Hysteresis for the Young: Search Capital and Unemployment

Cristina Lafuente*
Université Catholique de Louvain

Most up-to-date version here

February 15, 2023

This paper argues that search ability should be considered a distinct type of human capital. Workers are endowed with a search ability that determines their effectiveness of search, or their intrinsic job arrival rate. Workers build up their job search capital by interacting with the labour market, finding and moving on to different jobs. Long, stable employment spells without search erode their search capital over time. This channel has notable implications for modelling and policy in all labour markets, but it is particularly relevant in dual labour markets. In the presence of large, persistent negative shocks like the Great Recession, the inability of young workers to accumulate search capital can explain why they suffer larger increases in unemployment and long-term unemployment, something traditional hysteresis models struggle to explain. Using administrative data, I show that search capital, as proxied by the number of jobs a worker has had, is negatively correlated with unemployment duration. I build a heterogeneous agent search model with both productive and search human capital to show the effect that dynamic search capital has on workers' lifetime utility. The calibrated model shows that despite the protective effects of accumulating search capital against aggregate shocks, the cost in terms of uncertainty outweighs the benefits. The model favours active labour market policies over employment incentives to tackle long-term unemployment among young workers.

JEL classification: J24, J63, J64
Key words: search, unemployment, hysteresis, long-term unemployment, temporary contracts, active labour market policies

*Postdoctoral researcher at CORE, UCLouvain, Voie du Roman Pays 34, 1348 Ottignies-Louvain-la-Neuve, Belgium. Email: Cristina.Lafuente@uclouvain.be. I would like to thank my advisors Maia Güell and Ludo Visschers for all of their support and advice, as well as my current supervisor Philipp Kircher; I have also benefited from the comments and suggestions of Raquel Carrasco, Carlos Carrillo-Tudela, Andrew Clausen, Mike Elsby, José Ignacio García-Pérez, Rafael Lopes de Melo and Iourii Manovski. I also received excellent feedback from the attendees at the Fall Midwest Macro Meeting at SMU, the 2018 SED meeting and the 2018 EEA-ES meeting. 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

This paper introduces different search abilities among workers, which results in heterogeneous job finding rates among the unemployed. While other authors have considered the effects of different job finding rates on unemployment and long-term unemployment, this paper introduces explicitly dynamic learning and erosion of search skills, in a similar manner to learn-by-doing human capital accumulation. Interacting with the labour market successfully leads to increasing search capital, which can be thought of as a combination of network increase, knowing where to search and other skills that increase the job offer arrival rate of workers. Crucially, search capital does not increase the wage offer distribution, which is interpreted as a function of *productive* human capital. A very qualified worker can have a harder time finding a job if the last time she looked for one was decades ago, while a relatively young and unskilled worker can get multiple job offers a week if she knows places where she is likely to get an offer.

Search capital predicts lifetime patterns of accumulation and erosion that are different from productive human capital. While multiple short employment spells may grant lower returns in terms of productivity than more stable jobs (for example due to incentives of firms to invest in training), it can shorten workers' unemployment spells and make them more resilient to aggregate shocks that increase labour market tightness (many candidates for few jobs). These dynamics have different policy implications from traditional models on youth unemployment, temporary contracts and the unequal cost of recessions: as young workers are highly dependent on an abundance of entry jobs, their destruction in recessions hurts them relatively more than older workers with better search skills. This mechanism can explain the disproportionate impact of the Great Recession among the youth (Bell and Blanchflower (2011), Bentolila et al. (2022)).

These differences are exacerbated in labour markets characterised by slippery job ladders for new entrants. combined with very protected jobs for insiders. I therefore use a country with this features, Spain, to look for reduced-form evidence for search capital. Exploiting the clear distinction between temporary and permanent contracts and a rich administrative dataset, I find a negative correlation between the duration of unemployment and the number of previous jobs with different firms that a worker had in the past, controlling for tenure and employment experience. This correlation is robust to different specifications and controls, including individual fixed effects and separating by industry. The effects are stronger when we consider past but recent employment spells as opposed to older ones, which is compatible with the depreciation of search capital, and suggest that the effects of ex-ante heterogeneity may be hard to be eroded via search capital accumulation. Crucially, the number of jobs in the past also correlates positively with re-employment wages: they are not getting a wage cut as a way to get a way out of unemployment.

To illustrate the macro effects of search capital, I construct a heterogeneous agent model that bridges two strains of the literature: hysteresis life-cycle models and dual labour market models. Risk-averse workers face a frictional labour market where they can receive temporary and permanent job offers with different arrival and job destruction rates. Temporary jobs are destroyed more often, but they can be converted into permanent contracts, which allow workers to accumulate human capital. Unemployment benefits expire at a stochastic rate, and workers in temporary jobs may not be entitled to received them upon job destruction. However, workers can increase their search capital by taking new jobs, which increases the arrival rates of future jobs. Search capital depreciates over long employment spells.

The model features a trade-off between human capital, which affects the wage offer distribution, and search capital, which affects the arrival rate of jobs. Traditional hysteresis models (suach as Ljungqvist and Sargent (1998), Ljungqvist and Sargent (2008), Kitao et al. (2017)) rely solely on the first channel to explain long-term unemployment, and thus do not fit the patterns of younger workers, who are more sensitive to search frictions. While this can be alleviated by having a period of unstable jobs at the beginning of careers, it still fails to account for cyclical unemployment fluctuations among young workers. The addition of search capital addresses this issue. To show this, I calibrate the model to a pre- and post-Great Recession equilibria, and simulate a large heterogeneous agent economy as it suffers a once-and-for-all negative shock. This exercises delivers increases in long term unemployment by age groups that more closely resemble the data compared to a canonical model without search capital. The key is the reliance of young workers on a high availability of short-term jobs to improve their search abilities, while more mature workers are more sensitive to human capital considerations. The lack of temporary jobs in a recession hurts young workers more, and this shock is persistent in time, as they take longer to become proficient searchers, which in turns allows them to access stable jobs.

A natural question that arises from these results is if unstable careers with many job changes are good for workers in the long-run, as they can make them resilient to adverse aggregate shocks. However, the chronic uncertainty temporary jobs bring to lifetime savings and consumption can outweigh their positive ‘learning’ effects on job search. To show this, I simulate a large panel of workers in two scenarios: one without and one with a recession. Then I compare the lifetime utility of agents ex-ante. I then measure the willingness to pay to avoid the recession path of each worker, and compare “lucky” workers who get stable jobs soon to workers with more unstable careers. I find that while the cost of recessions is lower for workers with more unstable careers, those with stable careers achieve greater lifetime utility in both scenarios. Workers would prefer to avoid temporary contracts even with the protection they offer against non-trivial business cycle fluctuations. In other words, individual risk trumps aggregate risk.

In this way, search capital has important, but nuanced, implications for policy. Incentivising the creation of jobs for younger workers may be the most obvious one, but it is not: as the welfare exercise shows, more temporary contracts do not lead to higher welfare because they come at a large utility cost in terms of uncertainty. It is therefore unlikely that younger people would support a policy that subsidises the creation of low productivity, short jobs. Instead, this paper provides support for targeted active labor market policies that increase search capital without having to go through multiple short-term jobs. Such policy would limit dispersion in search capital at the beginning of workers lives. Giving young workers with low search capital a higher level of search ability allows them to behave more like older workers and be able to reject poor offers, waiting instead for better employment choices. This is unlikely to increase the incidence of long-term unemployment, since these workers are taking very short periods of time to move to jobs as a starting point. The only caveat to these policies is that there might be general equilibrium effects leading to congestion (Gautier et al. (2018)). A brief glance on the expenditure and usage of these policies at European level suggests that countries with more robust active search assistance methods do better in terms of youth unemployment compared to Southern European countries which rely on employment incentives instead.

The rest of the paper is organised as follows: section 2 introduces the concept of search capital by integrating it in a model of job search; section 3 presents the data and some empirical evidence; section 4 presents the results of the calibrated model; section 5 concludes.

2 A model of heterogenous workers

This section introduces the quantitative, heterogeneous agent model featuring search and productive human capital. In order to highlight the contribution of search capital and motivate the empirical exercise and the calibration strategy, I introduce first an static model. Then I consider how other channels interact with the core mechanism: different types of jobs, accumulation dynamics and self-insurance. The goal of full model is to evaluate the quantitative contribution of search capital and analyse its welfare consequences.

Consider the problem of a risk-averse job seeker, drawing employment-wage offers from a continuous distribution. Time is continuous and discounted at rate r. Workers are endowed with search capital s and productive human capital h, which translates into wages $w(h) = w \cdot h$ for simplicity. While searching in unemployment, a worker receives unemployment benefits b.[1] The utility function is set to $u(c) = log(c)$ and there is no saving or borrowing. The stochastic arrival rate of offers is given by $\alpha(s)$, with $\alpha'(s) > 0$,

[1]The assumption that benefits or flow utility in unemployment is not related to human capital will be relaxed later.

$\alpha''(s) < 0$, and a stochastic job destruction rate is given δ. The CDF of the wage offer distribution is $F(w_i)$, and fulfills the conditions in Van den Berg (1994).[2] This is a partial equilibrium setting, so the wage distribution should be thought of as a distribution of firm (or job) productivity, indexed by i.

Value of unemployment is given by the bellman equation

$$rU(s,h) = u(b) + \alpha(s) \int \max\{W(w_i, s, h) - U(s,h), 0\}, dF(w_i). \tag{1}$$

and the value of employment at wage w by

$$rW(w,s,h) = u(wh) + \delta(U(s,h) - W(w,s,h)). \tag{2}$$

As implied by the *max* operator in 1, the choice variable of the worker is the reservation wage $w = w_R$ which makes her indifferent between employment an unemployment ($w_R : W(w_R, s, h) - U(s,h) = 0$). This wage solves the maximization problem in 1 and allows us to rewrite this equation as

$$rU(s,h) = u(b) + \alpha(s) \int_{w_R} W(w_i, s, h) dF(w_i),$$

We can combine both equations to obtain the equilibrium flow value of unemployment

$$rU(s,h) = \frac{(r+\delta)}{r+\delta+\alpha(s)(1-F(w_R))} u(b) + \frac{\alpha(s)}{r+\delta+\alpha(s)(1-F(w_R))} \int_{w_R} u(w_i h) dF(w_i). \tag{3}$$

This flow value determines the reservation wage or the "pickiness" of the unemployed. As in the regular model, it is a weighted (or rather discounted) average between the return to unemployment b and the expectation of what the agent would gain if accepting a different offer in the future. The reservation wage is then given by

$$u(w_R h) = \frac{(r+\delta)}{r+\delta+\alpha(s)(1-F(w_R))} u(b) + \frac{\alpha(s)}{r+\delta+\alpha(s)(1-F(w_R))} \int_{w_R} u(w_i h) dF(w_i). \tag{4}$$

Productivity h enter twice in this equation: the returns of employment on the left-hand side and the return to the expected value of continuing the search on the right hand side. In the current setting where b is a constant, h increases the wedge between unemployment and employment, so productivity *decreases* reservation wages. This is because workers draw employment offers from a better distribution, so the opportunity cost of being unemployed is higher. However, if unemployment benefits were proportional

[2]These conditions are less strict that the assumption of log-concavity in Burdett (1981) and Burdett and Ondrich (1985). The conditions in Van den Berg (1994) are satisfied by most common distributions used in the empirical literature - and in the numerical exercises here.

to productivity,[3] this channel is shut down. For example, with log or linear utility, it is easy to show that in the case of proportional benefits ($b(h) = bh$) the reservation wage is independent of h. In this case, productivity has no effect on unemployment duration.

On the other hand, search capital increases the value of continuing search by allowing the unemployed to sample the wage distribution more often. As in models of consumer search, sampling from more firms (shops) makes the worker (consumer) more selective, or less desperate. Search capital also diminishes the importance of unemployment benefits by shortening the expected duration of unemployment. To see this, consider expected duration of unemployment (E) which in this environment is given by

$$E(s,h) = \frac{1}{\alpha(s)(1 - F(w_R(s,h)))}, \tag{5}$$

which is part of the effective discount rate in the denominator of 4. This is important because it diminishes the power of explanations of unemployment duration that rely on high unemployment benefits, like hysteresis. Instead, because the first order effect (through increasing the value of continuing search) dominates, higher search capital leads to more "pickiness", but of a very different kind than higher unemployment benefits: being able to sample more offers increases the availability of good jobs, something more closely related to labour demand than labour supply.

In the end, does search capital increase or decrease unemployment duration? Under the weak assumptions of Van den Berg (1994), a higher job arrival rate unambiguously decreases unemployment duration. Intuitively, since search capital increases w_R in so far as they are good payouts from searching longer, it is the expectation of a good outcome which makes unemployment spells shorter. If instead expected wages are low, sampling more offers does not increase the value of expected unemployment and search capital reduces duration. In this case, unemployment benefits become more relevant. This leads us to consider the joint impact of human capital (as in productivity on the job) and search capital (as productivity in search). Figure 1 shows a sample of reservation wages obtained by solving equation 4 with the parametrization of table 1.[4]

Low productivity (h) workers cannot hope to get high wages, so if their arrival rate ($\alpha(s)$) is low they will take any offer they receive, leading to a low reservation wage. But if they are very good searchers they have a fair chance to get the jobs at the tail of the distribution. Since their productivity is low, this is the only way they can get a high paying job (relative to unemployment benefits) so they have a high reservation wage. For a high productivity worker, the expected payout of any wage is very good relative to unemployment. Therefore low s, low h workers will be the least picky. Workers with

[3]This proportionality could be justified as a "cheap" way of introducing replacement ratios without introducing history dependence (and hence another state variable).

[4]The values in this table are chosen from the averages in the data used for calibration later and normalizing unemployment benefits to 1.

Figure 1: Reservation baseline wages

Notes: Results of solving equation 4 for $\alpha(s) = \bar{\alpha}s$, $u(c) = log(c)$ and the parameters in table 1.

high search capital and high productivity will be more patient, but they do not need to wait as long as the ones with low productivity to get a good offer. This is reflected in the left panel of figure 1. A for the slope, notice it is steeper at low levels of search capital were offers arrive every 10 months or more ($\alpha(s) \leq 0.1$).

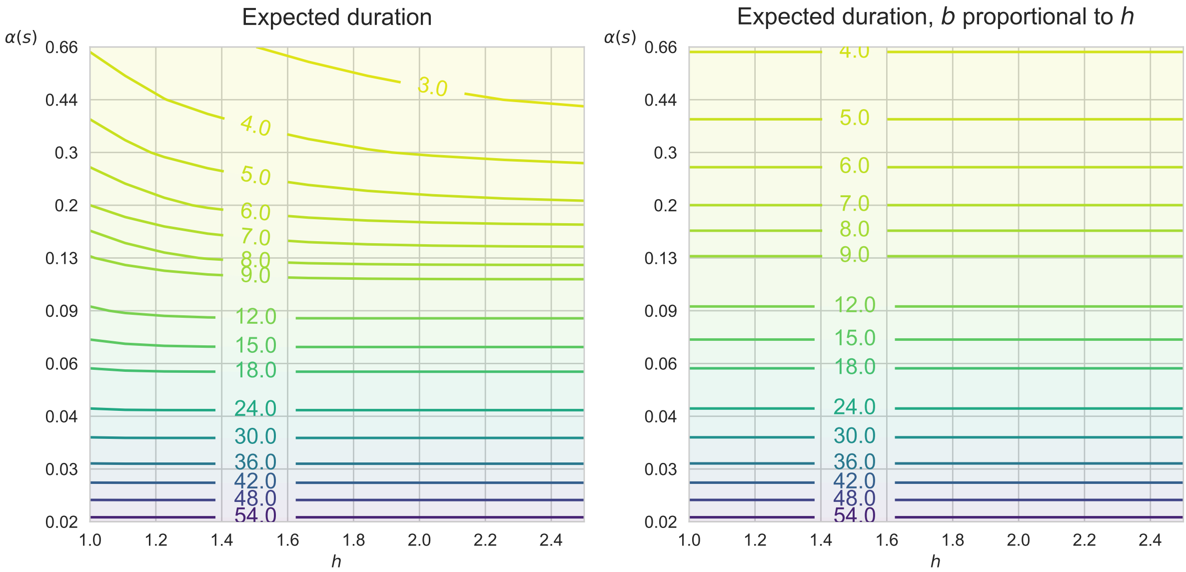
Table 1: Baseline parameters

$\bar{\alpha}$	δ	b	r	$F(w)$
0.13	0.05	1	0.02	$\mathcal{LN}$(0.5,1)

If unemployment benefits are proportional to productivity, the marginal gain of keeping searching depends only on baseline salary or match productivity dispersion. Just as workers with no human capital can only get better wages trough netter matches, high-skilled workers with proportional benefits do not get an 'employment premium'. Therefore reservation wages do not depend on productivity, only search capital. This is shown in the right picture of figure 1.

How does this translate into duration of unemployment? Figure 2 shows the implied expected duration (in months) for the baseline calibration in table 1. The high productivity, high search capital are the ones with the lowest duration: They are less choosy than the low productivity workers, so they leave faster. But they get out much faster than the ones with low search capital, high productivity, who, despite having the lowest reservation wage end suffer very long unemployment spells. Note that even if productive human capital and search capital are completely orthogonal, on average high productivity workers have shorter unemployment spells, as predicted by classical models. Search capital or differences in arrival rates make most of the variation in duration.

Figure 2: Average (expected) duration



Notes: Results from equation 5 using the solution to 4 for $\alpha(s) = \bar{\alpha}s$, $u(c) = log(c)$ and the parameters in table 1.

Comparing the left panel and right panels of figure 2, high search capital, high productive workers have longer duration under proportional benefits. That is, higher unemployment benefits do nothing or very little for productive workers with low arrival rates. The isoquants of duration in the left panel curve *down*, meaning lower duration under constant benefits. But this is true only for high search capital workers. Proportional benefits increase duration for highly productive workers with high search capital, by reducing the surplus from employment, which leads them to higher baseline wages.

Consider how this differs from the classical hysteresis channel in Kitao et al. (2017), where differences in unemployment duration come mostly from differences in employment surplus. Young workers with low productivity have some of the highest surplus of employment, since they have lower assets and employment allows them to accumulate productive human capital. This leads the model to predict they will have very short unemployment spells, which are at odds with the data. Their solution is to restrict the arrival rate (through minimum wages) to increase their unemployment duration. This is different from saying young workers have a *naturally* low job arrival rate, because in that case they will still take very poorly paid jobs, which can and will have consequences later in life. Instead, in a model with high minimum wages young workers are trading off long employment spells in exchange for a higher employment wage. This might be the optimal thing to do if given the option, as we will see later in the model with heterogeneous jobs. The implications for policy radically very different. In fact, In fact, a planner may wish to impose minimum wages to prevent desperate young workers from taking very bad jobs.

2.1 Heterogenous jobs

Heterogeneous arrival rates can only explain part of unemployment variation. As many studies have suggested, heterogeneity in job destruction rates plays a substantial role and its effects are boosted by search capital.

Consider the same model but with two types of jobs: long-jobs or "permanent" jobs and short jobs or "temporary jobs".[5] Permanent jobs last for long but they have a low job finding rate, while temporary jobs are short but easy to find. Although the model is partial equilibrium, it is reasonable to assume that the temporary wage distribution is more concentrated than the permanent one.[6] Temporary job offers are therefore assumed to be drawn from a different distribution of permanent jobs, which also has lower variance.

In this environment, the worker chooses two reservation wages $\{w_{RT}, w_{RP}\}$.[7] The value functions are:

$$rU(h,s) = u(b) + \alpha_T(s)\int_{w_{RT}}(W_T(w_i,h,s) - U(h,s))dF_T(w_i) + \alpha_P(s)\int_{w_{RP}}(W_P(w_i,h,s) - U(h,s))dF_P(w_i),$$

$$rW_T(w,h,s) = u(w_T(h)) + \delta_T(U(h,s) - W_T(w,h,s)),$$

and

$$rW_P(w,h,s) = u(w_P(h)) + \delta_P(U(h,s) - W_P(w,h,s)).$$

The conditions for the setting the reservation wages are

$$rW_T(w_{RT},h,s) = rU(h,s) \quad \text{and} \quad rW_P(w_{RP},h,s) = rU(h,s).$$

Note that in the case of human capital entering multiplicative in both types of jobs ($w_T(h) = wh$ and $w_P(h) = wh$) the condition above implies they choose the *same* reservation wage for both kinds of jobs.[8] This is irrespective of one type of job having a higher job destruction rate or a different wage offer distribution. What matters for reservation

[5] Although I am borrowing the notation from the dual-labour market literature, temporary jobs here can easily represent entry jobs, mini jobs, internships, informal jobs, contractor jobs or any kind of volatile, less regulated jobs. In the same way, permanent jobs stand in for regular, secure employment, which in the cases of most European countries means much higher employment protection.

[6] This would be the case under common assumptions: permanent jobs are an investment to the firm, which takes in more risk than a temporary job. Or simply since unemployed workers and temporary job offers meet more frequently, negotiation and competition bring wages closer. Or since temporary job offers are met more often by unemployed than employed workers, the baseline wages are lower and more concentrated.

[7] The reservation wages are optimal policies which depend on the state vector $\{h, s\}$: $w_{RT}(s,h)$ and $w_{RP}(s,h)$. For clarity of exposition I refer to these simply as w_{RT}, w_{RP}.

[8] The condition above is similar to a directed search setup, where workers decide whether to enter the temporary or the permanent job market. In that case, workers queue up as to make them indifferent from searching in one market or the other, which results in the same flow value of unemployment. Here, under random search workers can queue in both markets at the same time, but through their reservation wages they can effectively "specialise" in one type of job or the other.

wages is the value of carry on with search, and in a static environment where productive and search capital are constant the opportunity cost of rejecting the job is the same in both cases. This does not mean that the worker is going to reject both types of jobs at the same rate. If, as we assumed, the distribution of temporary wages is more concentrated than permanent wages then the worker would likely reject less frequently permanent offers. The worker is balancing the two wage distributions by agreeing on a wage that compensates for the promised value of keeping searching.

If we consider temporary jobs as “dead end” jobs, or jobs that do not value human capital ($w_T(h) = w$) then the reservation ages will be different.[9] Workers with high human capital would prefer permanent jobs, even from the low end of the distribution, to temporary jobs. This is irrespective of risk aversion, as it is about the forgone returns to productive human capital that are lost by accepting a job where that human capital is not valued.[10]

The value of keeping search in this case is

$$rU(h,s) = \frac{u(b)(r+\delta_T)(r+\delta_P)+\alpha_T(s)(r+\delta_P)\int_{w_{RT}} u(w_{Ti}(h))dF_T(w_T)+\alpha_P(s)(r+\delta_T)\int_{w_{RP}} u(w_{Pi}(h))dF_P(w_P)}{\alpha_T(s)(1-F_T(w_{RT})+\alpha_P(s)(1-F_T(w_{RP})+(r+\delta_P)(r+\delta_T)} \tag{6}$$

which is again the weighted (discounted) average of staying unemployed and the expected value of getting a temporary or a permanent job.

