained by the willingness of the individuals to make labour state transitions (i.e. starting a search activity) when they look for a better job that can guarantee them a higher wage profile, a feature present in the empirical evidence on the life-cycle paths of wage dynamics, and consequently satisfying the permanent income hypothesis. Thus, a transitory increase in wealth can allow individuals to start a new search in order to exploit labour market opportunities allowing for consumption smoothing over the life-cycle.

On the other side, the negative permanent effect on the transition probabilities of an increase in wealth could be explained by the fact that the increase in wealth would play the role of a close substitute to the labour income flow. In this sense, the permanent increase in wealth disincentives individuals from starting a new search in order to find a better job. Then, the resulting drop in the transition probabilities as concerns the movements into out-of-labour force and unemployment.

However, the estimated impact of wealth is larger for the probability of transitioning to out-of-labour force than for the probability to transitioning to the unemployment state. Indeed, a well-established result across the different model specifications is that a temporary increase of $ 100,000 dollars in wealth leads, on average, to an increase of 50 percent in the probability of transitioning to out-of-labour force, but it increases the probability of becoming unemployed only by 30 percent. On the other hand, a permanent increase in wealth decreases the probability to transitioning into out-of-labour force by roughly 60 percent, and that to unemployment by 40 percent.

Thus, these findings reveals the presence of differences in the behaviour of agents when one examines their transitions into the non-employment states, i.e., the “exit margin”.

Therefore, it is possible to argue that a theoretical model not including the presence of the out-of-labour force workers or lumping them together with employed workers into a large non-employment state, as it is currently done in the literature, is not supported by the empirical findings.

However, one more point needs to be discussed. Indeed, it is also found in the results that the quantitative impact of wealth on the transition probabilities falls by two-third when the model specification includes the labour income variable. This result does not rule out the qualitative difference in terms of different effects produced by a change in wealth on the transition probabilities. However, it substantially affects the magnitude of the estimated values. I believe that this puzzling result can be rationalized if the relationship between wealth and wage is described as a convex combination, i.e., agents are at an interior point when we consider a positive amount of both variables. Looking at the correlation matrix, it can be observed how the correlation between the two variable is a figure around 40 percent. Hence, one can consider wage as a variable relaxing the binding constraint on wealth in terms of financing search, providing a further margin affecting the individuals’ decision to transition into the two non-employment states.

Finally, while these findings cannot be compared with previous literature given the novelty of this work as concerns the impact of wealth on the probability to becoming either inactive or unemployed, it is anyway possible to compare them with results from the probability to becoming an entrepreneur. For example, Hurst and Lusardi (2004) use a methodology similar to the one used in this study and in this sense one can try to somewhat outline some similarities. They find, using U.S. data, that an increase in wealth of $ 100,000 dollars would increase the probability of business ownership by 10 percent.[107]

Thus, It would be possible to claim that wealth greatly affects the different choice of agents between starting a new searching or moving towards the self-employment state. Indeed, it would appear that wealth plays a much effective role in determining the probability of transitioning to out-of-labour force or unemployment, compared to its impact on the probability of becoming self-employed.

[107] Sauer and Wilson (2016) propose a similar test for female entrepreneurship using UK data and they find that an increase in £1,000 pounds in liquidity raises the probability of starting a business by 8.5 percent relative to the sample mean. However, their results are largely affected by the particular sample composition and the personal wealth measures and entrepreneurship indicators used.

Table 4.1

Summary Statistics

	Pooled Sample	OLF_{t+1}	U_{t+1}	No Transition	(2) vs. (3)	(2) vs. (4)	(3) vs. (4)
# Observations	*276,686*	*7,063*	*5,271*	*264,352*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Employed	75.01%	74.78%	68.62%	75.14%	7.57***	-0.69	-10.83***
Unemployed	5.84%	25.22%	0.00%	5.44%	42.15***	69.92***	-17.42***
Out of labour force	19.15%	0.00%	31.38%	19.42%	-56.83***	-41.25***	21.66***
Part-time employed	21.18%	40.01%	26.14%	20.58%	16.24***	39.62***	9.87***
Sex: male	48.56%	34.40%	50.10%	48.90%	-17.75***	-24.09***	1.73*
Age	35.99	30.57	33.31	36.19	-13.12***	-38.54***	-17.13***
Labour market experience	16.37	11.38	14.24	16.54	-13.9***	-35.58***	-13.75***
Marital status: married	52.96%	43.08%	38.61%	53.51%	5.00***	-17.35***	-21.5***
-"-: Widowed/separated/divorced	13.06%	9.68%	14.80%	13.12%	-8.71***	-8.46***	3.58***
-"-: Single	33.98%	47.23%	46.59%	33.37%	0.70	24.35***	20.14***
Household size	3.47	3.76	3.58	3.46	5.79***	15.12***	5.29***
Ethnic group: White	81.75%	77.16%	73.69%	82.03%	4.46***	-10.50***	-15.58***
-"-: Black	11.59%	14.97%	19.22%	11.35%	-6.26***	9.42***	17.74***
-"-: Asian	2.72%	3.19%	3.04%	2.70%	0.47	2.49**	1.49
-"-: Other	3.94%	4.69%	4.06%	3.92%	1.67*	3.28***	0.53
Education: University	20.14%	13.80%	13.30%	20.45%	0.81	-13.71***	-12.78***
-"-: Less than University	34.27%	34.53%	30.28%	34.34%	4.99***	0.33	-6.16***
-"-: High school	31.94%	33.00%	34.02%	31.87%	-1.18	2.01**	3.3***
-"-: Less than high school	13.64%	18.66%	22.41%	13.33%	-5.12***	12.94***	19.09***
Panel B							
Homeowner	66.79%	62.96%	56.90%	67.09%	6.83***	-7.29***	-3.65***
	[0.47]	[0.48]	[0.50]	[0.47]			
Mortgaged home	49.80%	45.84%	39.94%	50.10%	6.56***	-7.07***	-12.65***
	[0.50]	[0.50]	[0.49]	[0.50]			
Other rental property	2.83%	1.91%	1.67%	2.87%	1.00	-4.80***	-12.58***
	[0.17]	[0.14]	[0.13]	[0.17]			
Stocks	1,926.1	1,148.7	1,267.5	1,960.0	-0.61	-4.98***	-8.55***
	[13,515.3]	[8,480.5]	[13,053.1]	[16,362.4]			
Cash wealth	15,960.5	7,327.6	8,910.7	16,331.8	-3.26***	-17.78***	-13.5***
	[41,848.0]	[23,396.6]	[30,538.3]	[42,386.7]			
Liquid wealth	17,880.8	8,476.37	10,178.17	18,285.64	-3.11***	-17.64***	-17.61***
	[45,961.3]	[26,226.24]	[34,507.86]	[46,531.43]			
Real estate property	30,546.7	27,411.99	22,888.60	30,783.13	4.87***	-4.21***	-4.50***
	[66,060.9]	[53,046.89]	[48,258.35]	[66,667.58]			
Insurance policy	64,123.5	33,069.61	37,563.01	65,482.76	-2.29**	-18.14***	-5.47***
	[147,824.7]	[101,673.09]	[115,868.47]	[149,285.73]			
Total wealth	110,416.6	68,365.53	69,571.14	112,354.53	-0.51	-20.95***	-6.45***
	[173,778.9]	[124,240.68]	[137,171.99]	[175,317.98]			
Wage	1,882.0	1,029.42	1,311.84	1,916.13	-8.40***	-27.82***	9.89***
	[2,640.0]	[1,595.73]	[2,138.15]	[2,666.21]			
Spouse's wage	654.8	646.99	423.55	659.62	7.45***	-0.58	1.03
	[1,790.9]	[1,864.96]	[1,299.85]	[1,797.02]			
Household equalized income	4,547.5	4,206.69	3,479.49	4,577.94	9.62***	-6.97***	-4.92***
	[4,408.0]	[4,510.55]	[3,623.33]	[4,416.49]			
Government transfers income	58.06	82.01	92.15	56.73	-2.20**	8.15***	-6.92***
	[215.4]	[252.6]	[255.2]	[257.5]			
Parental support income	1.17	0.58	2.09	1.17	-1.89*	-0.77	-4.52***
	[63.49]	[19.52]	[63.54]	[64.26]			

Notes: Averages (and standard deviations for selected variables) from SIPP 1996-2013. The variables included in the summary statistics are usually observed once per year in each panel, and each panel runs between 36 and 60 months. Furthermore, the topical module registers it only for the fourth month of the reference wave. However, not all the panels start to collect data in the same month, thus the time interval between the observations in two consecutive panels might be larger or smaller than one year. All financial values are in real terms at 1995 prices. The Price Consumption Expenditure Index (PCE) is used to deflate the nominal values. Liquid wealth and Total wealth are defined in net terms.*** indicates a significant level of 1 percent. ** indicates a significant level of 5 percent. * indicates a significant level of 10 percent.

Table 4.2

Correlation matrix

	Transition Inactivity	Transition Unemployment	No transition	Sex: Male	Age	Labour market exper.	Marital status: Single	Household size	Race: White	Education: Universiy	Education: Less than university	Education: High school	Education: Less than high school	Liquid Wealth	Total Wealth	Wage	Spouse's wage	Hhold's Income
Transition Inactivity	1																	
Transition Unemp.	-0.02*	1																
No transition	-0.74*	-0.64*	1															
Sex: Male	-0.04*	0.01*	0.03*	1														
Age	-0.07*	-0.03*	0.08*	-- 0.02*	1													
Labour market exper	-0.06*	-0.02*	0.07*	-0.02*	0.98*	1												
Marital status: Single	0.04*	0.03*	-0.06*	0.07*	-0.57*	-0.56*	1											
Household size	0.02*	0.01*	-0.03*	-0.02*	-0.19*	-0.16*	-0.01*	1										
Race: White	-0.01*	-0.02*	0.03*	0.04*	0.04*	0.04*	-0.12*	-0.11*	1									
Education: Universiy	-0.02*	-0.02*	004*	0.02*	0.11*	-0.01*	-0.10*	-0.05*	0.01*	1								
Education: Less than university	0.01	-0.01*	0.01*	-0.04*	-0.03*	-0.05*	0.03*	0.02*	-0.01*	-0.34*	1							
Education: High school	0.01	0.01*	-0.01*	0.01*	-0.02*	0.01*	0.01*	0.17*	-0.03*	-0.20*	-0.29*	1						
Education: Less than high school	0.02*	0.03*	-0.04*	0.02*	-0.05*	0.07*	0.04*	-0.08*	0.09*	0.28	-0.04*	-0.11*	1					
Liquid Wealth	-0.03*	-0.02*	0.04*	0.10*	0.27*	0.22*	-0.14*	-0.03*	0.10*	0.32	-0.028	-0.12*	-0.17*	1				
Total Wealth	-0.03*	-0.03*	0.05*	0.14*	0.24*	0.19*	-0.24*	-0.11*	0.08*	0.32	-0.05*	-0.11*	-0.15*	0.42*	1			
Wage	0.05*	0.03*	0.05*	0.22*	0.24*	0.18*	-0.19*	-0.11*	0.08*	0.32*	-0.04*	-0.11*	-0.15*	0.42*	0.46*	1		
Spouse's wage	-0.00*	-0.01*	0.01*	-0.13*	0.11*	0.08*	-0.22*	0.01*	0.06*	0.13*	-0.01*	-0.04*	-0.07*	0.08*	0.12*	0.04*	1	
Hhold's Income	-0.01*	-0.03*	0.03*	0.05*	0.05*	0.01*	-0.05*	0.11*	0.09*	0.26*	0.00	-0.11*	-0.15*	0.29*	0.36*	0.57*	0.35*	1

