What Do Worker Flows Say about the Wage Gains from Unemployment Insurance?

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This version: Feb., 2019

Very Preliminary and Incomplete

Abstract

How large are the effects of unemployment insurance on re-employment wages? Search theory holds that UI increases accepted wages by making workers more selective about the jobs they accept. We show that the standard search model puts strong testable restrictions on the magnitude of this selectivity effect, given observed worker flows. A simple formula links the effect of UI on wages to its effect on job-finding hazard and to the size of frictional wage dispersion. Given the model-implied magnitude of the latter, the implied wage gain from UI cannot be very large. Our own empirical analysis using SIPP shows that, for high-wealth workers, the effects of UI on both duration and wages are close to zero, consistent with the model's predictions. However, for liquidity-constrained workers, the estimated wage effect of UI is substantially larger than what a standard search model implies given its estimated effect on the job-finding hazard. We conclude that large estimated wage gains from UI are likely not due to selectivity alone.

JEL Classification: *Keywords:* Unemployment insurance, search frictions, frictional wage dispersion.

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1 Introduction

A robust prediction in search models of unemployment is that unemployment insurance (UI) affects average future wages upon finding a job. The central insight generating this result is that workers face a tradeoff between the rate at which they find a job and the wage they receive. Unemployment insurance alters this tradeoff by making workers more selective about the wages they accept, thereby raising the average accepted wage while lowering the job-finding probability. We refer to this effect on wages and job-finding rates as the *selectivity effect* of UI. The magnitude of such selectivity-driven wage gains from UI is of interest for policy analysis, since it points to a benefit of unemployment insurance beyond its consumption smoothing effect. A substantial body of empirical work has therefore investigated the intriguing question of whether UI indeed increases wages in the data, with mixed results.[1]

In this paper, we contribute to this research by asking two complementary theoretical questions. First, what magnitude of wage gains from UI should we expect theoretically? In other words, what magnitude of wage elasticities would canonical search models would predict, when reasonably parameterized to be consistent with observed worker flows? Second, we are interested in using theory to disentangle the *channels* through which UI affects wages. The selectivity effect described above is one natural channel, but it is not the only mechanism through which wages could respond to UI. For example, a standard Nash bargaining model predicts that UI raises wages by affecting the worker outside option in bargaining, and hence would raise wages even if it had no affect on average match quality. Does search theory make testable predictions about the relative size of these mechanisms? We address these questions by showing theoretically that prominent search models do make sharp predictions regarding the magnitude of the selectivity effect. Next, we assess these predictions using our own empirical estimates from the Survey of Income and Program Participation.

Our analysis centers around two key objects of interest. The first is the elasticity of the job-finding hazard with respect to unemployment benefits, henceforth the hazard elasticity, which has been estimated in numerous empirical studies. The second is the elasticity of the average post-unemployment wage with respect to unemployment benefits, henceforth the wage elasticity. The key insight is that the standard search model puts testable restrictions on what *combinations* of these two quantities can be observed in the data. Specifically, we show that the wage elasticity is proportional to the hazard elasticity, where the factor of proportionality is a simple function of a measure of frictional wage dispersion, namely

[1] In particular, Nekoei and Weber (2017), discussed in more detail below, find large positive effects of UI on wages, while other studies find coefficients that are close to zero or even negative.

the mean-min wage ratio. In other words, given the mean-min ratio, the standard search model implies a very simple mapping between the two elasticities. Furthermore, it is known from Hornstein et al. (2011) (henceforth HKV) that the model-implied mean-min ratio can be calculated as a function of observed worker flows for a large family of search models. For any given observed hazard elasticity, a smaller mean-min ratio implies a smaller wage elasticity. Intuitively, an increase in unemployment insurance moves the worker along the job-finding hazard/average wage locus in the direction of a lower job-finding probability and higher wages. The slope of this locus depends on how dispersed wages are: if wages are not very dispersed, making workers more selective about which wages they accept does not result in large expected wage gains. As a result, to the extent that UI affects both wages and job-finding rates through selectivity, the magnitude of these effects is disciplined by observed worker flows.

This argument enables us to make testable predictions about the size of the model-implied selectivity effect. Suppose that a particular search model implies a small mean-min ratio (in fact, HKV show that this is the case for the baseline sequential search model). Such a model therefore implies an upper bound on the wage elasticity for any given hazard elasticity. If an empirical estimate of the hazard elasticity is available, we can calculate the model-implied on the selectivity effect of UI on wages. If this is smaller than the true wage elasticity in the data, the discrepancy points to wage gains from UI that are *not* due to selectivity. We implement this reasoning empirically by empirically estimating the wage elasticity and the hazard elasticity in SIPP. For high-wealth individuals, the estimates for both the wage elasticity and the hazard elasticity are not significantly different from zero. However, for low-wealth individuals, we estimate a large and positive wage elasticity, and, similarly to Chetty (2008), a positive but modest hazard elasticity. The combination of these two estimates can be rationalized by our formula if the mean-min ratio is at least 2. However, as shown by HKV, the baseline sequential search model would imply a significantly smaller mean-min ratio. Adding on-the-job search to the model increases the model-implied mean-min ratio and hence the model-implied wage elasticity, but a significant discrepancy remains. We conclude that the standard sequential search model - in which the only wage gain from UI *is* due to selectivity - does not rationalize the observed combination of a large wage elasticity and a modest hazard elasticity.

We also assess the ability of other prominent search models to generate a large selectivity effect. First, consider directed search models. In such models, an unemployed worker targets a particular wage, hence there is not necessarily a relationship betwesn wage dispersion and the wage elasticity. Nonetheless, we show that the model still implies a tight link between the wage elasticity and the hazard elasticity, for much the same reason as a random search model.

A worker faces a tradeoff between the wage and the job-finding hazard, and an increase in UI moves the optimal choice along the wage-hazard locus. We show that the slope of this wage hazard locus is still disciplined by observed worker flows, hence a given decrease in the hazard cannot imply too large an increase in the wage. We then turn to two models that break this tight link between the job-finding hazard and the accepted wage: Nash bargaining and sequential auctions. A Nash bargaining model implies that UI affects wages through the outside option in addition to the selectivity effect, hence the hazard elasticity no longer constrains the wage elasticity. Finally, we consider sequential auctions models along the lines of Postel-Vinay and Robin (2002), with occasionally renegotiated take-it-or-leave-it offers. It is well known that such models can generate a much larger magnitude of frictional wage dispersion by inducing workers to accept low initial wages. Interestingly, we show that the ability to generate large wage dispersion does not necessarily translate into the ability to generate a large wage elasticity to UI. In a sequential auctions models, workers encountering higher-productivity firms have an incentive to accept lower wages. Since initial accepted wages are decreasing in productivity, the selectivity effect of UI on wages is typically negative. The sequential auctions model may well generate a large and positive wage elasticity due to the outside option effect, since firms make workers take-it-or-leave-it offers. But, as in the Nash bargaining model, this effect is distinct from the selectivity effect. To sum up, given observed worker flows, the search models we consider either do not generate a large wage elasticity, or generate it through a channel other than the selectivity effect.

