Unemployment History and Frictional Wage Dispersion

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Abstract

Recent evidence shows that baseline search models struggle to match the observed levels of wage dispersion. This paper studies a random matching search model with human capital losses during unemployment. Wage dispersion increases, as workers accept lower wages to avoid long unemployment spells. The model explains between a third and half of the observed residual wage dispersion. When adding on-the-job search, the model accounts for all of the residual wage dispersion and generates substantial dispersion even for high values of non-market time. The paper thus addresses the trade-off between explaining frictional wage dispersion and the cyclical behavior of unemployment.

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Keywords: Search and matching; frictional wage dispersion; unemployment history; skill loss; unemployment volatility.

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1 Introduction

A fundamental question in labor economics is why wages vary so much across workers. The effect of worker characteristics such as education or tenure on wages are well documented. However, worker characteristics can only explain a fraction of the observed wage dispersion in the data. Once one controls for these characteristics, the residual still displays a large amount of dispersion. Therefore, observationally similar workers are paid different wages.

Search models of the labor market can explain why apparently similar workers are paid different wages. In these models, workers adopt a reservation wage strategy when looking for jobs. Job offers are only available with a given frequency, so workers accept a job offer if the associated wage is above their reservation value. This acceptance rule by workers generates wage dispersion, even among identical workers. However, recent work by Hornstein, Krusell, and Violante (2011) shows that baseline search models fail to generate significant wage dispersion. The authors use the ratio between the mean and minimum wage observation, the mean-min or Mm ratio, to measure wage dispersion. In search models the Mm ratio is a function of labor-market flows and preference parameters, for which reliable estimates exist. These estimates imply an Mm ratio in search models of around 1.05, implying that the mean wage is 5% higher than the minimum observed wage. By contrast, the residual in a Mincerian regression, with as many controls as possible, gives a 50-10 percentile ratio between 1.7 and 1.9. Given that this 50-10 percentile ratio is a reasonable empirical counterpart to the Mm ratio, the gap between the two values is remarkable.

This paper introduces a search model in which workers lose some human capital during unemployment. Workers become less productive while they remain unemployed, so wages depend on workers' unemployment histories—their cumulative time spent in unemployment. The paper addresses the following question: What happens to wage dispersion among identical workers if they lose human capital during unemployment? The model generates further wage dispersion compared to baseline search models because workers adjust their search behavior. The intuition is the following. Unemployment "hurts" workers. They lose human capital during unemployment, which depreciates their wages. Since workers are aware that longer unemployment spells lead to larger wage losses, they are willing to accept lower wages to leave unemployment more quickly. With a lower reservation wage, wage dispersion increases among identical workers.

The paper shows that wage dispersion increases significantly if workers lose some human capital during unemployment. The Mm ratio does not rely on any assumption about the underlying distribution of match productivities and is uniquely determined by a set of parameters for which reliable estimates exist. Wage dispersion increases significantly. The model explains roughly between a third and half of the observed residual wage dispersion, whereas the baseline model accounts for only 6% of wage dispersion.[1]

The paper then adds on-the-job search to the framework with loss of human capital during unemployment. The Mm ratio is again uniquely determined by a set of parameters for which reliable estimates exist. Adding on-the-job search further increases wage dispersion. The model with unemployment history and on-the-job search delivers an Mm ratio of 2.07, thus accounting for all of the observed residual wage dispersion. The model also addresses the trade-off found by Hornstein et al. (2011) between explaining frictional wage dispersion and the unemployment volatility puzzle. Matching the cyclical behavior of unemployment and vacancies requires high values for non-market time. However, high values of non-market time make the frictional wage dispersion problem worse. I show that even with high values of non-market time commonly used in the literature the model with unemployment history and on-the-job search closely matches the observed wage dispersion.

The model incorporates workers' loss of human capital during unemployment in the following way. Workers' human capital depreciates at a constant rate while they stay in unemployment. This feature is introduced in an otherwise typical search model, the Pissarides (1985) random matching model. Each match between the firm and the worker has a match-specific productivity. In contrast to the standard model, the productivity of the match further depends on the worker's human capital, which is uniquely determined by her unemployment history. When the worker and the firm meet, they start producing if the match-specific productivity is above their reservation value.

Initially, the paper assumes that unemployment benefits are proportional to workers' human capital. As a result, benefits gradually decrease while workers stay unemployed. There is no reason to believe that benefits should satisfy this property, but this assumption greatly simplifies the solution. However, the paper also solves

[1]Using estimates from the Panel Study of Income Dynamics (PSID), the Mm ratio in the model with loss of human capital equals 1.15. By contrast, the 50-10 percentile ratio in the PSID is 1.34. Using labor market flows from the Current Population Survey (CPS) the Mm ratio is between 1.21 and 1.26 in the model with loss of human capital, whereas the value in the baseline search model is 1.05. Empirically, the 50-10 percentile ratio in the CPS is around 1.8.

the model with constant unemployment benefits using numerical methods and shows that wage dispersion is similar. With proportional benefits, a closed form solution exists. The Mm ratio is independent of any distributional assumption for match productivities. Evaluating the Mm ratio only requires knowledge of a few parameters, namely the depreciation rate of human capital during unemployment, labor market flow rates, the interest rate, and the replacement ratio—i.e. the ratio of benefits to the average wage.

The paper contains some empirical work to quantify the amount of wage dispersion consistent with the data. A key parameter in the model is the rate at which workers' human capital depreciates during unemployment. The paper uses the Panel Study of Income Dynamics (PSID), a large panel of US workers, to construct workers' unemployment history and estimate the human capital depreciation rate. The regression results indicate that an additional month of unemployment history is associated with a 1.22% wage loss. Because the model assumes that human capital losses are permanent, the empirical part of the paper shows that these losses are indeed persistent. The Mm ratio in the model is then compared to the 50-10 percentile ratio of the residual in the Mincerian regression.

Related literature. This paper is motivated by the findings in Hornstein et al. (2011) that baseline search models fail to generate significant wage dispersion.[2] The paper is also related to two literatures.

First, a large empirical literature explores the effects of job displacement on workers' earnings. The literature finds that job displacement causes large and very persistent earning losses to displaced workers.[3] The estimated earnings losses are larger than the ones in this paper. The difference in their estimates comes from their focus on displaced workers, a subset of unemployed workers who usually suffer larger losses.[4] Using the estimates from the job displacement literature would only increase wage dispersion, so this difference is not problematic. However, the empirical work in this paper is better suited for the quantitative evaluation of the model for two reasons. First, only some unemployed workers are displaced. Second, the empirical work focuses on how wage losses depend on workers' unemployment history.

The second literature introduces the loss of human capital during unemployment into search models. Aside from modeling differences, these papers answer different questions. Ljungqvist and Sargent (1998) offer an explanation for the high unemployment in Europe compared to the US—see also den Haan, Haefke, and Ramey (2005), and Ljungqvist and Sargent (2007) and (2008). Pissarides (1992) finds that unemployment becomes more persistent when unemployed workers lose skills and studies the implications for long term unemployment. Pavoni (2009), Pavoni and Violante (2007) and Shimer and Werning (2006) study unemployment insurance. In Burdett, Carrillo-Tudela, and Coles (2011) workers search on-the-job and accumulate human capital when they are employed. However, they assume that employed and unemployed workers receive job offers at the same rate. This assumption implies very large Mm ratios of 2.5 even without human capital accumulation, but it is not supported by data. Coles and Masters (2000) find that with long-term unemployment and training, job creation subsidies are a more efficient policy than training. Instead, this paper studies to what extent human capital losses during unemployment can account for the observed wage dispersion.

The paper starts with the main model with loss of skills during unemployment. Section 3 contains the empirical work. Section 4 shows the results for the main model. The following sections contain the extensions of the model. First, using numerical methods section 5 derives the solution when unemployed workers receive constant benefits and shows that both models generate very similar amounts of wage dispersion. Second, section 6 shows that wage dispersion increases further if the model also includes returns to experience, although most of the improvement is due to the effect of unemployment history. In the final extension, section 7 adds on-the-job search to the model with unemployment history and shows that the model matches the observed wage dispersion closely. Finally, section 8 discusses the trade-off between frictional wage dispersion and labor market fluctuations.

[2]Mukoyama and Şahin (2009) also identified the relationship between the job finding rate—or unemployment duration—and wage dispersion. However, they do not explore the capacity of search models to generate significant wage dispersion.

[3]The size of the earnings losses varies depending on the data source and the period or location studied. Couch and Placzek (2010), Jacobson, LaLonde, and Sullivan (1993), Schoeni and Dardia (2003), von Wachter, Song, and Manchester (2009) use administrative data; Ruhm (1991) and Stevens (1997) use the PSID; and Carrington (1993), Farber (1997), Neal (1995) and Topel (1990) use the Displaced Worker Survey (DWS).

[4]Formally, displaced workers are defined as workers who are fairly attached to their job and are involuntarily separated from it, with little chance of being recalled by their employer or finding a similar job within a reasonable span of time. To select workers who are attached to their job, the job displacement literature usually focuses on workers with a minimum tenure on a job. The job loss must also be involuntary, so quits, temporary layoffs and firings for cause are not job displacements.

2 The Labor Market

The model builds on the random matching model of Pissarides (1985). Time is continuous. There are two agents in the economy, firms and workers. They are infinitely-lived, risk neutral and discount future income at a rate $r > 0$. Workers search for jobs and firms for job applicants. The labor force size is normalized to 1. Labor market flows are determined by a matching function $m(v, u)$, where v and u denote the vacancy and unemployment rates. Market tightness θ is defined as the ratio of vacancies to unemployed workers, so $\theta = v/u$. Assume that the matching function is increasing in both its arguments, concave and that it displays constant returns. Workers find jobs at a rate $\lambda(\theta) = m(v, u)/u$ and firms receive applicants at a rate $q(\theta) = m(v, u)/v$. The properties of the matching function imply that $\lambda(\theta) = \theta q(\theta)$. If the labor market is tight (i.e. θ is high, so there are many vacancies for a given number of unemployed workers) workers find jobs more easily and firms have more difficulty finding applicants, so $\partial\lambda/\partial\theta \geq 0$ and $\partial q/\partial\theta \leq 0$. Separations occur at an exogenous rate s.[5] The paper only considers the steady-state, so for simplicity the derivations drop θ from the notation, except for section 8, which discusses labor market fluctuations.