Table 4.3
Benchmark model

Dependent Variable	(1) **OLF_{t+1}**	(2) **U_{t+1}**	(3) **OLF_{t+1}**	(4) **U_{t+1}**	(5) **OLF_{t+1}**	(6) **U_{t+1}**
Panel A: Calculations						
Predicted probability	*0.0255*	*0.0190*	*0.0255*	*0.0190*	*0.0255*	*0.0190*
% Level wealth effect	*49.8%*	*30.0%*	*16.5%*	*18.4%*	*49.8%*	*29.8%*
% Permanent wealth effect	*-58.0%*	*-42.1%*	*-18.8%*	*-21.1%*	*-46.3%*	*-38.4%*
Panel B: Level Effects						
Liquid Wealth	0.0127***	0.0057***	—	—	0.0127***	0.0056***
	[0.0018]	[0.0014]			[0.0018]	[0.0014]
Total Wealth	—	—	0.0042***	0.0035***	—	—
			[0.0004]	[0.0003]		
Labour Market State: Employed	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Unemployed	—	—	—	—	0.0439***	—
					[0.0008]	
-"-: Out of labour force	—	—	—	—	—	0.0111***
						[0.0006]
Female	-0.0146***	0.0013***	-0.0137***	0.0022***	-0.0153***	0.0033***
	[0.0006]	[0.0005]	[0.0006]	[0.0005]	[0.0006]	[0.0005]
Ethinc group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	0.0033***	0.0086***	0.0029***	0.0081***	-0.0001	0.0084***
	[0.0009]	[0.0007]	[0.0009]	[0.0007]	[0.0009]	[0.0002]
-"-: Asian	0.0029	0.0011	0.0023	0.0005	0.0012	0.0002***
	[0.0017]	[0.0015]	[0.0017]	[0.0015]	[0.0017]	[0.0015]
-"-: Other	0.0026	0.0008	0.0024*	0.0005	0.0022	0.0002
	[0.0014]	[0.0013]	[0.0014]	[0.0013]	[0.0014]	[0.0013]
Log(Age)	-0.0718***	-0.0523***	-0.0727***	-0.0539***	-0.0703***	-0.0497***
	[0.0065]	[0.0057]	[0.0065]	[0.0057]	[0.0063]	[0.0057]
Log(Labour market experience)	-0.0038***	-0.0020***	-0.0038***	-0.0020***	-0.0037***	-0.0020***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0034	-0.0021	-0.0035	-0.0022	-0.0032	-0.0027
	[0.0029]	[0.0026]	[0.0029]	[0.0026]	[0.0029]	[0.0026]
-"-: Widowed/Divorced/Separated	0.0055	-0.0026	0.0056	-0.0028	0.0047	-0.0026
	[0.0038]	[0.0032]	[0.0038]	[0.0032]	[0.0038]	[0.0033]
Log(Household size)	-0.0119***	-0.0033***	-0.0123***	-0.0037***	-0.0121***	-0.0036
	[0.0019]	[0.0016]	[0.0018]	[0.0016]	[0.0018]	[0.0016]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0378***	0.0265***	0.0384***	0.0268***	0.0403***	0.0242***
	[0.0040]	[0.0037]	[0.0040]	[0.0036]	[0.0039]	[0.0037]
-"-: High school	0.0709***	0.0399***	0.0717***	0.0405***	0.0724***	0.0375***
	[0.0046]	[0.0043]	[0.0046]	[0.0043]	[0.0045]	[0.0043]
-"-: Less than high school	0.1121***	0.0692***	0.1133***	0.0701***	0.1164***	0.0652***
	[0.0054]	[0.0050]	[0.0054]	[0.0050]	[0.0053]	[0.0043]
Panel C: Mean Effects						
Liquid Wealth	-0.0275***	-0.0137***	—	—	-0.0245***	-0.0129***
	[0.0025]	[0.0018]			[0.0024]	[0.0018]
Total Wealth	—	—	-0.0090***	-0.0075***	—	—
			[0.0005]	[0.0004]		
Log(Age)	0.0481***	0.0448***	0.0501***	0.0479***	0.0475***	0.0428***
	[0.0067]	[0.0059]	[0.0067]	[0.0058]	[0.0065]	[0.0059]
Log(Labour market experience)	0.0040***	0.0032***	0.0040***	0.0031***	0.0037***	0.0036***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0004]

Table 4.4 continued in next page

	(1) OLF$_{t+1}$	(2) U$_{t+1}$	(3) OLF$_{t+1}$	(4) U$_{t+1}$	(5) OLF$_{t+1}$	(6) U$_{t+1}$
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0029	-0.0055**	0.0037	-0.0047*	0.0048	-0.0050*
	[0.0030]	[0.0027]	[0.0030]	[0.0027]	[0.0030]	[0.0027]
-"-: Widowed/Divorced/Separated	-0.0079	0.0032	-0.0079*	0.0034	-0.0073*	0.0037
	[0.0041]	[0.0034]	[0.0040]	[0.0034]	[0.0040]	[0.0034]
Log(Household size)	0.0181***	0.0039	0.0193***	0.0050***	0.0177***	0.0031*
	[0.0020]	[0.0017]	[0.0020]	[0.0017]	[0.0020]	[0.0017]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0362***	-0.0257***	-0.0379***	-0.0274***	-0.0385***	-0.0232***
	[0.0040]	[0.0037]	[0.0040]	[0.0037]	[0.0040]	[0.0037]
-"-: High school	-0.0708***	-0.0359***	-0.0733***	-0.0385***	-0.0735***	-0.0334***
	[0.0047]	[0.0043]	[0.0047]	[0.0043]	[0.0046]	[0.0043]
-"-: Less than high school	-0.1099***	-0.0602***	-0.1138***	-0.0642***	-0.1170***	-0.0573***
	[0.0056]	[0.0051]	[0.0056]	[0.0051]	[0.0054]	[0.0051]
Panel D: Calculated Permanent Effects						
Liquid Wealth	-0.0148***	-0.0080***	—	—	-0.0118***	-0.0073***
	[0.0014]	[0.0010]			[0.0014]	[0.0010]
Total Wealth	—	—	-0.0048***	-0.0040***	—	—
			[0.0003]	[0.0003]		
Log(Age)	-0.0236***	-0.0075***	-0.0226***	-0.006***	-0.0228***	-0.0069***
	[0.0015]	[0.0013]	[0.0015]	[0.0013]	[0.0015]	[0.0013]
Log(Labour market experience)	0.0003*	0.0012***	0.0002*	0.0012***	0.0001	0.0016***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married with/without Spouse	-0.0006	-0.0077***	0.0002	-0.007***	0.0017**	-0.0078***
	[0.0009]	[0.0008]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
-"-: Widowed/Divorced/Separated	-0.0024**	0.0006	-0.0023**	0.0006	-0.0026***	0.0011
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
Log(Household Size)	0.0062***	0.0006	0.007***	0.0013**	0.0055***	-0.0004
	[0.0007]	[0.0006]	[0.0007]	[0.0006]	[0.0007]	[0.0006]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0016*	0.0008	0.0005	-0.0006	0.0018**	0.001
	[0.0010]	[0.0008]	[0.0010]	[0.0009]	[0.0009]	[0.0008]
-"-: High school	0.0001	0.004***	-0.0016	0.002**	-0.0011	0.0041***
	[0.0010]	[0.0009]	[0.0010]	[0.0009]	[0.0010]	[0.0009]
-"-: Less than high school	0.0022*	0.009***	-0.0005	0.006***	-0.0006	0.0079***
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
#Observations	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*
Log-likelihood	*-29,862.6*	*-24,031.1*	*-29,773.5*	*-23,906.4*	*-28,564.1*	*-23,880.4*
χ^2	*4,750.6****	*3,098.5****	*4,863.5****	*3,228.5****	*7,187.7****	*3,378.0****

Notes: Each column presents marginal effects and robust standard errors, clustered at the individual level [in brackets] from a random effects probit model. Wealth and all financial values are in $100,000 and in real terms at 1995 prices. The Price Consumption Expenditure (PCE) Index is used to deflate the nominal values. The specification also includes 50 state dummy variables. The asterisks denote the following level of significance: *** <1%, ** <5%, and * <10%.

Table 4.4

Robustness in terms of alternative specifications

Dependent Variable	(1) **OLF_{t+1}**	(2) **U_{t+1}**	(3) **OLF_{t+1}**	(4) **U_{t+1}**	(5) **OLF_{t+1}**	(6) **U_{t+1}**
Panel A: Calculations						
Predicted probability	*0.0255*	*0.0190*	*0.0255*	*0.0190*	*0.0255*	*0.0190*
% Level wealth effect	*41.2%*	*-28.2%*	*0.39%*	*0.52%*	*11.4%*	*8.9%*
% Permanent wealth effect	*-48.4%*	*-29.4%*	*-1.18%*	*-1.58%*	*-12.3%*	*-19.5%*
Panel B: Level Effects						
Liquid wealth	0.0557***	0.0373***	—	—	—	—
	[0.0101]	[0.0072]				
$(\text{Liquid wealth})^2$	-0.0254	-0.0325***	—	—	—	—
	[0.0216]	[0.0096]				
$(\text{Liquid wealth})^3$	-0.0086	0.0127***	—	—	—	—
	[0.0184]	[0.0046]				
$(\text{Liquid wealth})^4$	0.0072	-0.0023***	—	—	—	—
	[0.0064]	[0.0008]				
$(\text{Liquid wealth})^5$	-0.0010	0.0001***	—	—	—	—
	[0.0007]	[0.0001]				
Liquid wealth percentile	—	—	0.0001***	0.0001***	—	—
			[0.0001]	[0.0001]		
Log(Liquid wealth)	—	—	—	—	0.0029***	0.0017***
					[0.0004]	[0.0003]
Missing liquid wealth dummy	—	—	—	—	0.0168***	0.0106***
					[0.0033]	[0.0028]
Female	-0.0144***	0.0016***	-0.0146***	0.0017***	-0.0144***	0.0018***
	[0.0006]	[0.0005]	[0.0006]	[0.0005]	[0.0006]	[0.0005]
Ethnic group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	0.0025***	0.0076***	0.0018**	0.0068***	0.0019**	0.0070***
	[0.0009]	[0.0007]	[0.0009]	[0.0007]	[0.0009]	[0.0007]
-"-: Asian	0.0027	0.0008	0.0028	0.0007	0.0028	0.0007
	[0.0017]	[0.0015]	[0.0017]	[0.0015]	[0.0017]	[0.0015]
-"-: Other	0.0023*	0.0005	0.0025*	0.0004	0.0024*	0.0004
	[0.0014]	[0.0013]	[0.0014]	[0.0013]	[0.0014]	[0.0013]
Log(Age)	-0.0745***	-0.0546***	-0.0726***	-0.0533***	-0.0729***	-0.0534***
	[0.0065]	[0.0057]	[0.0065]	[0.0057]	[0.0065]	[0.0057]
Log(Labour market experience)	-0.0037***	-0.0020***	-0.0038***	-0.0020***	-0.0038***	-0.0020***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married with/without Spouse	-0.0031	-0.0018	-0.0031	-0.0018	-0.0032	-0.0019
	[0.0029]	[0.0026]	[0.0029]	[0.0026]	[0.0029]	[0.0026]
-"-: Widowed/Divorced/Separated	0.0057	-0.0023	0.0058	-0.0023	0.0058	-0.0024
	[0.0038]	[0.0032]	[0.0038]	[0.0032]	[0.0038]	[0.0032]
Log(Household size)	-0.0122***	-0.0035**	-0.0127***	-0.0037**	-0.0127***	-0.0037**
	[0.0018]	[0.0016]	[0.0019]	[0.0016]	[0.0019]	[0.0016]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0380***	0.0266***	0.0381***	0.0269***	0.0380***	0.0265***
	[0.0040]	[0.0037]	[0.0040]	[0.0037]	[0.0040]	[0.0036]
-"-: High school	0.0714***	0.0401***	0.0715***	0.0406***	0.0715***	0.0402***
	[0.0046]	[0.0043]	[0.0046]	[0.0043]	[0.0046]	[0.0043]
-"-: Less than high school	0.1129***	0.0697***	0.1132***	0.0703***	0.1132***	0.0700***
	[0.0054]	[0.0050]	[0.0054]	[0.0050]	[0.0054]	[0.0050]
Panel C: Mean Effects						
Liquid wealth	-0.1236***	-0.1074***	—	—	—	—
	[0.0103]	[0.0095]				

