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Abstract

In the last recession, the increase in long-term unemployment has been higher for younger workers than for older age groups. I propose a novel mechanism, search capital, to explain long-term unemployment patterns across different ages along the business cycle: ceteris paribus workers who have been successful in finding jobs in the recent past become more efficient at finding jobs in the present. Search ability increases with successful search experience and depreciates with tenure if workers do not search often enough. In labour markets where short-term jobs are a significant share of employment, this mechanism can explain cyclical bursts of long-term unemployment. Using Spanish administrative data, I provide empirical evidence that search capital, as proxied by the number of temporary jobs a worker has had, is negatively correlated with unemployment duration. The addition of search capital to a standard search model manages to replicate these empirical findings while also generating increases of long-term unemployment by age and along the business cycle that are consistent with the data. Although workers with stable jobs have higher welfare than workers with many employment spells when the economy is booming, they suffer higher losses during recessions because of their lower search capital.

Keywords

search, unemployment, long-term unemployment, temporary contracts

JEL classification: J24, J63, J64

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For a more updated version please check http://bit.ly/search-capital

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Max Weber Fellow, 2019-2020

1 Introduction

Not all unemployed workers find jobs at the same speed. Those taking longer to find jobs are particularly hurt by unemployment: job seekers' welfare is negatively affected during long spells of unemployment (Krueger and Mueller (2010)) and they suffer persistent wage losses upon re-entering the labour market (Couch and Placzek (2010)). While long-term unemployment has been steadily declining since the 1980's in most developed countries, there have been noticeable increases after the Great Recession – both in the US and Europe. This has renewed interest in understanding the channels behind the increases in long-term unemployment – see Mukoyama and Şahin (2009) and Hornstein (2012) for example. Several authors (Mukoyama et al. (2018) and Faberman and Kudlyak (2019) among others) have noted that there seems to be unexplained heterogeneity in job finding rates among the unemployed – that is, some workers are fundamentally better at finding jobs than others.

These differences can be explained, this paper proposes, by workers having intrinsically different search skills. Moreover, these search skills may evolve over time: more exposure to the labour market makes workers more proficient at finding jobs, while less experienced workers and those who have not looked for a job in the recent past are less successful at finding other jobs. This dynamic accumulation and deterioration suggest that search skills are a particular kind of human capital: one that is related to job search, therefore I refer to it as search capital.[1]

The appeal of this treatment of search skills is threefold: first, it is one of the principles behind active labour market policies or policies targeted at improving the search skills of workers. These policies have been very relevant in many countries and the focus of a long micro-economic literature (see Bentolila and Jansen (2016) for a recent review) but it has received very little attention from labour macro-economists. Second, it is a departure from the more conventional view of job search as something workers have to put effort into, a notion that has led to counter-intuitive results that are not often backed by the data.[2] Models with search effort often feature workers who are not actively searching and thus are not actually unemployed, but out of the labour force. Models with search effort are thus more appropriate to explain labour market participation than unemployment duration.

Lastly, search capital fundamentally affects workers with little search experience and thus can help explain some recent developments in youth unemployment in Europe. In particular, while younger workers have lower long-term unemployment rates than the general population (as figure 1 shows) they also saw higher increases during the 2008

[1]Other authors have use the same term for different concepts. See for example Carrillo-Tudela and Smith (2017) for a different use of search capital.

[2] One main implication of these models is that search effort should decline in recessions, as shown in Mukoyama et al. (2018)

Figure 1: Share of unemployed workers who have been searching for a year or more

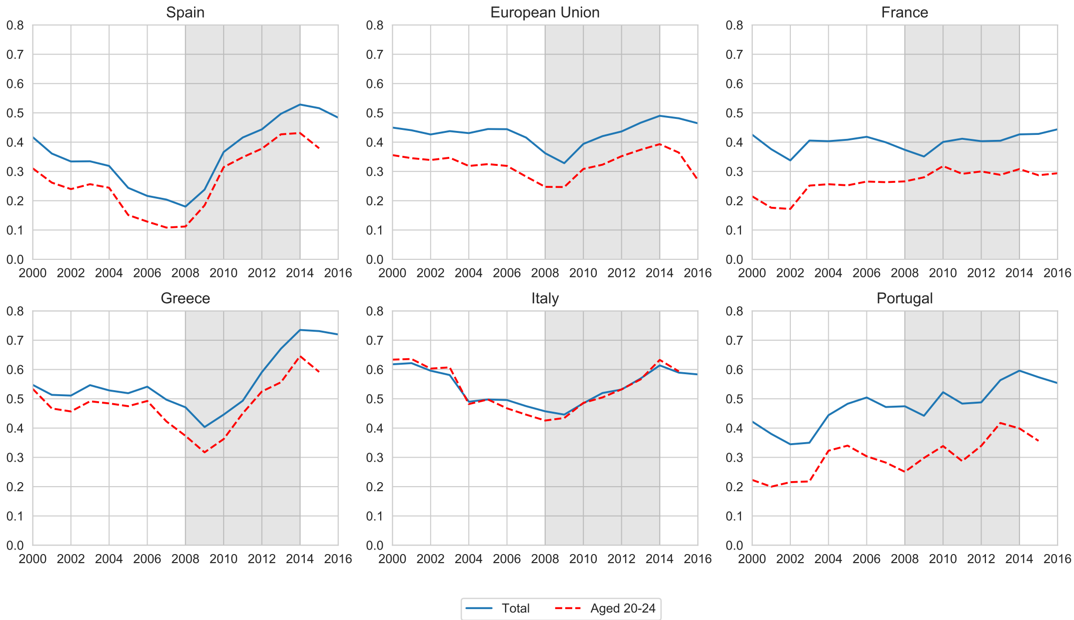
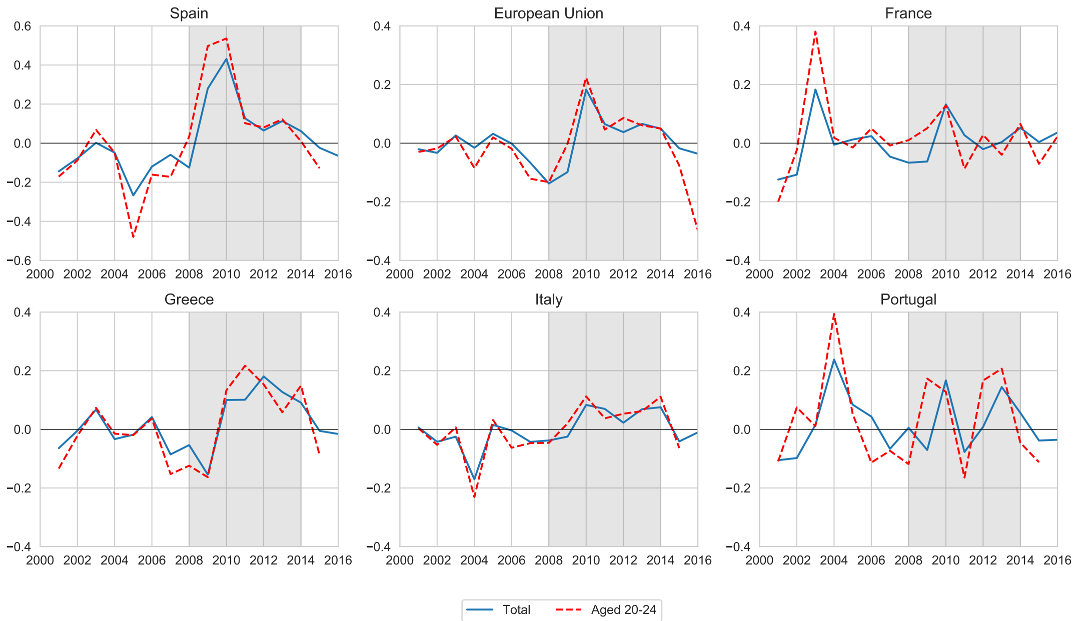


Figure 2: Annual log change on the share of unemployed workers who have been searching for a year or more



Notes: Solid lines depict the overall long-term unemployment (LTU) share for all of the labour force. Dashed lines show the same statistic but for workers of 20-24 years of age. Shaded areas mark the 2008 recession. Data from OECD (2020).

Great Recession (figure 2). The red dashed spikes in figure 2 show that youth long-term unemployment rates have increased relatively more than the rest of the population in Southern European countries – and in the European Union as a whole. This is important to note because experiencing long-term unemployment in the years that workers should be accumulating human capital can have long-lasting consequences. The fact that young people saw the greatest increases is difficult to explain using conventional long-term unemployment models such as Ljungqvist and Sargent (2008) and Kitao et al. (2017). While these models have been successful in explaining the high long-term unemployment rates in Europe by focusing on human capital shocks to older workers, they do not explain why young workers should suffer from higher increases in long-term unemployment during recessions.

This paper argues that differences in search capital among the unemployed, amplified by dual labour markets, can explain why recessions affect young workers more than other age groups: young workers rely heavily on easy-to-find temporary jobs to gain search capital, but these jobs are much less abundant during recessions. The lack of opportunities makes them less competitive compared to older age groups that have had time to accumulate search experience. Because they take longer to gain search capital, their unemployment spells also become longer. Older workers who have lost their jobs after a long tenure will also have lower search capital, but for them this channel is less relevant as they can afford to wait for better offers since they have also accumulated assets and human capital. Their unemployment duration is therefore less affected by the recession: they were taking longer to find jobs before and after the recession.

Search capital is not easily observable in the data. However, dual labour markets[3] can help identify the effects of search capital. These markets are characterized by the coexistence of large groups of workers with secure jobs while others are subject to many unstable jobs. This naturally leads to large differences in exposure to job search, amplifying the differences in search capital. I use the case of Spain to illustrate the effects of search capital, as it has both a very volatile long-term unemployment rate and a very stark dual market structure. In particular, I argue that the characteristics of the Spanish labour market allow me to use temporary jobs as a proxy search capital. Using administrative data, I show that workers with more temporary contracts in the past have shorter unemployment duration, even when controlling for individual fixed effects and a rich set of individual characteristics. These workers also tend to get better daily wages, which shows that their lower unemployment duration is not a result of lowering their standards or temporary contracts affecting their productivity in a negative way.

While these correlations provide suggestive evidence of individual effects, it does not necessarily imply that search capital can play a significant role in explaining the aggregate

[3] Dual labour markets are characterised by the coexistence of highly protected jobs with a large sector of the economy in less protected (and often temporary) jobs.

patterns of figures 1 and 2. To this end, I introduce search capital into a search model and calibrate it using Spanish data. The model can reproduce the job finding rate patterns amongst younger workers and replicate the disparities in long-term unemployment rates that we observe after the Great Recession. Regressions on the simulated data show coefficients close to those of the empirical regressions. Search capital can therefore have both individual and aggregate effects in long-term unemployment rates.

The link between search capital and temporary work suggests that exposure to temporary contracts has unambiguously positive effects on workers. Because temporary contracts improve search capital among the unemployed they increase average job finding rates, which mechanically reduce long-term unemployment as noted by Güell (2003). Using the results from the model simulation, I show that workers who have fewer jobs over their lifetime achieve higher lifetime utility, in a good steady-state. This is despite workers who have been exposed to more temporary contracts accumulate higher levels of search capital. In other words, too much exposure to temporary contracts leads to poorer outcomes, in accordance with findings in the empirical literature (see García-Pérez et al. (2016)). However, when considering the effects of the Great Recession, search capital protects the youngest workers by allowing them to bounce back faster and spend less time unemployed. The welfare gains are substantial for these workers, as they are less able to smooth consumption. These results indicate that active labour market policies can have a very positive impact on young workers, as these policies can help them gain search skills without suffering the uncertainty effects of long exposure to unstable jobs.

The rest of the paper is structured as follows: Section 2 discusses search capital and its implications in more detail, as well as explaining how it relates to similar channels in the literature; Section 3 provides empirical evidence at the individual level; Section 4 develops and calibrates a theoretical search model with search capital; Section 5 concludes.

2 Search Capital, Dual Labour Markets and LTU

This section describes search capital in more detail, places it in the context of related ideas in the literature and explains how it relates to long-term unemployment. In particular, I explain how the interaction of search capital with a dual labour market can amplify the effects of a recession on long-term unemployment.

2.1 Search Capital

I define search capital as the set of skills that help workers find jobs. For example: knowing the places they should apply to (applying for jobs that match worker's skills, diversifying their search, etc), knowing how to prepare for the different stages of the recruitment processes (interviews, tests, etc) or having the right connections. These skills are related to active labour market policies aimed at improving the search skills of unemployed workers, as opposed to those focused on their human capital.[4] While some of these skills can be learned after a failed application (a bad interview can help improve the next one) throughout this paper I assume that workers are likely to learn more through successful search. That is, when workers are offered and accept a job. Workers use their previous successful experience to improve their job search in the future.[5] On the other hand, if workers do not actively engage in searching their search skills will depreciate over time. This is the case of both inactive workers and those with a job that do not engage in on-the-job search. This implies that after a long tenure in their previous job workers may face a very different job market from the last time they searched. The focus of this paper is on the dynamics of search skills or the search capital of workers.

This treatment has some advantages: first, it makes a mapping between an unobserved variable (search capital) and an observable outcome: number of successful job searches or jobs held by the worker. Second, it makes search capital dynamics easier to incorporate to model, while modelling as a learning process through failed applications as well can become more complicated and has the potential to imply that search skills increase with time in unemployment. There is ample empirical evidence that long-term unemployed workers have lower job finding rates (see for example Blanchard and Landier (2002), Hornstein (2012)). Assuming that search capital improves only with success keeps it separate from duration dependence and its determinant channels. This doesn't rule out that search capital can be defined in broader terms and allow for a richer learning process.[6] Narrowing the definition makes it easier to map to the data, while still retaining the two main features of search capital: workers become more proficient searchers over time as they get new jobs and search capital does not depreciate as long as the workers keep searching.

Note however that search capital is different from search effort: it is not costly for the worker to accumulate search capital and the worker cannot chose to gain it or not. Search capital increases parsimoniously over time in a similar way as human capital increases in learning-by-doing models. It is also unrelated to the productivity of the worker. The best searcher doesn't necessarily have to be the best possible candidate for the job.

2.2 Related literature

The focus of this paper is on the consequences at the macro level of search capital, not on disentangling its determinants – whether it be networks, soft skills or matching

[4]See Bentolila and Jansen (2016) for an overview of these policies in Europe and long-term unemployment.

[5]In particular, I will model being a more efficient searcher as being able to receive more offers per period.

[6]The mapping between number of jobs held and search capital that I will use in the empirical part would still exist if workers learned something from their failed or rejected applications.

technology. However, there is some empirical and theoretical literature that is related to the possible channels of search capital.

In particular, there is a growing experimental empirical literature on how workers look for jobs. For example, Belot et al. (2015) provided unemployed workers in Scotland with a customized job search portal which suggested jobs where people with similar backgrounds to them had successfully found jobs in the past. This feature increased the number of interviews they received and significantly increased the offers they received relative to other similar workers. Notice that what improved their employment prospects was the fact that they were shown where similar people to themselves found jobs *successfully*. The job search portal improved the search strategy of workers that had a more narrow focus in their search.

Search capital is also connected to some of the most recent network literature. For example, Arbex et al. (2016) develop a similar model where workers use their contacts to climb the job ladder faster. Workers receive job offers from an external, constant arrival rate and their network, which is made out the firms her previous co-workers work in. Although it is not the main focus of their paper, the implications align with my model: by finding jobs, workers increase their future chances of finding better jobs in the future, reducing the time they spend unemployed and gaining better wages for themselves. In a related empirical paper, Witte (2018) designs an experiment where a set of workers is hired for a day, after which they are asked to refer some friends to work the next day. The authors had previously mapped the network structure of the neighbourhood where the workers lived. They find that the workers choose to refer the most popular person in their network, not the most productive or able individual for the job. This shows a combination of two things: to be hired from referral workers needed to be in the network but they also needed some interpersonal skills, as popularity matters. Moreover, when the researchers introduced people from outside the network into the firm, the outsider became part of the network and was referred back in subsequent rounds. This shows that becoming part of the network comes from being in touch with other co-workers, which supports the assumption of search capital increasing after a successful job is held. Although search capital is not *only* referring to networks but more generally search skills, it shares some of their mechanics.

This paper is also related to thin markets as developed in Bradley et al. (2018). In their paper, workers differ in the number of prospective offers waiting for them in the job market. Workers can only access the market at a stochastic rate and offers arrive at a stochastic frequency. If when workers access the market they choose to reject all of the offers, these disappear and the worker starts from zero prospects. This mechanism generates a falling exit rate from unemployment, as a worker which flows into unemployment with employment prospects finds a job very quickly. She has access to a larger pool of offers relative to other unemployed workers. This is related to how workers with search capital are also more likely to get out of unemployment faster. Thus one could see the latent variable of external offers as approximating search capital. However their dynamics imply that the longer a worker is employed, she's also more likely to have a large set of offers – and because their estimated rate of accessing the market for employed workers is very low, this implies that workers with longer tenures are the ones with higher search capital. By contrast in this paper search capital depreciates over time when workers don't search, which are workers in long matches. The other main difference with their paper is that here the focus is on how the differences in search abilities affect the aggregate dynamics of unemployment, in particular for the young.

Finally, search capital as introduced in this paper is different from search capital as defined by Carrillo-Tudela and Smith (2017). They refer to the ability of the worker to recall previous employers while employed at another firm, helping them search on the job, while I am referring to the ability of workers to find jobs from unemployment in different firms. This is an important distinction in the empirical model: I do not count recalls back from unemployment as increasing search capital, as the worker doesn't necessarily learn anything by being ask to come back to work at the same firm. Their model is also silent about the implications for unemployment duration, while here it is a central issue.

2.3 The link to long-term unemployment

In the last 30 years there have been substantial waves of de-regularization of the labour market across Europe, mostly targeting entry jobs. The introduction of temporary jobs in Spain, France and Italy in the late 80's and early 90's is an example of this. But even the de-regularization of mini-jobs in Germany or the increased used of zero hour contracts in the UK reflect this growing tendency. Note that in all cases regular, protected employment is still the main share of all employment, but there is also a share of employment concentrated in these unstable jobs. In all of these cases, younger workers are the most affected by unstable contracts. This dual labour market structures create a divide between workers who are frequently in-and-out of jobs and workers who have heavily protected long-term jobs. For the former search skills are crucial, as they need to be able to find a new contract before or soon after the current one expires. For workers in secure long-term jobs there are little incentives for them to engage in job search. Their income is more dependent on human capital accumulation and promotions than in changing jobs. This divide generates large differences in search capital levels.

A dual labour market is a necessary but not sufficient condition for search capital to have a significant effect on unemployment dynamics. In particular, if when workers are young search capital is relevant but not later in life it may cause disparities among young workers alone that dissipate as workers achieve regular employment. Big cyclical swings in the economy are also required. To see this, consider an economy with a dual labour market. During expansions, stable jobs are rarely destroyed and temporary workers comprise most of the unemployment pool. Search capital creates some differences among these workers, in particular the more experienced versus new entrants to the job market. But these differences are limited when job offers are abundant, so even bad workers can quickly improve their search capital. However, when a substantial amount of regular workers lose their jobs during a recession the composition of the unemployment pool changes considerably. There is more heterogeneity in the search capital levels of the unemployed. As job offers become hard to find, there is an intense competition for few vacancies. Workers with low search capital will have longer unemployment spells – therefore increasing long-term unemployment during recessions.

The most affected workers in this case are the youngest: when the economy is booming, they have easy access to temporary contracts that allow them to become better searchers. Thanks to their increased search skills, they are also more likely to find permanent jobs. During recessions temporary jobs are harder to find as they are competing against more and better searchers. As a result, they are unable to accumulate search capital and suffer longer spells of unemployment. Older workers who lose a long-term job also suffer if their search capital is low. But some of them will still have some search experience they can rely on, so overall the impact is not as great as for younger workers.

2.4 Other explanations of LTU

Search capital is not the only channel behind the spike in long-term unemployment we have seen in the last recession, but it provides an explanation of the differences between age groups that is missing from the literature in long-term unemployment. In what follows I turn to the two main strands of the literature to review their contribution and how search capital can interact and complement them.

Unemployment Benefits

It is a well-known theoretical result that a higher unemployment income results in higher unemployment in almost every search model. Consider for example Mortensen (1970): a worker draws a wage offer from a given distribution, then she decides whether to accept the job or to reject the offer and keep searching. The worker sets a reservation wage strategy which depends positively on their unemployment income. She internalizes that she is going to be unemployed for longer in return for a higher future wage. Being richer makes the worker more selective. This is a mechanism that drives more sophisticated models such as Kitao et al. (2017).

The empirical literature seems to confirm these patterns: Lalive (2007), and Krueger and Mueller (2010) find longer periods of unemployment benefits (UB hereafter) result in longer spells of unemployment. Krueger and Mueller (2010) find that time devoted to search increases as the date of benefit exhaustion approaches, but then it is reduced substantially. This implies that although longer UB entitlements can lead to longer unemployment spells they appear to keep the unemployed searching for work. Wadsworth (1991) similarly finds that UB recipients are more attached to the labour market. It seems to be the case in the literature that entitlement (how long benefits last) is more important than the quantity of benefits. This also appears to be consistent with the fact that Northern European countries, where workers are given their benefits in a block payment, have lower unemployment duration overall than other European countries which are more generous with length of claiming period.

An overly generous benefit can thus lead to longer unemployment duration as an equilibrium outcome. Because the quantity and duration of unemployment benefits are usually linked to past wages and job duration, workers coming from longer past tenures are expected to take longer to find jobs. The increase in long-term unemployment rates could be explained by high income and wealthy workers choosing to wait for a better job.

While the generosity of unemployment benefits is a good explanation for the increase in LTU in general, it fails to account for the increase among young workers as they tend to not qualify for unemployment benefits – and where they are, benefits are not generous and for a short period of time. In contrast, search capital can explain why individuals with little to no unemployment benefits spend a long time unemployed.

Human Capital Depreciation

A popular explanation of long-term unemployment increases during a recession is that technology shocks can produce redundancies that lead to an immediate and persistent deterioration of productive human capital. This makes it harder for those affected to find subsequent employment. Ljungqvist and Sargent (1998) called this "turbulence".

In a more recent paper, Ljungqvist and Sargent (2008) present a model in which, upon losing their job, some workers suffer a sudden and permanent loss of human capital. This leads to lower expected future wages and search effort. Combined with a generous unemployment benefit, individuals who suffer these human capital shocks are discouraged from searching for a new job, leading to long-term unemployment. In a similar way, Carrillo-Tudela and Visschers (2013) look at mismatch across occupations and find that most unemployment generated during recessions is what they call "resting" unemployment – workers looking for a job in their previous occupation instead of switching careers. These workers prefer to wait in unemployment in their occupation-specific job market during a recession, in the hopes that their human capital doesn't fully deteriorate, leading to longer durations of unemployment.

This sudden loss of human capital, it can be argued, is driven by idiosyncratic shocks to labour demand. For example, in Spain the collapse of the construction sector left many workers unemployed and with a set of skills which is no longer desired by firms. Related industries like building material providers, real estate and financial services also suffer major job losses. More importantly the budget readjustment of 2011 meant a considerable shrinkage of public sector employment.