Assume that workers gradually lose human capital during unemployment at a constant rate δ. The loss depends on the time the worker spends in unemployment, so workers' unemployment history plays an important role in the model. Throughout the paper unemployment history is defined as the cumulative duration of unemployment spells and is denoted by γ.

Workers are identical when they first join the labor market. However, they find and lose jobs randomly, so in equilibrium they accumulate different unemployment histories. Let $G^U(\gamma)$ and $G^E(\gamma)$ denote the endogenous distributions of unemployment history among unemployed and employed workers. To ensure that these distributions are stationary, assume that workers leave the labor force at a rate μ and are replaced by new workers with zero unemployment history.

Given the focus on residual wage dispersion, human capital in the model is net of other controls such as education. Thus, human capital depends only on unemployment history. Let $h(\gamma)$ denote workers' human capital. Normalizing $h(0) = 1$, the constant depreciation rate during unemployment implies that human capital is given by $h(\gamma) = e^{-\delta\gamma}$. When the worker and the firm meet they draw a productivity parameter p from a known distribution $F(p)$. The productivity of the match is determined by the product of the match-specific productivity p and the worker's human capital $h(\gamma)$, i.e. by $h(\gamma)p$.

Workers do not accumulate human capital when they are employed. This assumes that human capital losses are permanent. Section 3 provides empirical support for this assumption and shows that these losses are long-lived. Section 6 studies an extension of the model in which workers also accumulate human capital when they are employed, so that losses incurred during unemployment are not fully permanent. In this case workers have further incentives to gain employment and wage dispersion increases. However, most of the increase in wage dispersion comes from the effect of unemployment history.

Assume that workers' value of non-market activities is proportional to human capital, i.e. unemployed workers receive flow payments $bh(\gamma)$. With this assumption, payments during unemployment are proportional to workers' human capital level $h(\gamma)$ and decrease at the rate δ while they remain unemployed. This assumption greatly simplifies the analysis and allows for a closed-form solution. Section 5 solves the model with constant b numerically and assesses how this assumption changes the results.

Unemployed workers accept a job if the match-specific productivity is above their reservation productivity. Given that human capital decreases while the worker stays unemployed, the reservation productivity may depend on unemployment history γ. Section 2.1 assumes that wages are determined by Nash Bargaining, which implies that firms and workers choose the same reservation productivity. To avoid unnecessary complications in the notation, I use this result already and denote the reservation productivity for firms and workers by p^*_γ.

Let $U(\gamma)$ be the value function of an unemployed worker with unemployment history γ and $W(\gamma, p)$ the value function of an employed worker in a job with match-specific productivity p. The asset equation for the unemployed worker is

$$(r + \mu)U(\gamma) = bh(\gamma) + \lambda \int_{p^*_\gamma}^{p^{max}} (W(\gamma, y) - U(\gamma))dF(y) + \frac{\partial U(\gamma)}{\partial\gamma}. \tag{1}$$

The left-hand side of (1) represents the returns to being unemployed with unemployment history γ, taking into

[5] As Hornstein et al. (2011) show, adding endogenous separations as in Mortensen and Pissarides (1994) increases wage dispersion. However, the results are almost identical because wages are very persistent in the data.

account that workers leave the labor force at a rate μ—so $r+\mu$ can be interpreted as the effective discount rate. On the right-hand side, the first term corresponds to payments workers receive during unemployment. The second term captures the option value of being unemployed, namely that at rate λ the worker receives a job offer with expected gain $\int_{p^*_\gamma}^{p^{max}}(W(\gamma,y)-U(\gamma))dF(y)$. The last term captures the depreciation of the value of unemployment $U(\gamma)$ due to human capital losses.

Wages depend on workers' human capital and the match-specific productivity. Let $w(\gamma,p)$ denote the wage of a worker with unemployment history γ employed in a job with match-specific productivity p. The asset equation for the employed worker is

$$(r+\mu)W(\gamma,p)=w(\gamma,p)-s(W(\gamma,p)-U(\gamma)). \tag{2}$$

The intuition is similar. The worker receives a wage $w(\gamma,p)$ and loses the job at a rate s, which carries a net loss of size $W(\gamma,p)-U(\gamma)$.

To find successful candidates, firms post vacancies at cost k. As section 2.1 shows, with Nash Bargaining the reservation productivity p^*_γ is the same for firms and workers, so the firm hires a worker with unemployment history γ if $p\geq p^*_\gamma$. The firm receives applications from unemployed workers with unemployment history γ given by the endogenous distribution $G^U(\gamma)$. The asset equation for vacancies is

$$rV=-k+q\int_0^\infty\left[\int_{p^*_\gamma}^{p^{max}}(J(\gamma,y)-V)dF(y)\right]dG^U(\gamma). \tag{3}$$

Assume free entry in the market for vacancies, meaning that firms post vacancies until $V=0$.

When production begins, the worker produces $h(\gamma)p$. Firms pay wages to workers, so firms' profits are given by $h(\gamma)p-w(\gamma,p)$. The asset equation for a filled job position is

$$(r+\mu)J(\gamma,p)=h(\gamma)p-w(\gamma,p)-s(J(\gamma,p)-V). \tag{4}$$

The above equation captures that the filled position produces a flow $h(\gamma)p-w(\gamma,p)$, and that at rate s the job is destroyed, with a net loss of $J-V$.

2.1 Reservation productivity and wages

This section derives two important results about the reservation productivities. First, given the assumption that unemployment benefits and match productivities are proportional to human capital, the reservation productivity p^*_γ is independent of γ. This greatly simplifies the analysis. Second, I find an expression that links wages and the reservation productivity.

Wages are determined by Nash Bargaining. When the worker and the firm meet, if $p\geq p^*_\gamma$ production begins and they split the surplus. Given workers' bargaining strength β, the wage is the solution to

$$w(\gamma,p)=\underset{w(\gamma,p)}{\arg\max}(W(\gamma,p)-U(\gamma))^\beta(J(\gamma,p)-V)^{1-\beta}. \tag{5}$$

The surplus of the match is given by $J(\gamma,p)-V+W(\gamma,p)-U(\gamma)$. Nash Bargaining implies that the worker gets a share β of the surplus and the firm a share $1-\beta$. Combining (5) and the asset equations for the worker and the firm (2) and (4) gives the Nash Bargaining condition

$$\beta J(\gamma,p)=(1-\beta)(W(\gamma,p)-U(\gamma)). \tag{6}$$

In particular, (6) implies that the reservation productivity is the same for workers and firms. Substituting the asset equations (2) and (4) into the sharing rule (6) implies that wages are given by

$$w(\gamma,p)=\beta h(\gamma)p+(1-\beta)(r+\mu)U(\gamma). \tag{7}$$

Two properties about p^*_γ are useful. Consider a firm and a worker that meet and draw a productivity parameter p. Accepting the offer has a value $W(\gamma,p)$ to the worker. If she rejects the offer the worker walks away with $U(\gamma)$. It follows that p^*_γ satisfies $W(\gamma,p^*_\gamma)=U(\gamma)$. Similarly, if production starts the match has a value $J(\gamma,p)$ for the firm. If the firm does not hire the worker it gets the value of a vacancy $V=0$. Thus, the reservation productivity p^*_γ satisfies $J(\gamma,p^*_\gamma)=0$. Evaluating the asset equations for an employed worker and a filled job position (2) and (4) at $p = p^*_\gamma$, and using that $W(\gamma, p^*_\gamma) = U(\gamma)$ and $J(\gamma, p^*_\gamma) = 0$ implies that $(r + \mu)U(\gamma) = w(\gamma, p^*_\gamma)$ and $h(\gamma)p^*_\gamma = w(\gamma, p^*_\gamma)$. Combining these two results gives

$$(r + \mu)U(\gamma) = h(\gamma)p^*_\gamma. \tag{8}$$

Substituting (8) into (7) gives that wages $w(\gamma, p)$ and p^*_γ are linked through the following expression, $w(\gamma, p) = h(\gamma)(\beta p + (1 - \beta)p^*_\gamma)$.

Proposition 1. *The reservation productivity p^*_γ is independent of γ, i.e. $p^*_\gamma = p^*$.*

The proof is included in the theoretical appendix. The assumption of proportional benefits $bh(\gamma)$ is crucial for this result. Intuitively, in the wage bargaining process the worker expects to be compensated for giving up $U(\gamma)$. While the value of output $h(\gamma)p$ decreases with unemployment, so does the value of benefits $bh(\gamma)$. The first process raises the reservation productivity, as better matches are required if $h(\gamma)$ is low, and the second lowers it. Given that all quantities are proportional to $h(\gamma)$ these two opposing effects cancel out, and the reservation productivity stays constant. The appendix formally proves this result by guessing a solution and proving that the guess is correct. By contrast, when benefits are constant this result disappears. With constant benefits b, the worker expects to be compensated for giving up b, but the value of output $h(\gamma)p$ decreases with unemployment. Workers and firms require then better matches for longer unemployment histories. However, it is worth noting that while the reservation productivity is constant and independent of unemployment history, the reservation *wage* is given by $h(\gamma)p^*$ and is decreasing in unemployment history. Proposition 1 implies that equilibrium wages are given by

$$w(\gamma, p) = h(\gamma)(\beta p + (1 - \beta)p^*). \tag{9}$$

2.2 The Mm ratio

As Hornstein et al. (2011) show, in most search models one can derive the Mm ratio without assuming any distribution of match-specific productivities $F(p)$. This property represents a major advantage over other measures of wage dispersion, such as the variance. I show that the Mm ratio in the model displays the same property and is independent of the distribution $F(p)$.