What does this model change in predictions over the previous one with one type? Figure 3 shows the reservation wages for each type of job, under the “dead end” interpretation of temporary jobs ($w_T(h) = h$) and the human capital approach ($w_T(h) = wh$). The parameters are displayed in table 2, which shows the calibrated parameters for two types of jobs and illustrates the wage offer distributions. I use log normal distributed wages with different variances and means, which overall reflect the hiring wage distributions later in the data. The monthly hazard rates are used to pin down the job arrival and destruction rates.

Table 2: Baseline parameters, two types of jobs

$\bar{\alpha_T}$	$\bar{\alpha_P}$	δ_P	δ_T	b	r	$F_T(w)$	$F_P(w)$
0.13	0.02	0.05	0.007	1	0.02	$\mathcal{LN}(0.5,1)$	$\mathcal{LN}(0.99,1.3)$

The general pattern from figure 1 is preserved in the second row, where both permanent and temporary wages are proportional to productivity. As noted, both temporary and permanent wages are set at the same level, but that does not mean they are accepted at the same rate. The least selective are the highly productive but bad searchers, with the most selective bring the low productive but high searchers.

[9]A less extreme assumption would be to have them interact differently with human capital, not just not interact at all. In this case there will also be different reservation wages.

[10]In this environment, if a worker with high productivity accepts a job that does not value it could be thought as ‘mismatch’. This idea is explored in Dolado et al. (2009).

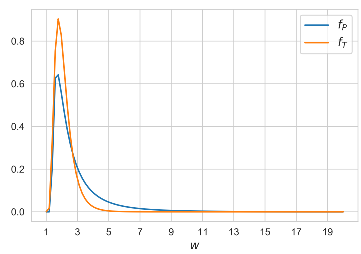
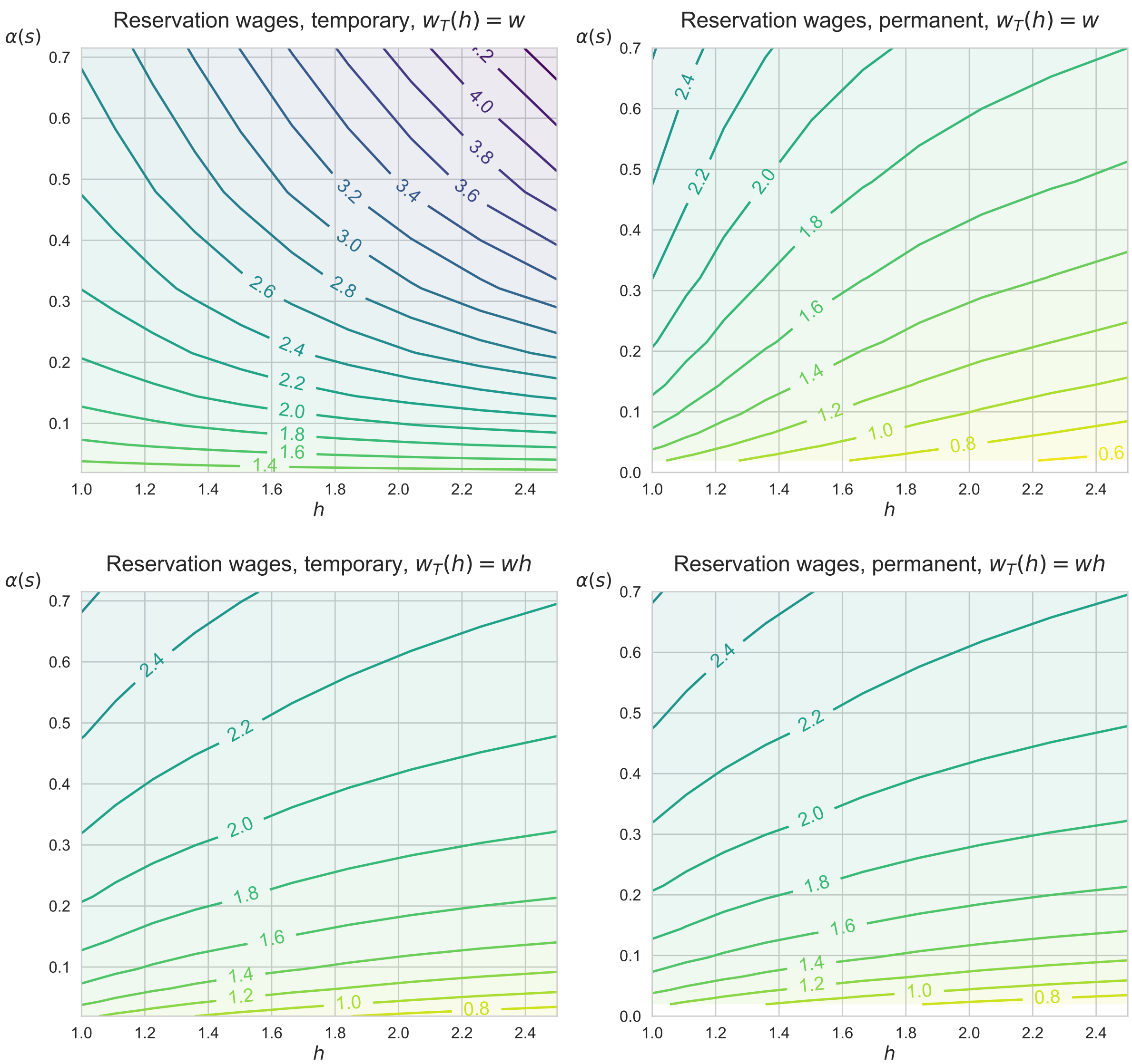


Figure 3: Reservation baseline wages



Notes: Results of solving for the reservation wage vector using equation 6 for $\alpha_i(s) = \bar{\alpha}_i s$, $u(c) = log(c)$ and the parameters in table 2

On the other hand, when temporary jobs do not depend on productivity they are strongly rejected by the highly productive and good searchers. Since the mean of the distribution is 2.13, a reservation wage of 4.5 as in the most extreme case of the top left panel means they are almost always rejected. Workers in the "dead-end" world have lower permanent reservation wages than the workers in the regular world, as they are relatively much more valuable. In both cases, reservation wages for permanent jobs respond to productive (↓) and search (↑) capital in the same way as the baseline. But when temporary jobs are dead-end jobs, productivity *increases* the reservation wage, particularly among good searchers. As before, bad searchers cannot afford to turn down offers, so they will accept most of either kind of jobs, but they will reject temporary jobs more often. As permanent jobs are hard to come by, this will be reflected in their unemployment duration.

Figure 4 shows the implied expected duration of unemployment, given the reservation wage rules. The workers who exit unemployment fastest in the dead-end jobs case (top left and bottom left) are the high search capital and low productivity ones. This is a "churners equilibrium", where the shortest unemployment duration corresponds to workers who gain nothing from waiting, since they will achieve the same wages anyway in both cases. In the case of temporary wages proportional to productivity (top right panel), the resulting pattern is the same as in the baseline case with only one job: the fastest to exit are high search capital, high productivity workers. This is because they take temporary jobs, which still pay much more than unemployment. They are more selective than highly skilled but bad searcher workers, but their high search ability compensates for their higher rejection rate.

Notice how in both the "dead end" scenario (top left) and the proportional wages scenario (top right) productivity only seems to affect duration for high levels of search capital. In the case of productive temporary wages, letting unemployment benefits vary with productivity (bottom right panel) gives the same result as in the previous case as well. Highly skilled but bad searchers are not affected by higher unemployment benefits.

Things are more interesting for the "dead end" jobs scenario with proportional unemployment benefits, in the bottom left. Since now workers with high productivity can wait longer, those with low search capital become almost permanently unemployed. This is a result of familiar forces of hysteresis: their earnings are high in unemployment, so they can afford to reject temporary wage offers which offer them much less than a permanent job. But because they are very bad searchers, permanent job offers arrive very rarely. In other words, search capital exacerbates hysteresis and boosts the variance of unemployment.

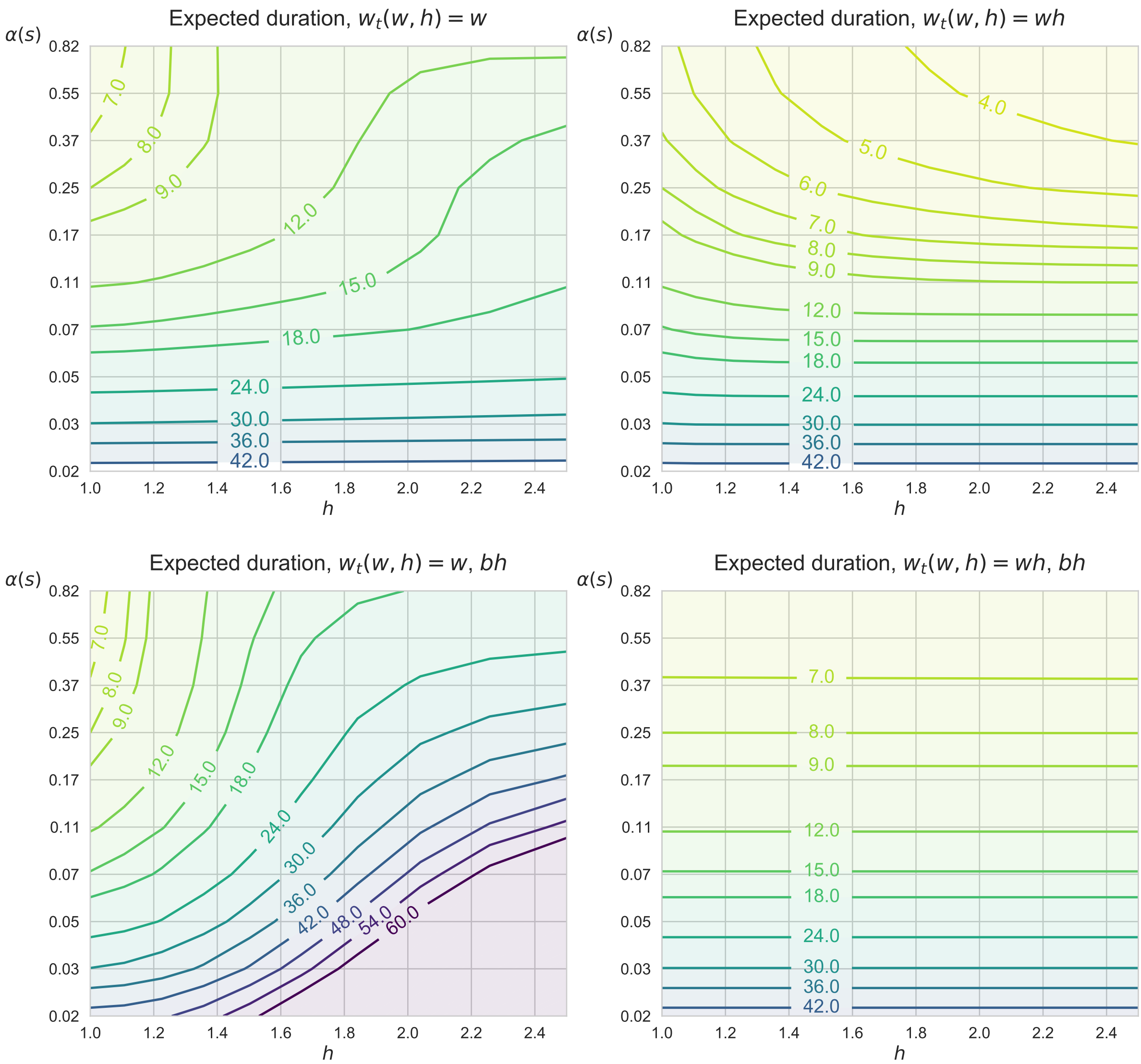
For this to happen in a model of search capital, it is necessary to have good quality jobs coexisting with easy to get poor jobs. This setup echoes European labour market institutions that protect most employment contracts at the expense of precarious employment, be it temporary, zero-hours or mini jobs. Crucially, long unemployment duration is not coming from the fact that highly skilled workers have to start from zero with very high benefits, which means they have no incentives to accept jobs. In the bottom left panel of figure 4 we see that workers with low productivity leave unemployment much faster at any arrival rate, particularly among the ones with the worst search capital level.

Instead, long durations in a search capital model come from the *realistic* hope of high skilled workers that they will be able to get a good job if they wait long enough. But some of them have much fewer opportunities of accessing these jobs. In other words, it is not that the jobs these workers want do not exist anymore (which would be pushing them back to $h = 1$), they still exist but they are very hard to get. This has very different policy implications than the original hysteresis papers.

2.2 Unemployment composition

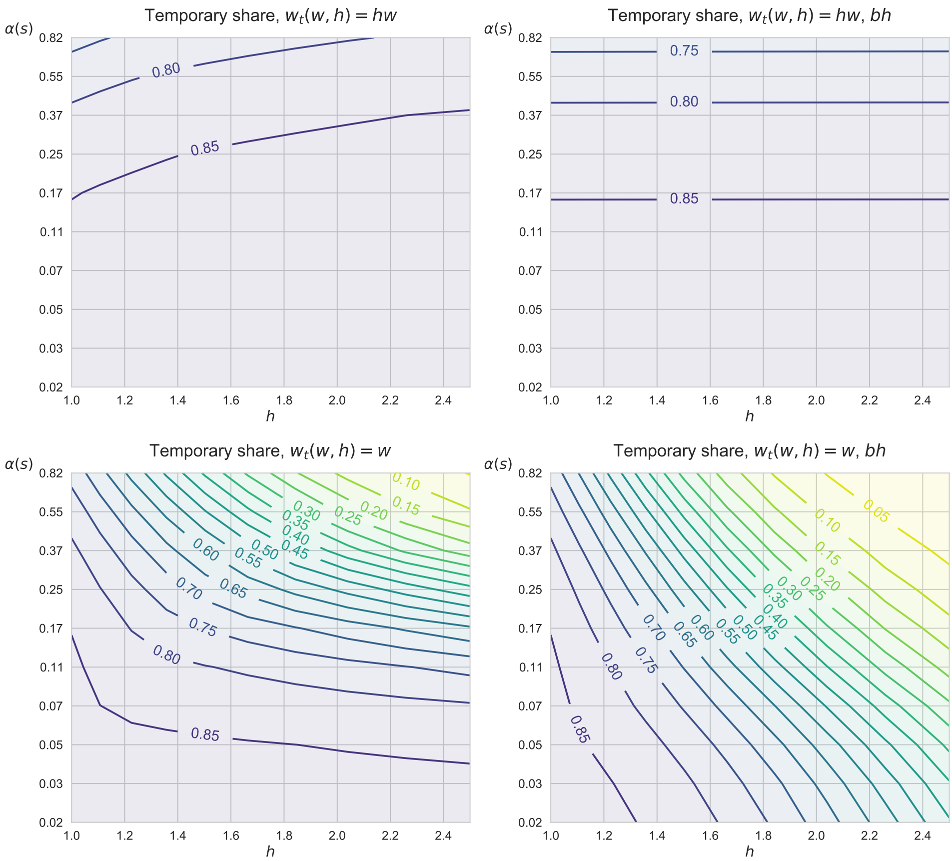
In the baseline model, when all the jobs have the same expected wage schedule and destruction rates, it is straightforward to see that in any given point we would expect to find the high unemployment duration workers dominating the pool of unemployment:

Figure 4: Average (expected) duration



Notes: Results from equation 5 using the solution for the reservation wage vector from 6 for $\alpha_i(s) = \bar{\alpha}_i s$, $u(c) = log(c)$ and the parameters in table 2

Figure 5: Probability of accepted job being temporary



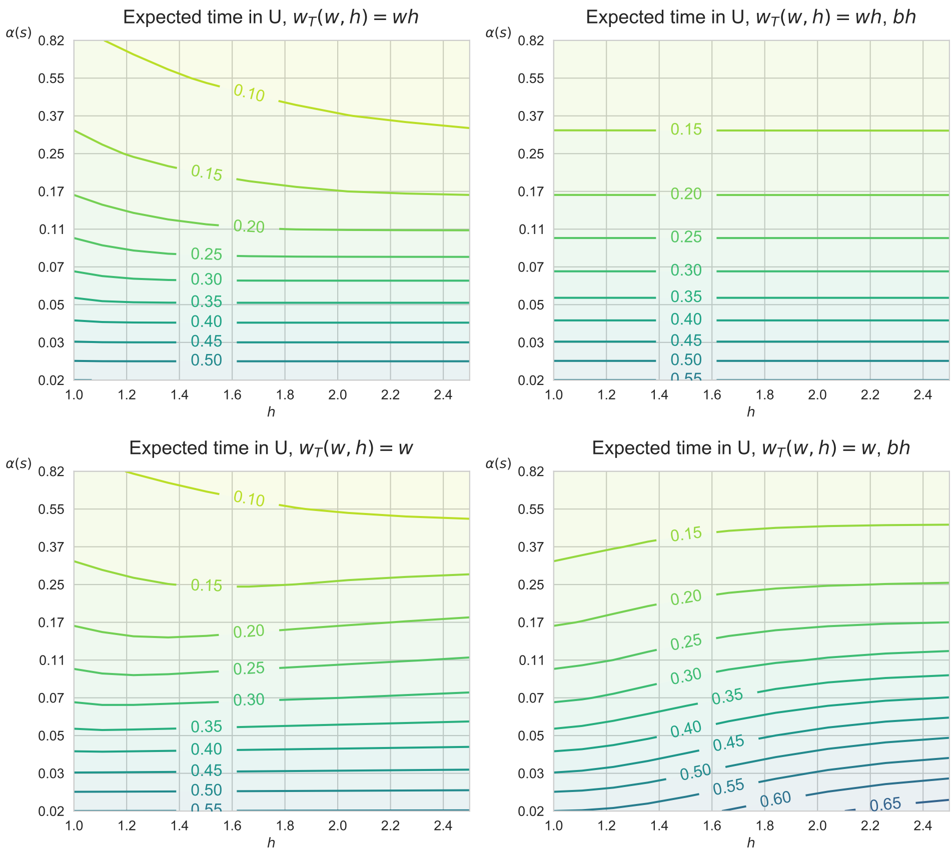
Notes: Results from equation 5 using the solution for the reservation wage vector from 6 for $\alpha_i(s) = \bar{\alpha}_i s$, $u(c) = log(c)$ and the parameters in table 2

good searchers leave soon and are rarely seen in unemployment, while bad searchers are almost always there.

In the case of 2 types of jobs this may not be the case: good searchers with low productivity may be coming in and out of unemployment very frequently, since they take mainly temporary jobs. But those who take more payment jobs are likely out of unemployment for longer. In the case of dead-end jobs, we saw that good searchers of low productivity had the lowest unemployment duration. But figure 5 shows that they also a high likelihood of accepting temporary jobs. On the other hand, good searchers with high productivity had longer unemployment spells on average but they accept mostly permanent jobs. Regardless of the benefit schedule, there is sorting in the dead-end job scenario: the higher productivity, the higher the likelihood of of getting a permanent contract. As hinted before, high benefits for highly skilled workers help them get a permanent contract – at the expense of longer durations, particularly for the low search capital workers. Bad searchers, in all scenarios (except in the dead-end, proportional benefits case), have the highest acceptance rate of temporary jobs and the highest duration, which means they will dominate the unemployment pool.

With the wage acceptance rules, the baseline job finding probabilities and the job

Figure 6: Probability of being in unemployment



Notes: Results from equation 5 using the solution for the reservation wage vector from 6 for $\alpha_i(s) = \bar{\alpha}_i s$, $u(c) = log(c)$ and the parameters in table 2

destruction rates, the model reduces to a markov chain for each worker. The stationary distribution then corresponds to the probability of finding each worker in a state in any given period, or equivalently the share of time each worker spends in unemployment in her lifetime. Figure 6 shows that in any scenario, good searchers are rarely seen in unemployment. Productivity, on the other hand, may increase, decrease or be orthogonal to overall time in unemployment. When benefits are not related to productivity, highly productive workers spent the shortest time unemployed, on average. But when productivity is related to benefits, in the case of dead-end jobs higher productivity workers spend more time in unemployment. In this case, it would need to be that search ability and productivity are very highly correlated to undo this result.

Note that the trade-off between better paid jobs, more stable jobs and more time in unemployment means that it may not be case the case than unemployment is always welfare-reducing. It may be that there is a positive optimal unemployment duration, depending on productivity and the job arrival rate of stable jobs.[11] If workers are risk

[11]This would be a constrained optimal, in the sense that if the planner could remove search frictions then all workers would choose the highest, most stable paying job. Search frictions put a constraint in this problem. The existence of unemployment and mismatch shows makes this restriction desirable.

averse, then a worker in a string of highly paid short jobs may be doing worse than a worker in a regular long-term job. This would make policies targeting workers to get stable jobs and wait longer welfare enhancing, particularly for highly skilled workers.

2.3 Human capital dynamics

So far the assumption is that workers have the same type over their entire lifetime, so the unemployment rate and duration distribution are given by underlying distribution of types. But just as workers accumulate human capital with work experience, they can also improve their search skills over time.

The crucial difference in this case is that being employed for long in the same job is unlikely to improve search capital, regardless of the microfoundational story: not interacting with the job market would lead to lose sight of where the current job opportunities are; staying the the same job is unlikely to improve a worker's network. While in the case of the "churning" workers, who are coming and going in the market, they are likely improving their network and search skills over time. The high likelihood of being unemployed incentivise them to invest in search capital, as it makes unemployment spells shorter.

A natural way of modelling this is to assume that search skills improve after gaining a new employment contract. Getting different jobs is crucial to networks, but also for knowing which door to knock in the future, should the need for employment arise again. On the other hand, unemployed workers are unlikely to improve their network while unemployed, and similarly it is more likely that they learn from successes than failures to secure a job. In a random search setting, where not forming a match on contact is because the worker turns down the job, it is hard to argue that finding an undesirable job is going to help find a desirable one.[12] For the current setting, search capital is assumed to increase with accepted offers only.

The following equations characterise this dynamic problem:

$$rU(h,s) = u(b) + \alpha_T(s)\int_{w_{RT}} (W_T(w_i,h,s') - U(h,s))dF_T(w_i) + \alpha_P(s)\int_{w_{RP}} (W_P(w_i,h,s') - U(h,s))dF_P(w_i),$$

$$rW_T(w,h,s) = u(w_T(h)) + \delta_T(U(h,s) - W_T(w,h,s)) + \pi_s(W_T(w,h,s') - W_T(w,h,s)),$$

[12] In a model where there are different hiring stages and reaching one of them, even if the job does not materialise, accepting jobs do not necessarily increase search skills. But in such a model, unemployment duration exhibits negative duration dependence or equivalently the hazard rate exhibits positive duration dependence. This would contradict a large body of empirical evidence.

and

$$rW_P(w,h,s) = u(w_P(h)) + \delta_P(U(h,s) - W_P(w,h,s)) + \\ \pi_s(W_P(w,h,s'') - W_P(w,h,s)) + \pi_h(W_P(w,h',s) - W_P(w,h,s)),$$

where π_h and π_s denote the instantaneous transition probabilities of increasing h and decreasing s, respectively. That is, $h' > h$ and $s'' < s < s'$.

