Worker heterogeneity and employer screening in a search and matching model

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Abstract

I investigate the quantitative performance of a search and matching model with heterogenous workers and employer screening in explaining long term unemployment and negative duration dependence in job finding rates. In my model, workers are heterogenous in productivity and some of them can lead to inefficient matches if employed. Worker's heterogeneity together with firm screening determine an endogenous positive link between productivities and job finding rates. The results of the baseline calibration show that the model can generate a higher share of long term unemployment than a model with homogeneous job finding rates and a similar profile of negative duration dependence with the one observed in the Current Population Survey (CPS) data. These results rely on the assumptions that the share of workers leading to inefficient matches is high enough and that the screening technology is sufficiently noisy.

JEL classification: J64
Keywords: long term unemployment, negative duration dependence, worker heterogeneity, screening

1 Introduction

This paper investigates to what extent unobserved worker's heterogeneity in job finding rates can offer an explanation for the share of long term unemployed in total unemployment. We analyze this question by adopting the view of frictional labor markets from the search and matching literature. This view implies that workers and firms need time to search for each other and to form a match. However, the literature has shown that if we assume unemployment as purely the outcome of random search and matching, then the duration profile of the unemployed is skewed to much shorted durations than what we observe empirically. Consequently, bad luck in finding a job is not a compelling explanation for the relatively high share of long term unemployed in total unemployment.

The empirical literature has also documented that job finding probabilities are negatively correlated with unemployment duration. This has been labeled in the literature

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as negative duration dependence in job finding rates. Obviously, this is just another way of looking at the same problem: if workers at longer durations simply have lower chances of getting a job, then they will need more time to find a job.

The explanation to this empirical puzzle that I am going to explore here is that workers are heterogeneous in their job finding probabilities. The empirical literature has shown that workers' observable characteristics explain little of the decay in job finding probabilities at longer unemployment durations. This implies that either there is some unobserved source of heterogeneity which makes some workers get employed harder than others or that all workers experience decreasing chances of getting a job as their spell progresses. In this paper we are interested in isolating the effect of heterogeneity, thus we will abstract from the second explanation.

In order to answer our research question we will build upon the employer screening model described in Kroft et al. (2013). The formulation of the economic environment in our model is very similar to theirs. Workers are heterogenous in labor productivity which is unobservable to the firms when meeting. Firms have to commit before matching to a fixed wage which is constant for the whole duration of the match. Some unemployed have a productivity higher than the wage while others lower than the wage. Throughout the paper we will label the first category as high types and the second category as low types. Thus firms want to avoid matching with the low types and screen workers through a noisy interview. The interview is informative about worker's productivity, thus workers with higher productivity will have on average higher chances of getting employed. This means that the screening mechanism together with workers' heterogeneity in productivities will endogenously generate heterogeneity in job finding rates. One key parameter of heterogeneity in job finding rates is the acceptance rate at the interview stage which is determined in equilibrium.

I calibrate the model on US data to match the unemployment rate and the average job finding probability from the Current Population Survey (CPS). I do not explicitly target the duration profile in the CPS. Worker's heterogeneity is calibrated using the micro wage estimates from the Panel Survey of Income Dynamics (PSID).

The results of my calibration exercise show that the model can generate an empirically reasonable degree of negative duration dependence in job finding rates and a higher degree of long term unemployment compared to a constant duration model. However, this relies on assuming a relatively high share of unemployed who would form inefficient matches if employed (about 50%) and a noise of the interview with a dispersion similar to the one in productivity. Intuitively, in order to get a relatively high share of long term unemployment of around 20%, the share of the low types in unemployment must be high enough as some of them are lucky at the interview stage. Additionally, matching the long term unemployment is also dependent on the screening precision: if it is too high, then the model either matches a too low average job finding rate rate or a too low long term unemployment; if precision is too low, the heterogeneity in job finding rates decreases too much and the model behaves similar to a constant duration model.

My model is similar to the one used by Kroft et al. (2013). However, there are several important differences between their setup and the one in this paper. First, they consider a two type heterogeneity while I use a continuous distribution of types that is calibrated in order to reflect an empirically reasonable amount of heterogeneity in labor productivity. Second, I endogenize the unemployment productivity distribution by taking into account the steady state flows between employment and unemployment. This is important for the research question as it pins down endogenously the degree of heterogeneity in job finding rates of the unemployed. Third, I also take into account the fact that there are flows between unemployment and non-participation. This is important for the research question as the rate of exit to non-participation is an important determinant of unemployment duration. Clearly, not taking into account this feature can bias the results towards longer unemployment durations. Finally, Kroft et al. (2013) do not make a quantitative assessment of the screening model, as their purpose is to prove that such a model is consistent with the results of their audit study. In the current paper, I solve for the equilibrium allocation and discuss its quantitative performance.

