Search Capital and Unemployment Duration* (Preliminary)

Cristina Lafuente†
University of Edinburgh

September 1, 2018

I propose a novel mechanism called search capital to explain long term unemployment patterns across different ages: 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 search experience and depreciates with tenure if workers do not search often enough. This leaves young (who have not gained enough search experience) and older workers in a disadvantaged position, making them more likely to suffer long term unemployment. I focus on the case of Spain, as its dual labour market structure favours the identification of search capital. I provide empirical evidence that search capital affects unemployment duration and wages at the individual level. Then I propose a search model with search capital and calibrate it using Spanish administrative data. The addition of search capital helps the model match the dynamics of unemployment and job finding rates in the data, specially for younger workers.

JEL classification: J24, J63, J64
Key words: search, unemployment, long-term unemployment, temporary contracts

*For a more updated version please check `sites.google.com/view/clafuente/research`

†I would like to thank my supervisors Maia Güell and Ludo Visschers for all of their support and advice; I have also benefited from the comments and suggestions of Raquel Carrasco, Carlos Carrillo-Tudela, Andrew Clausen, Mike Elsby, Julia Faltermeier, José Ignacio García-Pérez, Philipp Kircher, Chiara Lavaca, Rafael Lopes de Melo and Iourii Manovski. I also received feedback from the attendees at the annual SaM conference, the SED meeting 2018 and the EEA-ES meeting 2018. I would also like to thank the ESRC and MacCalm for their financial support; University of Pennsylvania and UPF for their hospitality. Finally I would like to thank the INE and Seguridad Social for kindly providing the data. Any remaining errors are my own.

1 Introduction

Most classical explanations of long term unemployment (LTU thereafter) relate mostly to older workers, whether is by depreciation of their human capital due to an exogenous shock, as in Ljungqvist and Sargent (2008), or because they are better insured (unemployment benefits, own savings) against unemployment. However, these explanations don't apply so well to younger workers, which have low tenures (and thus have lower benefits) and have not yet accumulated much human capital. In the last recession the young have been hit harder by long term unemployment, as figures 1 and 2 shows for different European countries. This paper introduces a novel mechanism that can help explain these patterns by treating job finding as a skill that is learned and forgotten over time. This skill is separate from traditional human capital because it is unrelated to workers productivity on the job, but it accumulates process. I refer to this skill as search capital.

In particular, I characterise this skill as the one that make workers searching for employment more successful by finding jobs faster. Workers with high search capital receive more offers in any given period and thus have a wider choice of jobs, making them more likely to find a better job, faster. Because of this they will be less likely to remain unemployed for long periods of time. Workers' search capital increases by successfully finding a job, in the sense that workers use their previous experience (the places they applied to, the way they pass the different stages of recruitment processes) to search more efficiently next time they face unemployment. While some of these skills can be learnt after a failed application workers are likely to learn more through successful search. However search capital deteriorates if it is not used, as recent experiences are more relevant than those in the distant past. This implies that proficient searchers are the ones that have had more recent exposure to search, while new entrants to the job market and workers with long tenures are going to be relatively worse at finding jobs.

In this paper I will be focusing on the case of Spain, the country in figures 1 and 2 where the increase in youth LTU has been more pronounced after Greece. The dual labour market structure that characterises Spain generates substantial heterogeneity in labour market experiences among the unemployed, which can be used to identify search capital. Workers in temporary contracts, which rarely ends in promotion to regular contracts, are forced to constantly search for employment. Workers with permanent contracts enjoy longer job tenures and rarely experience unemployment and thus do not accumulate search capital. Using administrative data for Spain, I find a negative correlation between the number of temporary jobs and unemployment duration, which I use as proxy for search capital. I also test whether workers with more temporary contracts in the past

Figure 1: Youth and overall long term unemployment

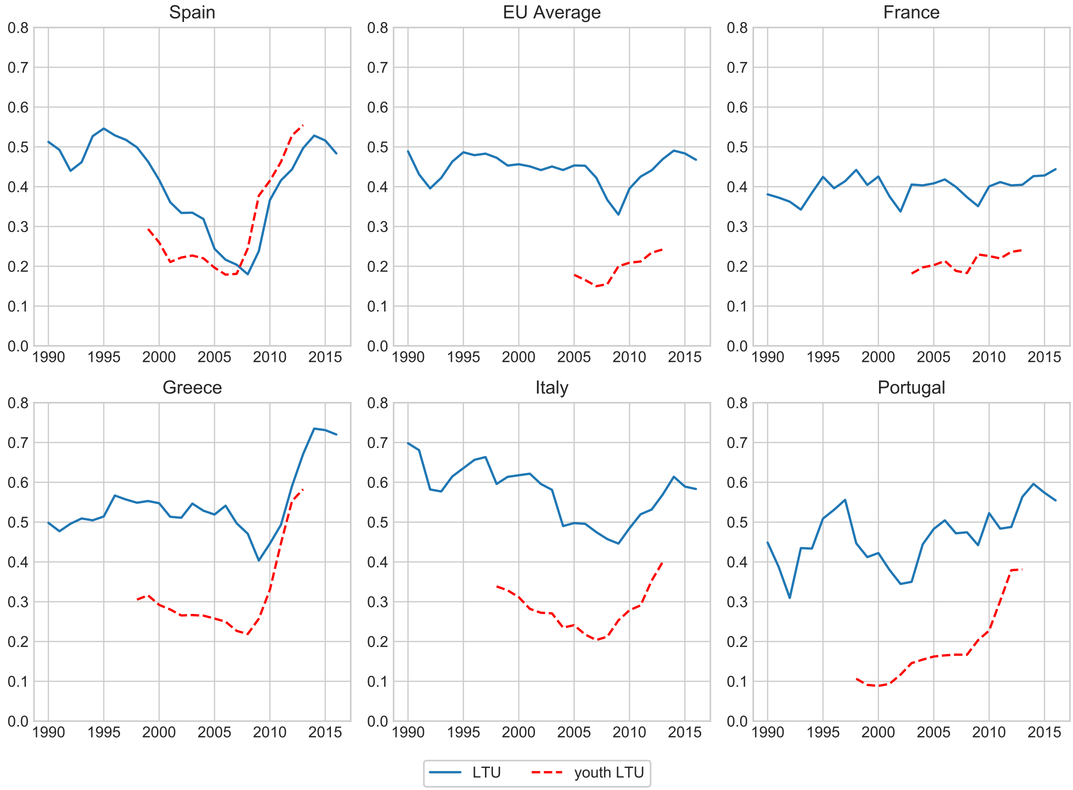


Figure 2: Youth and overall long term unemployment, annual log change

Source: OECD (2017)

find worse jobs in the future by looking at wages and duration of the next job. I find a small but positive effect on wages, and a positive effect on duration after controlling for individual fixed effects. This provides some evidence at the individual level to support the search capital channel.

I then propose a dynamic search model to quantify the effect that search capital differences have on aggregate outcomes. In particular, I focus on the differences in job finding rates and unemployment duration among different age groups. The model generates life-cycle dynamics that closely match the data. The addition of search capital helps explain the labour market flows of young workers and generates substantial differences in unemployment durations among workers of the same age group. Over time, workers become worse at searching as they settle into stable jobs, their search skills deteriorating as a result. This could potentially pose a problem if these workers where to lose their jobs, as an inflow of inefficient searchers can result in more long term unemployment.

The rest of the paper is structured as follows: Section 2 explains search capital in more depth and compares it to other mechanisms in the literature that may have similar effects; Section 3 provides empirical evidence at the individual level; Section 4 presents a theoretical search model that incorporates search capital and calibrates it for Spain; Section 5 concludes.

2 Search Capital and Long Term Unemployment

This section explains more extensively what I refer to as search capital and how it relates to long term unemployment (LTU thereafter). In particular, the interactions of search capital with a dual labour market can have amplifying effects on unemployment. Then I identify and review the other main explanations in the literature that could also drive an increase in long term unemployment and how they relate to search capital.

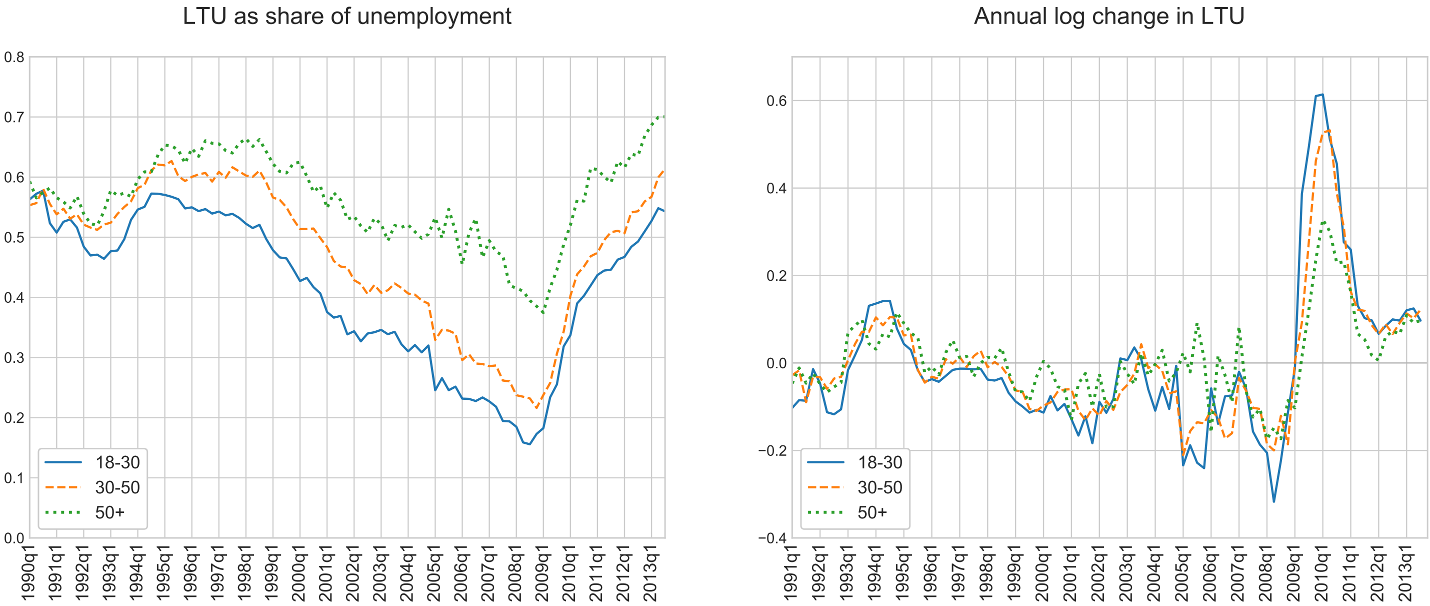
2.1 Search Capital, Dual Labour Markets and LTU

Earlier I defined search capital as the set of skills that help workers find jobs. For example, knowing the places they should apply to (applying for the right kind of jobs for the productive skills workers have, diversifying their search, etc) or knowing how to prepare for the different stages of recruitment processes (interviews, tests, etc). While some of these skills can be learnt after a failed application (a disastrous interview can help improve next one) workers are likely to learn more through successful search - which means they can use their previous experience should they need to find a job again. Being a more efficient searcher translates into being able to apply to more jobs and increases the chances of being offered the job after the application process. That is the approach I follow in the theoretical model of Section 4.

This treatment has some advantages: first, it makes a mapping between an unobservable 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 fail applications as well can become more complicated and potentially imply that search skills increase with time in unemployment. It is a well known result that long term unemployed workers have lower job finding rates (see for example Blanchard and Landier (2002), Hornstein (2012)) so this is not a desirable feature a priori. Thinking of search capital as improving only with success keeps it separate to duration dependence and its determinants. This doesn't rule out that search capital can be defined in broader terms, allowing for a richer learning process, but narrowing the definition makes it easier to work with. The correlation between number of jobs held and search capital would still hold if workers also learnt from their failed or rejected applications.

The empirical strategy of Section 3 relies in this correlation. However how can we know that people that have had more jobs are less productive, or have different preferences to other workers? The interaction of search capital with dual labour markets helps with some of these concerns. For example, in Spain a large share (30%) of workers are employed under *temporary contracts*, with finite duration and low protection in the form of severance payments. The other 70% of the employed hold *permanent contracts*, which have increasing wages and severance with tenure, so these workers 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. In other European countries jobs are also unstable for the young, but what sets Spain apart is that even in their late twenties, temporary jobs are common. A possible explanation is that high skill workers enter the market particularly late as well, with the average age of graduation being 27 (OECD (2014)) but engineering, architecture and other technical degrees the average is over 30. This is mostly due to students finishing their degrees after an average of 5 years more than the official time. The result is a growing stock of workers who are frequently searching in the labour market, while simultaneously the security of permanent jobs builds a stock of workers that are very unlikely to ever search again.

Figure 3: Long term unemployment in Spain, by age



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

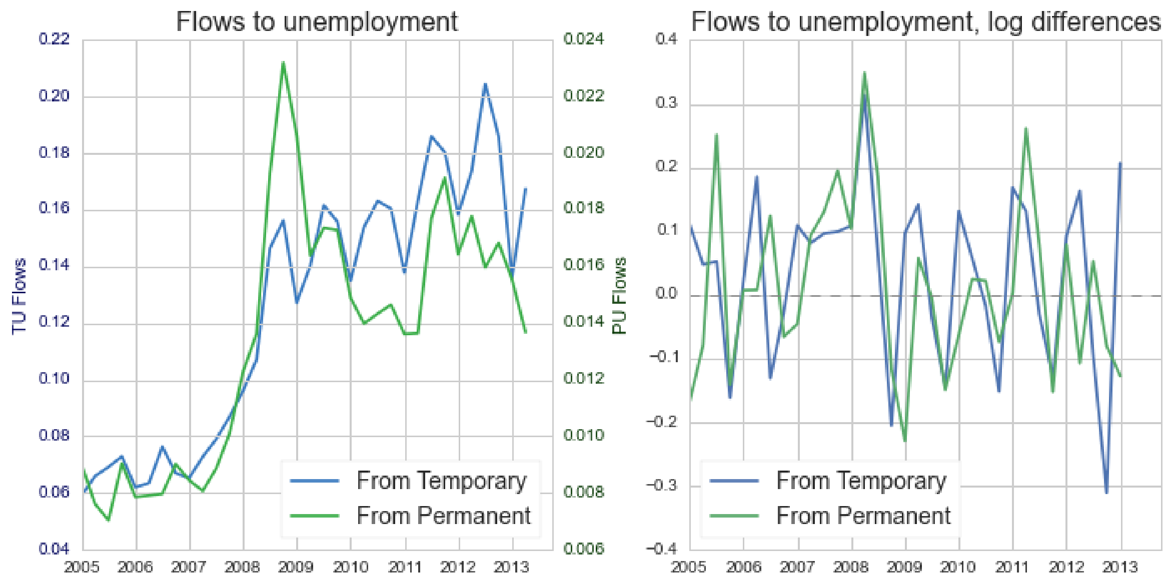
Search capital as introduced in this paper is different from search capital as defined by Carrillo-Tudela and Smith (2017).[1] They refer to the ability of the worker to recall previous employers while employed at another firm, helping them search on the job, while I am referring to the ability of workers 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 learns 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.

The link to Long Term Unemployment

As temporary workers are the ones that find themselves more frequently unemployed, during economic expansions search capital is fairly homogeneous across workers. The expansion of 1995-2008 in Spain, together with the job-creation effect of temporary contracts (Güell and Hu (2006)) meant that long-term unemployment fell for all age groups as shown in figure 3. This implies that the overall search capital of the unemployed increased during this period. These falling LTU patterns have reversed since 2009, with some au-

[1]They present job capital as the ability of the worker to recall past employers, so that if current employment ends the worker can go back to their previous employer instead of "falling off the ladder" and start again from a very low productivity job. This has implications for the wage setting process, as firms engage in Bertrand competition to poach workers from other firms. In their model, search capital can also depreciate so that contacts of the worker in their previous job may vanish - so some unlucky workers may not have to option to go back to their past firm.