Search capital accumulation alters the model in two directions: The value of unemployment goes up, since accepting a future offer would mean an greater search ability in the future – unemployment is a "learning opportunity". On the other hand, the value of employment goes down in so far as it can lead to the destruction of search capital over time. For permanent jobs, the positive effects of productive human capital accumulation via π_h are likely to dominate, as they have a direct impact on wages, while search capital is important for future unemployment spells only. Since the destruction rate δ_P is low for permanent contracts, productivity will dominate and the overall value of a permanent job goes up. For the same reason, search capital matters more for temporary workers, since job destruction is more frequent. But precisely because job destruction is more frequent, search capital depreciation may not happen after all.

Accumulation of human capital over time makes the type distribution endogenous: High search capital helps workers find permanent jobs, which in turn increase their productive capital, so both types of human capital become positively correlated. This correlation weakens over time, as workers' search capital gets eroded over time. But until the permanent job arrives, we will also expect to see workers with high-to-medium levels of search capital still churning in and out of unemployment.

A life-cycle pattern emerges: young workers rely on easy to access job to climb the job ladder not just in terms of wages,[13] but to accumulate search capital. Eventually they settle into permanent jobs, accumulate productive human capital and either stay there reaping the benefits or use their high search skills to get to better paid jobs. In the unlikely case they lose their permanent job, as long as their search skills have not deteriorated, they expect to get back up in employment soon. However, some displaced workers may suffer considerable loses if their search capital has deteriorated and they either start accepting temporary jobs or wait for a stable job.[14]

The prevalence of long-term unemployment depends then on two parameters: the frequency of destruction of long matches and how easy it is for new entrants to gain a job – the temporary job finding rate. Here is when the type of business cycles becomes relevant: in a long expansionary period when low productivity jobs are abundant and

[13] I further discuss the links to job ladder models in section 5.

[14] This is a link to 'rest' unemployment and occupational choice models Carrillo-Tudela and Visschers (2013), which I discuss in section 5.

tenured workers rarely (if ever) lose their job, long term unemployment becomes a rare occurrence. The effects of a recession depend on how much they affect the two channels: recessions that do not translate into the loss of jobs of tenured workers will only hurt temporarily new entrants by a lower availability of entry jobs. It is important here to note that even if the job destruction rate increases for temporary jobs, so far as these affect moderately good searchers the increase in unemployment will be short-lived. A deep recession which translates into more senior workers also losing their jobs will lead to a much worse scenario: the destruction of entry jobs condemns young workers to long unemployment spells, but the increase in job destruction for mature workers also increases the prevalence of long-term unemployment. Fluid economies where workers change jobs often are more resilient to business cycle shocks, because the average employed worker is a good searcher. "Sclerotic" economies in which some workers never move will tend to accumulate a stock of long tenure jobs during expansions that is destroyed in recessions (as in Costain et al. (2010)) with long-lasting consequences. The paradox in the later case is that low productivity workers but with high search capital will suffer shorter unemployment spells than unluckily highly skilled, poor searchers who happen to lose their job.

These mechanics connect the empirical findings of the scarring effect of entering the job market in a recession (Bell and Blanchflower (2011), Schaefer and Singleton (2019)) and *turbulence*, an increase in the frequency that high skilled workers suffer a displacement shock (Ljungqvist and Sargent (2008),Kitao et al. (2017)). This is usually linked to structural technical change. Search human capital magnifies the impact of technical change and provides an explanation as to why looking at demographics (particularly age) alone will do a poor job in explaining the prevalence of long-term unemployment: bad searchers belong to different age groups, only employment histories can disentangle the two groups.[15]

The introduction of life-cycle dynamics also rises a crucial question: can workers insure against negative labour market shocks in later life by having exposure to temporary contracts early in life? Or a related policy relevant question: can exposure to temporary jobs be *good* for workers in the long run? The answer depends crucially on the nature of aggregate shocks: mild business cycles shocks result in long-term jobs being clearly preferable. But long-term jobs may be less attractive in an environment where large (but infrequent) negative aggregate shocks that destroy secure jobs. In the latter, exposure to risk of long-term unemployment may make temporary jobs preferable, at least in early life. To answer these questions, we need to enrich the model.

[15]It is worth noting that heterogeneity in job finding rates has already been pointed out as an explanation for the large increases in long-term unemployment during the Great Recession (Hornstein (2012), Barnichon and Figura (2015)).

2.4 Other self-insurance channels

There are three issues relating to worker's ability to self-insure against negative shocks that need to be addressed before taking the model to the data: job mobility, self-insurance though savings and public insurance though unemployment benefits.

First, since search capital accumulation comes from job finding, we need to consider the possibility of on-the-job search. The negative effects of search capital depreciation can be easily negated if workers switch jobs from time to time. This is particularly relevant for temporary workers, for three reasons: first, the high temporary job destruction rate is a large incentive to search on the job; second, because there is no productive capital accumulation in temporary jobs the only way to increase income over time is to find better paid jobs, which again encourages on-the-job search; and finally, since job destruction rates (even for high paying jobs) are high, investing in search capital is very attractive. On the other hand, permanent jobs offer the worker stable employment with increasing earnings, so all of these channels are much less relevant for permanent workers. The assumption that these contracts increase the productivity of the worker can easily justify a "no on-the-job search" clause: in exchange for staying in the firm, workers are rewarded with learning opportunities. It is not in the interest of the firm to provide search capital – quite the opposite. Although it would be hard to monitor and enforce that the worker does not search on the job, the incentives for workers to do so are already weak in a permanent job. I therefore assume that there is no on the job search in permanent contracts, but allow temporary workers to search on the job.[16]

The next addition to the model is the introduction of self-insurance through savings, as in Cozzi and Fella (2016). A model where workers with high wages can use their past earnings to wait for better jobs makes investment in productive human capital much more attractive. It also makes specialising in temporary jobs a viable option: highly paid temporary workers can use their savings to smooth out frequent unemployment spells. In principle, a risk averse worker is more likely to prefer the former, as it involves less income fluctuations over time. But in a recession the length of expected unemployment may make temporary jobs a more attractive option. Self-insurance enriches the model by introducing a welfare trade-off for temporary contracts that is very relevant for policy analysis. It is also a key feature of hysteresis models (Kitao et al. (2017)).

The final addition to the model is the expiration of unemployment insurance. In a model of long-term unemployment, it is crucial to incorporate this feature for two reasons: in contribution-based systems which prevail in most of Europe, many workers in temporary jobs may not be eligible to claim unemployment insurance, particularly younger workers. Neglecting this aspect will misrepresent the problem faced by young

[16] An alternative specification would impose a cost of search in the job, which comes at the detriment of accumulating human capital and/or wages, which would result in workers choosing not to search while on a permanent job.

workers who have to make decisions about human capital investment under the pressure from low income and savings. This makes temporary jobs riskier for the worker. The second reason is that even an unemployed worker with high benefits may lose them if they are unemployed for a long time. Although in the US this is partially mitigated by automatic extensions of unemployment assistance during recessions, in contribution-based social security this is not the case. For example, in Spain at the peak of unemployment in 2013 almost half of the unemployed had no unemployment benefits (Lafuente (2019)). This changes the welfare considerations significantly and makes waiting strategies more risky. Recall that the structure of unemployment benefits has important consequences for the composition of the unemployment pool, particularly in dual-labour market economies.

2.5 Full model

We can now characterize the full model. Time is discrete, and one time unit t corresponds to a month. There is a large (but finite) number of risk-averse agents in the economy with identical preferences given by the CRRA utility function

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}. \tag{7}$$

They live indefinitely but face a stochastic retirement shock ρ upon which they leave the labour force permanently and get a utility value of zero. The number of agents is constant in equilibrium, so a newborn agent enters every period to replaced a retired one. Additionally, they discount the future at rate $\tilde{\beta}$ so their effective discount rate is $\beta = \tilde{\beta} + \rho$.

Agents are heterogeneous not in preferences but *endowments*: agents have four state variables: income y, assets (a), search (s) and productive human capital (h). Every period they make a consumption and savings decisions, given their endowments. They face a borrowing constraint such that assets cannot be negative: $a \geq 0$.[17] Savings earn a fixed, constant interest rate r. It is assumed that agents are born with zero assets and there are no bequests.

Agents supply labour inelastically to a frictional central job market. Depending on wether they are matched with a job, agents can be employed on a permanent contract (P), employed on a temporary contract (T) or unemployed (U).

Bellman Equations: Employed workers

At the beginning of each period employed agents work, earn wages $w(h)$ and make decisions for next period. First, they choose whether to quit or stay, given the continuation value of staying. This value depends on the likelihood of four different shocks: they re-

[17] This limits their self-insurance capabilities.

ceive an external offer (α_{PT}), they are dismissed (δ_0), their productivity grows ($g_h(h,h')$) or their search capital depreciates ($d(s,s')$). Job quitters get no unemployment benefits.

In the case of receiving an external offer, permanent workers are offered a temporary contract with wage $\tilde{w}$ drawn from the distribution $F_T(\tilde{w})$. They accept it if its continuation value is greater than staying. This does not represent on-the-job search for permanent workers, but an exogenous shock similar to a breakup of the match.[18] In case of dismissal, workers transit to unemployment with unemployment benefits b, but they may suffer a hysteresis shock with probability λ which means their productivity is reset to zero. A Value of $\lambda = 1$ means that all productivity gains are job-specific, and represent the most drastic case of traditional human capital depreciation. If workers are neither dismissed or receives an offer, then their productive and search capital evolves according to a markov process: with probability $g_h(h,h')$ productive human capital increases to the next level. If that doesn't happen, search capital depreciates to the previous level with probability $d(s,s')$.[19]

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

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

$$\begin{aligned}
\tilde{V}^P(w,a',h',s') = \alpha_{PT} \int max\{V^P(w,a,h,s), V^T(\tilde{w},a,h,s)\}dF_T(\tilde{w}) + \\
\delta_P(\lambda V^U(b,a',0,s) + (1-\lambda)V^U(b,a',h,s)) + (1-\delta_P-\alpha_{PT})\Big(g_h(h,h')V^P(w,a',h',s) + \\
(1-g_h(h,h'))[d(s,s')V^P(w,a',h,s') + (1-d(s,s'))V^P(w,a',h,s)]\Big) \quad (8)
\end{aligned}$$

st.

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

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

Temporary workers face a similar problem: first they work, earn a wage w (which does not depend on their productivity h) and make decisions for next period. They can quit to unemployment, knowing they will not receive any benefits in this case, or stay. The value of staying depends on the likelihood of similar shocks to permanent workers: they can be offered a promotion to a permanent contract α_{TP}, find another temporary job ($\alpha_T T$) or be dismissed (δ_T). This job destruction shock is more likely than for permanent workers:$\delta_T > \delta_P$.

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

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

In the case of receiving a promotion, workers can accept it or return to unemployment without benefits. Promotions are assumed to be offered when the contract is over (or the legal limit to renew temporary contracts is reached), which means a rejection constitutes a voluntary quit, which does not entitle workers with unemployment benefits. Alternatively, when workers find a job (which is more likely the higher they search capital s) they receive an offer of wage $\tilde{w}$ from the same distribution of temporary wages $F_t(w)$ with the accept and immediately start in the new job or stay in the current one. If they chose to move, their search capital grows to the next level with probability $g_s(s, s')$. If they are dismissed, they may not be eligible to claim unemployment benefits, which happens with probability δ_{T0}. Since it is assumed that all temporary workers engage in on the job search, search capital does not depreciate during a temporary job.[20]

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

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

$$\begin{aligned}\tilde{V}^T(w, a', h', s') = \alpha_{TP} \max\{V^0(a', h, s), V^P(w, a', 0, s)\}+ \\ \alpha_{TT} \int_0^{\bar{w}} \max\{V^T(w, a', h, s), \mathbb{E}_{s'}(V^T(\tilde{w}, a', h, s'))\} dF_T(\tilde{w})+ \\ \delta_T \Big[\delta_{T0} V^U(0, a', h, s) + (1-\delta_{T0}) V^U(b, a', h, s)\Big] + (1 - \delta_T - \alpha_{TT} - \alpha_{TP}) V^T(w, h, a', s)\end{aligned} \tag{9}$$

st.

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

$$\mathbb{E}_{s'}(V^T(\tilde{w}, a', h, s')) = g_s(s, s') V^T(\tilde{w}, a', h, s') + (1 - g_s(s, s')) V^T(\tilde{w}, a', h, s)$$

Bellman Equations: Unemployed workers

Unemployed workers receive b in every period if they are entitled to benefits and zero otherwise.[21] Like employed workers, in the current period they work, make decisions about consumption and job acceptance rules for the next period.

They can receive a permanent job offer with probability $\alpha_P(s)$, which consists of an entry wage offer w draw from the distribution $F_P(w)$. Alternatively, they receive a temporary job offer with probability $\alpha_T(s)$ drawn from a distribution $F_T(w)$. Both of these job finding probabilities increase with search capital, but as before it is assumed that temporary job offers are much more likely than permanent: $\alpha_T(s) > \alpha_P(s)$. If they

[20] The high job destruction rate implies jobs do not last long, which provides some justification to this assumption.

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

accept either job, their search capital may grow to the next level with markov probability $g_s(s, s')$. Workers are assumed not to know whether accepting the job would increase their search capital when they make their decision. That is, some jobs are more informative than others, but that is not known to the workers when they are offered the job – they learn it once they are employed.[22] If they do not receive an offer, workers lose their benefit entitlement next period with probability δ_0. Because all workers are actively searching, search capital does not depreciate while unemployed.

The value functions of unemployed workers are then given by:

$$V^U(b,a,h,s) = \max_{a'} u(c(b,a)) + \beta\Big(\alpha_T(s)\int_0^{\bar{w}} \max\{V^U(b,a',h,s), \mathbb{E}_{s'}(V^T(w,a',h,s'))\} dF_T(w) + \\ \alpha_P(s)\int_0^{\bar{w}} \max\{V^U(b,a',h,s), \mathbb{E}_{s'}(V^P(w,a',h,s'))\} dF_P(w) + \\ (1-\alpha_T-\alpha_P)[(1-\delta_0)V^U(b,a',h,s) + \delta_0 V^U(0,a',h,s)]\Big) \quad (10)$$

st.

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

$$\mathbb{E}_{s'}(V^P(\tilde{w},a',h,s')) = g_s(s,s')V^P(\tilde{w},a',h,s') + (1-g_s(s,s'))V^P(\tilde{w},a',h,s)$$

$$\mathbb{E}_{s'}(V^T(\tilde{w},a',h,s')) = g_s(s,s')V^T(\tilde{w},a',h,s') + (1-g_s(s,s'))V^T(\tilde{w},a',h,s)$$

Solving the model

A solution to the individual agent's problem is a set of policy rules regarding:

- savings: $\bar{a}_U(y,a,s,h)$,$\bar{a}_T(y,a,s,h)$, $\bar{a}_P(y,a,s,h)$;
- reservation wages: $\bar{w}_{UT}(y,a,s,h)$, $\bar{w}_{UP}(y,a,s,h)$, $\bar{w}_{TT}y,a,s,h)$ and $\bar{w}_{PT}(y,a,s,h)$;
- quitting decisions: $q_P(y,a,s,h)$, $q_T(y,a,s,h)$ and $q_{TP}(y,a,s,h)$.

Here $\bar{a}_i$ denotes the optimal choice of assets next period a' for a worker in state $i = \{U,T,P\}$, $\bar{w}_{UT}$ the reservation wage for an unemployed worker receiving an offer from contract type $i = \{T,P\}$, $\bar{w}_{TT}(y,a,s,h)$ the reservation offer for a temporary worker to switch jobs, $\bar{w}_{PT}(y,a,s,h)$ the reservation offer for a permanent worker to accept a temporary contract, $q_i(y,a,s,h)$ the binary variable that equals one when worker on contract $i = \{T,P\}$ chooses to quit to unemployment and $q_{TP}(y,a,s,h)$ the binary variable which equals 1 when a temporary worker rejects to continue in permanent position.

By the standard properties of bellman equations these policy rules exist and the individual problem can be solved by conventional methods. However, note that the

[22] An alternative specification when they know for sure does not alter results of the estimation significantly.

discrete choices of the reservation wage and quit rules create discontinuities in the value functions, which complicates finding a numerical solution to the problem.

The aggregate economy at time t is characterised by a measure $\mathbf{\Gamma_t}$ of workers distributed across employment/unemployment states and state variables:

$$\mathbf{\Gamma_t} = \sum_w \sum_a \sum_h \sum_s \Big(\Gamma_{P,t}(w,a,h,s) + \Gamma_{T,t}(w,a,h,s)\Big) + \sum_a \sum_h \sum_s \Big(\Gamma_{U,t}(b,a,h,s) + \Gamma_{U,t}(0,a,h,s)\Big). \tag{11}$$

The unemployment rate of the economy is then given by

$$u = \frac{\sum_a \sum_h \sum_s (\Gamma_U(b,a,h,s) + \Gamma_U(0,a,h,s))}{\mathbf{\Gamma}}.$$

Note that by setting the problem in an infinite horizon we do not need to keep track of the age distribution. This follows because old and young agents have the same risk preferences and discounting, but they have different endowments. This is feature of the model, in that it does not rely on preference heterogeneity to determine the stationary distribution, but rather on human capital heterogeneity, which is endogenous and determined by labour market frictions.[23] By choosing the rate of decay ρ we can get average work-life expectancy and make it very rare that a worker is still "alive" by the age of retirement. In particular, the law of motion of the *panel* economy is

$$\mathbf{\Gamma_{t+1}} = (1-\rho)\mathbf{\Gamma_t} + \rho\mathbf{\Gamma^B}, \tag{12}$$

where $\mathbf{\Gamma_B}$ is the distribution of new entrants "born" into the labour market in each period, which are assumed to enter with no assets or productive human capital. For a large number of agents, this translates into an approximately stationary $\mathbf{\Gamma}$.

In order to estimate the model, the targets will be different moments by age, which means we care about a *longitudinal* economy where age e substitutes time t:

$$\mathbf{\Gamma_{e+1}} = (1-\rho)\mathbf{\Gamma_e} + \mathbf{\Gamma^B}(e), \tag{13}$$

where $\Gamma^B(e)$ contains a different measure of workers that enter the market at age e. Since exit is regulated by ρ, one can choose $\mathbf{\Gamma^B}(e)$ to replicate the age composition of the labour force. Then I use this age distribution to draw values to build Γ_0, the initial value of equation 12, and thereby the age composition of the stationary panel economy. The panel economy will be used to get business cycle moments, while the longitudinal economy will also be used to evaluate welfare.

[23]This in an advantage of partial equilibrium. Since we are focusing on the welfare of workers in this paper, labour demand and firms are secondary to the problem at hand: the consequences of introducing search capital for unemployment dynamics and the welfare of workers.

Implications

The expected duration of unemployment E_U is now a more complicated object because the reservation wages change every period if the worker is out of the stationary state where $\bar{a}_U(y, a, s, h) = a$. Moreover, unemployed workers who lose their benefits will change their reservation wage rules downwards immediately. To see this, notice that rejecting an offer does not disqualify a worker for unemployment benefits, which means the value of continuing searching is larger for workers with benefits. This reproduces the empirical evidence that finds a discontinuous increase in exit hazard of the employed around the time of benefit expiration.

For simplicity, consider the case of a worker with no unemployment benefits in period t who is at the stationary level of assets $\bar{a}$. The expected duration of this worker is:

$$E_U(0, a, h, s) = \frac{1}{\alpha_T(s)(1 - F_T(\bar{w}_{UT}(0, \bar{a}, s, h))) + \alpha_P(s)(1 - F_P(\bar{w}_{UP}(0, \bar{a}, s, h)))}. \quad (14)$$

As in the reduced-form model, the expected duration of unemployment depends on how selective the worker is with respect to each contract: workers that are very selective on temporary contracts (high $\bar{w}_{UT}$) will have a significantly longer unemployment spell, as $\alpha_P(s) > \alpha_T(s)$. The effect of search capital on duration is ambiguous. While higher search capital leads to higher arrival rates of job offers, its impact on reservation wages is more nuanced for temporary workers: Search capital facilitates climbing the "job-wage ladder" by making it more likely to move to better paid temporary jobs without having to transit to unemployment. This increases the value of accepting a temporary job, which reduces the reservation wage with respect to the static model without on-the-job search. Learning, or increasing the level of search capital by accepting a job, also increases the value of taking a job, reducing reservation wages. Which effect dominates depends on how likely is a worker to find a job while employed, which depends on the relative value of the arrival rate $\alpha_{TT}(s)$ and the expected duration of the job, given by δ_T. Jobs that do not last long do not offer many possibilities to move up the job ladder − but high search capital workers will be more able to make job-to-job transitions. This is an important point because on-the-job search is traditionally been used as the channel that makes workers accept wages below unemployment benefits. In contrast, this channel is less important for workers with low search capital. Instead, learning or increasing search capital by accepting jobs is the force driving reservation wages down for low search capital workers, and the more so if learning technology is concave and workers learn more with the first job than with subsequent jobs.

The effect of search capital on reservation wages is therefore ambiguous, depending on the strength of learning, job mobility and job destruction. This means that we may see a non-monotonic relation between search capital and unemployment duration: workers with low search capital may be accepting poor jobs as learning opportunities, compared to workers with the same assets, income and productivity but higher search capital.

The relation between of productive human capital and duration is also more complicated: temporary jobs do not value productivity, but they offer a way to get promoted to one. This means that workers with high human capital will be more willing to accept temporary jobs. This will likely be the case for workers at the highest levels, since the difference in value between *any* permanent contract and unemployment is very large. For workers with less productive human capital this effect is weaker, so they are likely to be more selective with the jobs they get. For workers at the lowest levels, while there is a preference for permanent jobs because of human capital accumulation (on top of higher employment duration) the difference between unemployment and employment in general is not very large, which means they may actually be more selective in terms of starting wages than workers with higher productive human capital. And of course the effect of productive human capital interacts with those of search capital. The relationship of productivity with unemployment duration is therefore ambiguous.

The ambiguity of the predictions of the model is an important feature: the model has the flexibility to encompass different economies, depending on the parameters of governing labour market flows. That is, the fluidity and efficiency of the underlying labour market change the predictions for unemployment levels and duration, *even when underneath the labour market has a dual structure*. That is, dual labour markets can work very well or very poorly in this model. Temporary contracts may increase welfare or reduce it. And this means that the effects of temporary contracts may change with the business cycle. To find out the effect, we need to look at the data.