As in Hornstein et al. (2011), define the replacement ratio ρ as the ratio of unemployment benefits to the average wage. Workers receive different unemployment benefits depending on their human capital. As a result, one must compare average benefits with average wages to find the replacement ratio. More specifically, ρ is given by $\rho = b\bar{h}/\bar{w}$, where $\bar{h} = E[h(\gamma)]$ is the average human capital and $\bar{w}$ the average observed wage, which is given by

$$\bar{w} = E(w(\gamma, p)|p \geq p^*) = \int_0^\infty \left(\int_{p^*}^{p^{max}} w(\gamma, p) \frac{dF(p)}{1 - F(p^*)} \right) dG^E(\gamma). \tag{10}$$

Taking expectations of wages in (9) gives that $\bar{w} = \bar{h}(\beta\bar{p} + (1 - \beta)p^*)$, where $\bar{p} = E(p|p \geq p^*) = \int_{p^*}^{p^{max}} p dF(p)/(1 - F(p^*))$. This implies that $b = \rho(\beta\bar{p} + (1 - \beta)p^*)$.

From (9) wages are proportional to human capital $h(\gamma)$. Taking the logarithm of (9), and using that $\log(h(\gamma)) = -\delta\gamma$, shows that log wages are linear in unemployment history γ with a coefficient of δ. Therefore, $h(\gamma)$ can be removed from wages by controlling for unemployment history in a Mincerian wage regression—as is done in the next section. The objective of this paper is to show that even after controlling for workers characteristics, and in particular after controlling for unemployment history and $h(\gamma)$, the model generates large amounts of wage dispersion. As a result, I focus on the dispersion of wages net of human capital, which are equal to $\beta p + (1 - \beta)p^*$. Therefore, the Mm ratio is given by

$$Mm = (\beta\bar{p} + (1 - \beta)p^*)/p^*. \tag{11}$$

Asset equation (4) and wages (9) imply that $(r + \mu + s)J(\gamma, p) = (1 - \beta)h(\gamma)(p - p^*)$. Substituting this result, the Nash Bargaining condition (6) and (8) into (1) implies

$$\frac{r + \mu + \delta}{r + \mu} p^* = b + \beta\lambda \int_{p^*}^{p^{max}} \frac{p - p^*}{r + \mu + s} dF(p). \tag{12}$$

The above equation allows for a simple expression for the Mm ratio

$$Mm = \frac{\frac{r+\mu+\delta}{r+\mu} + \frac{\lambda^*}{r+\mu+s}}{\rho + \frac{\lambda^*}{r+\mu+s}}, \tag{13}$$

where $\lambda^* = \lambda(1 - F(p^*))$ is the job finding rate. The appendix shows how to derive the Mm ratio from (12) in more detail.[6]

The Mm ratio in (13) measures wage dispersion without relying on any distributional assumption about $F(p)$. While it depends on the job finding rate $\lambda^* = \lambda(1 - F(p^*))$, this rate is eventually determined by data and no functional assumption for $F(p)$ is required. Substituting $\delta = 0$ yields the Mm ratio in the Pissarides (1985) model.[7] The relationship between the job finding and separation rates and the Mm ratio is intuitive. With higher λ^*, workers find jobs more quickly and the value of workers' outside option increases. Workers respond to the higher outside option by increasing their reservation productivity, which lowers wage dispersion and the Mm ratio. The Mm ratio is thus decreasing in λ^*. The separation rate has the opposite effect, so higher separation rates increase the Mm ratio. Finally, a higher δ makes unemployment more costly for workers. Workers are willing to lower their reservation productivity to leave unemployment more rapidly, which increases the Mm ratio.

One only requires knowledge of r, ρ, s, λ^*, μ and δ to assess the amount of wage dispersion in the model. Reliable estimates for these parameters can be found from data. The next section uses micro data to estimate them and quantify wage dispersion in the model.

3 Empirical work

The empirical work uses data from the 1968-1997 waves of the PSID. The data appendix describes the sample selection. The main motivation for using the PSID is that it follows workers over time. In the model wages depend on workers' unemployment history. Given the panel structure of the PSID, I construct workers' unemployment history to estimate the depreciation rate δ. The panel structure has the further advantage of allowing for fixed effects estimation. There may be some unobserved characteristics that make some workers more productive than others. If less productive workers are more likely to be unemployed, the estimation may be biased. By controlling for workers' constant unobserved characteristics, fixed effects estimation solves this problem. An additional concern may be that when a worker joins the sample, previous unemployment history is unknown. However, when a worker joins the sample, prior unemployment history remains constant in later observations, so worker fixed effects control for it.

3.1 Human capital depreciation rate

In the model, δ captures the percentage wage loss caused by unemployment history, which consists of the worker's accumulated unemployment spells. The PSID asks workers how many weeks they were unemployed in the previous year. The answers to this question allow me to construct workers' unemployment history. Let the variable $Unhis$ capture unemployment history in months. To estimate δ, regress the log of wages on $Unhis$ and other covariates X

$$\log W = -\delta \; Unhis + \beta X + \varepsilon. \tag{14}$$

[6] The Mm ratio in (11) can be thought of as the *conditional* Mm ratio, i.e. the ratio of the average to the minimum wage using wages net of human capital $h(\gamma)$. The conditional Mm ratio is the focus of this paper and Hornstein et al. (2011). Because the model assumes proportional benefits and that workers can have infinite lifetimes, some workers may accumulate infinite unemployment histories. Even though the mass of workers with such extreme unemployment durations is close to zero, these workers' human capital and reservation wage approach zero. As a result, the *unconditional* Mm ratio is infinite, where the *unconditional* Mm ratio is defined as the ratio of the average observed wage to the minimum observed wage without controlling for human capital $h(\gamma)$—i.e. the Mm ratio using wages in (9). However, the unconditional Mm ratio is finite and within observable values if one assumes either finite lifetimes or a lower bound for benefits, without affecting the *conditional* Mm ratio. In particular, section 5 proves that when benefits are constant the reservation wage w^* is always greater than benefits b. This implies that the unconditional Mm ratio is smaller than $1/\rho$. With a replacement rate $\rho = 0.4$, the unconditional Mm ratio is thus lower than 2.5, well within observed unconditional Mm ratios. Intuitively, if part of workers' benefits are constant, workers that accumulate too much unemployment history drop out of the labor force. This induces an upper bound on the amount of unemployment history workers may accumulate (or equivalently a lower bound for human capital), which leads to a bounded and realistic unconditional Mm ratio. The conditional Mm ratio is practically the same whether benefits are constant or proportional to human capital, as section 5 proves, so the results for the conditional Mm ratio are unaffected. Proposition 2 and section 5 provide further details. I am indebted to an anonymous referee for helpful comments and suggestions on this issue.

[7] With $\delta = 0$ the Mm ratio is $Mm = [1 + \lambda^*/(r + \mu + s)]/[\rho + \lambda^*/(r + \mu + s)]$, as in Hornstein et al. (2011).

In the above regression equation, δ gives the percentage wage loss for an additional month of unemployment history. Taking the logarithm of wages in (9) shows that log wages are linear in unemployment history γ, with a coefficient δ. Therefore, wage equation (9) is the theoretical equivalent to the regression in (14). This empirical strategy thus provides an estimate that can be consistently used in the calibration of the model.

The results are included in Table 1. Column (1) corresponds to the regression with worker fixed effects. Fixed effects regression controls for all constant characteristics, so in column (1) X also includes potential experience (cubic), regional dummies, and one-digit occupational dummies. The regression gives an estimate for δ of 0.0122, i.e. a 1.22% monthly depreciation rate. This is the value used in the calibration.[8]

TABLE 1. AROUND HERE

Alternative specifications of the regression in (14) show that the estimate for δ is very robust. The results are shown in Table 1. Column (2) gives the estimate for δ in the cross-sectional regression, without fixed effects. Not having fixed effects, the regression adds several time-invariant regressors to X. Covariates X in column (2) include the covariates in column (1) plus race dummies, educational dummies and year-dummies. Column (3) corresponds to the same regression as in column (1), but with two-digit occupations. The regression has fewer observations because it covers only the years 1975-1997, as the PSID did not record two-digit occupations before 1975. However, running column (1) for the same years as in column (3) gives very similar results. Column (4) includes the quadratic $Unhis^2$. The results are robust and significant by occupation, with estimates of δ ranging from 0.006 to 0.017. Including industry does not change the results.[9]

3.2 Long-lasting effects of unemployment history

The model in section 2 relies on permanent human capital losses. To investigate whether there is empirical support for this assumption, I regress log wages on two variables. One contains unemployment history in recent years, the other includes any older unemployment history, i.e. prior to what is considered recent years. If losses are long-lasting, older unemployment history should have an effect on wages, and its magnitude should be similar to the one estimated in (14).

The following estimation equation regresses log wages on: (1) total unemployment history accumulated in the previous 5 years (call it *recent* or *short-term* unemployment history and denote it by $Unhis^{ST}$); (2) total unemployment history accumulated prior to the previous 5 years (call it *old* or *long-term* unemployment history and denote it by $Unhis^{LT}$). The regression model is given by

$$\log W = -\delta^{ST}\ Unhis^{ST} - \delta^{LT}\ Unhis^{LT} + \beta X + \varepsilon. \tag{15}$$

The coefficients δ^{ST} and δ^{LT} capture the effect of recent and old unemployment history on wages. Vector X contains the same worker characteristics as in the estimation equation (14).

The results are included in table 1, column (5). As one would expect, recent unemployment has a strong effect on wages, with δ^{ST} equal to 0.0161. However, so does old unemployment history. The regression gives an estimate for δ^{LT} of 0.0104, which is close to the value for δ of 0.0122. This means that one month of

[8]Most estimates from the displacement literature are not directly comparable because they lack information on unemployment duration. However, two studies provide comparable estimates and find similar results. Neal (1995), Table 3, reports that an additional week of unemployment is associated with a 0.37% wage loss. This implies a monthly depreciation rate of 1.59%. Addison and Portugal (1989) find a similar monthly value of 1.44%. These estimates are larger compared to 1.22% in this paper, but otherwise similar. As mentioned in the introduction, these papers generally find larger values because they focus on displaced workers, a subset of the unemployed that are likely to suffer larger losses. Using their values strengthens the results, as section 4 shows.