It is also worth mentioning that in my model two key features from the Kroft et al. (2013) paper are shut down. First, I do not take into account employer duration discrimination. This would interact with unobserved heterogeneity at the interview stage and generate true duration dependence: firms will know that long term unemployed will be on overage of a lower quality, so their threshold for getting hired will be higher compared with the short term unemployed. This feature is worth investigating in future work as it brings an extra channel to the link between heterogeneity and long term unemployment. Second, they also include a call-back decision based on duration and other observable characteristics at the interview stage. They introduce this feature in order to be able to interpret the empirical result from their audit study. However, in this paper I am concerned with explaining the role of unobserved heterogeneity, thus a call-back decision which is partially based on observable characteristics is not very meaningful.

This paper is part of the recent literature which analyzes the role of heterogeneity in job finding rates. Hornstein (2012) has a very similar research question as ours but he assumes exogenously the heterogeneity in job finding rates. Villena-Roldan (2010) builds a search and matching model where high productivity workers have higher job finding probabilities. However, in his model search is non-sequential as employers receive multiple applications and choose the best one. He also does not aim to match the share of long term unemploymment or the degree of negative duration dependence. Ahn and Hamilton (2014) analyze the role of heterogeneity for the duration distribution in the CPS but they do not formulate a structural model and use instead a state-space Kalman filter. Hall and Schulhofer-Wohl (2015) analyze the role of heterogenous job seekers in measuring matching efficiency. Jarosch and Pilossoph (2016) build a search and matching model with heterogenous job seekers, but their aim is to analyze the role of statistical discrimination towards the long term unemployed.

The contributions of this paper are as follows. First, it shows that heterogeneity in job finding rates resulting from workers' heterogeneity in productivity can generate a reasonable amount of negative duration dependence and a relatively high long term unemployment rate. Second, it calibrates a search and matching screening model using empirically reasonable targets and shows under which conditions this model is able to endogenously generate negative duration dependence and a high share of long term unemployed. Third, this paper aims to explain quantitatively the heterogeneity in job finding rates as an equilibrium outcome.

2 The screening model with interview signaling

2.1 The economic environment

Consider a labor market with search frictions where workers and firms meet randomly. Time is continous and meetings occur according to a Poisson process with a rate given by the constant returns to scale matching technology $M(U, V)$ which depends on the mass of workers and firms participating in the market. This implies that workers will meet a firm at a rate $m_u(x) = M(1, x)$ and a firm will meet a worker at a rate $m_v = M(\frac{1}{x}, 1)$ where $x = \frac{V}{U}$ is the market tightness.

Workers are heterogenous with respect to their productivity y which is distributed according to a lognormal distribution with mean parameter μ_y and variance parameter σ_y. Firms post vacancies at a cost c in order to meet a worker. Upon meeting a worker, firms do not observe the worker's productivity and have to commit to a predetermined wage w. Matching with a worker with productivity y creates a continuous production flow y up to the point when the match is destroyed exogenously at rate δ. Thus workers with productivity y lower than w will form ex-post inefficient matches. This offers a natural criterion of classifying workers in two categories: workers with $y < w$ will be labeled as low types and workers with $y > w$ as high types.

In order to avoid losses coming from inefficient matches, firms screen workers at no cost through a interview. The outcome of the interview is a signal z which reflects the worker's productivity y with some noise ϵ: $z = y\epsilon$. The noise has also a lognormal distribution with mean parameter μ_ϵ and variance parameter σ_ϵ^2. The distributional assumption for ϵ guarantees that a worker with productivity y has a better chance of drawing a signal value that is close to his productivity. Nevertheless, high types can draw low enough signals which would make them look as low types and low types can draw high enough signals which can make them look like a high type.

Worker's home production is assumed to bring a return at most equal to w. This insures that all workers have an incentive to search and that they will never refuse a job offer. Also, the informational friction makes low types search, as they have a positive probability of being confused with a high type. Together with the fact that wages are fixed at value w, these assumptions insure that the worker's behavior or his outside option are irrelevant. This is done deliberately in order to study only the effects of employer screening on job creation.