2 The Earnings-Hazard Locus

This section illustrates, under minimal assumptions, that a standard reservation-wage model generally implies a relationship between the wage elasticity and the hazard elasticity. Consider a setting in which an unemployed worker receives wage offers at rate λ_u. Conditional on receiving an offer, he draws a wage from a distribution F, which we assume to be differentiable with density f. Suppose that the worker accepts if and only if the wage is greater than or equal to a reservation wage w_R. In this setting, the probability of becoming employed is

$$H = Prob\left(w \geq w_R\right) = \lambda_u \left(1 - F\left(w_R\right)\right), \tag{2.1}$$

and the average wage accepted out of unemployment is

$$\overline{w} = \mathbb{E}\left(w | w \geq w_R\right) = \frac{1}{1 - F\left(w_R\right)} \int_{w_R}^{\infty} w f\left(w\right) dw \tag{2.2}$$

Define the mean-min ratio $\mu = \overline{w}/w_R$. We can now compare the changes in $\ln \overline{w}$ and $\ln H$ resulting from the same small change in $\ln w_R$. Differentiating (2.1) with respect to w_R, we obtain

$$\frac{d \ln H}{d \ln w_R} = -\frac{w_R f(w_R)}{1 - F(w_R)} \tag{2.3}$$

Similarly, differentiating (2.2) with respect to w_R, we obtain

$$\frac{d\overline{w}}{dw_R} = (\overline{w} - w_R) \frac{f(w_R)}{1 - F(w_R)}, \tag{2.4}$$

which, expressed in elasticity terms, gives

$$\frac{d \ln \overline{w}}{d \ln w_R} = \frac{w_R}{\overline{w}} \frac{d\overline{w}}{dw_R} = \left(\frac{\mu - 1}{\mu} \right) \frac{w_R f(w_R)}{1 - F(w_R)} \tag{2.5}$$

Combining (2.3) with (2.5), we get

$$d \ln \overline{w} = -\left(\frac{\mu - 1}{\mu} \right) d \ln H \tag{2.6}$$

Suppose now we are interested in the response of the average wage to unemployment benefits, b. Denote by $\epsilon_{w,b} = d \ln \overline{w}/d \ln b$ the elasticity of average wages with respect to unemployment benefits, and by $\epsilon_{H,b} = d \ln H/d \ln b$ the elasticity of the unemployment exit hazard with respect to unemployment benefits. We then have:

Result 1. *Assume that b affects both $\overline{w}$ and H only through w_R. Then*

$$\epsilon_{w,b} = -\left(\frac{\mu - 1}{\mu} \right) \epsilon_{H,b} \tag{2.7}$$

This simple formula shows that there is a simple mapping between $\epsilon_{H,b}$ and $\epsilon_{w,b}$, and that this mapping depends on a measure of frictional wage dispersion. To understand the intuition for this result, it is useful to think of the worker as facing a tradeoff between the job-finding probability H and the average accepted wage $\overline{w}$. An increase in the reservation wage moves the worker along the H-$\overline{w}$ locus in the direction of lower H and higher $\overline{w}$. In other words, to the extent that UI affects $\overline{w}$ through increased selectivity, it must also affect H. Moreover, the *slope* of this wage-hazard locus depends on how dispersed wages are.[2] If wages are not very dispersed, an increase in the reservation wage leads to a fall in the job-finding probability without a large corresponding rise in the expected wage. To illustrate

[2] This logic and the ensuing discussion assumes that search is random. The directed search model we consider in section 4.1 displays the same intuition in even starker terms, since there the worker literally faces a tradeoff between the job-finding probability and the wage.

this intuition in the simplest possible way, consider a two-point distribution: the offered wage is w_l with probability $1-\pi$ and $w_h > w_l$ with probability π. A rise in the reservation wage from w_l to w_h lowers the job-finding probability from 1 to π; but the size of the associated expected wage increase, from $\pi w_h + (1-\pi) w_l$ to w_h, depends additionally on the magnitude of w_h relative to w_l. In short, increased selectivity does not lead a large expected wage gain if workers have nothing to be selective about.

The formula in (2.7) requires a minimal set of economic assumptions, as it relies on the mathematical link between $Prob\,(w \geq w_R)$ and $\mathbb{E}\,(w|w \geq w_R)$. In particular, so far we have placed no restrictions on the decision-theoretic process that determines the reservation wage rule, nor on how the reservation wage responds to unemployment insurance. Instead, what is key is that the worker's acceptance strategy is in fact *a reservation wage rule*.[3] The important substantive assumption is that unemployment insurance affects both $\overline{w}$ and H only through the reservation wage; in other words, both $\epsilon_{w,b}$ and $\epsilon_{H,b}$ are entirely due to the selectivity effect. In this environment, this would amount to assuming that unemployment insurance does not affect the arrival rate λ_u, nor does it affect the distribution of wages faced by the worker, F. Of course, this assumption needs to be relaxed in many prominent search models; in those cases, one can think of (2.7) as a useful benchmark. For example, the job offer arrival rate may depend on the worker's endogenous choice of search effort, which in turn responds to unemployment insurance. Unemployment insurance would then affect the job-finding rate through both the reservation wage rule and search effort, but only the former effect matters for the expected wage. In this case (2.7) likely places an *upper bound* on $\epsilon_{w,b}$. On the other hand, it is also possible for unemployment insurance to affect wages directly independently of the job acceptance probability. In particular, such an effect of UI on wages is a feature of the standard Pissarides model with Nash bargaining, as well as models with occasionally renegotiated take-it-or-leave-it offers such as Postel-Vinay and Robin. In such cases, UI can raise wages directly through its effect on the worker outside option without any corresponding effect on the job-finding hazard. We explore this mechanism in detail in Sections 4.2 and 4.3. In short, to the extent that the effect of UI is driven *only by worker selectivity*, its magnitude is disciplined by the formula in (2.7).

The relationship provided by (2.7) thus serves as a testable prediction of the standard reservation-wage model regarding the magnitude of the selectivity effect of UI. In particular, it provides a means of predicting $\epsilon_{w,b}$ given $\epsilon_{H,b}$ and μ; conversely, knowledge of both $\epsilon_{H,b}$ and $\epsilon_{w,b}$ enables a researcher to assess the empirical performance of a particular model if

[3]For example, we have so far made no assumptions about risk aversion, or about the absence or presence of on-the-job search. These assumptions would affect the relationship in (2.7) only to the extent that they affect μ.

it makes testable predictions for μ. This is crucial, since it is well known from HKV that many search models do make sharp predictions for μ given other observables, namely the replacement rate and worker flows.[4] We exploit the insight of HKV below in Section 3, when we derive the implications of (2.7) for the standard sequential search model. In particular, as shown in HKV, the baseline search model implies that μ cannot be very large, which in turn means that $\epsilon_{w,b}$ cannot be too large for a given $\epsilon_{H,b}$. In other words, if the model implies small frictional wage dispersion, then it cannot generate a large selectivity effect of UI on wages, unless there is a *very* large selectivity effect of UI on the job-finding rate. An extension allowing for on-the-job search in section 3.1 allows the model to be consistent with larger value of μ; as a result, it allows the model to be consistent with a larger effect of UI on post-unemployment wages. Interestingly, the effect of UI on the average steady-state *lifetime wage* satisfies the same formula as in the model without on-the-job search, because on-the-job search has two opposing effects on this elasticity. It allows the model to be consistent with a larger wage dispersion, which, as explained above, makes it consistent with a larger wage elasticity. On the other hand, on-the-job search directly dampens the effect of UI on lifetime wages, since it mutes the importance of initial accepted wages for lifetime wages. As a result, UI has a larger effect on initially accepted wages than it does not steady-state lifetime wages. Moreover - as pointed out in HKV and as confirmed in our own empirical analysis - even with on-the-job search, this baseline model falls short of generating the mean-min ratio in the data.