In this case, the end of a long-term job sees part of the human capital of the worker vanish, leading to subsequent job losses. This has been well documented in the displaced worker literature (see Jacobson et al. (1993) and Couch and Placzek (2010) for updated results). If the worker is also entitled to high unemployment benefits then she may be discouraged to search. This mechanism cannot fully explain how more experience of temporary contracts (or recent unemployment spells) lead to shorter durations unless temporary contracts increase a worker's human capital more so than a stable contract. However Dolado et al. (2012) have argued that there is no incentive to invest in human capital for temporary workers, documenting a lower incidence of on-the-job training provided by firms compared to permanent workers. In this way permanent contracts could incentivise firm-specific human capital investment while temporary contracts improve transferable skills, leading to observed shorter unemployment spells for those with temporary contracts. Lazear (2009) proposes a model where workers choose to specialise in different kinds of skills depending on how likely it is that an exogenous lay-off could happen, this leads to diversification of human capital in those industries/occupations where jobs are more unstable.

Crucially, the depreciation of human capital cannot explain why long-term unemployment has risen so dramatically among young workers who have not accumulated enough working experience to suffer a great loss. Kitao et al. (2017) argue that higher minimum wages are to blame, but then why are some young workers finding jobs much faster than others? The proliferation of temporary contracts and apprenticeships does not imply that minimum wages are too high, but shows that minimum wages are easily circumvented.

A related issue is the depreciation of human capital *during* unemployment. This could induce *negative duration dependence* – lower exit rates the longer a worker is unemployed. Note that search capital does not decrease with unemployment duration, as workers do not lose any of their search skills while looking for jobs. Therefore this is a separate issue from search capital.

3 Empirical Analysis

Before introducing the structural model, a natural question that arrises is how can we measure search capital in the data, or even provide some empirical evidence supporting this mechanism. The main implication of search capital is that job mobility should be correlated with shorter unemployment spells. In this section I test this implication using administrative data from a country with a marked dual market, Spain. The richness of the data allows me to address some of the main empirical challenges that arise when measuring search capital via labour mobility, or more precisely, the number of temporary contracts with different firms that a worker has experienced.

3.1 Measuring search capital in Spain

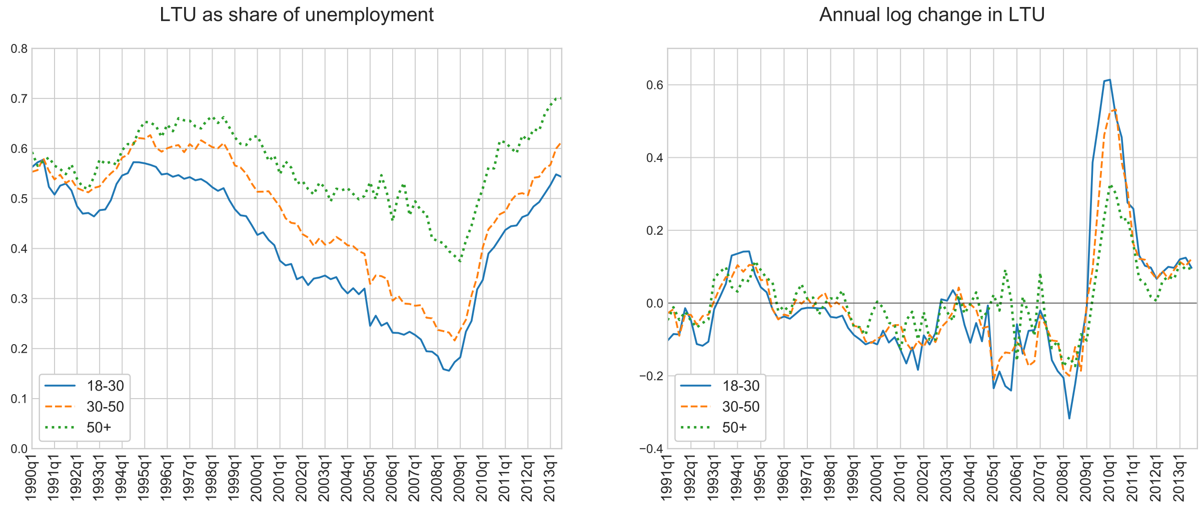
As argued in section 2.3, dual labour markets amplify the effects of search capital on unemployment duration by creating large differences of search skills among the unemployed. This makes Spain an obvious candidate to investigate the effects of search capital, since 30% of workers are employed under *temporary contracts*, that is, contracts with a finite duration and low protection in the form of severance payments. The other 70% hold *permanent contracts*, which have increasing wages and severance with tenure, so these workers have little incentive to change jobs after finding permanent employment. Temporary jobs do not immediately translate into stable employment (see for example Güell and Petrongolo (2007); García-Pérez and Muñoz-Bullón (2011)) but instead they often lead to other temporary contracts or unemployment. These contracts were created in 1986 as a compromise between more flexibility in the labour market and keeping the labour protection of regular employment. By 1992 their use was widespread. While mostly young workers are under temporary contracts, they constitute a substantial part of total employment for all ages. In this way, temporary contracts are the primary way of hiring for firms, representing 90% of total hiring in the last 10 years.

On the other hand, permanent contracts are subject to one of the most stringent employment regulations in Europe. Severance payments (prior to the 2012 reform) amounted to 45 days per year of service in case of unfair dismissal and 20 in case of a justified economic reason.[7] This increasing severance package, together with wages being protected by industry or regional collective agreements, make permanent jobs not only appealing for workers, but give them very little incentives to ever leave them. This clear divide is also present in the public sector, where temporary contracts also abound. In fact, having served in some of these contracts can be very important to get access to full civil servant jobs. These are even more protected than private sector jobs.

So while most temporary contracts don't serve as stepping stones for long-term jobs, most workers eventually get a permanent contract. This is precisely the kind of environment where search capital matters: most temporary workers know they have to look for other jobs soon and that they will likely have to go through a series temporary jobs before getting a stable job. Moreover, as this dynamic is widely known there is little reason for

[7]In case of some permanent contracts it was 33 days per year of service. Because of read tape costs, firms would often prefer to pay the unfair severance in order to avoid going to court. See table A.1 in Bentolila et al. (2012).

Figure 3: Long-term unemployment in Spain, by age



Source: Own calculations from the Spanish Labour Force Survey (INE (2013))

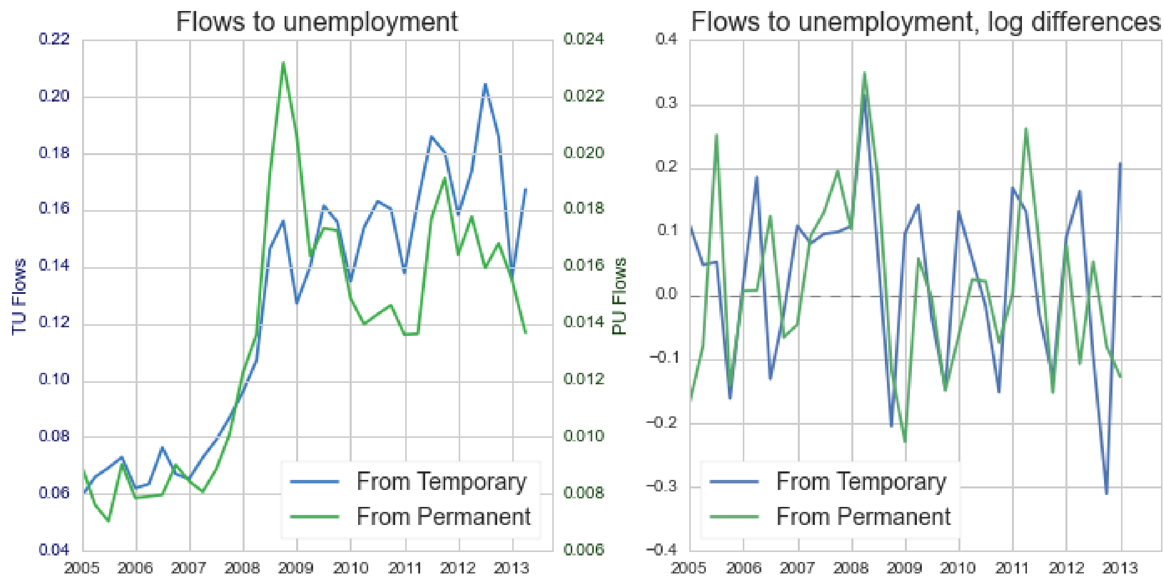
a stigma attached to losing a temporary job.[8] In this way, workers who have experienced several temporary jobs become more proficient at searching. As for permanent workers, they have few incentives to keep searching for jobs (and most vacancies are temporary jobs as well) and over time job-to-job flows fall. The implication is that their search capital may deteriorate, as they have been out of the job market for a long time.

As discussed before, search capital doesn't make much difference during an economic boom – it is during a recession that differences in search capital should cause large effects and become visible in the data. In particular, long-term unemployment should particularly increase more for younger workers. The left panel of figure 3 shows evolution of the share of long-term unemployment (defined as one year or more) over total unemployment (LTU rate thereafter). Starting from similar magnitudes as older age groups in 1990, the youth (18 to 30 years old) LTU rate declined faster after the 1993 recession. Temporary contracts played a significant role in the overall decline of LTU, as Güell and Hu (2006) have noted. It stayed lower than for prime age (30 to 50) and older workers (50+) thereafter, but as the right panel shows, the year-to-year increase was larger (over 60%) than for other workers. This was also true in the 1993 recession, but this time it peaked earlier and stayed high until 2013 when the overall unemployment rate reached its peak at 27%.

If this increase in duration of unemployment came mostly from a fall in the job finding rate as opposed to a change in the composition of the unemployment pool, then search capital would not offer a good explanation for it. As explained above, there has also to

[8]There are many types of temporary jobs, and while not getting promoted in a one year permanent job may not necessary be a bad signal, chaining many very short (daily or weekly) temporary contracts may have a different effect. But overall, workers getting their first permanent job have had a average of 4 temporary contracts first, so a temporary contract not converted to a permanent one is not likely a bad signal for a prospective employer. It is just the way the market works.

Figure 4: Flows into unemployment, by contract type



Source: Own calculations from INE, *Encuesta de la población activa* (Labour Force Survey), 2013

be a large influx of different kinds of workers into unemployment for search capital to make a significant difference in long-term unemployment. Figure 4 shows the quarterly employment to unemployment flows or job destruction rates in Spain. The first panel shows that the magnitude of flows is of the order of 10 times larger for temporary (left side scale) than permanent (right side scale) jobs. However not only did the permanent job destruction rate also increase during this period, peaking at the same time as the temporary. As the right panel shows, its relative annual change was of similar magnitude as the temporary destruction rate. This shows two things: the job destruction for permanent contracts was also high during this period and this increase happened at the same time as the increase in temporary lay-offs. These observed dynamics are entirely consistent with a standard search and matching model with match quality and aggregate shocks, as in Costain et al. (2010).[9]

Given all of the above, using the number of temporary jobs to identify search capital offers several advantages in Spain: clearly defined and differentiated temporary contracts are very common and constitute the easiest way out of unemployment. They are widely used to accommodate demand fluctuations among firms and as such losing a job is not

[9]In their model some workers start with high match productivity and thus are promoted to a permanent contract. But stochastic productivity shocks can effectively make them less productive than the hiring threshold. They are kept employed because firing the worker forces firms to pay a lump-sum tax, which for some workers is high enough to keep them in. This is the risk that firms incur when promoting workers, and thus they promote more during a period of economic boom. The main driving factor behind the increase in unemployment is not temporary contracts, but high severance payments that prevent firing unproductive permanent workers.

likely to constitute a bad signal for the worker. Over time, workers find permanent jobs and then job-to-job transitions fall. Big cyclical fluctuations in job destruction for both temporary and permanent jobs make it possible to observe all kinds of workers in the unemployment pool at some point.

3.2 Measuring search capital with temporary contracts

Using temporary contracts to measure search capital poses several empirical challenges. The strategy is to isolate as many confounding factors as possible and aim at a simple, reduced form approach: regressing the log duration of unemployment (in weeks) on the number of previous temporary jobs (TCs) and other control variables:

$$log(weeks)_{i,t} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \beta_4 LastP_{i,t} + \gamma CLAIM_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{1}$$

Where $log(weeks)_{i,t}$ is the natural logarithm of the duration of completed unemployment spells, $TCs_{i,t}$ the number of temporary jobs, $CLAIM_{i,t}$ a vector of dummies for unemployment benefit duration, $Ten_{i,t}$ and $Exp_{i,t}$ years of tenure and experience respectively, $LastP_{i,t}$ an indicator dummy if the last job was permanent and $X_{i,t}$ a vector of personal characteristics.

The first question that arises is how to count the number of temporary contracts. It is not an uncommon event to see a worker having multiple temporary contracts with the same firm separated by very short periods of unemployment.[10] Counting all of these contracts separately would lead to a biased estimate of the search abilities of the worker, as being recalled to a previous job doesn't require any search on the side of the worker. A temporary contract is only counted if it is coming from a different firm than the previous employer, both from unemployment of from other employment.

Given this high recall rate, an alternative measure could be the number of past unemployment spells. However, this would rule out search on the job. As I am aiming to capture the search skills of the worker these transitions cannot be ignored. There is no reason to believe that on-the-job search does not improve search capital.

Another alternative measure could be the number of permanent contracts for both types of jobs. There are a number of reasons as to why having many permanent jobs may have a different effect on unemployment duration. Separations from permanent jobs are much less frequent than separations from temporary jobs, as the different scales of figure 4 showed. Moreover, separations from permanent jobs are more likely to be quits as opposed to lay-offs, which is expected given the higher employment protection of these

[10] This is different from *discontinuous employment*, a type of contract that links a worker with a firm to work at certain times of the year only. The classical example are firms that manufacture Christmas sweets that only work on certain months of the year. The rest period between work is not counted as unemployment.

contracts. For this reason, having many permanent contracts may not send the same signal in the job market as having many temporary contracts. But it still signals that the worker was able to successfully find a job, which is why I chose to include in the regression above a variable for number of permanent contracts. This allows temporary and permanent contracts to have different effects on unemployment duration.

A natural concern is how to disentangle the effects of search capital from human capital. While having many jobs shows that the worker is a good searcher, it can also signal that the worker has accumulated transferable skills across different jobs. However, human capital accumulation is related to the *time* the worker spent employed in the past, while purely the number of jobs is related to mobility. Human capital accumulation is related to the amount of time a worker has spent in their job while search capital is related to the number of different jobs the worker has found (and accepted). Consider two workers with the same work experience of 2 years. One of them had two one-year temporary contracts while the other had a single two-year contract. The worker with two jobs will have higher search capital but the same human capital as the other – they have both been employed for two years. Since both contracts were temporary, it is hard to argue that the worker on the 2-year contract accumulated firm-specific as opposed to transferable human capital. Recall that the renewal rate of these contracts is very low. Then the work experience $Exp_{i,t}$ variable should capture the human capital effect while the number of temporary contracts is only related to job mobility and search.

I also include two variables to control for specific human capital accumulation and loss when entering unemployment: tenure in the previous job ($Ten_{i,t}$) and an indicator for the last job being permanent ($LastP_{i,t}$). Tenure is measured as the years of job experience accumulated in the previous job only, while work experience ($Exp_{i,t}$) is measured as years of accumulated employment prior to the last job. Its inclusion aims to capture the specific effect that the last job had on the current unemployment spell. This effect is also related to the loss or depreciation of search capital, as it measures how long the worker has been employed since the last time she switched jobs. However, it is not possible to disentangle this with the loss of specific human capital and other correlates with tenure: the extension of unemployment benefits, the entitlement to severance payment or the fact that the worker had time to accumulate assets and self-insure against unemployment. Untangling these effects is left for the structural model. Here this variable is necessary to control for the influence of these channels on unemployment duration. Similarly, the indicator for the last job being permanent captures the availability of severance payments to the worker (if she didn't quit) and any signalling effects that coming from a permanent contract could have in the job market.

Another challenge that naturally arises when using temporary contracts as a proxy for search capital is unobserved heterogeneity. That is, workers that have accumulated several temporary contracts share some unobserved characteristic driving them back and forward from unemployment. I address this issue in different ways. First, exploiting the panel dimension of the data I run the regression of equation 1 adding an individual fixed effects variable. In this specification, the interpretation of the coefficient on the number of temporary contracts changes: in the pooled sample, β_1 represents the marginal effect of having had one more temporary contract in the past on log weeks in unemployment (percentage increase in weeks) *across* workers. In the fixed effects regressions it represents the effect of one additional temporary contract on the difference in duration of unemployment spells *across time* within workers. That is, if it is positive (negative) then as the worker accumulates temporary contracts her unemployment spells get longer (shorter) over time. Then the panel regression aims to measure the effect of accumulating search capital over time, while the pooled regressions measure the overall effect across workers. Individual fixed effects absorb the unobserved heterogeneity that is fixed over time, part of which could be the difference on starting levels of search capital: some workers may be naturally better at finding jobs than others, and these differences may persist over time. In the results I interpret the change in β_1 before and after fixed effects as partly coming from this source.

I also address the unobserved heterogeneity coming from productivity differentials across workers by including log wages in the previous job as a control. This reduces the sample but provides with a proxy for both productivity of the worker in her previous match and the amount of unemployment insurance the worker is receiving today. This is a noisy estimate but it aims to capture differences across workers in different wage levels. This variable is also directly related to the generosity of unemployment benefits, which is based on the last 3 months of wages. In extended regressions I include the observed unemployment benefit as well, but I can only observe this variable in a sub-sample of workers and it is a noisy measure, as I cannot assign observed unemployment benefits to specific unemployment spells within the fiscal year. Later I show that this variable has little effect on the estimated coefficients.

As well as the generosity of unemployment benefits, an important factor that determines unemployment duration is the extension of those benefits – for how long can workers claim unemployment assistance. This can also interact with the number of temporary contracts the worker has had: workers that have more jobs often may also struggle to accumulate enough employment spells to qualify for benefits. This is often the case among young workers. To tackle this concern, I include a dummy vector $CLAIM$, taking the value 1 if the worker was entitled for is 3, 6, 12, 18 or 24 months of unemployment insurance. These dummies are important to control for the spikes in job exit rates close to the expiration of benefits (Card et al. (2007)) but also to account for the effect of unemployment insurance on unemployment duration more generally. Three months is the minimum entitlement period in Spain, requiring a year of employment.[11] After that, each

[11] This can be accumulated over one or multiple job spells.

year of employment increases the unemployment benefit allowance by 3 months and up to 24 months. After 24 months, under certian circumstances (mainly having dependents) the worker may be entitled to a reduced unemployment assistance. These cases are not common in my sample, as there are few completed spells after that threshold in the data.

There is also the potential issue of sample selection: I look at *completed* unemployment spells, which leaves out a sizeable proportion of the sample, as unemployment was very high towards the end of the study period. To complement the analysis above and to deal with the issue of sample selection I run a logistic regression using as dependent variable the probability that an unemployment spell will last more than one (LTU_1) and two (LTU_2) years. These will include unfinished spells as well. As the average spell in Spain is close to a year, I use the two year mark to signal long-term unemployment more effectively. But given the increase in long-term unemployment in Spain during the recession, skilled searchers having even a small advantage in finding a job could protect them from very long unemployment spells during recessions.

Lastly, even if there is a negative correlation between duration of unemployment and temporary jobs this may be measuring something different from search capital, if workers are accepting worse jobs which are easier to find. Then the correlation will not support the idea of search capital, as better searchers should also find better wages, or at least wages that are not worse than their peers with less search experience. In order to address this concern, I regress the log wage at the next employment spell out of unemployment on the same explanatory variables in equation 1:

$$\log(\text{wage}_{t+1}) = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \gamma CLAIM_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \beta_4 LastP_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{2}$$

This last variable corresponds to the independent variable in equation 1, and aims to capture the direct effect of longer unemployment duration on the wage. Because this variable is going to be correlated with all of the other right hand side variables, the coefficient on all of these variables should be interpreted as their direct effect on wages, independent of their effect on unemployment duration. Time spent in unemployment can also have a separate effect on wages if for example there is discrimination in the labour market against workers with longer unemployment duration.

Another possible problem is that even if workers with more jobs in the past find jobs faster and better paid, these jobs are better paid because they are worse quality jobs. If workers with more temporary contracts would find jobs faster but these jobs were shorter then the effect of the number of temporary contracts could be related to some unobserved characteristic other than search capital. That is, workers with high search capital would have a preference for shorter jobs. Although this is a possibility, it would be in contradiction with the dynamics of the Spanish labour market as described in section 3.1 where young workers have mainly temporary contracts but eventually settle into longer employment spells. To address this issue I follow two different approaches. First, I run the logistic model in equation 3 on the probability of the next job being permanent as opposed to temporary. If the coefficient of β_1 is positive, having had more jobs in the past would make it more likely that the next job is permanent – and thus higher quality. The log duration of unemployment is included in this equation for the same reasons as in equation 2.

$$\mathrm{P}(\mathrm{PC}_{t+1}|U_t)_{i,t} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \gamma CLAIM_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \beta_4 LastP_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{3}$$

Second, I consider the duration of the next job as an indicator of the quality of the next job. This is because only 8% of all unemployment spells in the sample end in a permanent contract. I also consider instead of the duration of the first job out of unemployment the total length of the employment spell. That is, if a worker moves job-to-job I count all the time she is employed before returning to the unemployment pool. This is important since the fact that a worker has shorter jobs may mean that she is climbing the job ladder faster. Then whether exiting unemployment leads to a long or a short period of employment (in different jobs) is a better proxy for job quality approximated by job stability.

$$\log(\mathrm{weeksE})_{i,t+1} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \gamma CLAIM_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \beta_4 LastP_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{4}$$

Finally, in all regressions I include controls for other individual characteristics in the vector $X_{i,t}$: industry[12] and occupation of the previous job, gender, a quadratic polynomial on age, dummies for the highest educational level recorded,[13] an indicator variable if the worker was born outside of Spain, an indicator variable if last job ending on a quit, an indicator variable if last job was part-time, an indicator if the worker was subject to a collective dismissal, provincial dummies and yearly dummies. These last set of dummies are important as they take care of the changing labour market conditions during this period.[14] These controls are present in all regressions.

3.3 The Data

While the Spanish labour market makes it easy to identify search capital using temporary contracts, we still need detailed panel data with enough variation across time and individuals to see if workers do get progressively better at searching. Working histories datasets, provided by certain social security administrations, are fit for this purpose.

[12] I include two different dummies if the last job was in construction: one if the spell ended before 2007 and another if it ended after. This allows to capture the burst of the construction bubble in Spain.

[13] These are: middle school (*ESO*), high school diploma (*Bachiller*) and college or above (*Diplomado* or *Licenciado*)

[14] Changing the yearly dummies with output growth does not alter the results.

Table 1: Descriptive Statistics

	mean	std	min	25%	50%	75%	max
Weeks	30.06	41.36	0	5.71	14.86	36.71	459.86
Temporary contracts	4.65	6.22	0	1	3	6	314
Permanent contracts	0.64	1.31	0	0	0	1	80
Tenure (years)	0.875	1.861	0	0.071	0.252	0.805	39.27
Experience (years)	7.019	6.37	0	2.21	5.17	10.021	45.30
Age	33.60	8.78	21	26	32	40	54
Male	0.562	0.50					
Foreign born	0.14	0.35					
Quit	0.14	0.347					
Education, secondary	0.42	0.50					
Education, pre-college	0.23	0.42					
Education, college	0.14	0.34					
Part-time	0.10	0.31					
Affected by collective dismissal	0.004	0.064					
N=766,462							
$wage_{t-1}$ (euros, annual) ***N***= 555,302	21,983	106,778	0	13,081	16,459	21,414	$3.35*10^7$
$wage_{t+1}$ (euros, annual) ***N***= 557,478	25,883	187,124	0.03	13,907	17,146	22,453	$7.67*10^7$
UB_t (euros, annual) ***N***= 744,995	5907	20127.77	0	0	5,061	9,141	3,518,699

Source: MCVL, 2005-2013 waves. The sample is all completed unemployment spells, ending in employment, with wage information for the next job, workers aged 21-54, recalls and transitions from self-employment excluded. Wages and unemployment benefits are taken from the fiscal annex of the MCVL (2005-2013).