Figure 4: Flows into unemployment, by contract type



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

thors arguing that the rapid increase in unemployment (and the subsequent increase in LTU) is mainly driven by job destruction from temporary contracts[2]: Firms tend to prefer to reduce their temporary workforce rather than adjust wages and as a consequence there is too much firing in recessions. The volatility of temporary to unemployment flows does seem to play a significant role in the overall volatility of unemployment (Silva and Vázquez-Grenno (2013)). However the collapse of the construction sector (58% decline in employment from 2008 to 2013), and later a severe financial crisis translated into an increase in lay-offs from both kind of contracts[3], as figure 4 shows. The left panel presents the evolution of flows into unemployment from temporary (blue, left scale) and permanent (green,right scale) contracts. As the difference in scaling shows, separation rates from permanent contracts are about ten times smaller than those of temporary workers. However, the spike of 2008 is higher for permanent contracts (from 0.008 in 2007 to 0.023 in late 2008). The right panel of this figure shows the log difference of these series (log of the flow at time $t + 1$ - log of the flow at time t), where the magnitude of changes in 2008 is again very similar, so in relative terms the increase in job destruction rates from

[2]See for example Bentolila et al. (2012) for a comparison between the impact of the recession between France and Spain, where the differences are driven by the wider gap between permanent and temporary contracts in terms of severance payments. Temporary contracts are much easier to destroy in Spain in their model, so firms react to a fall in productivity by firing most of their temporary workforce.

[3]In fact, following the sovereign debt crisis triggered by these events and the Greece fallout, the government dismissed a significant number of their employees as well. More specifically, real estate lost 22% of its employment, financial services 11%, and 1.7% in the public sector in the 2005-2008 period, according to employment statistics from the Spanish National Statistics Institute (INE (2017)). In 2011 alone, the public sector lost 175,000 workers.

both types of contract was similar. Costain et al. (2010) explained these patterns in their paper as follows: falling productivity thresholds in booms leads to more conversions from temporary to permanent, this creates a growing stock of low productivity permanent workers that are dismissed in a recession.[4] The main driving factor behind the increase in unemployment is not temporary contracts, but high severance payments that prevent firing unproductive permanent workers.

How does this relate to search capital? Permanent workers have lower levels of search capital because they have been employed longer on average in the same firm, with few incentives to search.[5] When recessions destroy "safe" jobs, there is an influx of bad searchers into the unemployment pool. At the same time, there is more competition for fewer vacancies, so frequent searchers take these jobs first. As these jobs are also predominantly temporary contracts, they flow back into unemployment after not too long, and then again find another job with relative ease. This mechanism depresses the chances of finding jobs for both new entrants with little search experience and dismissed permanent workers. The combination of the market-driven heterogeneity in search abilities of the workforce with a severe recession makes Spain a good choice to test the effects of search capital[6]

However there are other explanations in the literature that can account for the rise in long term unemployment in Spain, although not necessarily for the youth. I highlight the main two competing theories next.

2.2 Related explanations of LTU

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

[4]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 are more likely going to promote during a period of economic boom.

[5] For example a worker in the public sector in Spain has to pass an examination process that is very different from private sector application process. In addition to this, public servants have very protected jobs.

[6]It is worth noting though that Spain is not an isolated case and that other Southern European countries with segmented labour markets, such as Italy and Portugal, also saw an increase in their long term unemployment rates. The relatively minor effects in France can be attributed to their milder recession: Search capital increases unemployment when general unemployment is high and there is an influx of bad searchers in the unemployment pool.

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) results 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 drastically. 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 durations overall.

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

In Spain, regular workers tend to have, on average, better paid jobs than temporary workers (because of seniority wage rules and better unionisation) but also because if they are laid off they receive severance payments that, in some cases, can be quite substantial. As more permanent workers have been dismissed in the recession, the composition of the unemployment pool has shifted towards richer individuals.

The generosity of benefits in Spain is high but in line with other European countries. For example, Stovicek et al. (2012) carry out a detailed comparative study of unemployment insurance and benefits across EU countries and Spain does not stand out in any dimension. While replacement rates are on the high end (approximately 70% on average[7]) the lack of other social benefits, such as housing assistance, child supplements or minimum income, means that Spain is not a particularly generous country for unemployed workers in European standards. The maximum extension of benefits is two years, similar to France, Portugal or the Netherlands. The median unemployment compensation

[7] Stovicek et al. (2012)

is 636.22 euros a month compared to the median gross wage of 1351.72 for temporary workers and 1446.75 for permanent workers.[8] In response to the rapid increase of LTU, Spain did not extend entitlement periods as many US states opted to do. Exhaustion of benefits became commonplace during the recession with close to 50% of all unemployed not receiving any benefits as of 2012.[9] It is hard to argue that the rise in LTU is driven by workers preferring to remain unemployed for a period of time beyond the exhaustion of their benefits.

While the generosity of unemployment benefits is a good explanation for the increase in LTU in general, it is not a good explanation for the increase in youth LTU as their lower wages and shorter tenures imply that many of them are not receiving unemployment benefits - and where they are, these are modest and only for a short period.

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

[8] These are based on calculations using the information in the tax data of the Social Security Working Lives Sample, once the bottom and top 1% percentiles have been removed. See Data section for a detailed account of how these were calculated.

[9]Based on the Spanish LFS and similar to Administrative data.

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 can't 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 an exogenous lay-off can happen, this leads to diversification of human capital in those industries/occupations where jobs are more unstable.

Crucially, the depreciation of human capital can't explain why long term unemployment has risen so dramatically among young workers. 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 using them to pursue jobs. Therefore this explanation does not compete with search capital.

3 Empirical Analysis

Search capital is not observable. Ideally one would like to measure search skills like networks or application strategy. However we may be able to identify skilled searchers by looking at their search outcomes: those who find better jobs faster, once controlling for all other observables, are likely to have better search skills. But these skills could be an inherent trait of the individuals, some people may be born with a natural advantage over others when it comes to finding jobs, having well-connected family or friends for example. This doesn't mean however that people don't get better at searching with time. In order to try to investigate this one would need 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.

3.1 The Data

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. 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 (size, location, tax code) and information on the job such as industry, occupational scale 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 has information on the self-employed.

The Spanish Social Security also provides a complementary dataset with income tax information, which can be linked to the working histories files via fiscal identifiers. This way it is possible to obtain detailed wage information for most jobs in the sample. It also holds records on 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. 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 can't accumulate enough working spells to be eligible within the year.

I use the 2005-2013 waves of the MCVL. The data contains past information and it would be tempting to use it to go back in time and approximate the workforce of previous years. However, as we go back into the past, the sample stops being representative as it turns younger and only those active in the present are represented in the past.

One concern that arises when using administrative data to study unemployment is that administrations only count registered unemployment spells. For those who can't or choose not to claim UB, the sample only has gaps. However with minor adjustments (using official definitions and labour laws) it is possible to reconstruct the unemployment series to be close to those coming from the Labour Force Survey: figure 5 shows that without any modifications, the Social Security quarterly unemployment rate is well below the LFS. Adding (1) the days in between finished jobs (2) uncompleted spells as of 2013 and (3) gaps between employment spells for those without the right to claim UB generates the 'MCVL expanded' series[10], which closely follows the LFS except from the 2005-2008 period. Here the difference is likely coming from the failure of the LFS to adequately capture short unemployment spells for young workers (Lafuente (2017)). There is also an issue around how the LFS classifies unemployment and non-participation, as the flows to employment for both groups are very similar for young workers. This suggests that the unemployment data from the LFS is very sensitive to the definition of unemployment, and thus that in Spain there is little evidence of the non-participants of working age to being completely detached from the labour market. In fact it is well documented that previous changes in this definition caused important breaks in the series. The MCVL is helpful for dealing with these breaks in the LFS data.

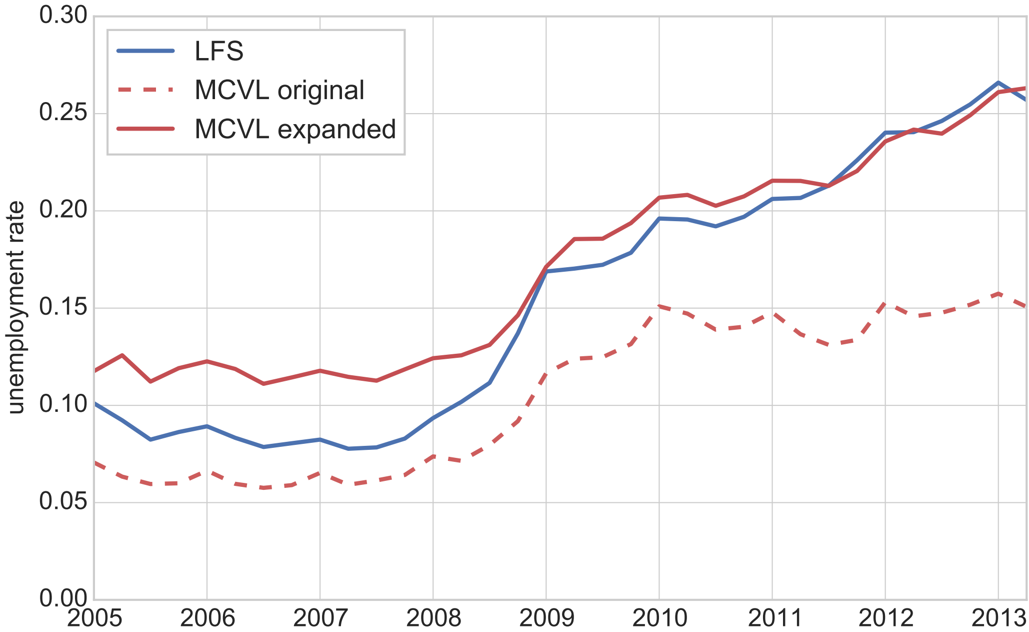
I choose to include all non-employment spells that: last longer than 15 days, do not end in recall or in retirement, come from either self-employment, quits[11] or have less than 6 months of previous employment spells (making them ineligible to claim benefits). This last condition ensures that those without the right to claim are included in the sample.[12] This ensures that spurious spikes in duration at the termination of benefits are ruled out.

[10]In practice, there are more restrictions on which gaps between employment spells are added, such as excluding recalls to the same firm. See Lafuente (2017) for more details.

[11]Workers who leave voluntarily their jobs do not have the right to claim unemployment benefits in Spain. The self-employed also had no right to claim unemployment compensation before 2012.

[12]Since the labour reform of 1992, it is necessary for all workers to have at least 12 months or employment contributions in order to claim UB. Before that requirement was lower: 6 months. The rule of thumb of 6 months is enough to add all workers at all times that were eligible and makes the data fit together better with the LFS. This requirement helps keep temporary workers with short unemployment/employment spells to stay in the sample, and thus helps to match the LFS unemployment series.

Figure 5: Unemployment rate in Spain, different datasets



Source: Own calculations from the Spanish Labour Force Survey (INE (2013)) and MCVL, 2005-2013 waves

These can have important effects in the estimation as noted by Alvarez et al. (2015).

3.2 Identification Strategy

The goal of the empirical model is to test for a relationship between past and present search outcomes, or how workers with different working histories but similar in all other ways can have different unemployment spells. In particular, do people who have found different jobs in the past have shorter unemployment spells than others with fewer jobs in the past? And if so, are the jobs they find better on average?

My main identification strategy is to use the number of temporary contracts held in the past as a proxy for search capital. There are several reasons for using this approach: first, it can be interpreted as the number of previous successes the worker has had finding a job with different firms. This is important because it is not searching per se that is of interest, but successful search. They indicate that the worker has had experience of search in the past and that she was good enough to obtain a job. Having worked in different firms also signals adaptability and it can be thought of as an indicator of transferable skills. This is what makes temporary jobs a better indication of search capital than permanent jobs, which usually imply that the worker won't search for a job for a

Table 1: Descriptive Statistics

	count	mean	std	min	25%	50%	75%	max
Weeks	703,061	31.66	42.01	2	6.57	16.29	38.71	462.86
Temporary contracts	703,061	6.29	6.29	0	2	5	8	251
Permanent contracts	703,061	3.79	5.72	0	0	2	5	232
$wage_{t-1}$ (euros, annual)	703,061	19879.72	331783.65	0.01	10334.04	15139.48	19817.51	256319430.50
$wage_{t+1}$ (euros, annual)	602,510	14610.17	63325.83	0.03	4016.85	12578.33	18066.59	28970452.81
UB_t (euros, annual)	694,728	6440.86	11417.19	0	2482.65	5414.58	9086.54	2315531.94
Tenure (years)	703,061	0.97	2.19	0	0.08	0.27	0.82	39.27
Experience (PC, years)	703,061	4.19	5.78	0	0	1.69	6.18	39.48
Experience (TC, years)	703,061	2.42	2.23	0	0.63	1.87	3.59	24.59
UB entitlement (months)	703,061	4.31	7.28	0	0	0	6	24.33
Age	703,061	32.75	8.90	20	25	31	39	54
Male dummy	703,061	0.56	0.50	0	0	1	1	1
Quit dummy	703,061	0.16	0.37	0	0	0	0	1

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

Table 2: Variables of interest

Effect	Control variable	Variable name
Unemployment benefits (quantity)	Observed daily benefits	UB
Unemployment benefits (duration)	Claim dummies for 3,6,12,18,24 months	claim3, claim6, ...
Severance Payments	Indicator for last permanent contract	Last P, tenure
Quality of previous matching	Observed past daily wages	log(past wage)
Quality of future matching	Observed future daily wages	log(wage)
Human Capital (general)	Work experience over potential experience	R. Experience
Human Capital (specific)	Tenure in the last job	Tenure
Search Capital (gain)	Number of temporary contracts held	No. T
Search Capital (atrophy)	Years since last unemployment spell	YEmp

long time. There are some caveats: the firm may "recall" the worker after they have been unemployed for some time, making unemployment an agreed holiday. This is especially true for very frequent jobs, sometimes lasting a day at a time. Using fiscal firm identifiers I exclude recalls and count temporary contract roll-outs (two or more temporary jobs in a row by the same firm) as only one job. This is to ensure there was search involved in the process of finding the next job.

An alternative measure can be the number of past unemployment spells. However, this would rule out search on the job. As I am aiming at capturing how up to date the worker is, these transitions can't be ignored. I also add the number of permanent contracts, but having had a permanent contract in the past can have negative connotations for future employers: to leave a permanent position the worker had to quit (low commitment) or the firm had to lay off the worker (low productivity). Temporary contracts do not have these negative connotations as they just end, and given the low rate of promotion this does not signal much about the worker. Some sectors have seasonal demand upswings (e.g. tourism and agriculture) for which temporary contracts are a natural choice, again having many temporary jobs in these sectors doesn't signal anything negative about the worker. I include both previous temporary and permanent jobs in my regressions, and as expected I find them to have different effects.

A more interesting question is how to capture search skill depreciation. Using time since last unemployment spell is a good proxy, but as argued before it also means ignoring on-the-job search. Tenure then becomes the best proxy variable, but using this it would be impossible to untangle how much of the effect is due to loss of search skills and how much to loss of specific human capital. Temporary contracts can still capture some of it: consider two workers with the same duration at their previous job, but where one of them had several temporary contracts before that job. The difference in unemployment duration will then be attributed to different search abilities, not to human capital.

Another variable that is closely related to this is unemployment entitlement period. It is a well know result that there are spikes in job exiting rates close to the expiration of benefits (Card et al. (2007)). This is partly a reflection of employment agencies only recording unemployment while benefits last, as is the case in Spain. These spikes are closely related to the amount of time since the worker was last unemployed, which is another reason to treat the time since last unemployment ($YEmp$) variable cautiously. I include dummies for 3, 6, 12, 18 and 24 months (denoted by the vector $CLAIM$) as these are the most common spikes to control for unemployment entitlement period.