Motivated by these observations, in Section 4 we next consider other prominent search models that do not fit exactly into the framework required for (2.7). First, in section 4.1 we consider directed search. With directed search, the worker no longer uses a reservation wage strategy, but still faces a tradeoff between the job-finding probability and the wage received. As a result, we will show that the model still implies a tight link between the wage elasticity and the hazard elasticity. Moreover, this link is characterized by the same formula as for the random search model, hence directed search implies elasticities of similar magnitudes to random search. We then consider two models that break this strong link by allowing for wages to be determined ex post. In Section 4.2 we consider Nash bargaining. Bargaining leads to an additional, direct effect of UI on wages through the worker outside option, which operates independently of the selectivity effect. In this case, $\epsilon_{w,b}$ can be substantially larger than predicted by (2.7). In Section 4.3 we consider a sequential-auctions model along the lines of Postel-Vinay and Robin. As with Nash bargaining, (2.7) no longer serves as a sufficient statistic for the wage elasticity, because take-it-or-leave-it offers lead to an independent effect

[4] A key advantage of this approach is that it does not require taking a stand on the distribution F; in particular, it does not require the knowledge of the hazard ratio $f(w_R)/(1-F(w_R))$.

of UI on wages through the outside option. While the model can be consistent with a larger wage dispersion (as is well recognized in the literature), this is accomplished by inducing workers to accept lower wage offers out of unemployment. In particular, initially accepted wage offers are decreasing in productivity, and hence the selectivity effect of UI on wages is *negative*. Thus, the ability of the model to generate large frictional wage dispersion need not translate into a large wage elasticity; and if it does generate a large wage elasticity, it is not by generating large wage dispersion, but by obviating the importance of wage dispersion for the wage elasticity. To emphasize this point, we are not suggesting that a large $\epsilon_{w,b}$ is not consistent with *any* search model. Instead, our analysis suggests that if $\epsilon_{w,b}$ is large, it is likely not due to selectivity alone.

3 Implications of the Random Search Model

We specialize the formula in (2.7) to a McCall sequential search model. Time is continuous. Workers are infinitely-lived, risk neutral, and discount the future at rate r. When unemployed, a worker receives wage offers at Poisson rate λ_u. Conditional on receiving an offer, the worker draws a wage from distribution F, and decides whether to accept or reject. When employed, a worker loses his job and goes back into unemployment at exogenous Poisson rate δ. Throughout the paper, we will assume that consumption when unemployed is $z = A + b$, where b denotes unemployment insurance and A stands for the combined value of leisure and home production. Flow consumption when employed at wage w is simply w. There is no on-the-job search.

Denote by $W(w)$ the value of being employed at wage w and by U the value of being unemployed. They satisfy the Bellman equations

$$rW(w) = w - \delta (W(w) - U) \tag{3.1}$$

and

$$rU = z + \lambda_u \int_0^\infty \max\{0, W(w) - U\} f(w)\, dw \tag{3.2}$$

A well-known result is that the worker accepts if and only if the wage is above the reservation wage, which is the unique value w_R satisfying $W(w_R) = U$. It is standard to show that this reservation wage satisfies[5]

$$w_R = z + \frac{\lambda_u}{r+\delta} \int_{w_R}^\infty (w - w_R) f(w)\, dw \tag{3.3}$$

[5]See, e.g. Rogerson, Shimer and Wright for a standard exposition.

The job-finding rate H and the average accepted wage $\overline{w}$ are then given in terms of w_R by (2.1) and (2.2). As above, define $\mu = \overline{w}/w_R$. Also, we define the replacement rate $\tau = z/\overline{w}$. As in Hornstein, Krusell and Violante, we can manipulate (3.3) and (2.2) to derive

$$w_R = z + \frac{H}{r+\delta}\left(\overline{w} - w_R\right) \tag{3.4}$$

and therefore

$$\mu = \frac{1 + \frac{H}{r+\delta}}{\tau + \frac{H}{r+\delta}} \tag{3.5}$$

Substituting this expression for μ into (2.7), we obtain the formula:

Result 2. *In the basic random search model,*

$$\epsilon_{w,b} = -\left(1-\tau\right)\left(\frac{1}{1+\frac{H}{r+\delta}}\right)\epsilon_{H,b} \tag{3.6}$$

Thus, the model makes a prediction about $\epsilon_{w,b}$ given $\epsilon_{H,b}$. The factor of proportionality depends on the replacement rate τ, the job-finding rate H, the job separation rate δ, and the discount rate r.

3.1 On-the-job search

It is well-known that on-the-job search allows the standard random search model to accommodate larger wage dispersion while still being consistent with observed unemployment-employment transitions. Since the previous section identified a clear role for frictional wage dispersion in determining the wage elasticity, it is important to consider how the presence of on-the-job search changes our wage elasticity formula. We therefore modify the above sequential search model to allow on-the-job search. Specifically, assume that an unemployed worker faces an arrival rate λ_u of wage offers, and an employed worker faces an arrival rate $\lambda_e \leq \lambda_u$. In either case, they draw a wage from the distribution F. Thus the model in the previous section is simply the special case with $\lambda_e = 0$.

Our expressions for U and $W(w)$ now satisfy the modified Bellman equations

$$rU = z + \lambda_u \int_0^\infty \max\left\{0, W(w) - U\right\} f(w)\, dw \tag{3.7}$$

and

$$rW(w) = w + \lambda_e \int_0^\infty \max\left\{0, W(w') - W(w)\right\} f(w')\, dw' - \delta\left(W(w) - U\right) \tag{3.8}$$

It is standard to show that an unemployed worker's optimal search strategy is still characterized by a reservation wage rule, and that this reservation wage satisfies

$$w_R = z + (\lambda_u - \lambda_e) \int_{w_R}^{\infty} \frac{1 - F(x)}{r + \delta + \lambda_e (1 - F(x))} dx \tag{3.9}$$

It is important to distinguish between the distribution of wages accepted *out of unemployment*and the steady-state cross-sectional distribution of wages for all employed workers. The former, which are the object of most empirical studies of the wage elasticity, have the cumulative distribution

$$F(w|w_R) := \frac{F(w) - F(w_R)}{1 - F(w_R)}, \tag{3.10}$$

and therefore have the mean

$$\overline{w} = \frac{1}{1 - F(w_R)} \int_{w_R}^{\infty} w f(w)\, dw \tag{3.11}$$

We denote $\mu = \overline{w}/w_R$. On the other hand, the overall cross-sectional wage distribution, which we denote $G(w|w_R)$ can be shown, in steady state, to satisfy

$$G(w|w_R) = \frac{\delta}{\delta + \lambda_e (1 - F(w))} \frac{F(w) - F(w_R)}{1 - F(w_R)} < F(w|w_R) \tag{3.12}$$

The overall distribution of wages of employed workers, which we refer to as *lifetime* wages, therefore first-order stochastically dominates the distribution of wages accepted out of unemployment. This is intuitive: workers initially accept wages out of unemployment according to the distribution F move on to higher wages throughout their employment spell. Denote by $\overline{w}_L$ the mean lifetime wage,

$$\overline{w}_L = \int_{w_R}^{\infty} w dG(w|w_R), \tag{3.13}$$

We denote $\mu_L = \overline{w}_L/w_R$. We will now characterize the elasticity of the post-unemployment wage, denoted $\epsilon_{w,b} = d\ln\overline{w}/d\ln b$, as well as the elasticity of the lifetime wage, denoted $\epsilon_{w,b}^L \equiv d\ln\overline{w}_L/d\ln b$.