3 Data and Empirical exercise

Disentangling search capital from other channels in the data presents different challenges. First, as highlighted in section 2.2, the composition of the unemployment pool will determine who we see in the data: workers with multiple short spells, if these are very short would be hard to capture in a dataset with low frequency, like quarterly labour force surveys or year-to-year surveys. Administrative datasets are the best option, where the unit of observation is an individual spell, not a quarterly observation per person.

Even with administrative data, is is not trivial to identify search. While search capital is not directly observable, search outcomes (job finding) are. Since the model implies that job mobility (which increases search capital) reduces the length of subsequent unemployment spells, a natural proxy for search capital is the number of jobs the worked has had in the past. That is, controlling for everything else, having had more jobs in the past means that an individual should be able to find a job faster. If we compare two individuals with the same age, education and job experience, the one that gathered that job experience in different firms should be the one that has an advantage over the other. Similarly, we should observe that tenure in the last firm is positively correlated with unemployment duration.

These predictions are clear, but sample selection is a concern. First, it is unlikely that long-tenured workers lose their jobs, and therefore we are unlikely to observe them. Second, in a country were workers climb the job ladder mostly job-to-job, without intermediate unemployment spells, then it is hard to observe search duration more than once of a given worker. Third, a country with a low incidence (or absence) of identifiable temporary contracts would make identification harder. As explained in the theory part, temporary contracts magnify search capital differences, but if we are unable to observe these in the data then that limits our ability to detect search capital.

In sum, we need a country with: good, available administrative data; high incidence of short-term contracts; high (frequent) incidence of unemployment; and large business cycle fluctuations – so we can observe long matches being broken. All of these factors point to Spain.

3.1 A dual-market economy

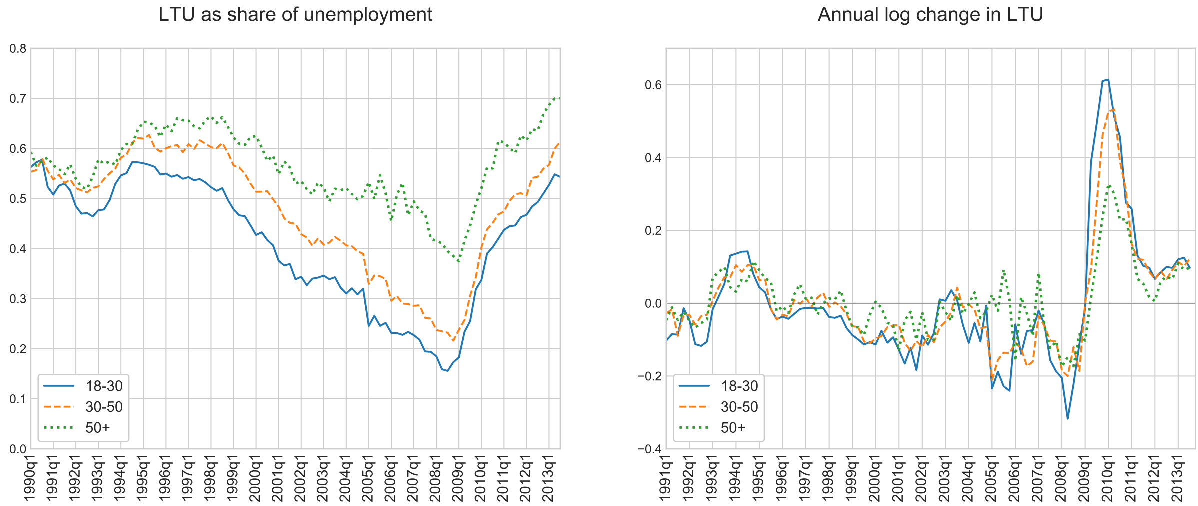
With an incidence of close to 30% of temporary employment in the 1992-2008 period, Spain is a classic example of a dual labour market. Temporary contracts are characterised by an agreed finite duration from the start, and low protection in the form of severance payments. Permanent contracts on the other hand have increasing wages and severance with tenure, so these workers have little incentive to change jobs after finding permanent employment. This clear divide is also present in the public sector, where temporary contracts also abound. In fact, having served in some of these contracts can be very important to get access to full civil servant jobs. These are even more protected than private sector jobs. Temporary jobs do not immediately translate into stable employment[24] but instead they often lead to other temporary contracts or (quite often) unemployment.

So while most temporary contracts don't serve as stepping stones for long-term jobs, most workers eventually get a permanent contract. This is precisely the kind of environment where search capital matters: most temporary workers know they have to look for other jobs soon and that they will likely have to go through a series temporary jobs before getting a stable job. Moreover, as this dynamic is widely known there is little reason for a stigma attached to losing a temporary job.[25] In this setting it is reasonable to expect that workers who have experienced several temporary jobs are more proficient

[24] See for example Güell and Petrongolo (2007); García-Pérez and Muñoz-Bullón (2011).

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

Figure 7: Long-term unemployment in Spain, by age



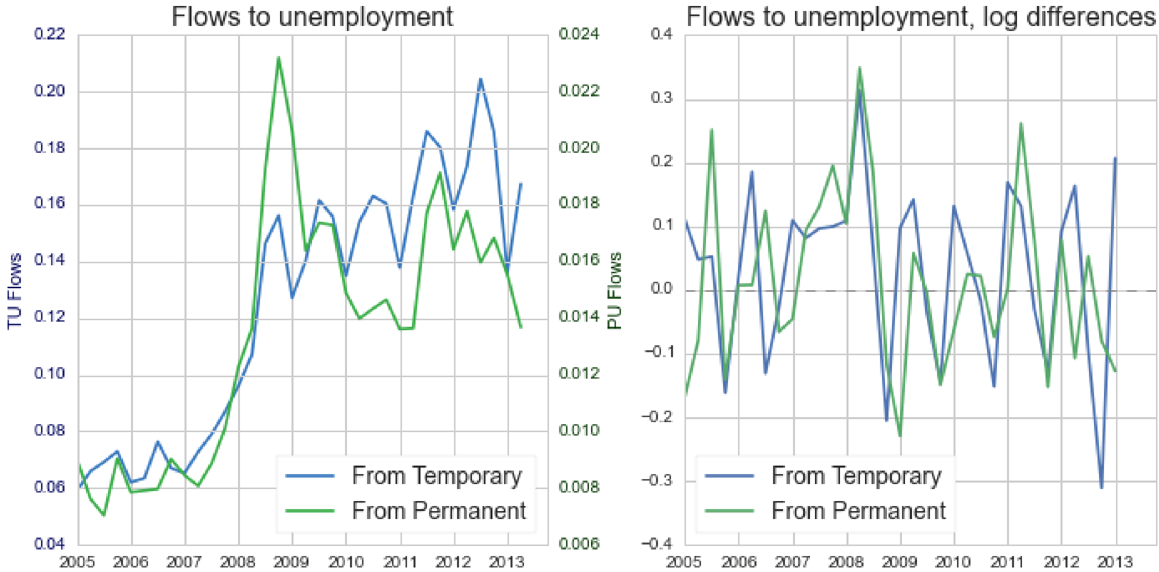
Source: Own calculations from the Spanish Labour Force Survey (INE (2013))

at searching. As for permanent workers, they have few incentives to keep searching for jobs (and most vacancies are temporary jobs as well) and over time job-to-job flows fall. The implication is that their search capital may deteriorate, as they have been out of the job market for a long time.

As discussed before, search capital doesn't make much difference during an economic boom – it is during a recession that differences in search capital would become visible in the data, though a more diverse unemployment pool. In particular, long-term unemployment should particularly increase more for younger workers. The left panel of figure 7 shows evolution of the share of long-term unemployment (defined as one year or more) over total unemployment (LTU rate thereafter). Starting from similar magnitudes as older age groups in 1990, the youth (18 to 30 years old) LTU rate declined faster after the 1993 recession. Temporary contracts played a significant role in the overall decline of LTU, as Güell and Hu (2006) have noted. It stayed lower than for prime age (30 to 50) and older workers (50+) thereafter, but as the right panel shows, the year-to-year increase was larger (over 60%) than for other workers. This was also true in the 1993 recession, but this time it peaked earlier and stayed high until 2013 when the overall unemployment rate reached its peak at 27%.

If this increase in duration of unemployment came mostly from a fall in the job finding rate as opposed to a change in the composition of the unemployment pool, then search capital would not offer a good explanation for it. As explained above, there has also to be a large influx of different kinds of workers into unemployment for search capital to make a significant difference in long-term unemployment. Figure 8 shows the quarterly employment to unemployment flows or job destruction rates in Spain. The first panel shows that the magnitude of flows is of the order of 10 times larger for temporary (left

Figure 8: Flows into unemployment, by contract type



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

side scale) than permanent (right side scale) jobs. However not only did the permanent job destruction rate also increase during this period, peaking at the same time as the temporary. As the right panel shows, its relative annual change was of similar magnitude as the temporary destruction rate. This shows two things: the job destruction for permanent contracts was also high during this period and this increase happened at the same time as the increase in temporary lay-offs. These observed dynamics are entirely consistent with a standard search and matching model with time-varying match quality and aggregate shocks, as in Costain et al. (2010).[26]

Given all of the above, using the number of temporary jobs to identify search capital offers several advantages in Spain: clearly defined and differentiated temporary contracts are very common and constitute the easiest way out of unemployment. They are widely used to accommodate demand fluctuations among firms and as such losing a job is not likely to constitute a bad signal for the worker. Over time, workers find permanent jobs and then job-to-job transitions fall. Big cyclical fluctuations in job destruction for both temporary and permanent jobs make it possible to observe all kinds of workers in the unemployment pool at some point.

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

3.2 Data description

Spain also offers one of the most easily accessible and complete administrative datasets: the *Muestra contínua de Vidas Laborales* (MCVL thereafter) which translates into "Continuous Sample of Working Histories". It consists of a sample of social security records amounting to 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) on a given year. After its introduction in 2004, 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 contains all of the employment, unemployment and retirement spells 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, some firm information at the establishment level (size, location, tax code, parent company identifier) and information on the job such as industry, occupational scale[27] and type of contract. It keeps track of changes of contract and changes in relation to social security (for example from unemployed to retirement). Self-employment spells are recorded as well. The Spanish Social Security also provides a complementary dataset with income tax information that can be linked to the working histories file via anonymized tax identifiers. This allows to obtain detailed wage information for many (but not all) jobs in the sample.[28] Unemployment benefits are also recorded, making it possible to approximate the amount of unemployment benefits received in the unemployment spells of the previous year.[29] These data are only available after 2005, and thus I use the 2005-2013 waves of the MCVL. Appendix 5 has more details on the data.

I use this dataset to construct monthly labour market flows, following the algorithm in Lafuente (2019).[30] I use the information on wages to build the wage-tenure distributions and calculate average unemployment benefits and replacement rates.

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

[28]It also contains information relating to severance payments, food coupons, dividends and any other form of transfer between the firm and the worker as payment for work services.

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

[30]Lafuente (2019) shows that flows built from the social security are consistent with those obtained from the LFS.

3.3 Identifying search capital

In the model, the parameters that govern search capital are: the level effect of search capital (s), the law of motion or stochastic rates of appreciation and depreciation ($g(s, s')$) and ($d(s, s')$) and the initial distribution of search capital (vector $\mathbf{s_0}$).

The characteristics of the Spanish job market favour an identification strategy that uses the number of temporary jobs as a proxy for search capital. This is because Spain is likely to be in the dead-end jobs ($w_T(w, h) = w$) scenario, where as shown in the left panels of figure 4 we should observe a negative correlation between unemployment duration and the number of temporary jobs held in the recent past. How much of this effect is due to dynamics or ex-ante differences between workers? Conditional on observing the same worker over time, the number of temporary jobs a worker accumulates between unemployment spells should be negatively correlated with subsequent unemployment duration. This conditional correlation would give us the dynamic effect only, once we also control for increases in productive human capital which come from tenure and work experience. That is, the *length* of the employment spell is what drives increases in productive human capital, while the *number* of employment spells is what drives search capital accumulation.

A natural concern is how to disentangle the effects of search capital from productive human capital. While having many jobs shows that the worker is a good searcher, it can also signal that the worker has accumulated transferable skills across different jobs. In the model in this paper, as in most of the literature, productive human capital accumulation happens as workers learn on the job. If there are other channels that increase productivity through job mobility, these are not possible to disentangle with the effects of search capital in the data. If these channels have to do with job mobility then there must be part of search capital, which implies search capital may have a direct impact on productive human capital. In the empirical literature there is some evidence that productive human capital and search capital are separate: Randomised control trials in the lab or job search platforms usually treat similar workers but induce some change in search capital, via nudging, counselling or specific job search sessions. These interventions are very unlikely to increase the productive human capital of workers, but rather how they present themselves to employers or which jobs their target. These studies tend to find small positive effects, which may have to do with the type of interventions they are allowed to perform and their scope. A notable exception is the experiment of Witte (2018), where the author is able to map the entire network in a neighbourhood and act as the employer, asking workers to refer others for work. He is able to measure the raw productivity of the workers in the job, and finds that the referred workers are less productive on the job. While networks are only part of search capital, this study shows that there are instances when a high job offer rate does not imply higher productivity. Similarly, many studies on inequality do find that the social background of workers determines much of their future job prospects.

It is hard to argue that individuals from wealthier, well-connected families have more job opportunities because they are inherently more productive. This inequality in opportunity in the labour market is largely what search capital in this paper aims to capture. Other modelling choices, while interesting, are beyond the scope of this paper.

Empirical equations

Following the predictions of the model, we should observe that workers with more temporary contracts in the past find higher re-entry wages on average, as so should the workers with longer tenures. In the dynamic model, workers accepting temporary jobs use them to climb the "search capital" ladder, so we should see a negative correlation between the number of temporary jobs in the past and subsequent job duration. Recall that these workers can only get wage increases through job switches, so higher switching and higher wages upon re-employment are the sign of a which search capital worker. Conditional on observing the same worker multiple times, the probability of accessing a permanent job should be higher as the number of previous jobs increases.

To test these hypothesis, I regress the log duration of unemployment (in weeks) on the number of previous temporary jobs (TCs) and other control variables:

$$log(weeks)_{i,t} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + +\delta X_{i,t} + \epsilon_{i,t} \tag{15}$$

Where $log(weeks)_{i,t}$ is the natural logarithm of the duration of completed unemployment spells, $TCs_{i,t}$ the number of temporary jobs, $Ten_{i,t}$ and $Exp_{i,t}$ years of tenure and experience respectively and $X_{i,t}$ a vector of personal characteristics.

The first question that arises is how to count the number of temporary contracts. It is not an uncommon event to see a worker having multiple temporary contracts with the same firm separated by very short periods of unemployment.[31] Counting all of these contracts separately would lead to a biased estimate of the search abilities of the worker, as being recalled to a previous job doesn't require any search on the side of the worker. A temporary contract is only counted if it is coming from a different firm than the previous employer, both from unemployment of from other employment.[32]

Another alternative measure could be the number of permanent contracts for both

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

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

types of jobs. There are a number of reasons as to why having many permanent jobs may have a different effect on unemployment duration. Separations from permanent jobs are much less frequent than separations from temporary jobs, as the different scales of figure 8 showed. Moreover, separations from permanent jobs are more likely to be quits as opposed to lay-offs, which is expected given the higher employment protection of these contracts. For this reason, having many permanent contracts may not send the same signal in the job market as having many temporary contracts – yet it implies that the worker was able to successfully find a job. The number of permanent contracts is therefore included in the regressions. This allows temporary and permanent contracts to have different effects on unemployment duration, wage and job stability.

As discussed above, we need to take into account productive human capital. In the model, accumulation of productive human capital happens as worker spends time in employment, while search capital accumulation happens as the worker finds and moves to different jobs. Consider two workers with the same work experience of 2 years. One of them had two one-year temporary contracts while the other had a single two-year contract. The worker with two jobs will have higher search capital but the same human capital as the other – they have both been employed for two years. Since both contracts were temporary, it is hard to argue that the worker on the 2-year contract accumulated firm-specific as opposed to transferable human capital. Recall that the renewal rate of these contracts is very low. Then the work experience $Exp_{i,t}$ variable should capture the human capital effect while the number of temporary contracts is only related to job mobility and search.

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

Another challenge that naturally arises when using temporary contracts as a proxy for search capital is unobserved heterogeneity. That is, workers that have accumulated several temporary contracts share some unobserved characteristic driving them back and forward from unemployment. I address this issue in different ways. First, exploiting the panel dimension of the data I run the regression of equation 15 adding an individual fixed effects variable. In this specification, the interpretation of the coefficient on the number of temporary contracts changes: in the pooled sample, β_1 represents the marginal effect of having had one more temporary contract in the past on log weeks in unemployment (percentage increase in weeks) *across* workers. In the fixed effects regressions it represents the effect of one additional temporary contract on the difference in duration of unemployment spells *across time* within workers. That is, if it is positive (negative) then as the worker accumulates temporary contracts her unemployment spells get longer (shorter) over time. Then the panel regression aims to measure the effect of accumulating search capital over time, while the pooled regressions measure the overall effect across workers. Individual fixed effects absorb the unobserved heterogeneity that is fixed over time, part of which could be the difference on starting levels of search capital: some workers may be naturally better at finding jobs than others, and these differences may persist over time. In the results I interpret the change in β_1 before and after fixed effects as partly coming from this source.

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

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

Lastly, even if there is a negative correlation between duration of unemployment and temporary jobs this may be measuring something different from search capital, if workers are accepting worse jobs which are easier to find (Gorjón et al. (2021)). Then the correlation will not support the idea of search capital, as better searchers should also find better wages, or at least wages that are not worse than their peers with less search experience. In order to address this concern, I regress the log wage at the next employment spell out of unemployment on the same explanatory variables in equation 15:

$$\log(\text{wage}_{t+1}) = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{16}$$

In this regression, $log(weeks)_{i,t}$ corresponds to the independent variable in equation 15, and aims to capture the direct effect of longer unemployment duration on the wage. Because this variable is going to be correlated with all of the other right hand side variables, the coefficient on all of these variables should be interpreted as their direct effect on wages, independent of their effect on unemployment duration. Time spent in unemployment can also have a separate effect on wages if for example there is discrimination in the labour market against workers with longer unemployment duration.

Another possible problem is that even if workers with more jobs in the past find jobs faster and better paid, the higher pay could be compensating a higher job destruction rate. Recall than in the model this would be evidence of climbing the ladder through churning in and out of employment, which is a possible equilibrium for workers with low human capital and high search capital. To test for this possibility I follow two different approaches. First, I run the logistic model in equation 17 on the probability of the next job being permanent as opposed to temporary. If the coefficient of β_1 is positive, having had more temporary jobs would be positively correlated with the probability of obtaining a permanent contract out of unemployment. Without controlling for fixed effects, this effect would just give us the pooled or cross-sectional effect of temporary contracts. Controlling for fixed effects, β_1 would give us the dynamic effect over time of accumulating different jobs.

$$\text{P}(\text{PC}_{t+1}|U_t)_{i,t} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \gamma CLAIM_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \beta_4 LastP_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{17}$$

Second, since observing a worker getting a permanent contract is a rare occurrence (only 8% of all unemployment spells in the sample end in a permanent contract) I consider the duration of the next employment spell. That is, I count all the time she is employed before returning to the unemployment pool, including job changes. This is important since the fact that a worker has shorter jobs may mean that she is climbing the job ladder faster. Then whether exiting unemployment leads to a long or a short period of employment (in different jobs) is a better proxy for job stability.

$$\log(\text{weeksE})_{i,t+1} = \beta_0 + \beta_1 TCs_{i,t} + \beta_2 log(weeks)_{i,t} + \beta_2 Ten_{i,t} + \beta_3 Exp_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{18}$$

Finally, in all regressions I include controls for other individual characteristics in the vector $X_{i,t}$: duration of the unemploymnt benefit entitlement, a dummy for if the last job was permanent, industry[33] and occupation of the previous job, gender, a quadratic polynomial on age, dummies for the highest educational level recorded,[34] an indicator variable if the worker was born outside of Spain, an indicator variable if last job ending on a quit, an indicator variable if last job was part-time, an indicator if the worker was subject to a collective dismissal, provincial dummies and yearly dummies. These last set of dummies are important as they take care of the changing labour market conditions during this period.[35] These controls are present in all regressions.

Table 3 shows the results.[36] Most of the predictions of the model are consistent with the correlations in the data: workers with more temporary contracts have on average shorter unemployment duration, which is reduced (but still signifficant) after controlling for fixed effects; workers with more temporary jobs get higher wages in the cross section and over time on average; while their next jobs tend to be more unstable (negatively correlated with next employment spell duration and probability of obtaining a permanent job), over time accepting jobs increases the probability of obtaining a permanent contract from unemployment. And when using long-term unemployment probability (shown in 9 in the appendix) the effect of temporary contracts is even stronger. This is consistent with the implication of the static model (and the literature) that workers in long-term unemployment are the ones that benefit most of higher arrival rates.

These results have a number of implications for the estimation of the model. First, the magnitude of the effect on unemployment duration is about a week of unemployment per contract (the average duration is 30 weeks). Not shown in the table is a quadratic term on the number of temporary contracts, whose coefficient turns out to have the opposite sign. But this curvature effect is small: it will take more than 100 temporary contracts for the marginal effect of an extra contract to turn negative. Recall that the average number of temporary contracts is 4 so the effect of exposure to temporary contracts on unemployment duration is 15% for the average worker. From the bottom 25th percentile (1 contract) to the top 75th (6 contracts), the effect is a 20% reduction. The number of

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

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

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

[36]More detailed results, including sex desegregated regressions, can be found in the appendix. Gender does not seem to change the sign and significance of the correlations.