The Spanish Social Security administration provides this information from 2004, releasing a sample of close to a million random observations each year. This is is the Muestra contínua de Vidas Laborales (MCVL) which translates into “Continuous Sample of Working Histories”. The data follows individuals through time, adding new observations for the ones dropping out (workers retiring or dying) keeping the sample representative from year to year. Specifically, it consists of a sample of 4% of the working population. The condition to be included in the sample is to have been affiliated with Social Security (either by working, receiving a public pension or being registered as unemployed) in the year of the publication of the dataset. After that year, the MCVL follows the same sample of workers over time, adding new observations each year to replace absences while keeping the sample representative of the population. This means that using the MCVL retrospectively (looking at earlier years than 2004) can lead to substantial biases as the sample becomes less representative of the population as we use data further back in time. That is, using the retrospective information to look at the 1992 recession would over-represent young workers with a high attachment to the labour market, so they are still in the labour force in 2004.

The MCVL comprises all of the job spells, unemployment spells and retirement periods that are registered by the administration for each individual in the sample. It contains information on personal characteristics (age, gender, date of birth, highest education attained) from the census (last wave dating to 2011), some firm information at the establishment level (size, location, tax code, parent company identifier) and information on the job such as industry, occupational scale[15] and type of contract. It keeps track of changes of contract and changes in relation to social security (for example from unemployed to retirement). The MCVL also records self-employment spells.

The Spanish Social Security also provides a complementary dataset with income tax information that can be linked to the working histories file via anonymized tax identifiers. This allows to obtain detailed wage information for many (but not all) jobs in the sample. It also contains information relating to severance payments, food coupons, dividends and any other form of transfer between the firm and the worker as payment for work services. Unemployment subsidies received in the last year are also recorded, making it possible to approximate the amount of unemployment benefits received in the unemployment spells of the previous year.[16] These data are only available after 2005, and thus I use the 2005-2013 waves of the MCVL.

One concern that arises when using administrative data to study unemployment is that administrations only count registered unemployment spells. A possible way to address this issue is to focus on non-employment spells rather than unemployment. But as shown in Lafuente (2019) very straightforward adjustments using official definitions and labour laws make the MCVL and the Labour Force survey comparable in the level of unemployment rate, worker flows and unemployment duration. I follow that approach and refer to the selected non-employment spells as unemployment thereafter.

The sample is comprised of all of the completed unemployment spells in the 2005-2013 period, ending in a permanent or temporary job excluding recalls to a previous employer, for workers aged between 25 and 55 years of age at the start of the unemployment spell. This makes a total of 766,462 observations of which 555,302 have observed wages in the previous job and 557,478 have observed wages in the next job. This last reduced sample will be used to test the second implication (better searchers get better wages). The main

[15]This is not the same as common occupational codes used in the Labour Force Survey, rather than a scale that goes from unqualified blue collar jobs to technical and managerial roles. A combination of both industry and occupational scale could be used to back out a noisy approximate of occupational codes, but at the same time the occupational scale is more directly linked to the type of skill: manual at one end and more cognitive at the other.

[16]If the worker has several unemployment episodes in the year for which she received unemployment compensation it is not possible to separate them. However, these occurrences are rare as most unemployed workers cannot accumulate enough working spells to be eligible within the year.

descriptive statistics are displayed in Table 1.

3.4 Results

Results are shown in tables 2 to 5. Table 2 and 3 show the results relating to duration of the unemployment spell, table 4 shows the regression results for wages in the next job and table 5 shows the results of regressing the duration of next employment spell until unemployment. In this last table there are also the results of regressing the probability that the next employment contract is permanent (with the alternative is temporary).

Duration of unemployment

Table 2 shows the results of the regression on duration of unemployment as described in equation 1. The first three columns correspond to pooled OLS regressions while columns 4-6 display the results with individual fixed effects. Standard errors are clustered at the individual level, allowing for individual serial correlation. In regressions (1) and (4) wages and unemployment benefits are not included, which allows to capture a larger share of observations. Columns (2) and (5) include a control for past wages and (3) and (6) controls for unemployment benefits.

The first thing to note is that the coefficient on the number of temporary contracts held in the past (TCs) is significant and negative even when controlling for individual fixed effects. Each temporary contract reduces the unemployment spell by 4% on average. The addition of past wages (column 2) and unemployment benefits does not affect this coefficient significantly. The coefficient of the quadratic term TCs^2 is positive in all regressions which means that the effects of search capital (as captured by temporary contracts) dampens over time. The coefficient is very small (less than $1e^{-5}$): it will take more than 100 temporary contracts for the marginal effect of an extra contract to turn negative. Recall that the average number of temporary contracts is 4 so the effect of exposure to temporary contracts on unemployment duration is 15% for the average worker.

The magnitude of the coefficient is reduced in the fixed effects regressions. This can be interpreted as the within-worker effect or the effect for each worker throughout their working life. The effect on pooled regressions can be interpreted then as the effect between different workers. The total effect of search capital is then composed of intrinsic individual differences and a dynamic component that is captured in the fixed effects regressions.

Recall that these are recent temporary contracts or temporary contracts held since 2005. Table 10 in the appendix shows the results when using all temporary contracts ever held. The coefficients are smaller in both the pooled and fixed effect regressions but remain significant at the 1 per thousand level. This can be explained by the depreciation effect of search capital: only *recent* contact with the job market improves workers' search

Table 2: Duration, contracts since 2005

	Pooled OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
No. T	-0.040***	-0.039***	-0.040***	-0.007***	-0.007***	-0.006***
	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0015)	(0.0014)
No. T^2	0.000***	0.000***	0.000***	0.000***	0.000*	0.000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	-0.034***	-0.034***	-0.036***	-0.003	-0.004	-0.003
	(0.0022)	(0.0020)	(0.0021)	(0.0024)	(0.0026)	(0.0026)
Last P	0.092***	0.052***	0.057***	0.071***	0.042***	0.055***
	(0.0034)	(0.0041)	(0.0041)	(0.0041)	(0.0055)	(0.0055)
Tenure	0.037***	0.035***	0.032***	0.058***	0.068***	0.063***
	(0.0016)	(0.0018)	(0.0018)	(0.0025)	(0.0032)	(0.0032)
Tenure^2	-0.001***	-0.001***	-0.001***	-0.003***	-0.003***	-0.003***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Experience	-0.020***	-0.020***	-0.023***	-0.016***	-0.024***	-0.033***
	(0.0008)	(0.0009)	(0.0009)	(0.0033)	(0.0041)	(0.0042)
Experience^2	0.000***	0.000***	0.000***	0.002***	0.002***	0.003***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Age	0.001*	0.001***	0.001***	0.016***	0.016***	-0.000
	(0.0002)	(0.0003)	(0.0003)	(0.0019)	(0.0025)	(0.0026)
log(past wage)		0.020***	0.021***		0.047***	0.050***
		(0.0028)	(0.0028)		(0.0035)	(0.0035)
log(UI)			0.001***			0.002***
			(0.0000)			(0.0000)
Constant	1.189***	0.689***	0.727***	0.257***	-0.334***	0.266**
	(0.0200)	(0.0361)	(0.0365)	(0.0642)	(0.0940)	(0.0954)
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓
Observations	741,337	530,073	524,294	764,466	543,492	537,533
Adjusted R^2	0.547	0.564	0.566	0.462	0.458	0.463
AIC	1916082	1370190	1353341	1470574	994298	975084

Robust standard errors (clustered at the individual level) in parentheses. Sample is all finished unemployment spells ending in employment, for workers aged 20-55. Excludes recalls (workers returning to the same firm), self-employed and spells shorter than 15 days. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

abilities and reduces unemployment duration. The appendix shows the results broken down by industry, gender and age groups (20-30, 30-40, 40-50 and over 50 years old). The negative coefficient associated with temporary contracts holds for: all industries (except mining and extraction), both genders (in fixed effects and pooled regressions) and for pooled regressions for all age groups. In the fixed effects regressions by age the significance of the coefficient falls below the 5% threshold except for workers in their 30s. Recall that in fixed effects regressions the coefficient can be interpreted as the average effect of finding different jobs on unemployment duration over time for an individual. It may take time for this effect to be significant so it is unlikely it will be seen for those in their very early careers. It is also remarkable that for both genders the coefficients are very similar not only for the number of temporary contracts but for every other variable. This can be explained by the sample which is composed of workers with a high attachment to the labour market.

The number of permanent contracts is also negatively correlated to unemployment duration. However, its coefficient is no longer significant after the inclusion of fixed effects. It is not surprising that the regressions fail to capture a significant effect across time as the number of permanent contracts is small for the majority of workers. In table 10 in the appendix where all permanent contracts are counted the coefficient becomes positive and significant. This evidence suggests that being good at searching in the past is not helpful for searching in the present. A high number of permanent contracts in these regressions signals the worker had many short and unstable jobs in the past before temporary contracts became the norm. This outdated experience seems to be harming current search outcomes. A possible interpretation of this result is that the introduction of temporary contracts made more clear to the worker and the firm that the labour relationship was not meant to last. Then workers can change their search and human capital strategies by being more open to changing jobs, for example.

The dummy for a permanent contract is always significant and positive. Workers coming from a permanent contract have between 5.5 and 9.2% longer unemployment spells in the cross section, with similar magnitudes in the fixed effect regression. This can be interpreted as permanent workers preferring to queue longer for permanent contracts or simply the effect of severance payments as an extension of unemployment benefits. Note that the amount of unemployment benefits is positively correlated to duration, and so are the entitlement dummies (not shown in the table). As discussed in the previous section, even if the measure of unemployment benefits is noisy in the data this variable can account for the difference between registered and unregistered unemployment.

As for the other job market experience variables, $Tenure$ and $Experience$, the results are more mixed. Tenure is positively correlated with duration and the magnitude of the coefficient increases after adding fixed effects to the regressions. The coefficient on the quadratic term is negative and significant. However, it takes a long time (between 20 and

30 years of tenure) for its overall effect to become negative. As discussed before, tenure is related to multiple channels: The loss of specific human capital and the magnitude of severance payments. It can also be interpreted as a fall in search capital over time if the worker stays in the same job for long.[17] On the other hand, job experience before the last employment spell is negatively correlated to duration both in the cross section and with individual fixed effects. Its quadratic coefficient is very small and positive. It takes more than 20 years for the marginal effect to become negative. The fact that the signs on tenure and experience have opposite signs could be interpreted as reflecting the different way workers accumulate human capital: after displacement workers could suffer a loss of specific human capital but not of general human capital – the skills they learned from previous jobs. Notice that in the pooled regressions the magnitude of the effect of one more temporary contract is larger than one more year of previous job experience and close to one more year of tenure (with reversed signs).

Finally, note how the log of past wages is positively correlated to duration, and its inclusion changes the magnitude of the constant as well. This could indicate that richer workers may have the financial capacity to wait longer for better matches.

To complement the previous analysis, table 3 shows the result of the logistic regression on the probability of becoming long-term unemployed. The first two columns show the results for the sample of all unemployment spells that started before 2012. Columns 3-4 show the results for the restricted sample of completed unemployment spells. Recall that this comparison provides a robustness check on sample selection: in all other regressions we need to observe the worker finding employment at the end of the unemployment spell. This is a useful exercise since by the end of 2013 there were many unfinished spells and therefore the results may be biased to only better searchers.

The number of temporary contracts is negatively correlated with the probability of long-term unemployment. This is true both when long-term unemployment is defined as 1 year or more or 2 years or more of unemployment. One extra temporary contract diminishes the probability of being unemployed for a year or more by 9.5% on average $(1 - e^{-0.1})$ and 13% the probability of being unemployed for two years or more. These coefficients are very similar when only considering finished spells. The quadratic term is positive but very small. On the other hand, both tenure and coming from a permanent contract increase the probability of long-term unemployment. Previous work experience decreases it. This mirrors the results of table 2. The quadratic effect in tenure is small: it takes more than 40 years for the overall effect to become negative. Using the total number of temporary and permanent contracts (shown in table 11 in the appendix) instead of recent ones has a similar effect to table 2: the coefficient of temporary contracts is reduced

[17] In principle, this is at odds with the mechanism in Bradley et al. (2018) where long-tenured workers entering unemployment have a large number of prospects or external offers. However it can be rationalised by their model if the worker is more likely to have rejected other external offers and therefore enters unemployment with less prospects.

Table 3: Prob of LTU, contracts since 2005

	All sample		Completed spells	
	$P(\geq 1year)$	$P(\geq 2years)$	$P(\geq 1year)$	$P(\geq 2yeasr)$
No. T	-0.100***	-0.143***	-0.100***	-0.146***
	(0.0010)	(0.0017)	(0.0012)	(0.0024)
No. T^2	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	-0.158***	-0.215***	-0.138***	-0.195***
	(0.0032)	(0.0051)	(0.0040)	(0.0069)
Last P	0.278***	0.269***	0.220***	0.198***
	(0.0085)	(0.0119)	(0.0097)	(0.0148)
Tenure	0.076***	0.024***	0.083***	0.055***
	(0.0032)	(0.0043)	(0.0041)	(0.0061)
Tenure^2	-0.002***	0.000	-0.002***	-0.001**
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Experience	-0.020***	-0.017***	-0.026***	-0.033***
	(0.0006)	(0.0009)	(0.0008)	(0.0013)
Age	0.025***	0.038***	0.013***	0.018***
	(0.0004)	(0.0006)	(0.0005)	(0.0007)
Constant	-2.350***	-3.609***	-1.652***	-2.500***
	(0.0453)	(0.0678)	(0.0516)	(0.0838)
Controls				
Years	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Occupation	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	969,290	969,290	741,337	741,337
AIC	808844.217	442075.213	613674.142	300443.668

Robust standard errors in parentheses. Sample is all finished unemployment spells ending in employment, for workers aged 20-55. Excludes recalls (workers returning to the same firm), self-employed and spells shorter than 15 days. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and the coefficient on permanent contracts becomes positive.

Table 4: Future Wages, contracts since 2005

	Pooled OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	log(next wage) all jobs	log(next wage) jobs > 3 months	log(next wage) jobs > 6 months	log(next wage) all jobs	log(next wage) jobs > 3 months	log(next wage) jobs > 6 months
No. T	0.0131***	0.0033***	0.0013	0.0014	0.0148***	0.0222***
	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0020)	(0.0048)
No. T^2	-0.0000***	-0.0000	0.0000	-0.0000	-0.0004***	-0.0006*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0003)
No. P	0.0024	0.0068***	0.0101***	-0.0007	0.0161***	0.0205***
	(0.0014)	(0.0009)	(0.0012)	(0.0017)	(0.0030)	(0.0038)
Last P	-0.0022	0.0067**	0.0067*	-0.0003	0.0000	0.0051
	(0.0028)	(0.0026)	(0.0030)	(0.0037)	(0.0044)	(0.0063)
Tenure	0.0073***	0.0046***	0.0045***	-0.0065***	-0.0056*	0.0005
	(0.0011)	(0.0011)	(0.0012)	(0.0018)	(0.0025)	(0.0035)
Tenure^2	-0.0004***	-0.0002***	-0.0002***	0.0003**	0.0004	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Experience	-0.0016**	0.0092***	0.0091***	0.0662***	0.0372***	0.0319***
	(0.0006)	(0.0005)	(0.0005)	(0.0029)	(0.0034)	(0.0049)
Experience^2	0.0000*	-0.0002***	-0.0002***	-0.0015***	-0.0012***	-0.0013***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Age	0.0019***	0.0009***	0.0010***	-0.0040**	-0.0081***	-0.0077**
	(0.0002)	(0.0001)	(0.0002)	(0.0014)	(0.0018)	(0.0026)
log(weeks)	-0.0687***	-0.0277***	-0.0285***	-0.0228***	-0.0161***	-0.0175***
	(0.0014)	(0.0011)	(0.0013)	(0.0011)	(0.0014)	(0.0020)
log(past wage)	0.0908***	0.1028***	0.1122***	-0.1493***	-0.0783***	-0.0816***
	(0.0025)	(0.0023)	(0.0028)	(0.0032)	(0.0042)	(0.0066)
Constant	8.3651***	7.8090***	7.7412***	11.1373***	10.6123***	10.6694***
	(0.2334)	(0.2609)	(0.3297)	(0.0459)	(0.0568)	(0.0858)
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓
Observations	425,230	209,215	142,536	434,803	213,628	145,363
Adjusted R^2	0.167	0.249	0.276	0.036	0.031	0.037
AIC	649,288	174,877	115,886	305,164	-159,320	-177,432

Robust standard errors (clustered at individual level) in parentheses. Sample is all finished unemployment spells ending in employment, for workers aged 20-55. Excludes recalls (workers returning to the same firm) and self-employment

Wages in the next job

Table 4 shows the outcomes of the wage regressions. The dependent variable *log(next wage)* is the natural logarithm of annual wages in the job after the current unemployment spell. Column 1 shows the results for all observations, column 2 only includes jobs that last at least three months and column 3 only considers jobs that last at least six months. These restrictions are meant to reduce the noise in the measurement of wages as almost half of all jobs with recorded wages last for less than 3 months. However, this makes the interpretation of the fixed effects coefficients as a dynamic effect over time more difficult.

The coefficient of the number of temporary contracts is positively correlated to wages in the next job in all regressions. It is significant at 1% per thousand in all regressions but two: polled for jobs longer than 6 months and in fixed effects for all wages. Accumulating temporary jobs does not lead to worse wages upon re-employment. Likewise, the coefficient on the number of permanent contracts is positive and significant in all but the unrestricted sample regressions (columns 1 and 4). Its coefficient is also larger than the one for temporary contracts. This suggests that workers with more permanent jobs search differently. Recall that in the first set of regressions the number of permanent contracts was not significantly correlated with duration once fixed effects were taken into account. The results from the regressions on wages show that when workers get a longer job they do find better paid jobs even if it takes them the same time to find them. This is consistent with workers gaining search capital both from temporary and permanent contracts but temporary jobs increase relatively more the search skills of workers over time.

The largest coefficients in the regressions are related to other variables like education or experience, as expected. In particular, past job experience is positively related to wages (except on the first regression) while tenure is positively correlated in the pooled regressions but negatively after controlling for individual fixed effects. The negative signs could indicate the effects of the loss of specific human capital. However, in the last column the coefficient is positive but not significant at 5%. In this regression the sample is restricted to long lasting jobs which suggests that tenure does not have a clear effect on future wages.

Finally, notice how longer unemployment spells are related to lower wages both in the cross section and with fixed effects. This relates to the literature on duration dependence where workers who are unemployed longer tend to accept lower wages. This could reflect a loss of human capital during the unemployment spell or simply the fall of the reservation wage over time.

Duration of next job spell

Lastly, table 5 shows the results of the regressions on next job duration. As before, the first three columns correspond to pooled regressions (one spell, one observation) and the last three are for fixed effect regressions as in table 2. Columns 1 and 4 show the regressions where duration of next job in log(weeks) is the dependant variable. Columns 2 and 4 have the next employment spell as the dependant variable – that is, considering not only how long the next job is but all the subsequent employment spells until the next time the worker is unemployed. This restriction generates a sample selection issue:

Table 5: Regressions on duration of next job

	Pooled data			Fixed Effects		
	(1) Duration of next job (log weeks)	(2) Duration of next employment spell	(3) $\Pr(P_{t+1} \mid U_t)$	(4) Duration of next job (log weeks)	(5) Duration of next employment spell	(6) $\Pr(P_{t+1} \mid U_t)$
No. T	-0.056***	-0.056***	-0.078***	0.058***	0.060***	0.464***
	(0.0024)	(0.0022)	(0.0017)	(0.0053)	(0.0056)	(0.0081)
No. T^2	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.008***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0003)
No. P	-0.016***	-0.025***	0.265***	0.049***	0.071***	-0.583***
	(0.0032)	(0.0033)	(0.0048)	(0.0066)	(0.0084)	(0.0117)
Last P	0.068***	0.074***	0.406***	-0.001	0.009	-0.334***
	(0.0085)	(0.0086)	(0.0131)	(0.0111)	(0.0113)	(0.0197)
Tenure	0.029***	0.005	0.002	-0.064***	-0.087***	0.003
	(0.0040)	(0.0040)	(0.0053)	(0.0061)	(0.0064)	(0.0121)
Tenure^2	-0.001***	-0.000	0.000	0.003***	0.004***	-0.000
	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0008)
Experience	0.059***	0.054***	0.011***	-0.378***	-0.637***	-0.113***
	(0.0016)	(0.0016)	(0.0024)	(0.0091)	(0.0095)	(0.0159)
Experience^2	-0.001***	-0.001***	0.000	-0.002***	-0.001	-0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0004)	(0.0005)
Age	-0.004***	-0.008***	-0.001	0.024***	0.047***	-0.078***
	(0.0005)	(0.0005)	(0.0008)	(0.0063)	(0.0070)	(0.0082)
log(weeks unemp)	0.191***	0.173***	0.012*	0.094***	0.105***	0.048***
	(0.0034)	(0.0038)	(0.0050)	(0.0038)	(0.0041)	(0.0064)
log(past wage)	0.014**	0.038***	0.055***	0.182***	0.175***	0.102***
	(0.0054)	(0.0056)	(0.0080)	(0.0067)	(0.0069)	(0.0140)
Constant	0.887***	1.262***	1.990***	1.566***	3.068***	
	(0.0656)	(0.0695)	(0.0872)	(0.1987)	(0.2121)	
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	-
Region	✓	✓	-	✓	✓	-
Observations	427,515	427,515	530,110	438,739	438,739	126,432
Adjusted R^2	0.167	0.184	–	0.085	0.153	–
AIC	1591865.244	1621002.168	361163.185	1288272.176	1310452.532	77881.855

Robust standard errors in parentheses. Sample is all finished unemployment spells ending in employment, for workers aged 20-55. Excludes recalls (workers returning to the same firm), self-employed and spells shorter than 15 days.

workers have to return to unemployment within the time window of the panel by the end of 2013) for their observation to be counted. Columns 3 and 6 show the results of the logistic regression where the dependent variable is the probability of obtaining a permanent job after the end of the current unemployment spell – which is one if the next job is permanent and zero if it is temporary. These regressions aim to capture how stable the jobs that are found by workers are.