Result 3. *In the job-ladder model described above, $\epsilon_{w,b}$ and $\epsilon_{w,b}^L$ satisfy*

$$\epsilon_{w,b}^L \approx -(1-\tau)\left(\frac{1}{1+\frac{H}{r+\delta}}\right)\epsilon_{H,b} \tag{3.14}$$

and

$$\epsilon^L_{w,b} \leq \epsilon_{w,b} \leq -(1-\tau)\left(\frac{1+\frac{\lambda_e}{\lambda_u}\frac{H}{r+\delta}}{1+\frac{H}{r+\delta}}\right)\epsilon_{H,b}, \tag{3.15}$$

with both inequalities strict as long as $\lambda_e > 0$.

The detailed derivations for (3.14) and (3.15) are in the online appendix. The approximate expression (3.14) follows from the expression (3.9) for the reservation wage combined with the fact that r is small compared to worker flows. The message of Result 3 is as follows. First, on-the-job search allows the model to be consistent with larger values of μ and μ_L. Since the formula for $\epsilon_{w,b}$ itself is still given by (2.7), this means the model is consistent with larger values of $\epsilon_{w,b}$. Second, when it comes to lifetime wages, $\epsilon^L_{w,b}$ in the model with on-the-job search is given by the same formula (3.6) as $\epsilon_{w,b}$ in the model without on-the-job search. To understand this somewhat surprising result, notice that on-the-job search leads to two opposing effects. First, it allows the model to be consistent with a larger value of frictional wage dispersion. On the other hand, on-the-job search itself dampens the response of lifetime wages to initial wages, hence to UI. For the same reason, $\epsilon^L_{w,b}$ is smaller than $\epsilon_{w,b}$ when on-the-job search is present. Finally, while $\epsilon_{w,b}$ can now be larger, it is still bounded above by the expression in (3.15), which can be computed from observed worker flows.

4 Other Models

4.1 Directed search

In a directed search model, workers no longer face a distribution of wages; instead, they face a function $\mathcal{P}(w)$ that determines the tradeoff between the wage received and the job-finding probability. An unemployed worker who decides to direct search toward the submarket offering wage w finds a job at rate $\mathcal{P}(w)$. Workers take this function as given. In such an environment, the value of being employed at wage w is still given by

$$rW(w) = w - \delta(W(w) - U), \tag{4.1}$$

and the value of being unemployed is

$$rU = z + \max_w \mathcal{P}(w)(W(w) - U) \tag{4.2}$$

Denote by w^* the solution to the maximization problem in (4.2); then the equilibrium job-finding rate is $H = \mathcal{P}(w^*)$. The first-order condition for (4.2) can be written as

$$\frac{w^* \mathcal{P}'(w^*)}{\mathcal{P}(w^*)} = -(1-\tau)^{-1}\left(1 + \frac{\mathcal{P}(w^*)}{r+\delta}\right), \tag{4.3}$$

where we again defined $\tau = z/w^*$. Noting that

$$\frac{d\ln H}{d\ln b} = \frac{w^* \mathcal{P}'(w^*)}{\mathcal{P}(w^*)} \frac{d\ln w^*}{d\ln b}, \tag{4.4}$$

we immediately obtain

Result 4. *In the directed search model,*

$$\epsilon_{w,b} = -(1-\tau)\left(\frac{1}{1+\frac{H}{r+\delta}}\right)\epsilon_{H,b} \tag{4.5}$$

Note that this is identical to formula (3.6) in the random sequential search model. Thus, although the dependence of the mapping on frictional wage dispersion no longer holds, its implications in terms of the replacement rate and observed worker flows still do. This is because the intuition in terms of the wage-hazard locus described for the random search model still applies here. In fact, in the directed search model, this intuition is borne out in even starker terms: the worker literally faces the tradeoff between the wage and the job-finding rate, as determined by $\mathcal{P}(w)$. The slope of the wage-hazard locus then depends on the elasticity of $\mathcal{P}$, which can be expressed in terms of the replacement rate and observed worker flows. In particular, as in (3.6), the formula (4.5) assigns a key role to τ in the determination of $\epsilon_{w,b}$. A higher τ implies that it was optimal for the worker to target wages close to the value of non-employment, which in turn indicates that $\mathcal{P}$ is very elastic with respect to w. But then, a given change in $\mathcal{P}$ induced by UI is accompanied by only a modest change in w.

4.2 Nash bargaining

This section and the next will provide examples that break the strong relationship between $\epsilon_{w,b}$ and $\epsilon_{H,b}$. To understand the mechanism, consider an environment in which matching is random and matches differ in *productivity*, y, which in turn affects the wage. Workers match with firms at rate λ_u, draw a match-specific productivity y from some distribution $\mathcal{F}(y)$, and decide to form a match if $y \geq y_R$. The job-finding rate is therefore $H = \lambda_u (1 - \mathcal{F}(y_R))$. Next, suppose that the wage w in a match of quality y depends on y but also depends directly on z, where as usual $z = A + b$. The wage elasticity will now consist of two terms: the effect on the wage through changing the reservation productivity y_R - the selectivity effect - and the direct effect through the outside option. To the extent that b affects $\overline{w}$ through y_R, it also affects H; hence the magnitude of $\epsilon_{w,b}$ is disciplined by $\epsilon_{H,b}$. Key will be the presence of the second term, which captures the direct effect of b on w through z. This effect through the outside option is not disciplined by $\epsilon_{H,b}$.