Firms take two decisons: whether to post a vacancy and whether to hire a worker given his interview signal z. I do not model explicitly the first decision and assume a free-entry condition which insures that the expected value of a posted vacancy is equal to zero. The second decision is central to the screening mechanism. Firms make expectations about the worker's productivity given the signal value, the population distribution of productivities and the distribution of possible signal draws. Thus a worker will be hired whenever the gain from hiring, that is the expected value of productivity given signal z, is higher than the cost, that is the wage w.

Workers transit between employment, unemployment and non-participation. As discussed earlier, a worker transits from unemployment to employment whenever he meets a firm and passes the interview. Matches are destroyed exogenously at a rate δ which gives rise to flows from employment to unemployment. Finally, unemployed exit permanently from the labor force at rate η. Each exit to non-participation of type y is replaced by a new entry of the same type y such that the size of the labor force and the productivity distribution of the workers in the labor force is constant over time. For simplicity, I assume that there are no flows between employment and non-participation.

2.2 Value functions and recursive formulation

The firm's problem can be characterized using the following recursive formulation in continous time:

$$
\begin{aligned}
rJ_u =& -c + m_v(x)\,(J_m - J_u) && (1)\\
J_m =& \int_0^\infty J_i(z)g(z)dz && (2)\\
J_i(z) =& \max\left\{J_u, \int_0^\infty J_f(y)g(y|U,z)dy\right\} && (3)\\
rJ_f(y) =& y - w + \delta(J_u - J_f(y)) && (4)\\
J_u =& 0 && (5)
\end{aligned}
$$

Firms discount time at rate r. The return from posting a vacancy rJ_u is given by the expected flow gain from matching minus the flow cost c of posting the vacancy. The expected flow gain from matching equals the arrival rate at which firms meet workers multiplied by the additional gain of a matching over a vacancy. When posting a vacancy, firms do no know what interview signals z their meetings will produce. As a result, the gain that firms have from matching is the expected value brought by an interview $J_i(z)$ over the distribution of signals $g(z)$. Furthermore, after discovering the interview signal z, firms do not know the productivity of the worker in order to compute the value of the match $J_f(y)$. Thus, the value of the interview will be determined by the expected value of a match over the distribution of productivity of the unemployed conditional on a given signal z denoted as $g(y|U,z)$. If the expected value of the match is higher than the value of keeping the vacancy open, then the vancacy is filled. Otherwise, the vacancy is kept open. The return of a filled vacancy with a worker with productivity y is given by the flow value of the profit $y - w$ plus the flow loss from job destruction which occurs at rate δ. Finally, the free-entry condition pins down the value of a vacancy at zero.

2.3 Hiring rule

The recursive formulation above implied that firms hire a worker with signal z only if the the expected value of the match is higher than the value of keeping the vacancy open. Using the definition of a filled job and the free-entry condition, firm's hiring rule becomes:

$$E(y|U,z) > w$$

where $E(y|U,z) = \int_0^\infty yg(y|U,z)dy$ is the expected value of productivity of an unemployed which gives in the interview a signal z. It can be shown that $E(y|U,z)$ is increasing in z as a result of the fact that $f(\epsilon)$ satisfies the monotone likelihood ratio condition (see appendix A for the proof). Intuitively, the higher is the value of the interview signal, the more likely is that a firm has met a high type. This insures that there exists a unique signal threshold equilibrium signal $\tilde{z}$ such that:

$$E(y|U, \tilde{z}) = w$$

Given this definition of $\tilde{z}$, the hiring rule can be restated using the indicator function as follows:

$$I_{\tilde{z}}(z) = \mathcal{I}(z > \tilde{z}) \tag{6}$$

The above rule implies that firms hire a worker when $I_{\tilde{z}}(z) = 1$ and keep the vacancy open when $I_{\tilde{z}}(z) = 0$. I will use in what follows the hiring rule in terms of $\tilde{z}$ to express the job arrival arrival rate and the equilibrium conditions.

2.4 The job arrival rate

In order to find a job, a worker must meet a firm and draw a signal higher than $\tilde{z}$. Thus *the instantaneous job finding rate (hazard rate)* of a worker with productivity y is given by:

$$h(y) = m_u(x)P(z > \tilde{z}|y) = m_u(x)\left[1 - F\left(\frac{\tilde{z}}{y}\right)\right] \tag{7}$$

where I have used the definition $z = \epsilon y$ and the fact that ϵ is independent of y. This means that only a fraction of meetings that a worker experiences end up in a match. This fraction is increasing in worker's productivity y and decreasing in the threshold signal $\tilde{z}$.

