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Learning about Labor Markets

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Abstract

We study a general equilibrium model of the labor market in which agents slowly learn about their suitability for jobs. Our model reproduces desirable features of the data, many of which standard models fail to replicate. We explore how, in such an environment, asymmetric information can lead to substantial misallocation. We calibrate our model to US data and quantify the welfare loss arising from misallocation due to informational frictions. The tractability of the model allows us to explore the responsiveness of wages and employment to an aggregate shock. We find that wage rigidity arises endogenously because of protracted learning, and in line with the data, the model is able to generate a larger and more persistent employment response.

Keywords: Learning, misallocation, labor markets, wage rigidity

JEL classification: D83, D61, J64

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1 Introduction

Recent empirical literature has documented that workers' labor market environments often do not perfectly align with their beliefs about those environments. Survey studies have found evidence of biased beliefs about job finding rates that suggests that workers underestimate high job finding rates and over-estimate low ones (see Mueller et al. (2021)). This suggests that workers frequently have incorrect beliefs when weighing their options in the labor market, such as deciding whether to switch locations or occupations or when assessing their outside option while negotiating with prospective employers. In this paper, we explore the allocative effects of such incorrect beliefs and quantify the welfare loss arising from missing information in labor markets. We do this by incorporating a simple informational friction into an otherwise standard labor market setting. Workers can choose among many markets but can only learn about a market's job finding rate by spending time in it. Workers are Bayesian, updating their beliefs and slowly building a complete picture of the market they inhabit. We show that, even though there is a large potential state space of individual labor market histories, workers in our model only need to keep track of two sufficient state variables. This sufficiently simplifies the model to allow us to embed our belief structure in a general equilibrium framework.

Our model can capture salient facts that models from the literature often fail to replicate. First, our model provides a natural interpretation for the finding in Mueller et al. (2021) that workers with high job finding rates underestimate their true job finding probabilities and, conversely, workers who have low job finding rates are overly optimistic. Second, since workers in our model negatively adjust their beliefs during times without job offers, the model can account for much of the measured wage dependence on unemployment duration in the data. While the existing literature has often attributed this dependence to human capital depreciation, our results suggest that these papers possibly overstate the role of human capital depreciation in generating this dependence. Third, as is pointed out by Hornstein et al. (2011), without a substantial cost associated with unemployment, the prototypical search model is unable to generate the level of frictional wage dispersion present in the data. As it turns out, variation in worker's beliefs reconcile wage dispersion in a natural way, and in the quantitative model the degree of misinformation in the economy is calibrated to target this moment directly. Fourth, following an aggregate shock to the economy, workers learn about the changing environment gradually. This creates sluggishness in the wage response and the model is able to generate wage rigidity as has been documented empirically.

Finally, we use our model to quantify the welfare loss arising from the informational friction and find that it is substantial. In comparison to a full information benchmark, welfare losses are approximately 36%. These losses arise as a result of ill-informed agents making *wrong* decisions because of the information available to them. In general equilibrium, misallocation becomes amplified since market tightness drops below the full information benchmark.

Related literature. In the model presented, workers learn about the state of their labor market through sequential sampling. The process of learning and search has been explored in previous work. The seminal paper is Rothschild (1974), where consumers update their beliefs over prices in a product market. In a labor market setting, Burdett and Vishwanath (1988) explore an environment in which workers update their beliefs regarding the distribution of wages that they sample from. As in our model, workers with worse realizations become more pessimistic and lower their reservation wage. Conlon et al. (2021) extend Burdett and Vishwanath's framework to include workers looking for jobs while in employment. The updating rule and parameters of the search model are carefully calibrated to U.S. data and the authors find that the social cost of information frictions is comparable to that of search frictions, which have dominated the macro-labor literature.

Our model also contributes to understanding the relationship between belief dispersion and wage rigidity. We show that slowly adjusting beliefs can be a major amplification mechanism in generating business cycle fluctuations. In a similar vein, Menzio (2022) considers a general equilibrium environment in which a share of workers' beliefs about the labor market evolves sluggishly. In contrast to Menzio (2022), agents in our model learn eventually about their true market conditions, but do so with a delay, triggering some of the same mechanisms emphasized in Menzio's work.