It is also important to have good control variables for the other factors detailed in section 2 that could also be related to past working histories but do not relate to search capital directly: human capital, incentives to search and matching factors. The most important of these controls is taken from the tax information file: past wages, unemployment benefits and severance payments. Past wages are related to productivity, both specific to the individual (more productive workers are likely to have higher wages on average) and to the match itself. I identify worker-firm pairs using their tax codes, ensuring I correctly identify the previous job. A caveat is that although the tax file only records annual wages, if the worker has more than one job with the same firm in the same year I assume the wages are constant among jobs within the year in the same firm. As I am excluding recalls from the sample, this should not make a significant difference.

Some firm-worker pairs can't be identified because some firms have special fiscal identifiers (such as public administrations). The information added by this variable outweighs the potential concerns about noise and missing information, so it is included in all regressions. I also include the amount of unemployment benefits the worker receives while unemployed, which is directly related to past wages. As some workers are not entitled to any benefits (quits, self-employed, those who have not accumulated enough tenure) this variable can be interpreted as the effect of more generous benefits on duration, keeping previous wages constant - and keeping duration of benefits constant too. The only caveat is that unemployment benefits are recorded annually and do not distinguish between different unemployment spells. By linking the tax dataset to the working histories I count the days of unemployment within a year in which the worker was eligible to receive them and divide the total amount in euros by the days of unemployment. Figure 6 shows the resulting benefits and wages distribution. This measure is likely to be noisy - much more so than wages - so in some regressions I choose not to include it. In the results it can be seen that unemployment benefits don't seem to add much more information that wages and unemployment entitlement dummies. Finally, the tax dataset records severance payments separately from general wages as they are excluded from income tax computations - giving an incentive to the worker to report them truthfully. However, the data on severance payments is very noisy (only identified for 2% of permanent workers and 5% temporary workers). Given that most permanent jobs end in a dismissal (as opposed to a quit), a dummy taking the value 1 when the last job was permanent should suffice to control for severance payments, but I add the declared severance payments in the robustness check.

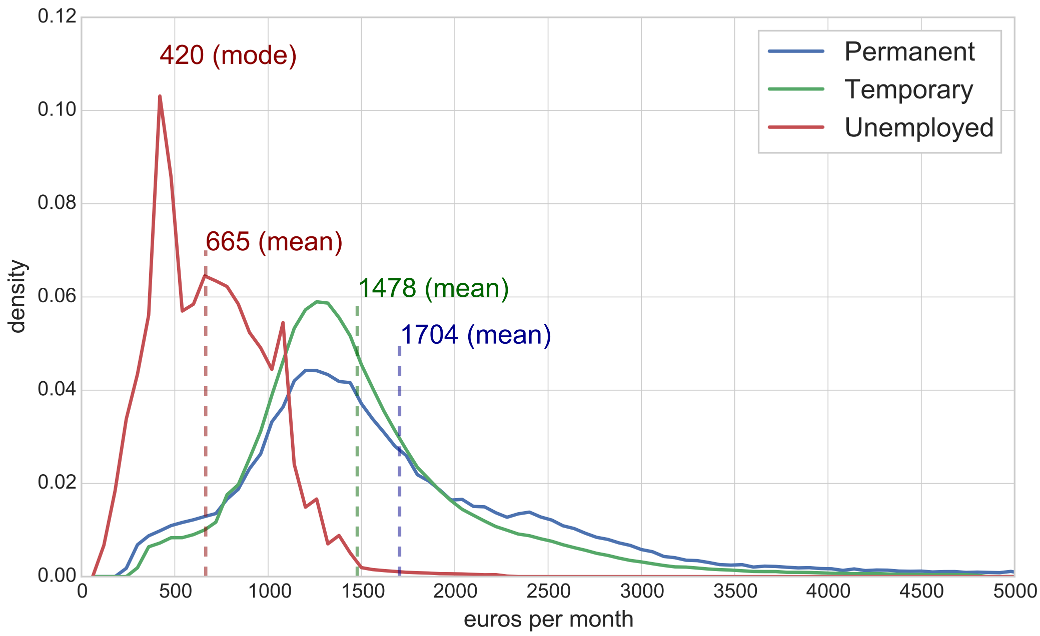
Other variables of interest are the controls for human capital, simply in the form of accumulated job experience in years[13] and past tenure for non-transferable human capital. The usual controls for age, gender and educational levels (split in 4 levels[14]) are included. I also include controls for industry at the one digit-level, province of residence and a proxy for occupational level.[15]

[13]In alternative specifications I rescale this variable as years of employment over years in the labour force. The results don't change substantially but affect the coefficients for age. I choose to retain age in the regressions, so I revert to use total years of experience.

[14]Base category being no formal education/finishing at most primary school, secondary education, pre-university education (including vocational training that requires a secondary education degree) and university education.

[15]Practically all formal jobs have their wages determined by collective agreements at the industry and/or regional levels. There agreements specify different lower bounds for salaries levels within the firm according to professional categories - manager, engineer/skilled analytical worker, high and low skill white collar jobs, etc. The combination of industry-professional category can provide a proxy for occupation, therefore I add these professional categories as controls. García-Pérez and Muñoz-Bullón (2011) argue that they provide a more accurate measure of skill requirement for the job.

Figure 6: Wage distributions



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

3.3 Empirical approach

Given the data and the variables, the empirical strategy is to regress the logarithm of weeks of unemployment against the explanatory variables discussed previously plus control variables for individual characteristics, as equation 1 shows. These include age (with a quadratic trend), gender, nationality, industry, region (at the province level) and occupational level. I also include dummies for part-time, collective dismissal and quits. Finally I include two specific dummies for workers coming from construction jobs: one after and one before 2008, the year of the collapse of the building sector.

$$log(weeks_t) = \beta_0 + \beta_1 No.T + \beta_2 YEmp + \gamma CLAIM + \beta_3 LastP + \beta_4 Ten + \beta_5 Exp + \beta_6 log(wage_{t-1}) + \beta_7 log(UB_t) + \delta X + \epsilon \quad (1)$$

The unit of observation is a complete unemployment spell: an unemployment spell that ends in a job or self-employment. I exclude self-employed that have lost their job to allow for an easier interpretation of the dummy for last permanent contract. In this way, each individual could be appearing multiple times in the regression, but still the sample will be representative of the unemployment pool: some workers find themselves more often unemployed while others rarely appear in the sample. As the aim is to capture the competition of different workers for jobs, the "one spell, one observation" approach is suitable.

A possible concern is that individuals that appear as unemployed multiple times have some unobserved characteristic driving them back and forward from unemployment. Many of these seemingly quick employment/unemployment spells are driven by recalls: a worker returning to the same firm after a brief period of unemployment. I have restricted to sample to consider only workers that change firms to avoid recalls, so this frequent unemployment spells have to come from workers switching jobs. Finally, to address possible unobservable heterogeneity, I redo the exercise with individual fixed effects. Here the interpretation of the coefficients is different: in the pooled sample, β_1 would be 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 would represent the effect of one additional temporary contract on the difference in duration of unemployment spells across time for a single worker. That is, if it is positive (negative) then as the worker accumulates temporary contracts her unemployment spells get longer (shorter) over time. In this way the panel regression measures the effect of accumulating search capital over time, while the pooled regressions measure the effects across workers - some may be born with higher stocks of search capital than others.

The empirical strategy is more simple than in García-Pérez and Muñoz-Bullón (2011), but the variable of interest is different: here the interest lies in identifying systematic differences in completed unemployment spells, while García-Pérez and Muñoz-Bullón are concerned with estimating hazard rates for exiting unemployment - and ultimately whether or not they have an effect on future upgrades to permanent contracts.

Finally, to complement the analysis above I run a logistic model where I consider the probability that an unemployment spell will last more than a year (LTU_1) and two (LTU_2) against all the previous variables. As the average spell in Spain is close to a year, I use the two year mark to signal long term unemployment more effectively. The influence of the benefit claiming period ($claim12$ and $claim24$) will be clear here. But more importantly, 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. These probabilistic regressions consider the impact that one additional success can have on that outcome (long term unemployment).

Of course, it could be that workers with more temporary contracts happen to find jobs faster but these jobs are otherwise worse than the rest. I test for this in two ways: First I regress equation 2 using the information on the next job wages - excluding those who become self-employed.[16] Given that my wage data comes from annual sources and for some jobs it can be imprecise, I restrict the sample to workers who find a job that lasts at least 3 months. Unemployment duration is included as an explanatory variable on its own. This way any remaining effects of all of the other variables are to be interpreted as their independent effect on wages aside from its indirect effect on duration. Consider the case where the coefficient of temporary contracts is negative and significant in both duration and wage regressions. Then temporary contracts will be correlated with shorter unemployment spells, but also with lower wages. Its overall effect on wage will depend on how unemployment duration impacts wages: its effect on duration may be strong enough to have a positive wage impact overall.

$$\begin{aligned} log(wage_{t+1}) = \beta_0 + \beta_1 No.T + \beta_2 YEmp + \gamma CLAIM + \beta_1 No.T + \beta_3 LastP + \beta_4 Ten + \\ \beta_5 R.Exp + \beta_6 log(weeks_t) + \beta_7 log(wage_{t-1}) + \beta_8 log(UB_t) + \delta X + \epsilon \quad (2) \end{aligned}$$

There is also the concern (as discuss earlier in section 2) that temporary contracts fail to provide a stepping stone to more stable employment, and so the jobs found are more unstable (shorter) than average. Here it is good to remember that over 92% of the unemployment spells in the sample end in a temporary contract, so the chances of getting a permanent job out of unemployment are very small. It also makes sense that workers already employed in a temporary job have more leverage when negotiating the terms of future employment than the unemployed, so transitions to permanent jobs are not only promotions within firms but across firms too. Temporary contracts could reduce the average duration of future jobs or impact the chances of getting promoted to a permanent contract. To test this hypothesis, I run another regression with two alternative dependent variables: duration of next job (remember that all spells in the sample end in a job) and time until next unemployment spell. This last variable takes into account not only the next job, but any subsequent employment spell. This measure could be right-censored, especially for 2012-2013 observations. In the robustness checks I restrict this regression to early unemployment spells only. Equation 3 also incorporates the length of the current unemployment spell to control for any impact long durations could have - weaker bargaining position, discrimination, etc.

$$\begin{aligned} log(weeks_{t+1}) = \beta_0 + \beta_1 No.T_t + \beta_2 YEmp_t + \gamma CLAIM_t + \beta_3 LastP_t + \beta_4 Ten_{t-1} + \\ \beta_5 Exp_t + \beta_6 log(weeks_t) + \beta_7 log(wage_{t-1}) + \beta_8 log(UB_t) + \delta X + \epsilon \quad (3) \end{aligned}$$

[16]Not many do in the sample.

3.4 Results

Results are shown in tables 3 to 6. The first table has six columns: the first three correspond to a pooled OLS regression (each unemployment spell counts as one observation) while the others are fixed effects panel regressions. The difference among them is the addition of past wage and present UB variables. This is because not all observations have wage information from their previous job, as noted before. This is the reason why the number of observations of columns 2-3 and 5-6 is smaller.

Duration of unemployment

The first thing to note is that the number of temporary contracts held in the past ($No.T$) is significant and negative, even when controlling for individual fixed effects. Each temporary contract reduces the unemployment spell by 3% on average, with slightly higher effects (3.2%) once controlling for past wages (column 2) and unemployment benefits (column 3). Recall that the average number of temporary contracts is 4, so the effect of exposure to temporary contracts for the average worker is 12%. The magnitude of the effect is reduced in the fixed effects regressions. A possible interpretation of this is that this is the effect for each worker throughout their working life, whereas the effect on pooled regressions is the effect between different workers. An alternative explanation is that the effect of temporary contracts is reduced in the FE regressions because most of the ability to search is specific to each individual. Gaining more jobs does not greatly improve her chances of finding a job after controlling for individual effects. This would make the differences in search ability across workers more persistent.

The impact of temporary contracts on duration could be non-linear: after a certain amount of contracts the effect could turn positive. Table A2 in the appendix shows the results after adding a quadratic term for the number of contracts. It doesn't make a substantial difference for most of the sample: it requires more than 100 temporary contracts for the effect to turn positive, 99% of observations lie outside this range. Another possible caveat is that the effect of temporary contracts may vary for different industries. Table A3 in the appendix shows the results of the regression in column 2 (pooled OLS, controlling for past wages) for each industry in the next job. The coefficient on temporary jobs is always significant and negative, suggesting these results hold true in general.

The effect of the length of UB entitlement in months is large. All of the claim dummies are significant and positive. However, the biggest effect is not at the maximum entitlement period (24 months, $claim24$), but at 6 months in the pooled regressions and between 6 and 12 months in the panel regressions. Being entitled to between six months

Table 3: Regressions on Unemployment Duration

	Pooled OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(weeks)	log(weeks)	log(weeks)	log(weeks)	log(weeks)	log(weeks)
No. T	-0.030***	-0.032***	-0.032***	-0.005***	-0.005***	-0.005***
	(0.0038)	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0013)
YEmp	0.004***	0.003***	0.003***	0.003*	0.001	0.001
	(0.0008)	(0.0007)	(0.0007)	(0.0011)	(0.0013)	(0.0013)
3 months claim	0.154***	0.224***	0.226***	0.143***	0.179***	0.181***
	(0.0041)	(0.0043)	(0.0043)	(0.0048)	(0.0056)	(0.0057)
6 months claim	0.148***	0.228***	0.231***	0.165***	0.203***	0.205***
	(0.0053)	(0.0050)	(0.0050)	(0.0064)	(0.0075)	(0.0075)
12 months claim	0.109***	0.178***	0.181***	0.170***	0.200***	0.203***
	(0.0083)	(0.0074)	(0.0074)	(0.0110)	(0.0126)	(0.0127)
18 months claim	0.078***	0.143***	0.148***	0.160***	0.178***	0.181***
	(0.0111)	(0.0103)	(0.0103)	(0.0171)	(0.0195)	(0.0196)
24 months claim	0.011	0.046***	0.049***	0.113***	0.110***	0.113***
	(0.0127)	(0.0132)	(0.0132)	(0.0236)	(0.0270)	(0.0272)
Last P	0.111***	0.040***	0.041***	0.084***	0.039***	0.040***
	(0.0070)	(0.0046)	(0.0046)	(0.0050)	(0.0061)	(0.0061)
Tenure	0.011***	0.016***	0.016***	0.020***	0.027***	0.027***
	(0.0013)	(0.0012)	(0.0012)	(0.0019)	(0.0023)	(0.0023)
Experience	-0.010***	-0.007***	-0.007***	0.037***	0.041***	0.042***
	(0.0005)	(0.0005)	(0.0005)	(0.0029)	(0.0034)	(0.0034)
No. P	-0.038***	-0.035***	-0.035***	-0.008**	-0.008*	-0.008*
	(0.0023)	(0.0022)	(0.0022)	(0.0029)	(0.0032)	(0.0032)
age	-0.013***	-0.002	-0.001	-0.038***	-0.035***	-0.035***
	(0.0023)	(0.0017)	(0.0017)	(0.0048)	(0.0054)	(0.0054)
log(past wage)		-0.081***	-0.081***		-0.043***	-0.044***
		(0.0014)	(0.0014)		(0.0017)	(0.0018)
log(UI)			-0.002***			-0.001***
			(0.0001)			(0.0001)
Constant	1.074***	1.203***	1.169***	0.909**	0.993*	0.971*
	(0.1547)	(0.2370)	(0.2387)	(0.3275)	(0.4014)	(0.4024)
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓
Observations	587,222	465,832	461,369	587,222	465,832	461,369
Adjusted R^2	0.546	0.559	0.561	0.462	0.457	0.458
AIC	1,502,926	1,189,482	1,176,424	1,082,259	840,389	829,077

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.

and a year increases time in unemployment by 22.8% (after controlling for unemployment income, column 2). In the fixed effects regression, the effect is smaller, between 16 and 20%. This again may reflect that different people respond differently to the entitlement period of unemployment benefits. Once we remove that unobserved characteristic, the increase is smaller. Compared to the effect of unemployment income ($log(UB)$) it is clear that it is duration, not size of the benefits that drives longer unemployment duration.