The result from the pooled regressions show that the number of temporary contracts is negatively correlated with next job duration: new jobs are shorter the more temporary contracts the worker has. But in the fixed effects regressions as the worker accumulates more jobs over time the duration of next jobs becomes longer too. Likewise, the probability of getting a permanent job out of unemployment is negatively correlated with temporary contracts in the pooled regressions but positively correlated with fixed effects. The different impact in individual fixed effects suggests that there is an unobserved component that makes some workers more likely to have stable jobs. All regressions have controls for industry so this unobservable factor seems to be independent from industry composition. Another possible interpretation is that workers with many temporary contracts are very good at finding jobs and are therefore less concerned with employment stability. They may prefer more stable jobs but they are also willing to accept short jobs more often than workers who are not used to temporary contracts. This observation, together with the fact that people with more temporary jobs finds jobs faster, suggests a trade-off of waiting for a more stable job versus staying in unemployment for longer. There is some evidence of this effect in that the coefficient on the log duration of the unemployment spell in table 5 is always positive. What may be a good strategy when the job market is booming could turn into a higher chance of long-term unemployment during recessions: if the jobs available in recessions are worse then being willing to accept an unstable job can keep a worker out of long-term unemployment. Recall that the results from table 4 showed that on average workers with more temporary contracts tend to find higher wages. This suggests that some workers may specialize on better paid short term jobs. Nevertheless, the results after controlling for fixed effects suggest that leaving fixed individual preferences aside more temporary contracts seem to increase job stability as well as the probability of finding a permanent contract out of unemployment.

The number of permanent contracts follows the same patterns when considering the duration of next employment spell. However, the signs are reversed for the probability of obtaining a permanent job out of unemployment. This indicates that workers with many permanent contracts have some specific trait that makes them more likely to get another permanent contract in the cross section. But over time workers with more previous permanent contracts are less likely to get another directly out of unemployment. Here it is convenient to remember that we are observing the workers who eventually come back to unemployment. So if over time workers keep becoming unemployed their chances of finding a stable job also fall over time. Same applies to tenure in the previous job.

4 Theoretical Model

I have presented evidence of the positive effect that having more jobs can have on future unemployment outcomes, including controls for other potential explanations (human capital, incentives to search for jobs and ladder-claiming effects). Here I build a structural model with search capital alongside the two other main channels in the literature as presented in section 2.4: asset accumulation (workers with more temporary contracts save less and therefore accept any job) and hysteresis (workers with permanent contracts build up human capital and are willing to wait for a better job). In the model, search capital increases every time a worker finds and accepts a job and decreases over time if the worker does not search for a long time – which happens during long-term jobs. The main goal is to show that the introduction of search capital into a standard search model with asset accumulation can explain the different evolution of long-term unemployment rates across age groups in the data. Additionally, the model can also reproduce the reduce-form evidence presented in section 3.

The model joins two separate strands of the macro search literature. First, dynamic models with savings and human capital depreciation as proposed by Ljungqvist and Sargent (2008) and Kitao et al. (2017) give the resources and incentives for an older worker to remain in long-term unemployment. The resources come from longer prior employment spells which allow a worker to accumulate capital. The incentives are given by the worker's desire to smooth out income shocks arising from the loss of employment and human capital. In these models, the destruction of some human capital following job loss forces the worker to accept a lower wage than her previous one. In this way, what drives an older worker's willingness to wait for better jobs is the "job ladder" component of human capital. Second, the dual-market literature as developed by Blanchard and Landier (2002), Güell (2003), Costain et al. (2010) and Bentolila et al. (2012) among others. In these models, temporary contracts are modelled explicitly. However, most of these models focus on the relation between heterogeneous firing costs and unemployment. Therefore they assume hand-to-mouth, risk-neutral workers, which leaves out the desire to smooth out consumption. However, this mechanism plays a key role in shaping worker's preferences over temporary and permanent contracts. In their absence, most of the literature either assumes higher wages under permanent contracts or abstracts from workers' preferences altogether.[18]

In order to model the effects of search capital as workers age I use a dual-market

[18]A few notable exceptions to this include Alonso-Borrego et al. (2005) and Cozzi and Fella (2016). The latter shows the effect that risk aversion and consumption smoothing can have in the presence of tenure-increasing severance payments.

model that allows risk averse workers to save in the spirit of Cozzi and Fella (2016). In this way, a young worker does not have enough savings to smooth out consumption while unemployed which forces her to accept worse paying jobs. As the worker ages and if she manages to save she will become more selective in the jobs she chooses. Here, a permanent contract offers not only higher earnings but also a stable income. Search capital alters these patterns by making experienced young workers more efficient at searching and older workers in long matches less efficient at searching. An experienced young searcher can afford to be more selective because she receives offers more frequently while an older, recently unemployed worker may accept a lower paying job in order to regain search skills. Whichever is the most dominant effect is what drives the results from the model.

The addition of dual markets, savings, risk aversion and search capital makes for a rich but complicated model. In order to keep the model simple while retaining the core mechanisms outlined above I make some simplifying assumptions on other aspects of the economy. The main assumption is the absence of the firm's problem, making it a partial equilibrium model. Workers draw an offer from an exogenous distribution which they either accept or reject. The assumption of a fixed wage instead of wage bargaining or another wage-setting mechanism may be strong as it implies little correlation between present and future wages. An alternative would be to introduce some form of general human capital, as in Kitao et al. (2017). But because permanent jobs are very stable and workers can accumulate assets, the random search assumption is not as strong as it initially appears. In fact it is not too far from the match-specific productivity assumption in search and matching models. The other main assumption is the lack of wage bargaining. Its introduction would not change the results substantially as it would only introduce a connection between the outside option of workers and unemployment through less vacancy posting. There is also the concern that the wage distributions from the model would not correspond to those in the data, particularly for lower wages. Here, the introduction of expiring unemployment benefits implies that poor young workers are willing to accept the lowest offered wage.

Another important assumption is the introduction of a no-borrowing constraint that binds for the poorest individuals. This is important to account for financially constrained individuals, as a large share of unemployed workers was not receiving unemployment benefits after 2010. It helps match the observed wage distributions, especially at the lower end. It also gives risk averse workers incentives to self-insure against long unemployment spells that may bring them close to the constraint. The financial aspect of the model is not of primary interest but a similar framework could easily be adapted to consider financial problems, such as tightening borrowing constraints or housing. The fact that financial constraints are secondary in the model is helped by the partial equilibrium setup as households take the interest rate as given. Finally, in the model unemployment benefits expire and not all workers are allowed to claim them. This is an important feature to accurately reflect the problems young workers faced both before and during the crisis: as young workers do not accumulate enough assets the threat of low consumption makes them lower their standards for employment. Therefore they accepted very unstable and low paying jobs. As workers build up a stock of assets, they are able to raise their reservation wages and access better jobs.[19]

4.1 Value functions

Time is discrete, and one time unit t corresponds to a month. Workers are risk averse with a CRRA utility function

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}. \tag{5}$$

They live indefinitely but face a stochastic retirement shock ρ upon which they leave the labour force permanently and get a utility value of zero. Additionally they discount the future at rate $\tilde{\beta}$ so their effective discount rate is $\beta = \tilde{\beta} + \rho$.

All workers have two main state variables: assets (a) and search capital (s). They accumulate assets by making a saving decision every period. They face a borrowing constraint such that assets cannot be negative: $a \geq 0$. Savings earn a fixed, constant interest rate r. All workers are born with zero assets and there are no bequests.

Search capital s is a discrete variable that increases the job finding probability of workers. It increases with a stochastic probability each time a worker finds and accepts a job. That is, if a worker accepts a job, her search capital increases to the next level (s^+) with state-dependent probability $\pi^+_{s'|s}$. Note that this implies that the worker needs to accept the job for search capital to increase. As explained in section 2.1 this simplifying assumption makes the model more tractable and ensures that there is no duration-dependence of unemployment. Conversely, for an employed worker search capital depreciates to the lower level s^- with probability $\pi^-_{s'|s}$.

Workers can be employed on a permanent contract (P), employed on a temporary contract (T), unemployed with unemployment benefits (U) and unemployed without unemployment benefits (0).

Employed workers

At the beginning of each period employed workers with a permanent contract calculate the continuation value of their current match and decide whether to quit or stay in the next period. Then they make their consumption and saving decisions. If they decide to quit their job they exit to unemployment without benefits.[20] Temporary workers are

[19] The rules of unemployment benefits are specific for each country. The assumptions of the model are specific to the Spanish context as described in section 3.1.

[20] The lack of benefits after a quit reflects the institutional setting of Spain.

assumed to commit to stay until the end of the duration of the contract.[21]

Permanent workers earn a wage $w(h)$ which is strictly increasing in their level of match-specific human capital. All new permanent contracts start with zero human capital but wages differ by their initial level $w(0)$. Workers accumulate human capital over time with state-dependent probability $p(h)$. These probabilities create an increasing wages-tenure profile. Upon job loss all human capital is lost. A worker in a permanent contract faces an exogenous job destruction rate δ_P upon which they exit to unemployment with unemployment benefits. If the job is not destroyed with probability α_{PT} permanent workers receive an outside offer of a temporary contract. This offer consists of a wage $\tilde{w}$ drawn from the distribution $F_T(\tilde{w})$. Workers can then choose to accept the offer and switch to the temporary contract. There is no other on-the-job search for permanent workers. I consider this not a result of search on the side of the worker but as an exogenous shock similar to a breakup of the match.[22] If the worker stays in the permanent contract then her human capital may increase or her search capital would decrease.[23]

The value function for a permanent worker with human capital h and starting wage w is then given by:

$$V^P(w,h,a,s) = \max_{a'} u(c(w,a)) + \beta \max\{V^0(a',s), \tilde{V}^P(w,h',a',s')\} \tag{6}$$

$$\begin{aligned}\tilde{V}^P(w,h',a',s') = \alpha_{PT} \int max\{V^P(w,h,a,s), V^T(\tilde{w},a,s)\} dF_T(\tilde{w}) + \delta_P V^U(a',s) + \\ (1-\delta_P-\alpha_{PT})\Big[p(h)V^P(w,h',a',s) + (1-p(h))V^P(w,h,a',s^-)\Big]\end{aligned} \tag{7}$$

st.

$$c + a' = (1+r)a + w(h)$$

$$s^- = \pi^-_{s'|s} s^- + (1-\pi^-_{s'|s})s$$

Where $\tilde{V}^P(w,h,a,s)$ denotes continuation value of current employment. Apostrophes denote next period variables.

Temporary workers earn a wage w which does not depend on their human capital level. They face a higher job destruction shock (δ_T). If the match is destroyed with probability δ_{T0} workers exit to unemployment without benefits. With complementary probability $1-\delta_{T0}$ they exit to unemployment with benefits. This simplifying assumption captures

[21] This simplifying assumption allows to better match the flows in and out of temporary contracts. Since average contract length is short (12 months in the calibration), this assumption is not quite slavery.

[22] This exogenous rate is necessary to match the temporary rate we observe in the data. Transitions to temporary contracts from permanent are substantial among young workers.

[23] Allowing for both search capital depreciation and human capital accumulation shocks to happen together does not alter the results substantially, given the short period of time of the model – a month.

the empirical fact that some temporary workers do not accumulate enough employment contribution periods to be eligible for unemployment benefits. It reflects the fact that temporary jobs are riskier for the worker, not only because of the higher destruction rate but limited access to unemployment insurance.

If the match is not destroyed temporary workers can either be offered a promotion to a permanent contract with exogenous probability α_{TP}, find another temporary job with probability α_{TT} or stay in the current contract. If the worker is offered a promotion but rejects it she exits to unemployment without benefits – as this is a voluntary exit. This promotion shock represents temporary contracts in which the firm tries to retain the worker after the maximum period expires. It is also assumed that all temporary workers engage in on-the-job search. Since there is no trade-off of time or other resources between search and production all workers would chose to search if they where given the choice. Workers draw a new temporary wage offer from the same distribution $F_t(\tilde{w})$ as permanent workers. If they accept the outside offer workers may increase their search capital. Finally, temporary workers are also subject to search capital depreciation with the same probabilities as permanent workers. In the calibrated model search capital is mainly lost by workers on permanent workers since temporary contracts do not last long.

The value function of a temporary worker employed with wage w is then:

$$\begin{aligned} V^T(w,a,s) = \max_{a'} u(c(w,a)) + \beta\Big(&\alpha_{TP} \max\{V^0(a',s), V^P(w,0,a',s)\} + \\ &\alpha_{TT} \int_0^{\bar{w}} \max\{V^T(w,a',s), V^T(\tilde{w},a',s^+)\} dF_T(\tilde{w}) + \\ \delta_T\Big[\delta_{T0}V^0(a',s) + (1-\delta_{T0})V^U(a',s)\Big] &+ (1-\delta_T-\alpha_{TT}-\alpha_{TP})V^T(w,a',s^-)\Big) \end{aligned} \tag{8}$$

st.

$$c + a' = (1+r)a + w$$

$$s^+ = \pi^+_{s'|s}s^+ + (1-\pi^+_{s'|s})s$$

$$s^- = \pi^-_{s'|s}s^- + (1-\pi^-_{s'|s})s.$$

Unemployed workers

Unemployed workers receive b in every period if they are entitled to benefits and zero otherwise.[24] All unemployed workers search and receive a job offer of contract type $j \in \{P,T\}$. The arrival rate $\alpha_j(s)$ is increasing in search capital s. The job offer consists of an entry wage offer w draw from a contract-specific distribution $F_j(w)$. If they accept it

[24] When solving the model numerically they receive a subsistence amount close to zero.

their search capital may increase with probability $\pi^+_{s'|s}$. Because all workers are actively searching, search capital does not depreciate while unemployed. Finally, unemployed workers lose their benefit entitlement with probability δ_0 in each period. The stochastic benefit expiration rate simplifies the model as it is not necessary to keep track of previous employment history. The stock of search capital is the only other history-dependent state variable, alongside assets and human capital for permanent workers.

The value functions of unemployed workers are then given by:

$$\begin{aligned} V^U(a,s) = \max_{a'} u(c(b,a)) + \beta\Big(\alpha_T(s)\int_0^{\bar{w}} \max\{V^U(a',s), V^T(w,a',s')\} dF_T(w) + \\ \alpha_P \int_0^{\bar{w}} \max\{V^U(a',s), V^P(w,a',s')\} dF_P(w) + \\ (1-\alpha_T-\alpha_P)[(1-\delta_0 V^U(a',s) + \delta_0 V^0(a',s)]\Big) \end{aligned} \tag{9}$$

st.

$$c + a' = (1+r)a + b$$

$$s' = \pi^+_{s's} s' + (1-\pi^+_{s's})s$$

$$\begin{aligned} V^0(a,s) = \max_{a'} u(c(0,a)) + \beta\Big(\alpha_T(s)\int_0^{\bar{w}} \max\{V^0(a',s), V^T(w,a',s')\} dF_T(w) + \\ \alpha_P(s) \int_0^{\bar{w}} \max\{V^0(a',s), V^P(w,a',s')\} dF_P(w) + (1-\alpha_T(s)-\alpha_P(s))V^0(a')\Big) \end{aligned} \tag{10}$$

st.

$$c + a' = (1+r)a$$

$$s' = \pi^+_{s's} s' + (1-\pi^+_{s's})s$$

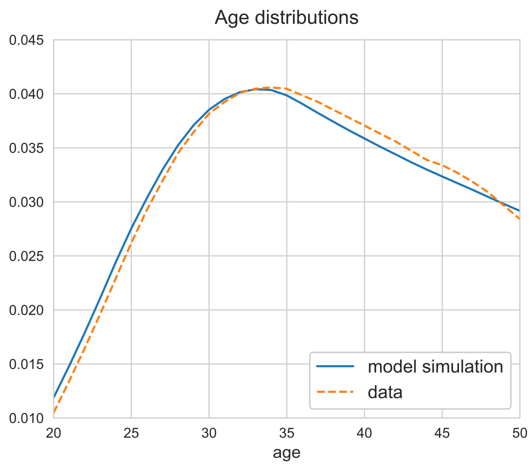
Solving and simulating the Model

A solution to the model is a set of reservation wage rules and policy functions for savings such that workers maximise their utility given their initial states and the reservation wages are consistent with the implied value functions.

I solve this problem by value function iteration. The use of first order conditions would be faster but it is complicated by the "kinks" that result from the various discrete choices workers have to make in the model: quit, accept a job, accept a promotion. The addition of search capital as discrete state variable adds to the dimensionality of the problem. Moreover, as the problem becomes highly non-linear close to the borrowing constraint (low assets/low wages combinations) functional approximation is complicated. All these factors make value function iteration a slow but safe choice.

After finding the policy rule of agents, we can simulate the economy to recreate the conditions of the dataset: 4 years of economic boom followed by 4 years of recession. The recession is modelled a one-off, permanent shock – so the economy instantly switches to recession parameters at the end of the 4th year.

Figure 5: Age distributions



I carry out this simulation in two steps: First, I construct a large panel of agents, all starting with zero assets but different levels of search capital and labour market states. The initial distribution of workers across job market states is set to replicate that of the data at age 20. The initial distribution of search capital and assets is discussed in the next section. Then I simulate the model for 481 periods (months) using the policy functions from the previous step to update the states. I allow for new entrants to come into the market later (starting as unemployed) in order to replicate the age composition of the labour force. This is done in the following way: at the beginning of each period some agents leave the market at the constant, exogenous rate ρ. Then new entrants come in so as to keep the number of agents in this period matching the age distribution, as pictured in the dashed line in figure 5. New entrants are born without search capital, which means that until 35 there are both new entrants with little job market experience and workers who have been active for some years. At age 35 the flow of new entrants stops and the population declines at the constant rate ρ. Figure 5 shows how the resulting age composition of the simulation matches the data closely. I repeat this simulation 200 times[25] to obtain the main moments used to calibrate the model: the distribution

[25] The size of the panel is very large – starting at 5000 agents. This results in very similar moments across simulations.

of labour status of workers at different ages, average unemployment duration and job finding rates.

The second step involves sampling from the previous simulation to construct a panel of workers of different ages. They constitute the economy-wide panel that I simulate forward for 8 years – 4 years with parameters from the boom period (2005-2008) and 4 years from the recession period (2009-2012).[26] The size of this simulation panel is close to that of the dataset: about 4 million observations in each period.[27] From this simulation I obtain an unemployment and temporary share series, as well as a panel of unemployment duration. I compare these aggregate simulated moments with the data, and use the model generated data to run regressions comparable to those in table 2.

4.2 Calibration

Preferences

I set the risk aversion parameter of the utility function to 2. Interest rates are set to 2% annual. The discount factor $\tilde{\beta}$ is set to $1/(1+r)$ which together with the exogenous retirement rate of 0.0027 gives a total discount factor β of 0.995. As described above, the retirement rate is set to match the age composition of the labour force.

Wage Distributions

The wage distributions that both employed and unemployed workers face are taken from the empirical wage distributions of workers younger than 25 in the 2005-2008 period. I select full-time workers that have found a job out of unemployment and subsequently hold it for a month or more. The assumption is that young workers accept all wages.[29] This identifying assumption implies that the resulting cross-sectional wage distributions are going to be the product of workers adjusting their reservation wages over time as they accumulate assets and search capital. This imposes the strong assumption that the wage offer distribution is the same for all workers. This may lead to excessive income risk. In the calibrated model the wage distributions of the economy are not too far off from the

[26] The number of workers who retire in this simulation is both from people reaching age 51 (which are still active, but I do not consider them in the model) and younger workers exiting the market. The number of new entrants in every period balances almost perfectly the entries and exits, but in some periods where this is not the case I allow for more entrants to keep the labour force constant throughout the simulation.

[27] Initially this simulation was also repeated several times but again the size of the panel means the moments are remarkbly close across simulations.

[29] For temporary jobs the wage distributions from young ages are remarkably similar to all workers. This is not the case for permanent jobs which suggests that contrary to the model assumption workers do keep some human capital or that they are less willing to accept low permanent wage offers. The difference between the initial distribution in the model and the overall wage distribution should be given by the difference in acceptance rates of workers over time. In the case of temporary workers this is driven by climbing the temporary job ladder.

Table 6: Calibration

Baseline Parameters – from the data

Parameter	Value	Source
$\alpha_T(1)$	0.1308	UT transition rates at age 20 (2005-2008)
$\alpha_P(1)$	0.0207	average UP monthly flow (2005-2008)
α_{TP}	0.0206	average TP monthly flow (2005-2008)
δ_P	0.007	average PU monthly flow (2005-2008)
δ_T	0.043	average TU monthly flow (2005-2008)
δ_{T0}	0.283	average T0 monthly flow (2005-2008)
δ_0	0.08	average U0 monthly flow (2005-2008)
$F_T(w)$	-	wage distribution for TCs, <24 years old
$F_P(w)$	-	wage distribution for PCs, <24 years old
$w(h)$	-	tenure wage distribution
b	695.52	average UB
s_0,s_1,s_2	{0.666,1,1.333}	duration of unemployment for different NoTs
$\pi^+_{s'\|s}$	{0.5,0.5,0}	duration of unemployment for different NoTs
r	0.0016	2% annual[28]
$\tilde{\beta}$	0.998	1/(1+r)
ρ	0.0027	Age composition of the working population
σ	2.0	Literature

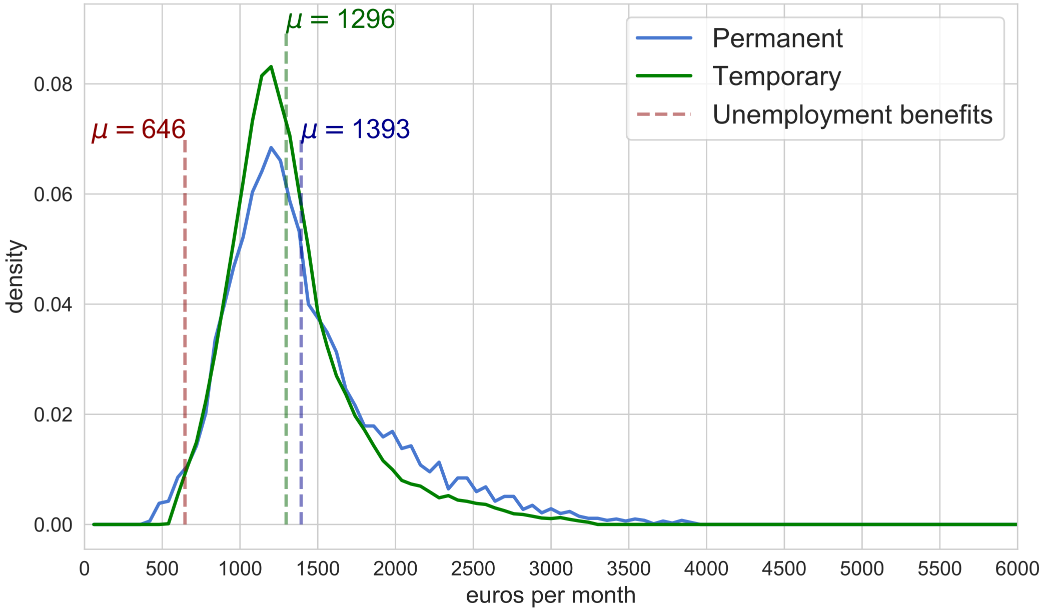
Baseline Parameters – calibrated

Parameter	Value	Target
$\pi^-_{s'\|s}$	{0,1/60,1/60}	depreciation occurs every 5 years on average
α_{PT}	0.0236	PT transition rate at age 20
α_{TT}	0.043	Average number of TCs and average quit rate from T

Recession Parameters

Parameter	Value	Source/Target
$\alpha_T(1)$	0.0663	UT transition rates at age 20 (2008-2012)
$\alpha_P(1)$	0.0102	average UP monthly flow (2008-2012)
α_{TP}	0.0176	average TP monthly flow (2008-2012)
δ_P	0.009	average PU monthly flow (2008-2012)
δ_T	0.0644	average TU monthly flow (2008-2012)
δ_{T0}	0.1801	average T0 monthly flow (2008-2012)
δ_0	0.054	average U0 monthly flow (2008-2012)
α_{TT}	0.021	Average number of TCs and average quit rate from T
α_{PT}	0.0236	PT transition rate at age 20 (2008-2012)

Figure 6: Wage distributions



Source: Own calculations and MCVL, 2005-2013 waves, fiscal annex

data. Unemployment benefits are set to the median – 646 euros a month.