Table 3: Correlations in the data

	Duration U_t		Re-employment wages		Duration E_{t+1}	$\Pr(P_{t+1}\|U_t)$	
	Pooled (1)	FE (2)	Pooled (3)	FE (4)	Pooled (5)	Pooled (6)	FE (7)
No. T	-0.040***	-0.007***	0.0033***	0.0148***	-0.056***	-0.078***	0.464***
	(0.0006)	(0.0009)	(0.0006)	(0.0020)	(0.0022)	(0.0017)	(0.0081)
No. P	-0.034***	-0.003	0.0068***	0.0161***	-0.025***	0.265***	-0.583***
	(0.0022)	(0.0024)	(0.0009)	(0.0030)	(0.0033)	(0.0048)	(0.0117)
Tenure	0.037***	0.058***	0.0046***	-0.0056*	0.005	0.002	0.003
	(0.0016)	(0.0025)	(0.0011)	(0.0025)	(0.0040)	(0.0053)	(0.003)
Tenure^2	-0.001***	-0.003***	-0.0002***	0.0004	-0.0000	0.000	-0.000
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0008)
Experience	-0.020***	-0.016***	0.0092***	0.0372***	0.054***	0.011***	-0.113***
	(0.0008)	(0.0033)	(0.0005)	(0.0034)	(00016)	(0.0024)	(0.0159)
Experience^2	0.000***	0.002***	-0.0002***	-0.0012***	-0.001***	0.000	-0.002***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0005)
Constant	1.189***	0.257***	7.8090***	10.6123***	1.263***	1.990***	-
	(0.0200)	(0.0642)	(0.2609)	(0.0568)	(0.0695)	(0.2121)	-
Controls							
Years	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	-	-
Observations	741,337	764,466	209,215	213,628	427,515	530,110	126,432
Adjusted R^2	0.547	0.462	0.249	0.031	0.184	-	-
AIC	1,916,082	1,470,574	174,877	-159,320	1,621,002	36,116	77,881

Notes: Robust standard errors (clustered at the individual level) in parentheses. FE refers to regressions with individual fixed effects. Sample is workers aged 20-55. Dependent variables are (1 and 2) all finished unemployment spells ending in employment, excluding recalls (workers returning to the same firm), self-employed and spells shorter than 15 days (3 and 4) wages observed in the next employment spell, including bonus and payments in kind, for jobs lasting longer than 3 months (5) duration of the next (completed) employment spell (6 and 7) indicator variable for whether the next job out of unemployment is with a permanent contract. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

permanent contracts work in a similar way.[37]

Workers with higher tenure in the last job tend to have longer employment spells. Notably, the effect is larger when controlling for fixed effects. For the same worker, having had a longer employment relation leads to longer unemployment spells, and this is controlling for coming from a permanent contract (see full table in appendix) which would control for being eligible for severance payments and adding a control for past wage. This can be explained either by hysteresis (loss of specific productivity upon job loss) or by depreciation of human capital. Note how the coefficients for previous work experience have opposite signs in duration. This points towards it being not a question

[37]The only exception being that the signs revers when considering the probability of obtaining a permanent contract from unemployment. Since these contracts are very secure, from an empirical point of view it makes sense that losing permanent contracts *repeatedly* for the same person results in lower chances of being offered one straight from unemployment. Recall that identification of search capital depends on the number of jobs not being attached a stigma on the side of employers, which is likely true for temporary jobs but not so clear for permanent ones.

of productive human capital: two workers can have spent identical time employed, but if one of them stayed for longer in the same firm compared to the other, she will have have a longer duration on average. This could reflect gains in productivity that lead to pickiness of jobs in the dead-end-jobs scenario, but also loses of search capital.

4 Estimation and Results

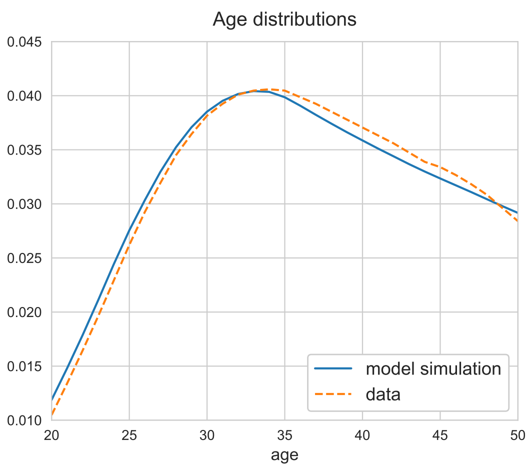
The goal of estimating the dynamic model described section 2.5 is threefold: first, to see what are the implications of search capital for unemployment duration in the Spanish economy –recall that the relationship of search and productive human capital is ambiguous and interacts with savings and income; second, to investigate the impact that search capital has in the aggregate economy when it suffers a large negative shock – that is, if search capital does matter for business cycle fluctuations; finally, we can evaluate the effect of search capital and temporary contracts have on welfare, both over the life cycle and in recessions.

4.1 Calibration and fit

Aggregation

First, we need to find parameters to fit moments in the data by age. This is done by simulating a longitudinal panel of workers. This subsection details how the aggregation is done and the law of motions of the aggregate economy are calibrated.

Figure 9: Age distributions



As noted in section 2.5, aggregating individuals into a panel economy is done in two steps: First, I construct a large longitudinal panel of agents, all starting with zero assets but different levels of search capital and labour market states. The initial distribution of workers across job market states is set to replicate that of the data at age 20. The initial distribution of search capital and assets is discussed in the next section. Then I simulate the model for 481 periods (months) using the policy functions from the previous step and the law of motion of equation 13 to update the distribution in the next period. Recall that in equation 13 we allow for new entrants to come into the market in every age-month in order to replicate the age composition of the labour force. This is done in the following way: at the beginning of each period some agents leave the market at the constant, exogenous rate ρ. Then new entrants come in so as to keep the number of agents in this period matching the age distribution, as pictured in the dashed line in figure 9. The parameter ρ and the newborn cohorts $\mathbf{\Gamma^B}(e)$ are set to replicate this pattern. New entrants are born without search capital, which means that until 35 there are both new entrants with little job market experience and workers who have been active for some years. All new entrants are unemployed. At age 35 the flow of new entrants stops ($\mathbf{\Gamma^B}(e) = 0$) and the population decays at the constant rate $\rho = 0.0027$.[38] Figure 9 shows the fit of the age composition of the calibrated longitudinal economy to the data.

I repeat this simulation 200 times[39] to obtain the main moments used to calibrate the parameters of the model: the distribution of labour status of workers at different ages, average unemployment duration and job finding rates.

The second step involves sampling from the longitudinal economy to construct a panel of workers of different ages. They constitute the economy-wide panel in equation 11, which follows the law of motion of 12. I use this law of motion to simulate forward for 8 years – 4 years with parameters from the boom period (2005-2008) and 4 years from the recession period (2009-2012).[40][41] The size of this simulation panel is close to that of the dataset: about 4 million observations in each period.[42] From this simulation I obtain an unemployment and temporary share series, as well as a panel of unemployment duration. I compare these aggregate simulated moments with the data, and use the model generated data to run regressions comparable to those in table 8.

Preferences

I set the risk aversion parameter of the utility function to 2. Interest rates are set to 2% annual. The discount factor $\tilde{\beta}$ is set to $1/(1+r)$ which together with the exogenous

[38] This corresponds to an expected working life of approximately 30 years.

[39] The size of the panel is very large – starting at 5000 agents at $\mathbf{\Gamma^B}(0)$.

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

[41] As it is common in the heterogeneous agent literature, I discard the first 12 months of the simulation until convergence to the stationary distribution is approximately reached.

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

Table 4: Calibration

Baseline Parameters – from the data

Parameter	Value	Source
$\alpha_T(1)$	0.1308	UT transition rates at age 20 (2005-2008)
$\alpha_P(1)$	0.0207	average UP monthly flow (2005-2008)
α_{TP}	0.0206	average TP monthly flow (2005-2008)
δ_P	0.007	average PU monthly flow (2005-2008)
δ_T	0.043	average TU monthly flow (2005-2008)
δ_{T0}	0.283	average T0 monthly flow (2005-2008)
δ_0	0.08	average U0 monthly flow (2005-2008)
λ	1	assumption (see description)
$F_T(w)$	-	wage distribution for TCs, <24 years old
$F_P(w)$	-	wage distribution for PCs, <24 years old
$g_h(h, h')$	-	tenure wage distribution
b	695.52	average UB
r	0.0016	2% annual[43]
$\tilde{\beta}$	0.998	1/(1+r)
ρ	0.0027	Age composition of the working population
σ	2.0	Literature

Baseline Parameters – calibrated

Parameter	Value	Target
s_0,s_1,s_2	{0.666,1,1.333}	duration of unemployment for different NoTs
$g(s, s')$	{0.5,0.5,0}	duration of unemployment for different NoTs
$d(s, s')$	{0,1/60,1/60}	depreciation occurs every 5 years on average
$\mathbf{s_0}$	-	average job finding rates by age
α_{PT}	0.0236	PT transition rate at age 20
α_{TT}	0.043	Average number of TCs and average quit rate from T

Recession Parameters

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

retirement rate of 0.0027 gives a total discount factor β of 0.995. As described above, the retirement rate is set to match the age composition of the labour force.

Wage Distributions

The wage distributions that both employed and unemployed workers face are taken from the empirical wage distributions of workers younger than 25 in the 2005-2008 period. I select full-time workers that have found a job out of unemployment and subsequently hold it for a month or more. The assumption is that young workers accept all wages.[44] This identifying assumption implies that the resulting cross-sectional wage distributions are going to be the product of workers adjusting their reservation wages over time as they accumulate assets and search capital. This imposes the strong assumption that the wage offer distribution is the same for all workers. This may lead to excessive income risk. In the calibrated model the wage distributions of the economy are not too far off from the data. Unemployment benefits are set to the median – 646 euros a month.

The resulting distributions are shown in figure 10. These wages are then binned from 60 to 6000 euros a month and normalized to give a discrete probability distribution.

To parametrise the markov process of productive human capital $g_h(h, h')$, I target the evolution of wage distributions on stayers. Here I assume for simplicity a linear wage increase with tenure so $w(h) = wh$. I then minimize the distance between the observed distributions for each tenure level and the implied distributions with a linear increase. The results are shown in figure 11.

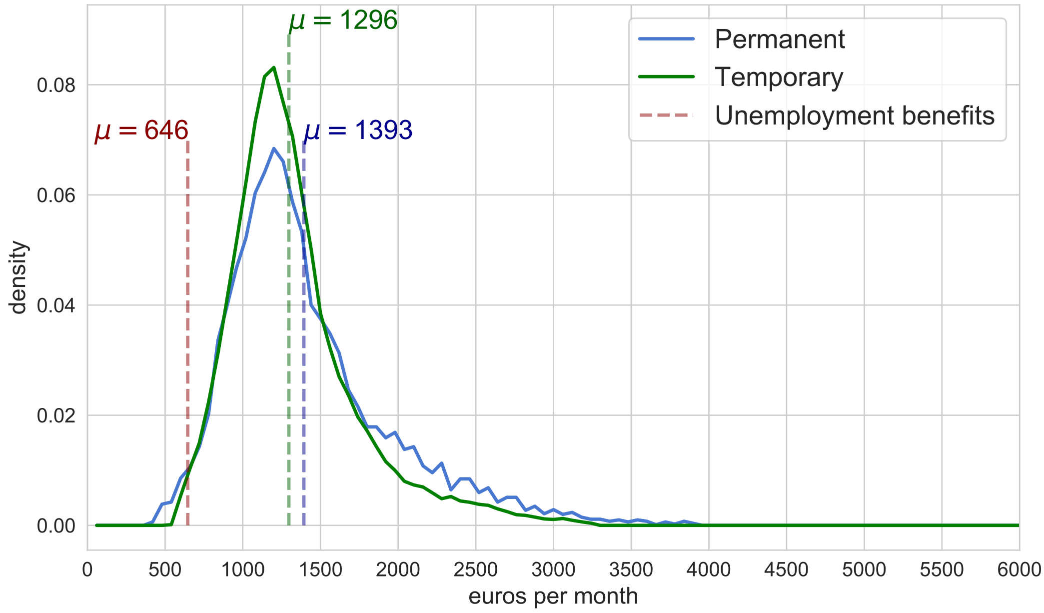
Employment shocks and job arrival rates

Figure 23 in the appendix shows the average monthly transitions age by age between employment an unemployment in the 2005-2008 period. This figure shows that the job separation rate is constant across most ages. In particular this seems to be the case for temporary contracts – as shown in the bottom left panel. The job expiration rates are set to match these levels.

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

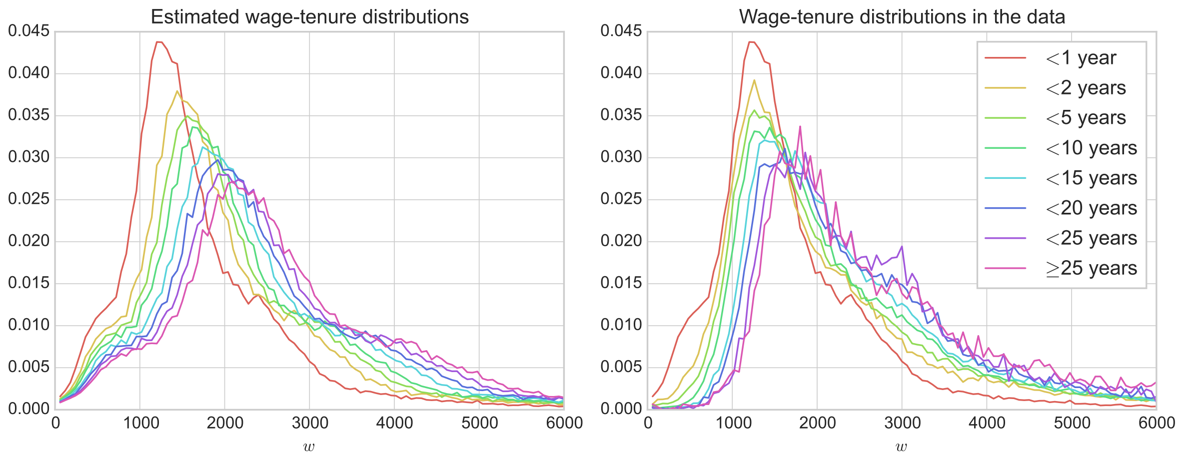
[44] For temporary jobs the wage distributions from young ages are remarkably similar to all workers. This is not the case for permanent jobs which suggests that contrary to the model assumption workers do keep some human capital or that they are less willing to accept low permanent wage offers. The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

Figure 10: Wage distributions



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

Figure 11: Tenure-Wage distributions



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

The permanent to temporary arrival rate is harder to calibrate as not all workers accept a temporary job from a permanent position. I take a similar approach by targeting the job switching rate at age 20. Then I solve the model and calculate how many permanent workers would switch if offered the average temporary wage. Given this estimate I update the job offer arrival rate and solve again until convergence.[45] Finally, the offer arrival rate for temporary workers α_{TT} is not directly observed in the data. I calibrate it by targeting the average number of temporary contracts in the data and the average quit rate. Too high values of α_{TT} make the number of temporary contracts overshoot and too low values overestimates the quit rate. On a first approximation, I set $\lambda = 1$, which means all human capital is lost on displacement from permanent contracts. This assumption puts a lot of weight into hysteresis shocks or human capital depreciation.[46] The consequences of this assumption are discussed further, in the results concerning welfare.

For the recession period I use the 2009-2013 equivalents of these transition rates, and re-calibrate α_{PT} and α_{TT} for the recession period. No other parameters are changed in the recession period.[47]

Search capital parameters

I assume a simple structure for search capital: three levels that result in three proportional job finding rates ($\alpha_j(s) = \bar{\alpha}_j s$). Search capital is not directly observable in the data, and the regressions of the previous section cannot be used simultaneously to pin down parameters and then asses the model fit. The approach is the following: I build the empirical unemployment duration histograms for workers at age 20, separated by the number of previous temporary jobs as figure 12 shows. There is a clear ordering in terms of duration: among workers with a high number of temporary contracts the spike of the histogram at 1 month or less is higher. There is a larger share of workers who find jobs within the first month of unemployment. I focus on the difference of the duration histograms at the first month and assume that these differences are reflecting different search capital levels. Workers with 8 temporary contracts or more have higher search capital than workers with 2 or less. This means their job arrival rate is higher so ceteris paribus there must be more workers leaving unemployment within the first month. For the 3 search capital levels I have imposed I choose 3 thresholds such that the distance of the duration histograms at one month or less is maximized. For example, in the left

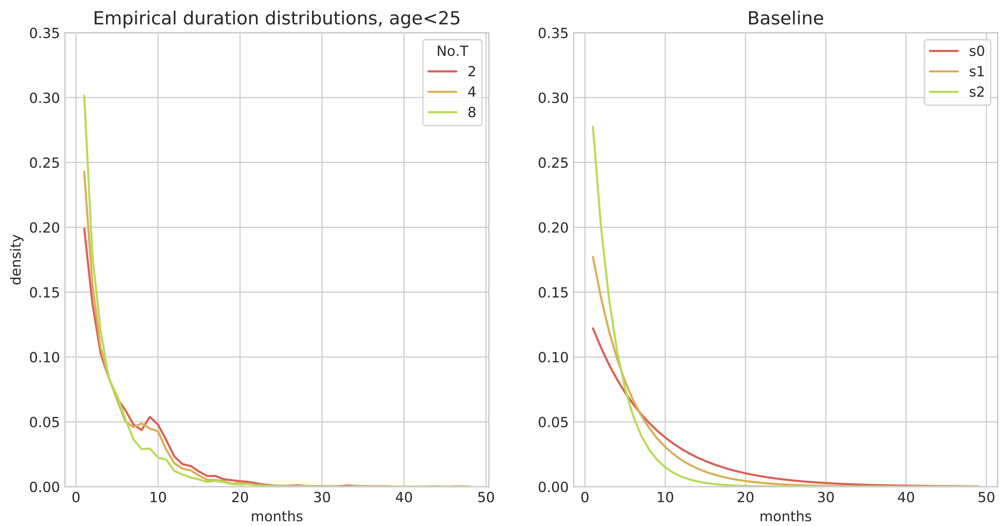
[45] $\alpha^1_{PT} = \alpha^0_{PT}/S_{PT}$ where S_{PT} is the proportion of permanent workers age 20 that accept an average temporary wage offer.

[46] The 2008 Recession in Spain had a strong occupational and industry component: both construction, real state, financial services and public servants were servery affected and jobs in these areas did not recover. It is therefore not unreasonable to set $\lambda = 1$.

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

panel of figure 12 the thresholds are: less than 2, between 2 and 4, and between 4 and 8 temporary contracts. Suppose that these distributions can be approximated by an exponential distribution with arrival rate $\alpha_j(s)$. After setting $s_1 = 1$ for the intermediate group s_0 and s_2 are chosen such that the difference in the resulting duration distribution at 1 month or less mirrors that of the data. Splitting workers into 2 or less, 2 to 4 and 4 to 8 results in the largest distance at one month or less between any three groups in the data. Therefore I set $g_s(s, s')$ to be 0.5 so it takes 2 contracts on average to progress to the next level of search capital. The values of s are then set targeting the distance at 1 month or less unemployed. That is, setting $s_1 = 1$, $s_0 = 0.6667$ and $s_2 = 1.666$ and plotting the implied histograms (right panel of figure 12) results in distances at one month that match those of the empirical histograms (left panel of figure 12).

Figure 12: Duration of unemployment by number of contracts and search capital level



Source: Own calculations from MCVL, 2005-2013 waves

The final parameter $d(s, s')$ cannot be directly pinned down by the data, so I set it targeting the decay in the unemployment to temporary flow by age. This results in a depreciation shock happening on average after approximately 5 years.

Initial distributions

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

For the initial distribution of search capital, newcomers that start unemployed without benefits are assumed to start from the lowest level of search capital (s_0) while unemployed with benefits are assumed to enter with the first level of search capital (s_1). This is because those receiving unemployment benefits must have accumulated enough job experience to be able to claim benefits. And indeed for unemployed workers less than 25 years old the average number of temporary jobs held before unemployment is lower among those without unemployment benefits (3 vs 5). Workers that enter the labour force with a permanent job at hand are also assumed to have gained search capital (s_1), as well as half of the temporary workers. The initial distribution of search capital is set to match the early unemployment rate (ages 20-25). The results are not sensitive to this distribution.[48]

4.2 Aggregate economy

Figures 13 show the resulting temporary share and unemployment rate by age from the first stage simulation. The model generates patterns of unemployment and temporary rates that are close to the data. Note that the unemployment rate is in monthly frequency, calculated using the administrative dataset, which manages to capture a larger share of frictional unemployment that the LFS fails to capture.[49] This explains the high unemployment even during the expansion period. Unemployment falls until age 40. Then it stabilises around 12%. Note that the increase in the number of unemployed who are not receiving unemployment benefits towards the end reflects a higher share of long-term unemployment. See also plot 25 in the appendix for more detailed results on the stocks of each labour state.

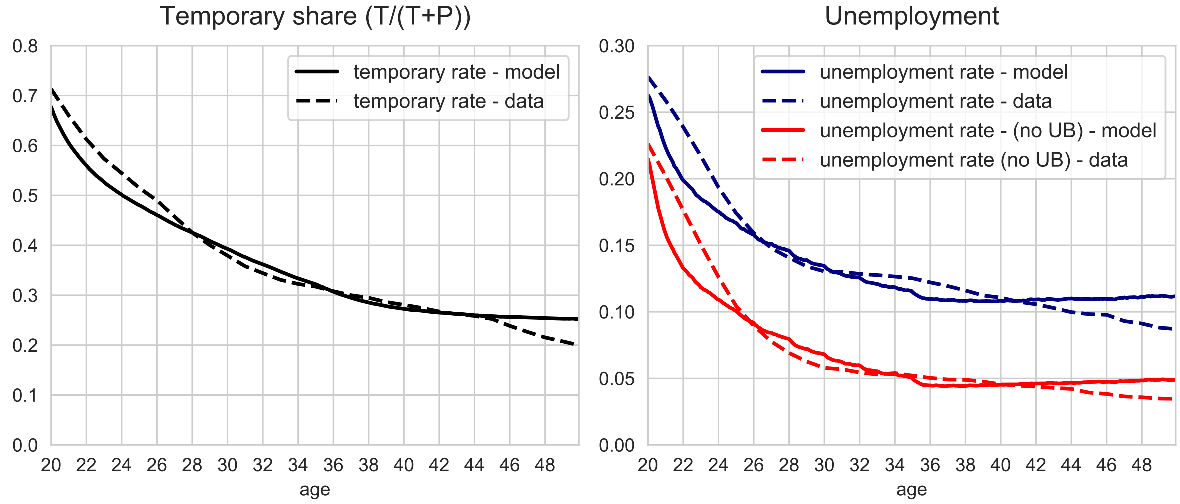
Figure 14 shows the evolution of search capital levels among the population over the life cycle. The first panel corresponds to all workers while the second focuses on the changes in the composition among the unemployed. The plot shows shares of each search capital level in the vertical axis. The first panel shows that the share of bad searchers (workers with the lowest level of search capital, s_0) is larger among the youngest and oldest age groups. There are also more workers with the highest level of search capital (s_2) among the older cohorts. The large share of good searchers among older workers reflects that search capital increases over time as individuals gain experience in the job market. But the distribution also becomes more polarized. That is, both extremes of search capital become more prevalent among older workers. This pattern reflects the polarizing nature of dual labour markets, as the older bad searchers are mostly permanent workers who have been sheltered from unemployment for a long time.

The right panel of figure 14 shows that the share of bad searchers among the unemployed decays monotonically with age. In contrast, the share of good searchers increases

[48] The only substantial change is when the flows from unemployment without benefit and temporary contracts reach their highest level.