On the other hand, $YEmp$ or years since last unemployment spell is significant at the 1% level and positive in all regressions. Controlling for fixed effects also reduces the size of its coefficient. The effect of tenure is greater (an increase of between 1.1 and 1.6% for each year in the last firm). A possible explanation is that a worker that keeps herself employed by different firms, making job-to-job transitions has her search skills relatively up to date. A worker who has "settled" in one company may not have any incentives to search outside the firm (either because of increases in job security, wages or both) and thus her search skills deteriorate faster. This interpretation is appealing since the other channels through which tenure may have an effect on unemployment duration are: benefit entitlement (already controlled for by *claim*), higher past wages (a variable on its own) and severance payment (only for those with a permanent contract, controlled for by *Last P*). The only explanations left are the search channel or a matching effect: since a long past tenure suggests a good match, the worker could be waiting for another good job.

Last P itself has a small but negative effect in the pooled regressions when controlling for wages and UB size. However in the fixed effect regressions it has a significant positive effect, extending unemployment duration by between 4 and 11%. This may be interpreted as the contract type being used as a signal of higher skill to employers. However the effect of higher skill could be partly controlled for by adding wages, although workers don't usually reveal their past wages (at least in their CVs) whereas the type of contract is something that can be easily verified. So across competing workers, having had a permanent contract helps them find a job. When considering the effect across time for individual workers in the FE regressions, the effect is clearly positive. This likely relates to matching in a similar way to tenure: the worker may not be willing to engage in temporary contracts again, but prefers to wait longer for a permanent position.

The rest of the variables have the expected signs. The only exception is the size of annual unemployment benefit (in logs, $log(UB)$) which is negative in pooled OLS. A 1% increase of UB *decreases* the length of unemployment by 0.2%. As discussed previously, it is the length, not the size of benefits that matters for durations. The amount of benefits a worker gets are related to their previous wage, so it could be that higher wage earners are also more skilled. However since wages themselves are being controlled for by *log(past wage)*, the remaining effect could be interpreted as people with family responsibilities (who get extra money) leaving unemployment slightly faster. In the fixed effects regression the sign becomes positive - although it is very small. This also signals that once these differences across individuals are removed, more UB means longer unemployment spells, but the effect enters mainly through length rather than the amount paid.

Other variables like the quadratic term on age, the gender and industry dummies can be seen in the appendix. There is a significant positive effect of being previously employed in construction (compared with the base of being employed in the agricultural sector) and the recession makes this effect even higher.

To complement the previous analysis, table 4 shows the result of the logistic regression on the probability of becoming long term unemployed. The first two columns take into account all unemployment spells, even those unfinished by the end of 2013. This could lead to misleading results for unemployment spells starting in 2012 onwards because of right-censoring of unemployment spells, so I consider only finished spells only in columns 3-4. The number of temporary contracts is negatively correlated with the probability of LTU, both when we consider LTU as 1 year or more or 2 years or more. In particular, one extra temporary contract diminishes the probability of LTU (as one or more years of unemployment) by 8.3% on average ($1-e^{-0.063}$), and 12.8% for two years or more. These coefficients increase to 8.6% and 12.6% respectively when only considering finished spells.

The coefficients on the right to claim dummies are all positively, as expected. Having the right to claim for 18 months increases by 2.86 ($e^{-1.105}$) the odds of ending in long term unemployment (over one year), with a similar magnitude for only unfinished spells. However, the quantity of unemployment benefits as measured by $log(UB)$ decreases the odds of LTU for finished and unfinished spells. This again points out at the strong effect of unemployment benefit duration compared to the amount workers receive. It is worth noticing that last wages are negatively correlated with probability of LTU for all durations (an increase in past wages by 1% decreases the chances of LTU by 20% for the average worker).

Years since last employment spell are also significant and positive. Its effects are relatively modest (an increase of 0.7-1.8% per extra year since last time employed). Given the small coefficients of this variable in the previous regression, these results suggests that having spent many years away from unemployment has a negative impact in future unemployment, spells, making them longer, as expected. The coefficients of tenure are stronger, suggesting that tenure could be a more robust indicator of search capital depreciation. The main difference between both is that years since last employment spell

Table 4: Probability of Long-Term Unemployment

	All Spells		Finished Spells	
	(1)	(2)	(3)	(4)
	$P(\geq 1year)$	$P(\geq 2years)$	$P(\geq 1year)$	$P(\geq 2years)$
No. T	-0.087***	-0.125***	-0.090***	-0.135***
	(0.0011)	(0.0020)	(0.0015)	(0.0031)
YEmp	0.007***	0.018***	0.003	0.015***
	(0.0013)	(0.0016)	(0.0018)	(0.0027)
3 months claim	0.481***	0.478***	0.481***	0.574***
	(0.0110)	(0.0163)	(0.0144)	(0.0239)
6 months claim	0.780***	0.656***	0.830***	0.770***
	(0.0115)	(0.0167)	(0.0149)	(0.0246)
12 months claim	1.045***	0.878***	1.063***	0.985***
	(0.0153)	(0.0209)	(0.0202)	(0.0314)
18 months claim	1.051***	0.789***	1.047***	0.935***
	(0.0196)	(0.0260)	(0.0272)	(0.0412)
24 months claim	0.498***	0.154***	0.642***	0.605***
	(0.0256)	(0.0352)	(0.0364)	(0.0569)
Last P	0.238***	0.227***	0.213***	0.179***
	(0.0104)	(0.0148)	(0.0134)	(0.0213)
Tenure	0.038***	0.016***	0.041***	0.031***
	(0.0022)	(0.0028)	(0.0031)	(0.0045)
Experience	-0.015***	-0.015***	-0.014***	-0.024***
	(0.0008)	(0.0011)	(0.0011)	(0.0018)
No. P	-0.146***	-0.195***	-0.124***	-0.174***
	(0.0038)	(0.0060)	(0.0053)	(0.0097)
log(past wage)	-0.211***	-0.229***	-0.266***	-0.333***
	(0.0035)	(0.0051)	(0.0043)	(0.0065)
log(UI)	-0.002***	-0.003***	-0.002***	-0.003***
	(0.0003)	(0.0004)	(0.0003)	(0.0005)
age	-0.018***	-0.044***	0.022***	0.032***
	(0.0031)	(0.0043)	(0.0041)	(0.0066)
Constant	-0.379***	-0.766***	0.790	0.614
	(0.0773)	(0.1137)	(0.5222)	(0.6264)
Controls				
Years	-	-	-	-
Industry	✓	✓	✓	✓
Occupation	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	726,839	726,839	461,369	461369
AIC	603,127	327,490	369,427	173,783

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.

ignores job-to-job transitions, while tenure resets with every new job. Finally, the coefficients for work experience are negative and significant, as in the previous table.

Lastly having lost a permanent contract is positively correlated with the chances of ending in long term unemployment. This corroborates the findings on the previous regression. The effects of age are once again quadratic, so although the linear coefficient is negative the square term is positive, indicating that both young people and mature workers are more likely to be found in long term unemployment than middle aged workers.

Wages in the next job

Table 5 shows the outcomes of wage regressions, where *log(next wage)* is the natural logarithm of annual wages in the job after the current unemployment spell. Column 1 show the results for all observations, while column 2 only includes jobs that last at least three months and columns 3 only considers jobs that last at least six months. These restrictions ensure that there is less noise in the dependent variable (log annual wages in the next job), at the expense of reducing the sample size.

The first variable is weeks of unemployment spell, which is significant and negative throughout all regressions. This suggests that the longer the unemployment spell, the lower future wages: each 1% increase in weeks of unemployment reduces future wages by between 2.9 and 10.61%. As both variables are in logs, this can be interpreted as a wage-unemployment elasticity. The negative coefficient implies that spending more time in unemployment reduces future wages of workers, so it becomes harder to justify that workers with longer unemployment spells are waiting for a better offer. This implies that variables that were negatively correlated to duration have a positive impact on wages by shortening the unemployment spell. The effects of these variables should be interpreted as their marginal effects independent of duration.

One of the variables that both reduces duration and increases wages is the number of temporary contracts. Its coefficient is small (between 0.89% and 0.18%). For a median annual wage of 20,672 euros, an extra temporary contract adds between 183 and 37 euros annually. The small effects suggest that the number of temporary contracts is only weakly positively related to wages, both directly and through its negative impact on unemployment duration. This is an important result because it shows that workers with more temporary contracts (that are better searchers) do not find worse jobs than other workers on average. There are in fact slightly better paid.

Years since last employment ($YEmp$) is significant and positive, suggesting that hav-

Table 5: Regressions on Future Wages

Sample	(1) log(next wage) all jobs	(2) log(next wage) jobs > 3 months	(3) log(next wage) jobs > 6 months
log(weeks)	-0.1061***	-0.0350***	-0.0295***
	(0.0016)	(0.0013)	(0.0015)
No. T	0.0089***	0.0026***	0.0018***
	(0.0003)	(0.0004)	(0.0005)
YEmp	0.0023***	0.0026***	0.0023***
	(0.0005)	(0.0004)	(0.0005)
3 months claim	0.0669***	-0.0069*	-0.0150***
	(0.0044)	(0.0035)	(0.0038)
6 months claim	0.1203***	0.0265***	0.0077
	(0.0047)	(0.0038)	(0.0041)
12 months claim	0.1479***	0.0454***	0.0192***
	(0.0060)	(0.0050)	(0.0056)
18 months claim	0.1447***	0.0525***	0.0345***
	(0.0078)	(0.0067)	(0.0075)
24 months claim	0.0726***	0.0291***	0.0201*
	(0.0096)	(0.0083)	(0.0095)
Last P	0.0191***	0.0152***	0.0113**
	(0.0043)	(0.0033)	(0.0036)
Tenure	0.0004	-0.0007	-0.0011
	(0.0008)	(0.0007)	(0.0008)
No. P	0.0025**	0.0093***	0.0127***
	(0.0010)	(0.0011)	(0.0013)
Experience	0.0107***	0.0055***	0.0039***
	(0.0003)	(0.0003)	(0.0003)
log(past wage)	0.1261***	0.0575***	0.0502***
	(0.0018)	(0.0014)	(0.0015)
age	0.0434***	0.0210***	0.0178***
	(0.0014)	(0.0011)	(0.0012)
Constant	7.1325***	8.0257***	8.0363***
	(0.2263)	(0.2689)	(0.3124)
Controls			
Years	✓	✓	✓
Industry	✓	✓	✓
Occupation	✓	✓	✓
Region	✓	✓	✓
Observations	465,832	199,679	123,238
Adjusted R^2	0.146	0.203	0.250
AIC	1,284,934	278,985	135,067

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) and self-employment ing spent long times since the last unemployment spell doesn't hurt the job prospects of workers. A possible interpretation could be that workers that have lost their search skills after a long period of employment eventually find similar jobs to other workers, reinforcing the idea that search skills are not the same as productive skills.

Log past wages are highly correlated with present wages, as expected. The coefficients of claiming period dummies become smaller for longer jobs, with 3 month claim coefficient turning negative for jobs longer than 3 months. These dummies represent the effects are over someone without the right to claim UB, suggesting that longer entitlement to unemployment benefits may improve wages via better matching quality or better outside option. The absence of the quantity of unemployment benefits is due to its effects on sample size, as it requires to match two firms and her unemployment benefits with the tax records.

The coefficient for the dummy for permanent contract is positive for all next job durations. The coefficient for tenure is insignificant, suggesting that maybe the effects of longer tenure (higher probability of depreciated search skills) are picked up by $LastP$ and $YEmp$. Age and work experience are significant and positive, as expected. I interpret this as evidence of human capital accumulation - aside from individual productivity which is meant to be captures by past wages.

Duration of next job spell

Finally table 6 shows the results of the regressions on next job duration. The first three columns are for pooled data (one spell, one observation) and the last three are for fixed effect regressions, as table 3 did. Columns 1 and 4 show the regressions where duration of next job in log(weeks) is the dependant variable, while 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 could be a better measure for temporary workers who may gain permanent contracts in subsequent jobs, or may get other temporary contracts. Finally columns 3 and 6 show the results of a 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. Only 8% of all unemployment spells in the sample end in a permanent contract, so this is a rare occurrence. These regressions aim to capture how stable the jobs that are found by workers are.

Looking at the pooled regressions, number of temporary contracts appears to be bad for job stability on average: new jobs are shorter the more temporary contracts you have.

Table 6: Regressions on duration of next job

	Pooled data			Fixed Effects		
	(1) Duration of next job (log weeks)	(2) Duration of next employment spell	(3) $\Pr(P_{t+1}\|U_t)$	(4) Duration of next job (log weeks)	(5) Duration of next employment spell	(6) $\Pr(P_{t+1}\|U_t)$
No. T	-0.051***	-0.013***	-0.068***	0.039***	0.019***	0.243***
	(0.0007)	(0.0003)	(0.0020)	(0.0054)	(0.0035)	(0.0081)
log(weeks)	0.180***	-0.006**	-0.016**	0.077***	-0.000	0.003
	(0.0029)	(0.0020)	(0.0057)	(0.0040)	(0.0021)	(0.0112)
YEmp	0.016***	0.008***	0.018***	-0.017***	-0.029***	-0.007
	(0.0012)	(0.0021)	(0.0020)	(0.0021)	(0.0024)	(0.0058)
3 months claim	0.114***	0.107***	0.022	-0.051***	-0.006	-0.044
	(0.0079)	(0.0063)	(0.0166)	(0.0105)	(0.0064)	(0.0292)
6 months claim	0.163***	0.176***	0.089***	0.031*	-0.054***	-0.003
	(0.0091)	(0.0087)	(0.0180)	(0.0136)	(0.0094)	(0.0366)
12 months claim	0.138***	0.117***	0.102***	0.097***	-0.107***	0.148*
	(0.0134)	(0.0153)	(0.0248)	(0.0220)	(0.0184)	(0.0580)
18 months claim	0.028	0.028	0.038	0.172***	-0.045	0.106
	(0.0184)	(0.0248)	(0.0324)	(0.0331)	(0.0327)	(0.0892)
24 months claim	-0.054*	-0.100**	0.005	0.333***	0.181***	-0.041
	(0.0232)	(0.0344)	(0.0397)	(0.0440)	(0.0517)	(0.1202)
Last P	0.105***	0.102***	0.393***	-0.079***	0.043***	-0.626***
	(0.0079)	(0.0073)	(0.0153)	(0.0112)	(0.0081)	(0.0248)
Tenure	0.003	0.045***	-0.004	-0.062***	0.009*	0.028**
	(0.0021)	(0.0039)	(0.0034)	(0.0040)	(0.0042)	(0.0103)
Experience (T)	0.037***	-0.009***	-0.053***	-0.413***	-0.512***	0.409***
	(0.0014)	(0.0010)	(0.0033)	(0.0093)	(0.0079)	(0.0257)
Experience (P)	0.016***	-0.002**	-0.002*	-0.211***	-0.780***	-0.177***
	(0.0007)	(0.0006)	(0.0012)	(0.0095)	(0.0102)	(0.0183)
No. P	-0.014***	-0.012***	0.293***	0.019***	0.084***	-0.592***
	(0.0021)	(0.0009)	(0.0058)	(0.0051)	(0.0119)	(0.0158)
log(past wage)	0.075***	0.045***	0.093***	-0.032***	0.015***	0.024**
	(0.0025)	(0.0018)	(0.0056)	(0.0034)	(0.0019)	(0.0094)
log(UI)	0.001***	0.001***	0.001*	-0.003***	-0.000	0.001*
	(0.0002)	(0.0001)	(0.0004)	(0.0002)	(0.0001)	(0.0007)
age	0.035***	0.020***	-0.004	0.266***	0.236***	0.032
	(0.0024)	(0.0019)	(0.0048)	(0.0127)	(0.0091)	(0.0268)
Constant	-0.091	-0.331	-3.395***	-2.746***	-1.853***	
	(0.3614)	(0.3031)	(0.0937)	(0.5832)	(0.3216)	
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	-	✓	✓	-
Region	✓	✓	-	✓	✓	-
Observations	461,300	357,914	472,006	461,300	357,914	77,992
Adjusted R^2	0.158	0.133	-	0.063	0.258	-
AIC	1,747,415	1,068,172	284,635	1,373,508	576,323	45,637

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.