Table 4.4 continued in next page

Table 4.4 continued from last page

	(1)	(2)	(3)	(4)	(5)	(6)
	OLF$_{t+1}$	**U$_{t+1}$**	**OLF$_{t+1}$**	**U$_{t+1}$**	**OLF$_{t+1}$**	**U$_{t+1}$**
(Liquid wealth)^2	0.1026***	0.1163***	—	—	—	—
	[0.0142]	[0.0148]				
(Liquid wealth)^3	-0.0338***	-0.0496***	—	—	—	—
	[0.0064]	[0.0080]				
(Liquid wealth)^4	0.0044***	0.0088***	—	—	—	—
	[0.0010]	[0.0016]				
(Liquid wealth)^5	-0.0002***	-0.0005***	—	—	—	—
	[0.0001]	[0.0001]				
Liquid wealth percentile	—	—	-0.0003***	-0.0003***	—	—
			[0.0001]	[0.0001]		
Log(Liquid wealth)	—	—	—	—	-0.0062***	-0.0054***
					[0.0004]	[0.0004]
Missing liquid wealth dummy	—	—	—	—	-0.0369***	-0.0362***
					[0.0041]	[0.0034]
Log(Age)	0.0527***	0.0493***	0.0501***	0.0484***	0.0507***	0.0487***
	[0.0067]	[0.0059]	[0.0067]	[0.0059]	[0.0067]	[0.0059]
Log(Labour market experience)	0.0039***	0.0031***	0.0039***	0.0030***	0.0039***	0.0030***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0027	-0.0055**	0.0026	-0.0055*	0.0028	-0.0053*
	[0.0030]	[0.0027]	[0.0030]	[0.0027]	[0.0030]	[0.0027]
-"-: Widowed/Divorced/Separated	-0.0085**	0.0026	-0.0087**	0.0024	-0.0088**	0.0024
	[0.0041]	[0.0034]	[0.0041]	[0.0034]	[0.0041]	[0.0034]
Log(Household size)	0.0182***	0.0039**	0.0190***	0.0044*	0.0192***	0.0045***
	[0.0020]	[0.0017]	[0.0020]	[0.0017]	[0.0020]	[0.0017]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0375***	-0.0269***	-0.0367***	-0.0272***	-0.0369***	-0.0273***
	[0.0040]	[0.0037]	[0.0041]	[0.0037]	[0.0040]	[0.0037]
-"-: High school	-0.0728***	-0.0379***	-0.0722***	-0.0386***	-0.0724***	-0.0381***
	[0.0047]	[0.0043]	[0.0047]	[0.0043]	[0.0047]	[0.0043]
-"-: Less than high school	-0.1128***	-0.0632***	-0.1129***	-0.0647***	-0.1131***	-0.0647***
	[0.0056]	[0.0051]	[0.0056]	[0.0051]	[0.0056]	[0.0051]
Panel D: Calculated Permanent Effects						
Liquid wealth	-0.0680***	-0.0702***	—	—	—	—
	[0.0078]	[0.0055]				
(Liquid wealth)^2	0.0772***	0.0838***	—	—	—	—
	[0.0198]	[0.0092]				
(Liquid wealth)^3	-0.0425**	-0.0369***	—	—	—	—
	[0.0180]	[0.0050]				
(Liquid wealth)^4	0.0118*	0.0066***	—	—	—	—
	[0.0065]	[0.0010]				
(Liquid wealth)^5	-0.0013	-0.0004***	—	—	—	—
	[0.0008]	[0.0001]				
Liquid wealth percentile	—	—	-0.0002***	-0.0002***	—	—
			[0.0001]	[0.0001]		
Log(Liquid wealth)	—	—	—	—	-0.0032***	-0.0037***
					[0.0003]	[0.0002]
Missing liquid wealth dummy	—	—	—	—	-0.0202***	-0.0256***
					[0.0024]	[0.0020]
Log(Age)	-0.0217***	-0.0053***	-0.0225***	-0.0048***	-0.0223***	-0.0046***
	[0.0015]	[0.0013]	[0.0015]	[0.0013]	[0.0015]	[0.0013]
Log(Labour market experience)	0.0002	0.0011***	0.0002	0.001***	0.0002	0.001***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*

Table 4.4 continued in next page

Table 4.4 continued from last page

	(1)	(2)	(3)	(4)	(5)	(6)
	OLF_{t+1}	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
-"-: Married	-0.0005	-0.0074***	-0.0005	-0.0074***	-0.0004	-0.0073***
	[0.0009]	[0.0008]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
-"-: Widowed/Divorced/Separated	-0.0028***	0.0003	-0.003***	0.0001	-0.003**	0.0001
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
Log(Household size)	0.006***	0.0004	0.0063***	0.0007	0.0064***	0.0008
	[0.0007]	[0.0006]	[0.0007]	[0.0006]	[0.0007]	[0.0006]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0006	-0.0003	0.0014	-0.0003	0.0011	-0.0007
	[0.0010]	[0.0009]	[0.0009]	[0.0008]	[0.0010]	[0.0008]
-"-: High school	-0.0014	0.0022**	-0.0008	0.002**	-0.001	0.0016*
	[0.0010]	[0.0009]	[0.0010]	[0.0009]	[0.0010]	[0.0009]
-"-: Less than high school	0.0001	0.0064***	0.0004	0.0057***	0.0001	0.0053***
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
#Observations	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*
Log-likelihood	*-29,789.9*	*-2,3934.6*	*-29,822.2*	*-23,919.7*	*-29,813.3*	*-23,906.0*
χ^2	*4,868.0****	*3,237.8****	*4,906.8****	*3,295.5****	*4,906.9****	*3,307.1****

Notes: Comments in Table 4.2 apply.

Table 4.5
Alternative definition of illiquid wealth

Dependent Variable	(1) **OLF$_{t+1}$**	(2) **U$_{t+1}$**	(3) **OLF$_{t+1}$**	(4) **U$_{t+1}$**	(5) **OLF$_{t+1}$**	(6) **U$_{t+1}$**
Panel A: Calculations						
Predicted probability	*0.0255*	*0.0190*	*0.0255*	*0.0190*	*0.0255*	*0.0190*
% Level wealth effect	*49.8%*	*29.5%*	*49.8%*	*29.5%*	*49.8%*	*28.9%*
% Permanent wealth effect	*-58.4%*	*-37.9%*	*-57.6%*	*-37.3%*	*-58.0%*	*-36.8%*
Panel B: Level Effects						
Liquid wealth	0.0127***	0.0056***	0.0127***	0.0056***	0.0127***	0.0055***
	[0.0019]	[0.0014]	[0.0019]	[0.0014]	[0.0019]	[0.0014]
Home owner	0.0065***	0.0060***	0.0036	0.0053***	0.0035	0.0053***
	[0.0019]	[0.0017]	[0.0023]	[0.0020]	[0.0023]	[0.0020]
Mortgage home	—	—	0.0039***	0.0009	0.0039***	0.0008
			[0.0016]	[0.0015]	[0.0016]	[0.0015]
Other rental property	—	—	—	—	0.0046	0.0065
					[0.0045]	[0.0043]
Female	-0.0147***	0.0015***	-0.0145***	0.0015***	-0.0145***	0.0014***
	[0.0006]	[0.0005]	[0.0006]	[0.0005]	[0.0006]	[0.0005]
Ethnic group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	0.0034***	0.0081***	0.0034***	0.0080***	0.0034***	0.0080***
	[0.0009]	[0.0007]	[0.0009]	[0.0007]	[0.0009]	[0.0007]
-"-: Asian	0.0030	0.0008	0.0029*	0.0008	0.0029*	0.0007
	[0.0017]	[0.0015]	[0.0017]	[0.0015]	[0.0017]	[0.0015]
-"-: Other	0.0026*	0.0005	0.0026*	0.0005	0.0026*	0.0005
	[0.0014]	[0.0013]	[0.0014]	[0.0013]	[0.0014]	[0.0013]
Log(Age)	-0.0737***	-0.0541***	-0.0732***	-0.0540***	-0.0734***	-0.0543***
	[0.0065]	[0.0057]	[0.0065]	[0.0057]	[0.0065]	[0.0057]
Log(Labour market experience)	-0.0037***	-0.0020***	-0.0037***	-0.0020***	-0.0037***	-0.0019***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0033	-0.0019	-0.0035	-0.0019	-0.0036	-0.0019
	[0.0029]	[0.0026]	[0.0029]	[0.0026]	[0.0029]	[0.0026]
-"-: Widowed/Divorced/Separated	0.0059	-0.0021	0.0058	-0.0021	0.0058	-0.0021
	[0.0038]	[0.0032]	[0.0039]	[0.0032]	[0.0039]	[0.0032]
Log(Household size)	-0.0133***	-0.0044***	-0.0133***	-0.0044***	-0.0133***	-0.0044***
	[0.0019]	[0.0016]	[0.0019]	[0.0016]	[0.0019]	[0.0016]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0376***	0.0267***	0.0376***	0.0268***	0.0376***	0.0266***
	[0.0040]	[0.0037]	[0.0040]	[0.0037]	[0.0040]	[0.0037]
-"-: High school	0.0707***	0.0402***	0.0707***	0.0401***	0.0707***	0.0401***
	[0.0046]	[0.0043]	[0.0046]	[0.0043]	[0.0046]	[0.0043]
-"-: Less than high school	0.1116***	0.0695***	0.1116***	0.0696***	0.1117***	0.0695***
	[0.0054]	[0.0050]	[0.0054]	[0.0050]	[0.0054]	[0.0050]
Panel C: Mean Effects						
Liquid wealth	-0.0277***	-0.0128***	-0.0274***	-0.0127***	-0.0274***	-0.0126***
	[0.0026]	[0.0018]	[0.0025]	[0.0018]	[0.0025]	[0.0018]
Home owner	-0.0059***	-0.0095***	0.0001	-0.0068***	0.0001	-0.0068***
	[0.0026]	[0.0018]	[0.0025]	[0.0022]	[0.0025]	[0.0022]
Mortgage home	—	—	-0.0084***	-0.0038**	-0.0084***	-0.0037***
			[0.0019]	[0.0017]	[0.0019]	[0.0017]
Other rental property	—	—	—	—	-0.0027	-0.0093*
					[0.0051]	[0.0049]
Log(Age)	0.0499***	0.0481***	0.0489***	0.0478***	0.0491***	0.0481***
	[0.0067]	[0.0059]	[0.0067]	[0.0059]	[0.0067]	[0.0059]

Table 4.5 continued in next page

Table 4.5 continued from last page

	(1) **OLF$_{t+1}$**	(2) **U$_{t+1}$**	(3) **OLF$_{t+1}$**	(4) **U$_{t+1}$**	(5) **OLF$_{t+1}$**	(6) **U$_{t+1}$**
Log(Labour market experience)	0.0041***	-0.0031***	0.0040***	-0.0030***	0.0040***	-0.0030***
	[0.0004]	[0.0004]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0028	-0.0057***	0.0033	-0.0054**	0.0034***	0.0053***
	[0.0030]	[0.0027]	[0.0030]	[0.0003]	[0.0031]	[0.0027]
-"-: Widowed/Divorced/Separated	-0.0082	0.0024	-0.0080*	0.0025	-0.0080**	0.0024
	[0.0041]	[0.0034]	[0.0041]	[0.0034]	[0.0041]	[0.0034]
Log(Household size)	0.0193***	0.0057***	0.0195***	0.0058***	0.0195***	0.0057***
	[0.0020]	[0.0017]	[0.0020]	[0.0017]	[0.0020]	[0.0017]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0360***	-0.0256***	-0.0362***	-0.0259***	-0.0363***	-0.0260***
	[0.0040]	[0.0037]	[0.0040]	[0.0037]	[0.0040]	[0.0037]
-"-: High school	-0.0705***	-0.0363***	-0.0710***	-0.0365***	-0.0710***	-0.0365***
	[0.0047]	[0.0043]	[0.0047]	[0.0043]	[0.0047]	[0.0043]
-"-: Less than high school	-0.1093***	-0.0611***	-0.1101***	-0.0615***	-0.1101***	-0.0615***
	[0.0055]	[0.0051]	[0.0056]	[0.0051]	[0.0056]	[0.0051]
Panel D: Calculated Permanent Effects						
Liquid wealth	-0.0149***	-0.0072***	-0.0147***	-0.0071***	-0.0148***	-0.0070***
	[0.0014]	[0.0010]	[0.0014]	[0.0010]	[0.0014]	[0.0010]
Home owner	0.0006	-0.0035***	0.0038***	-0.0015*	0.0038***	-0.0015*
	[0.0007]	[0.0006]	[0.0010]	[0.0009]	[0.0010]	[0.0009]
Mortgage home	—	—	-0.0045***	-0.0029***	-0.0046***	-0.0029***
			[0.0010]	[0.0009]	[0.0010]	[0.0009]
Other rental property	—	—	—	—	0.0019	-0.0028
					[0.0023]	[0.0021]
Log(Age)	-0.0239***	-0.0060***	-0.0243***	-0.0063***	-0.0244***	-0.0062***
	[0.0016]	[0.0013]	[0.0016]	[0.0013]	[0.0016]	[0.0013]
Log(Labour Market experience)	0.0003*	0.0011***	0.0003*	0.0011***	0.0003*	0.0011***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0005	-0.0076***	0.0002	-0.0073***	-0.0002	-0.0073***
	[0.0009]	[0.0008]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
-"-: Widowed/Divorced/Separated	-0.0023*	0.0003	-0.0022*	0.0004	-0.0022*	0.0004
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
Log(Household Size)	0.0061***	0.0013**	0.0063***	0.0013***	0.0063***	0.0013**
	[0.0007]	[0.0006]	[0.0007]	[0.0006]	[0.0007]	[0.0006]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0016	0.0008	0.0013	0.0007	0.0013	0.0007
	[0.0010]	[0.0008]	[0.0010]	[0.0009]	[0.0010]	[0.0009]
-"-: High school	0.0001	0.0039***	-0.0004	0.0036***	-0.0003	0.0036***
	[0.0010]	[0.0009]	[0.0010]	[0.0009]	[0.0010]	[0.0009]
-"-: Less than high school	-0.0023*	0.0085***	-0.0016	0.0081***	0.0016	0.0081***
	[0.0012]	[0.0010]	[0.0012]	[0.0010]	[0.0012]	[0.0010]
#Observations	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*
Log-likelihood	*-29,856.8*	*-24,008.3*	*-29,843.7*	*-24,002.7*	*-29,842.8*	*-24,000.8*
χ^2	*4,758.9****	*3,138.3****	*4,780.9****	*3,146.7****	*4,781.6****	*3,148.6****