2.5 Equilibrium equations

Using the characterization of the hiring rule above, I can restate the firm's problem in terms of two equilibrium equations:

$$w = \int_0^\infty yg(y|z, U)dy \tag{8}$$

$$c = m_v(x)\int_{\tilde{z}}^\infty \int_0^\infty \frac{y - w}{r + \delta} g(y|z, U)g(z)dy\, dz \tag{9}$$

Intuitively, the first equation pins down the hiring threshold $\tilde{z}$, while the second equation pins down market tightness x. In order to fully characterize the equilibrium, I need to express the density $g(y|z, U)$ which depends on how the firms form their believes about worker's productivity.

2.6 Bayesian updating on the productivity distribution

The firm's prior beliefs about the unemployed workers' productivity is given by their population distribution $g(y|U)$. After receiving the signal z, firms update their beliefs given the value of z and its distribution $g(z)$. Formally, the distribution of productivities of the unemployed given the signal z is given by Bayes' rule:

$$g(y|z, U) = \frac{g(z|y)g(y|U)}{g(z)} \tag{10}$$

where conditioning on U is omitted from the densities of z given that only the unemployed draw signals. Furthermore, it can be shown that $g(z|y) = \frac{1}{y} f(\frac{z}{y})$ (see appendix B) where $f(\cdot)$ is the density function of the noise ϵ. Intuitively, given the worker's productivity, the likelihood of the firm to receive a signal z is determined by the likelihood of drawing a signal $\epsilon = \frac{z}{y}$.

2.7 Steady state flows and the productivity distribution of the unemployed

I assume in this paper that steady-state distributions exist across: i) productivities, ii) labor market status and iii) productivities conditional on labor market status. This also implies the existence of steady-state unemployment levels for each productivity type y. Let $g(U|y)$ be the share of unemployed workers of type y out of all type y workers in the labor force. Given that there are no flows between employment and non-participation, the share of the type y employed is $1 - g(U|y)$. At the steady-state, the inflows to unemployment are equal to the outflows from unemployment for each type:

$$\delta(1 - g(U|y)) = h(y)g(U|y) \tag{11}$$

This equation gives the unemployment rate of type y workers:

$$g(U|y) = \frac{\delta}{\delta + h(y)}$$

By integrating over the distribution of types, I get the total mass of unemployed which is equal to the unemployment rate given that the labor force is normalized to one:

$$u = \int g(U|y)g(y)dy = \int \frac{\delta}{\delta + h(y)} g(y)dy$$

Finally, the steady-state productivity distribution of unemployed workers is computed using Bayes' rule:

$$g(y|U) = \frac{g(U|y)g(y)}{u} = \frac{\frac{\delta}{\delta+h(y)} g(y)}{\int_y \frac{\delta}{\delta+h(y)} g(y)} \tag{12}$$

A few remarks regarding these results are necessary. First, note that with no heterogeneity the productivity distribution of the unemployed is the same the one across the whole population. Second, with heterogeneity, the distribution of productivities across the unemployed is shaped not only by the population distribution $g(y)$, but also by the hazard rate function $h(y)$: for higher productivities the hazard rate will be higher and thus the mass of unemployed relative to the whole population will be lower. In other words, the average productivity of the unemployed will be lower than the average productivity of the agents in the whole labor force (and correspondingly, average productivity of the employed agents will be higher).

2.8 Equilibrium definition

I can now formally define the equilibrium of the model:

A steady-state equilibrium for the economy described in section 2.1 consists in labor market tightness x, signal threshold $\tilde{z}$ and the unemployed productivity density $g(y|U)$ such that:

1. *the equilibrium conditions* (8) *and* (9) *hold;*
2. *the flows from unemployment to employment are consistent with the meeting technology and the hiring rule* (6)*;*
3. $g(y|U)$ *is given by* (12) *such that it is consistent with equal inflows and outflows from unemployment for each type* y*;*
4. *the distribution* $g(y|z,U)$ *that firms use to form expectations about workers productivity is consistent with the realized distribution given by* (10) *.*