This is true when future job duration is restricted to 6 months at least (for consistent wages and to keep very short/menial jobs out of the sample). But when we look at its impact through time in the fixed effects regressions, as the worker accumulates more jobs the duration of next jobs becomes longer too. This suggests that learning to search helps workers get jobs with longer durations as well as higher paying jobs, within individuals. These results are the same for the probability of getting a permanent job out of unemployment. The fact that we need to control for individual fixed effects to see a positive impact suggests that there is an unobserved component that makes some workers more prone to stability. All regressions have controls for occupational level and industry, so this unobservable factor seems to be independent from sectoral composition. Another interpretation is that workers with many temporary contracts are very good at finding jobs, and are less concerned with employment stability - this is not to say that they wouldn't prefer more stable jobs, but that they are 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. 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 (as the rise in part-time and shorter TC suggest) being willing to accept an unstable job can keep a worker out of long term unemployment.

Conversely, years since last unemployment spell ($YEmp$) has a positive impact in the cross section, but the fixed effects regressions shows a negative correlation with future employment duration.

Longer unemployment spells ($log(weeks)$) have an ambiguous effect of future job stability: they are positively correlated to duration of the next job (columns 1 and 4) but mildly negatively with the duration of the next job spell (taking into account future jobs as well). It also reduced the odds of being hired with a permanent contract out of unemployment in the pooled regression (column 3), but it becomes insignificant in the panel regression (6). Past wages and unemployment benefits generally increase next job duration and the odds of being hired with a permanent contract, except in the fixed effects regression on duration of the next job. Age is positively related to job duration, and more strongly so if we consider continuous employment instead of just one job (columns 2 and 5 versus 1 and 4).

4 Theoretical Model

I have presented evidence of the positive effect of having more jobs can have in future unemployment outcomes, including controls for other potential explanations (human capital, incentives to search and ladder-claiming effects).

Here I present a search model with savings that introduces search capital as a mechanism that affects workers job finding probabilities that evolves through time as the worker learns to search. The goal of the model is to show that the introduction of search capital into an otherwise conventional model helps to explain the evolution of unemployment patterns through a workers life (particularly in the early years). A standard model with a constant, single job finding rate produces flat flows throughout a workers life. With search capital, the composition of the unemployment pool changes over time, as searchers get better with age.

The model joins two separate strands of the search literature. First, dynamic models with savings and human capital depreciation as in Ljungqvist and Sargent (2008) and Kitao et al. (2017) give the means and motive for older workers to remain unemployed for long. The means are that older workers have more resources to wait for better employment, whereas the motive is the desire to smooth out income shocks derive from the loss of employment (and human capital). In this models the loss of human capital upon job loss means that the jobs they are going to find once unemployed are worse than the job they lost. In this way it is the 'ladder' component of human capital that motivates older workers to wait. The second strand is the dual-market literate as in 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 are focusing on the relation between heterogeneous firing costs and unemployment, so they assume hand-to-mouth, risk neutral workers, which leaves out the consumption smoothing motive. These mechanisms should play a key role in shaping worker's preferences over temporary and permanent contracts. In their absence, most of the literature imposes the conversion of temporary contracts into permanent ones, or assumes higher wages under permanent contracts.[17]

In order to model the effects of search capital as workers age, I use a dual-market model that allows workers to save and be risk averse, in the spirit of Cozzi and Fella (2016). In this way, young workers would not have enough savings to smooth out consumption while unemployed so they will accept worse jobs. As they age, if they manage

[17] 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.

to save more, they will become more selective on their jobs they choose. Here a permanent contract offers not only higher *and* stable earnings. Search capital can alter these patterns, by making experienced young workers more efficient at search and older workers that lose a job after tenure less efficient at search. Which of the two effects dominates drives the results from the model.

Adding dual markets, savings, risk aversion and search capital makes for a rich but complicated model. In order to keep the model simple while retaining elements outlined above, I make some simplifying assumptions on other aspects of the economy.

The main assumption is the absence of the firm's problem from the model. Workers draw an offer from an exogenous distribution and accept or reject the job. 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 given how stable permanent jobs are, and because asset accumulation allows workers to increase their reservation wages, the random search assumption is not as strong as it initially appears. In fact it is not too far from match-specific productivity in search and matching models. Moving away from partial equilibrium, the ideal alternative would be to introduce wage bargaining. This would not change the results much, it would only introduce a connection between the external 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 wage of the distribution.

Another important assumption is the introduction of a no-borrowing constraint that binds for the poorest individuals. In light of the lack of unemployment benefits for a large share of workers as early as 2010. I consider this addition an important feature, and it helps match the observed wage distributions, especially at the lower end. It also gives risk averse workers incentives to save, in order to self-insure against long unemployment spells that may result in them being close to the constraint. The financial aspect of the model is not of primary interest, but a similar framework could easily be adapted to think about financial problems, such as tightening borrowing constraints or housing. The fact that financial constraints are secondary in the model is helped by its being a partial equilibrium model, so households take the interest rate as given. Finally, I will not look into inequality but search capital speaks to it from another point of view: the workers that achieve stability get the best outcomes, but are also exposed to greater risk if they lose their job.

There are other aspects of the model that are not very common: unemployment benefits expire and not all worker are covered by them. This is important to accurately reflect the problems young workers in Spain face, both before and during the crisis: as they have not accumulated enough assets, the threat of low consumption makes them lower their standards for employment such that very temporary, low wage jobs are accepted. As workers build up a stock of assets, they are able to raise their reservation wages and access better jobs.

4.1 Value functions

Time is discrete, and one time unit corresponds to a month. Workers are risk averse and live indefinitely. Agents can save but can't borrow. They accumulate capital by saving their income in each period, and can be employed with a permanent contract (P), employed with a temporary contract (T), unemployed with unemployment benefits (U) and unemployed without unemployment benefits (0). They are born with zero assets and an initial level of search capital s_0.

Search capital is discrete, increasing with a stochastic probability each time the worker finds a job from unemployment, and decreasing with a stochastic probability each period the worker is employed in a long-term (permanent) job.

Employed workers

Permanent and temporary jobs differ in four fundamental aspects: workers in permanent jobs accumulate job-specific human capital (h), which increases their wages. Both kinds of jobs suffer a stochastic, exogenous job destruction rate, but it hits temporary jobs more often($\delta_T >> \delta_P$). If a temporary job is destroyed, with probability δ_{T0} the worker is not eligible for unemployment benefits; permanent workers are always entitled to unemployment benefits after losing their jobs. Finally, permanent workers receive external (temporary) offers with probability α_{PT} and can choose to leave or stay, while temporary workers get a promotion to a permanent job with probability α_{TP}. I allow for them to refuse the offer and go back to the unemployment pool without benefits. By design, an entry-level ($h = 0$) permanent job is always preferable to a temporary job with the same wage: in a permanent position wages can only increase and unemployment risk is lower (and always insured). Permanent workers suffer a stochastic risk of search capital depreciation $\pi^-_{s'|s}$ each period, while temporary workers are able to keep their search capital. This assumption reflects both that temporary workers change jobs often (so they are able to keep their knowledge "fresh") and that many permanent workers are likely to retire in the job they get.

This is the continuation value if the worker chooses to stay in her current employment, but I allow workers to quit to unemployment if they find it more profitable. This could be the case if the worker accepts a low wage job when assets are low, but as she builds up capital she decides to search again. I assume temporary quitters are not entitled to benefits, but permanent workers are. The value functions thus are:

$$V^T(w,a,s) = u(c(w,a)) + \beta \max\{V^0(a',s), \tilde{V}^T(w,a',s)\} \tag{4}$$

$$\tilde{V}^T(w,a',s) = \alpha_{TP} \max\{V^0(a',s), V^P(w,0,a',s)\} + \delta_T V_0^U(a',s) + (1-\delta_T-\alpha_{TP})V^T(w,a',s) \tag{5}$$

st.

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

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

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

st.

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

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

Where $\tilde{V}^j(w,h,a,s)$ denotes continuation value of current employment and apostrophes denote next period variables. No time subscripts are necessary as the four state variables suffice to describe the workers' problem. Search capital depreciation follows a Markov process with downgrading probability of $\pi^-_{s'|s}$ and upgrading probability of 0 - the assumption is that any external job offers arrive exogenously and don't contribute to search capital.

Human capital is limited to the firm, and this could be a strong assumption. However it is equivalent to models with full depreciation of human capital upon job loss. I also choose to ignore retirement decisions by assuming a stochastic drop-out rate ($\beta = \tilde{\beta} + \rho$). The reasons for this are that I am more interested in young and middle aged worker's dynamics, as other authors have written extensively over how long-term unemployment interacts with retirement decisions.[18] A straightforward extension would be to set the model in finite time and introduce age-specific shocks, like retirement. This would help match the older workers' unemployment. Asset accumulation still affects the patterns of unemployment over the lifetime via reservation wages, whereby older workers are able to afford to wait longer.

Unemployed workers

If receiving unemployment benefits agents receive b and if they run out of benefits they receive zero[19] and have to use their assets for consumption - as a retired person would do. All unemployed agents search for a job each period, and successfully get a job offer of type $j \in \{P, T\}$. The arrival rate $\alpha_j(s)$ is increasing in search capital s. The job consists of a take-it-or-leave it entry wage offer w. If she accepts it, with probability $\pi^+_{s'|s}$ her search capital increases and with complementary probability (1-$\pi^+_{s'|s}$) she stays at her current level. The assumption here is that only successful searchers contribute to increase workers' search capital.

If receiving unemployment benefits, the worker can lose her benefits with probability δ_0 in each period. The stochastic benefit expiration rate helps to keep the model simple by not keeping track of previous employment history. The stock of search capital is the only history-dependent state variable, besides from assets and human capital for permanent workers.

$$\begin{aligned} V^U(a,s) = u(c(b,a)) + \beta\Big(\alpha_T(s)\int_0^{\bar{w}} \max\{V^U(a',s), V^T(w,a',s')\}dF(w) + \\ \alpha_P\int_0^{\bar{w}} \max\{V^U(a',s), V^P(w,a',s')\}dF(w) + \\ (1-\alpha_T-\alpha_P)[(1-\delta_0 V^U(a',s) + \delta_0 V^0(a',s)]\Big) \end{aligned} \tag{8}$$

st.

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

[18]See Kitao et al. (2017), Ljungqvist and Sargent (2008)

[19]Technically they receive 1 unit to prevent them from starving.

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

$$V^0(a,s) = u(c(0,a)) + \beta\Big(\alpha_T(s)\int_0^{\bar{w}} \max\{V^0(a',s), V^T(w,a',s')\}dF(w) + \alpha_P(s)\int_0^{\bar{w}} \max\{V^0(a',s), V^P(w,a',s')\}dF(w) + (1-\alpha_T(s)-\alpha_P(s))V^0(a')\Big) \quad (9)$$

st.

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

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

Solving the Model

A solution to the model is a set of reservation wage rules and policy functions for savings such that: (1) workers maximise their utility given their initial states (2) 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 discrete choices (accept/reject a job for the unemployed and quit for the employed). 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 VFI a slow but safe choice.

Once the policy functions have been found, I simulate the economy from 40 years to find a steady state for the economy and see the evolution of unemployment through the working lives of workers. This also provides moments to compare to the data: average stock of employment/unemployment and flows between states at each age and in the aggregate.

4.2 Calibration

Preferences

The utility function is CRRA, with a risk aversion parameter of 2. Interest rates are set to 2% annual. The discount factor β is set to 0.98.

Table 7: Calibration

Parameter	Value	Target
$F_T(w)$	-	wage distribution for TCs
$F_P(w)$	-	wage distribution for PCs new hires
b	695.52	average UB
$\alpha_T(1)$	0.116	UT transition rates at age 20
$\alpha_P(1)$	0.019	UP transition rates at age 20
α_{TP}	0.023	average TP flow
α_{PT}	0.226	average PT rates, modified*
δ_P	0.007	average PU flow
δ_T	0.030	average TU flow
δ_{T0}	0.15	average T0 flow
δ_0	0.079	average U0 flow
$p(h)$	-	tenure wage distribution
s_0,s_1,s_2	{0.666,1,1.666}	duration of unemployment for different NoTs
$\pi^+_{s'\|s}$	{1,1,0}	duration of unemployment for different NoTs
$\pi^-_{s'\|s}$	{0,0.0507,0.0507}	5 year average
r	0.0016	2% annual[20]
β	0.98	
σ	2.0	Literature

* consistent with the share of workers at age 20 that accept an average temporary the job offer.

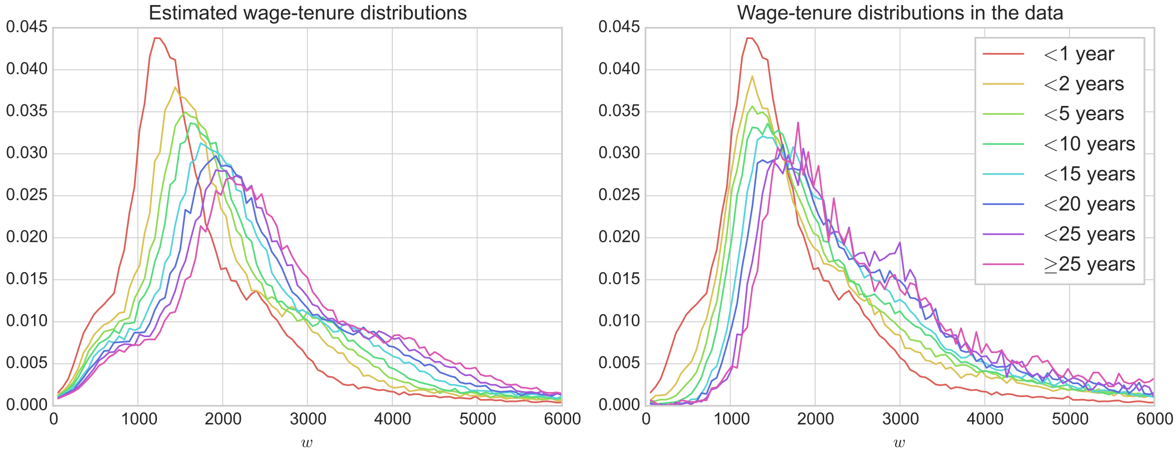
Wage Distributions

The wage distributions that workers face are taken from the actual wage distributions in the years 2005-2008 as shown in figure 6. They are binned from 60 to 6000 euros a month and normalised. I let the distribution of wages out of unemployment vary, but when temporary workers get a promotion they start from their temporary wage. To get the human capital coefficients that drive wage increases for permanent workers I look at the evolution of wage distributions on stayers. Here I assume for simplicity a linear wage increase with tenure (so $w(h) = w * h$) and minimize the distance between the observed distributions. The results are shown in picture 7. These assumptions ensure that wage evolution is consistent with the data.

Employment shocks and job arrival rates

Figure 8 shows the average monthly transitions age by age between employment an unemployment, for temporary and permanent contracts. The first thing the plot shows is that there are reasons to prefer a constant job separation rate, at least from temporary

Figure 7: Tenure-Wage distributions



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

contracts (bottom left panel). Job expiration being constant is more difficult to justify but keeping track of past tenure can make the model too large. Simply controlling for age could solve this issue. At present the model relies on the change of reservation wages/job finding rates through time to match young workers unemployment rates.

Getting an estimate of job offers arrival rates is not trivial, as they are a combination of reservation wages and actual job arrival rates. I choose to target job finding rates at age 20 - the age I take as a "start of the working life" for workers. By assuming new entrants have no assets and no search capital, I can take the job finding rates in the data as the true arrival rate of offers, as these workers accept any wage offer they receive. This ensures reservation wages do not cloud the calibration. In the results it can be seen that this assumption makes the patterns of job finding rates consistent with the data.