[9]The PSID does not contain information on firms. It could be that lower wages are associated with higher unemployment history because firms experiencing negative shocks tend to both layoff more workers and pay lower wages if there is rent sharing. However, the analysis is able to identify this for sectors that receive negative shocks. The estimate for δ barely changes when controlling for industries and its interaction with time dummies. Further, the job displacement literature finds almost the same results when controlling for firm and industry fixed effects. These observations suggest that this should not be a source of concern. Another competing story is that wage losses take place immediately upon separation and are independent of unemployment duration. Unfortunately, the PSID does not have information on the number of unemployment spells. However, one can test this hypothesis by adding a dummy variable to the regression model in (14) that equals one if a worker experienced at least one unemployment spell in the previous year. If losses are sunk and unemployment duration has no effect, most of wage losses will be captured by the dummy variable instead of unemployment history—especially since most unemployment durations in the data are relatively short. This alternative regression yields a very similar and significant estimate for δ of 1.16%, suggesting that there is indeed duration dependence. As in Elsby, Hobijn, and Şahin (2013) and Shimer (2012), the separation rate in the PSID is extremely low compared to the job finding rate, so the probability of multiple spells during a period is very low and does not affect the results. I am thankful to an anonymous referee for helpful suggestions on this issue.

unemployment history accumulated more than 5 years ago is associated with a 1.04% wage loss, which is a very persistent effect. The results are similar when one sets 3 or 7 years as the threshold for recent years. These results are consistent with the findings of the job displacement literature and support the assumption of long-lasting effects of unemployment history on wages.[10]

3.3 Labor market transition rates

Given that the model shows a direct link between labor market flows and the Mm ratio, this section estimates labor market transition rates in the PSID. Section 4 uses these estimates to compare the Mm ratio in the model with its empirical counterpart in the PSID. Since labor market flows are different in the CPS, section 4 further quantifies the amount of wage dispersion using labor market flows from the CPS.

The estimation strategy is the following. The PSID gives workers' employment status at the time of the interview and the time elapsed between interviews. With these two pieces of information I estimate the transition rates as continuous time Markov chains.[11] This probabilistic model arises when workers can find and lose jobs (i.e. change state) between two employment status observations, and they find and lose jobs (i.e. change state) with a frequency given by Poisson processes. As a result, the assumptions in the probabilistic model and the model are the same. Let E and U denote employed and unemployed status, and let $P_{EE}(t)$ denote the probability of observing an employment status E at an interview and E again at the next interview, when the time between interviews is t. This probability takes into account that workers can find and lose jobs between employment status observations. The probability $P_{UE}(t)$ is defined similarly. These probabilities are given by

$$P_{EE}(t) = \frac{\lambda^*}{s+\lambda^*} e^{-(\lambda^*+s)t} + \frac{s}{s+\lambda^*}, \tag{16}$$

$$P_{UE}(t) = \frac{s}{s+\lambda^*} - \frac{s}{s+\lambda^*} e^{-(\lambda^*+s)t}. \tag{17}$$

Applying Maximum Likelihood Estimation to the above expressions gives the estimates for the separation and job finding rates s and λ^*.

3.4 Correcting for selection bias

Attrition in panels may lead to selection bias problems. Individuals drop from the sample, and the reason may not be random. What determines whether we observe an individual may be correlated with wages. To control for selection bias, consider the following Heckman (1979) two-steps procedure. I use the number of children under 18 and marital status as a determinant of whether the individual stays in the sample or not. Intuitively, married workers with young children are less likely to move and leave the sample than non-married workers without children. The regression model exploits the hypothesis that these variables affect the probability of sample selection, but are not directly correlated with wages, to produce Heckman's two-step correction term. More specifically, the two-step procedure runs the following probit regression

$$s_i^* = Z_i \gamma + v_i, \tag{18}$$

where s_i^* is the latent variable, such that $s_i^* > 0$ if the worker is present in the sample. The regressors in Z_i include those in X, plus number of children under 18, marital status and number of periods present in the sample. The number of children and marital status are highly significant in the first stage. The Likelihood-Ratio test is included in Table 1. The probit estimation produces the Heckman correction term $\hat{\lambda}$, that is then added as a covariate in (14). Column (6) in Table 1 displays the results. The estimates of δ in columns (2) and (6) are very close, so selection bias does not appear to affect the estimate for δ.

4 Quantitative results

To estimate the empirical Mm ratio, I use the 50-10 percentile ratio of the residual of log-wages in a Mincerian wage regression. Although the Mm ratio is the ratio of the average wage to the minimum wage, using the 10th percentile reduces the measurement error associated with the minimum observation. Consider the residual of wage regression (14) with fixed effects. Given that the dependent variable is log-wages, one must take the

[10] Section 6 studies wage dispersion when workers accumulate some human capital when they are employed in a job, so that human capital losses are less permanent. In this case wage dispersion is even larger.

[11] See Ross (2007) for an exposition of this type of processes.

exponential of the residual before extracting the 50th and 10th percentiles. The resulting 50-10 percentile ratio has a value of 1.34.[12]

First, let us quantify wage dispersion based on the PSID. The Mm ratio in (13) is uniquely determined by r, ρ, s, λ^*, μ and δ. The earlier estimations give δ, λ^*, and s. The value for μ is consistent with a working life of 40 years on average. The interest rate r corresponds to a 5% yearly rate, which implies a monthly value of 0.0041. Finally, as in Hornstein et al. (2011) assume that the replacement ratio ρ is 0.4.[13] Table 2 reports the results. With PSID flows, the model generates an Mm ratio of 1.15. By contrast, the Mm ratio in the baseline model equals 1.04.

TABLE 2. AROUND HERE

While the PSID is representative of the US economy, labor market flows are different in the CPS—the CPS is a very representative sample of the US labor market and provides, among others, the estimates for the unemployment rate in the US. In general, the PSID is a more stable sample of workers than the CPS. Both the job finding and separation rates are smaller in the PSID, but relative to the separation rate the job finding rate is higher in the PSID. As a result, I quantify the amount of wage dispersion consistent with CPS labor market flows.

Similar to Hornstein et al. (2011), assign a value of 0.43 to the job finding rate and a value of 0.03 to the separation rate. Table 3 reports the results. With CPS labor flows, the Mm ratio is around 1.05 in the baseline model, which corresponds to $\delta = 0$. The model with loss of human capital during unemployment delivers a significantly higher Mm ratio of 1.21. Empirically, Hornstein et al. (2011) report that the 50-10 percentile ratio in the CPS is between 1.7 and 1.9. Intuitively, the Mm ratio increases with CPS flows because what matters for wage dispersion is the relative size of λ^* and s, given values for μ and δ. While both λ^* and s are higher in the CPS, the ratio λ^*/s is higher in the PSID. Thus the increase in the Mm ratio.[14]

TABLE 3. AROUND HERE

Some wage dispersion remains unexplained with human capital decay, but the above results show that the model is a significant improvement over the baseline and accounts for around a third and half of the observed wage dispersion.

5 Labor market with constant benefits

The previous sections assumed that unemployed workers receive benefits that are proportional to their human capital. With this assumption reservation productivities are independent of unemployment history, thus simplifying the model and allowing for a closed form solution. To understand how this assumption may affect the results, note that a drop in unemployment benefits worsens the value of workers' outside option. Workers respond to this by lowering their reservation productivity. This property may suggest that by assuming decreasing benefits workers become less picky, thus potentially driving the results. To address this concern, this section studies a version of the previous model with constant benefits b and analyzes how this new assumption affects wage dispersion.

Reservation productivities depend now on unemployment history γ, so one can not simplify the notation p^*_γ. Equations (1) through (8) remain the same, except that $bh(\gamma)$ should be replaced by b. Following the same procedure as in section 2, wages are given by

$$w(\gamma, p) = h(\gamma)(\beta p + (1 - \beta)p^*_\gamma). \tag{19}$$

[12] Hornstein, Krusell, and Violante (2007) follow a similar approach and find a similar Mm ratio for the PSID after controlling for fixed effects. The Mm ratio does not change significantly when adding unemployment history because the Mincerian regression in (14) already includes a rich set of worker characteristics that determine human capital. Unemployment history is likely to be correlated with these worker characteristics. Therefore, some of the effects of unemployment history on wages are already captured by other worker characteristics when unemployment history is not included in the regression.

[13] This value comes from Shimer (2005). Some papers use higher values for ρ. Hall and Milgrom (2008) choose $\rho = 0.71$ and Hagedorn and Manovskii (2008) $\rho = 0.955$. As Hornstein et al. (2011) point out, with higher replacement ratios search models match the volatility of unemployment, but generate less wage dispersion, making the frictional wage dispersion problem worse. Section 8 discusses wage dispersion with higher replacement ratios in more detail.

[14] Using the comparable estimates in Neal (1995) and Addison and Portugal (1989) give larger Mm ratios. The depreciation rate from Neal (1995) implies that the Mm ratio equals 1.19 with PSID flows and 1.26 with CPS flows. Similarly, the depreciation rate in Addison and Portugal (1989) gives an Mm ratio of 1.17 with PSID flows and 1.24 with CPS flows.

The next proposition characterizes workers' search behavior, and provides some important results about reservation productivities p^*_γ. The following results are independent of any distributional assumption for $F(p)$.