2.9 Monthly job finding rates and long term unemployment

An unemployed worker of type y can find a job according to a Poisson shock which arrives at rate $h(y)$. Additionally, he can also exit the labor force according to a Poisson shock which arrives at rate η. In the terminology commonly used in the survival analysis literature these two shocks are called competing risks [1]. Thus the *unconditional probability that type* y *agent finds a job between months* i *and* $i+1$ is given by:

$$\int_i^{i+1} h(y)\exp(-((h(y)+\eta))ds = \frac{h(y)}{h(y)+\eta}\exp(-(h+\eta)i)\left[1-\exp(-(h(y)+\eta))\right]$$

where I used the fact that both shocks have constant duration. This can be written as the product of the probability that the stays unemployed i months $S(i|h)$ and the *individual monthly job finding probability* p^y_{UE}:

$$\int_i^{i+1} h(y)\exp(-((h(y)+\eta))ds = S(i|y)p^y_{UE}$$

where

$$S(i|y) = \exp(-(h(y)+\eta)i)$$
$$p^y_{UE} = \frac{h(y)}{h(y)+\eta}\left[1-\exp(-(h(y)+\eta))\right]$$

The *job finding probability at duration* i UE_i is defined as the share of unemployed exiting between durations i and $i+1$ out of all unemployed who survive up to duration i:

$$UE_i = \frac{\int_0^\infty \int_i^{i+1} h(y)\exp(-((h(y)+\eta))g(y|U)\,ds\,dy}{\int_0^\infty S(i|y)g(y|U)\,dy}$$
$$= \frac{\int_0^\infty p^y_{UE} S(i|y)g(y|U)\,dy}{S(i)} = \int_0^\infty p^y_{UE}\frac{S(i|y)g(y|U)}{S(i)}\,dy$$

It can be shown that $\int_0^\infty S(i|y)g(y|U)dy = S(i)$ by using the conditional probability definition for the density and Bayes' rule. Moreover, it is useful for interpretation

[1] The job destruction risk δ does not influence a worker's job finding chances. However, if in the data a worker finds a job and losses it between two survey observations, his new job will not be counted as a EU flow. This is the so called time aggregation problem. However, Shimer (2012) has shown that the time aggregation problem is not that important in the case of the EU flows because the probability of losing a job is relatively small compared to the probability of finding a job. In the method used to compute the job finding rates in this paper I have abstracted from the time aggregation problem.

to recognize that the term $\frac{S(i|y)g(y|U)}{S(i)}$ is the conditional density of productivities for unemployed with a duration at least equal to i. Let this density be denoted as $g(y|D > i)$. Thus the duration specific job finding probability is nothing more than the average individual monthly job finding probabilities for workers who have have a duration at least i. The density $g(y|D > i)$ varies with duration i due to a *composition effect*: the relative share of high productivity workers in the remaining unemployment pool decreases because high types have a higher hazard rate ($h(y)$) and thus the weight of high p^y_{UE} at high durations will be lower. This effect creates observed negative duration dependence in UE_i. In the literature on survival analysis this effect is referred to as *the effect of unobserved heterogeneity on job finding rates* or *the dynamic selection effect*.

Finally, the *average monthly job finding probability* UE_m is given by the share of all observed exits from unemployment out of all unemployment observations at a monthly frequency. This means that I have to take account of exits and unemployment observations by integrating across types and summing over all possible monthly durations:

$$\begin{aligned} UE_m =& \frac{\sum_{i=0}^{\infty}\int_0^{\infty} p^y_{UE} S(i|y)g(y|U)dy}{\sum_{i=0}^{\infty}\int_0^{\infty} S(i|y))g(y|U)dy} = \sum_{i=0}^{\infty}\int_0^{\infty} p^y_{UE}\frac{S(i|y)g(y|U)}{\sum_{j=0}^{\infty} S(j)}dy \\ =& \sum_{i=0}^{\infty}\int_0^{\infty} p^y_{UE}\frac{S(i|y)g(y|U)}{S(i)}dy\frac{S(i)}{\sum_{j=0}^{\infty} S(j)} = \sum_{i=0}^{\infty} UE_i\omega_i \end{aligned}$$

The last equality shows that the average job finding probability is equivalent to average of duration specific job finding rates UE_i using as weights ω_i the *duration i incidence*, that is the share of duration i observations out of all monthly unemployment observations.

Similarly, I can define individual, duration specific and average exit rates to non-participation:

$$\begin{aligned} p^y_{UN} &= \frac{\eta}{h(y)+\eta}\left[1-\exp(-(h(y)+\eta))\right] \\ UN_i &= \int_0^{\infty} p^y_{UN} g(y|d \geq i)\; dy \\ UN_m &= \sum_{i=0}^{\infty} UN_i\omega_i \end{aligned}$$

The second expression shows that the exits to non-participation will also exhibit duration dependence. With a similar argument as before, a decrease of the share of high types with duration will increase the average p^y_{UN}. Thus, even with a constant duration exit rate η, the duration specific hazard rates UN_i will exhibit positive duration dependence.