The resulting distributions are shown in figure 6. These wages are then binned from 60 to 6000 euros a month and normalized to give a discrete probability distribution.

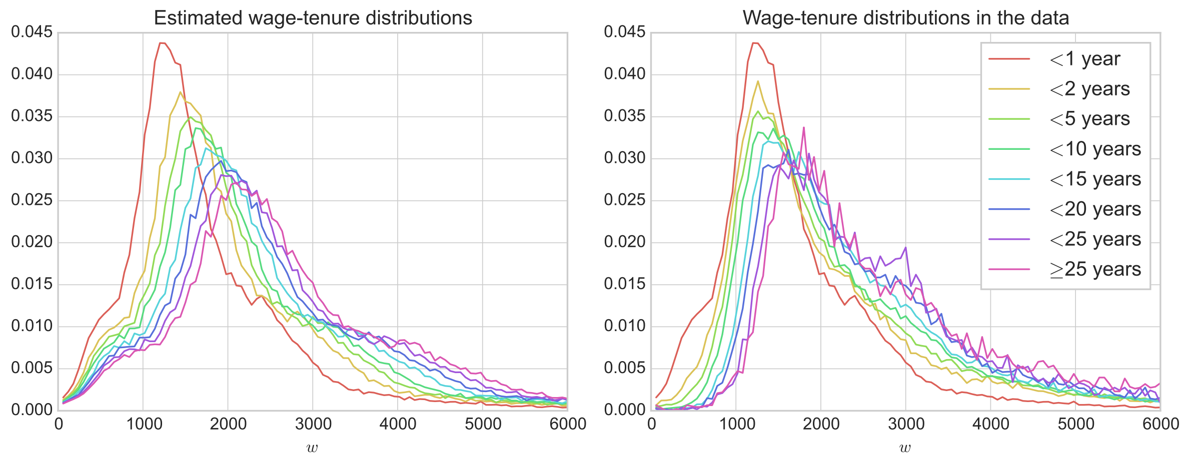
To parametrise the returns to human capital function $w(h)$ for permanent workers I target the evolution of wage distributions on stayers. Here I assume for simplicity a linear wage increase with tenure so $w(h) = w * h$. I then minimize the distance between the observed distributions for each tenure level and the implied distributions with a linear increase. The results are shown in figure 7.

Employment shocks and job arrival rates

Figure 18 in the appendix shows the average monthly transitions age by age between employment an unemployment in the 2005-2008 period. This figure shows that the job separation rate is constant across most ages. In particular this seems to be the case for temporary contracts – as shown in the bottom left panel. The job expiration rates are set to match these levels.

On the other hand, setting the job finding rate is not trivial: it is a combination of reservation wages, actual job arrival rates and search capital composition. Therefore I choose to target job finding rates at age 20 – the age the model takes as the start of the working life. The job finding rate corresponds to the model offer arrival rate as at the beginning of their working life workers have no assets and no search capital (if unemployed).

Figure 7: Tenure-Wage distributions



Source: Own calculations and MCVL, 2005-2013 waves, fiscal annex

The permanent to temporary arrival rate is harder to calibrate as not all workers accept a temporary job from a permanent position. I take a similar approach by targeting the job switching rate at age 20. Then I solve the model and calculate how many permanent workers would switch if offered the average temporary wage. Given this estimate I update the job offer arrival rate and solve again until convergence.[30] Finally, the offer arrival rate for temporary workers α_{TT} is not directly observed in the data. I calibrate it by targeting the average number of temporary contracts in the data and the average quit rate. Too high values of α_{TT} make the number of temporary contracts overshoot and too low values overestimates the quit rate.

For the recession period I use the 2009-2013 equivalents of these transition rates, and re-calibrate α_{PT} and α_{TT} for the recession period. No other parameters are changed in the recession period.[31]

Search capital parameters

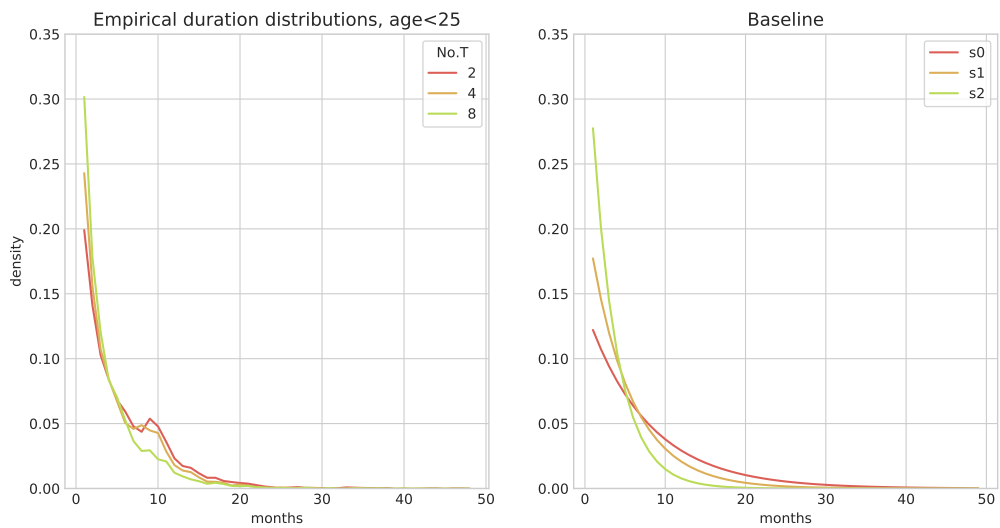
I assume a simple structure for search capital: three levels that result in three proportional job finding rates ($\alpha_j(s) = \bar{\alpha}_j s$). Search capital is not directly observable in the data, and the regressions of the previous section cannot be used simultaneously to pin down parameters and then asses the model fit. The approach is the following: I build the empirical unemployment duration histograms for workers at age 20, separated by the number of previous temporary jobs as figure 8 shows. There is a clear ordering in terms

[30] $\alpha^1_{PT} = \alpha^0_{PT}/S_{PT}$ where S_{PT} is the proportion of permanent workers age 20 that accept an average temporary wage offer.

[31] The data shows that wage distributions did not substantially change in this period. This is true even for new hires. As a robustness check I recalculate the wage distributions for both periods – there is very little difference in the results.

of duration: among workers with a high number of temporary contracts the spike of the histogram at 1 month or less is higher. There is a larger share of workers who find jobs within the first month of unemployment. I focus on the difference of the duration histograms at the first month and assume that these differences are reflecting different search capital levels. Workers with 8 temporary contracts or more have higher search capital than workers with 2 or less. This means their job arrival rate is higher so ceteris paribus there must be more workers leaving unemployment within the first month. For the 3 search capital levels I have imposed I choose 3 thresholds such that the distance of the duration histograms at one month or less is maximized. For example, in the left panel of figure 8 the thresholds are: less than 2, between 2 and 4, and between 4 and 8 temporary contracts. Suppose that these distributions can be approximated by an exponential distribution with arrival rate $\alpha_j(s)$. After setting $s_1 = 1$ for the intermediate group s_0 and s_2 are chosen such that the difference in the resulting duration distribution at 1 month or less mirrors that of the data. Splitting workers into 2 or less, 2 to 4 and 4 to 8 results in the largest distance at one month or less between any three groups in the data. Therefore I set $\pi^+_{s'|s}$ to be 0.5 so it takes 2 contracts on average to progress to the next level of search capital. The values of s are then set targeting the distance at 1 month or less unemployed. That is, setting $s_1 = 1$, $s_0 = 0.6667$ and $s_2 = 1.666$ and plotting the implied histograms (right panel of figure 8) results in distances at one month that match those of the empirical histograms (left panel of figure 8).

Figure 8: Duration of unemployment by number of contracts and search capital level



Source: Own calculations from MCVL, 2005-2013 waves

The final parameter $\pi^-_{s'|s}$ cannot be directly pinned down by the data, so I set it targeting average depreciation occurring every 5 years.

Initial distributions

In order to match the job finding rates in the data it is important to acknowledge that some workers enter the labour market with a job in hand. I set the initial distribution of workers among states (unemployed with and without benefits, employed with a temporary and permanent contract) to match the data at age 20. All workers enter the market with zero assets.

For the initial distribution of search capital, newcomers that start unemployed without benefits are assumed to start from the lowest level of search capital (s_0) while unemployed with benefits are assumed to enter with the first level of search capital (s_1). This is because those receiving unemployment benefits must have accumulated enough job experience to be able to claim benefits. And indeed for unemployed workers less than 25 years old the average number of temporary jobs held before unemployment is lower among those without unemployment benefits (3 vs 5). Workers that enter the labour force with a permanent job at hand are also assumed to have gained search capital (s_1), as well as half of the temporary workers. The initial distribution of search capital is set to match the early unemployment rate (ages 20-25). The results are not sensitive to this distribution.[32]

4.3 Results

First stage simulation

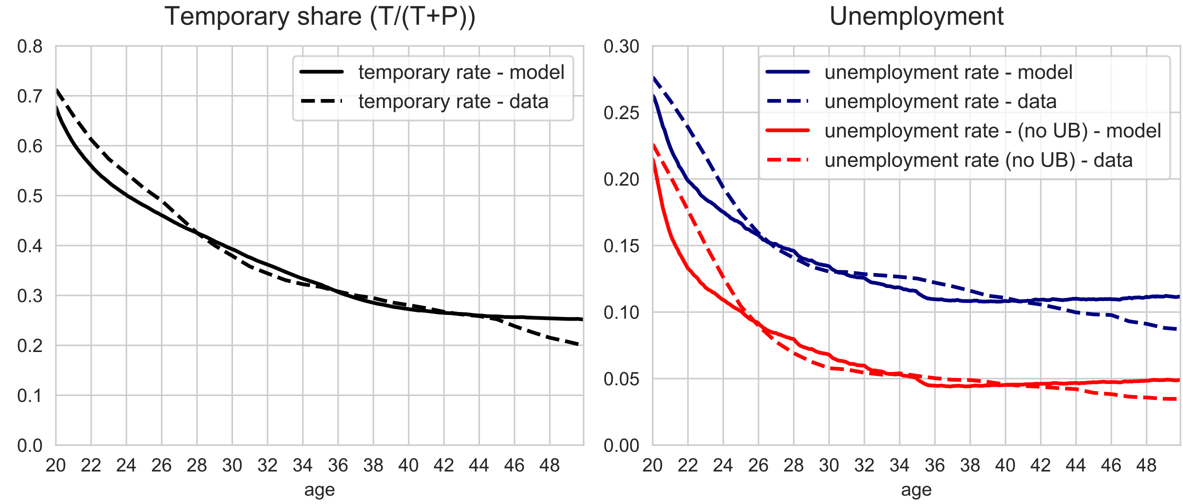
Figures 9 show the resulting temporary share and unemployment rate by age from the first stage simulation. The model generates patterns of unemployment and temporary rates that are close to the data. Note that the unemployment rate is in monthly frequency, calculated using the administrative dataset, which manages to capture a larger share of frictional unemployment that the LFS fails to capture.[33] This explains the high unemployment even during the expansion period. Unemployment falls until age 40. Then it stabilises around 12%. Note that the increase in the number of unemployed who are not receiving unemployment benefits towards the end reflects a higher share of long-term unemployment. See also plot 20 in the appendix for more detailed results on the stocks of each labour state.

Figure 10 shows the evolution of search capital levels among the population over the life cycle. The first panel corresponds to all workers while the second focuses on the changes in the composition among the unemployed. The plot shows shares of each search capital level in the vertical axis. The first panel shows that the share of bad searchers

[32]The only substantial change is when the flows from unemployment without benefit and temporary contracts reach their highest level. See appendix for more.

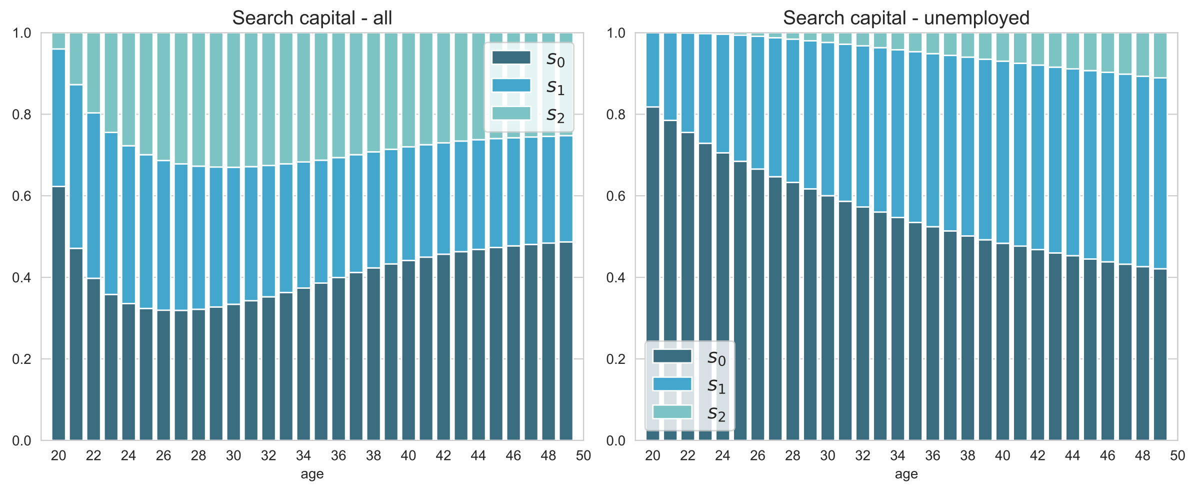
[33]See Lafuente (2019) for more details about comparing unemployment for the LFS and administrative data in Spain.

Figure 9: Unemployment rates and temporary shares by age



Notes: Evolution of the unemployment rate and the temporary share (number of employed with temporary contracts over total number employed) by age. Model output derived from 20 first stage simulations, with a panel of 16,000 workers entering the labour force at 20.

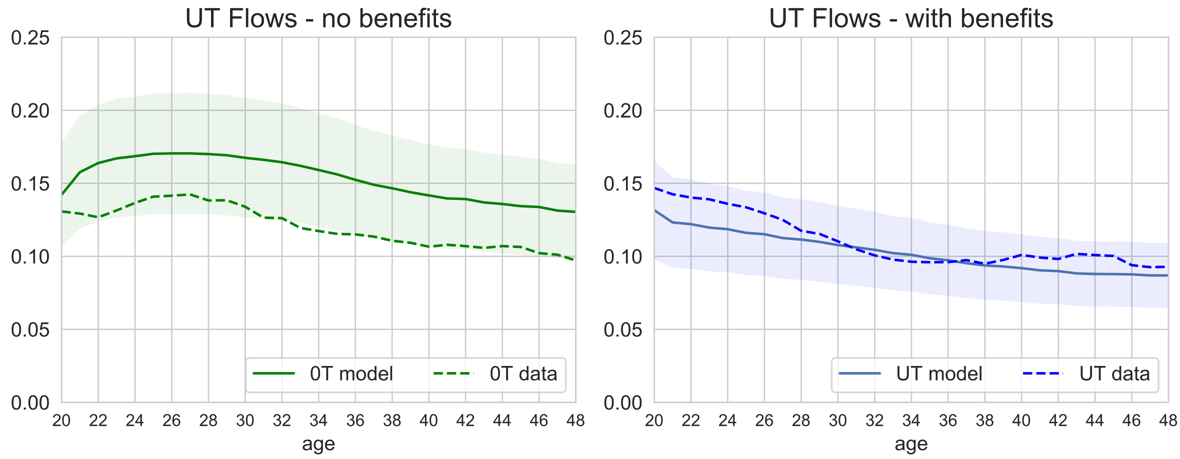
Figure 10: Search capital by age



Notes: Evolution of the share of the workforce with low (s_0), average (s_1) and high (s_0) search capital levels, by age and for all workers and unemployed only. Data derived from the first stage simulation, a panel of 16,000 workers entering the labour force at 20.

(workers with the lowest level of search capital, s_0) is larger among the youngest and oldest age groups. There are also more workers with the highest level of search capital (s_2) among the older cohorts. The large share of good searchers among older workers reflects that search capital increases over time as individuals gain experience in the job market. But the distribution also becomes more polarized. That is, both extremes of search capital become more prevalent among older workers. This pattern reflects the polarizing nature of dual labour markets, as the older bad searchers are mostly permanent workers who have been sheltered from unemployment for a long time.

Figure 11: Unemployment to Temporary flows, by benefit entitlement



Notes: Evolution of Model output derived from 20 first stage simulations, with a panel of 16,000 workers entering the labour force at 20. Shaded areas denote the average +/- one standard deviation across simulations. Each flow is derived as XY_t/X_t, where XY_t is the gross flow between state X at time t to state Y at $t+1$ and X_t is the stock of workers in state X at time t.

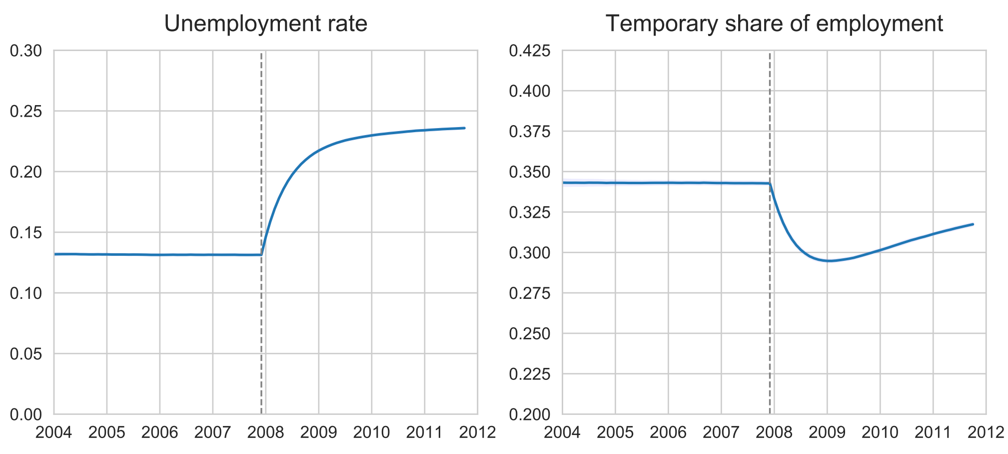
The right panel of figure 10 shows that the share of bad searchers among the unemployed decays monotonically with age. In contrast, the share of good searchers increases over time but is never above 20%. Younger workers are the worst searchers because of their inexperience in the labour market – they have not had time to accumulate search capital. They compensate for their lower job finding rate by accepting very low paying jobs, as figure 11 shows. Older unemployed workers are better searchers. Recall that the first stage simulation reproduces the conditions of a period of economic expansion. Under these conditions, most older workers are employed in permanent contracts and rarely lose their jobs. These employed workers have lower search capital but their unemployed peers have been more exposed to unemployment spells and thus are better searchers. Note as well that these workers have also managed to accumulate some human capital and save, so they can afford to take a longer time to find a better match. This is reflected in their lower job finding rate in figure 11. Finally, figure 11 shows the temporary job finding rates or unemployment to temporary (UT) flows. The flows into permanent contracts are not shown here as they are very small, between 2% and 3% – in accordance with the data. These and other flows are shown in figure 21 in the appendix. The model does overshoot the job finding rate of workers without benefits but it manages to capture its hump-shape and slope well. This shape reflects the patterns of search capital as discussed in figure 10: Younger workers with little savings are not very selective in their jobs, but they are not good searchers either – so the job finding rate increases until the age of 26-27, as in the data. After that, workers accumulate assets that allows them to be more selective in the jobs they take, driving the job finding rate down. For workers with benefits the job finding rate monotonically decreases with age, which is in line with the data. From the age of 24 it is consistently below the job finding rate without benefits in the data, while in the model this happens almost from the beginning. Unemployed workers with benefits can always be more selective in their jobs, and this effect dominates the increase in search capital over time.

These results highlight an important outcome of the model: search capital dynamics are important for younger workers, who are also less likely to receive benefits. Conversely, for older workers asset accumulation dynamics are more important than search capital.

Second stage simulation: Economy wide shock

As previously discussed in section 2.1, search capital effects on aggregate employment dynamics should be more relevant in a recession: more older workers enter unemployment and young workers find it harder to access their first job. In this subsection I analyse the effects of a one-off shock to the baseline calibration by switching the parameters governing job market transitions to the average of the 2009-2013 period. As table 6 shows, the shock consists of: a reduction of average job finding rates and contract promotion frequency and an increase in the exogenous separation probabilities. The simulation uses 4 years of expansion parameters and 4 years of recession parameters. This gives a total of 8 years which matches the window of the empirical regressions data.

Figure 12: Simulation results, Recession shock at 48 months



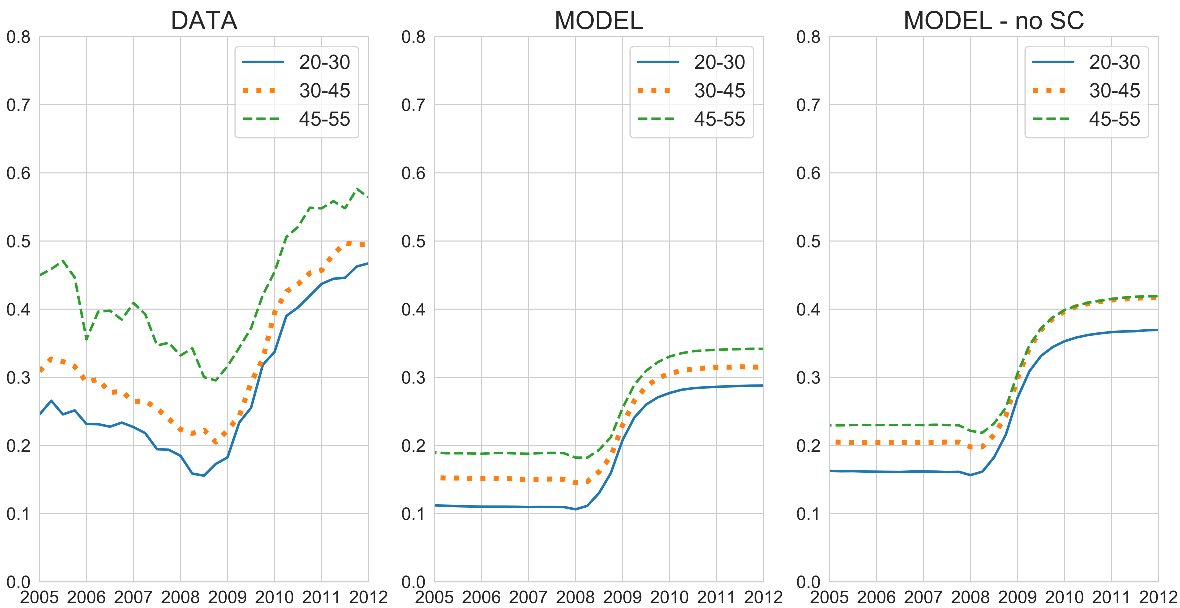
Notes: Evolution of the unemployment rate and the temporary share – number of employed with temporary contracts over total number employed. Data is derived from the second stage simulation of 2 million workers for 8 years, recession shock after 4 years – marked with a dashed line.