Proposition 2. ***a.*** *There exists $\bar{\gamma}$ such that $p^*_{\bar{\gamma}} = p^{max}$, and the reservation wage of workers with $\gamma = \bar{\gamma}$ is given by $w(\bar{\gamma}, p^*_{\bar{\gamma}}) = b$. Furthermore, $\bar{\gamma} = -\log(b/p^{max})/\delta$.*
b. *The reservation productivity p^*_γ is increasing in γ.*
c. *The reservation wage $w(\gamma, p^*_\gamma)$ is decreasing in γ.*

Corollary. *The job finding probability $\lambda(1 - F(p^*_\gamma))$ is decreasing in γ.*

The proofs are included in the appendix, but the intuition is the following. When bargaining over wages, both workers and firms receive their outside option plus a share of the surplus of the match. The worker's outside option $U(\gamma)$ includes the constant benefits b, so the worker must always get a payment of b at the very least. While benefits are constant, the potential output $h(\gamma)p$ decreases with unemployment history. Eventually, if the worker stays unemployed for too long, no matches yield a productivity p that is high enough to cover b. At that point no matches are profitable, and the worker drops from the labor force. The proposition shows in result (a) that if unemployment history goes beyond $\bar{\gamma}$, workers leave the labor force. A similar mechanism explains result (b) that p^*_γ is increasing in γ. Benefits b are constant, but output $h(\gamma)p$ and the surplus of the match decrease with higher unemployment history γ. The higher γ gets, the better matches are required for the match to be profitable. In the previous sections, assuming decreasing benefits $bh(\gamma)$ lowered the reservation productivities by lowering the worker's outside option $U(\gamma)$. The additional assumption that benefits are proportional to $h(\gamma)$ gives the constant reservation productivity in section 2. Result (c) in the proposition shows that, while the reservation productivity is increasing in unemployment history, the reservation *wage* is decreasing in unemployment history, as one would expect from empirical observations. Finally, the result of the corollary, that the job finding probability is decreasing in unemployment history γ, follows from the increasing reservation productivity.[15]

Because the reservation productivity p^*_γ depends on γ if benefits are constant, a closed form expression is not straightforward, so the model must be solved numerically. Further, one needs to assume a functional form for the distribution of match-specific productivities $F(p)$. To simplify the calculations, assume that $F(p)$ follows a uniform with support $[0, p^{max}]$.[16] Consider (1), with constant b instead of $bh(\gamma)$, as a differential equation. Integrating it gives the following expression for $U(\gamma)$

$$U(\gamma) = \frac{b}{r+\mu} + \lambda \int_\gamma^{\bar{\gamma}} e^{-(r+\mu)(\Gamma-\gamma)} \left[\int_{p^*_\Gamma}^{p^{max}} (W(\Gamma, p) - U(\Gamma)) dF(p) \right] d\Gamma. \tag{20}$$

Substituting wages from (19) into the asset equation for $J(\gamma, p)$ implies that $(r+\mu+s)J(\gamma, p) = (1-\beta)h(\gamma)(p - p^*_\gamma)$. Combining this result with the Nash Bargaining condition (6) and (20) gives

$$p^*_\gamma h(\gamma) = b + \int_\gamma^{\bar{\gamma}} e^{-(r+\mu)(\Gamma-\gamma)} \left[\alpha \int_{p^*_\Gamma}^{p^{max}} h(\Gamma)(p - p^*_\Gamma) dF(p) \right] d\Gamma, \tag{21}$$

where $\alpha = \beta\lambda(r+\mu)/(r+\mu+s)$. Equation (21) can be solved numerically. Using numerical integration and iteration methods gives p^*_γ for a grid $\{\gamma_1 = 0, \gamma_2, ..., \gamma_n = \bar{\gamma}\}$ of the possible unemployment histories $[0, \bar{\gamma}]$. The theoretical appendix provides the details of the computational strategy.

5.1 Endogenous unemployment history distribution

With constant benefits, deriving the Mm ratio requires knowledge of the endogenous distributions of unemployment histories. Let $G^U(\gamma)$ and $G^E(\gamma)$ denote the cumulative density functions of the distributions of unemployment histories among unemployed and employed workers.

These endogenous distributions are determined by labor market flows. First, consider the group of unemployed workers with unemployment history lower than γ. In steady-state, stationarity requires that the flows

[15] The result of the corollary is supported by recent evidence from structural estimates in Alvarez, Borovickova, and Shimer (2014) and experimental results in Kroft, Lange, and Notowidigdo (2013).

[16] The parameter p^{max} plays no role in the results, as p^*_γ and p^{max} keep the same ratio.

in and out of this group must be equal. For $\gamma \leq \bar{\gamma}$, this condition implies the following flow equation

$$g^U(\gamma)u + \lambda \left[\int_0^{\gamma} (1 - F(p_\gamma^*)) dG^U(\gamma) \right] u + \mu G^U(\gamma) u = s G^E(\gamma)(1-u) + \mu. \tag{22}$$

The left-hand side corresponds to flows out of the group of unemployed workers with unemployment history lower than γ. The first term represents the workers in that group who have exactly γ unemployment history; the second term those who find a job; and the third term those who leave the labor force. The right-hand side of (22) captures the flows in. The first term corresponds to the employed workers with unemployment history lower than γ who lose their jobs and the last term to new entrants (workers leaving the labor force are replaced by new entrants with zero unemployment history).

Similarly, consider now the group of employed workers with unemployment history lower than γ. For $\gamma \leq \bar{\gamma}$, the following flow equation holds

$$(s + \mu) G^E(\gamma)(1-u) = \lambda \left[\int_0^{\gamma} (1 - F(p_\gamma^*)) dG^U(\gamma) \right] u. \tag{23}$$

The intuition is similar. The left-hand side of (23) captures the flows out of the group of employed workers with unemployment history lower than γ, and the right-hand side are the flows in.

Only workers with unemployment history lower than $\bar{\gamma}$ find jobs,[17] so for $\gamma > \bar{\gamma}$

$$g^U(\gamma)u + \lambda \left[\int_0^{\bar{\gamma}} (1 - F(p_\gamma^*)) dG^U(\gamma) \right] u + \mu G^U(\gamma) u = s G^E(\bar{\gamma})(1-u) + \mu, \tag{24}$$

$$(s + \mu) G^E(\bar{\gamma})(1-u) = \lambda \left[\int_0^{\bar{\gamma}} (1 - F(p_\gamma^*)) dG^U(\gamma) \right] u. \tag{25}$$

To simplify the exposition, define $\Phi(\gamma)$ as $\Phi(\gamma) = \mu[\lambda(1 - F(p_\gamma^*)) + s + \mu]/[s + \mu]$. The above flow equations give $g^U(\gamma)$ as a function of $g^U(\bar{\gamma})$

$$g^U(\gamma) = g^U(\bar{\gamma}) \ \exp\left[\int_\gamma^{\bar{\gamma}} \Phi(y) dy \right], \text{ for } \gamma \leq \bar{\gamma} \tag{26}$$

$$g^U(\gamma) = g^U(\bar{\gamma}) \ e^{\mu(\bar{\gamma} - \gamma)}, \text{ for } \gamma > \bar{\gamma}. \tag{27}$$

The derivations are included in the appendix. Integrating (26) between 0 and $\bar{\gamma}$, and (27) between $\bar{\gamma}$ and infinity gives the following identities

$$G^U(\bar{\gamma}) = g^U(\bar{\gamma}) \int_0^{\bar{\gamma}} \exp\left[\int_\Gamma^{\bar{\gamma}} \Phi(y) dy \right] d\Gamma, \tag{28}$$

$$1 - G^U(\bar{\gamma}) = \frac{1}{\mu} g^U(\bar{\gamma}). \tag{29}$$

Using the above equations gives $g^U(\bar{\gamma})$. Given $g^U(\gamma)$, combining (23) and (25) gives $g^E(\gamma)$

$$g^E(\gamma) = \frac{1 - F(p_\gamma^*)}{\int_0^{\bar{\gamma}} (1 - F(p_\Gamma^*)) dG^U(\Gamma)} g^U(\gamma). \tag{30}$$

5.2 Calibration and results

Except for b and λ, the calibration is the same as in section 2. The calibration of b and λ must match two targets. In line with the choice of a replacement ratio ρ in the previous sections, the first target imposes that ρ be around 0.40, i.e. benefits b must be around 40% of average wages $\bar{w}$, where average wages are given by

$$\bar{w} = \int_0^{\bar{\gamma}} \left[\int_{p_\Gamma^*}^{p^{max}} w(\Gamma, p) \frac{dF(p)}{1 - F(p_\gamma^*)} \right] dG^E(\Gamma). \tag{31}$$

[17] The results are the same if workers are replaced after $\bar{\gamma}$ by new workers with zero unemployment history.

The second target imposes that the average job finding rate $\lambda^e = \lambda \int_0^{\bar{\gamma}} (1 - F(p^*_\Gamma)) dG^U(\gamma)$ in the model must match its empirical counterpart. These two targets and the rest of equations in the model imply unique values for b and λ.

Figure 1 depicts the reservation productivities p^*_γ as a function of unemployment history γ over its support $[0, \bar{\gamma}]$. As proposition 2 shows, the reservation productivity is increasing in γ and reaches the maximum value p^{max} when $\gamma = \bar{\gamma}$. Figure 2 shows the probability density function $g^E(\gamma)$ as a function of γ over its support $[0, \bar{\gamma}]$.