Under Nash bargaining, the wage is set to maximize the weighted product of the worker's surplus from working and the firm's surplus from employing the worker. Denote by $\xi \in [0, 1]$ the worker bargaining weight. A standard argument yields[6]

$$w(y) = \xi y + (1 - \xi) y_R \tag{4.6}$$

As usual, define $\overline{w} = \mathbb{E}(w(y) | y \geq y_R)$, $w_R = w(y_R)$, and $\mu = \overline{w}/w_R$. Additionally, defining $\overline{y} = \mathbb{E}(y|y \geq y_R)$, we have

$$\frac{d \ln \overline{y}}{d \ln b} = -\left(\frac{\overline{y} - y_R}{\overline{y}}\right) \epsilon_{H,b} \tag{4.7}$$

The reservation productivity y_R satisfies

$$y_R = z + \frac{\xi \lambda_u}{r + \delta} \int_{y^R}^{\infty} (y - y_R) \, d\mathcal{F}(y), \tag{4.8}$$

implying that

$$\frac{dy_R}{db} = \frac{1}{1 + \xi \frac{H}{r+\delta}} \tag{4.9}$$

Differentiating (4.6) with respect to b and using (4.9) yields

$$\epsilon_{w,b} = \xi \frac{\overline{y}}{\overline{w}} \epsilon_{y,b} + \frac{1 - \xi}{1 + \xi \frac{H}{r+\delta}} \frac{b}{\overline{w}} \tag{4.10}$$

Finally, note that $\overline{w} - w_R = \xi(\overline{y} - y_R)$ and μ is still given by (3.5). Substituting this into (4.10) together with (4.7) gives

Result 5. *In the Nash bargaining model,*

$$\epsilon_{w,b} = -(1 - \tau) \left(\frac{1}{1 + \frac{H}{r+\delta}}\right) \epsilon_{H,b} + \frac{1 - \xi}{1 + \xi \frac{H}{r+\delta}} \frac{b}{\overline{w}} \tag{4.11}$$

As anticipated, $\epsilon_{w,b}$ is the sum of the familiar term depending on $\epsilon_{H,b}$ and a new term

[6] This formula for the wage uses the free entry condition that drives profits, but this zero-profit assumption is in fact not necessary for any of the derivations here.

that capturing the direct effect through the outside option. The presence of the latter allows $\epsilon_{w,b}$ to be sizable even if $\epsilon_{H,b}$ is not. In fact, consider the case when the distribution of y is degenerate at $\overline{y}$, so that UI has no effect whatsoever on H.[7] There would still be an effect of UI on wages through bargaining, equal to the latter term. Not surprisingly, the magnitude of the outside option effect is decreasing in ξ, the bargaining weight of the worker: the lower is ξ, the more weight is attached in the bargaining problem to the outside option rather than productivity. In the extreme case when $\xi = 0$, we have $w = z$ and $\epsilon_{w,b} = b/z$, independently of $\epsilon_{H,b}$.

4.3 Sequential auctions

Finally, let us consider a simple sequential auctions model along the lines of Postel-Vinay and Robin. The previous section has already illustrated that ex post wage renegotiation has the ability to decouple the wage elasticity from the hazard elasticity and from frictional wage dispersion. We confirm that the same is true in the sequential auctions model. In addition, we confirm the intuition of section 4 that on-the-job search dampens the effect of UI on lifetime wages. As above, we consider a setting in which unemployed workers match with firms at rate λ_u, draw a match-specific productivity y from some distribution $\mathcal{F}(y)$, and decide to form a match if $y \geq y_R$. Upon matching, the firm makes the worker a take-it-or-leave-it offer. Employed workers can search on the job as well: they meet poaching firms at rate λ_e, whose productivity is likewise drawn from distribution $\mathcal{F}$. In the event of meeting a competing firm, Bertrand competition determines whether the worker switches jobs, as well as the new wage. Wages are renegotiated only in case of meeting a competing firm and otherwise fixed.

Take-it-or-leave-it offers conveniently imply that $y_R = z$. Next, letting $\omega_u(y)$ be the reservation wage of an unemployed worker meeting a firm of productivity y, we have

$$\omega_u(y) = z - \frac{\lambda_e}{r+\delta} \int_z^y (1 - \mathcal{F}(x))\, dx \tag{4.12}$$

The average wage accepted out of unemployment then satisfies

$$\overline{w} = \frac{1}{1-\mathcal{F}(z)} \int_z^\infty \omega_u(y)\, d\mathcal{F}(y) \tag{4.13}$$

[7] As mentioned in the introduction, we are focusing on the partial-equilibrium effect of UI only: the thought experiment concerns changing UI for an individual worker, which would have no effect on entry.

from which we can get

$$\frac{d\overline{w}}{dz} = \frac{\mathcal{F}'(z)}{1-\mathcal{F}(z)}(\overline{w}-z) + \left[1 + \frac{\lambda_e}{r+\delta}(1-\mathcal{F}(z))\right] \tag{4.14}$$

Define $\epsilon_{w,b} = d\ln\overline{w}/d\ln b$. From (4.14), we conclude:

Result 6. *In the sequential-auctions model,*

$$\epsilon_{w,b} = -\left(\frac{\overline{w}-z}{\overline{w}}\right)\epsilon_{H,b} + \frac{b}{\overline{w}}\left[1 + \frac{\lambda_e}{r+\delta}(1-\mathcal{F}(z))\right] \tag{4.15}$$

where

$$\overline{w} = z - \frac{\lambda_e}{r+\delta}\int_z^\infty \frac{(1-\mathcal{F}(x))^2}{1-\mathcal{F}(z)}dx < z \tag{4.16}$$

5 Empirical Analysis

Each search model discussed in the previous sections exhibited a linear relationship between the wage elasticity and the hazard elasticity. To understand whether these relationships are consistent with the data, we estimate each using the Survey of Income and Program Participation (SIPP). Our findings suggest that, at least for unemployed workers whose wealth places them in the first quintile, the search models surveyed in the previous sections underpredict their responsiveness to changes in unemployment benefits. This suggests that 'selectiveness' alone cannot explain the behavior of liquidity-constrained workers.

We establish these findings using two approaches. First, we directly estimate the hazard elasticity and wage elasticity using SIPP panels from 1990 to 2008. Second, we use estimates from the literature analyzing the labor market effects of unemployment insurance. In both cases, the observed elasticities are inconsistent with those predicted by search models, suggesting that the behavior of workers is driven by factors other than selectiveness.

5.1 Data

The SIPP is a panel dataset with separate surveys conducted annually from 1984 to 1993, and then during 1996, 2001, 2004, and 2008. Each survey follows a household for 16 to 36 months, with interviews every four months for each "wave" of respondents. Each interview includes detailed information about the previous four months on the employment, income, and various types of benefit recipiency, including unemployment insurance. Employment variables are coded down to a weekly frequency, which gives us a more precise picture of worker employment spells than can be offered by other publicly available datasets. Although information on wealth is not available in the core questionnaire, it is surveyed in a "topical modules" roughly once every year for most SIPP panels. This allows us to link 2129 unemployment spells to reported asset and debt portfolios, including characteristics on the liquidity of a household's wealth.

We use SIPP panels from 1990 to 2008 and restrict the sample to unemployment spells for males age 21 and older with at least 3 months work experience, who took up UI within one month of job loss, and who are not on a temporary layoff[8]. This leaves yields 2129 unemployment spells in which an individual takes up unemployment insurance and reports their wealth. As controls, we observe race, marital status, age, years of education, as well as tenure, industry, occupation, and wage at their previous job. Demographic characteristics are included in the online appendix.

One important dimension along which we differ from the previous literature is that we use earnings (measured over a quarter), rather than wages. The reason is three-fold: while the data has a sizeable sample of observed earnings before and after unemployment spells (in which wealth is also observed), hours data is missing from many of these observations. In addition, many workers are salaried, rather than hourly, making their hours subject to a great deal of measurement error (and in turn, their wage rate). Finally, the models we study assume a worker maximizes his lifetime *income*, rather than wages. While this is an innocuous distinction if hours are included as a control when determining wage dispersion, our approach is no less valid[9].