Unlike the models discussed, in our framework there is no uncertainty over the distribution of prices or wages, but rather over the frequency to which job offers arrive. The most comparable paper to ours is Potter (2021). Like here, the uncertainty is over a worker's labor demand, measured as the frequency of job offers. Relative to Potter (2021) and the preceding literature we make two novel theoretical contributions. First, the the model is derived in a general equilibrium setting. This allows us to make predictions over the welfare cost of uncertainty. Crucially, it also allows worker's information (or lack of) to be endogenous to the model, rather than imposed upon it. Second, we do not rely on agents optimizing under the "anticipated utility" framework of Kreps (1998). In our setting, an agent fully internalizes how their beliefs will change tomorrow when making decisions today.

Modern surveys have allowed researchers to assess whether worker's expectations are consequential for their realizations. Stephens (2004) finds that respondents reported beliefs over their opportunities are informative for future outcomes. Although workers beliefs have predictive power over realizations, as in our model, there exists systematic biases, see Spinnewijn (2015) and Mueller et al. (2021) for evidence from survey responses, Falk et al. (2006) from the laboratory, and Mueller and Spinnewijn (2022) for a comprehensive overview. In particular, Mueller et al. (2021) documents that unemployed workers with poor labor market prospects tend to overly optimistic, and the unemployed with better prospects tend to be overly pessimistic, a feature that the model naturally reconciles.

Outline. The rest of the paper is structured as follows. Section 2 presents motivating empirical evidence. Section 3 derives the baseline model. For the purpose of comparison, section 4 presents the full information case. Section 5 calibrates the model and section 6 presents the results and implications of the model. Section 7 examines the response of the economy to an aggregate shock and section 8 concludes.

2 Empirical Motivation

The model presented in the next section features workers updating their perception about their labor market prospects while in unemployment. There are several relatively recent labor market surveys that elicit expectations about job finding rates, wages, and income risk from respondents. For a comprehensive overview of the literature and related surveys see the handbook chapter Mueller and Spinnewijn (2022), and the references contained therein. To motivate the specific learning mechanism present in our framework we will rely on the Survey of Consumer Expectations (SCE), a data set that is maintained by the Federal Reserve Bank of New York and is a representative survey of approximately 1,300 individuals living across the United States, from June 2013 until June 2021. The aim of this section is to present two pieces of supportive evidence for our mechanism. First, that the unemployed update their beliefs about their job finding probability within an unemployment spell and do so in a way that is consistent with our model. Second, that an unemployed worker's beliefs about their job finding probability are consequential for future wages.

Mueller et al. (2021) document that in the cross-section, elicited beliefs about job finding rates decline with the duration of unemployment. However, this decline is the result of dynamic selection rather than *true* duration dependence, implying that as workers spend longer in unemployment, they do not revise down their beliefs about finding a job. In our model, workers learn about the likelihood of finding a job when unemployed. However, beliefs about one's employment opportunities can improve as well as deteriorate. If a worker receives many job offers, which are rejected, in our framework it is likely that they revise their belief about finding a job upward. On the contrary, if a worker receives no job offers, as time passes, they will update their perceived chances of finding a job downward. Respondents in the SCE are asked on a monthly basis, "*the percent chance that within the coming 3*

Table 1: Perceived 3-month job-finding probability and unemployment duration

	Full sample			Spells without job offers		
	(1)	(2)	(3)	(1)	(2)	(3)
Log unemployment duration months	-0.185*** (0.015)	-0.157*** (0.017)	-0.083* (0.044)	-0.171*** (0.028)	-0.141*** (0.030)	-0.145** (0.066)
Demographic controls		x			x	
Spell fixed effects			x			x
Observations	2609	2584	2609	722	714	722
R^2	0.087	0.145	0.790	0.072	0.183	0.768

The dependent variable in each case is the log of the elicited 3-month job-finding probability. Included in the controls are: gender and race dummies; age and age squared; dummies for household income; and dummies for level of education. Robust standard errors are reported in the parentheses, and the asterisks represent the conventional levels of significance. All regressions are weighted using appropriate sampling weights.

months, you will find a job that you will accept". To understand how the duration of the unemployment spell impacts beliefs we regress the log of the elicited probability on the log of unemployment duration. Results are presented in Table 1. The left hand panel considers all unemployed workers. On a quarterly basis, survey respondents are asked how many job offers they received in the previous four months. If respondents indicate zero offers, we can identify specific unemployment spells to which we know the unemployed worker has not received an offer. The results in which the sample is restricted to such spells are presented in the right hand panel of Table 1.