Figure 12 shows the simulated unemployment and the temporary share series. Unemployment rises to close to 25%, which is in line with the data. The temporary share implied by the model falls at the beginning but rises afterwards. While the initial fall of the temporary share is observed in the data, its subsequent increase is not. This fall is driven by a steady decline in the total number of permanent jobs, as figure 22 in the appendix shows.

Long-term unemployment and search capital

The model is successful in replicating the relatively larger increase in long-term unemployment among younger workers, as figures 13 and 14 show.

Figure 13: Long-term unemployment rates by age



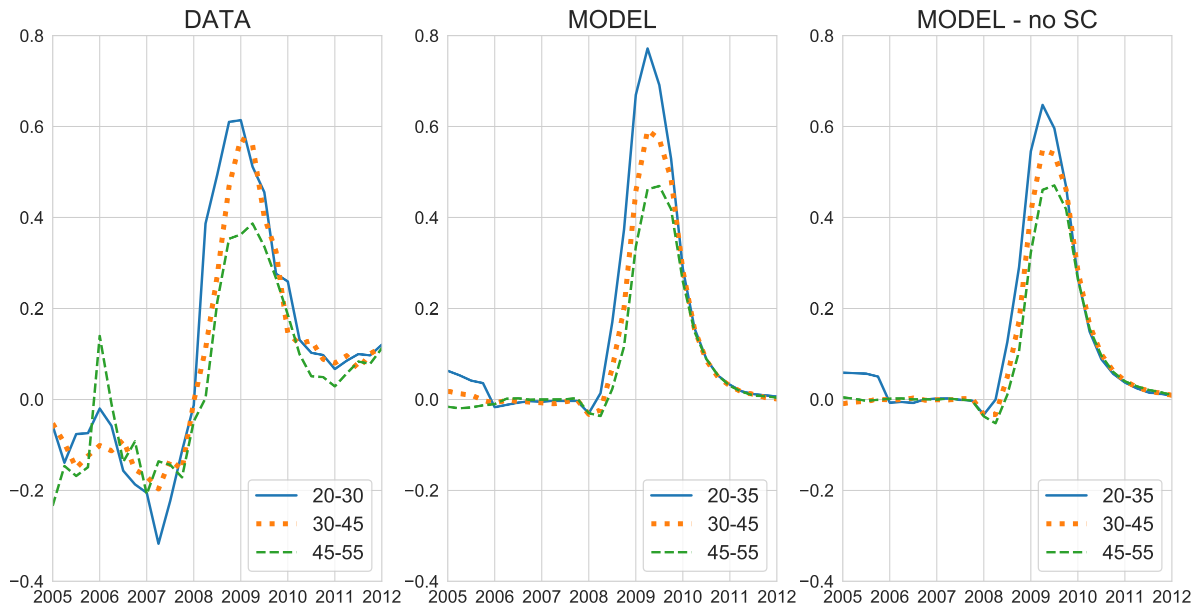
Notes: Quarterly changes in long-term unemployment share. *Data* panel data source the Spanish LFS, years 2004-2012. *Model* panel data is derived from 20 second stage simulations of 2 million workers each for 8 years, recession shock after 4 years. *Model - No SC* data derived from the same simulation but without search capital.

The first panels in both figures show the increase in the data, as reflected in figure 3.[34] The other two panels present the equivalent plot generated from the model simulation output. The middle panel shows the results of the baseline model and the rightmost panel shows the results of the simulation when search capital is shut down – all workers have the middle level of search capital.

In levels, figure 13 shows that the model with search capital is able to replicate the ordering we observe in the data. That is, the long-term unemployment rate is highest among the older age group, followed by the middle aged and the young. This relative ranking does not change after the shock, both in the data and in the model. Without search capital, the middle age group follows very closely the older age group. After the shock, the LTU rate of the middle aged is identical to the older workers. This is at odds with the data. In both models the long-term unemployment rate is lower than in the

[34] The data however is split into different age categories (20-30, 30-45 and 45-55) to accommodate for the fact that in the model agents enter the labour market at age 20. This split of the data also ensures an even split of observations in the model generated data. The pattern is very similar to that of figure 3.

Figure 14: Annual changes in long-term unemployment by age



Notes: Quarterly changes in long-term unemployment share. *Data* panel data source the Spanish LFS, years 2004-2012. *Model* panel data is derived from 20 second stage simulations of 2 million workers each for 8 years, recession shock after 4 years. *Model - No SC* data derived from the same simulation but without search capital.

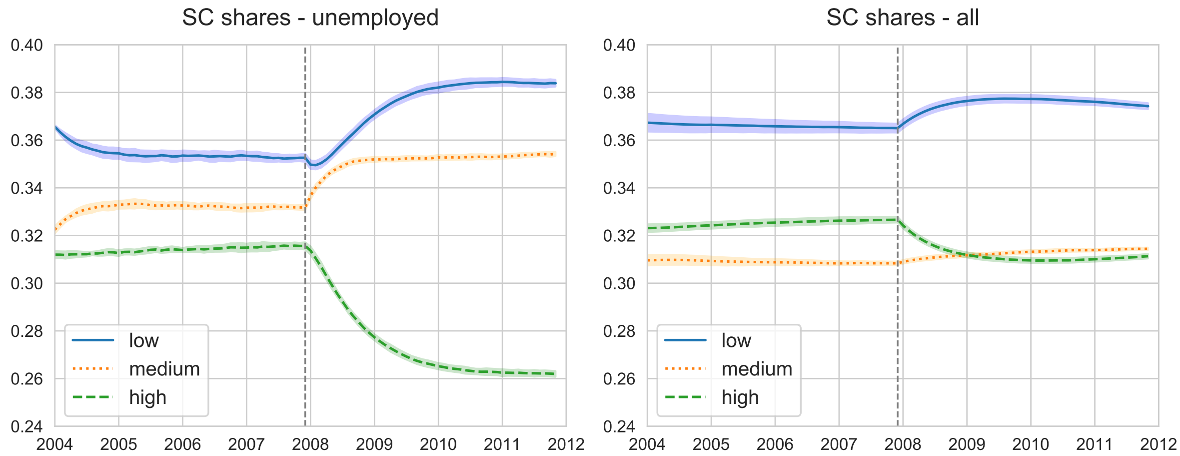
data – this is a mechanical effect of the higher job finding rate as explained in figure 11.

In relative changes, figure 14 shows that in the the model with search capital the youngest group of workers suffer the highest increase, almost doubling of the oldest age group. The difference between oldest and youngest is higher than in the data, but the magnitudes are not far off. In the model without search capital the differences across age groups are smaller. The addition of search capital to the model amplifies the response of long-term unemployment among young workers, closing the gap in levels with older cohorts.

The model with search capital can help explain why long-term unemployment increases relatively more for the young: in recessions it is harder for them to find jobs to gain search capital. As they are still learning who to search (reflected by their lower search capital on average) the lack of learning opportunities leaves them to suffer longer unemployment spells. Among older workers the results are more mixed: some workers who lose a long-term job also find themselves in unemployment with low search capital, but others still retain some of their search skills, making the average do much better than the younger cohorts.

The reduced availability of temporary contracts drives this result, as shown in figure 15. Comparing both panels, the changes among the unemployed are larger in magnitude

Figure 15: Search Capital simulation results, recession shock at 48 months



Notes: Share of the workforce with low (s_0), average (s_1) and high (s_0) search capital levels, over time and by labour market state. Data is derived from 20 second stage simulations of 2 million workers each for 8 years, recession shock after 4 years – marked with a dashed line.

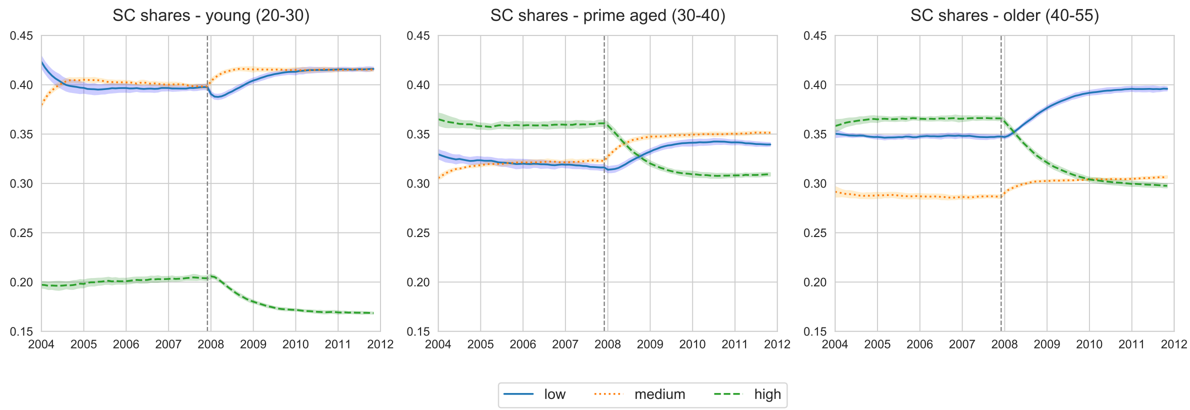
and drive the results for the overall population. There are fewer workers with high search capital among the unemployed – resulting in a further fall of the job-finding rate. That is, the recession makes temporary contracts more scarce and unemployed workers are also worse at finding jobs. This implies that unemployment increases both because of the fall in the job finding rate (fewer jobs are available) and changes in composition of the unemployment pool (workers are worse searchers overall). Search capital makes these negative changes in composition become deeper and more permanent, as the inability of young workers to accumulate search capital damages them in the long-term.[35]

Figure 16 illustrates the changes in search capital by age groups. Young workers have the highest share of low search capital of all the age groups. After the shock, the proportion of high search capital falls, resulting in an increase of the middle level of search capital. This pattern shows the effects of the slowing down of the take up of temporary contracts. As these jobs are harder to find in recessions, young people are unable to accumulate search capital. However, the most drastic changes in search capital happen among the older cohorts: the proportion with low search capital increases substantially. This is because more long-tenured workers are dismissed in the recession, but while in the boom they were able to climb back up the job ladder (and increase their search capital) in the recession they stayed unemployed longer.

The fact that the changes in search capital composition are more dramatic among older workers would indicate that they should suffer a higher increase in long-term un-

[35] Notice that if we were to decompose the duration of unemployment post-recession, search capital would not affect duration dependence – if anything, duration dependence would be negative because as workers consume their savings they become less selective in the jobs they pick. However, it would be very difficult to correctly identify the changes in search capital as changes in heterogeneity. This is because search capital is both unobservable and time-varying.

Figure 16: Search Capital simulation results by age group, recession shock at 48 months



Notes: Share of the workforce with low (s_0), medium (s_1) and high (s_0) search capital levels, over time and by age group. Data is derived from 20 second stage simulations of 2 million workers each.

employment compared to the youngest cohort. However, the interaction of search capital with the capital accumulation explains why it is not the case: older workers suffered higher long-term unemployment rates before the recession because they were more selective in the jobs they took. While they become less selective after the recession, they are still much more so than younger workers. This effect dominates the changes in the search capital composition.

Empirical correlations

The fact that search capital helps explain the higher increase in long-term unemployment among the young is not surprising – after all it is a mechanism that is embedded in the model precisely for that reason. But can the model generated data reproduce the patterns found in the empirical exercise of section 3? Table 7 compares the results of running the model equivalent of the empirical equivalent of equation 1 in section 3. I sample the completed unemployment spells over the 8 year period of the simulation – same time window as in the data. Then I transform duration from months (the period length in the model) into log weeks and regress it against a series of key variables: the number of different contracts the worker had, age, duration, tenure, experience and a dummy that reflects whether workers received unemployment benefits at the beginning of their spell. Because the level of unemployment benefits in the model is fixed for all workers, it is more convenient to capture its effects in a dummy reflecting both the entitlement and generosity of benefits. The rest of the variables are in comparable magnitudes to the ones described in section 3. I then run a reduced form version of the regressions in table 2.

Table 7 compares the results of both regressions. The coefficient for the number of temporary contracts is significant, negative and close to the one in the empirical regression. It is important to note that this coefficient is not targeted in the calibration. The coefficient of permanent contracts is also significant and negative, but of a smaller magni-

Table 7: Regressions on Log duration in weeks

	Model	Reduced Empirical Regression	Full Empirical Regression
No. T	-0.030***	-0.0488***	-0.040***
	(0.000)	(0.00057)	(0.0007)
No. P	-0.0146***	-0.0747***	-0.036***
	(0.001)	(0.0016)	(0.0021)
Last P	-0.0146***	0.1683***	0.057***
	(0.0010)	(0.1683)	(0.0041)
Tenure	0.0454***	0.1415***	0.032***
	(0.001)	(0.0024)	(0.0018)
Tenure^2	-0.0023***	-0.0061***	-0.001***
	(3.49e-05)	(0.0002)	(0.0001)
Experience	0.0020***	-0.0445***	-0.023***
	(0.000)	(0.0009)	(0.0009)
Experience^2	3.364e-05	0.0010***	0.000***
	(2.1e-05)	(3.3e-05)	(0.0000)
Age	0.0193***	0.001***	0.001***
	(0.000)	(0.0003)	(0.0003)
log(past wage)	-0.0818***	0.0933***	0.021***
	(0.000)	(0.0031)	(0.0028)
UB dummy	0.3250***	0.350***	-
	(0.002)	(0.0039)	-
Constant	2.8908	2.186***	0.727***
	(0.004)	(0.0320)	(0.0365)
Observations	2,014,028	543,529	524,294
Adjusted R^2	0.064	0.112	0.566

Notes: Model data derived from the second stage simulation of 2 million workers for 8 years, recession shock after 4 years. Completed spells only for model-data and empirical regressions columns. Robust standard errors in parentheses. Second column restricts the number of variables in the empirical regression to match the model variables. Third column (*Full Empirical Regression*) is taken from table 2, column 3. *** $p < 0.001$

tude. Thus a model where search capital increases with the number of jobs a worker has can produce similar correlations as we observe in the data. The rest of the parameters are significant (except for the squared term on experience) but have different magnitudes or signs. This reflects that for all that it has, the model abstracts from some channels that play a role in the data. For example, the dummy for whether the last contract was permanent is negative in the model and positive in the data. The model does not take into account severance payments (which would be reflected by this variable) or targeting of permanent workers for other permanent jobs. There is no labour productivity in the model that could be reflected by the wage either, no human capital captured by experience as all human capital is specific. The model is not intended to capture these but the effect of search capital as measured by temporary contracts, so it would be surprising if it could match the other coefficients as well.

The impact of temporary contracts on welfare

One of the main implications of search capital is that workers with more jobs than average have better future employment prospects. A natural question then is if workers that have been more exposed to temporary contracts have higher welfare overall. On the one hand, higher search capital allows workers to climb the temporary ladder faster and have shorter unemployment spells should they suffer a displacement shock. However workers are risk averse and prefer stability over large income fluctuations. Unstable employment forces them to increase precautionary savings and delay consumption. Periods of unemployment limit the ability of workers to build up capital, specially for young workers.

Using the results from the first stage calibration with expansion parameters, I calculate the present discounted utility of workers who participate in the labour force for 30 years. I then compare two groups: those who got fewer contracts than average (temporary or permanent) and those who got more. For the case of temporary workers, the average is 7.96. Close to 60% of workers have fewer than that amount by the age of 50.[36]

Table 8: Present-discounted lifetime utility, by number of contracts

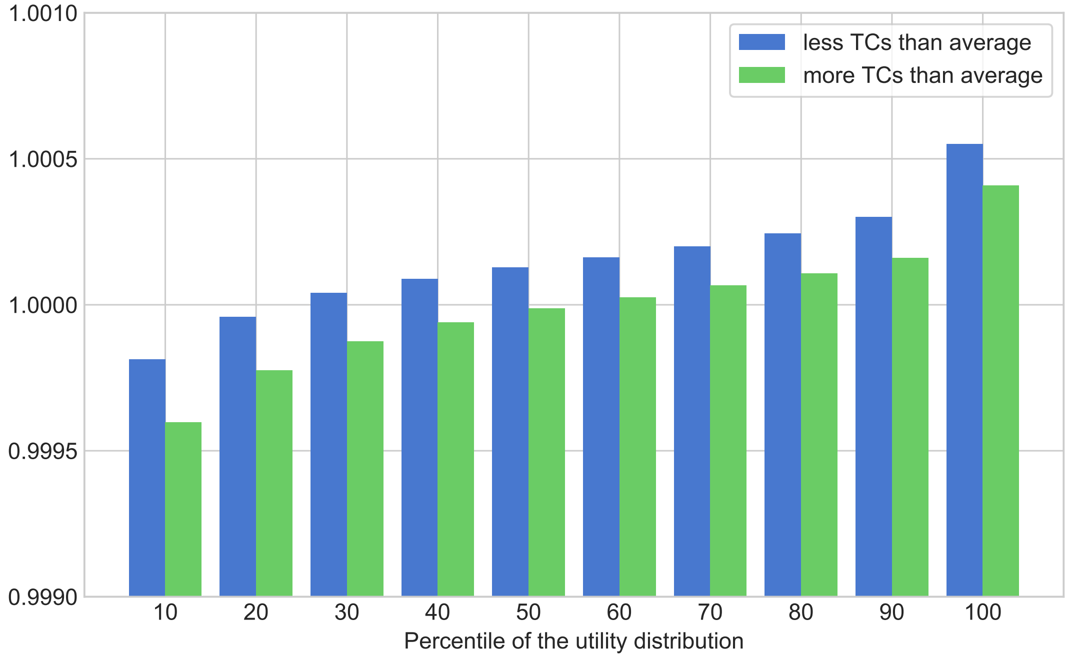
	Fewer TCs	More TCs	Fewer PCs	More PCs
Average	168.582	168.553	168.576	168.563
Std.	0.0386	0.0431	0.0445	0.0415

Present discounted utility measured in utils. Data derived from a simulated panel of 10,000 workers entering the labour force at 20 and exiting at 50.

Looking at the distributions of lifetime utility is a simple way of assessing how relatively well-off are workers that are more exposed to temporary contracts than those who have less exposure. First, table 8 shows that, on average, workers with fewer temporary contracts achieve higher lifetime utility. There is also higher dispersion in outcomes, as the standard deviation is higher for those with more temporary contracts. These differences are smaller when we consider permanent contracts instead. It is still preferable, on average, to have fewer permanent contracts. In other words, workers can expect to have higher welfare if they have a more stable working life. Figure 19 shows that this is not only true for the average worker (in terms of lifetime utility) but across the distribution, from individual from worst to best outcomes, workers with less temporary contracts achieve higher welfare. Another way of reading figure 19 is that the average worker with

[36] See figure x in the appendix

Figure 17: Present-discounted lifetime utility, relative to average, by deciles



Notes: Present discounted utility relative to the average worker. *More temporary contracts* refers to the group of workers with more than the average number of temporary contracts (7.96) by the end of the sample. Data derived from a simulated panel of 10,000 workers entering the labour force at 20 and exiting at 50.

more temporary contracts in the top 60th decile of the utility distribution gains the same utility as the average worker with less temporary contracts in the 30th percentile.

Table 9: Monthly Consumption Equivalent Loses of the Recession

	Absolute		Share of average consumption		
	Fewer TCs	More TCs	Fewer TCs	More TCs	Difference
25th percentile	254.77	229.48	0.170	0.188	1.88%
50th percentile	120.14	108.51	0.062	0.068	0.6%
75th percentile	61.21	57.66	0.026	0.028	0.2%

Notes: Increases in monthly consumption (in euros and relative to average monthly consumption) that make the average worker in the given percentile indifferent between the scenario with and without the recession shock. Data derived from 2 simulated economies of 2 million workers for 8 years – one with a recession shock after 4 periods and one without.

However the recession has the potential to reverse this result, as workers entering the unemployment pool with higher search capital face shorter unemployment spells and possibly better outcomes than their peers. To quantify this, I fist calculate the welfare losses of workers in the 25th, 50th and 75th percentiles of the consumption distribution

– conditional on experiencing at least one unemployment spell in the recession. That is, I calculate the path of consumption for these percentiles with and without the recession happening after 4 years. I then calculate by how much consumption would need to increase in each period (a month) so that discounted lifetime utility at the moment of the recession is equated in both cases. As before, I distinguish two groups: those who at the start of the recession have had more temporary contracts than average and fewer contracts than average. The first four columns of table 9 show the result of this calculation, in absolute (euros) and relative to average consumption in their percentile. The losses from the recession differ substantially among percentiles, as the top group is likely to not lose its job and only suffer in so far they have to climb the job ladder more slowly. For the bottom 25th percentile unemployment happens more often and it is harder to exit to employment. For this group the differences in temporary contracts reflect the differences that search capital makes in terms of unemployment duration. As the last column shows, for the bottom 25th percentile of the distribution having had more temporary contracts than average at the beginning of the recession translates into 1.88% lower loses of average consumption. The loss differential is substantially reduces but still positive for the 50th and 75th percentiles. They lose 0.6% and 0.2% less, respectively.

The conclusion of this small welfare exercise is that, overall, the potential gains in search capital do not compensate workers from taking temporary contracts. But search capital could substantially improve the welfare of workers who lose their job in a recession. In particular, it helps the poorest workers most as they are the ones who suffer more from prolonged unemployment spells.

5 Conclusion

Treating job search as a skill that can be gained and forgotten over time brings new insights to old problems. It provides an explanation as to why the increase in long-term unemployment can be larger for younger workers than older ones. During expansions, the availability of temporary jobs helps young workers to accumulate search capital and progressively become better searchers. In recessions these jobs are more scarce, so young workers are unable to accumulate search capital which increases LTU. Older workers' search capital does not depend so much on the availability of temporary jobs and thus their job finding prospects are hurt relatively less during recessions. Labour markets in which some workers are over-protected from unemployment while others experience it very frequently exacerbate the differences in search capital, which could potentially expose the economy to sharp increases in long-term unemployment, particularly among the young.

Using a detailed administrative dataset I use the number of temporary jobs held by a worker as a proxy for search capital, as temporary workers are more exposed to unemployment. Using tenure, work experience, wages in the last job and other controls, I regress duration of completed unemployment spells against the number of temporary contracts held to date finding a significant negative correlation. The effects are still significant after introducing individual fixed effects. It could be that workers who are more exposed to temporary contracts find worse jobs, but regressions on future wages show a positive effect, both by reducing duration of unemployment (which is negatively linked to wages) and directly, although this last effect is more modest. The number of temporary jobs is negatively correlated with duration of the next job and probability of finding a permanent contract, but after controlling for fixed effects its coefficient turns positive in both regressions. This suggests that as workers accumulate search experience they get better jobs, faster.

The empirical evidence provides support for search capital being significant for individual outcomes. To address the impact in the aggregate labour market I build a search model with savings and risk aversion and introduce search capital. I use the empirical wage distributions and transition rates in Spain to calibrate the model. The addition of search capital to the model helps to reconcile the patterns of long-term unemployment and job finding rates through the last recession, especially for young people. In particular, while LTU is more prevalent among older workers in booms and recessions alike, young workers suffer the highest increase in relative terms. The model manages to match these aggregate moments while still delivering observable effects at the individual level through its link with temporary contracts, in line with the empirical evidence. Overall, workers achieve a higher lifetime utility through fewer stable jobs, but in a recession the accumulation of search experience via temporary contracts helps alleviate somewhat the effect of the recession for the most vulnerable workers. Search capital could enrich the hysteresis literature by improving the performance of models for younger workers along the business cycle.