The SIPP employs a stratified sample design whose primary sampling units changed in 1992, 1996, and 2004. We use of this survey structure to obtain accurate estimates of subsample variance, while accounting for design change by specifying the primary sampling units during each design regime (1990-1991,1992-1993,etc.) with a unique identifier. That is, an individual from the first sampling unit in 1990 would not be assigned to the same variance strata as an individual from the first sampling unti in 2001. We weight all of our results using person weights for individuals at the start of their unemployment spells. Estimates clustered at the state-level show similar levels of significance and are included in the online appendix.

Previous work has shown that households commonly misreport their unemployment benefits. To handle this, we follow the previous literature and proxy for unemployment insurance by individual using state-month average weekly benefit and maximum weekly benefit levels, to handle this measurement error. We use data on UI laws by state from the Employment

[8]See Griffy (2018), Chetty (2008) and Meyer (1990) for three examples using the same selection criteria.

[9]Nekoei and Weber (2017) are faced with a similar problem and likewise use earnings rather than hourly wages.

and Training Administration. This includes the maximum benefit an individual could receive, as well as the average benefit an individual received in each state and year from 1990 to 2016. We use average benefits to proxy for UI benefits, but repeat the results with reported benefits in the online appendix. To accommodate potential changes in unemployment insurance generosity that may be correlated with changes to the replacement rate, we use the length of unemployment insurance eligibility at the state-month level. This is obtained from the Employment and Training Administration.

5.2 Wage Elasticity Specification and Findings

We use two specifications to show the importance of heterogeneity in estimating the wage elasticity. First, we estimate a Mincer equation on all unemployment spells in our sample under the following specification:

$$ln(W_{i,k+1,t}) = \beta_0 + \beta_1 ln(UI_{i,t,s,k}) + \beta_1^j UIDur_{i,t,s} + \delta_t + \delta_s + \beta_1 X_{i,t,k} + \epsilon_{i,t,s,k} \tag{5.1}$$

Our estimate of interest is β_1. If $\beta_1 > 0$, it suggests that higher *levels* of unemployment insurance increase earnings upon exiting unemployment. In this specification, β_1 is directly an estimate of the wage elasticity for the entire sample.

We are primarily focused on the responsiveness of groups that are likely constrained to changes in their unemployment insurance. To estimate this effect, we stratify our sample into quintiles across the liquid wealth distribution. We interact this indicator for wealth quintile with UI generosity as well as the state potential unemployment insurance duration variable. While these are our primary interactions of interest, we also interact the quintile indicator with education level. The reason is that many college graduates in our sample take on debt and appear in the lowest wealth quintile, but have a different earnings process than individuals with less than a college degree. Thus, Equation 5.1 becomes

$$ln(W_{i,t,k+1}) = \sum_{j=1}^{5} (\beta_1^j \mathbf{1}_{Q_{i,k,j}} \beta_0 + \beta_1^j \mathbf{1}_{Q_{i,k,j}} ln(UI_{i,t,s,k}) + \beta_1^j \mathbf{1}_{Q_{i,t,s,k}} Dur_{t,s} + \beta_1^j \mathbf{1}_{Q_{i,t,k}} ED_{i,t}) \tag{5.2}$$

$$+ \delta_t + \delta_s + \beta_1 X_{i,t,k} + \epsilon_{i,t,s,k} \tag{5.3}$$

where k is the current employment or unemployment spell for individual i at time t in liquidity quintile j. β_1^j and β_2^j are indicators for an individual in net liquid wealth quintile j

at the start of a spell. A positive β_1^j indicates that more generous unemployment insurance is associated with better employment outcomes for quintile j. A negative β_2^j indicates that extending unemployment insurance benefits results in worse re-employment outcomes. Note that the vector of covariates, $X_{i,t,k}$ include age, race, marital status, education, tenure, industry and occupation of previous job, a log-wage spline, as well as state and year fixed effects as controls. We interact liquidity quintile with education level[10], to control for the effect that college debt might have on earnings outcomes.

As shown in Table 1, increases in the replacement rate generosity of a state's unemployment insurance system have a significantly positive effect on the employment outcomes for low-wealth individuals. A one percent increase in unemployment insurance causes between a 0.42 and 0.46 percent increase in earnings during the quarter following an unemployment spell. By itself, this finding is notable: any model in which agents are able to respond to income risk (i.e., a model in which the permanent income hypothesis holds) would suggest that benefits accrued during unemployment should have a negligible effect on behavior. Instead, our evidence suggests that the search behavior of low-wealth workers is affected by changes in benefits.

5.3 Hazard Elasticity Specification and Findings

We use two proportional hazard models to estimate the elasticity of the hazard rate. Proportional hazard models are the standard method of estimating the hazard rate out of unemployment. We start by following much of the previous literature and estimate a Cox Proportional Hazard model (CPH). The CPH model assumes that the rate at which an individual leaves is the product of an underlying "baseline" hazard and a set of observables. The CPH model is specified as

$$h(t|X) = \lambda(t)\phi(X) \tag{5.4}$$

where $\lambda(t)$ is the (potentially un-specified) baseline hazard, which we allow to differ by wealth quintile, and $\phi(x) = exp(X\beta)$. X is a vector of covariates, including unemployment insurance. We allow the baseline hazard to differ by wealth quintile. The multiplicative structure allows the hazard to be linear in logs,

$$ln(h_{i,t}) = \alpha_0 + \beta_1^j \mathbf{1}_{Q_{i,j}} \times ln(UI_i) + \beta_2^j \mathbf{1}_{Q_{i,j}} \times (Dur_i \times ln(UI_i)) + \beta_3 X_{i,t} \tag{5.5}$$

Here, β_1^j is the estimate of the hazard elasticity. A negative β_1^j indicates that within

[10] We define these levels as less than high school, high school, some college, college, and post-college.

	(1) Full Sample	(2) Wealth Sample	(3) Wealth Interaction	(4) Wealth Interaction
log UI Benefit	0.117	0.196		
	(0.152)	(0.185)		
Net Liq Q1 X × log UI Benefit			0.420*	0.459**
			(0.227)	(0.232)
Net Liq Q2 X × log UI Benefit			0.239	0.263
			(0.231)	(0.234)
Net Liq Q3 X × log UI Benefit			0.0870	0.0988
			(0.246)	(0.248)
Net Liq Q4 X × log UI Benefit			0.194	0.191
			(0.215)	(0.225)
Net Liq Q5 X × log UI Benefit			0.0688	0.122
			(0.240)	(0.240)
Observations		2129	2129	2135
State FE	X	X	X	X
Year FE	X	X	X	X
Qtile X Wage Spline			X	X
Qtile X Ed			X	X

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Estimates of earnings elasticity. Columns (1) and (2) both estimate Equation 5.1, first for the universe of observed unemployment spells in the SIPP, and then for the sample of unemployment spells in which wealth is observed. Columns (3) and (4) report the estimated coefficients of interest from Equation 5.2, with potential UI duration as a covariate in (3) and observed unemployment duration as a covariate in (4). Standard errors are Taylor Linearized SEs constructed using the survey design.

net liquidity quintile j, more generous unemployment insurance systems cause individuals to remain unemployed longer, i.e. that their hazard of leaving unemployment has decreased.