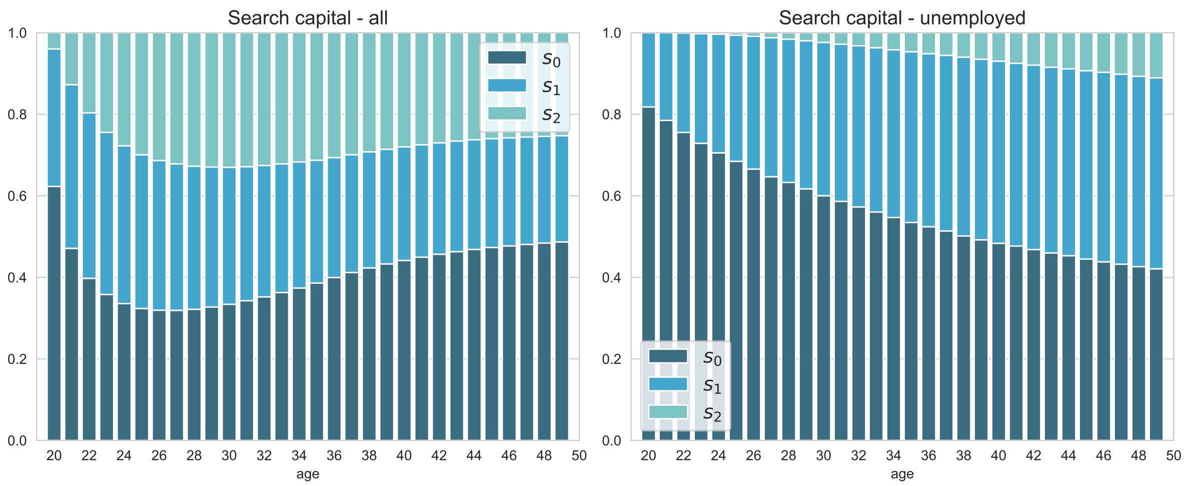
[49] See Lafuente (2019) for more details about comparing unemployment for the LFS and administrative data in Spain.

Figure 13: Unemployment rates and temporary shares by age



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

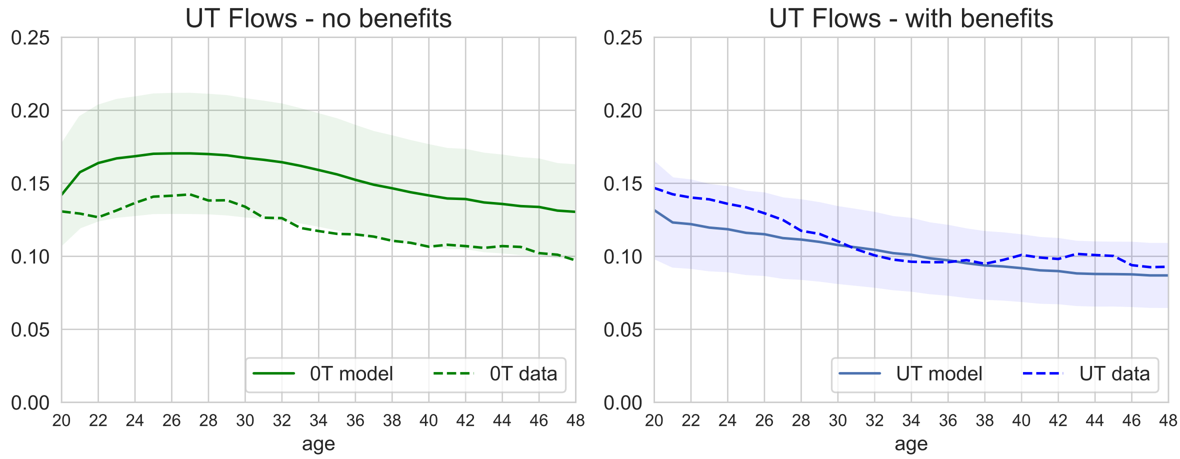
Figure 14: Search capital by age



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

over time but is never above 20%. Younger workers are the worst searchers because of their inexperience in the labour market – they have not had time to accumulate search capital. They compensate for their lower job finding rate by accepting very low paying jobs, as figure 15 shows. Older unemployed workers are better searchers. Recall that the first stage simulation reproduces the conditions of a period of economic expansion. Under these conditions, most older workers are employed in permanent contracts and rarely lose their jobs. These employed workers have lower search capital but their unemployed peers have been more exposed to unemployment spells and thus are better searchers. Note as

Figure 15: Unemployment to Temporary flows, by benefit entitlement



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

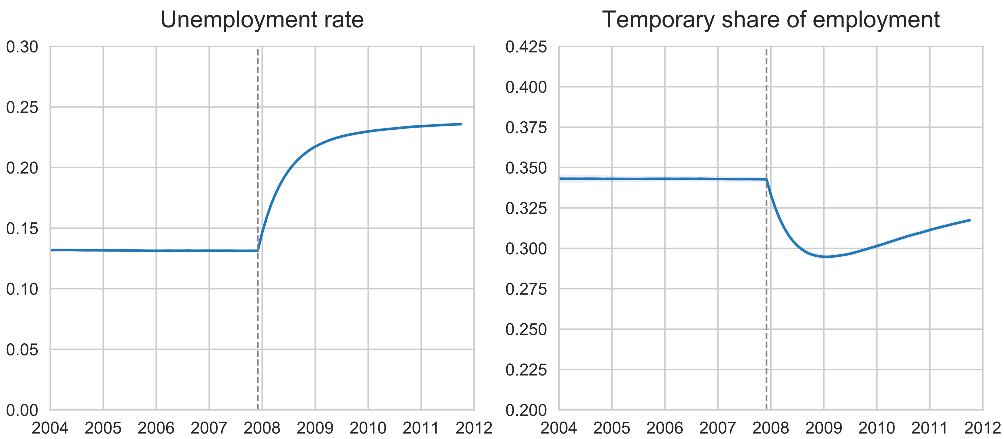
well that these workers have also managed to accumulate some human capital and save, so they can afford to take a longer time to find a better match. This is reflected in their lower job finding rate in figure 15. Finally, figure 15 shows the temporary job finding rates or unemployment to temporary (UT) flows. The flows into permanent contracts are not shown here as they are very small, between 2% and 3% – in accordance with the data. These and other flows are shown in figure 26 in the appendix. The model does overshoot the job finding rate of workers without benefits but it manages to capture its hump-shape and slope well. This shape reflects the patterns of search capital as discussed in figure 14: Younger workers with little savings and productive human capital are not very selective in their jobs, but they are not good searchers either – so the job finding rate increases until the age of 26-27, as in the data. After that, workers accumulate assets that allow them to be more selective in the jobs they take. The composition of the unemployment pool also changes: there are only workers with low productivity focusing on (well-paid) temporary jobs and displaced permanent workers with low search capital – hence the setting of $d(s's)$. These two forces drive the average job finding rate down. For workers with benefits the job finding rate monotonically decreases with age, which is in line with the data. From the age of 24 it is consistently below the job finding rate without benefits in the data, while in the model this happens almost from the beginning. Unemployed workers with benefits can always be more selective in their jobs, and this effect dominates the increase in search capital over time.

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

4.3 Aggregate shock

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

Figure 16: Simulation results, Recession shock at 48 months



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

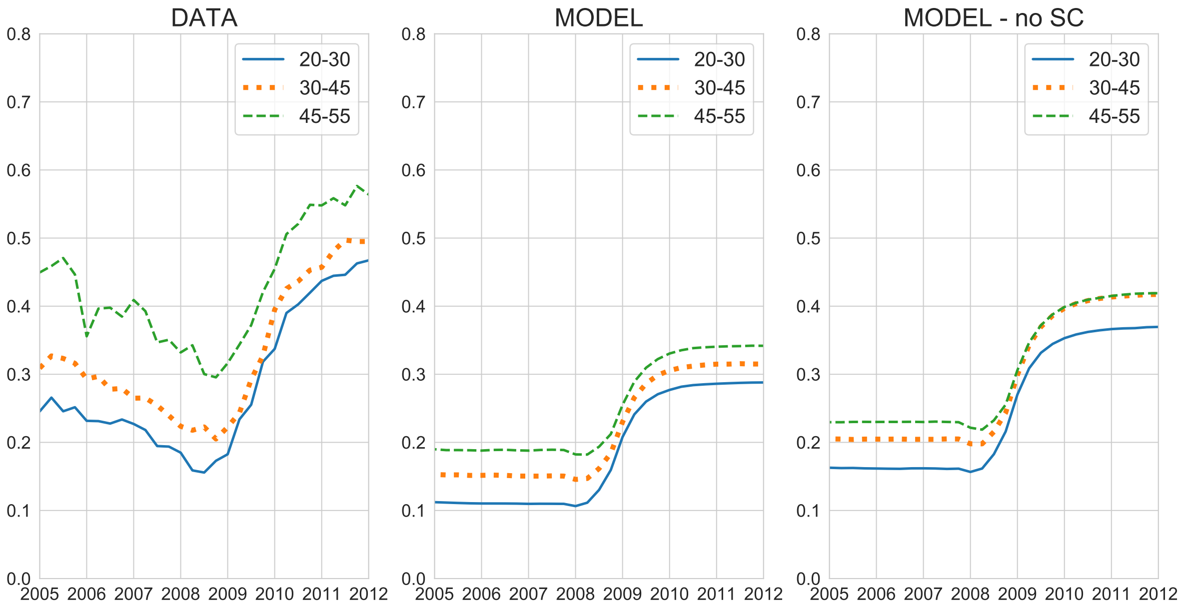
Figure 16 shows the simulated unemployment and the temporary share series. Unemployment rises to close to 25%, which is in line with the data. The temporary share implied by the model falls at the beginning but rises afterwards. While the initial fall of the temporary share is observed in the data, its subsequent increase is not. This fall is driven by a steady decline in the total number of permanent jobs, as figure 27 in the appendix shows.

The model is successful in replicating the relatively larger increase in long-term unemployment among younger workers, as figures 17 and 18 show.

The first panels in both figures show the increase in the data, as reflected in figure 7.[50] The other two panels present the equivalent plot generated from the model simulation output. The middle panel shows the results of the baseline model and the rightmost

[50]The data however is split into different age categories (20-30, 30-45 and 45-55) to accommodate for the fact that in the model agents enter the labour market at age 20. This split of the data also ensures an even split of observations in the model generated data. The pattern is very similar to that of figure 7.

Figure 17: Long-term unemployment rates by age



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

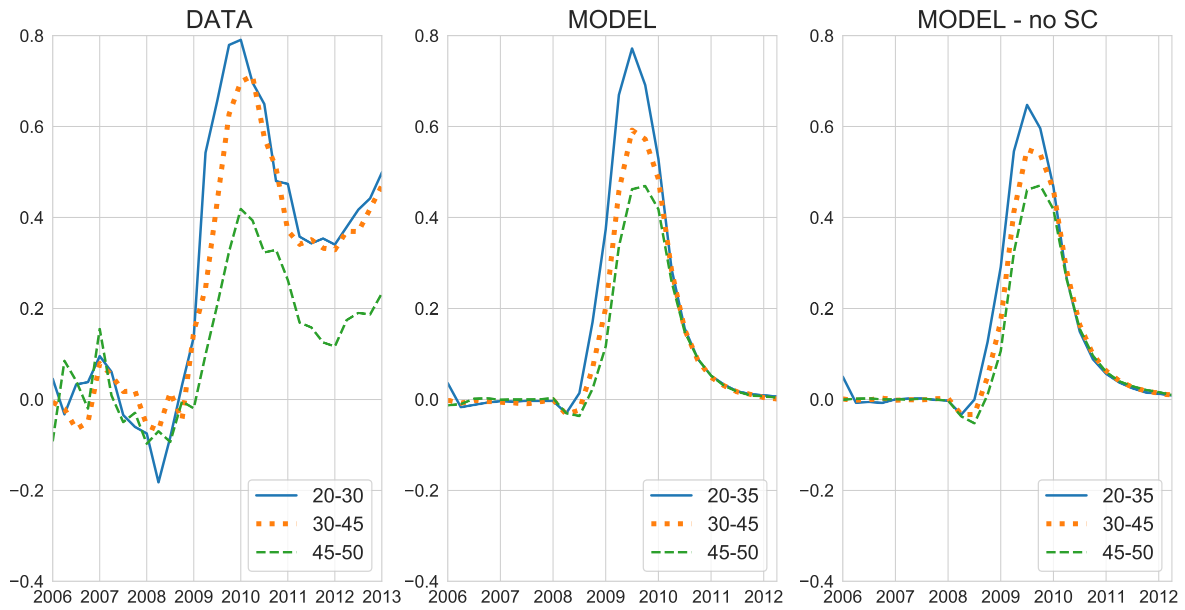
panel shows the results of the simulation when search capital is shut down – all workers have the middle level of search capital.

In levels, figure 17 shows that the model with search capital is able to replicate the ordering we observe in the data. That is, the long-term unemployment rate is highest among the older age group, followed by the middle aged and the young. This relative ranking does not change after the shock, both in the data and in the model. Without search capital, the middle age group follows very closely the older age group. After the shock, the LTU rate of the middle aged is identical to the older workers. This is at odds with the data. In both models the long-term unemployment rate is lower than in the data – this is a mechanical effect of the higher job finding rate as explained in figure 15.

In relative changes, figure 18 shows that in the the model with search capital the youngest group of workers suffer the highest increase, almost doubling of the oldest age group. The difference between oldest and youngest is higher than in the data, but the magnitudes are not far off. In the model without search capital the differences across age groups are smaller. The addition of search capital to the model amplifies the response of long-term unemployment among young workers, closing the gap in levels with older cohorts.

The model with search capital can help explain why long-term unemployment in-

Figure 18: Annual changes in long-term unemployment by age



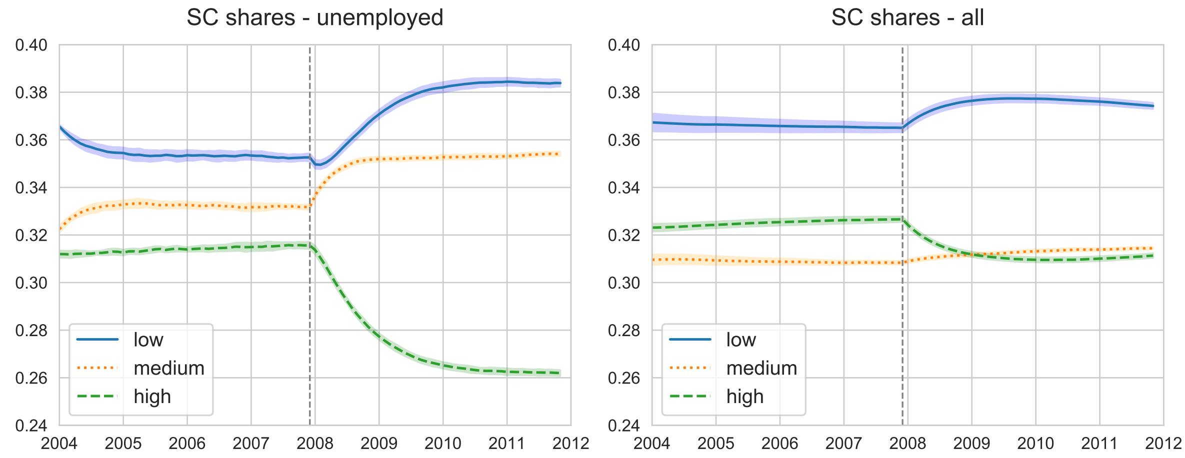
Notes: Quarterly changes in long-term unemployment share. *Data* panel data source the Spanish LFS, years 2004-2012. *Model* panel data is derived from 20 second stage simulations of 2 million workers each for 8 years, recession shock after 4 years. *Model - No SC* data derived from the same simulation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

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

The reduced availability of temporary contracts drives this result, as shown in figure 19. Comparing both panels, the changes among the unemployed are larger in magnitude and drive the results for the overall population. There are fewer workers with high search capital among the unemployed – resulting in a further fall of the job-finding rate. That is, the recession makes temporary contracts more scarce and unemployed workers are also worse at finding jobs. This implies that unemployment increases both because of the fall in the job finding rate (fewer jobs are available) and changes in composition of the unemployment pool (workers are worse searchers overall). Search capital makes these negative changes in composition become deeper and more permanent, as the inability of young workers to accumulate search capital damages them in the long-term.[51]

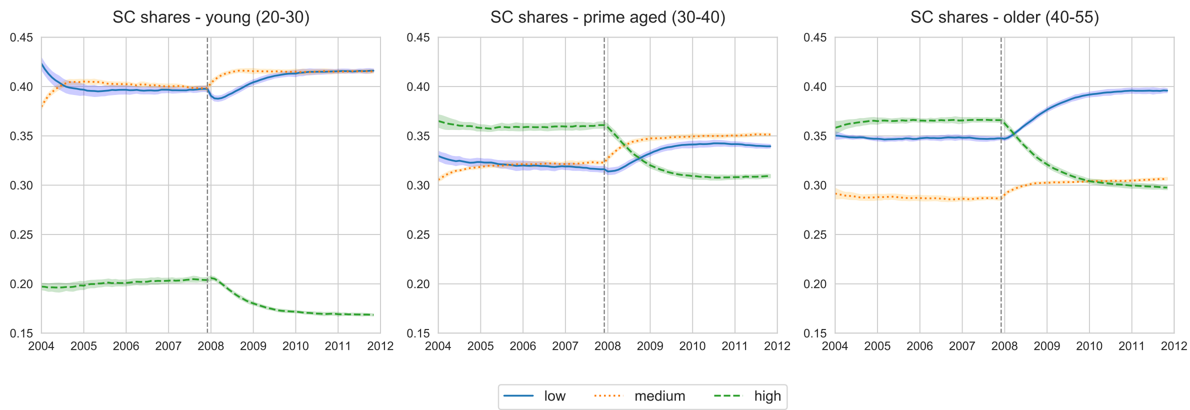
[51] Notice that if we were to decompose the duration of unemployment post-recession, search capital would not affect duration dependence – if anything, duration dependence would be negative because as

Figure 19: Search Capital simulation results, recession shock at 48 months



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

Figure 20: Search Capital simulation results by age group, recession shock at 48 months



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

Figure 20 illustrates the changes in search capital by age groups. Young workers have the highest share of low search capital of all the age groups. After the shock, the proportion of high search capital falls, resulting in an increase of the middle level of search capital. This pattern shows the effects of the slowing down of the take up of temporary contracts. As these jobs are harder to find in recessions, young people are unable to accumulate search capital. However, the most drastic changes in search capital happen among the older cohorts: the proportion with low search capital increases substantially. This is because more long-tenured workers are dismissed in the recession, but while in the boom they were able to climb back up the job ladder (and increase their search capital)

workers consume their savings they become less selective in the jobs they pick. However, it would be very difficult to correctly identify the changes in search capital as changes in heterogeneity. This is because search capital is both unobservable and time-varying.

in the recession they stayed unemployed longer.

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

4.4 Welfare

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

Using the results from the first stage calibration with expansion parameters, I calculate the present discounted utility of workers who participate in the labour force for 30 years. I then compare two groups: those who got fewer contracts than average (temporary or permanent) and those who got more. For the case of temporary workers, the average is 7.96. Close to 60% of workers have fewer than that amount by the age of 50.[52]

Table 5: Present-discounted lifetime utility, by number of contracts

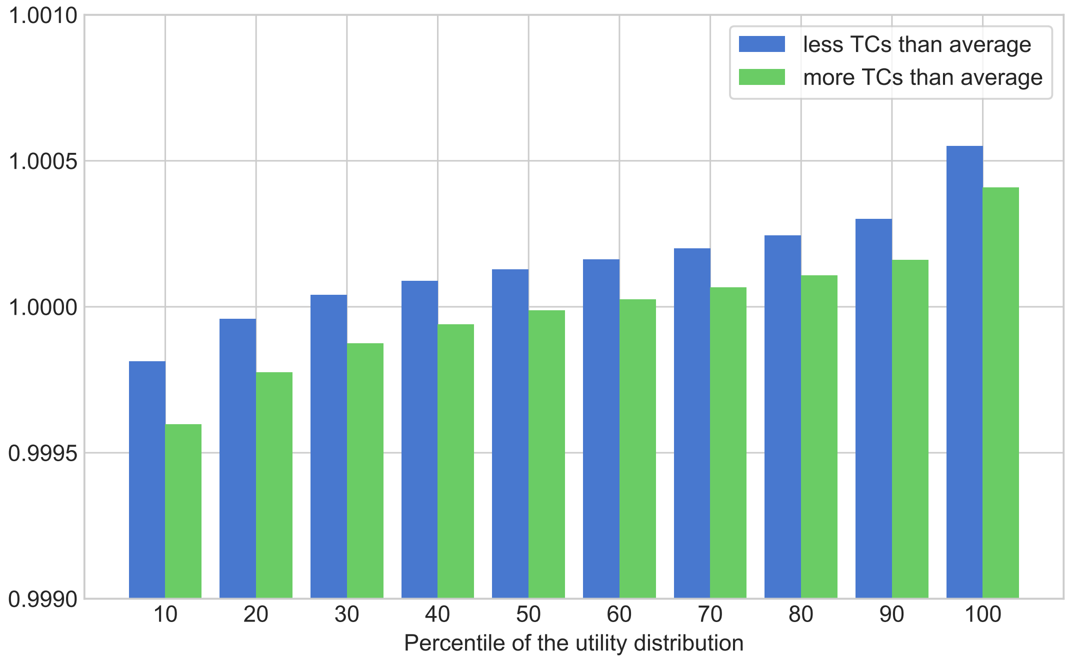
	Fewer TCs	More TCs	Fewer PCs	More PCs
Average	168.582	168.553	168.576	168.563
Std.	0.0386	0.0431	0.0445	0.0415

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

Looking at the distributions of lifetime utility is a simple way of assessing how relatively well-off are workers that are more exposed to temporary contracts than those who have less exposure. First, table 5 shows that, on average, workers with fewer temporary contracts achieve higher lifetime utility. There is also higher dispersion in outcomes, as

[52]See figure 22 in the appendix

Figure 21: Present-discounted lifetime utility, relative to average, by deciles



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

the standard deviation is higher for those with more temporary contracts. These differences are smaller when we consider permanent contracts instead. It is still preferable, on average, to have fewer permanent contracts. In other words, workers can expect to have higher welfare if they have a more stable working life. Figure 24 shows that this is not only true for the average worker (in terms of lifetime utility) but across the distribution, from individual from worst to best outcomes, workers with less temporary contracts achieve higher welfare. Another way of reading figure 24 is that the average worker with more temporary contracts in the top 60th decile of the utility distribution gains the same utility as the average worker with less temporary contracts in the 30th percentile.