The results from the full sample are consistent with the findings of Mueller et al. (2021). Absent any controls the elasticity of the perceived job finding rate with respect to unemployment duration is -0.185, implying that someone with 10% longer spent in unemployment will believe they have a 1.85% lower probability of finding a job in three months. The fact that those in unemployment longer have more pessimistic beliefs could be because they reduce their beliefs while in unemployment, i.e., *true* duration dependence. Alternatively, it could be because of dynamic selection, i.e., those who believe they have a high probability of finding a job are correct, and consequently leave unemployment faster. Comparing column one with column two and three, one can see that as more time invariant characteristics are controlled for, duration dependence diminishes. In the case of the full sample, once spell fixed effects are included the majority of the duration dependence has dissipated, and the coefficient on log duration is no longer significant at the five percent level.

As discussed, our model implies that a worker's perception of the job finding rate can rise or fall, depending on circumstance. Since, good news comes in the form of job opportunities, and bad news is the absence of new information, restricting the sample to those who do not

Table 2: Wages and perceived job finding probability

	Log re-entry wage			
	(1)	(2)	(3)	(4)
Log elicited 3 month job finding probability	0.528***	0.951***	0.518***	0.906***
	(0.198)	(0.295)	(0.182)	(0.276)
Year fixed effects	x	x	x	x
Demographic controls			x	x
Estimator	OLS	IV	OLS	IV
Observations	266	266	266	266
R^2	0.090	0.065	0.280	0.260

The instrument for the 3-month job finding probability is their answer to the question same question for a 12 month time horizon, where we assume a constant finding probability. Included in the controls are: gender and race dummies; year dummies; age and age squared; and dummies for level of education. Robust standard errors are reported in the parentheses, and the asterisks represent the conventional levels of significance. All regressions are weighted using appropriate sampling weights.

receive job offers provides an interesting test of the model's mechanism. Results presented in columns one and two look similar across the full and restricted sample. That is, those who have spent longer in unemployment are more pessimistic about their probability of finding a job. However, once the spell fixed effect is included in column three, the picture is quite different. This column represents *true* duration dependence since time invariant unobservables within a given unemployment spell are controlled for. When we restrict the sample to those we can be sure have not received a job offer, there is a clear sign of *true* duration dependence. Unemployed workers without job offers reduce their perceived probability of finding a job 1.45% following a 10% increase in the length of their unemployment spell.

Another stark prediction of the model is that beliefs matter for realized wages. First, if a worker believes they are likely to find a job, they are more *picky* in which jobs they accept and will thus only accept higher wage offers. Second, wages will be the result of a bargaining protocol between the worker and the firm. If a worker has higher beliefs about their employability, that corresponds to a higher outside option. To see whether higher beliefs do materialize in higher wages, the log wage following an unemployment spell is regressed on the unemployed workers log of elicited three month job finding probability before they start the job. Results are presented in Table 2. There are two potential sources of bias we envisage from this regression, which it appears act in opposite directions. First, there are likely characteristics that determine a worker's market wage and employability omitted from the specification. In an ideal world we would like to control for these with fixed effects, but our data does not allow this without identification being governed by a handful of observations. However, when one includes control variables for gender, ethnicity, education and age, the coefficient of interest changes very little, potentially suggesting that this bias is small in magnitude. The second source of bias is attenuation bias from measurement error in the elicited 3 month job finding probability. If respondents answer this question with error because of a misunderstanding of probability, or because of an inclination to answer with round numbers for example, the coefficient of interest will be biased downwards. To control for this, the 3 month job finding probability is instrumented in a first stage with the answer to the same question over a 12 month window. Then, assuming a constant job finding probability we compute our 3 month instrument. Our preferred specification from Table 2, the IV regression with controls suggests a 10% higher job finding probability results in 9% higher wages when a worker finds a job.

3 The Baseline Model

We now turn to our model setup. As the data clearly show, beliefs change endogenously with individual experiences in the labor market and play a substantial role in wage setting. While most models of the labor market incorporate only the latter feature, our model is designed to showcase the interaction between both mechanisms.