Notes: Comments in Table 4.2 apply.

Table 4.6

Specifications using salary income

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
Panel A: Calculations						
Predicted probability	*0.0255*	*0.0190*	*0.0254*	*0.0189*	*0.0254*	*0.0189*
% Level wealth effect	*42.4%*	*17.9%*	*20.9%*	*11.6%*	*20.5%*	*12.7%*
% Permanent wealth effect	*-43.5%*	*-12.1%*	*-13.0%*	*-1.6%*	*-13.0%*	*-4.8%*
Panel B: Level Effects						
Liquid wealth	0.0108***	0.0034**	0.0053***	0.0022	0.0052***	0.0024*
	[0.0018]	[0.0014]	[0.0017]	[0.0013]	[0.0017]	[0.0013]
Home owner	0.0010	0.0035*	0.0040*	0.0051***	0.0042**	0.0048***
	[0.0023]	[0.0020]	[0.0020]	[0.0019]	[0.0020]	[0.0018]
Mortgage home	0.0033**	-0.0001	0.0018	-0.0008***	0.0017	-0.0008
	[0.0016]	[0.0015]	[0.0015]	[0.0014]	[0.0015]	[0.0014]
Log(Household income)	0.3544***	0.3423***	—	—	—	—
	[0.0151]	[0.0141]				
Log(Wage)	—	—	0.0161***	0.0111***	0.0162***	0.0108***
			[0.0001]	[0.0001]	[0.0001]	[0.0001]
Government transfers	—	—	—	—	1.0070***	-0.9489***
					[0.0960]	[0.1179]
Other parental support	—	—	—	—	-2.1398*	0.8661*
					[1.0935]	[0.4589]
Female	-0.0141***	0.0022***	-0.0053***	0.0073***	-0.0053***	0.0074***
	[0.0006]	[0.0005]	[0.0005]	[0.0005]	[0.0005]	[0.0005]
Ethnic group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	0.0021***	0.0062***	0.0022***	0.0060***	0.0023***	0.0057***
	[0.0009]	[0.0007]	[0.0008]	[0.0007]	[0.0008]	[0.0007]
-"-: Asian	0.0029*	0.0010	0.0008	-0.0009	0.0008	-0.0005
	[0.0017]	[0.0015]	[0.0015]	[0.0014]	[0.0015]	[0.0014]
-"-: Other	0.0024*	0.0001	0.0003	-0.0014	0.0002	-0.0012
	[0.0014]	[0.0013]	[0.0013]	[0.0012]	[0.0013]	[0.0012]
Log(Age)	-0.0749***	-0.0546***	-0.0817***	-0.0655***	-0.0820***	-0.0648***
	[0.0065]	[0.0056]	[0.0056]	[0.0050]	[0.0056]	[0.0050]
Log(Labour market experience)	-0.0038***	-0.0020***	-0.0037***	-0.0020***	-0.0037***	-0.0020***
	[0.0003]	[0.0003]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0040	-0.0028	-0.0042	-0.0033	-0.0038	-0.0037
	[0.0029]	[0.0026]	[0.0026]	[0.0024]	[0.0026]	[0.0023]
-"-: Widowed/Divorced/Separatec	0.0074*	-0.0013	-0.0017	-0.0061***	-0.0028	-0.0052*
	[0.0038]	[0.0032]	[0.0034]	[0.0029]	[0.0034]	[0.0029]
Log(Household size)	-0.0197***	-0.0101***	-0.0033*	0.0010	-0.0035***	0.0013
	[0.0019]	[0.0016]	[0.0017]	[0.0015]	[0.0017]	[0.0015]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0399***	0.0291***	0.0414***	0.0325***	0.0415***	0.0323***
	[0.0040]	[0.0036]	[0.0034]	[0.0032]	[0.0034]	[0.0032]
-"-: High school	0.0727***	0.0429***	0.0708***	0.0443***	0.0710***	0.0438***
	[0.0046]	[0.0043]	[0.0040]	[0.0037]	[0.0040]	[0.0037
-"-: Less than high school	0.1147***	0.0728***	0.1092***	0.0730***	0.1092***	0.0725***
	[0.0054]	[0.0050]	[0.0046]	[0.0043]	[0.0046]	[0.0043]
Panel C: Model Average Effects						
Liquid wealth	-0.0219***	-0.0056***	-0.0087***	-0.0025	-0.0084***	-0.0033*
	[0.0025]	[0.0018]	[0.0022]	[0.0016]	[0.0022]	[0.0017]
Home owner	0.0033	-0.0041*	-0.0019	-0.0079***	-0.0022	-0.0075***
	[0.0025]	[0.0022]	[0.0022]	[0.0020]	[0.0022]	[0.0020]

	(1) OLF$_{t+1}$	(2) U$_{t+1}$	(3) OLF$_{t+1}$	(4) U$_{t+1}$	(5) OLF$_{t+1}$	(6) U$_{t+1}$
Mortgage home	-0.0056***	0.0008	-0.0031	0.0011	-0.0031*	0.0011
	[0.0019]	[0.0017]	[0.0017]	[0.0016]	[0.0017]	[0.0016]
Log(Household income)	-0.5117***	-0.6149***	—	—	—	—
	[0.0207]	[0.0207]				
Log(Wage)	—	—	-0.0217***	-0.0159***	-0.0219***	-0.0155***
			[0.0002]	[0.0002]	[0.0002]	[0.0002]
Government transfers	—	—	—	—	0.2659	-2.0189*
					[0.6330]	[1.1107]
Other parental support	—	—	—	—	-1.3279***	1.6066***
					[0.1651]	[0.0919]
Log(Age)	0.0514***	0.0486***	0.0667***	0.0639***	0.0673***	0.0625***
	[0.0067]	[0.0058]	[0.0058]	[0.0052]	[0.0058]	[0.0052]
Log(Labour market experience)	0.0038***	0.0028***	0.0047***	0.0037***	0.0048***	0.0036***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0036	-0.0041	0.0046*	-0.0022	0.0040	-0.0015
	[0.0030]	[0.0027]	[0.0027]	[0.0025]	[0.0027]	[0.0024]
-"-: Widowed/Divorced/Separatec	-0.0107***	0.0005	0.0021	0.0087***	0.0037	0.0070***
	[0.0040]	[0.0033]	[0.0036]	[0.0031]	[0.0036]	[0.0030]
Log(Household size)	0.0278***	0.0140***	0.0043**	-0.0029*	0.0047***	-0.0034***
	[0.0020]	[0.0017]	[0.0018]	[0.0016]	[0.0018]	[0.0016]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0401***	-0.0310***	-0.0397***	-0.0321***	-0.0396***	-0.0322***
	[0.0040]	[0.0037]	[0.0035]	[0.0032]	[0.0035]	[0.0032]
-"-: High school	-0.0753***	-0.0430***	-0.0708***	-0.0415***	-0.0710***	-0.0413***
	[0.0046]	[0.0043]	[0.0040]	[0.0037]	[0.0040]	[0.0037]
-"-: Less than high school	-0.1163***	-0.0700***	-0.1118***	-0.0697***	-0.1117***	-0.0695***
	[0.0055]	[0.0050]	[0.0048]	[0.0044]	[0.0048]	[0.0044]
Panel D: Calculated Permanent Effects						
Liquid wealth	-0.0111***	-0.0023**	-0.0033***	-0.0003	-0.0033***	-0.0009
	[0.0014]	[0.0010]	[0.0012]	[0.0009]	[0.0012]	[0.0009]
Home owner	0.0044***	-0.0006	0.0021**	-0.0029***	0.0019**	-0.0026***
	[0.0010]	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
Mortgage home	-0.0023**	0.0007	-0.0013	0.0003	-0.0014	0.0003
	[0.0010]	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
Log(Household income)	-0.1573***	-0.2726***	—	—	—	—
	[0.0108]	[0.0115]				
Log(Wage)	—	—	-0.0056***	-0.0048***	-0.0057***	-0.0047***
			[0.0001]	[0.0001]	[0.0001]	[0.0001]
Government transfers	—	—	—	—	-0.3209***	0.6577***
					[0.1109]	[0.0938]
Other parental support	—	—	—	—	-1.8738*	-1.1528
					[1.0389]	[0.7657]
Log(Age)	-0.0235***	-0.006***	-0.0151***	-0.0015	-0.0147***	-0.0024*
	[0.0016]	[0.0013]	[0.0014]	[0.0012]	[0.0014]	[0.0012]
Log(Labour market experience)	0.0001	0.0008***	0.001***	0.0017***	0.0011***	0.0016***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0004	-0.007***	0.0004	-0.0056***	0.0002	-0.0053***
	[0.0009]	[0.0008]	[0.0008]	[0.0007]	[0.0008]	[0.0007]
-"-: Widowed/Divorced/Separatec	-0.0032**	-0.0008	0.0004	0.0026***	0.0008	0.0019**
	[0.0012]	[0.0010]	[0.0011]	[0.0009]	[0.0011]	[0.0009]
Log(Household size)	0.008***	0.004***	0.001*	-0.0018***	0.0017***	-0.0021***
	[0.0007]	[0.0006]	[0.0007]	[0.0006]	[0.0006]	[0.0006]

	(1)	(2)	(3)	(4)	(5)	(6)
	OLF_{t+1}	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0002	-0.0018**	0.0017**	0.0004	0.0019**	0.0001
	[0.0010]	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
-"-: High school	-0.0026***	0.0001	0.0001	0.0028***	0.0001	0.0025***
	[0.0010]	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0008]
-"-: Less than high school	-0.0015	0.0028***	-0.0026**	0.0033***	-0.0025**	0.003***
	[0.0012]	[0.0010]	[0.0011]	[0.0009]	[0.0011]	[0.0009]
#Observations	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*	*276,686*
Log-likelihood	*-29,504.3*	*-23,463.7*	*-21,843.4*	*-18,636.7*	*-21,794*	*-18,492.3*
χ^2	*5,306.4****	*3,901.6****	*14,392.5****	*10,247.1****	*14,456.5****	*10,458.2****

Notes: Comments in Table 4.2 apply.