FIGURES 1. AND 2. AROUND HERE

Similar to the model with proportional benefits, wages are proportional to human capital $h(\gamma)$, with $w(\gamma, p) = h(\gamma)(\beta p + (1-\beta) p^*_\gamma)$. The focus of the paper is on residual wage dispersion, and given that one can control for $h(\gamma)$ in wage regressions, I focus on the wage dispersion generated by $\beta p + (1-\beta) p^*_\gamma$. Using that the lowest reservation productivity corresponds to $\gamma = 0$, the Mm ratio is given by

$$Mm = \int_0^{\bar{\gamma}} \left[\int_{p^*_\Gamma}^{p^{max}} (\beta p + (1-\beta) p^*_\Gamma) \frac{dF(p)}{1 - F(p^*_\Gamma)} \right] dG^E(\Gamma) / p^*_0. \tag{32}$$

Tables 2 and 3 summarize the results for the Mm ratio with PSID and CPS flows. With constant benefits, the Mm ratio is 1.16 with PSID flows and 1.22 with CPS flows. Although unemployment punishes workers less when benefits are constant, the Mm ratio is similar than in the model with proportional benefits. Intuitively, this is due to the fact that workers with low unemployment history behave in a very similar way than workers in the model with proportional benefits—their reservation productivity is similar. Given that the distribution of workers is very concentrated on workers with low unemployment history, the Mm ratio is barely affected.[18]

6 Unemployment history and returns to experience

This section extends the model in section 2 and allows workers to accumulate human capital when they are employed. Workers recover some of the human capital they lose during unemployment, so human capital losses are not fully permanent. Assume that human capital depreciates at a constant rate δ_u during unemployment and appreciates at a rate δ_e when workers are employed. As a result, employment history—the cumulative duration of employment spells—becomes a new state variable. An important restriction on δ_e is that it must not exceed the effective discount rate $r + \mu$, otherwise the present value of wage payments is infinite. Denote unemployment and employment history by γ_u and γ_e. The assumptions about the human capital process imply that $h(\gamma_u, \gamma_e) = e^{\delta_e \gamma_e - \delta_u \gamma_u}$. As in the model with unemployment history, benefits are proportional to human capital, so unemployed workers receive flow payments $bh(\gamma_u, \gamma_e)$. Following the same procedure as in proposition 1, it is straightforward that the value functions are proportional to human capital $h(\gamma_u, \gamma_e)$ and that the reservation productivity is independent of (γ_u, γ_e). The Bellman equations are given by

$$(r + \mu) U(\gamma_u, \gamma_e) = bh(\gamma_u, \gamma_e) + \lambda \int_{p^*}^{p^{max}} (W(\gamma_u, \gamma_e, y) - U(\gamma_u, \gamma_e)) dF(y) - \delta_u U(\gamma_u, \gamma_e), \tag{33}$$

$$(r + \mu) W(\gamma_u, \gamma_e, p) = w(\gamma_u, \gamma_e, p) - s(W(\gamma_u, \gamma_e, p) - U(\gamma_u, \gamma_e)) + \delta_e W(\gamma_u, \gamma_e, p), \tag{34}$$

$$(r + \mu) J(\gamma_u, \gamma_e, p) = h(\gamma_u, \gamma_e) p - w(\gamma_u, \gamma_e, p) - sJ(\gamma_u, \gamma_e, p) + \delta_e J(\gamma_u, \gamma_e, p), \tag{35}$$

where p^* is the reservation productivity, which is independent of (γ_u, γ_e). Assuming that the worker and the firm share the surplus according to Nash Bargaining and combining the Bellman equations, one can prove that wages are proportional to human capital and are given by $w(\gamma_u, \gamma_e, p) = h(\gamma_u, \gamma_e)(\beta p + (1-\beta) p^*)$. As in the model with unemployment history, the focus of the paper is on residual wage dispersion. Given that wages are proportional to human capital $h(\gamma)$ and that unemployment history is observable, human capital $h(\gamma_u, \gamma_e)$ can

[18] Further, with constant benefits workers with below average unemployment history are less picky and have lower reservation productivity (Proposition 2). Given that the model tries to match a replacement ratio of 40%, workers with below average unemployment history must be less picky than workers in the model with proportional benefits, which requires a lower value for b. Because the Mm ratio relies on the lowest reservation productivity, this mechanism increases the Mm ratio. However, the resulting increase is mild. In particular, if b is chosen to match the replacement ratio in the model with proportional benefits, the same b almost matches the replacement ratio when benefits are constant, because a large mass of workers (those with low unemployment history) have almost the same reservation productivity.

be removed from wages using a Mincerian regression, as is done in section 3. Let $\hat{w} \equiv w/h$ denote wages *net* of human capital. Using the Bellman equations and the Nash Bargaining rule gives

$$\left(\frac{r+\mu+\delta_u}{r+\mu-\delta_e}\right)p^* = b + \lambda^* \int_{p^*}^{p^{max}} \left(\frac{\hat{w}(y)-p^*}{r+\mu+s-\delta_e}\right)\cdot\frac{dF(y)}{1-F(p^*)}, \tag{36}$$

where $\lambda^* \equiv \lambda(1-F(p^*))$ is the job finding rate. The Mm ratio is given by $Mm = \bar{\hat{w}}/p^*$, where $\bar{\hat{w}} \equiv E(\hat{w}|p \geq p^*)$ is the observed average wage *net* of human capital $h(\gamma)$, and is equal to $\bar{\hat{w}} = \int_{p^*}^{p^{max}} \hat{w}(y)dF(y)/(1-F(p^*))$. Using (36) gives the Mm ratio

$$Mm = \frac{\frac{r+\mu+\delta_u}{r+\mu-\delta_e} + \frac{\lambda^*}{r+\mu+s-\delta_e}}{\rho + \frac{\lambda^*}{r+\mu+s-\delta_e}}. \tag{37}$$

The appendix contains the details of the derivations.

From (37), one can recover the Mm ratio in the baseline model, the model with unemployment history and the model with returns to experience by setting the appropriate rate to zero. Substituting $\delta_e = 0$ into (37) gives the Mm ratio with unemployment history in (13). When $\delta_u = 0$, (37) gives the Mm ratio in the model with returns to experience in Hornstein et al. (2011), equation (6). Finally, setting $\delta_e = \delta_u = 0$ delivers the Mm ratio in the baseline search model.

Wage dispersion increases in the model with both unemployment history and returns to experience. Clearly, if we set δ_u equal to the depreciation rate δ in the model with unemployment history (section 2), the Mm ratio in (37) is always strictly greater than the Mm ratio with unemployment history alone given by (13). However, to allow for comparison between the extended model in this section and the one in the main text, consider the case where $\delta = \delta_e + \delta_u$. With this assumption, compared to an employed worker the human capital of an unemployed worker depreciates at the same rate in both models.[19] For standard parameter values wage dispersion is larger even with this restriction. Substitute $\delta = \delta_e + \delta_u$ into (37), which gives

$$Mm = \frac{\frac{r+\mu+\delta-\delta_e}{r+\mu-\delta_e} + \frac{\lambda^*}{r+\mu+s-\delta_e}}{\rho + \frac{\lambda^*}{r+\mu+s-\delta_e}}. \tag{38}$$

Take derivative with respect to δ_e to get

$$\frac{\partial Mm}{\partial \delta_e} = \frac{\rho[\delta(r+\mu+s-\delta_e)^2 + \lambda^*(r+\mu-\delta_e)^2] - \lambda^*[(r+\mu-\delta_e)^2 - \delta s]}{(r+\mu-\delta_e)^2[\rho(r+\mu+s-\delta_e)+\lambda^*]^2}. \tag{39}$$

The sign of the above derivative is ambiguous, but for standard parameter values it is clearly positive.[20] Intuitively, there are two effects at play when δ_e increases. First, an increase in δ_e lowers δ_u due to the restriction $\delta = \delta_u + \delta_e$. As a result wage dispersion decreases. Second, an increase in δ_e lowers the rate at which future payment flows are discounted, because of human capital accumulation. This lowers the reservation productivity and increases wage dispersion. Equation (39) shows that for standard parameter values the drop in the reservation productivity clearly dominates, so overall wage dispersion increases.

Given $\delta = 0.0122$ from section 3, the only parameter left to calibrate is δ_e. Following Hornstein et al. (2011), set δ_e equal to 0.0017 monthly, which implies that wages double over workers' working life. Table 3 reports the results. The Mm ratio is larger than in the baseline, although clearly most of the increase in wage dispersion comes from human capital depreciation. The Mm ratio equals 1.26, whereas it equals 1.21 when workers do not accumulate human capital during employment (i.e. when $\delta_e = 0$). With returns to experience and no human capital depreciation during unemployment, the Mm ratio equals only 1.076. The model with human capital accumulation alone is unable to generate sizable wage dispersion, as shown in Hornstein et al. (2011). This shows that the depreciation of human capital due to unemployment history is an important mechanism that generates sizable amounts of wage dispersion.

[19] With returns to experience, if a worker is unemployed her human capital depreciates at rate δ_u, whereas if she were employed her human capital would appreciate at a rate δ_e. With unemployment history alone, an unemployed worker loses human capital at a rate $\delta = \delta_u + \delta_e$, whereas her human capital would remain constant if she were employed.

[20] In particular, $\delta s - (r+\mu)^2 \leq -[(r+\mu-\delta_e)^2 - \delta s]$, since $0 \leq \delta_e < r+\mu$. If $\delta s - (r+\mu)^2 > 0$, the derivative $\partial Mm/\partial\delta_e$ is always positive. For standard calibrations $\delta s - (r+\mu)^2 > 0$ is clearly satisfied.

7 Unemployment history and on-the-job search

In baseline search models, workers hold their jobs until separation occurs, so workers must go through unemployment to change jobs. Hornstein et al. (2011) show that adding on-the-job search increases wage dispersion among identical workers. Intuitively, if workers can search for jobs when they are employed, they still hold the option to search when they accept an offer. Therefore, unemployed workers are willing to accept lower wages and wage dispersion increases. Hornstein et al. (2011) quantify wage dispersion in a search model with on-the-job search using empirical evidence on job-to-job transitions. The Mm ratio is similar to the value in the model with loss of human capital during unemployment, between 1.16 and 1.27. This section quantifies wage dispersion when both features are combined in a search model.

Assume now that workers can also search on the job in the model with unemployment history and proportional benefits $bh(\gamma)$ of section 2. Unemployed workers receive job offers at a rate λ^u, and employed workers receive job offers at a rate λ^w. Given the paper's focus on the steady state, without loss of generality assume that $F(p^*) = 0$. Therefore, λ^u is the job finding rate. This assumption makes the exposition simpler, but the results are the same without it. The asset equations for unemployed workers (1) and vacancies (3) remain unchanged. The asset equation for employed workers is now given by

$$\begin{aligned}(r+\mu)W(\gamma,p) = w(\gamma,p) + \lambda^w \int_p^{p^{max}} (W(\gamma,y) - W(\gamma,p))dF(y) \\ - s(W(\gamma,p) - U(\gamma)).\end{aligned} \tag{40}$$

Compared to (2), equation (40) captures that employed workers receive job offers at a rate λ^w. If the productivity is above the current level p they change jobs. Similarly, the asset equation for a filled vacancy is now given by

$$(r+\mu)J(\gamma,p) = h(\gamma)p - w(\gamma,p) - [s + \lambda^w(1-F(p))](J(\gamma,p) - V). \tag{41}$$

Intuitively, firms get a net flow $h(\gamma)p - w(\gamma,p)$. The job is destroyed either because of separation, which happens with frequency s, or because the worker finds a better job, which happens with frequency $\lambda^w(1-F(p))$.