However the recession has the potential to reverse this result, as workers entering the unemployment pool with higher search capital face shorter unemployment spells and possibly better outcomes than their peers. To quantify this, I fist calculate the welfare losses of workers in the 25th, 50th and 75th percentiles of the consumption distribution – conditional on experiencing at least one unemployment spell in the recession. That is, I calculate the path of consumption for these percentiles with and without the recession happening after 4 years. I then calculate by how much consumption would need to increase in each period (a month) so that discounted lifetime utility at the moment of the recession is equated in both cases. As before, I distinguish two groups: those who at the start of the recession have had more temporary contracts than average and fewer contracts

Table 6: Monthly Consumption Equivalent Loses of the Recession

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

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

than average. The first four columns of table 6 show the result of this calculation, in absolute (euros) and relative to average consumption in their percentile. The losses from the recession differ substantially among percentiles, as the top group is likely to not lose its job and only suffer in so far they have to climb the job ladder more slowly. For the bottom 25th percentile unemployment happens more often and it is harder to exit to employment. For this group the differences in temporary contracts reflect the differences that search capital makes in terms of unemployment duration. As the last column shows, for the bottom 25th percentile of the distribution having had more temporary contracts than average at the beginning of the recession translates into 1.88% lower loses of average consumption. The loss differential is substantially reduces but still positive for the 50th and 75th percentiles. They lose 0.6% and 0.2% less, respectively.

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

5 Conclusion

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

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

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

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

References

Abebe, G., S. Caria, M. Fafchamps, P. Falco, S. Franklin, S. Quinn, and F. Shilpi (2020). Marching frictions and distorted beliefs: Evidence from a job fail experiment. *Department of Economics, Oxford University (mimeo).*

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.

Arbex, M. A., D. O'Dea, and D. G. Wiczer (2016). Network search: climbing the job ladder faster.

Barnichon, R. and A. Figura (2015). Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics 7*(4), 222–49.

Bell, D. N. and D. G. Blanchflower (2011). Young people and the great recession. *Oxford Review of Economic Policy 27*(2), 241–267.

Belot, M., P. Kircher, and P. Muller (2015). Providing advice to job seekers at low cost: An experimental study on on-line advice.

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).

Bentolila, S., F. Felgueroso, M. Jansen, and J. F. Jimeno (2022). Lost in recessions: youth employment and earnings in spain. *SERIEs 13*(1), 11–49.

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

Bover, O., M. Arellano, and S. Bentolila (2002). Unemployment duration, benefit duration and the business cycle. *The Economic Journal 112*(479), 223–265.

Bradley, J. and A. Gottfries (2018). A job ladder model with stochastic employment opportunities. Technical report, Institute for the Study of Labor (IZA).

Burdett, K. (1981). A useful restriction on the offer distribution in job search models. In *Studies in Labor Market Behavior: Sweden and the United States. Stockholm: IUI Conference Report.*

Burdett, K. and J. I. Ondrich (1985). How changes in labor demand affect unemployed workers. *Journal of Labor Economics 3*(1, Part 1), 1–10.

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.

Carrillo-Tudela, C. and L. Visschers (2020). Unemployment and endogenous reallocation over the business cycle.

Cingano, F. and A. Rosolia (2012). People i know: job search and social networks. *Journal of Labor Economics 30*(2), 291–332.

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

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

Dolado, J. J., M. Jansen, and J. F. Jimeno (2009). On-the-job search in a matching model with heterogeneous jobs and workers. *The Economic Journal 119*(534), 200–228.

García-Pérez, J. I., I. Marinescu, and J. Vall Castello (2019). Can fixed-term contracts put low skilled youth on a better career path? evidence from spain. *The Economic Journal 129*(620), 1693–1730.

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.

Gautier, P., P. Muller, B. van der Klaauw, M. Rosholm, and M. Svarer (2018). Estimating equilibrium effects of job search assistance. *Journal of Labor Economics 36*(4), 1073–1125.

Glitz, A. (2017). Coworker networks in the labour market. *Labour Economics 44*, 218–230.

Gorjón, L., A. Osés, S. de la Rica, and A. Villar (2021). The long-lasting scar of bad jobs in the spanish labour market. *Documento de trabajo*.

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.

Hällsten, M., C. Edling, and J. Rydgren (2017). Social capital, friendship networks, and youth unemployment. *Social Science Research 61*, 234–250.

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

INE (2013). Encuesta de la población activa.

Jarosch, G. and L. Pilossoph (2019). Statistical discrimination and duration dependence in the job finding rate. *The Review of Economic Studies 86*(4), 1631–1665.

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.

Korpi, T. (2001). Good friends in bad times? social networks and job search among the unemployed in sweden. *Acta sociologica 44*(2), 157–170.

Lafuente, C. (2019). Unemployment in administrative data using survey data as a benchmark. *SERIEs*, 1–39.

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.

Machin, S. and A. Manning (1999). The causes and consequences of longterm unemployment in europe. *Handbook of labor economics 3*, 3085–3139.

Mouw, T. (2003). Social capital and finding a job: do contacts matter? *American sociological review*, 868–898.

Mukoyama, T., C. Patterson, and A. Şahin (2018). Job search behavior over the business cycle. *American Economic Journal: Macroeconomics 10*(1), 190–215.

Schaefer, D. and C. Singleton (2019). Cyclical labor costs within jobs. *European Economic Review 120*, 103317.

Van den Berg, G. J. (1994). The effects of changes of the job offer arrival rate on the duration of unemployment. *Journal of Labor Economics 12*(3), 478–498.

Witte, M. (2018). Job Referrals and Strategic Network Formation – Experimental Evidence from Urban Neighbourhoods in Ethiopia. Working paper, University of Oxford.

Wright, R., P. Kircher, B. Julien, and V. Guerrieri (2017). Directed search: A guided tour.

Appendix

A. Links to other models

The modelling of search and productive capital in this paper can be considered a (large) extension of Burdett and Ondrich (1985). In their paper, search capital is a "type 1" demand shock (increased arrival rate) while productivity is a "type 2" shock (increase in the mean of the distribution). Their paper does not have heterogeneous types, as their intent was to show under which conditions the Philipps curve is downward or upwards slopping.

Hysteresis and reallocation models

This paper present an alternative to hysteteris models, where technology shocks 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 phenomenon "turbulence", and expanded the model in Ljungqvist and Sargent (2008) and Kitao et al. (2017). In the first paper they 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 Kitao et al. (2017) they add different human capital levels as educational levels and self-insurance mechanisms.

However, the depreciation of human capital cannot explain why long-term unemployment has risen so dramatically among young workers who have not accumulated enough working experience to suffer a great loss. Kitao et al. (2017) argue that higher minimum wages in Europe are to blame, but this ignores the abundance of internships, training contracts, or even subsidised temporary contracts available to firms that hire young workers. All of these irregular, slippery entries to the job market effectively circumvent minimum wage legislation. Some countries explicitly have lower minimum wages for younger workers. The model presented here shows how to explain the increase in youth unemployment without having to assume higher minimum wages.

This is not to say the the hysteresis does not play a role: the estimated model here shows that the main driver of the decline of the job finding rate as workers age is higher private and public insurance of older workers. This allows them to wait longer after displacement. Therefore enriching a hysteresis model with search capital does not alter its most powerful predictions, but gives it more nuanced. And crucially, it tilts the policy implications in favour of interventions that reduce mismatch, such as targeted active labour market policies. Lowering unemployment benefits alone is not going to help bad searchers much (and have large welfare implications). Neither it addresses the inequality in the labour market that arises from heterogeneous search ability.

A related interpretation is Carrillo-Tudela and Visschers (2020). In their model, workers are endowed with a specific occupation productivity that evolves over time. Unemployed workers can choose to relocate to other occupational markets only if their specific productivity is low enough. This gives rise to “rest” unemployment, where workers of occupations that have been particularly hit by negative aggregate shocks choose to stay in their occupation market, as transiting to other occupations is costly. In recessions, workers wait to weather out the recession, echoing the longer waiting times of older workers in the hysteresis models.

In this context, search capital can be interpreted as a lower mobility costs across markets, allowing workers to switch markets at ease should they find themselves unemployed. Low search capital workers on the other hand would face larger relocation costs. The resulting extra frictions and impact on unemployment would depend on search capital heterogeneity among workers. If workers in long marches lose this search capital, then rest unemployment goes up, and as in the case of classical hysteresis models it is not only a question of losses of productive skills but loses of search skills. This would produce a fall in the aggregate matching efficiency, which is what Barnichon and Figura (2015) documents for the US in the Great Recession.

Dual labour markets

Search capital also contributes to our understanding of dual-labour market dynamics. This literature, developed among others by Blanchard and Landier (2002), Güell (2003), Costain et al. (2010) and Bentolila et al. (2012) considers the heterogeneity in jobs along the permanent-temporary divide explicitly. However, their focus is on severance payments introducing distorting the hiring incentives of firms. Firms always prefer to hire a worker with a temporary contract because the costs down the line associated with separation.

One neglected aspect of these models is that workers often are indifferent between a permanent and a temporary contract, since they are assumed to be hand-to-mouth and risk-neutral workers. Most of the literature addresses this issue by either assuming higher wages under permanent contracts or abstracting from workers' preferences altogether.[53] This distorts the welfare considerations of temporary contracts, since there is a larger cost beyond a higher time spent in unemployment: the impossibility to effective smooth consumption under temporary contracts.

One key contribution of this paper is to show that the welfare effects of temporary contracts are very large. So large in fact that workers would prefer to be at risk of long-

[53] 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.

term unemployment than suffer frequent income fluctuations. While this result means that temporary contracts are not good for workers, prior work took this as a given. Note that in a classical dual labour market model (like Costain et al. (2010) or Bentolila et al. (2012)) a worker may not necessarily prefer a low wage permanent job to a series of well-paid temporary contracts. The often recommendation of banning these contracts comes from the consequences they have for aggregate employment fluctuations or mismatch (Dolado et al. (2009)).

The empirical literature takes more care of the long-term consequences of individuals to temporary contracts (García-Pérez et al. (2019), Gorjón et al. (2021)), which is closer to the intentions of this paper. The contribution here is to provide a theoretical model as to why can workers choose to "specialise" in these contracts, which the empirical researcher can interpret as being trapped in bad jobs (Gorjón et al. (2021)). The nuance of this paper is to say that workers taking many temporary jobs do so because their chances of getting a stable job are very low. The calibration shows that in the long-run they will be worse off than the workers who get a stable contract that allows them to accumulate human capital. This is consistent with the negative effects found in Gorjón et al. (2021) being particularly relevant for low-skilled workers and women, who are likely to suffer career interruptions which would separate them from a long-term match.

Microfoundations and experimental evidence on search

The focus of this paper is on the consequences at the macro level of search capital, not on disentangling its determinants – whether it be networks, soft skills or matching technology. However, there is some empirical and theoretical literature that is related to the possible channels of search capital.

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

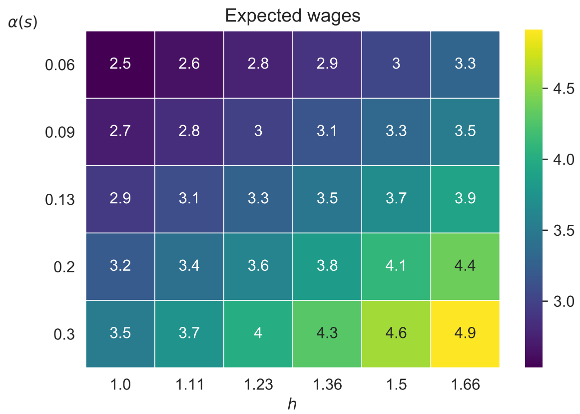
The idea of search capital is intimately related to what sociologists refer to as "social capital" (Korpi (2001), Mouw (2003), Hällsten et al. (2017)). Search capital encompasses a wider range of mechanisms other that networks, but given the persistent effects of search capital found in the empirical part, it is likely that network effects (particularly strong ties) are important. Note that the data demands of studying social capital means that most of these studies were conducted in Nordic countries, where youth unemployment is lower. Interestingly, Korpi (2001) finds that contact with the employment agency was strongly correlated with job finding, more so than the network. This suggests that a well-functioning public employment agency is important for youth unemployment.

Economists have also studied the importance of networks for employment outcomes. For example, Arbex et al. (2016) develop a similar model where workers use their contacts to climb the job ladder faster. Workers receive job offers from an external, constant arrival rate and their network, which is made out the firms her previous co-workers work in. Although it is not the main focus of their paper, the implications align with my model: by finding jobs, workers increase their future chances of finding better jobs in the future, reducing the time they spend unemployed and gaining better wages for themselves. In a related empirical paper, Witte (2018) designs an experiment where a set of workers is hired for a day, after which they are asked to refer some friends to work the next day. The authors had previously mapped the network structure of the neighbourhood where the workers lived. They find that the workers choose to refer the most popular person in their network, not the most productive or able individual for the job. This shows a combination of two things: to be hired from referral workers needed to be in the network but they also needed some interpersonal skills, as popularity matters. Moreover, when the researchers introduced people from outside the network into the firm, the outsider became part of the network and was referred back in subsequent rounds. This shows that becoming part of the network comes from being in touch with other co-workers, which supports the assumption of search capital increasing after a successful job is held. Crucially, the positive effect is purely on search capital, not productivity. In a related paper, Abebe et al. (2020) also find that a job fair helps both side of the market get a better information set, which again is related to a pure search effect, not a productivity increase. Glitz (2017) also examines the effects of networks in re-employment rates of male workers in Germany, using administrative data. His proxy variable is the lagged employment rate of previous co-workers prior to displacement. He finds it has a positive effect on the employment probability a year after displacement. There is no significant effect on re-employment wages. Cingano and Rosolia (2012) find similar results in Veneto, Italy.

Search effort

Note as well that search capital is not chosen, as it would be the case in models that feature “search effort”. If workers can choose their job arrival rate they will unanimously prefer a high one, and the only thing preventing them to do so would be to put a cost to that choice. In this case, if we imposed a flat search cost, workers with the highest to win would choose the highest search effort. Figure 22 shows expected wages for the sample before. Higher productivity workers (high h) have the highest to win from going from the lowest to the highest arrival rate, so they will choose the highest search effort. This makes sense, as their distribution is better.

Figure 22: Average wages



Lower productivity workers are likely to choose lower levels of the arrival rate, since even modest increases of the arrival rate level from the bottom levels get them relatively high returns in form of expected wages. For a flat cost of search effort, high workers would put more effort and the duration matrix would be reduced along the main diagonal. This would result in a positive correlation between productive capital and search capital, so there could not be workers with high productivity and low arrival rates or vice-versa.

Although this would imply higher variation in unemployment duration, by considering the extreme cases along the main diagonal, the explanation would boil down to the same mechanism as with only productive capital: workers with low human capital do not that much to gain from employment relative to unemployment, so they are choosing to stay unemployed longer. If we introduce increases of productive capital by employment over time, then a model with search effort would fail to account for youth unemployment, since they are the ones with most to gain in the long run from exerting more search effort. In other words, it is hard to explain why a worker with low search capital will not choose to get more if given the chance at a cost. On top of this, search effort models are hard to reconcile with empirical evidence on search behaviour (Mukoyama et al. (2018)).

Finally, note that in the case of unemployment benefits proportional to wages all workers would choose the same effort level, in which case search effort does not explain any variation in unemployment duration.

Job ladder models

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

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

Directed search models

The "dead end" jobs scenario in 2 resembles a directed search model (Wright, Kircher, Julien, and Guerrieri (2017)) where highly skilled workers are choosing to queue for long for well-paid jobs, while low skilled workers chose to queue for low paying but easy to get jobs. But a model with random search and search capital can explain why some high skilled workers are still going to find jobs relatively fast and why some low skilled workers can take longer. It is not that they are queuing in the wrong places, just that good searchers get a pass to skip the line, or get access to markets with better waiting times to wages ratios. The random search model does it with one single market, wage dispersion and two types of jobs.

On the other hand, both the baseline model with a single type and the model with temporary wages proportional to productivity deliver the opposite prediction to directed search models: the highly productive workers are going to get, on average, the shorter queuing times, because the low quality jobs pay well, the opportunity cost of not accepting *any* job is large. The constraint they face is their search capital, which is going to limit how often they can sample from the wage distribution. This leads to workers with the same earnings potential to (seemingly) choose worse queues. Search capital says that this is motivated by their relative desperation when facing a low job arrival rate. They take worse options because they feel they will have few offers to chose from. This poses interesting questions for matching models with two-sided heterogeneity, as low search capital can create or exacerbate mismatch.

In the case when unemployment benefits are proportional to productivity, the relative opportunity cost is the same for all human capital levels, so all workers queue in lines of the same length but different wage levels (according to their productivity). Again, workers with low search capital get queues with worse queuing times and wages.

Empirical unemployment duration studies

Search capital is naturally related to empirical duration studies, which seek to disentangle the role of heterogeneity from pure duration dependence in unemployment duration (Machin and Manning (1999), Bover et al. (2002), Jarosch and Pilossoph (2019) to name a few). Empirically, observed unemployment duration distributions do not follow an exponential distribution, which would be the case if there was a constant hazard rate of leaving unemployment. In the model above, as in many search models, this hazard rate is constant for an individual of a given human capital vector. Since search capital is unobservable in a regular labour market dataset, it would be considered by an empirical researcher as unobserved heterogeity, which is hard to disentangle from pure duration dependence sue to dynamic selection.

Consider the consequences of figure 6 for finding evidence of search capital in the data: good searchers are rarely in the unemployment pool, and highly skilled workers (when positively related to search capital) are also not often there. For empirical duration studies that require multiple spells to estimate the hazard function, their sample would be biased towards the good searchers. Bad searchers, who are the ones with longer duration, would be hard to capture, which means it would be hard to disentangle if unobserved heterogeneity (search capital in this case) is driving the results. It would be easy to conclude, in a world with good searchers coming in and out of unemployment at a high rate and bad searchers staying unemployed for long, that there is negative duration dependence, as staying unemployed for longer than average is a good signal of being a bad searcher – which means the worker would be unemployed for a long time.

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

B. Data details

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

C. Institutional context

Temporary contracts were created in 1986 as a compromise between more flexibility in the labour market and keeping the labour protection of regular employment. By 1992 their use was widespread. While mostly young workers are under temporary contracts, they constitute a substantial part of total employment for all ages. In this way, temporary contracts are the primary way of hiring for firms, representing up to 90% of total hiring since 1992.

On the other hand, permanent contracts are subject to one of the most stringent employment regulations in Europe. Severance payments (prior to the 2012 reform) amounted to 45 days per year of service in case of unfair dismissal and 20 in case of a justified economic reason. In case of some permanent contracts it was 33 days per year of service. Because of read tape costs, firms would often prefer to pay the unfair severance in order to avoid going to court. See table A.1 in Bentolila et al. (2012). This increasing severance package, together with wages being protected by industry or regional collective agreements, make permanent jobs not only appealing for workers, but give them very little incentives to ever leave them.

Descriptive statistics

The sample is comprised of all of the completed unemployment spells in the 2005-2013 period, ending in a permanent or temporary job excluding recalls to a previous employer, for workers aged between 20 and 50 years of age at the start of the unemployment spell. This makes a total of 766,462 observations of which 555,302 have observed wages in the previous job and 557,478 have observed wages in the next job. This last reduced sample will be used to test implications 4 to 6 (better searchers get better wages). Descriptive statistics are displayed in Table 7.

Table 7: Descriptive Statistics

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

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

D. Detailed Empirical results

Results are shown in tables 8 to 11. Table 8 and 9 show the results relating to duration of the unemployment spell, table 10 shows the regression results for wages in the next job and table 11 shows the results of regressing the duration of next employment spell until unemployment. In this last table there are also the results of regressing the probability that the next employment contract is permanent (with the alternative is temporary).

In these tables there is an extra variable reported, $CLAIM$. This is because an important factor that determines unemployment duration is the extension of unemployment benefits – for how long can workers claim unemployment assistance. This can also interact with the number of temporary contracts the worker has had: workers that have more jobs often may also struggle to accumulate enough employment spells to qualify for benefits. This is often the case among young workers. To tackle this concern, I include a dummy vector $CLAIM$, taking the value 1 if the worker was entitled for is 3, 6, 12, 18 or 24 months of unemployment insurance. These dummies are important to control for the spikes in job exit rates close to the expiration of benefits (Card et al. (2007)) but also to account for the effect of unemployment insurance on unemployment duration more generally. Three months is the minimum entitlement period in Spain, requiring a year of employment.[54] After that, each year of employment increases the unemployment benefit allowance by 3 months and up to 24 months. After 24 months, under certain circumstances (mainly having dependents) the worker may be entitled to a reduced unemployment assistance. These cases are not common in my sample, as there are few completed spells after that threshold in the data.

Duration of unemployment

Table 8 shows the results of the regression on duration of unemployment as described in equation 15. The first three columns correspond to pooled OLS regressions while columns 4-6 display the results with individual fixed effects. Standard errors are clustered at the individual level, allowing for individual serial correlation. In regressions (1) and (4) wages and unemployment benefits are not included, which allows to capture a larger share of observations. Columns (2) and (5) include a control for past wages and (3) and (6) controls for unemployment benefits.

The first thing to note is that the coefficient on the number of temporary contracts held in the past (TCs) is significant and negative even when controlling for individual fixed effects. Each temporary contract reduces the unemployment spell by 4% on average. The addition of past wages (column 2) and unemployment benefits does not affect this coefficient significantly. The coefficient of the quadratic term TCs^2 is positive in all regressions which means that the effects of search capital (as captured by temporary

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

Table 8: Duration, contracts since 2005

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

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

contracts) dampens over time. The coefficient is very small (less than $1e^{-5}$): it will take more than 100 temporary contracts for the marginal effect of an extra contract to turn negative. Recall that the average number of temporary contracts is 4 so the effect of exposure to temporary contracts on unemployment duration is 15% for the average worker.

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

Recall that these are recent temporary contracts or temporary contracts held since 2005. Table 12 in the appendix shows the results when using all temporary contracts ever held. The coefficients are smaller in both the pooled and fixed effect regressions but remain significant at the 1 per thousand level. This can be explained by the depreciation effect of search capital: only *recent* contact with the job market improves workers' search abilities and reduces unemployment duration. The appendix shows the results broken down by industry, gender and age groups (20-30, 30-40, 40-50 and over 50 years old). The negative coefficient associated with temporary contracts holds for: all industries (except mining and extraction), both genders (in fixed effects and pooled regressions) and for pooled regressions for all age groups. In the fixed effects regressions by age the significance of the coefficient falls below the 5% threshold except for workers in their 30s. Recall that in fixed effects regressions the coefficient can be interpreted as the average effect of finding different jobs on unemployment duration over time for an individual. It may take time for this effect to be significant so it is unlikely it will be seen for those in their very early careers. It is also remarkable that for both genders the coefficients are very similar not only for the number of temporary contracts but for every other variable. This can be explained by the sample which is composed of workers with a high attachment to the labour market.