Table 4.7
The role of gender

	Pooled sample		Males		Females	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
Panel A: Calculations						
Predicted probability	*0.0254*	*0.0189*	*0.0180*	*0.0195*	*0.0323*	*0.0184*
% Level wealth effect	*21.2%*	*11.6%*	*27.0%*	*8.2%*	*15.8.%*	*18.5%*
% Permanent wealth effect	*-11.8%*	*-4.8%*	*-17.7%*	*-7.2%*	*-6.8.%*	*-5.0%*
Panel B: Model Level Effects						
Liquid wealth	0.0054***	0.0022	0.0050***	0.0016	0.0051*	0.0034
	[0.0017]	[0.0013]	[0.0020]	[0.0017]	[0.0028]	[0.0022]
Log(Wage)	0.0161***	0.0111***	0.0102***	0.0119***	0.0214***	0.0100***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0003]	[0.0002]
Log(Spouse's wage)	0.0002	0.0004**	0.0007**	-0.0005	-0.0001	0.0010***
	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Home owner	0.0040*	0.0051***	0.0049*	-0.0006	0.0035	0.0092***
	[0.0020]	[0.0019]	[0.0026]	[0.0027]	[0.0031]	[0.0026]
Mortgage home	0.0018	-0.0009*	0.0022	0.0005	0.0011	-0.0022
	[0.0015]	[0.0014]	[0.0018]	[0.0019]	[0.0023]	[0.0020]
Female	-0.0053***	0.0072***	—	—	—	—
	[0.0006]	[0.0005]				
Ethnic group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	0.0023***	0.0059***	0.0015	0.0033***	0.0025*	0.0069***
	[0.0008]	[0.0007]	[0.0009]	[0.0011]	[0.0014]	[0.0009]
-"-: Asian	0.0009	-0.0009	-0.0009	-0.0031	0.0025	0.0004
	[0.0016]	[0.0014]	[0.0019]	[0.0021]	[0.0024]	[0.0020]
-"-: Other	0.0003	-0.0014	0.0011	-0.0033*	-0.0011	-0.0002
	[0.0013]	[0.0012]	[0.0015]	[0.0018]	[0.0020]	[0.0018]
Log(Age)	-0.0816***	-0.0653***	-0.0641***	-0.0727***	-0.1002***	-0.0573***
	[0.0056]	[0.0050]	[0.0074]	[0.0073]	[0.0084]	[0.0070]
Log(Labour market experience)	-0.0037***	-0.0020***	-0.0026***	-0.0021***	-0.0048***	-0.0020***
	[0.0002]	[0.0002]	[0.0003]	[0.0004]	[0.0005]	[0.0004]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0046*	-0.0042*	-0.0060*	-0.0084***	-0.0029	-0.0024
	[0.0027]	[0.0024]	[0.0035]	[0.0035]	[0.0041]	[0.0033]
-"-: Widowed/Divorced/Separated	-0.0018	-0.0061**	0.0046	-0.0017	-0.0066	-0.0069*
	[0.0034]	[0.0029]	[0.0048]	[0.0045]	[0.0051]	[0.0039]
Log(Household size)	-0.0033**	0.0009	-0.0012	-0.0009	-0.0066***	0.0033
	[0.0017]	[0.0015]	[0.0021]	[0.0021]	[0.0027]	[0.0022]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0414***	0.0324***	0.0248***	0.0348***	0.0550***	0.0305***
	[0.0034]	[0.0033]	[0.0042]	[0.0044]	[0.0054]	[0.0046]
-"-: High school	0.0709***	0.0442***	0.0423***	0.0355***	0.0960***	0.0515***
	[0.0040]	[0.0037]	[0.0048]	[0.0052]	[0.0063]	[0.0053]
-"-: Less than high school	0.1093***	0.0729***	0.0707***	0.0687***	0.1415***	0.0739***
	[0.0046]	[0.0043]	[0.0056]	[0.0060]	[0.0074]	[0.0062]
Panel C: Model Average Effects						
Liquid wealth	-0.0087***	-0.0025	-0.0084***	-0.0031	-0.0070*	-0.0031
	[0.0022]	[0.0017]	[0.0024]	[0.0021]	[0.0036]	[0.0028]
Log(Wage)	-0.0217***	-0.0159***	-0.0153***	-0.0174***	-0.0275***	-0.0145***
	[0.0022]	[0.0002]	[0.0003]	[0.0003]	[0.0004]	[0.0003]
Log(Wage spouse)	-0.0004	-0.0006***	-0.0008***	-0.0006*	-0.0003	-0.0011***
	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
Home owner	0.0019	-0.0080***	-0.0022	0.0002	0.0030	-0.0134***

	(1)	(2)	(3)	(4)	(5)	(6)
	[0.0022]	[0.0020]	[0.0028]	[0.0029]	[0.0034]	[0.0029]
	OLF_{t+1}	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
Mortgage home	-0.0032*	0.0013	-0.0043**	0.0006	-0.0014	0.0019
	[0.0017]	[0.0016]	[0.0021]	[0.0022]	[0.0027]	[0.0023]
Log(Age)	0.0667***	0.0636***	0.0569***	0.0726***	0.0795***	0.0530***
	[0.0058]	[0.0052]	[0.0076]	[0.0075]	[0.0087]	[0.0072]
Log(Labour market experience)	0.0047***	0.0037***	0.0033***	0.0036***	0.0060***	0.0039***
	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0005]	[0.0005]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0045	-0.0009	-0.0028	0.0097***	0.0076*	-0.0073***
	[0.0028]	[0.0025]	[0.0037]	[0.0036]	[0.0043]	[0.0035]
-"-: Widowed/Divorced/Separated	0.0021	0.0087***	-0.0065	-0.0030	0.0093*	0.0093***
	[0.0036]	[0.0031]	[0.0050]	[0.0047]	[0.0054]	[0.0041]
Log(Household size)	0.0043***	-0.0028*	0.0010	-0.0013	0.0071***	-0.0057***
	[0.0018]	[0.0016]	[0.0022]	[0.0022]	[0.0029]	[0.0024]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0400***	-0.0320***	-0.0246***	-0.0364***	-0.0520***	-0.0291***
	[0.0035]	[0.0032]	[0.0043]	[0.0045]	[0.0056]	[0.0046]
-"-: High school	-0.0708***	-0.0416***	-0.0449***	-0.0322***	-0.0936***	-0.0497***
	[0.0040]	[0.0037]	[0.0049]	[0.0052]	[0.0064]	[0.0054]
-"-: Less than high school	-0.1183***	-0.0697***	-0.0759***	-0.0659***	-0.1417***	-0.0708***
	[0.0048]	[0.0044]	[0.0058]	[0.0061]	[0.0076]	[0.0063]
Panel D: Calculated Permanent Effects						
Liquid wealth	-0.0030***	-0.0009	-0.0032***	-0.0014	-0.0022	-0.0009
	[0.0012]	[0.0263]	[0.0441]	[0.0014]	[0.0023]	[0.0011]
Log(Wage)	-0.0063***	-0.0052***	-0.0052***	-0.0065***	-0.0064***	-0.0043***
	[0.0002]	[0.0004]	[0.0002]	[0.0004]	[0.0005]	[0.0002]
Log(Wage spouse)	0.0001	-0.0003*	-0.0002	0.0002	0.0002	-0.0003
	[0.0009]	[0.0008]	[0.0002]	[0.0002]	[0.0001]	[0.0002]
Home owner	-0.0022***	-0.0034***	0.0032***	-0.0003	0.0005	-0.0043***
	[0.0016]	[0.0013]	[0.0014]	[0.0012]	[0.0012]	[0.0014]
Mortgage home	-0.0014	-0.0003	-0.0021**	0.0016	-0.0002	-0.0003
	[0.0014]	[0.0014]	[0.0011]	[0.0013]	[0.0014]	[0.0015]
Log(Age)	-0.0154***	-0.0024	-0.0076***	-0.0005	-0.0212***	-0.0045**
	[0.0011]	[0.0012]	[0.0023]	[0.0023]	[0.0025]	[0.0025]
Log(Labour market experience)	0.0014***	0.0023***	0.0013***	0.0023***	0.0013***	0.0028***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0006]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0008	-0.0054***	-0.0032***	0.0016	0.0054***	-0.0102***
	[0.0013]	[0.0018]	[0.0014]	[0.0015]	[0.0012]	[0.0010]
-"-: Widowed/Divorced/Separated	0.0004	0.0034***	-0.0020	0.0015	0.0033	0.0026**
	[0.0014]	[0.0012]	[0.0016]	[0.0011]	[0.0029]	[0.0015]
Log(Household size)	0.0015*	-0.0022***	0.0024***	-0.0020***	0.0012	-0.0025***
	[0.0016]	[0.0014]	[0.0018]	[0.0011]	[0.0014]	[0.0018]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0025**	0.0006	0.0001	-0.0022	0.0031**	0.0010
	[0.0016]	[0.0011]	[0.0012]	[0.0016]	[0.0013]	[0.0011]
-"-: High school	0.0001	0.0036***	-0.0034**	0.0032***	0.0024*	0.0025*
	[0.0012]	[0.0012]	[0.0017]	[0.0011]	[0.0013]	[0.0017]
-"-: Less than high school	-0.0032***	0.0039***	-0.0054***	0.0035**	-0.0004	0.0037**
	[0.0015]	[0.0014]	[0.0015]	[0.0015]	[0.0021]	[0.0018]
#Observations	*276,686*	*276,686*	*134,351*	*134,351*	*142,335*	*142,335*
Log-likelihood	*-21,841.9*	*-18,632.9*	*-7,946.8*	*-8,387.8*	*-13,697.4*	*-9,999.5*
χ^2	*14,390.6****	*10,248.9****	*5,257.7****	*6,023.8****	*9,187.7****	*4,335.5****

Notes: Comments in Table 4.2 apply.

Table 4.8

Specifications controlling for occupation and industry among the employed

Dependent Variable	(1) **OLF$_{t+1}$**	(2) **U$_{t+1}$**	(3) **OLF$_{t+1}$**	(4) **U$_{t+1}$**	(5) **OLF$_{t+1}$**	(6) **U$_{t+1}$**
Panel A: Calculations						
Predicted probability	*0.0203*	*0.0162*	*0.0202*	*0.0161*	*0.0249*	*0.0170*
% Level wealth effect	*60.1%*	*27.2%*	*53.5%*	*26.1%*	*59.0%*	*27.1%*
% Permanent wealth effect	*-56.7%*	*-38.3%*	*-50.1%*	*-40.4%*	*-50.2%*	*-38.2%*
Panel B: Model Level Effects						
Liquid wealth	0.0122***	0.0044***	0.0108***	0.0042***	0.0147***	0.0046***
	[0.0016]	[0.0013]	[0.0015]	[0.0013]	[0.0019]	[0.0014]
Home owner	0.0036*	0.0044**	0.0032***	0.0048***	0.0033***	0.0047***
	[0.0021]	[0.0021]	[0.0022]	[0.0020]	[0.0021]	[0.0021]
Mortgage home	0.0016	0.0017	0.0014	0.0015	0.0013	0.0015
	[0.0015]	[0.0015]	[0.0014]	[0.0015]	[0.0014]	[0.0014]
Female	-0.0120***	0.0016***	-0.0111***	0.0016***	-0.0189***	-0.0002
	[0.0005]	[0.0005]	[0.0005]	[0.0005]	[0.0007]	[0.0006]
Ethnic group: White	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Black	-0.0004	0.0048***	-0.0002	0.0049***	0.0008	0.0070***
	[0.0008]	[0.0008]	[0.0008]	[0.0007]	[0.0010]	[0.0008]
-"-: Asian	-0.0019	-0.0016	-0.0017	-0.0016	0.0011	-0.0008
	[0.0017]	[0.0017]	[0.0017]	[0.0017]	[0.0021]	[0.0018]
-"-: Other	0.0014	0.0003	0.0011	0.0002	0.0038**	0.0011
	[0.0013]	[0.0014]	[0.0013]	[0.0014]	[0.0016]	[0.0015]
Log(Age)	-0.0524***	-0.0328***	-0.0327***	-0.0224***	-0.0667***	-0.0309***
	[0.0060]	[0.0060]	[0.0056]	[0.0058]	[0.0072]	[0.0063]
Log(Labour market experience)	-0.0029***	-0.0021***	-0.0025***	-0.0019***	-0.0038***	-0.0024***
	[0.0002]	[0.0003]	[0.0002]	[0.0003]	[0.0003]	[0.0003]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	-0.0028	-0.0011	-0.0010	-0.0002	-0.0016	-0.0017
	[0.0027]	[0.0026]	[0.0025]	[0.0026]	[0.0031]	[0.0027]
-"-: Widowed/Divorced/Separated	0.0043	0.0005	0.0049	0.0013	0.0053	-0.0002
	[0.0036]	[0.0033]	[0.0033]	[0.0032]	[0.0042]	[0.0034]
Log(Household size)	-0.0121***	-0.0050***	-0.0107***	-0.0042***	-0.0121***	-0.0038**
	[0.0017]	[0.0016]	[0.0016]	[0.0015]	[0.0020]	[0.0016]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0355***	0.0112***	0.0259***	0.0049	0.0484***	0.0131***
	[0.0035]	[0.0042]	[0.0033]	[0.0040]	[0.0044]	[0.0044]
-"-: High school	0.0615***	0.0305***	0.0510***	0.0234***	0.0836***	0.0329***
	[0.0041]	[0.0048]	[0.0039]	[0.0047]	[0.0051]	[0.0051]
-"-: Less than high school	0.0984***	0.0515***	0.0819***	0.0399***	0.1400***	0.0556***
	[0.0048]	[0.0057]	[0.0046]	[0.0055]	[0.0061]	[0.0060]
Part-Time Worker	0.0642***	0.0353***	—	—	—	—
	[0.0011]	[0.0010]				
Union membership	—	—	0.0325***	0.0229***	—	—
			[0.0026]	[0.0023]		
Occupation: Skilled non-manual	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Skilled manual	—	—	—	—	-0.0041	-0.0108***
					[0.0036]	[0.0029]
-"-: Unskilled non-manual	—	—	—	—	-0.0023	-0.0080***
					[0.0027]	[0.0024]
-"-: Unskilled manual	—	—	—	—	-0.0001	-0.0107***
					[0.0029]	[0.0025]
Industry: Agric., Forestry, Fishing	—	—	—	—	*{Ref.}*	*{Ref.}*