As in section 2, reservation productivities are independent of unemployment history γ, so $p^*_\gamma = p^*$. The proof proceeds in the same way as in proposition 1. The intuition is similar. All payments, both during employment and unemployment, are proportional to human capital $h(\gamma)$. As a result, unemployment history γ is irrelevant for workers' reservation decision.

Using the asset equations one gets that wages take the form $w(\gamma,p) = h(\gamma)\hat{w}(p)$, where $\hat{w}(p)$ is independent of γ.[21] This shows that, as in the model with human capital losses during unemployment, log wages are linear in unemployment history with coefficient δ. Given the focus of the paper on wage dispersion among identical workers, I control for unemployment history and focus on the dispersion in wages $\hat{w}(p)$.

For a given $F(p)$, workers move jobs once they become employed. Let $G(p)$ denote the endogenous distribution of match productivities. The observed average of $\hat{w}(p)$, which is denoted $\bar{\hat{w}} = E(\hat{w}(p)|p > p^*)$, is thus given by $\bar{\hat{w}} = \int_{p^*}^{p^{max}} \hat{w}(y)dG(y)$. Given that $w(\gamma,p^*) = h(\gamma)p^*$, the Mm ratio equals $Mm = \bar{\hat{w}}/p^*$. Using the asset equation for unemployed workers (1) and the asset equation for employed workers (40) evaluated at $p = p^*$ gives the following equation

$$\begin{aligned}h(\gamma)p^* + \lambda^w \int_{p^*}^{p^{max}} (W(\gamma,y) - U(\gamma))dF(y) = \\ = \frac{r+\mu}{r+\mu+\delta}\left[bh(\gamma) + \lambda^u \int_{p^*}^{p^{max}} (W(\gamma,y) - U(\gamma))dF(y)\right].\end{aligned} \tag{42}$$

[21] Wages are the solution to the generalized Nash bargaining problem in (6). However, as Shimer (2006) shows, with Nash bargaining and on-the-job search the bargaining set is not convex and violates the Nash efficiency axiom, as in some cases the worker and the firm can agree on a wage that is strictly Pareto improving. To overcome this issue, I assume that job search is unobservable and that firms and workers cannot contract upon it, so workers must quit their job before negotiating with the new employer. An alternative assumption is that firms can make lump-sum transfers in a poaching auction, as in Moscarini (2005) and Papageorgiou (2014). Both assumptions would give the Nash bargaining solution and would not violate the Nash efficiency axiom, since on-the-job search is costless. I thank an anonymous referee for helpful suggestions on this issue.

It follows from the above equation that the Mm ratio is

$$Mm = \frac{1 + \frac{(\frac{r+\mu}{r+\mu+\delta})\lambda^u - \lambda^w}{r+\mu+s+\lambda^w}}{(\frac{r+\mu}{r+\mu+\delta})\rho + \frac{(\frac{r+\mu}{r+\mu+\delta})\lambda^u - \lambda^w}{r+\mu+s+\lambda^w}}, \tag{43}$$

where λ^u is the job finding rate and λ^w is the rate at which job offers arrive on the job. The appendix includes the details of the derivation.

By shutting down the appropriate channel, equation (43) provides the Mm ratio for the baseline search model, the model with unemployment history and the model with on-the-job search. If $\delta = 0$, the unemployment history mechanism is shut down and (43) gives the Mm ratio with on-the-job search. If $\lambda^w = 0$, on-the-job search is shut down and (43) corresponds to (13). Finally, setting both $\delta = 0$ and $\lambda^w = 0$ gives the Mm ratio in the baseline search model.

Wage dispersion, as measured by the Mm ratio in (43), depends uniquely on a few parameters, r, ρ, s, μ, λ^u, λ^w and δ. Further, it is independent of any distributional assumption about $F(p)$. The relationship between these parameters and wage dispersion is the same as before, only that now wage dispersion further depends on the arrival rate of offers on the job λ^w. Large values of λ^w imply that it is easier to switch jobs, making the option value of searching on the job larger. Workers thus accept lower wages and wage dispersion increases.

Similar to Hornstein et al. (2011), I follow Nagypal (2008) and choose the value for λ^w that is consistent with empirical job-to-job transitions. Using data from the Survey of Income and Program Participation (SIPP), Nagypal (2008) finds monthly job-to-job flows of around 2.2%. This implies a value for λ^w of around 0.07. The other parameters are the same as in section 4, in particular λ^u and s correspond to CPS flows. The model generates an Mm ratio of around 2.07 and accounts for all of the observed residual wage dispersion.[22]

8 Frictional wage dispersion and cyclical fluctuations

Hornstein et al. (2011) show that in search models frictional wage dispersion and unemployment volatility are closely related.[23] The baseline search model usually requires high values of the replacement ratio to match the cyclical volatility of unemployment. However, high values make the frictional wage dispersion problem worse because workers' outside option increases. As a result, workers wait longer to accept a job offer and wage dispersion decreases. Therefore, in search models there is a trade-off between matching the observed unemployment volatility and generating sizable wage dispersion.

This section calculates the Mm ratio in the model with both on-the-job search and unemployment history for the different values of the replacement ratio ρ used in the literature. Shimer (2005) uses a value of 0.40, which is the value used in the previous sections. Hall and Milgrom (2008) choose $\rho = 0.71$ based on data on the elasticity of labor supply. Finally, Hagedorn and Manovskii (2008) calibrate vacancy costs and get the highest value in the literature, around 0.95.

Table 4 gives the Mm ratio for the three values of the replacement ratio. The Mm ratio is 2.07 with a replacement ratio of 0.40, 1.84 if the replacement ratio is 0.71, and 1.68 with the highest replacement ratio of 0.95. Even for the highest value of the replacement ratio the amount of wage dispersion is large. Therefore, the model with both on-the-job search and unemployment history accounts for most of the observed residual wage dispersion.

TABLE 4. AROUND HERE

While the extension with on-the-job search is able to match the empirical wage dispersion closely, it could be the case that labor market fluctuations are lower than in the baseline model. To address this issue, I extend the model of section 5 to incorporate aggregate productivity and look at comparative statics.[24] In particular, the Bellman equations are the same except that now the match productivity is given by $h(\gamma)pz$, where as

[22] To illustrate the relative contribution of the model, when δ is equal to zero, i.e. there is on-the-job search but no loss of skills, the Mm ratio is 1.16, compared to 1.21 with loss of skills but no on-the-job search.

[23] See Shimer (2005), Mortensen and Nagypal (2007) and Pissarides (2009) for details on the unemployment volatility puzzle. Although unemployment volatility is low in the textbook search and matching model, the performance of RBC models improves with frictional labor markets, see Merz (1995) and (1999).

[24] Although wage dispersion is similar whether benefits are proportional or constant, the model with proportional benefits is not well suited to generate large labor market fluctuations, as it implies that benefits are procyclical. The Shimer puzzle arises because in expansions workers' outside option increases and workers are able to capture most of this increase through Nash Bargaining. Procyclical benefits would raise workers' outside option further and thus lower labor market fluctuations.

in Mortensen and Pissarides (1994) and chapter 2 of Pissarides (2000), z captures aggregate productivity. Combining (3) with the free entry condition $V = 0$ gives the job creation condition, which determines the equilibrium market tightness θ

$$\frac{k}{q(\theta)} = (1-\beta)\int_0^{\bar{\gamma}} \left[\int_{p_\Gamma^*}^{p^{max}} \left(\frac{h(\Gamma)(y - p_\Gamma^*)z}{r+\mu+s} \right) dF(y) \right] dG^U(\Gamma). \tag{44}$$

Initially aggregate productivity z is normalized to be equal to 1. Assume that the job offer arrival rate takes the form $\lambda(\theta) = m_0\theta^{1-\eta}$, which implies that $q(\theta) = m_0\theta^{-\eta}$. Based on Petrongolo and Pissarides (2001) and similar to Pissarides (2009), calibrate η to be 0.5 and set $\beta = \eta$. Given that the model must match the empirical job finding rate, one can normalize $\theta = 1$ as in Shimer (2005).[25] The remaining parameters c and m_0 are calibrated to match the empirical job finding rate and to ensure that the job creation condition holds.

Consider now an increase in z, in particular assume z equals 1.01 (i.e. a 1% increase). Given the new aggregate productivity, I use the algorithm in section 5 and numerically solve (44) by iteration to calculate the new reservation productivities p_γ^* and equilibrium market tightness θ.[26] The response of market tightness to the increase in z is larger in the model with unemployment history than in the baseline model (δ equal to 0), even after taking into account the endogenous response of labor productivity.[27] With a replacement ratio of 0.4, equilibrium tightness increases by 3.24% given a 1% increase in the endogenous labor productivity. By contrast, in the baseline model equilibrium tightness increases by 1.73%. This value is similar to the findings in Mortensen and Nagypal (2007) and Pissarides (2009), who report an elasticity of 1.71 and 1.72 respectively.[28] For a replacement ratio of 0.6, which lies at the lower bound of the values in Hall and Milgrom (2008), the equilibrium market tightness increases by 7.11% for a 1% increase in labor productivity, close to the empirical elasticity of 7.56.[29]

Intuitively, the model with human capital depreciation generates a higher level of fluctuations through the following two mechanisms. First, when aggregate productivity is low workers experience more and longer unemployment spells due to the low job finding rates and higher reservation productivity. The human capital of the pool of unemployed workers thus worsens in recessions and firms expected profits from hiring shrink. As a result, firms have fewer incentives to post vacancies compared to the model with no unemployment history. Second, workers with long unemployment histories have a value of non-market time that is close to their productivity in the market. This creates an endogenous measure of workers similar to workers in Hagedorn and Manovskii (2008). As in their paper, this leads to some endogenous wage rigidity and larger labor market fluctuations. Overall, the interaction of these two mechanisms increases volatility in the labor market.[30]

9 Conclusion

Motivated by the findings in Hornstein et al. (2011) that baseline search models fail to generate significant wage dispersion, this paper investigates how much wage dispersion arises if workers lose some skills during unemployment. I develop a search model in which workers gradually lose some human capital while they stay unemployed. The wage losses caused by unemployment matter for workers' search behavior. Knowing that unemployment hurts their earnings, workers lower their reservation productivity and accept lower wages to leave unemployment more quickly. The model generates significant wage dispersion among identical workers and is an important improvement over baseline search models. Using the measure proposed by Hornstein et al. (2011), the Mm ratio, the paper derives a closed form expression for wage dispersion that depends only on a

[25] It is clear by looking at the job creation condition that in steady state θc must equal a value that depends uniquely on model parameters and the job finding rate, hence the normalization. One can alternatively choose an empirical value for θ and choose the value for c that satisfies the job creation condition, as in Pissarides (2009). The results are unchanged.