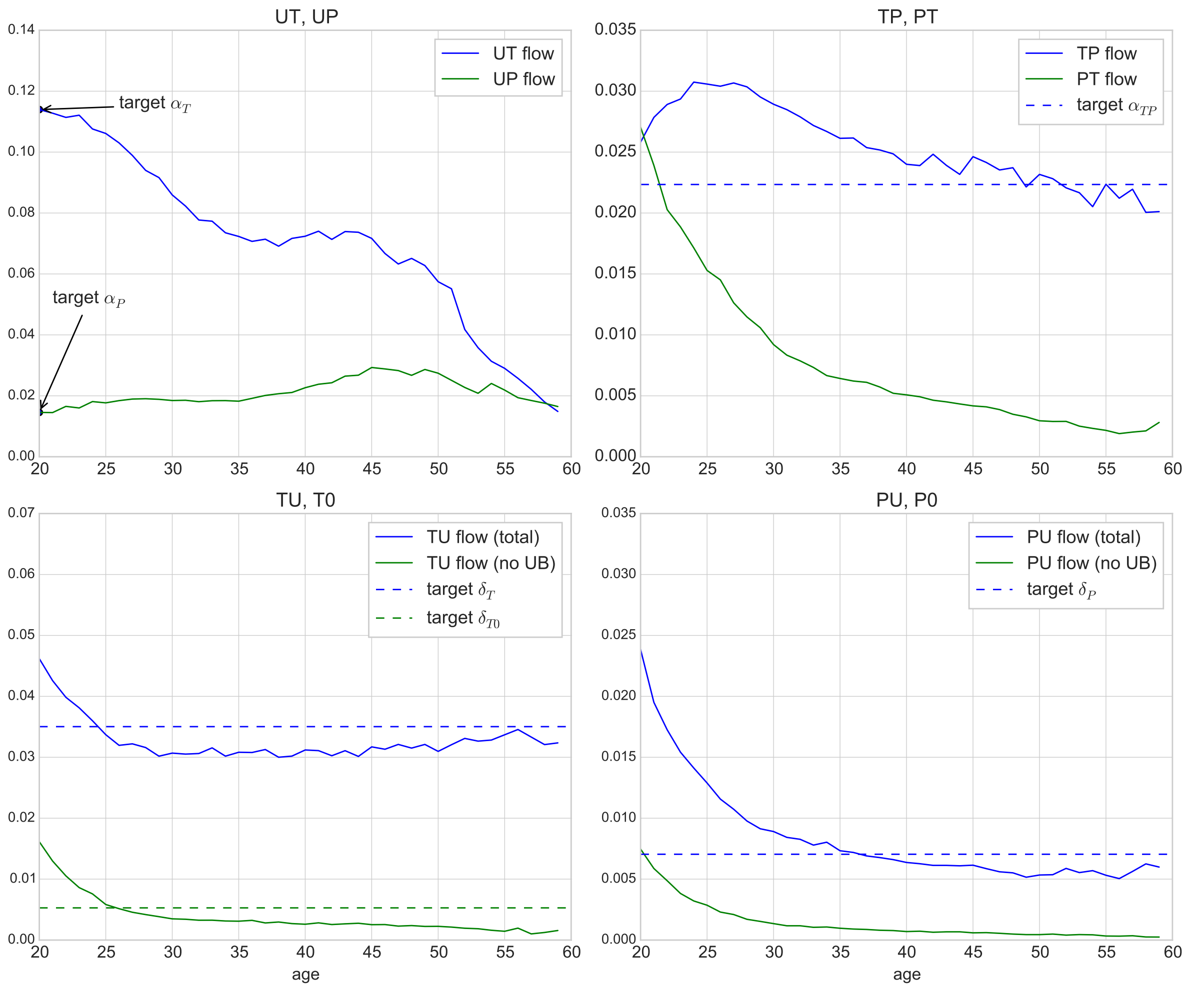
Finally the permanent to temporary arrival rate is subject to reservation wage constraints, as not all workers accept a job, not even the very young ones. I take a similar approach by targeting the job switching rate at age 20, solve the model, and then calculate how many permanent workers would switch if offered the average temporary wage. Given this estimate, I update[21] the job offer arrival rate and solve again.

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 parameters are not pinned down,

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

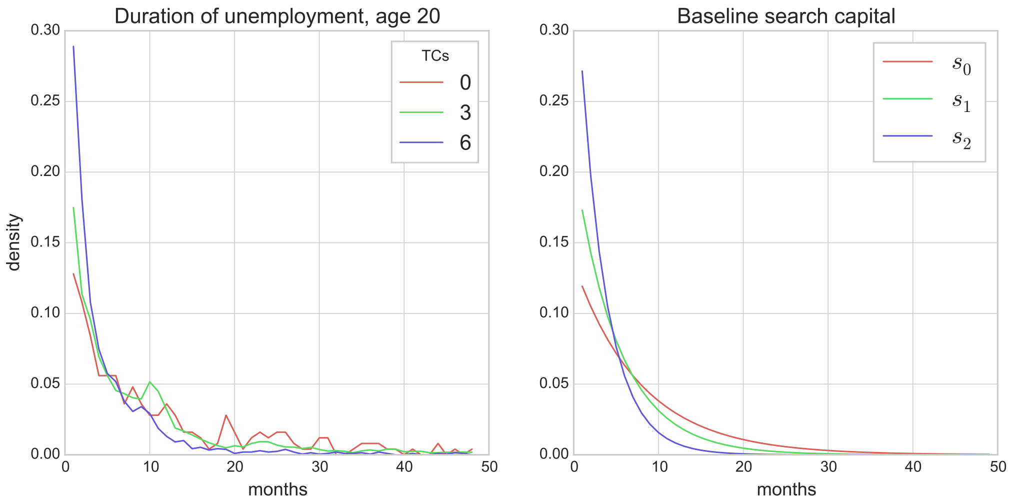
Figure 8: Quarterly Transition Rates by Age (pre 2008, SS)



Source: Own calculations from MCVL, 2005-2013 waves

so they could be estimated by minimising the distance to some moments in the data. Instead I take estimates of s by targeting the differences in job finding rates at age 20 with different number of jobs held before. Using the assumption that workers enter the labour market with no assets, figure 9 shows on the right the implied duration profiles at the three different levels of search capital (so that $s_2 > s_1 > s_0$) while the left panel shows a histogram of duration of unemployment in the data, separated by number of temporary contracts. The substantial differences at short durations of unemployment for even one temporary contract suggests that setting $\pi^+_{s'|s} = 1$ is reasonable. I repeat the exercise with smaller $\pi^+_{s'|s}$ to match the differences between the shortest durations. For $\pi^-_{s'|s}$, the depreciation rates of search capital, I target a search capital loss every 5 years of tenure. I can repeat the exercise with other depreciation rates (10,20,25) but the results are not very sensitive to these. In order to match the data the initial distribution of search capital is more important.

Figure 9: Duration of unemployment by number of contracts and search capital level



Source: Own calculations from MCVL, 2005-2013 waves

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. For assets I assume all individuals start from 0 at age 20. For search capital, it is important to acknowledge that some workers aged 20 have had temporary jobs before entering unemployment for the first time. Therefore I choose give the lowest level of search capital (s_0) to new entrants (unemployed with no benefits) and level one to the rest. This is because in the data 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 job at hand are also assumed to be regular workers.

4.3 Results

Baseline Calibration

Figure 10 to 12 present the main results. Figure 10 shows the evolution of the shares of the three levels of search capital through workers lives, for all workers (left panel) and the unemployed (right panel). Over time, workers find stable jobs and search capital decreases: the proportion of bad searchers (s_0) increases with time. During the first five years, the stock of good searchers (s_2) increases as workers go through chains of temporary contracts, but then it decreases again to steady-state levels. By the time workers are 40, the overall search levels have reached steady state. Notice that the distribution is polarized by the end, with bad and good searchers having the highest shares. If we look at the unemployment pool, we see that at the beginning unemployed agents are not good searchers. Then as time goes by search capital increases - workers become more experienced in the labour market - but only at the end the stock of very good searchers increases as well. This is interesting because it shows that older unemployed workers are better searchers on average, so their lower transition rates to employment come from their higher levels of self insurance that allows them to be more selective with their future jobs. This is the same mechanism as in the turbulence literature, which proves adequate to describe older worker dynamics.

Figure 10: Search Capital by age

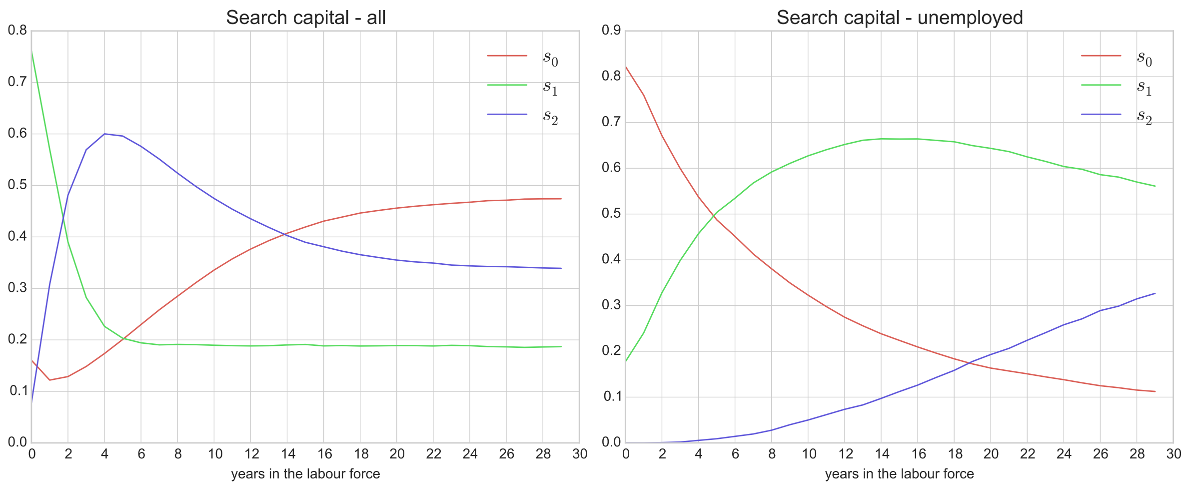


Figure 11 shows the evolution of unemployment and the temporary share of employment in the data and in the model. Having an accurate description of the temporary share of jobs is important for matching the average number of jobs workers have. The left panel of figure 11 shows that the model performs well, matching the temporary share for all ages until age 45, where it stays constant instead of steadily declining. These are the effects of the infinite horizon problem. In terms of unemployment, the right panel of figure 11 shows that the model does particularly well for overall unemployment, and underestimates unemployment without benefits for the young. This last result can be

Figure 11: Temporary share and Unemployment rate

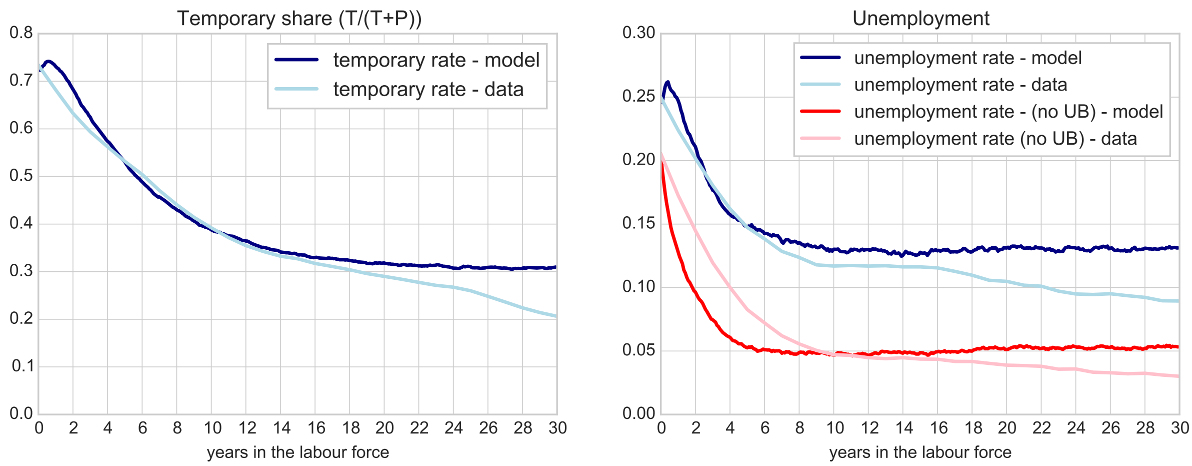
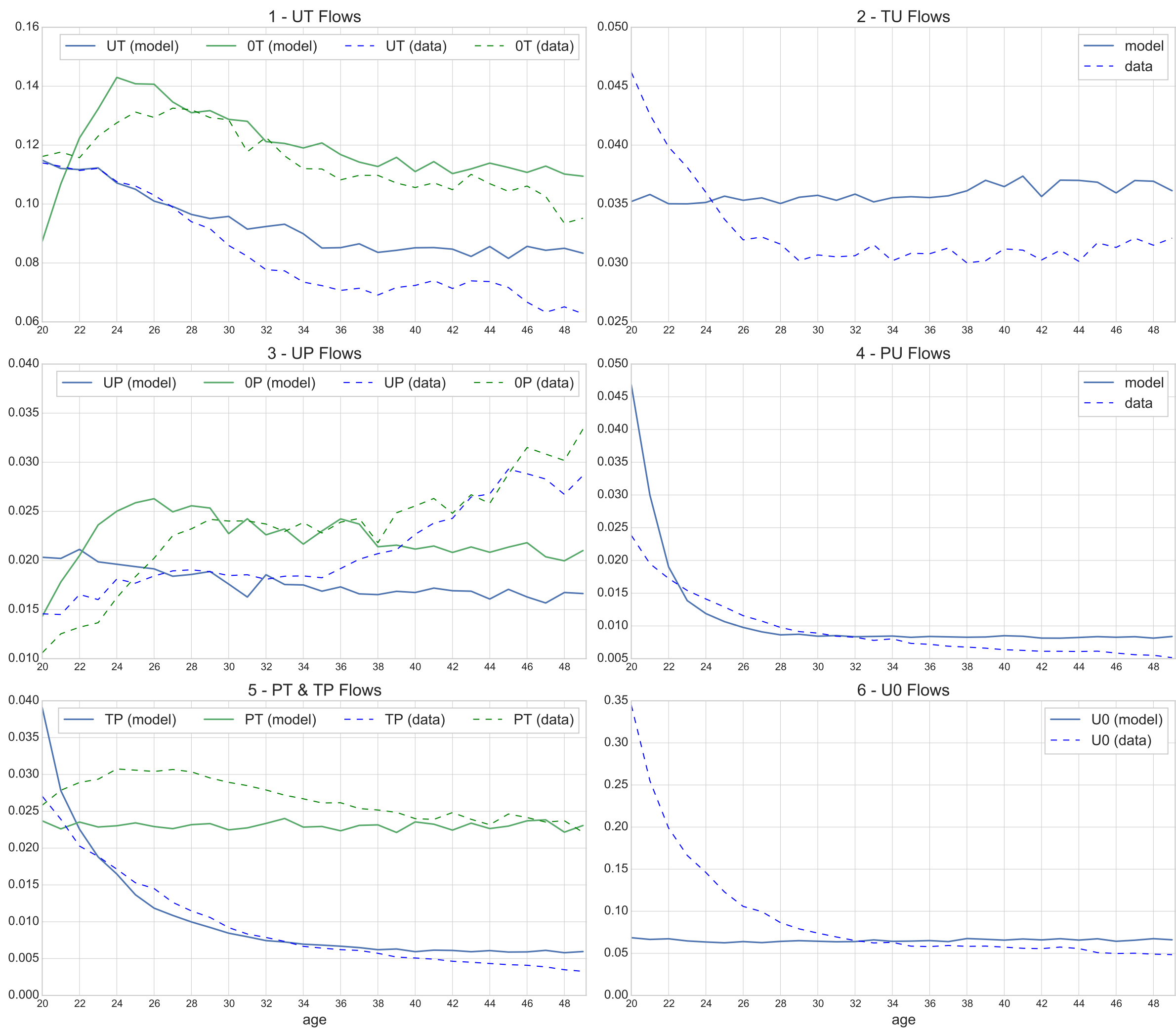


Figure 12: Transition rates



explained by the constant unemployment benefit expiration rate (U0) as panel 6 in figure 12 shows. While the inclusion of tenure related severance payments could be added in a similar manner to Dolado et al. (2016), making expiration of unemployment tenure related is more complicated, as not only tenure but past tenure becomes a state variable. An alternative would be to use the framework developed by Andersen et al. (2017).