Finally, search capital adds a different perspective to the debate on labour market institutions and flexibility in Europe: more dynamic and flexible labour markets are more volatile but can also be more resilient to aggregate shocks. Active labour market policies can play a significant role in alleviating the negative effects of dual labour markets, especially if targeted at the young.

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Appendix

Table 10: Duration, all contracts

	(1) log(weeks)	(2) log(weeks)	(3) log(weeks)	(4) log(weeks)	(5) log(weeks)	(6) log(weeks)
No. T	-0.011***	-0.011***	-0.011***	-0.004***	-0.004***	-0.003***
	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0008)	(0.0008)
No. T^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	0.003**	0.003**	0.003*	0.007*	0.005	0.007
	(0.0009)	(0.0011)	(0.0011)	(0.0032)	(0.0044)	(0.0044)
No. P^2	-0.000*	-0.000*	-0.000	0.000	0.000	-0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Last P	0.096***	0.049***	0.050***	0.070***	0.041***	0.053***
	(0.0039)	(0.0047)	(0.0047)	(0.0042)	(0.0057)	(0.0057)
Tenure	0.060***	0.058***	0.056***	0.058***	0.067***	0.061***
	(0.0016)	(0.0018)	(0.0018)	(0.0025)	(0.0032)	(0.0032)
Tenure^2	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Experience	-0.012***	-0.012***	-0.012***	0.015***	0.014***	0.015***
	(0.0005)	(0.0005)	(0.0006)	(0.0026)	(0.0033)	(0.0034)
Age	-0.000	0.000	0.000	0.010***	0.010***	-0.006*
	(0.0003)	(0.0003)	(0.0003)	(0.0019)	(0.0024)	(0.0025)
log(past wage)		0.017***	0.017***		0.045***	0.048***
		(0.0030)	(0.0030)		(0.0035)	(0.0035)
log(UI)			0.000***			0.002***
			(0.0000)			(0.0000)
Constant	0.959***	0.453***	0.463***	0.388***	-0.185*	0.375***
	(0.0229)	(0.0412)	(0.0416)	(0.0622)	(0.0895)	(0.0910)
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓
Observations	741,337	530,073	524,294	764,466	543,492	537,533
Adjusted R^2	0.534	0.552	0.553	0.461	0.457	0.462
AIC	1938484.567	1385204.236	1368651.439	1471385.406	995040.426	976111.074

Standard errors (clustered at the individual level) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Prob of LTU, all contracts

	All sample		Completed spells	
	$P(\geq 1year)$	$P(\geq 2years)$	$P(\geq 1year)$	$P(\geq 2yeasr)$
No. T	-0.036***	-0.049***	-0.038***	-0.053***
	(0.0006)	(0.0009)	(0.0007)	(0.0013)
No. T^2	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	0.001**	0.002***	0.005***	0.007***
	(0.0003)	(0.0003)	(0.0008)	(0.0011)
Last P	0.184***	0.163***	0.164***	0.132***
	(0.0078)	(0.0110)	(0.0090)	(0.0138)
Tenure	0.142***	0.106***	0.145***	0.138***
	(0.0033)	(0.0045)	(0.0043)	(0.0064)
Tenure^2	-0.004***	-0.002***	-0.004***	-0.004***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Experience	-0.027***	-0.026***	-0.031***	-0.040***
	(0.0006)	(0.0009)	(0.0008)	(0.0013)
Age	0.026***	0.040***	0.014***	0.018***
	(0.0004)	(0.0006)	(0.0005)	(0.0007)
Constant	-2.634***	-3.984***	-1.939***	-2.871***
	(0.0448)	(0.0673)	(0.0513)	(0.0835)
Controls				
Years	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Occupation	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	969,290	969,290	741,337	741,337
AIC	808844.217	442075.213	613674.142	300443.668

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Duration by age, contracts since 2005

	20-30		30-40		40-50		50-60	
	Pooled	Fixed effects	Pooled	Fixed effects	Pooled	Fixed effects	Pooled	Fixed effects
No. T	-0.031***	-0.001	-0.039***	-0.009***	-0.042***	-0.003	-0.042***	-0.009
	(0.0012)	(0.0021)	(0.0011)	(0.0025)	(0.0015)	(0.0021)	(0.0029)	(0.0052)
No. T^2	0.000	0.000	0.000***	0.000**	0.000***	0.000	0.000***	0.000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
No. P	-0.027***	0.002	-0.030***	0.001	-0.040***	-0.005	-0.046***	-0.033***
	(0.0048)	(0.0075)	(0.0028)	(0.0046)	(0.0035)	(0.0062)	(0.0070)	(0.0085)
3 months claim	0.088***	0.020*	0.166***	0.083***	0.137***	0.076***	0.169***	0.131***
	(0.0061)	(0.0085)	(0.0069)	(0.0099)	(0.0095)	(0.0139)	(0.0191)	(0.0327)
6 months claim	0.102***	0.059***	0.160***	0.092***	0.123***	0.116***	0.168***	0.139***
	(0.0073)	(0.0112)	(0.0079)	(0.0127)	(0.0108)	(0.0178)	(0.0211)	(0.0402)
12 months claim	0.105***	0.130***	0.114***	0.086***	0.054***	0.060*	0.117***	0.198**
	(0.0116)	(0.0206)	(0.0109)	(0.0194)	(0.0147)	(0.0273)	(0.0284)	(0.0616)
18 months claim	0.126***	0.111*	0.084***	0.100***	0.026	0.009	0.041	0.084
	(0.0196)	(0.0453)	(0.0138)	(0.0282)	(0.0187)	(0.0400)	(0.0371)	(0.0902)
24 months claim	0.150***	0.215	0.047**	0.160***	-0.052*	0.022	-0.080*	0.046
	(0.0392)	(0.1179)	(0.0173)	(0.0407)	(0.0205)	(0.0449)	(0.0407)	(0.1115)
Last P	0.045***	0.022*	0.061***	0.064***	0.051***	0.032*	0.090***	0.124***
	(0.0063)	(0.0092)	(0.0069)	(0.0104)	(0.0096)	(0.0148)	(0.0195)	(0.0336)
Tenure	0.060***	0.132***	0.045***	0.071***	0.042***	0.078***	0.031***	0.033*
	(0.0053)	(0.0098)	(0.0039)	(0.0074)	(0.0036)	(0.0074)	(0.0062)	(0.0150)
Tenure^2	-0.007***	-0.018***	-0.003***	-0.005***	-0.001***	-0.004***	-0.001***	-0.001*
	(0.0008)	(0.0022)	(0.0004)	(0.0009)	(0.0002)	(0.0004)	(0.0002)	(0.0006)
Experience	-0.064***	-0.147***	-0.008***	-0.028**	0.003	-0.021	0.006	-0.030
	(0.0033)	(0.0089)	(0.0023)	(0.0094)	(0.0022)	(0.0123)	(0.0034)	(0.0367)
Experience^2	0.002***	0.015***	-0.001***	0.003***	-0.000***	0.002***	-0.000**	0.002**
	(0.0003)	(0.0008)	(0.0001)	(0.0004)	(0.0001)	(0.0003)	(0.0001)	(0.0008)
log(past wage)	-0.003	0.027***	0.022***	0.055***	0.049***	0.086***	0.062***	0.072**
	(0.0039)	(0.0052)	(0.0048)	(0.0067)	(0.0071)	(0.0095)	(0.0142)	(0.0231)
log(UI)	0.002***	0.003***	0.000***	0.002***	0.000	0.002***	0.000	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Constant	1.260***	0.819***	0.685***	0.185	0.273**	-0.332	-0.038	-0.293
	(0.0571)	(0.0962)	(0.0616)	(0.1161)	(0.0849)	(0.1978)	(0.1686)	(0.5979)
Observations	207,312	207,312	179,115	179,115	109,203	109,203	28,664	28,664
Adjusted R^2	0.556	0.477	0.567	0.447	0.586	0.425	0.596	0.381
AIC	504422.055	330127.188	469821.899	308143.571	293321.623	191643.050	78017.485	45818.670

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Duration by age, all contracts

	20-30		30-40		40-50		50-60	
	Pooled	Fixed effects	Pooled	Fixed effects	Pooled	Fixed effects	Pooled	Fixed effects
No. T	-0.012***	-0.003	-0.010***	-0.002	-0.010***	-0.001	-0.010***	-0.011*
	(0.0005)	(0.0015)	(0.0007)	(0.0018)	(0.0009)	(0.0015)	(0.0011)	(0.0054)
No. T^2	0.000***	0.000	0.000***	0.000	0.000***	0.000*	0.000***	0.000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NoP	0.002	0.014	0.000	0.005	0.001	0.003	0.003*	-0.005
	(0.0020)	(0.0078)	(0.0027)	(0.0089)	(0.0013)	(0.0130)	(0.0014)	(0.0380)
No. P^2	0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.002
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0014)
3 months claim	0.096***	0.019*	0.194***	0.086***	0.184***	0.078***	0.230***	0.133***
	(0.0064)	(0.0085)	(0.0072)	(0.0099)	(0.0097)	(0.0139)	(0.0195)	(0.0327)
6 months claim	0.109***	0.058***	0.192***	0.097***	0.178***	0.119***	0.236***	0.140***
	(0.0075)	(0.0111)	(0.0082)	(0.0127)	(0.0111)	(0.0177)	(0.0214)	(0.0403)
12 months claim	0.114***	0.127***	0.155***	0.090***	0.121***	0.063*	0.199***	0.201**
	(0.0117)	(0.0206)	(0.0111)	(0.0194)	(0.0150)	(0.0273)	(0.0285)	(0.0616)
18 months claim	0.129***	0.107*	0.131***	0.103***	0.095***	0.011	0.127***	0.088
	(0.0197)	(0.0452)	(0.0140)	(0.0282)	(0.0190)	(0.0401)	(0.0375)	(0.0903)
24 months claim	0.143***	0.211	0.104***	0.166***	0.014	0.023	-0.004	0.048
	(0.0399)	(0.1178)	(0.0175)	(0.0408)	(0.0206)	(0.0449)	(0.0409)	(0.1114)
Last P	0.043***	0.016	0.061***	0.065***	0.038***	0.031*	0.068**	0.127***
	(0.0065)	(0.0093)	(0.0077)	(0.0107)	(0.0113)	(0.0152)	(0.0219)	(0.0348)
Tenure	0.094***	0.132***	0.076***	0.075***	0.066***	0.079***	0.052***	0.033*
	(0.0055)	(0.0097)	(0.0040)	(0.0075)	(0.0037)	(0.0074)	(0.0063)	(0.0151)
Tenure^2	-0.010***	-0.018***	-0.005***	-0.005***	-0.002***	-0.004***	-0.002***	-0.001*
	(0.0009)	(0.0022)	(0.0004)	(0.0009)	(0.0002)	(0.0004)	(0.0002)	(0.0006)
Experience	-0.076***	-0.147***	-0.015***	-0.039***	-0.002	-0.028*	-0.001	-0.037
	(0.0035)	(0.0089)	(0.0028)	(0.0095)	(0.0025)	(0.0122)	(0.0038)	(0.0370)
Experience^2	0.004***	0.015***	-0.000	0.003***	-0.000***	0.002***	-0.000	0.002**
	(0.0003)	(0.0008)	(0.0001)	(0.0004)	(0.0001)	(0.0003)	(0.0001)	(0.0008)
log(past wage)	-0.006	0.027***	0.013**	0.054***	0.051***	0.086***	0.058***	0.073**
	(0.0041)	(0.0052)	(0.0051)	(0.0067)	(0.0074)	(0.0095)	(0.0142)	(0.0231)
log(UI)	0.001***	0.003***	0.000**	0.002***	-0.000***	0.002***	-0.000	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Constant	1.152***	0.826***	0.524***	0.238*	-0.051	-0.274	-0.274	0.537
	(0.0664)	(0.0961)	(0.0699)	(0.1150)	(0.0906)	(0.1981)	(0.1708)	(0.6724)
Observations	207,312	207,312	179,115	179,115	109,203	109,203	28,664	28,664
Adjusted R^2	0.550	0.477	0.555	0.446	0.570	0.425	0.580	0.381
AIC	507188.519	330119.362	474606.543	308208.015	297404.237	191646.153	79145.258	45836.120

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Duration by gender, contracts since 2005

	Female		Males	
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
No. T	-0.044***	-0.007***	-0.035***	-0.007***
	(0.0013)	(0.0016)	(0.0011)	(0.0016)
No. T^2	0.000***	0.000	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	-0.031***	0.006	-0.036***	-0.010*
	(0.0036)	(0.0060)	(0.0043)	(0.0048)
No. P^2	-0.000	-0.000	-0.000	0.000
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Last P	0.058***	0.052***	0.052***	0.053***
	(0.0063)	(0.0086)	(0.0057)	(0.0075)
Tenure	0.042***	0.065***	0.027***	0.061***
	(0.0029)	(0.0052)	(0.0023)	(0.0040)
Tenure^2	-0.002***	-0.003***	-0.001***	-0.003***
	(0.0002)	(0.0004)	(0.0001)	(0.0003)
Experience	-0.026***	-0.044***	-0.026***	-0.018**
	(0.0015)	(0.0066)	(0.0013)	(0.0056)
Experience^2	0.001***	0.002***	0.000***	0.002***
	(0.0001)	(0.0003)	(0.0000)	(0.0002)
Age	-0.001**	-0.008*	0.004***	0.006
	(0.0004)	(0.0041)	(0.0004)	(0.0033)
log(past wage)	0.014***	0.039***	0.025***	0.057***
	(0.0041)	(0.0053)	(0.0039)	(0.0048)
log(UI)	0.001***	0.002***	0.001***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.709***	0.629***	0.740***	-0.037
	(0.0508)	(0.1491)	(0.0524)	(0.1237)
Observations	231,426	231,426	292,868	292,868
Adjusted R^2	0.593	0.461	0.548	0.466
AIC	602572.674	420071.213	746315.377	531037.002

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Duration by gender, all contracts

	Female		Males	
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
No. T	-0.013***	-0.005***	-0.010***	-0.003*
	(0.0006)	(0.0013)	(0.0006)	(0.0012)
No. T^2	0.000***	0.000***	0.000***	0.000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. P	0.009***	0.031***	0.000	-0.006
	(0.0017)	(0.0066)	(0.0013)	(0.0054)
No. P^2	-0.000**	-0.000*	0.000	-0.000
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Last P	0.058***	0.044***	0.040***	0.054***
	(0.0067)	(0.0087)	(0.0066)	(0.0076)
Tenure	0.070***	0.067***	0.050***	0.062***
	(0.0030)	(0.0052)	(0.0023)	(0.0041)
Tenure^2	-0.003***	-0.003***	-0.002***	-0.003***
	(0.0002)	(0.0004)	(0.0001)	(0.0003)
Experience	-0.032***	-0.051***	-0.028***	-0.020***
	(0.0019)	(0.0067)	(0.0016)	(0.0057)
Experience^2	0.001***	0.002***	0.001***	0.002***
	(0.0001)	(0.0003)	(0.0000)	(0.0002)
Age	-0.002***	-0.011**	0.005***	0.003
	(0.0005)	(0.0040)	(0.0005)	(0.0032)
log(past wage)	0.007	0.039***	0.023***	0.056***
	(0.0043)	(0.0053)	(0.0042)	(0.0048)
log(UI)	0.000***	0.002***	0.001***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.512***	0.711***	0.514***	0.100
	(0.0572)	(0.1462)	(0.0606)	(0.1195)
Observations	231,426	231,426	292,868	292,868
Adjusted R^2	0.579	0.461	0.539	0.466
AIC	610433.684	420054.501	752262.660	531097.453

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Unemployment Duration, by next job industry, contracts since 2005

	Extractive Ind	Manufactures (1)	Manufactures (2)	Manufactures (3)	Energy and gas	Construction	Retail and repairs	Transport	Hospitality	Communications	Financial	Real state	Professional	Auxiliary services	Public Admin	Education	Health and ss	Other services
No. T	-0.004	-0.027***	-0.030***	-0.026***	-0.019*	-0.026***	-0.022***	-0.044***	-0.038***	-0.036***	-0.045***	-0.032**	-0.033***	-0.045***	-0.034***	-0.039***	-0.051***	-0.040***
	(0.0245)	(0.0034)	(0.0032)	(0.0053)	(0.0084)	(0.0012)	(0.0012)	(0.0028)	(0.0013)	(0.0028)	(0.0082)	(0.0111)	(0.0024)	(0.0013)	(0.0032)	(0.0035)	(0.0028)	(0.0019)
No. T^2	0.000	0.000	0.000*	-0.000	-0.000**	0.000***	0.000	0.000***	0.000***	0.000*	0.001***	0.001	0.000***	0.000***	-0.000	0.000	0.000***	0.000***
	(0.0012)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0006)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
No. P	0.006	-0.052***	-0.008	-0.039*	-0.028***	-0.023***	-0.052***	-0.042***	-0.041***	-0.007	-0.023	-0.010	-0.037***	-0.027***	-0.055***	-0.037***	-0.012	-0.040***
	(0.0498)	(0.0067)	(0.0080)	(0.0170)	(0.0026)	(0.0053)	(0.0074)	(0.0097)	(0.0038)	(0.0088)	(0.0174)	(0.0163)	(0.0088)	(0.0077)	(0.0103)	(0.0077)	(0.0072)	(0.0064)
3 months claim	-0.007	0.133***	0.170***	0.178***	0.167***	0.126***	0.115***	0.150***	0.119***	0.116***	0.176***	0.087*	0.173***	0.171***	0.069***	0.135***	0.154***	0.130***
	(0.0980)	(0.0185)	(0.0173)	(0.0348)	(0.0418)	(0.0076)	(0.0080)	(0.0165)	(0.0081)	(0.0226)	(0.0417)	(0.0438)	(0.0168)	(0.0083)	(0.0143)	(0.0171)	(0.0160)	(0.0139)
6 months claim	0.028	0.128***	0.139***	0.150***	0.171***	0.108***	0.133***	0.119***	0.101***	0.123***	0.150**	0.096	0.154***	0.143***	0.122***	0.120***	0.135***	0.153***
	(0.1176)	(0.0212)	(0.0200)	(0.0393)	(0.0466)	(0.0090)	(0.0092)	(0.0188)	(0.0103)	(0.0261)	(0.0534)	(0.0496)	(0.0196)	(0.0104)	(0.0166)	(0.0202)	(0.0186)	(0.0166)
12 months claim	0.078	0.102**	0.171***	0.168**	0.132*	0.034*	0.128***	0.078**	0.072***	0.096*	0.129	0.127	0.152***	0.077***	0.085***	0.110***	0.088**	0.135***
	(0.1561)	(0.0317)	(0.0283)	(0.0558)	(0.0656)	(0.0140)	(0.0136)	(0.0266)	(0.0165)	(0.0380)	(0.0761)	(0.0699)	(0.0290)	(0.0163)	(0.0254)	(0.0320)	(0.0280)	(0.0250)
18 months claim	0.026	0.082*	0.123***	0.231**	0.078	0.029	0.106***	0.078*	-0.018	0.029	0.099	0.138	0.083*	0.023	0.038	0.032	-0.007	0.037
	(0.2014)	(0.0417)	(0.0363)	(0.0713)	(0.1033)	(0.0204)	(0.0189)	(0.0347)	(0.0258)	(0.0479)	(0.1090)	(0.1051)	(0.0387)	(0.0221)	(0.0367)	(0.0457)	(0.0401)	(0.0359)
24 months claim	-0.089	0.013	0.094*	0.119	0.159	-0.010	0.038	0.019	-0.034	0.089	-0.228	-0.067	0.053	-0.038	0.033	-0.018	-0.066	0.015
	(0.3019)	(0.0511)	(0.0422)	(0.0823)	(0.0897)	(0.0253)	(0.0227)	(0.0437)	(0.0330)	(0.0602)	(0.1569)	(0.1143)	(0.0481)	(0.0275)	(0.0413)	(0.0621)	(0.0499)	(0.0465)
Last P	0.100	0.050**	0.088***	0.064	0.064	0.049***	0.063***	0.095***	0.060***	0.026	0.019	0.003	0.070***	0.077***	0.066***	0.084***	0.161***	0.044**
	(0.1028)	(0.0185)	(0.0186)	(0.0354)	(0.0410)	(0.0090)	(0.0082)	(0.0167)	(0.0085)	(0.0230)	(0.0456)	(0.0393)	(0.0163)	(0.0098)	(0.0179)	(0.0187)	(0.0180)	(0.0142)
Tenure	0.075	0.024**	0.007	0.005	0.018	0.039***	0.015***	0.023**	0.050***	0.083***	0.038	0.017	0.027***	0.059***	0.032***	0.032***	0.065***	0.040***
	(0.0520)	(0.0076)	(0.0070)	(0.0146)	(0.0177)	(0.0041)	(0.0035)	(0.0070)	(0.0049)	(0.0110)	(0.0201)	(0.0168)	(0.0079)	(0.0045)	(0.0064)	(0.0085)	(0.0079)	(0.0067)
Tenure^2	-0.005	-0.001*	-0.001	-0.000	-0.001	-0.002***	-0.000**	-0.001	-0.002***	-0.005***	-0.000	-0.000	-0.002**	-0.002***	-0.001***	-0.001**	-0.002***	-0.002***
	(0.0040)	(0.0003)	(0.0003)	(0.0008)	(0.0009)	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0008)	(0.0009)	(0.0006)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)
Experience	-0.028	-0.016***	-0.027***	-0.011	-0.023***	-0.015***	-0.017***	-0.023***	-0.015***	-0.033***	-0.018	-0.017*	-0.026***	-0.020***	-0.020***	-0.026***	-0.042***	-0.024***
	(0.0187)	(0.0034)	(0.0032)	(0.0061)	(0.0071)	(0.0015)	(0.0016)	(0.0038)	(0.0025)	(0.0060)	(0.0101)	(0.0077)	(0.0035)	(0.0020)	(0.0029)	(0.0040)	(0.0036)	(0.0032)
Experience^2	0.000	0.000**	0.000***	0.000	0.001**	0.000**	0.000***	0.000**	0.000	0.001***	0.001*	0.001	0.001***	0.000***	0.000***	0.001***	0.001***	0.001***
	(0.0005)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
age	0.008	0.002	0.006***	0.003	0.004	0.007***	0.003***	0.002	-0.001*	0.002	-0.006	0.003	0.001	-0.001	0.002*	0.001	0.001	-0.001
	(0.0073)	(0.0012)	(0.0012)	(0.0023)	(0.0022)	(0.0004)	(0.0005)	(0.0013)	(0.0006)	(0.0019)	(0.0043)	(0.0024)	(0.0013)	(0.0006)	(0.0009)	(0.0012)	(0.0010)	(0.0009)
Constant	-0.329	1.139***	1.023***	1.377***	0.910***	0.857***	1.208***	0.679***	0.663***	0.910***	1.531***	1.127***	1.180***	0.802***	1.588***	1.231***	0.096	1.097***
	(0.4477)	(0.0847)	(0.1060)	(0.1650)	(0.2329)	(0.0536)	(0.0528)	(0.1175)	(0.1078)	(0.1752)	(0.2770)	(0.2587)	(0.0919)	(0.0643)	(0.0920)	(0.0887)	(0.0850)	(0.1193)
Controls																		
year dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
industry dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
occupation dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	742	21,890	23,762	6,212	4,612	111,934	98,583	28,718	95,887	14,398	4,054	3,102	26,788	116,934	31,146	22,934	40,762	39,050
Adjusted R^2	0.487	0.540	0.502	0.541	0.570	0.505	0.549	0.552	0.581	0.568	0.555	0.592	0.562	0.551	0.616	0.571	0.645	0.608
AIC	1924.274	55468.694	60465.077	15648.804	11778.686	271598.181	237587.273	76455.564	241899.204	36192.775	10326.069	7358.783	66832.071	307983.537	75466.161	56306.548	116146.031	100512.497