[26] More specifically, I guess an initial value for θ. This guess implies a value for $\lambda(\theta)$, which can then be used to derive the new reservation productivities p_γ^*. Given these reservation values one can derive the new equilibrium θ. This routine is iterated until convergence.

[27] That is, in each scenario the percentage change in market tightness is divided by the percentage change in the endogenous labor productivity to get the "implied" elasticity. If one did not take into account that labor productivity is endogenous, the difference between the two models would be even larger.

[28] To allow for a comparison between the baseline and the model with unemployment history, in each simulation b and m_0 are chosen so that all economies have initially the same job finding rate and replacement ratio.

[29] The endogenous distribution of unemployment history is a state variable, which complicates the study of the model's business cycle dynamics. Although the comparative statics exercise shows that the response of unemployment is larger in the model with human capital, an analysis of the fully dynamic model is beyond the scope of the paper and is left for future research.

[30] I am indebted to the associate editor and an anonymous referee for helpful comments and suggestions on this issue.

few parameters. Combining the theoretical predictions of the model and estimates from micro data, the model explains between a third and half of the observed residual wage dispersion, whereas the baseline model explains only 6%. When workers can also search on-the-job the model accounts for the observed residual wage dispersion. Even for high values of non-market time the framework with both unemployment history and on-the-job search generates large amounts of wage dispersion. The paper thus addresses the trade-off in search models between matching frictional wage dispersion and the cyclical behavior of unemployment and vacancies.

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Table 1: THE EFFECT OF UNEMPLOYMENT HISTORY ON WAGES

	(1)	(2)	(3)	(4)	(5)	(6)
Unhis	-.0122 (.00043)	-.0107 (.00098)	-.0143 (.00057)	-.0164 (.00082)		-.0101 (.00034)
$Unhis^2$				.0001 (.00002)		
$Unhis \leq 5$ years					-.0161 (.00064)	
$Unhis > 5$ years					-.0104 (.00049)	
Occ 1-Digit	yes	yes		yes	yes	yes
Occ 2-Digit			yes			
Fixed Effects	yes		yes	yes	yes	
Heckman						yes
N	34,542	42,203	25,178	34,542	34,542	43,260
LR test, $\chi^2(1)$						157.28

Note.- *Unhis* contains unemployment history in months. $Unhis \leq 5$ corresponds to the variable $Unhis^{ST}$ in regression (15) and includes unemployment history in the last 5 years. $Unhis > 5$ corresponds to the variable $Unhis^{LT}$ in regression (15) and includes unemployment history prior to the last 5 years. Numbers in brackets indicate standard errors. The $\chi^2(1)$ is the likelihood ratio test for selection bias. *N* shows the number of observations in the regression. Section 3 describes the regressions in each of the columns.

Table 2: The Mm ratio with PSID flows

Empirical				1.3367
Baseline model				1.0357
	$\lambda^* - 1std$	1.0380	$s - 1std$	1.0349
	$\lambda^* + 1std$	1.0336	$s + 1std$	1.0364
Proportional benefits $bh(\gamma)$				1.1529
	$\lambda^* - 1std$	1.1628	$s - 1std$	1.1497
	$\lambda^* + 1std$	1.1441	$s + 1std$	1.1560
Constant benefits b				1.1600
	$\lambda^* - 1std$	1.1686	$s - 1std$	1.1567
	$\lambda^* + 1std$	1.1522	$s + 1std$	1.1632

Note.- Table 2 shows the Mm ratio when the job finding and separation rates are taken from PSID estimates. Baseline model refers to the model with δ equal to 0. The $bh(\gamma)$ and b models correspond to the models with proportional and constant benefits. The cell $\lambda^* - 1std$ gives the Mm ratio evaluated at the value of λ^* minus one standard deviation of the estimate for λ^* in the PSID.

Table 3: THE Mm RATIO WITH CPS LABOR FLOWS

Source	Mm ratio
Empirical	1.80
Baseline model	1.05
Proportional benefits $bh(\gamma)$	1.210
Constant benefits b	1.219
Returns to experience and unemployment history	1.258

Note.- Table 3 shows the Mm ratio when the job finding and separation rates are taken from Shimer (2005). The empirical value is taken from Hornstein et al. (2011). Baseline model refers to the model with δ equal to 0. The $bh(\gamma)$ and b models correspond to the models with proportional and constant benefits. The last row corresponds to the model with accumulation and depreciation of human capital.

Table 4: The Mm ratio with unemployment history and on-the-job search

Calibration source	ρ	Mm ratio
Shimer (2005)	0.40	2.07
Hall & Milgrom (2008)	0.71	1.84
Hagedorn & Manovskii (2008)	0.95	1.68

Note.- The table gives the value of the Mm ratio for different values of the value of non-market time using CPS labor market flows.

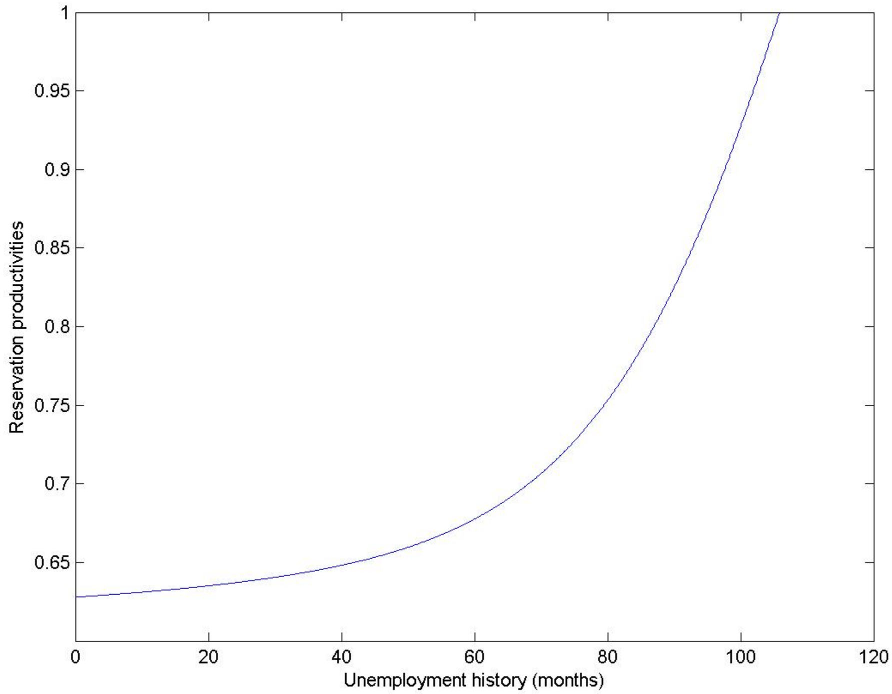

Figure 1: Reservation productivities p^*_γ with constant b

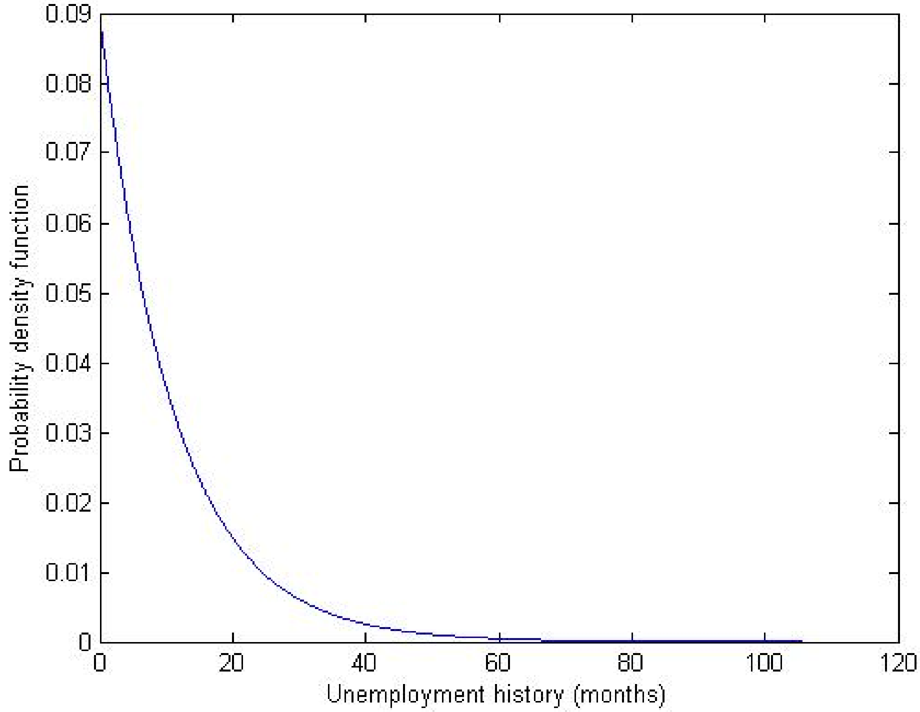

Figure 2: Distribution of unemployment history with constant b