Long term unemployment (LTU) is measured in the CPS as the share of ongoing spells with a reported duration of 27 weeks or more. For consistency with the labor market flows that are computed at monthly frequency, I define here LTU as the proportion of monthly unemployment observations with a duration of at least 6 months. Using the notation from above, LTU is defined by:

$$LTU = \frac{\sum_{i=6}^{\infty} S(i)}{\sum_{i=0}^{\infty} S(i)} = \sum_{i=6}^{\infty}\omega_i \tag{13}$$

The last equality shows that LTU is equivalent with the duration incidence function accumulated forward starting with month 6.

3 Baseline calibration

I calibrate the parameters of the model by assigning an empirical target to each one of them. The parameters and the corresponding targets are summarized in table 1. The model contains a set of parameters that are standard to most search and matching models, that is μ, δ, c and r. All the other parameters are specific to the screening model. I start by discussing the calibration of the latter.

Table 1: Parameter values and targets for baseline calibration

	Calibration	Target/Source
μ_y	0	FL (2001)
σ_y^2	0.7521	
μ_ϵ	0.0000	-
σ_ϵ^2	0.7521	$\sigma_\epsilon^2 = \sigma_y$
δ	0.0300	$u = 6.0\%$
μ	0.7577	$UE_m = 0.25$
η	0.0833	$E_\eta(d) = 12$
w	0.6120	$G(w\|U) = 0.5$
c	10.3409	$x = 1$
r	0.0033	$e^{12r} = 1.04$

The variance of the productivity of the workers in the labor force σ_y^2 is calibrated using the estimates of Floden and Linde (2001) on micro data from the Panel Study of Income Dynamics. They identify σ_y^2 as the residual variance in normalized log wages after controlling for observable characteristics and measurement errors. Wages are normalized such that $\mu_y = 0$. Clearly, adopting their estimates is inconsistent with the fact that in my model all workers receive one unique wage and that there are no idiosyncratic productivity shocks. While relaxing these assumptions is certainly an important step in future work, this is beyond the scope of this paper. Here I use the wage estimates in Floden and Linde (2001) only for introducing in the model a reasonable degree of heterogeneity among worker's unobservable productivity.

The noise of the signal is given by σ_ϵ^2. This parameter is particularly difficult to estimate form micro-data as employer's perceptions at the interview stage are unobservable. I assume that noise distribution is the same as for productivity, thus $\sigma_\epsilon^2 = \sigma_y^2$.

The wage w determines the share of the low types in the labor force. In our model, low types can either get employed and form inefficient matches or remain unemployed. One natural way of calibrating this parameter would be to estimate from micro-data the share of inefficient matches in the employment pool and target this figure. However, given that this figure is not observable, I target instead the share of low types in the unemployment pool. Specifically, I assume that half of the workers in the unemployment pool would lead to inefficient matches if employed.

The arrival rate of the exit shocks from unemployment to non-participation η is calibrated such that an unemployed waits on average 12 months to exit the labor force, conditional on not finding a job. Equivalently, the monthly probability that an unemployed exits the labor force conditional on not finding a job is 0.08. The value of this parameter is important for determining the size of LTU. If the unemployed exit to non-participation sufficiently fast, then LTU will always be small irrespective of how hard will it be to get a job.

I do not target this parameter explicitly using gross worker flows data from the CPS for several reasons. First, data on worker flows show an average UN rate of almost 20% which is well above the rate of 8% implied by our η. Most studies in the literature interpret this high figure partly coming from classification errors between U and N. By adjusting for classification error, Elsby, Hobijn and Sahin (2015) found a value of around 15%. Second, I have to take account of the fact that many workers exit the labor force because of temporary idiosyncratic shocks and they reenter after a certain time. Our model abstracts from these temporary exits as the η shocks stands only for permanent exits. Unfortunately, the CPS does not allow us to follow individuals in order to compute the fraction of UN flows which are due to permanents exits[2].