	(1) OLF$_{t+1}$	(2) U$_{t+1}$	(3) OLF$_{t+1}$	(4) U$_{t+1}$	(5) OLF$_{t+1}$	(6) U$_{t+1}$
-"-: Mining	—	—	—	—	0.0153	-0.0163
					[0.0162]	[0.0118]
-"-: Utilities	—	—	—	—	0.0051	-0.0174
					[0.0170]	[0.0138]
-"-: Construction	—	—	—	—	0.0018	-0.0044
					[0.0088]	[0.0066]
-"-: Manufacturing	—	—	—	—	0.0057	-0.0040
					[0.0083]	[0.0063]
-"-: Wholesale Trade	—	—	—	—	-0.0013	-0.0067
					[0.0089]	[0.0069]
-"-: Retail Trade	—	—	—	—	0.0001	-0.0069
					[0.0082]	[0.0064]
-"-: Transportation & Warehousing	—	—	—	—	0.0008	-0.0089
					[0.0094]	[0.0071]
-"-: Information	—	—	—	—	0.0011	-0.0117
					[0.0095]	[0.0075]
-"-: Finance and Insurance	—	—	—	—	0.0041	-0.0114
					[0.0091]	[0.0072]
-"-: Real Estate and Rental and Leasing	—	—	—	—	0.0060	-0.0222***
					[0.0102]	[0.0083]
-"-: Professional, Scientific & Technical	—	—	—	—	0.0015	-0.0091
					[0.0090]	[0.0070]
-"-: Management of Companies/ Enterprises	—	—	—	—	0.0001	0.0611
					[0.0001]	[0.0507]
-"-: Administrative and Support, Waste Management and Remediation Services	—	—	—	—	-0.0028	-0.0116*
					[0.0085]	[0.0065]
-"-: Educational Services	—	—	—	—	0.0045	0.0001
					[0.0101]	[0.0088]
-"-: Health Care and Social Assistance	—	—	—	—	0.0085	-0.0087
					[0.0086]	[0.0069]
-"-: Arts, Entertainment, and Recreation	—	—	—	—	-0.0060	-0.0087
					[0.0099]	[0.0081]
-"-: Accommodation and Food Services	—	—	—	—	-0.0047	-0.0064
					[0.0083]	[0.0065]
-"-: Other Services (exc. Public Administration)	—	—	—	—	-0.0009	-0.0001
					[0.0090]	[0.0071]
-"-: Public Administration	—	—	—	—	0.0167	0.0215
					[0.0172]	[0.0132]
Panel C: Model Average Effects						
Liquid wealth	-0.0237***	-0.0106***	-0.0210***	-0.0107***	-0.0272***	-0.0111***
	[0.0023]	[0.0017]	[0.0022]	[0.0016]	[0.0028]	[0.0018]
Home owner	-0.0013	-0.0057**	-0.0012	-0.0052*	-0.0011	-0.0052**
	[0.0023]	[0.0022]	[0.0021]	[0.0022]	[0.0022]	[0.0021]
Mortgage home	-0.0031*	-0.0037*	-0.0030*	-0.0036	-0.0032*	0.0037*
	[0.0017]	[0.0018]	[0.0016]	[0.0018]	[0.0016]	[0.0018]
Log(Age)	0.0290***	0.0288***	0.0131**	0.0184***	0.0378***	0.0251***
	[0.0062]	[0.0062]	[0.0058]	[0.0060]	[0.0074]	[0.0065]
Log(Labour market experience)	0.0030***	0.0029***	0.0025***	0.0027***	0.0032***	0.0034***
	[0.0003]	[0.0004]	[0.0003]	[0.0004]	[0.0004]	[0.0004]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.0039	-0.0034	0.0021	-0.0049*	0.0055	-0.0039
	[0.0028]	[0.0027]	[0.0026]	[0.0027]	[0.0033]	[0.0029]
-"-: Widowed/Divorced/Separated	-0.0057	-0.0004	-0.0066*	-0.0013	-0.0075	0.0003
	[0.0038]	[0.0034]	[0.0035]	[0.0033]	[0.0044]	[0.0036]
Log(Household size)	0.0159***	0.0054***	0.0146***	0.0040**	0.0209***	0.0040***
	[0.0019]	[0.0017]	[0.0017]	[0.0016]	[0.0022]	[0.0018]

Table 4.8 continued in next page

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	(1) OLF$_{t+1}$	(2) U$_{t+1}$	(3) OLF$_{t+1}$	(4) U$_{t+1}$	(5) OLF$_{t+1}$	(6) U$_{t+1}$
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	-0.0337***	-0.0099**	-0.0243***	-0.0031	-0.0487***	-0.0125***
	[0.0035]	[0.0043]	[0.0034]	[0.0041]	[0.0044]	[0.0045]
-"-: High school	-0.0624***	-0.0271***	-0.0515***	-0.0193***	-0.0874***	-0.0303***
	[0.0041]	[0.0049]	[0.0039]	[0.0047]	[0.0052]	[0.0052]
-"-: Less than high school	-0.0994***	-0.0444***	-0.0828***	-0.0320***	-0.1398***	-0.0493***
	[0.0050]	[0.0058]	[0.0047]	[0.0056]	[0.0063]	[0.0061]
Part-time	-0.0743***	-0.0493***	—	—	—	—
	[0.0017]	[0.0017]				
Union membership	—	—	-0.0494***	-0.0318***	—	—
			[0.0036]	[0.0028]		
Occupation: Skilled non-manual	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Skilled manual	—	—	—	—	0.0031	0.0112***
					[0.0039]	[0.0031]
-"-: Unskilled non-manual	—	—	—	—	0.0075**	0.0088***
					[0.0030]	[0.0026]
-"-: Unskilled manual	—	—	—	—	0.0066**	0.0144***
					[0.0031]	[0.0027]
Industry: Agric., Forestry, Fishing	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Mining	—	—	—	—	-0.0156	0.0134
					[0.0176]	[0.0124]
-"-: Utilities	—	—	—	—	-0.0106	0.0072
					[0.0181]	[0.0143]
-"-: Construction	—	—	—	—	-0.0019	0.0080
					[0.0095]	[0.0071]
-"-: Manufacturing	—	—	—	—	-0.0107	0.0013
					[0.0089]	[0.0068]
-"-: Wholesale Trade	—	—	—	—	-0.0037	0.0010
					[0.0097]	[0.0075]
-"-: Retail Trade	—	—	—	—	0.0014	0.0032
					[0.0089]	[0.0069]
-"-: Transportation & Warehousing	—	—	—	—	-0.0079	0.0059
					[0.0101]	[0.0076]
-"-: Information	—	—	—	—	-0.0025	0.0091
					[0.0102]	[0.0081]
-"-: Finance and Insurance	—	—	—	—	-0.0113	0.0059
					[0.0098]	[0.0078]
-"-: Real Estate and Rental and Leasing	—	—	—	—	-0.0041	0.0200*
					[0.0111]	[0.0089]
-"-: Professional, Scientific & Technical	—	—	—	—	-0.0031	0.0090
					[0.0096]	[0.0076]
-"-: Management of Companies/ Enterprises	—	—	—	—	0.0001	-0.0646
					[0.0001]	[0.0623]
-"-: Administrative and Support, Waste Management and Remediation Services	—	—	—	—	0.0049	0.0123*
					[0.0092]	[0.0071]
-"-: Educational Services	—	—	—	—	0.0003	-0.0066
					[0.0109]	[0.0096]
-"-: Health Care and Social Assistance	—	—	—	—	-0.0119	0.0007
					[0.0092]	[0.0074]
-"-: Arts, Entertainment, and Recreation	—	—	—	—	0.0068	0.0052
					[0.0107]	[0.0089]
-"-: Accommodation and Food Services	—	—	—	—	0.0062	0.0036
					[0.0090]	[0.0070]

Table 4.8 continued in next page

Table 4.8 continued from last page

	(1)	(2)	(3)	(4)	(5)	(6)
	OLF$_{t+1}$	**U$_{t+1}$**	**OLF$_{t+1}$**	**U$_{t+1}$**	**OLF$_{t+1}$**	**U$_{t+1}$**
-"-: Other Services (exc. Public Administration)	—	—	—	—	0.0060	-0.0040
					[0.0097]	[0.0078]
-"-: Public Administration	—	—	—	—	-0.0143	-0.0196
					[0.0191]	[0.0154]
Panel D: Calculated Permanent Effects						
Liquid wealth	-0.0115***	-0.0062***	-0.0103***	-0.0065***	-0.0125***	-0.0065***
	[0.0013]	[0.0009]	[0.0013]	[0.0009]	[0.0016]	[0.0010]
Home owner	0.0023**	-0.0014	0.0021	-0.0013	0.0020	-0.0011
	[0.0009]	[0.0009]				
Mortgage home	-0.0015	-0.0023**	-0.0014	-0.0021**	-0.0012	-0.0020**
	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0009]	[0.0009]
Log(Age)	-0.0233***	-0.0041***	-0.0197***	-0.0039***	-0.0289***	-0.0058***
	[0.0015]	[0.0014]	[0.0014]	[0.0014]	[0.0018]	[0.0015]
Log(Labour market experience)	0.0001	0.0008***	0.0001	0.0009***	-0.0006***	0.001***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Marital Status: Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Married	0.001	-0.0047***	0.0011	-0.0052***	0.0039***	-0.0057***
	[0.0008]	[0.0008]	[0.0008]	[0.0008]	[0.0010]	[0.0008]
-"-: Widowed/Divorced/Separated	-0.0014	0.0001	-0.0017	0.0001	-0.0022	0.0001
	[0.0012]	[0.0010]	[0.0011]	[0.0010]	[0.0014]	[0.0010]
Log(Household size)	0.0038***	0.0004	0.004***	-0.0002	0.0089***	0.0002
	[0.0007]	[0.0006]	[0.0006]	[0.0006]	[0.0008]	[0.0006]
Education: University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
-"-: Less than university	0.0018**	0.0012	0.0015*	0.0018**	-0.0003	0.0006
	[0.0009]	[0.0008]	[0.0008]	[0.0008]	[0.0011]	[0.0009]
-"-: High school	-0.0009	0.0034***	-0.0005	0.0041***	-0.0038***	0.0026***
	[0.0009]	[0.0009]	[0.0009]	[0.0008]	[0.0012]	[0.0010]
-"-: Less than high school	-0.001	0.0071***	-0.0009	0.0079***	0.0002	0.0063***
	[0.0011]	[0.0010]	[0.0011]	[0.0010]	[0.0015]	[0.0012]
Part-time	-0.0101***	-0.0141***	—	—	—	—
	[0.0010]	[0.0010]				
Union membership	—	—	-0.0169***	-0.0088***	—	—
			[0.0019]	[0.0013]		
Occupation: Skilled non-manual	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Skilled manual	—	—	—	—	-0.001	0.0004
					[0.0015]	[0.0012]
-"-: Unskilled non-manual	—	—	—	—	0.0051***	0.0008
					[0.0012]	[0.0011]
-"-: Unskilled manual	—	—	—	—	0.0065***	0.0037***
					[0.0012]	[0.0010]
Industry: Agric., Forestry, Fishing	—	—	—	—	*{Ref.}*	*{Ref.}*
-"-: Mining	—	—	—	—	-0.0003	-0.0029
					[0.0061]	[0.0046]
-"-: Utilities	—	—	—	—	-0.0055	-0.0102**
					[0.0061]	[0.0049]
-"-: Construction	—	—	—	—	-0.0001	0.0036
					[0.0034]	[0.0025]
-"-: Manufacturing	—	—	—	—	-0.005	-0.0027
					[0.0032]	[0.0024]
-"-: Wholesale Trade	—	—	—	—	-0.0051	-0.0057**
					[0.0036]	[0.0028]