A critique of the Cox Proportional Hazard model is that selection on unobservables over spells may bias the results of the Cox Proportional Hazard model (Lancaster, 1979). For this reason, we also estimate a mixed proportional hazard model (MPH). The MPH model uses a "mixing distribution" to account for selection bias in the hazard rate; intuitively, a draw from the mixing distribution controls for the same type of variation that a group-level fixed effect would, and allow individuals to "mix" over these different fixed effects. This gives the model more flexibility in dealing with unobserved heterogeneity, and controls for the selection bias that results in the Cox PH model. Our specification takes the following form:

$$h(t|v_l, X) = v_k \lambda(t) \phi(X_{i,t}) \tag{5.6}$$

where v_l is the unobserved heterogeneity or error term. As before, $\phi(x) = exp(X\beta)$, yielding the log-linear specification

$$ln(h_{i,t}) = \alpha_0 + \beta_1^j \mathbf{1}_{Q_{ij}} ln(UI_i) + \beta_2^j \mathbf{1}_{Q_{ij}} (Dur_i \times ln(UI_i)) + \beta_3 X_{i,t} + ln(v_l) \qquad (5.7)$$

β_1^j is again the estimate of the hazard elasticity and retains the same interpretation as Equation 5.5.

As with the earnings elasticity, we find a significantly negative effect on the unemployment hazard for low-wealth individuals, indicating that as replacement rates rise, low-wealth individuals spend a longer duration searching for new employment. This is shown in Table 2. Under both the Cox and Mixed Proportional Hazard models we find that increases in unemployment insurance cause a decrease in the hazard rate, ranging from a -0.64 percent decline in the probability of exiting unemployment to a -0.84 percent decline as a result of a one percent increase in benefits.

	(1) Full Sample	(2) Wealth Sample	(3) Cox Model	(4) MPH Model
main				
log UI Benefit	-0.159	-0.159		
	(0.229)	(0.229)		
Net Liq Q1 × log UI Benefit			-0.643**	-0.840**
			(0.299)	(0.355)
Net Liq Q2 × log UI Benefit			-0.600*	-0.509
			(0.319)	(0.353)
Net Liq Q3 × log UI Benefit			-0.578	-0.532
			(0.363)	(0.378)
Net Liq Q4 × log UI Benefit			-0.140	-0.0990
			(0.281)	(0.303)
Net Liq Q5 × log UI Benefit			-0.402	-0.165
			(0.267)	(0.357)
Observations	2564	2564	2564	2564
State FE	X	X	X	X
Year FE	X	X	X	X
Wealth Quintile FE			X	X
Qtile X Wage Spline			X	X
Qtile X Ed			X	X

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Estimates of hazard elasticity. Columns (1) and (2) both estimate Equation 5.5, first for the universe of observed unemployment spells in the SIPP, and then for the sample of unemployment spells in which wealth is observed. Columns (3) and (4) report the estimated coefficients of interest from Equation 5.5 and Equation 5.7, respectively.

5.4 Estimates of the Mean-to-Minimum Earnings Ratio

In addition to focusing on earnings dispersion rather than wage dispersion, our empirical findings are specific to earnings at jobs *accepted out of unemployment*. Thus, previous estimates of wage and earnings dispersion aren't necessarily appropriate for our analysis. We follow Hornstein et al. (2011) and focus on the 50-10 ratio of residual earnings. The at-population-means residual earnings are reported in Table 3, as well as the 50-10, the 50-5, and the 50-1 ratios.

	1st	5th	10th	25th	50th	75th	90th	95th	99th	Mean	Mean-10	Mean-5	Mean-1
Pooled	644.23	1768.89	2448.64	4072.47	5936.92	8091.45	10412.85	12325.42	17162.26	6364.67	2.6	3.6	9.88
1st Quintile													
(1)	781.33	1615.8	2248.12	3739.19	5545.39	7510.82	9679.81	11706.75	16191.55	5944.45	2.64	3.68	7.61
(2)	838.66	1639.77	2261.8	3737.07	5492.86	7393.3	9714.5	11477.2	16250.04	5901.2	2.61	3.6	7.04
2nd Quintile													
(1)	364.51	1297.91	1863.7	3115.12	4670.15	6101.07	8126.47	9725.4	13339.2	4898.96	2.63	3.77	13.44
(2)	415.7	1338.26	1872.23	3075.51	4630.8	6077.6	8216.62	9480.71	13185.56	4894.5	2.61	3.66	11.77
3rd Quintile													
(1)	715.55	1797.18	2347.49	3755.49	5283.61	7335.12	9144.17	10501.93	13466	5669.41	2.42	3.15	7.92
(2)	686.8	1751.13	2389.32	3819.83	5278.41	7235.57	8949.69	10547.82	13417.31	5638.84	2.36	3.22	8.21
4th Quintile													
(1)	824	2628.74	3135.93	4880.01	6964.31	9287.51	12024.22	14157.4	20794.16	7471.66	2.38	2.84	9.07
(2)	845.83	2649.68	3149.13	5087.51	6968.97	9171.04	12077.06	14311.37	18776.38	7458.16	2.37	2.81	8.82
5th Quintile													
(1)	766.84	2180.31	3468.78	5357.17	8344.62	11143.91	14900.83	17989.43	21985.19	8752.31	2.52	4.01	11.41
(2)	791.21	2263.07	3243.36	5340.17	8061.71	11020.6	14500.12	16780.63	22817.57	8719.4	2.69	3.85	11.02

Table 3: Residual earnings dispersion in our SIPP sample. Rows labeled "(1)" refer to empirical specification Equation 5.2 with potential unemployment insurance duration included as a covariate, and rows labeled "(2)" refers to the same specification with observed unemployment duration. The "Pooled" row employs specification Equation 5.1. In the final three columns, we document the residual wage dispersion as measured by the 50-10, 50-5 and 50-1 earnings ratios.

5.5 The Earnings-Hazard Locus in the Data

Our derivations in section 3 and section 4 show that if the selectivity channel plays a key role in a workers application strategy, then Equation 2.7 should hold when evaluated at observed values of the earnings and hazard elasticities, and the mean-min ratio. For convenience, the result of our previous derivation is reiterated:

$$\epsilon_{w,b} = -\left(\frac{\mu - 1}{\mu}\right)\epsilon_{H,b}$$

Our estimates suggest that for low-wealth individuals the earnings elasticity lies between 0.42 and 0.46 (Table 1), and that the hazard elasticity sits around -0.64 using the specification common to the related literature, and could be as high as -0.84, when we employ a more robust estimator. We find that μ, the mean-to-min ratio varies from 2.6 using a conservative

10th percentile estimate of the minimum earnings, to a ratio of close to 10 when the 1st percentile of the quarterly earnings distribution is used[11]. These ratios result in empirical estimates of $\frac{\mu-1}{\mu}$, of -0.6 for the most conservative mean-min ratio to -0.90 for the mean-to-1st percentile ratio. Below, we evaluate Equation 2.7 for each of the five wealth quintiles:

Estimates	Mean-Min (μ) and $-\frac{\mu-1}{\mu}$	Hazard Elasticity	Implied Earnings Elasticity	Estimated Earnings Elasticity
Cox Proportional Hazard				
1st Quintile	2.64, −0.621	−0.64	0.399	0.42
2nd	2.63, −0.620	−0.60	0.372	0.24
3rd	2.42, −0.587	−0.58	0.339	0.09
4th	2.38, −0.580	−0.14	0.081	0.19
5th	2.52, −0.603	−0.40	0.242	0.07
Mixed Proportional Hazard				
1st	2.64, −0.621	−0.84	0.522	0.42
2nd	2.63, −0.620	−0.51	0.315	0.24
3rd	2.42, −0.587	−0.53	0.312	0.09
4th	2.38, −0.580	−0.10	0.057	0.19
5th	2.52, −0.603	−0.17	0.100	0.07

Table 4: Comparison of the earnings elasticity implied by our estimates of the hazard elasticity and the mean-min ratio and the estimated elasticity from the SIPP. Because of the difference in estimated hazard rates

With the notable exception of the first wealth quintile using estimates from the Cox Proportional Hazard Model, the implied earnings elasticity generally exceeds the estimated earnings elasticity (though many of the earnings elasticities are not detectably different from zero). This is neither a failure nor an endorsement of our sufficient statistic: instead, it indicates that with the exception of low-wealth workers, selectivity is not the primary source of wage dispersion. This, however, has implications for frictional models of the labor market. It indicates that many of the *surveyed models* that produce wage dispersion through worker selectivity are not consistent with our empirical analysis[12]. We now explore the implications of our estimated earning and hazard elasticities for the models surveyed in sections 3 and 4.

6 Quantifying Model-Implied Worker Selectivity

To understand whether the sources of wage dispersion produced by the models surveyed in 3 and 4 are consistent with the channels that we observe in the data, we use common calibrations and compare the implied selectivity. Worker selectivity over wages out of unemployment is one of several channels through which frictional wage dispersion arises. For

[11] The appropriate measure is the mean earnings, rather than the 50th percentile, but when we repeat the procedure using the 50th percentile, the 50-10 ratio is 2.42. This can be calculated from the table.

[12] We have also chosen the most conservative estimate of the mean-min ratio of the available set; were we to repeat the calculations using the mean-1 ratio, the implied earnings elasticity would far exceed the estimated elasticity.

a model to be consistent with our findings, it must generate earnings dispersion in like with our estimates, *and* that earnings dispersion must be generated through selectivity on jobs accepted out of unemployed.

6.1 Baseline Calibration

We assume that in each of the surveyed models, the time period is one month. We allow an annual interest rate of 5% appropriately adjusted to a monthly frequency (0.0041). For models with an exogenous separation rate and no on-the-job search, Shimer (2012) calculates a monthly separation rate of 0.03.

Where appropriate, we estimate components from the data. We assume that the baseline calibration (generously) can match the hazard rate in the data, as well as the hazard elasticity. Then we compare the implied selectivity to the selectivity for the first quintile. We use the monthly hazard from Hornstein et al. (2011), $H = 0.43$, and assume that no firm would offer a wage lower than the reservation wage, thus implying that $\lambda_U = 0.43$. For the on-the-job search models, we follow Hornstein et al. (2011) and set $\lambda_E = 0.15$.

Estimates of the Nash Bargaining parameter vary substantially in the related literature. Broadly, they follow two trends: calibrations in which a workers outside option makes them close to indifferent between employment and unemployment feature a small bargaining weight, and calibrations in which a workers outside option approaches their unemployment benefits include a higher bargaining weight. These two calibrations can roughly be traced back to Shimer (2005) and Hagedorn and Manovskii (2008), for calibrations with higher and lower bargaining weights, respectively. We show results for both calibrations, $\xi = 0.7$ and $\xi = 0.052$, and conclude that neither calibration is consistent with our empirical analysis. As shown in Hornstein et al. (2011), larger values of τ, the replacement rate, *decrease* wage dispersion; we report results for both calibrations initially, ($\tau = 0.4$ and $\tau = 0.955$), before adopting the more conservative value, $\tau = 0.4$ from Shimer (2005) for models other than those that feature bargaining.

The model-implied earnings elasticity in the sequential auctions model includes the firm-productivity distribution. A precise estimate of the earnings elasticity would require a functional form assumption about this distribution. Instead, we consider two cases for the productivity distribution. In the first case, the productivity distribution is degenerate at the outside option, $F(z) = 1$, meaning that the average wage in the economy is approaching $\bar{w} = \tau = 0.4$. In the second case, we assume that the distribution is disperse and bounded below by z, meaning that $F(z) = 0$ and that the average wage is approaching $\bar{w} = 0.01$.

6.2 Implied Selectivity and Earnings Elasticity by Model

To be consistent with our empirical findings for low-wealth workers, a model must both generate earnings dispersion to a degree consistent with the data, and do so through the same channels as the data. The first line in Equation 6.1 is our estimate of implied selectivity in the data. The second line shows the distinction between a model that generates large earnings responses due to selectivity, and those that have different channels.

$$\epsilon_{w,b} = \underbrace{-\left(\frac{\mu-1}{\mu}\right)\epsilon_{H,b}}_{\textit{Implied Selectivity}} \tag{6.1}$$

$$\epsilon_{w,b} = \underbrace{-\left(\frac{\mu-1}{\mu}\right)\epsilon_{H,b} + \text{Other Factors}}_{\textit{Implied Earnings Elasticity}} \tag{6.2}$$

This means that a model may generate earnings dispersion in line with that observed in the data, but may still do so through channels that are inconsistent with our findings. In Table 5, we show the "Hazard Coefficient," as well as the "Implied Selectivity," which is directly comparable to our estimates in Table 4. The final column shows the overall elasticity, including other factors.

Model and Measure	Hazard Coefficient	Implied Selectivity	Implied Earnings Elasticity
Sequential Search			
Shimer (2005)	−0.044	0.028	0.028
Hagedorn and Manovskii (2008)	−0.003	0.002	0.002
On-the-Job Search			
Re-Employment Earnings	−0.238	0.153	0.153
Lifetime Earnings	−0.044	0.028	0.028
Directed Search			
Shimer (2005)	−0.044	0.028	0.028
Nash Bargaining			
Shimer (2005)	−0.044	0.028	0.041
Hagedorn and Manovskii (2008)	−0.003	0.002	0.549

Table 5: Estimates of the model implied selectivity and the overall earnings elasticity. The implied selectivity is comparable to the estimates from Table 4, while the implied earnings elasticity may include other channels through which unemployment benefits affect earnings.

7 Conclusion

There is a growing literature trying to empirically estimate the wage effects of unemployment insurance. Our analysis contributes to the effort of using search theory to interpret these empirical estimates, and hopefully shed light on the mechanisms behind them. The main insight is that the degree of frictional wage dispersion implies restrictions on what combinations of hazard and wage elasticities are plausible. The main lesson we have drawn from this is that standard search models tend to imply a small selectivity effect of unemployment insurance. To the extent that we do see large wage elasticities in the data, we may perhaps want to look to channels other than worker selectivity to explain them. Our discussion suggests that bargaining is a promising factor in this regard.

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