The targets of the rest of the parameters are relatively standard for a typical search and matching model. The matching efficiency parameter μ is set such that the average job finding rate is equal tot 0.25 which is the CPS average over 1994-2015. Intuitively, a higher matching efficiency means that all workers experience more meetings per time unit, thus the job finding rate increases. The job destruction rate δ is set such that the unemployment rate is 6% which is the CPS average over 1994-2015. For a given value of the UE flows, the size of the unemployment stock is completely determined by the job destruction rate. The vacancy cost c is calibrated such it equals the expected gain from posting a vacancy when market tightness x is normalized to 1. Finally, the instantaneous interest rate r is set such that the annual interest rate is equal to 4%.

4 Results

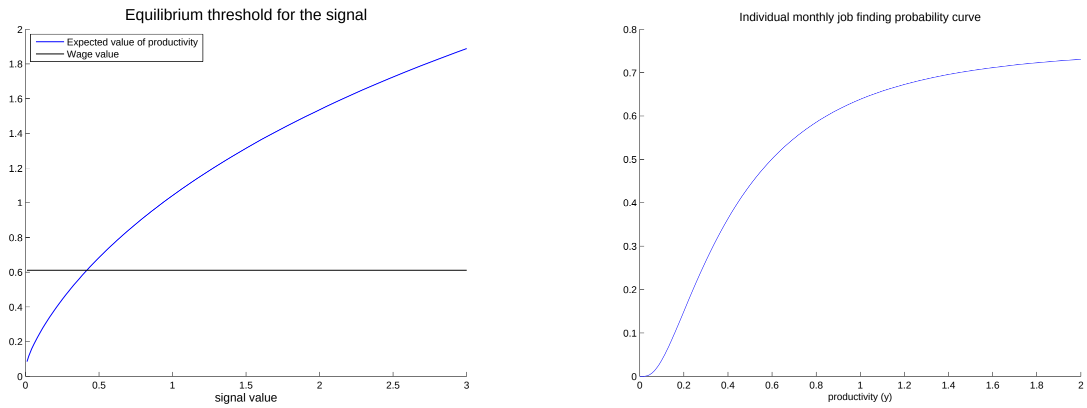
4.1 Equilibrium signal threshold and job finding rates

The left panel of figure 1 depicts how the equilibrium threshold signal value is determined. The conditional expected productivity curve is increasing in the signal value as discussed in section 2.4. For any finite and non-zero σ_ϵ the curve is concave and thus $\tilde{z}$ is lower than w. To get some intuition on why this is the case, I briefly discuss the limiting cases of σ_ϵ. As the noise of the signal decreases, this curve converges asymptotically to a straight line. Productivity is perfectly observable, thus $z = y$, $\tilde{z} = w$ and only efficient matches are formed. Conversely, if the noise of the signal increases, then the curve becomes more concave up to the point when it converges to a horizontal line equal to $E(y|U)$. As long as $w < E(y|U)$ firms will post vacancies and will hire all workers that they meet. Intuitively, when the noise is infinitely large, firms cannot use the interview to distinguish between high and low types and will hire all workers as long as this brings a surplus in expectation.

In the right panel of figure 1, I can see how the individual monthly job finding rate curve depends on productivity. The curve is increasing, thus job finding rates increase with productivity asymptotically up to the point when all meetings results in a match. The convexity of the curve for low values of y and concavity for high values of y is a consequence of the the fact that ϵ is lognormally distributed.

[2]Preliminary calculations using the 2008 panel of the Survey of Income and Program Participation show that around 60% of UN flows are not followed by a re-entry into the labor force in a period of 36 months. Approximating the permanent exits using this share, I get a monthly average UN of 9%.

Figure 1: Equilibrium threshold and job finding rates curve



4.2 Duration specific job finding probabilities and the composition effect

The left panel of figure 2 shows that the duration specific job finding rates UE_i decrease significantly with duration. The pattern of the duration dependence is similar to the one emprically documented by other studies using CPS data. For example, using CPS data from 2008-2011, Kroft et al. (2013) found a decrease in job finding probabilities from about 35% at zero months to approximately 10% at 8 months after which the pattern is almost flat.

As discussed in section 2.9, the observed decrease in job finding rates from our model is entirely due to a dynamic selection effect. The left panel of figure 2 shows how the productivity distribution of the unemployed changes conditional on survival time. As duration increases, less high types remain in the unemployment pool and the distribution of productivities shifts to lower productivities. This in turn leads to lower observed job finding rates at high durations.

The right panel of figure 2 also depicts the selection effect generated by the heterogeneity in job finding rates between the productivity distribution in the population $g(y)$ and the one of the unemployed $g(y|U)$. Because the low types have lower job finding rates, they will need more time to exit unemployment and thus they will be proportionally more in the unemployment pool than in the labor force. In our calibration I target a share of the low types in unemployment of 50%. This corresponds to a share of low types in the labor force of 29%.