The number of permanent contracts is also negatively correlated to unemployment duration. However, its coefficient is no longer significant after the inclusion of fixed effects. It is not surprising that the regressions fail to capture a significant effect across time as the number of permanent contracts is small for the majority of workers. In table 12 in the appendix where all permanent contracts are counted the coefficient becomes positive and significant. This evidence suggests that being good at searching in the past is not helpful for searching in the present. A high number of permanent contracts in these regressions signals the worker had many short and unstable jobs in the past before temporary contracts became the norm. This outdated experience seems to be harming current search outcomes. A possible interpretation of this result is that the introduction of temporary contracts made more clear to the worker and the firm that the labour relationship was not meant to last. Then workers can change their search and human capital strategies by being more open to changing jobs, for example.

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

As for the other job market experience variables, $Tenure$ and $Experience$, the results are more mixed. Tenure is positively correlated with duration and the magnitude of the coefficient increases after adding fixed effects to the regressions. The coefficient on the quadratic term is negative and significant. However, it takes a long time (between 20 and 30 years of tenure) for its overall effect to become negative. As discussed before, tenure is related to multiple channels: The loss of specific human capital and the magnitude of severance payments. It can also be interpreted as a fall in search capital over time if the worker stays in the same job for long.[55] On the other hand, job experience before the last employment spell is negatively correlated to duration both in the cross section and with individual fixed effects. Its quadratic coefficient is very small and positive. It takes more than 20 years for the marginal effect to become negative. The fact that the signs on tenure and experience have opposite signs could be interpreted as reflecting the different way workers accumulate human capital: after displacement workers could suffer a loss of specific human capital but not of general human capital – the skills they learned from previous jobs. Notice that in the pooled regressions the magnitude of the effect of one more temporary contract is larger than one more year of previous job experience and close to one more year of tenure (with reversed signs).

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

To complement the previous analysis, table 9 shows the result of the logistic regression on the probability of becoming long-term unemployed. The first two columns show the results for the sample of all unemployment spells that started before 2012. Columns 3-4 show the results for the restricted sample of completed unemployment spells. Recall that this comparison provides a robustness check on sample selection: in all other regressions

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

Table 9: Prob of LTU, contracts since 2005

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

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

we need to observe the worker finding employment at the end of the unemployment spell. This is a useful exercise since by the end of 2013 there were many unfinished spells and therefore the results may be biased to only better searchers.

The number of temporary contracts is negatively correlated with the probability of long-term unemployment. This is true both when long-term unemployment is defined as 1 year or more or 2 years or more of unemployment. One extra temporary contract diminishes the probability of being unemployed for a year or more by 9.5% on average ($1 - e^{-0.1}$) and 13% the probability of being unemployed for two years or more. These coefficients are very similar when only considering finished spells. The quadratic term is positive but very small. On the other hand, both tenure and coming from a permanent contract increase the probability of long-term unemployment. Previous work experience decreases it. This mirrors the results of table 8. The quadratic effect in tenure is small: it takes more than 40 years for the overall effect to become negative. Using the total number of temporary and permanent contracts (shown in table 13 in the appendix) instead of recent ones has a similar effect to table 8: the coefficient of temporary contracts is reduced and the coefficient on permanent contracts becomes positive.

Table 10: Future Wages, contracts since 2005

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

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

Wages in the next job

Table 10 shows the outcomes of the wage regressions. The dependent variable *log(next wage)* is the natural logarithm of annual wages in the job after the current unemployment spell. Column 1 shows the results for all observations, column 2 only includes jobs that last at least three months and column 3 only considers jobs that last at least six months. These restrictions are meant to reduce the noise in the measurement of wages as almost half of all jobs with recorded wages last for less than 3 months. However, this makes the interpretation of the fixed effects coefficients as a dynamic effect over time more difficult.

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

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

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

Table 11: 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	-0.056***	-0.056***	-0.078***	0.058***	0.060***	0.464***
	(0.0024)	(0.0022)	(0.0017)	(0.0053)	(0.0056)	(0.0081)
No. T^2	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.008***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0003)
No. P	-0.016***	-0.025***	0.265***	0.049***	0.071***	-0.583***
	(0.0032)	(0.0033)	(0.0048)	(0.0066)	(0.0084)	(0.0117)
Last P	0.068***	0.074***	0.406***	-0.001	0.009	-0.334***
	(0.0085)	(0.0086)	(0.0131)	(0.0111)	(0.0113)	(0.0197)
Tenure	0.029***	0.005	0.002	-0.064***	-0.087***	0.003
	(0.0040)	(0.0040)	(0.0053)	(0.0061)	(0.0064)	(0.0121)
Tenure^2	-0.001***	-0.000	0.000	0.003***	0.004***	-0.000
	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0008)
Experience	0.059***	0.054***	0.011***	-0.378***	-0.637***	-0.113***
	(0.0016)	(0.0016)	(0.0024)	(0.0091)	(0.0095)	(0.0159)
Experience^2	-0.001***	-0.001***	0.000	-0.002***	-0.001	-0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0004)	(0.0005)
Age	-0.004***	-0.008***	-0.001	0.024***	0.047***	-0.078***
	(0.0005)	(0.0005)	(0.0008)	(0.0063)	(0.0070)	(0.0082)
log(weeks unemp)	0.191***	0.173***	0.012*	0.094***	0.105***	0.048***
	(0.0034)	(0.0038)	(0.0050)	(0.0038)	(0.0041)	(0.0064)
log(past wage)	0.014**	0.038***	0.055***	0.182***	0.175***	0.102***
	(0.0054)	(0.0056)	(0.0080)	(0.0067)	(0.0069)	(0.0140)
Constant	0.887***	1.262***	1.990***	1.566***	3.068***	
	(0.0656)	(0.0695)	(0.0872)	(0.1987)	(0.2121)	
Controls						
Years	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	-
Region	✓	✓	-	✓	✓	-
Observations	427,515	427,515	530,110	438,739	438,739	126,432
Adjusted R^2	0.167	0.184	–	0.085	0.153	–
AIC	1591865.244	1621002.168	361163.185	1288272.176	1310452.532	77881.855

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

Duration of next job spell

Lastly, table 11 shows the results of the regressions on next job duration. As before, the first three columns correspond to pooled regressions (one spell, one observation) and the last three are for fixed effect regressions as in table 8. Columns 1 and 4 show the regressions where duration of next job in log(weeks) is the dependant variable. Columns 2 and 4 have the next employment spell as the dependant variable – that is, considering not only how long the next job is but all the subsequent employment spells until the next time the worker is unemployed. This restriction generates a sample selection issue:

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

The result from the pooled regressions show that the number of temporary contracts is negatively correlated with next job duration: new jobs are shorter the more temporary contracts the worker has. But in the fixed effects regressions as the worker accumulates more jobs over time the duration of next jobs becomes longer too. Likewise, the probability of getting a permanent job out of unemployment is negatively correlated with temporary contracts in the pooled regressions but positively correlated with fixed effects. The different impact in individual fixed effects suggests that there is an unobserved component that makes some workers more likely to have stable jobs. All regressions have controls for industry so this unobservable factor seems to be independent from industry composition. Another possible interpretation is that workers with many temporary contracts are very good at finding jobs and are therefore less concerned with employment stability. They may prefer more stable jobs but they are also willing to accept short jobs more often than workers who are not used to temporary contracts. This observation, together with the fact that people with more temporary jobs finds jobs faster, suggests a trade-off of waiting for a more stable job versus staying in unemployment for longer. There is some evidence of this effect in that the coefficient on the log duration of the unemployment spell in table 11 is always positive. What may be a good strategy when the job market is booming could turn into a higher chance of long-term unemployment during recessions: if the jobs available in recessions are worse then being willing to accept an unstable job can keep a worker out of long-term unemployment. Recall that the results from table 10 showed that on average workers with more temporary contracts tend to find higher wages. This is consistent with an equilibrium where some workers specialize on better paid short term jobs. Nevertheless, the results after controlling for fixed effects suggest that more temporary contracts seem to increase the probability of finding a permanent contract out of unemployment, which again points towards this variable being a good proxy for search capital accumulation.

The number of permanent contracts follows the same patterns when considering the duration of next employment spell. However, the signs are reversed for the probability of obtaining a permanent job out of unemployment. This indicates that, in the cross section, workers with many permanent contracts are the ones that are likely to have higher human capital both search and productive related. These are the workers that "wait" for permanent contracts to arrive. But over time workers with more previous permanent contracts are less likely to get another directly out of unemployment. Here it is convenient to remember that we are observing the workers who eventually come back to unemployment from a permanent contract, which is also rare and may be a bad signal to employers.

Robustness

Table 12: Duration, all contracts

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

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

Table 13: Prob of LTU, all contracts

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

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

Table 14: Duration by age, contracts since 2005

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

Standard errors in parentheses

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

Table 15: Duration by age, all contracts

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

Standard errors in parentheses

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

Table 16: Duration by gender, contracts since 2005

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

Standard errors in parentheses

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

Table 17: Duration by gender, all contracts

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

Standard errors in parentheses

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

Unemployment Duration, by next job industry, contracts since 2005

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

Standard errors in parentheses

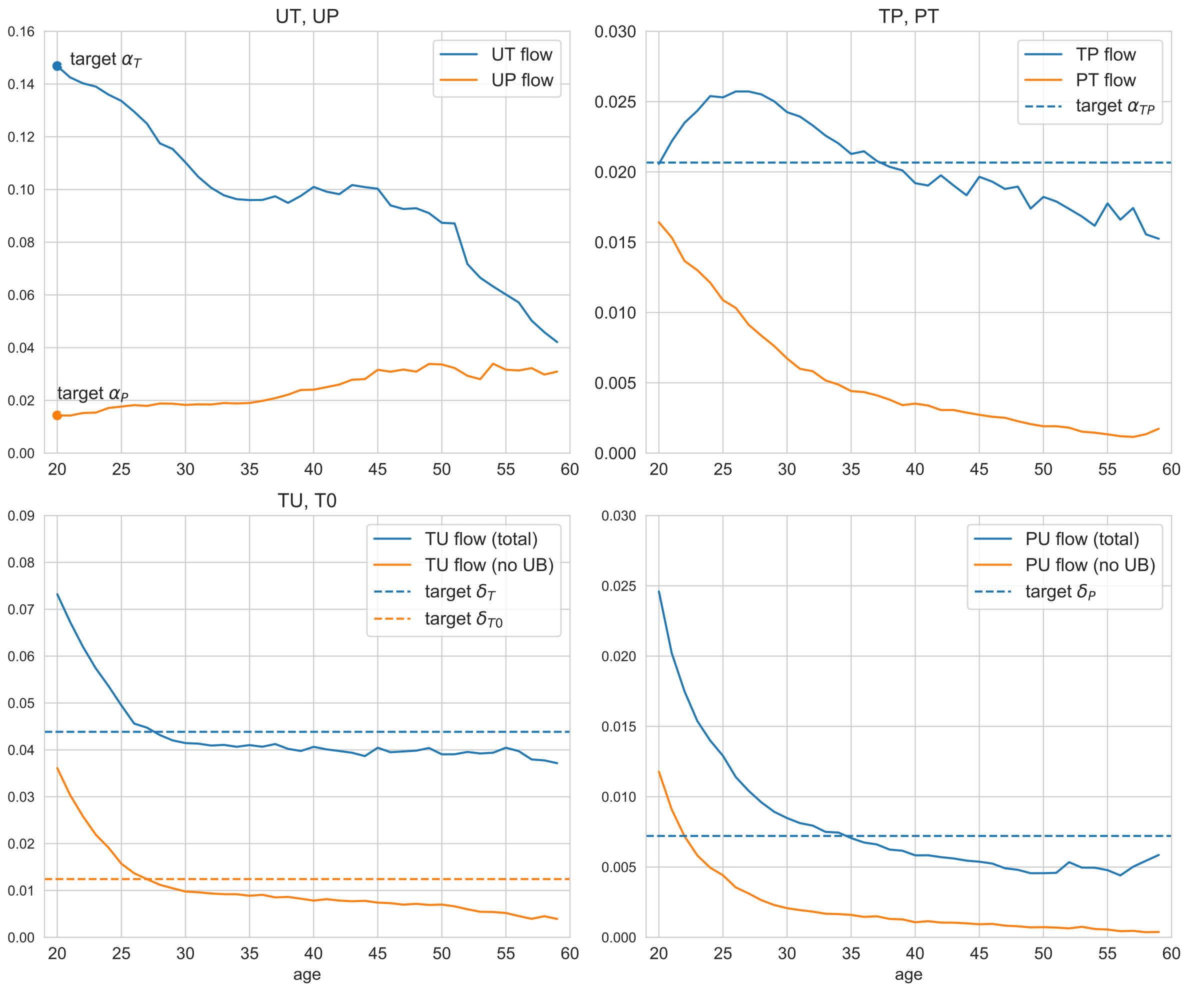
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Unemployment Duration by industry, fixed effects, contracts since 2005

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

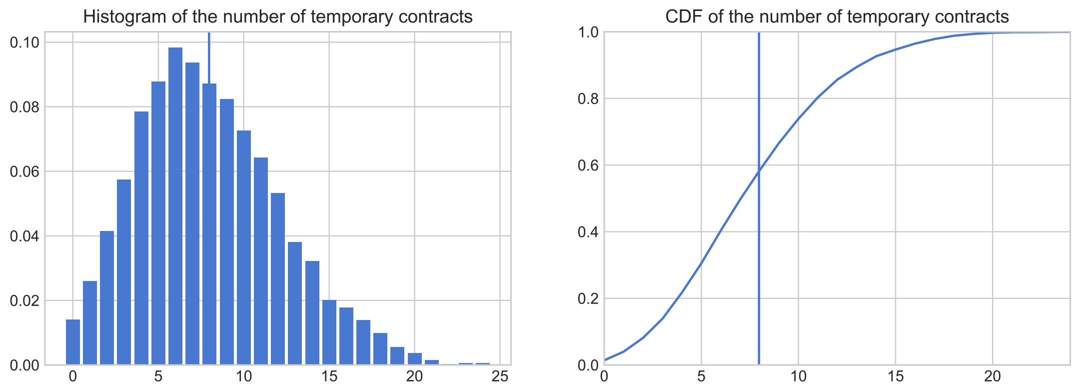
E. Further results and targets

Figure 23: Quarterly Transition Rates by Age (2005-2008)



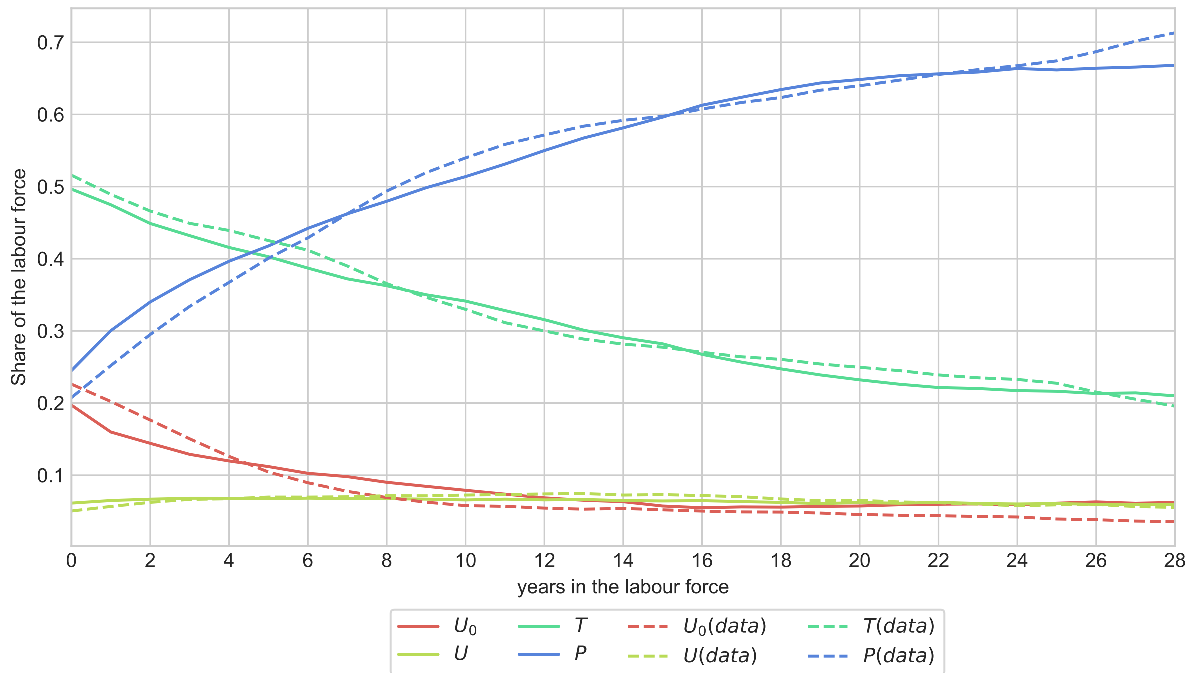
Source: Own calculations from MCVL, 2005-2013 waves

Figure 24: Temporary contract distribution, first stage simulation



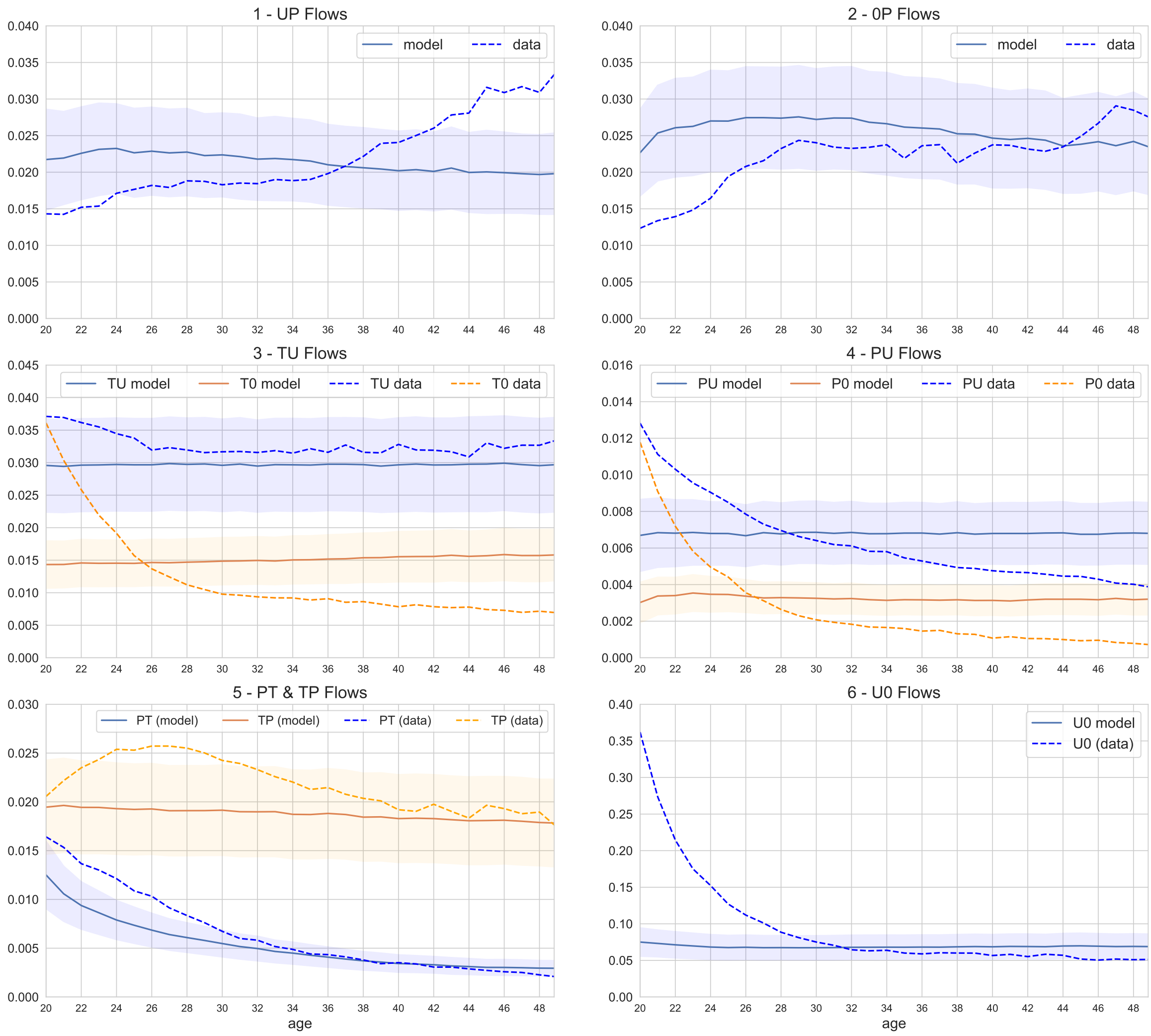
Notes: Distribution of the number of temporary contracts workers have by the end of the second stage simulation. Vertical line marks the average (7.96). Data derived from a simulated panel of 10,000 workers entering the labour force at 20 and exiting at 50.

Figure 25: Stocks by age



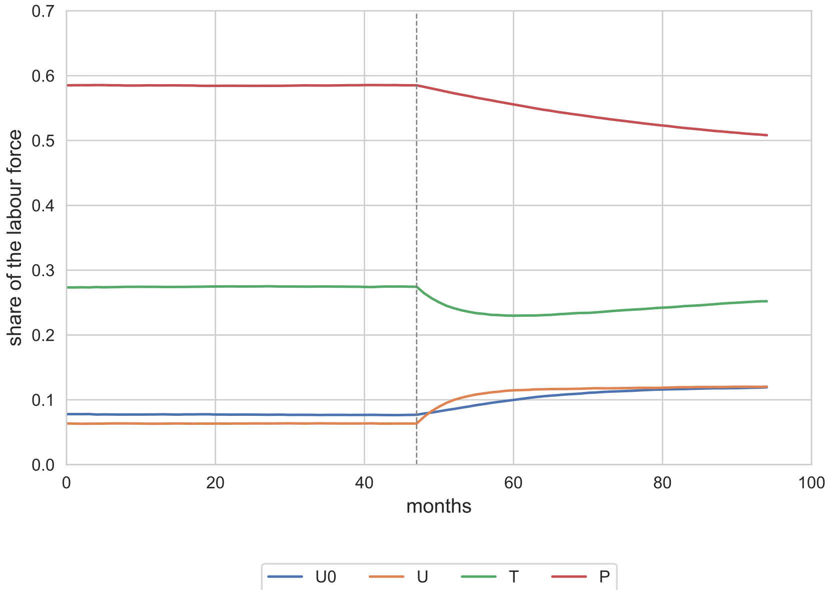
Notes: Evolution of the share of the workforce in a permanent job (P), temporary job (T), unemployed with UB (U) and unemployed without UB ($U0$) by age. Data derived from the first stage simulation, a panel of 16,000 workers entering the labour force at 20 and exiting at 50.

Figure 26: Flows by age



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

Figure 27: Employment Stocks simulation results, recession shock at 48 months



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