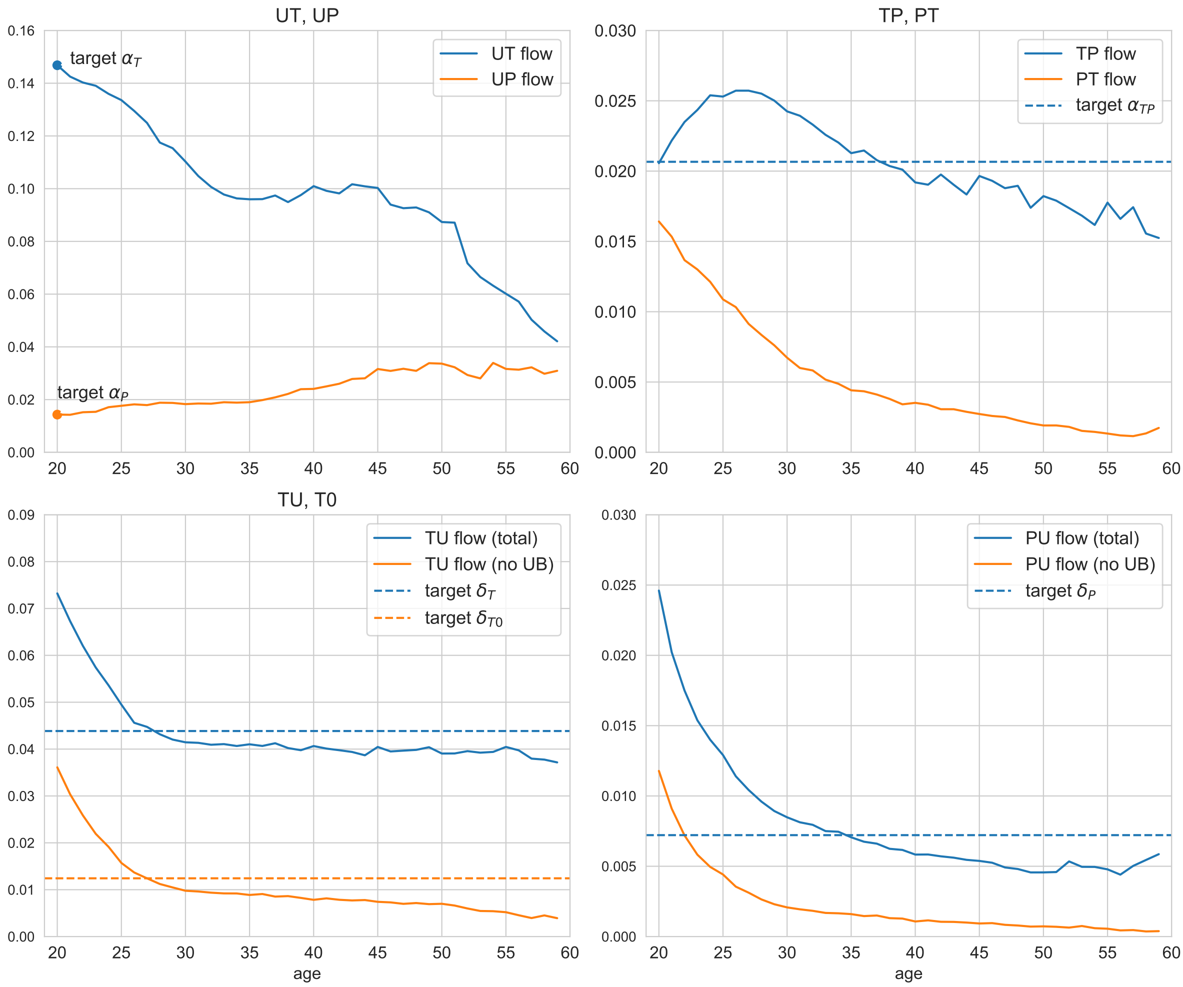
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Unemployment Duration by industry, fixed effects, contracts since 2005

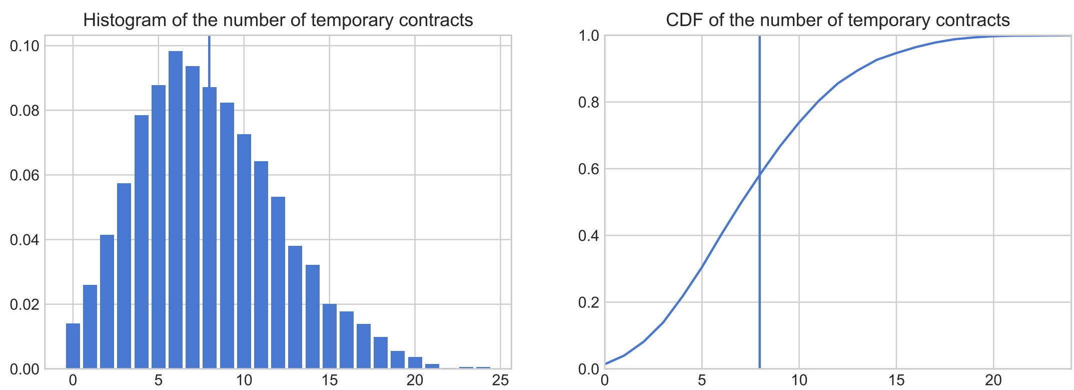
	Extractive Ind	Manufactures (1)	Manufactures (2)	Manufactures (3)	Energy and gas	Construction	Retail and repairs	Transport	Hospitality	Communications	Financial	Real state	Professional	Auxiliary services	Public Admin	Education	Health and ss	Other services
No. T	-0.215	-0.052***	-0.040***	0.030*	-0.041*	-0.006*	-0.028***	-0.013***	-0.005	-0.014	-0.038	0.009	-0.010	-0.023***	-0.019*	-0.026**	-0.008*	-0.005
	(0.1143)	(0.0135)	(0.0099)	(0.0134)	(0.0175)	(0.0029)	(0.0048)	(0.0038)	(0.0025)	(0.0075)	(0.0335)	(0.0965)	(0.0076)	(0.0035)	(0.0079)	(0.0082)	(0.0035)	(0.0028)
No. T^2	0.007	0.001*	0.001***	-0.000*	0.001**	0.000***	0.001***	0.000**	0.000*	0.000	0.002*	-0.006	0.000	0.000***	0.000	0.001*	0.000*	0.000*
	(0.0038)	(0.0005)	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0008)	(0.0053)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0000)
No. P	0.375	-0.007	-0.015	0.004	-0.007	-0.016	-0.004	-0.017	-0.003	0.029	-0.005	-0.064	-0.020	-0.010	0.031	0.018	0.018	0.013
	(0.5660)	(0.0098)	(0.0336)	(0.0679)	(0.0047)	(0.0114)	(0.0082)	(0.0104)	(0.0048)	(0.0284)	(0.0899)	(0.1441)	(0.0169)	(0.0084)	(0.0170)	(0.0203)	(0.0214)	(0.0070)
3 months claim	-0.102	0.135**	0.130***	0.121	0.081	0.126***	0.102***	0.149***	0.110***	0.186***	0.269*	0.333*	0.129**	0.189***	0.017	0.098**	0.108***	0.100***
	(0.3163)	(0.0441)	(0.0362)	(0.0945)	(0.1374)	(0.0112)	(0.0149)	(0.0298)	(0.0120)	(0.0508)	(0.1326)	(0.1589)	(0.0405)	(0.0152)	(0.0357)	(0.0344)	(0.0287)	(0.0302)
6 months claim	-0.157	0.102	0.118*	0.110	0.005	0.126***	0.149***	0.159***	0.142***	0.069	0.386	-0.069	0.126*	0.166***	0.099*	0.033	0.194***	0.139***
	(0.3720)	(0.0553)	(0.0486)	(0.1326)	(0.1687)	(0.0146)	(0.0190)	(0.0348)	(0.0167)	(0.0646)	(0.2118)	(0.2757)	(0.0593)	(0.0205)	(0.0475)	(0.0451)	(0.0354)	(0.0400)
12 months claim	-1.338*	0.111	0.143	0.251	-0.013	0.051*	0.122***	0.157**	0.213***	0.109	-0.209	1.268**	0.259**	0.076*	0.140	0.078	0.081	0.143
	(0.6646)	(0.0852)	(0.0767)	(0.2065)	(0.1885)	(0.0246)	(0.0297)	(0.0532)	(0.0299)	(0.1033)	(0.3028)	(0.4507)	(0.0899)	(0.0364)	(0.0885)	(0.0824)	(0.0573)	(0.0733)
18 months claim	-0.284	0.195	0.151	0.234	0.360	0.011	0.143**	0.273***	0.179***	-0.188	0.383	1.229*	0.041	0.068	0.175	-0.199	0.152	0.258*
	(0.3081)	(0.1369)	(0.1054)	(0.2612)	(0.3534)	(0.0416)	(0.0490)	(0.0782)	(0.0499)	(0.1520)	(0.4422)	(0.5383)	(0.1420)	(0.0522)	(0.1422)	(0.1314)	(0.0900)	(0.1147)
24 months claim	0.623	-0.122	0.159	-0.340	1.391*	0.044	0.153*	0.206	0.367***	-0.070	0.726*	-0.167	0.001	-0.058	0.278	0.009	0.127	0.455**
	(0.9031)	(0.1450)	(0.1326)	(0.4122)	(0.6202)	(0.0589)	(0.0661)	(0.1138)	(0.0822)	(0.2804)	(0.3559)	(0.5001)	(0.1944)	(0.0843)	(0.1494)	(0.1998)	(0.1366)	(0.1492)
Last P	-0.729*	0.039	0.118*	0.072	0.200	0.041**	0.043**	0.082**	0.034**	0.075	-0.101	0.082	0.023	0.059***	0.082*	0.059	0.140***	0.028
	(0.2967)	(0.0412)	(0.0463)	(0.1137)	(0.1416)	(0.0148)	(0.0147)	(0.0300)	(0.0120)	(0.0539)	(0.1519)	(0.1700)	(0.0429)	(0.0167)	(0.0381)	(0.0399)	(0.0369)	(0.0308)
Tenure	0.063	0.028	0.029	0.053	0.152*	0.059***	0.025**	0.050**	0.083***	0.099**	0.236**	-0.023	0.057*	0.123***	0.050*	0.083**	0.093***	0.074***
	(0.1629)	(0.0211)	(0.0211)	(0.0529)	(0.0701)	(0.0077)	(0.0095)	(0.0160)	(0.0095)	(0.0324)	(0.0904)	(0.1225)	(0.0237)	(0.0098)	(0.0223)	(0.0256)	(0.0177)	(0.0210)
Tenure^2	-0.013	-0.001	-0.003*	-0.002	-0.014***	-0.003***	-0.002*	-0.002*	-0.005***	-0.004	-0.020***	0.008	-0.003*	-0.006***	-0.002	-0.006*	-0.004**	-0.006**
	(0.0177)	(0.0009)	(0.0012)	(0.0020)	(0.0039)	(0.0007)	(0.0008)	(0.0010)	(0.0009)	(0.0023)	(0.0059)	(0.0069)	(0.0011)	(0.0007)	(0.0014)	(0.0025)	(0.0012)	(0.0020)
Experience	0.012	0.048	0.009	0.043	-0.073	0.042***	0.034***	0.005	-0.013	-0.009	-0.101	-0.088	-0.002	0.024*	-0.038	0.012	-0.123***	-0.037*
	(0.1545)	(0.0268)	(0.0256)	(0.0629)	(0.0794)	(0.0078)	(0.0093)	(0.0173)	(0.0085)	(0.0296)	(0.0933)	(0.1530)	(0.0247)	(0.0098)	(0.0226)	(0.0212)	(0.0178)	(0.0182)
Age	-0.054	0.001	0.041*	-0.053	-0.007	0.019***	0.016*	0.020	-0.019**	0.031	0.092	0.110	0.034	0.006	0.054**	-0.033*	0.030*	0.006
	(0.1445)	(0.0188)	(0.0198)	(0.0537)	(0.0417)	(0.0054)	(0.0066)	(0.0133)	(0.0060)	(0.0214)	(0.0790)	(0.0703)	(0.0201)	(0.0076)	(0.0203)	(0.0166)	(0.0150)	(0.0141)
Constant	3.287	-0.012	-0.836	0.500	1.623	0.006	0.661**	-0.400	1.319***	-0.115	-1.586	-0.447	0.604	0.104	-0.067	2.904***	-1.002	0.561
	(4.5510)	(0.6212)	(0.6252)	(1.5494)	(1.3083)	(0.1837)	(0.2385)	(0.4707)	(0.2099)	(0.6184)	(2.0725)	(2.4036)	(0.6685)	(0.2521)	(0.7127)	(0.5477)	(0.5234)	(0.4564)
Controls																		
year dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
industry dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
occupation dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	742	21890	23762	6212	4612	111934	98583	28718	95887	14398	4054	3102	26788	116934	31146	22934	40762	39050
Adjusted R^2	0.742	0.412	0.414	0.470	0.491	0.432	0.466	0.395	0.491	0.366	0.541	0.725	0.441	0.431	0.448	0.437	0.370	0.410
AIC	-236.452	17868.260	21278.753	2872.469	1585.802	183730.388	104102.853	42147.507	145916.125	13899.751	900.487	-3430.862	17944.140	179065.701	20490.684	21957.426	73461.910	41484.108

Figure 18: Quarterly Transition Rates by Age (2005-2008)



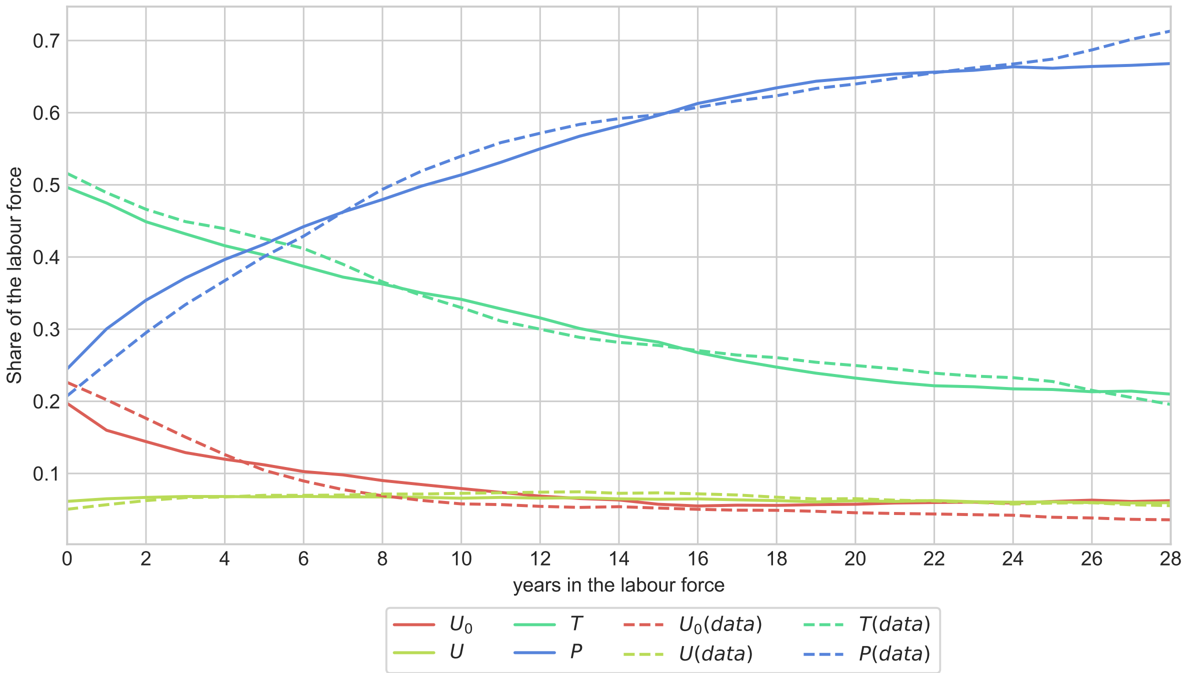
Source: Own calculations from MCVL, 2005-2013 waves

Figure 19: Temporary contract distribution, first stage simulation



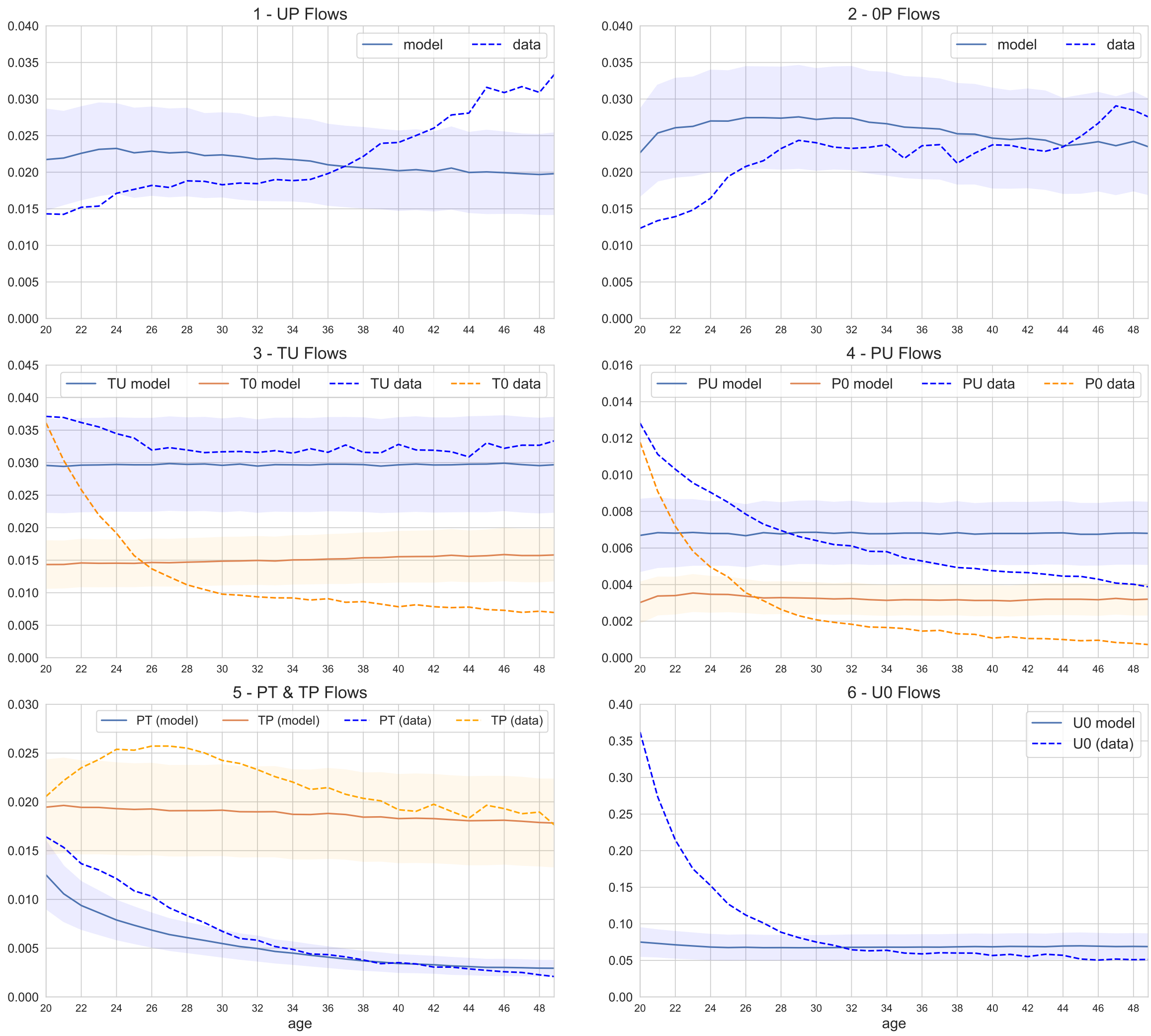
Notes: Distribution of the number of temporary contracts workers have by the end of the second stage simulation. Vertical line marks the average (7.96). Data derived from a simulated panel of 10,000 workers entering the labour force at 20 and exiting at 50.

Figure 20: Stocks by age



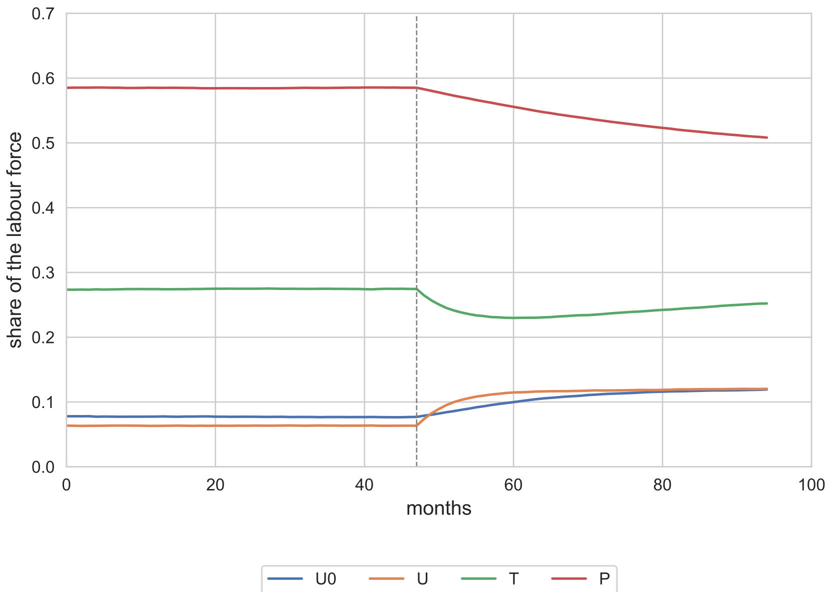
Notes: Evolution of the share of the workforce in a permanent job (P), temporary job (T), unemployed with UB (U) and unemployed without UB ($U0$) by age. Data derived from the first stage simulation, a panel of 16,000 workers entering the labour force at 20 and exiting at 50.

Figure 21: Flows by age



Notes: Flows between labour states: permanent job (P), temporary job (T), unemployed with UB (U) and unemployed without UB ($U0$) by age. Each flow is derived as XY_t/X_t, where XY_t is the gross flow between state X at time t to state Y at $t+1$ and X_t is the stock of workers in state X at time t. Shaded areas denote the average +/- one standard deviation across simulations. Data derived from the first stage simulation, a panel of 16,000 workers entering the labour force at 20.

Figure 22: Employment Stocks simulation results, recession shock at 48 months



Notes: Evolution of the share of the workforce in a permanent job (P), temporary job (T), unemployed with UB (U) and unemployed without UB ($U0$). Data is derived from the second stage simulation of 2 million workers for 8 years, recession shock after 4 years – marked with a dashed line.

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