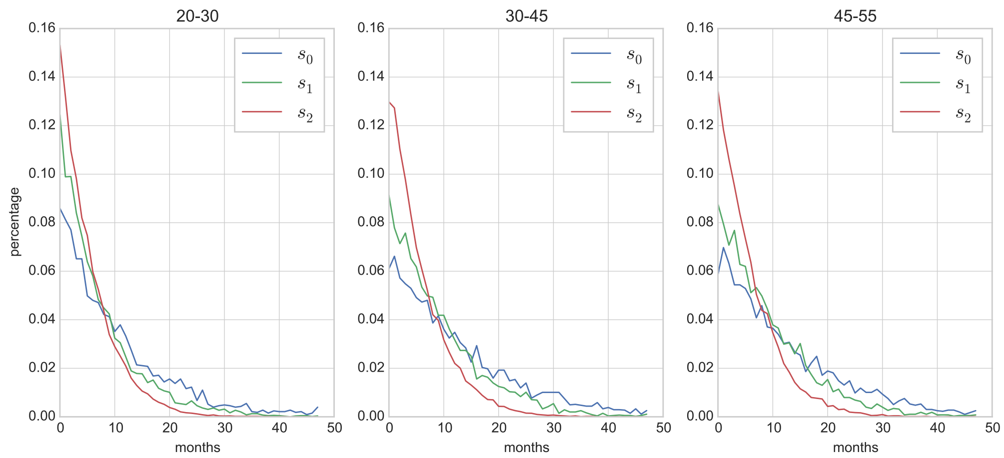
In terms of other flows, figure 12 shows yearly averages of monthly transition rates in the data and in the model, so that the data point at age 20 represents the 12 month average between years 20 and 21. The model matches the evolution of temporary job finding rates well (panel 1), with flows from unemployment without benefits (0T) being above those from unemployment (UT) both in the model and in the data. The evolution of search capital explains the high transition rates of those aged 20-30, and follows the decline over the 30s. Transition rates from regular unemployment are slightly above the data after age 30, staying above 8% per month, but they also follow a pattern of steady decline. Unemployed at age 30 are better searchers, but also have accumulated enough wealth and benefits to self insure against unemployment risk, allowing them to be more selective with the jobs they get. Flows to permanent jobs (UP, panel 2) are close to the data, but the model overestimates them for young people (less than 28 years old) and underestimates them for over 40's. This is likely to be what is driving the decline of the temporary share in the data (figure 11. A likely explanation for this is the lack of transferable human capital: older workers may still carry some knowledge from their previous jobs that gets them better wages.

The permanent to temporary transition rate (PT, panel 5) follows its data counterpart closely: it overshoots at the beginning[22] but then follows the data remarkably well. These transitions defy conventional explanations, as in most models of dual labour markets with temporary contracts workers always prefer a permanent job to a temporary one. Here this is still true for permanent jobs with the same wage as a current job, but workers may be tempted to leave for better outcomes, even if these are uncertain. Switching jobs increases their search capital, which is another form of self-insurance against risks and allows them to climb the wage ladder. An alternative interpretation would be to increase the firing rate for permanent workers, but with advance notice - that is, giving workers time to find a temporary job before their current contract ends. This would add to the instability of permanent contracts for young workers.

Job destruction rates from temporary contracts (panel 2) do not follow the patterns in the data, which is to be expected since a constant job firing rate was assumed, how-

[22] Recall that the flow plots are yearly averages: by construction the PT rate at age 20 matches the data exactly.

Figure 13: Duration of unemployment, by search capital



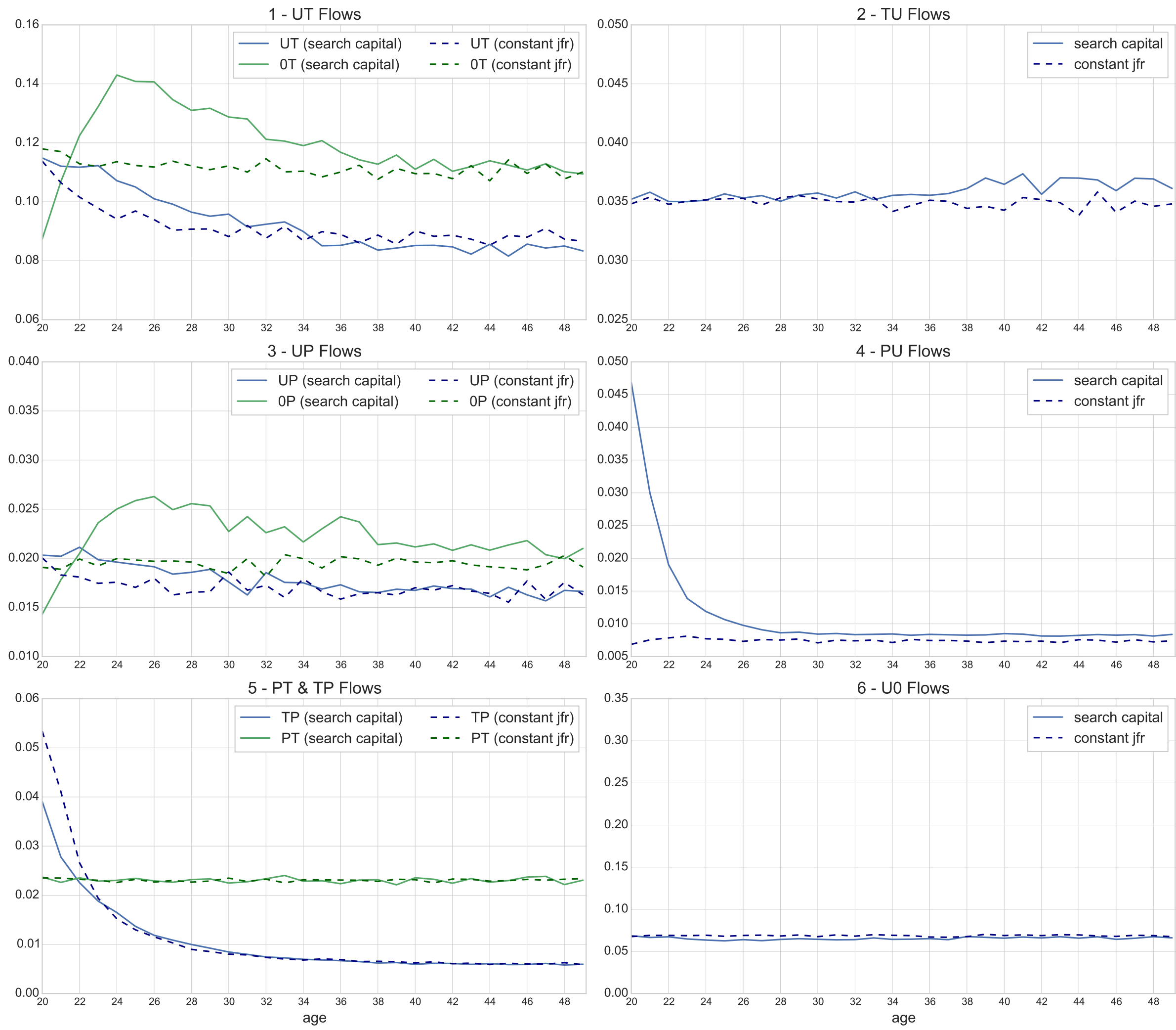
ever job separations from permanent contracts (panel 4) do follow the pattern in the data (overshooting at the very beginning). The difference here is that for young workers with a low wage permanent contract it is profitable to quit after some period of saving, to unemployment. Recall that the assumption, based on the data, was that quitters from permanent contracts get unemployment benefits, but that this is not the case for temporary jobs. This could be the driving difference, but there is an upwards trend in the temporary separation rate for older workers: older unemployed individuals may take temporary jobs to bump their savings up, and then quit. Their search capital is high on average (as figure 10 showed) and they can therefore afford to quit and search again.

Finally, if we look at duration of unemployment by age, figure 13 shows that the gap between high skilled searchers (s_2) and the rest widens with age, with low skilled searchers and moderately skilled searchers become closer. The bulk of these long term unemployed workers over 2 years is almost entirely made up of moderately and low skilled searchers (s_1 and s_0). Notice that if we considered all search abilities the duration distribution would become more skewed towards the extremes, which can cause observational duration dependence.

No search capital

To better understand what search capital adds to the model, figure 14 shows monthly flows with and without search capital - so there is a constant job finding rate. The main difference is that job finding rates are flatter: the temporary job finding rate among unemployed workers without benefits who are younger than 35 is lower and constant. For unemployed workers with UB the results are similar, indicating that its decline over time is driven by asset accumulation only. These patterns also hold for transitions to permanent jobs (panel 3). Another significant difference is the permanent separation rate in panel 4: under a constant job finding rate it is flat and low. Search capital can explain the patterns of the data better (as the same panel in figure 12 indicated) as young workers quit low wage permanent contracts in search of better outcomes. However here the absence of search capital makes these quits unprofitable. This is for further work.

Figure 14: Transition rates without search capital



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 young workers can be stuck in long term unemployment, especially in a recession when they have to compete for fewer jobs with better searchers. For older workers, having outdated knowledge of the job market can also hurt their chances of finding one, even if they retain some of their past human capital. 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.

Using a detailed administrative dataset I identify 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. Years since last unemployment spell, a variable intended to capture search skill depreciation, is positively correlated with duration, while tenure and duration of unemployment benefits also seem to play a major role.

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. 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 for the years 2005-2008 in Spain to calibrate the model. The addition of search capital to the model helps to reconcile the patterns of unemployment and job finding rates through a worker's lifetime, especially for young people. As workers get older the unemployed get better at searching, but overall search capital decreases as workers find stable jobs. These results are based on a limited partial equilibrium setting, but a model with an aggregate matching function and firms could provide further insights, as could adding a more detailed human capital accumulation process and retirement. Search capital could enrich the hysteresis literature by improving the performance of models for younger workers.

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 a segmented labour market.

References

Alonso-Borrego, C., J. Fernández-Villaverde, and J. E. Galdón-Sánchez (2005). Evaluating labor market reforms: a general equilibrium approach. Technical report, National Bureau of Economic Research.

Alvarez, F. E., K. Borovickova, and R. Shimer (2015). A nonparametric variance decomposition using panel data. Technical report, Mimeo, University of Chicago.

Andersen, T. M., C. Ellermann-Aarslev, et al. (2017). Job duration and history dependent unemployment insurance. Technical report, CEPR Discussion Papers.

Bentolila, S., P. Cahuc, J. J. Dolado, and T. Le Barbanchon (2012). Two-tier labour markets in the great recession: France versus spain. *The Economic Journal 122*(562).

Blanchard, O. and A. Landier (2002). The perverse effects of partial labour market reform: fixed-term contracts in france. *The Economic Journal 112*(480).

Card, D., R. Chetty, and A. Weber (2007). The spike at benefit exhaustion: Leaving the unemployment system or starting a new job? Technical report, National Bureau of Economic Research.

Carrillo-Tudela, C. and E. Smith (2017). Search capital. *Review of Economic Dynamics 23*, 191–211.

Carrillo-Tudela, C. and L. Visschers (2013). Unemployment and endogenous reallocation over the business cycle.

Costain, J. S., J. F. Jimeno, and C. Thomas (2010). Employment fluctuations in a dual labor market.

Couch, K. A. and D. W. Placzek (2010). Earnings losses of displaced workers revisited. *The American Economic Review 100*(1), 572–589.

Cozzi, M. and G. Fella (2016). Job displacement risk and severance pay. *Journal of Monetary Economics 84*, 166–181.

Dolado, J. J., E. Lalé, and N. Siassi (2016). From dual to unified employment protection: Transition and steady state.

Dolado, J. J., S. Ortigueira, and R. Stucchi (2012). Does dual employment protection affect tfp? evidence from spanish manufacturing firms.

García-Pérez, J. I. and F. Muñoz-Bullón (2011). Transitions into permanent employment in spain: An empirical analysis for young workers. *British Journal of Industrial Relations 49*(1), 103–143.

Güell, M. (2003). Fixed-term contracts and the duration distribution of unemployment.

Güell, M. and B. Petrongolo (2007). How binding are legal limits? transitions from temporary to permanent work in spain. *Labour Economics 14*(2), 153–183.

Güell, M. and L. Hu (2006). Estimating the probability of leaving unemployment using uncompleted spells from repeated cross-section data. *Journal of Econometrics 133*(1), 307 – 341.

Hornstein, A. (2012). Accounting for unemployment: the long and short of it.

INE (2013). Encuesta de la población activa.

INE (2017). Ocupados por tipo de jornada, sexo y rama de actividad. valores absolutos y porcentajes respecto del total de cada rama.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *The American economic review*, 685–709.

Kitao, S., L. Ljungqvist, and T. J. Sargent (2017). A life-cycle model of trans-atlantic employment experiences. *Review of Economic Dynamics 25*, 320–349.

Krueger, A. B. and A. Mueller (2010). Job search and unemployment insurance: New evidence from time use data. *Journal of Public Economics 94*(3), 298–307.

Lafuente, C. (2017). The best of two worlds: Assessing the use of administrative data for the study of unemployment using the labour force survey as a benchmark.

Lalive, R. (2007). Unemployment benefits, unemployment duration, and post-unemployment jobs: A regression discontinuity approach. *The American economic review 97*(2), 108–112.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of political economy 117*(5), 914–940.

Ljungqvist, L. and T. J. Sargent (1998). The european unemployment dilemma. *Journal of political Economy 106*(3), 514–550.

Ljungqvist, L. and T. J. Sargent (2008). Two questions about european unemployment. *Econometrica 76*(1), 1–29.

Mortensen, D. T. (1970). Job search, the duration of unemployment, and the phillips curve. *The American Economic Review 60*(5), 847–862.

OECD (2014). Education at a glance 2014.

OECD (2017). Unemployment by duration: incidence.

Silva, J. I. and J. Vázquez-Grenno (2013). The ins and outs of unemployment in a two-tier labor market. *Labour Economics 24*, 161–169.

Stovicek, K., A. Turrini, et al. (2012). Benchmarking unemployment benefit systems. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Wadsworth, J. (1991). Unemployment benefits and search effort in the uk labour market. *Economica*, 17–34.

Appendix

A.1 Robustness Checks

Table A1 below shows the coefficients for the controls on table 3. In particular, education, sex, dummy for foreign born, industry of precious employment, dummy for quit, part-time in the previous job.

Table A2 shows the results of adding a quadratic term for number of temporary contracts in the main regressions of tables 3 - 6. Nothing really significant changes, although the quadratic term is significant for regressions on duration of unemployment (columns 1-2) and duration of next job (column 4). In all regressions, the number of temporary contracts needed to turn the sign of the effect is over 100.

Table A3 presents the results of the regressions on unemployment duration (table 3 by industry of next job. The coefficient on number of temporary jobs (No. T) is significant and negative in all regressions. The results are consistent to those in table 3.