Table 4.8 continued in next page

Table 4.8 continued from last page						
-"-: Retail Trade	—	—	—	—	0.0016	-0.0037
					[0.0032]	[0.0025]
	(1)	(2)	(3)	(4)	(5)	(6)
	OLF_{t+1}	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**	**OLF_{t+1}**	**U_{t+1}**
-"-: Transportation & Warehousing	—	—	—	—	-0.0071*	-0.003
					[0.0037]	[0.0027]
-"-: Information	—	—	—	—	-0.0014	-0.0027
					[0.0037]	[0.0029]
-"-: Finance and Insurance	—	—	—	—	-0.0072**	-0.0055**
					[0.0035]	[0.0027]
-"-: Real Estate and Rental and Leasing	—	—	—	—	0.0019	-0.0022
					[0.0041]	[0.0033]
-"-: Professional, Scientific & Technical	—	—	—	—	-0.0016	-0.0001
					[0.0035]	[0.0027]
-"-: Management of Companies/ Enterprises	—	—	—	—	0.0001	-0.0035
					[0.0000]	[0.0269]
-"-: Administrative and Support, Waste Management and Remediation Services	—	—	—	—	0.0021	0.0007
					[0.0034]	[0.0026]
-"-: Educational Services	—	—	—	—	0.0049	-0.0066*
					[0.0039]	[0.0035]
-"-: Health Care and Social Assistance	—	—	—	—	-0.0034	-0.008***
					[0.0032]	[0.0025]
-"-: Arts, Entertainment, and Recreation	—	—	—	—	0.0007	-0.0035
					[0.0040]	[0.0033]
-"-: Accommodation and Food Services	—	—	—	—	0.0015	-0.0028
					[0.0032]	[0.0024]
-"-: Other Services (exc. Public Administration)	—	—	—	—	0.0051	-0.0042
					[0.0034]	[0.0027]
-"-: Public Administration	—	—	—	—	0.0024	0.002
					[0.0078]	[0.0062]
#Observations	*260,519*	*223,706*	*260,519*	*223,706*	*211,533*	*212,046*
Log-likelihood	*-23,745.9*	*-17,261.5*	*-21,311.8*	*-16,522.0*	*-21,864.1*	*-16,848.6*
χ^2	*3,430.6****	*1,899.9****	*7,335.9****	*3,071.9****	*4,611.2****	*2,153.7****

Notes: Comments in Table 4.2 apply.

CHAPTER 5:

CONCLUSIONS

In this Ph.D. thesis, I study the behaviour of a frictional labour market model encompassing the presence of three labour market states: employment, unemployment and out-of-labour force. More precisely, I investigate whether out-of-labour force and unemployment are two different labour market states. A negative answer might support the assumption that a model with only two labour market states (i.e., employment and unemployment) is still an appropriate approach to analyse the dynamics of labour market, as it is commonly assumed in the standard search and matching model. However, a positive answer would be requiring a new theoretical framework (including both out-of-labour force and unemployment) to study the dynamics of the labour market. This exercise is mainly performed by two different steps.

Firstly, I assess the overall validity of a frictional model with three labour market states, investigating the business cycle behaviour of a textbook search model including the out-of-labour force participation margin, in terms of direct transition of inactive workers into employment, further augmented for heterogeneity in home productivity and endogeneous separation.

Secondly, I investigate the empirical behaviour of individuals classified into the unemployment and out-of-labour force state along two margins: the “entry margin” and the “exit margin”. The entry margin is defined in terms of potential differences in the entry wage for newly hired workers coming from the two non-employment states. The exit margin is defined in terms of non-employment labour market outcomes, i.e., I test the choice of agents between flowing either into unemployment or into out-of-labour force, using wealth as our main explanatory variable.

In Chapter 2, I analyse the business cycle properties of a modified Mortensen-Pissarides model, i.e., a model including three labour market states. I investigate whether this model is able to replicate the volatility of the labour market variables such as unemployment, job-finding rate, vacancies and the vacancy-searchers ratio. In Chapter 3, I empirically examine the response of real wages to aggregate cyclical indicators, more specifically, unemployment rate and aggregate labour productivity, for the U.S. economy, using a longitudinal dataset, the Survey of Income and Program Participation (SIPP). In Chapter 4, using the same longitudinal panel dataset, I empirically investigate the relationship between wealth and labour market transitions for the U.S. workers.

In terms of results, in Chapter 2 of this Ph.D. thesis, I show that a three labour market state model is able to generate large volatilities for key labour market variables and replicate the most relevant empirical worker flows.

Previous papers investigating the business-cycle moments of a frictional labour market model have been unsuccessful in rationalizing the large volatilities of key labour market variables such as vacancies, job-finding rate and unemployment. Different solutions have been proposed such as wage rigidities (Shimer, 2005), institutional factors (Hall, 2005), small rents (Hagedorn and Manovskii, 2008), asymmetric information on worker productivity (Kennan, 2010). However, all the contributions have focused on a framework with only two labour market states (i.e., employment and unemployment). Few exceptions are Garibaldi and Wasmer (2005), Haefke and Reiter (2006), Veracierto (2008), Ebell (2011) and Campolmi and Gnocchi (2016) that examine the business cycle performance of models including endogenous labour force participation. However, the models of these authors do not allow for inactive workers to direct transition into employment, hence inactive workers cannot be part of the large group of job searchers and cannot fill a vacancy. Such chance is totally reserved to the unemployed workers.

The benchmark model I develop in Chapter 2 is able to explain around 50 percent of the empirical unemployment volatility, a result that constitutes a substantial improvement compared to the usual values (close to one-tenth the empirical analog) obtained by standard search model. I am also able to generate substantial fluctuations in the job-finding rate, vacancies and labour market tightness for values that represent around 50-60 percent of their empirical counterparts. Moreover, the model performs well in replicating the empirical value for the Beveridge Curve. Indeed, I find a value from our simulation close to 70 percent of the empirical counterpart.

Furthermore, I am able to replicate the empirical values for the most relevant worker flows. Indeed, the model is successful in reproducing the out-of-labour force to employment flow, a statistical measure that previous papers have failed to match. The model is also able to explain 60 percent of the employment to unemployment worker flow, 70 percent of the unemployment to employment worker flow and 65 percent of the employment to out-of-labour force worker flow, even if the model performance is less accurate for the two worker flows between unemployment and out of labour force. In this case, the model overpredicts the flows by a factor close to 50 percent.

The reasonable performance of the model in replicating volatile second moments relies on two channels. The first channel, and the more relevant in terms of impact on the creation of vacancies, is the existence of frictions in the “full discovery” of the new value of the idiosyncratic variable. Indeed, the model is specified such that the value for home productivity is “common knowledge” for all the agents in the market only at the end of the period and not at its occurrence at the beginning of the same, as it is the case for the aggregate productivity shock. This implies that when there is a positive aggregate productivity shock, it is a good moment for firms to open new vacancies and for workers to accept jobs offered to them. Hence, firms and workers form new matches. However, the survival of these new matches at the end of each period is conditional to the new draws for the values of home productivity, given that a high draw of home productivity would bring the worker to quit the job. Since firms are forward-looking agents, they know a fraction of newly formed matches will be destroyed for newly matched employees drawing high values of home productivity, and they will increase the number of vacancies posted on the market. This produces large fluctuations in vacancies, and it brings to large fluctuations for the other labour market variables as well. The second channel is the introduction of a third margin, i.e., the inactive workers. Indeed, it allows to redefine the mass and the flows of workers between the three labour market states.

A useful extension of the present model would involve a closer examination of labour market policies over the business-cycle. Works by Alvarez and Veracierto (2000), and Jung and Kuester (2015), have focused on different instruments that might be taken into account. For example, Garibaldi and Wasmer (2005), Kim (2008), and Mitman and Rabinovich (2011) discuss in their works the effects of the level of and eligibility for unemployment benefit. Despite the presence of a large literature on the insurance role played by this labour market policy, different findings on the qualitative and quantitative effects of this measure have been found. While, on one side, it seems evident the negative link between unemployment benefits and worker flows into the employment state, given that more generous unemployment benefits increase the workers' outside option and consequently wages, making the firms less willing to post vacancies, on the other side, it has been showed the existence of a positive link between unemployment benefits and labour market participation since an increase in unemployment benefits magnifies the labour supply answer in terms of a large increase in the participation to the labour market among the non-eligible, i.e., largely inactive workers, with a further positive effect in terms of a lower unemployment to out-of-labour force transition rate.

Incorporating this feature into the present work could produce interesting results in terms of a richer dynamics as regards the interaction between labour market variables. Furthermore, the presence of insurance measures for “non-employed” individuals might be seen as a remedy to the slack performance of the model as concerns the replication of gross worker flows between unemployment and out-of-labour force.

A further interesting extension of this exercise would be to check the extent to which the conclusions reached in this work are affected when one considers alternative models of formation of matches. Indeed, Fujita and Ramey (2012) have examined the ability of a Mortensen-Pissarides model to replicate labour market facts when on-the-job search is allowed. Their findings suggest that the model is able to rationalize Beveridge Curve, together with producing a volatile job finding rate and job separation rate. Including this additional margin to my model could improve the dynamic interrelationship between vacancy and labour productivity when job to job search is allowed.

Lastly, it has to be noted how this study has been developed by considering an idiosyncratic shock that strictly affects workers’ side. However, in reality it is possible to observe also match-specific idiosyncratic shocks and in this sense a focus on the firms’ side should provide further insights.

In Chapter 3 of this Ph.D. thesis, I show that real wages for newly hired workers coming from out-of-labour force behave differently, over the cycle, from the real wages for newly hired workers coming from unemployment. I investigate the cyclical behaviour of real wages by estimating a wage equation in terms of the response to some aggregate cyclical indicators, specifically the unemployment rate and the aggregate labour productivity. I perform this exercise for different groups of workers, namely, the job stayers, the newly hired workers from unemployment, the newly hired workers from out-of-labour force and the job changers. Therefore, I move one step forward compared to the standard empirical specifications of previous models. Indeed, prior studies, apart from the established interest in the standard categories of workers such as ongoing workers and job changers, have focused on either individuals classified as unemployed or individuals gathered into a large "black-box", i.e., the non-employment state, to study the cyclical behaviour of real wages. I propose a new approach in investigating this relationship by disentangling the group of non-employment in the unemployed and the out-of-labour force workers and I estimate the cyclicality of real wages not only for individuals belonging to the unemployment state, but also for individuals classified as inactive workers.

Previous works investigating the cyclical behavior of real wages have found a large procyclicality for the wage of newly hired workers, while a substantial lower cyclicality has been observed for the overall wages, a result suggesting real wages of job stayers are less responsive to the cycle. More in details, Haefke, Sonntag and Van Rens (2013), using data from Current Population Survey for the U.S. economy, show how the real wages of new hires is more sensitive than the real wages of ongoing workers to labour productivity shocks. Their findings suggest a value close to one as regards the elasticity of real wages for new hires, compared to values close to 0.2-0.3 for the elasticity of real wages for job stayers. Kudlyack (2014), who uses data from the National Longitudinal Survey of Youth for the U.S. economy, finds similar values to those in Haefke, Sonntag and Van Rens (2013).