4.3 Duration incidence and long term unemployment

Figure 3 shows the forward accumulated duration incidence function ω_i for durations up to 6 months. As shown in equation 13, the observation corresponding to month 6 in this curve determines the value of LTU. I first compare the curve generated by the model with the corresponding curve computed using CPS data. I see that as duration increases, the share of ongoing unemployment observations in the model remains relatively close to the CPS figures. The model generates a long term unemployment of 17.6% while in the CPS it stands at 23.4%.

Figure 2: Duration specific job finding rates and the selection effect

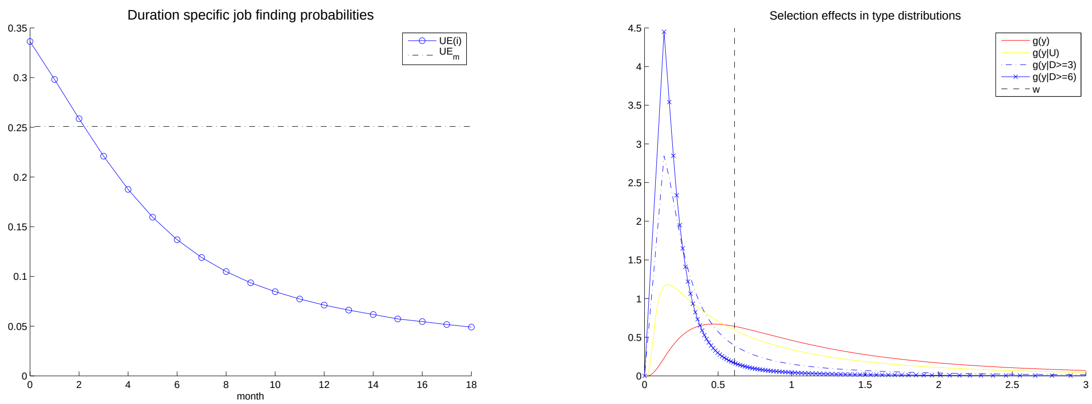
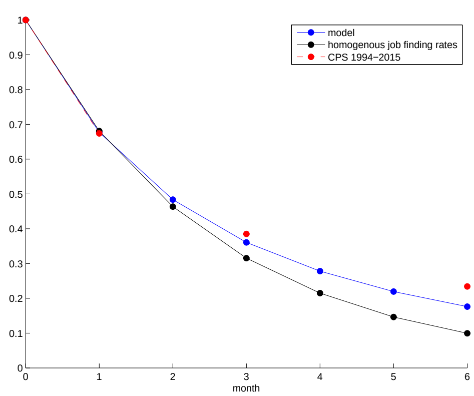


Figure 3: Cumulated duration incidence



The figure also includes the curve corresponding to a model where heterogeneity is shut down, that is when $h(y)$ is constant across types. I calibrate this model by matching the same targets as the screening model: I take $\eta = 1/2$ and I calibrate the hazard rate to employment such that it matches a job finding rate of 25%. It can be seen that as duration increases, the model without heterogeneity underpredicts the CPS figures more as long term unemployment reaches only 10%. Thus the screening model performs much better than the model without heterogeneity in explaining a relatively high share of long term unemployment.

5 Conclusion

The results in this paper show that a search and matching model with employer screening and worker heterogeneity in productivity can explain endogenously a significant part of the share in long term unemployment. However, future work needs to be done in order to check whether this result holds in a more general framework. Most importantly, the model completely abstracts from the worker's side and assumes that all workers accept the same wage. By linking wages to worker's productivity the model would clearly be a more realistic description of the labor market. Additionally, by introducing a worker's acceptance decision, some workers might search more in order to find a job where their return from working is higher. Hopefully, this would help the model in generating a high share of long term unemployment even with a low share of workers leading to inefficient matches. Another natural extension is to consider the role of true duration dependence in generating long term unemployment. This could be introduced endogenously as a result of statistical discrimination in a similar way as in Kroft et al. (2013). Lastly, recent emprirical studies like Krueger et al. (2014) have argued that many outflows from unemployment to non-participation are the result of discouragement in search effort. Thus a richer framework for modeling transitions from unemployment to non-participation is also required for a realistic account of long term unemployment.

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Appendix

A Existence and uniqueness of the hiring rule threshold

B Derivation of the signal density conditional on type