Table A1: Regressions on Duration - controls

	Pooled OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(weeks)	log(weeks)	log(weeks)	log(weeks)	log(weeks)	log(weeks)
quit	-0.185***	-0.302***	-0.297***	-0.200***	-0.261***	-0.259***
	(0.00394)	(0.00398)	(0.00401)	(0.00466)	(0.00566)	(0.00568)
Construction (post 2008)	0.545***	0.838***	0.868***	0.358***	0.523***	0.537***
	(0.00926)	(0.0112)	(0.0116)	(0.00818)	(0.0105)	(0.0109)
Construction (pre 2008)	0.226***	0.510***	0.538***	0.0650***	0.228***	0.240***
	(0.0104)	(0.0115)	(0.0118)	(0.00909)	(0.0116)	(0.0119)
male	0.0185***	0.0253***	0.0238***	-	-	-
	(0.00368)	(0.00390)	(0.00389)	-	-	-
High School	-0.0523***	-0.0464***	-0.0463***	-	-	-
	(0.00419)	(0.00456)	(0.00455)	-	-	-
Baccalaureate	-0.0782***	-0.0691***	-0.0694***	-	-	-
	(0.00558)	(0.00542)	(0.00541)	-	-	-
College	-0.0591***	-0.0467***	-0.0474***	-	-	-
	(0.00622)	(0.00628)	(0.00627)	-	-	-
part-time	0.0394***	-0.00223	-0.0125**	-0.0534***	-0.0773***	-0.0816***
	(0.00432)	(0.00407)	(0.00405)	(0.00478)	(0.00558)	(0.00559)
foreign_born	-0.0523***	-0.0576***	-0.0560***	-	-	-
	(0.00545)	(0.00594)	(0.00594)	-	-	-
Extractive Ind.	0.455***	0.756***	0.782***	0.286***	0.464***	0.481***
	(0.0316)	(0.0334)	(0.0337)	(0.0463)	(0.0510)	(0.0516)
Manufactures (primary)	0.444***	0.731***	0.760***	0.287***	0.447***	0.461***
	(0.0112)	(0.0122)	(0.0125)	(0.0111)	(0.0135)	(0.0138)
Manufactures (machinery)	0.453***	0.755***	0.785***	0.330***	0.497***	0.511***
	(0.0105)	(0.0119)	(0.0123)	(0.0105)	(0.0127)	(0.0130)
Manufactures (detail and repair)	0.459***	0.753***	0.782***	0.321***	0.478***	0.487***
	(0.0143)	(0.0156)	(0.0159)	(0.0174)	(0.0197)	(0.0199)
Energy, gas, residual treatment	0.482***	0.782***	0.814***	0.299***	0.465***	0.482***
	(0.0177)	(0.0186)	(0.0189)	(0.0196)	(0.0220)	(0.0223)
Retail and repairs	0.486***	0.772***	0.805***	0.299***	0.454***	0.471***
	(0.00983)	(0.0108)	(0.0112)	(0.00790)	(0.0101)	(0.0105)
Transport and storage	0.408***	0.702***	0.735***	0.278***	0.427***	0.447***
	(0.0107)	(0.0128)	(0.0130)	(0.0116)	(0.0141)	(0.0145)
Hospitality	0.429***	0.709***	0.739***	0.289***	0.439***	0.455***
	(0.00896)	(0.0109)	(0.0113)	(0.00872)	(0.0113)	(0.0116)
Communication and IT	0.455***	0.739***	0.768***	0.259***	0.412***	0.424***
	(0.0120)	(0.0136)	(0.0139)	(0.0140)	(0.0159)	(0.0163)
Financial	0.423***	0.719***	0.751***	0.238***	0.410***	0.430***
	(0.0173)	(0.0188)	(0.0191)	(0.0225)	(0.0251)	(0.0253)
Real State	0.489***	0.765***	0.793***	0.318***	0.458***	0.469***
	(0.0190)	(0.0207)	(0.0211)	(0.0250)	(0.0287)	(0.0291)
Professional services	0.465***	0.733***	0.762***	0.261***	0.411***	0.426***
	(0.0110)	(0.0123)	(0.0126)	(0.0105)	(0.0126)	(0.0129)
Auxiliary services (cleaning, gardening, rental)	0.398***	0.658***	0.685***	0.221***	0.362***	0.376***
	(0.00935)	(0.0109)	(0.0112)	(0.00779)	(0.00979)	(0.0101)
Public Administration	0.565***	0.848***	0.879***	0.302***	0.462***	0.478***
	(0.0122)	(0.0123)	(0.0127)	(0.0105)	(0.0124)	(0.0127)
Education	0.509***	0.789***	0.823***	0.247***	0.396***	0.414***
	(0.0125)	(0.0131)	(0.0135)	(0.0125)	(0.0146)	(0.0149)
Health and Social Services	0.412***	0.699***	0.729***	0.325***	0.477***	0.494***
	(0.0113)	(0.0126)	(0.0129)	(0.0124)	(0.0144)	(0.0147)
Other Services	0.461***	0.724***	0.752***	0.261***	0.393***	0.405***
	(0.0102)	(0.0120)	(0.0123)	(0.0100)	(0.0122)	(0.0125)
Observations	587222	465832	461369	587222	465832	461369
Adjusted R^2	0.546	0.559	0.561	0.462	0.457	0.458
AIC	1502925.7	1189482.3	1176423.7	1082258.0	840389.4	829077.3

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.

Table A2: Quadratic term for temporary contracts

	(1) log(weeks) (OLS)	(2) log(weeks) (FE)	(3) log(next wage) (OLS)	(4) Duration of next employment spell (years)
No. T	-0.040***	-0.014***	0.009***	-0.024***
	(0.0007)	(0.0020)	(0.0004)	(0.0005)
No. T^2	0.000***	0.000***	-0.000	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
YEmp	0.002***	0.001	0.002***	0.008***
	(0.0007)	(0.0013)	(0.0005)	(0.0021)
3 months claim	0.222***	0.177***	0.067***	0.102***
	(0.0042)	(0.0056)	(0.0044)	(0.0063)
6 months claim	0.224***	0.199***	0.120***	0.166***
	(0.0049)	(0.0075)	(0.0047)	(0.0086)
12 months claim	0.171***	0.194***	0.148***	0.102***
	(0.0073)	(0.0126)	(0.0060)	(0.0152)
18 months claim	0.135***	0.173***	0.145***	0.015
	(0.0102)	(0.0195)	(0.0078)	(0.0247)
24 months claim	0.040**	0.109***	0.073***	-0.101**
	(0.0132)	(0.0270)	(0.0096)	(0.0343)
Last P	0.032***	0.036***	0.019***	0.096***
	(0.0045)	(0.0061)	(0.0043)	(0.0073)
Tenure	0.015***	0.026***	0.000	0.043***
	(0.0012)	(0.0023)	(0.0008)	(0.0039)
Experience	-0.007***	0.040***	0.011***	-0.002***
	(0.0005)	(0.0034)	(0.0003)	(0.0006)
log(past wage)	-0.080***	-0.043***	0.126***	0.045***
	(0.0013)	(0.0017)	(0.0018)	(0.0017)
age	-0.001	-0.023***	0.043***	0.020***
	(0.0016)	(0.0054)	(0.0014)	(0.0019)
log(weeks)			-0.106***	-0.008***
			(0.0016)	(0.0020)
log(UI)				0.001***
				(0.0001)
Constant	1.214***	0.648	7.132***	-0.279
	(0.2354)	(0.4052)	(0.2263)	(0.3046)
Controls				
Years	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Occupation	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	465832	465832	465832	357914
Adjusted R	0.560	0.458	0.146	0.134
AIC	1188835	840068.483	1284936.423	1067594.896

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.

Table A3: Regressions on Unemployment Duration, by next job industry

	log(weeks)																		
	Agriculture	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	-0.018***	-0.011	-0.031***	-0.022***	-0.019***	-0.033***	-0.019***	-0.021***	-0.026***	-0.026***	-0.025***	-0.024***	-0.018*	-0.029***	-0.034***	-0.034***	-0.032***	-0.029***	-0.031***
	(0.0019)	(0.0125)	(0.0023)	(0.0018)	(0.0034)	(0.0043)	(0.0008)	(0.0011)	(0.0012)	(0.0010)	(0.0016)	(0.0052)	(0.0072)	(0.0016)	(0.0008)	(0.0017)	(0.0023)	(0.0013)	(0.0013)
YEmp	-0.002	-0.005	-0.001	0.004	0.002	0.001	-0.001	0.000	0.001	0.010***	0.008	0.010	0.015*	0.003	0.008***	0.001	0.006	0.020***	0.006
	(0.0045)	(0.0124)	(0.0029)	(0.0026)	(0.0052)	(0.0063)	(0.0015)	(0.0017)	(0.0030)	(0.0027)	(0.0046)	(0.0075)	(0.0068)	(0.0035)	(0.0018)	(0.0024)	(0.0046)	(0.0032)	(0.0033)
3 months claim	0.183***	0.121	0.187***	0.220***	0.271***	0.239***	0.185***	0.188***	0.228***	0.211***	0.225***	0.254***	0.174**	0.268***	0.264***	0.132***	0.194***	0.238***	0.245***
	(0.0276)	(0.1059)	(0.0233)	(0.0217)	(0.0438)	(0.0508)	(0.0101)	(0.0104)	(0.0226)	(0.0117)	(0.0266)	(0.0501)	(0.0545)	(0.0200)	(0.0098)	(0.0171)	(0.0213)	(0.0189)	(0.0193)
6 months claim	0.206***	0.160	0.205***	0.220***	0.214***	0.234***	0.198***	0.213***	0.192***	0.221***	0.252***	0.214***	0.155*	0.264***	0.261***	0.188***	0.195***	0.235***	0.256***
	(0.0315)	(0.1428)	(0.0262)	(0.0246)	(0.0480)	(0.0532)	(0.0120)	(0.0118)	(0.0254)	(0.0150)	(0.0302)	(0.0603)	(0.0616)	(0.0227)	(0.0121)	(0.0192)	(0.0243)	(0.0221)	(0.0233)
12 months claim	0.191***	0.275	0.175***	0.205***	0.217***	0.181*	0.136***	0.196***	0.200***	0.179***	0.247***	0.266**	0.092	0.247***	0.193***	0.184***	0.130***	0.163***	0.202***
	(0.0489)	(0.1675)	(0.0385)	(0.0336)	(0.0652)	(0.0761)	(0.0184)	(0.0169)	(0.0355)	(0.0235)	(0.0451)	(0.0824)	(0.0851)	(0.0336)	(0.0185)	(0.0276)	(0.0387)	(0.0327)	(0.0366)
18 months claim	0.181**	0.112	0.189***	0.178***	0.410***	0.116	0.146***	0.177***	0.200***	0.065	0.188**	0.150	0.161	0.156***	0.163***	0.172***	0.037	0.015	0.138**
	(0.0597)	(0.2093)	(0.0491)	(0.0441)	(0.0832)	(0.1129)	(0.0264)	(0.0233)	(0.0475)	(0.0374)	(0.0606)	(0.1124)	(0.1147)	(0.0472)	(0.0255)	(0.0408)	(0.0535)	(0.0493)	(0.0501)
24 months claim	0.226**	0.121	0.100	0.143**	0.218*	0.188	0.090**	0.121***	0.148*	-0.071	0.161*	-0.082	-0.078	0.075	-0.002	0.045	-0.061	-0.101	0.069
	(0.0850)	(0.2866)	(0.0644)	(0.0538)	(0.1007)	(0.1131)	(0.0340)	(0.0294)	(0.0614)	(0.0477)	(0.0804)	(0.1627)	(0.1458)	(0.0613)	(0.0339)	(0.0507)	(0.0790)	(0.0637)	(0.0696)
Last P	-0.027	0.179	0.029	0.066**	0.029	0.019	0.015	0.042***	0.069**	0.034**	0.051*	0.009	-0.032	0.046*	0.017	-0.019	0.068**	0.058**	0.020
	(0.0292)	(0.1234)	(0.0229)	(0.0227)	(0.0443)	(0.0470)	(0.0124)	(0.0101)	(0.0212)	(0.0116)	(0.0257)	(0.0501)	(0.0505)	(0.0189)	(0.0104)	(0.0183)	(0.0208)	(0.0197)	(0.0196)
Tenure	0.021**	-0.006	0.008	-0.004	0.004	0.009	0.015***	0.004	0.018**	0.032***	0.006	0.025	0.004	0.010	0.029***	0.017***	0.020**	0.027***	0.015*
	(0.0077)	(0.0292)	(0.0052)	(0.0045)	(0.0082)	(0.0109)	(0.0032)	(0.0026)	(0.0054)	(0.0047)	(0.0079)	(0.0129)	(0.0118)	(0.0058)	(0.0031)	(0.0043)	(0.0068)	(0.0056)	(0.0064)
No. P	-0.050***	-0.003	-0.051***	-0.011	-0.024	-0.027***	-0.021***	-0.060***	-0.040***	-0.035***	-0.021*	-0.010	-0.004	-0.040***	-0.023***	-0.059***	-0.023***	-0.015*	-0.046***
	(0.0067)	(0.0546)	(0.0051)	(0.0089)	(0.0198)	(0.0043)	(0.0055)	(0.0043)	(0.0060)	(0.0026)	(0.0093)	(0.0178)	(0.0216)	(0.0084)	(0.0036)	(0.0063)	(0.0069)	(0.0059)	(0.0059)
Experience	-0.008***	-0.007	-0.002	-0.010***	-0.007*	-0.005	-0.011***	-0.008***	-0.010***	-0.009***	-0.004	0.002	0.003	-0.000	-0.008***	-0.004**	-0.009***	-0.011***	-0.003
	(0.0018)	(0.0113)	(0.0018)	(0.0018)	(0.0034)	(0.0033)	(0.0008)	(0.0010)	(0.0018)	(0.0011)	(0.0029)	(0.0062)	(0.0043)	(0.0021)	(0.0009)	(0.0013)	(0.0021)	(0.0015)	(0.0018)
log(past wage)	-0.041***	-0.066	-0.077***	-0.086***	-0.075***	-0.072***	-0.064***	-0.068***	-0.075***	-0.083***	-0.082***	-0.139***	-0.042*	-0.091***	-0.081***	-0.064***	-0.085***	-0.128***	-0.095***
	(0.0067)	(0.0488)	(0.0070)	(0.0072)	(0.0148)	(0.0150)	(0.0036)	(0.0032)	(0.0076)	(0.0036)	(0.0071)	(0.0130)	(0.0173)	(0.0053)	(0.0027)	(0.0049)	(0.0056)	(0.0054)	(0.0051)
age	0.004	0.044	0.002	-0.002	0.009	-0.024	-0.001	0.007*	-0.013	-0.010**	-0.026**	0.015	-0.005	-0.008	-0.003	-0.004	0.020**	0.009	-0.010
	(0.0071)	(0.0399)	(0.0068)	(0.0066)	(0.0123)	(0.0135)	(0.0031)	(0.0033)	(0.0071)	(0.0037)	(0.0094)	(0.0190)	(0.0167)	(0.0066)	(0.0030)	(0.0050)	(0.0071)	(0.0055)	(0.0059)
Constant	1.478***	0.474	1.643***	1.570***	1.853***	1.920***	1.500***	1.592***	1.314***	1.047***	1.509***	1.899***	1.095*	1.960***	1.220***	1.969***	1.478***	0.606***	1.247***
	(0.1941)	(0.9736)	(0.1662)	(0.1614)	(0.3374)	(0.3276)	(0.0900)	(0.0884)	(0.1972)	(0.1176)	(0.2464)	(0.4034)	(0.4665)	(0.1503)	(0.0800)	(0.1276)	(0.1531)	(0.1335)	(0.3743)
Controls																			
year dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
industry dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
occupation dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	11034	596	15055	16359	4323	3489	67225	64521	16371	51602	11434	3115	2222	19950	87080	23193	16399	29802	22049
Adjusted R^2	0.575	0.484	0.544	0.510	0.542	0.586	0.509	0.547	0.574	0.592	0.570	0.566	0.596	0.564	0.565	0.617	0.576	0.660	0.595
AIC	25959	1548	37858	41103	10791.130	8806	162699	154858	43103	129922	28624	7806	5312	49479	224697	55336	39398	82515	55867

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.