Using data from the "Quadros de Pessoal", an employers/employees longitudinal dataset for the Portuguese economy, Carneiro, Guimares and Portugal (2012) and Martins, Solon and

Thomas (2012) find that the real wages of newly hired workers, using the unemployment rate as the aggregate cyclical indicator, is strongly procyclical. Carneiro, Guimares and Portugal (2012) find a value for the semi-elasticity of real wage for marginal workers of 2.20 percentage points, while Martins, Solon and Thomas (2012) find a value of 1.60 percentage points, assuming a fall of one percentage point in the unemployment rate. Both values are larger than the semi-elasticity of wage for job stayers. When the aggregate labour productivity is taken into account as the reference cyclical indicator, Carneiro, Gumares and Portugal (2012) find a value for the elasticity of real wage close to 1.10 percentage points, while Martins, Solon and Thomas (2012) find a value close to 0.50 percentage points (and they are still larger than the analog value for the job stayers). However, Gertler, Huckfeldt and Trigari (2016) investigating the relationship between real wages and unemployment rate, using data from the Survey of Income and Program Participation (SIPP) over the period 1990-2012, for the U.S. economy, find that the strong procyclicality of real wages of newly hired workers coming from unemployment disappears when job to job movements are taken into account. Indeed, they find a value for the semi-elasticity of real wages equal to 0.155 percentage points, very close to 0.160 reported for job stayers, while the semi-elasticity of wages for job changers is equal to 1.90 percentage points.

However, the controversy in the literature between these two different approaches has been developed along a sharply stylized definition of the labour market. Works dealing with the search and matching model have dismissed any complication in the way they have traced out the economic structure of their models, embracing the basic assumption popularizing the relevance of only two labour market states: employment and unemployment.

Using data for the U.S. economy, from the Survey of Income Participation Program, over the 1996-2013 period, I document the large presence of direct flows of workers from the out-of-labour force state to the employment state and I estimate a model where it is allowed for entry wages for marginal workers coming from both unemployment and out-of-labour force. I identify four different groups of workers: job stayers, newly hired workers from unemployment, newly hired workers from out-of-labour force and job changers, with this last group being defined as, respectively, (i) individuals making a job to job transition with a monthly break between consecutive spells of employment, and (ii) individuals making a job to job transition with weekly's (shorter than one month) break between consecutive periods in the employment state.

Estimating the model according the two different approaches used in the literature, i.e., the one proposed by Carneiro, Guimares and Portugal (2012), allowing for staggered wages (they assume wages are set one year in advance), which it is labeled as CGP model, and the other one used by Gertler, Huckfeldt and Trigari (2016) that use higher-frequency data, which is labeled as GHT, I find, for the case with non-employed workers grouped together in one large "non-employment" state, a value for the semi-elasticity of real wage for job stayers and marginal workers close to 0.20 and 0.227 percentage points, when I use the GHT specification, and values of 1.452 and 1.704 percentage points, with the CGP specification, that are more procyclical compared to the values for the job stayers. Introducing the distinction between marginal workers from unemployment and marginal workers coming from out-of-labour force, I find a percentage value for the semi-elasticity of wages for marginal workers coming from unemployment and out-of-labour force, with the GHT specification, of 0.194 and 0.328 percentage points, compared to 0.204 for job stayers, and a percentage value of 1.575 and 2.201, compared to 1.454 for job stayers, when the CGP model is used. This implies that there exists a substantial wedge between the two measures of the semi-elasticity of real wages for the new hires belonging to the two different groups, with the real wages for new hires coming from out-of-labour force more procyclical than the real wages for new hires coming from unemployment.

When job changers are introduced in the model to control for the presence of individuals making job to job movements able to explain the large procyclicality of real wages of newly hired in the context of a “cyclical job-upgrading” environment, I find estimates of 0.317 percentage points for new hires from out-of-labour force and 0.194 percentage points for new hires from unemployment, when the GHT approach is used, and estimates of 2.222 and 1.610 percentage points for the semi-elasticity of real wage of new hires from, respectively, out-of-labour force and unemployment, when it is used the CGP model. Furthermore, it can be also observed that there is evidence of a larger procyclicality in the real wages of job changers, with values of 0.373 and 2.342 percentage points. To test the robustness of this empirical analysis, I repeat this exercise using the aggregate labour productivity as the cyclical indicator and I find that the elasticity of real wages of newly hired workers from unemployment is equal to 0.945 percentage points and for the newly hired workers coming from out-of-labour force is equal to 1.006 percentage points, for the GHT specification, while it is equal to 0.991 and 1.055 percentage points, respectively, for new hired from unemployment and out-of-labour force, with the CGP model.

The results of the present study strengthen the conclusions from previous papers regarding the pro-cyclicality of the real wages of newly hired workers. However, this analysis is based on the hiring wage as the relevant variable to be investigated. Nevertheless, some recent works like Rudanko (2009) have pointed out that the labour market is largely made up of long-term employment relationships, where decisions about the creation of new matches depend not only on the current hiring wage, but also on the expectations of agents as regards the duration of the match, since this factor can affect wages in the case of long-term labour contracts. Thus, the relevance of the initial hiring wage as the relevant variable to be considered for this investigation would need to be further investigated, as clearly stated by Martins, Solon and Jonathan (2012), analysing the duration of the employment relationship, the evolution of wages and productivity in these relationships and the dependence of the hiring wage from macroeconomic conditions (present, expected and past).

Moreover, some literature has emphasised the presence of asymmetries in the cyclicality of real wage. Martins (2007) shows that real wages are substantially more procyclical during recessions than during expansion. Thus further research on this aspect is expected.

Further possible extensions of this chapter could be made. For instance, one could introduce more heterogeneity in the model across different groups of workers. This heterogeneity could provide different matching rates across the different education groups, genders, occupations, firm size, etc. For instance, in some papers like Beaudry and DiNardo (1991) it has been argued that low educated and low income workers may experiment initial lower and rigid wages. Another possible extension could be to estimate the elasticity of real wages for new hires across different labour market experience/time of graduation groups. Kahn (2010) suggests that it is more likely that young job seekers that are recently graduated, but with little labour market experience, are the more affected by the time of college graduation. Who experiments poor labour market experience in terms of wages due to the poor economic conditions tends to have persistent negative wage effects. These results could suggest that newly hired workers graduated in bad economies could be more likely to develop an earning path with rigid wages.

Moreover, someone might investigate possible differences in the response of wages for marginal workers to aggregate productivity shocks in the aftermath of the Great Recession and before it.

Finally, a further extension of this research could focus on investigating the elasticity of real wages for newly hired workers using data from other labour markets like UK or Europe.

In Chapter 4 of this Ph.D. thesis, I show that wealth exerts a significant impact on the probability of transitioning in the non-employment states. More precisely, in this study I investigate how wealth can affect the "exit margin" for an individual in the labour market, i.e., the probability for individuals to transitioning into unemployment and out-of-labour force.

Researchers have shown that search and matching models including idiosyncratic home or market productivity shocks are able to replicate labour market transitions, but these models are usually developed in a framework with only two labour market states and with risk neutral agents. However, if one considers the transition into the non-employment states as the start of a new search activity, a not fully addressed question is: what can finance this search? In this sense a crucial role emerges for wealth. While a few papers (Bloemen and Stancanelli, 2001, and Algan, Chevron, Hairault and Langot, 2003) have examined whether wealth can finance active search, i.e., searching while individuals are in the unemployment state, no answer has been given to the question whether wealth can finance passive searching, i.e., searching while individuals are in the out-of-labour force state. In this work, I test the presence of heterogeneity in the exit margin, i.e., the existence of differences between the probability of transitioning into unemployment and the probability of transitioning into out-of-labour force. I develop this analysis by using the transitory-permanent decomposition wealth effect.

Using data from the Survey of Income Participation Program for the U.S. economy, over the period 1996-2013, I estimate the impact of wealth on the transition probabilities. I find that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and the probability of transitioning to unemployment, but values for the former transition probability are nearly twice as large as those for the latter. On the other side, I find that a permanent increase in wealth has a negative impact on both transition probabilities, with the coefficient for the transition probability to out-of-labour force much larger than that for the transition probability to unemployment. More precisely, I find that a transitory increase in individual wealth by $ 100,000 dollars increases by 50 percent the probability of transitioning to out-of-labour force and by 30 percent the probability of transitioning to unemployment. On the contrary, a permanent increase in individual wealth by $ 100,000 dollars decreases by 60 percent the probability of transitioning to out-of-labour force and by 40 percent the probability of transitioning to unemployment. Using as main regressor a broader definition of wealth (including all other forms of wealth reported in the dataset such as real estate property assets and life insurance policies) the estimates confirm that a transitory increase in wealth exerts a positive impact on the probability of transitioning to out-of-labour force and unemployment, while the sign is reversed for the permanent effect. However, coefficients are in this case roughly 50 percent lower than in the benchmark case.

Testing the robustness of our results by including in the model specification indicators of more illiquid forms of wealth such as home ownership, mortgaged home or other variables related to housing wealth, I find no substantial changes in the effect of wealth on the transition probabilities.

Controlling by gender, one can observe that a transitory increase in wealth makes males more likely to transitioning into out-of-labour force rather than in unemployment, while the effect is reversed for females, where an increase in wealth makes this group of individuals more likely to transitioning into unemployment. When it is considered the permanent effect of an increase in wealth, I find that males are less likely to transitioning into out-of-labour force than to unemployment and the same qualitative indication holds for females, even if the difference between the two coefficients is very small.

However, when I control for salary income, I find that estimates for the variable wealth confirm the standard qualitative results with the positive impact of a transitory increase in wealth on the probability of becoming inactive and unemployed, and a negative impact on the transition probabilities for the case of the permanent increase in wealth, but one can see that quantitatively the effect of wealth is now quite different from previous results. Indeed, I find that a transitory increase in wealth increases the probability to transitioning into out-of-labour force only by 20 percent, and the probability to transitioning into unemployment by roughly 12 percent. The values are negative and much lower for the permanent effect, 12 percent and 4 percent.

Similar results are reported when I control for both gender and salary income. Looking at the coefficients, I find that a temporary increase in wealth for males rises the probability of transitioning into out-of-labour force by 27 percent and that to transitioning into unemployment by 8 percent, while for females the values are 16 percent and 18 percent, respectively. Examining the effect of a permanent increase in wealth, I find in this case a fall in the probability of transitioning into the inactivity state by 18 percent compared to the value of 7 percent for unemployment for males, while the values are 7 percent and 5 percent for females.

The estimation of the causal relationship between wealth and labour market transition probabilities gives an empirical support to the theory identifying in wealth a key variable in determining labour market outcomes. However, it does not provide an answer on the identification of the forces at work, i.e., the channels by which wealth affects the individuals' decision in terms of search behaviour. Further investigations in this direction might be useful for a clear understanding of the dynamics of the exit margin. In this sense, developing a search and matching model with incomplete financial markets and calibrated with structural parameters, obtained from the estimates of the model discussed in this study, would help in highlighting these channels.

Moreover, while the main question addressed by this work is the effect of wealth in terms of the unconditional probability of individuals to transitioning into the non-employment states, other dimensions of the searching decision could play a role. For example, some papers like Algan, Chevron, Hairault and Langot (2009), using French data, take into account only the sub-sample of individuals who "voluntarily" quit the job. Thus, the estimated probabilities of transitioning into the non-employment states might be driven by two different searching decisions, i.e., voluntary and involuntary job separation. Given the limits of the SIPP data, it is not an easy task to disentangle the two groups of agents, but it is, nevertheless, an interesting future area of research.

Furthermore, the empirical analysis developed in this work does focus on the effect of wealth in terms of financing the search activity, but a thoroughly associated investigation on the duration of this search activity would be also required. Indeed, the effect of an increase in wealth should be explored together with the expected rate of survival in the new searching state. Individual experiencing a large wealth shock are generally more likely to finance a longer period of search regardless of what her demographic characteristics or other similar factors are. However, it is unclear whether the duration of unemployment and inactivity is expected to be monotonically decreasing in wealth or other effects prevail. Understanding these questions might also be useful in defining optimal insurance measures for non-employed individuals.

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