3.1 The Environment

Time is continuous and the economy consists of a continuum of infinitely lived workers and firms who discount the future at a constant rate r, and populate a continuum of identical markets $m \in [0, 1]$. In each market there is a potentially infinite supply of homogeneous firms who can enter and do so if it is profitable. Workers are *ex ante* homogeneous and can move between markets at a cost χ. Our interpretation of a market is a narrowly defined labor market, an area and occupation pair. Hence χ can be thought of as a catchall cost that embeds retraining and moving. Each worker has a unique suitability $s(m) \in [0, 1]$ for every market. The suitability of a particular market represents the share of jobs in that market a worker is able to do, the index s is unobservable to the worker. However, agents can learn about their suitability by spending time in the market. We assume that an individual's suitability s is random across market index m. Therefore, from an aggregate perspective and from the perspective of firms, all markets are identical. From the perspective of workers, markets are in principle heterogeneous according to their suitability parameter but *ex ante* identical, as suitability in a market is unobserved.

In addition to the informational friction described, the labor market is also characterized by search frictions. Every market m is modeled as in the canonical Diamond-Mortensen-

Pissarides model (DMP) (see e.g. Mortensen and Pissarides (1994)) with heterogeneity in match productivity. Unemployed workers meet open vacancies in a market according to a Cobb-Douglas matching function. Job offers arrive to workers at a contact rate $\tilde{\lambda}_s := s\overline{\lambda}$. Where $\overline{\lambda}$ is determined by the search frictions in the economy and s, the share of suitable offers is imperfectly observable. Once matched, a worker and a firm draw productivity $z \sim$ Pareto$(1, \alpha)$. Conditional on this draw, the worker and the firm engage in Nash bargaining, and, if this negotiation is successful, form a match that produces z units of output.

Two distinct shocks can dissolve a worker-firm match. First, with Poisson rate δ, workers are hit by a match destruction shock that forces them out of their match if employed but leaves them in their labor market (meaning workers retain all information they have collected on the market). Secondly, with Poisson rate η, a reallocation shock forces the worker to reallocate to a new market. If such a worker is in employment, the match is dissolved. This entails a full loss of information on the market environment. We interpret this shock as a reallocation to a new market that is necessary or desirable for reasons outside the model, such as moving locations for family reasons or because of preference shocks.

3.2 Worker Beliefs

For a worker in a market in which they are suitable for a share s of jobs, the *true* Poisson arrival rate is given by $\tilde{\lambda}_s := s\overline{\lambda}$. The contact rate $\overline{\lambda}$ is finite and will be endogenized later. At any time during a worker's career, if they so choose, a worker has the option to pay a cost χ and allocate to a new market. Since *ex ante* all markets are indistinguishable from a worker's perspective, they will move to their new market in a random fashion.

Assumption 1 *For any worker, the distribution of suitability s is idiosyncratic across markets and follows a uniform distribution on* $[0, 1]$.

Given rational expectation of workers, it follows immediately from assumption 1 that a worker's prior belief over the offer arrival rate is uniform on $[0, \overline{\lambda}]$. While it is difficult to support or reject this uniformity assumption empirically, it is easy to generalize the distributional assumption to allow for any suitability distribution (i.e. prior) that follows a truncated gamma distribution, which is a flexible family of distributions.

Once a worker is established in a particular market they receive job offers, and the frequency of these offers will help inform the worker regarding the underlying arrival rate in the market. Since workers only search for jobs in unemployment the information available to them is a series of lapsed time between job offers. As we show in appendix A.1, Bayesian updating yields a truncated Gamma posterior over arrival rates which is fully determined by two sufficient statistics: The length of time spent in unemployment in a given market and the total number of job offers received during that time. Although every worker has a rich history of employment and unemployment spells, only two statistics are sufficient to summarize a worker's beliefs, which simplifies the model enormously. Result 1 formalizes this insight.

Result 1 *For a given worker, let τ denote the time spent in unemployment in a given market and let n denote the number of encounters during that time span. If the worker's prior over the encounter rate is uniform on $[0, \overline{\lambda}]$, then the worker's posterior over the encounter rate is given by*

$$f(\lambda|n,\tau) = \frac{\tau^{n+1}}{\gamma(n+1, \tau\overline{\lambda})}\lambda^n e^{-\lambda\tau} \quad \textit{for } \lambda \in [0, \overline{\lambda}] \tag{Re. 1}$$

where $\gamma(\cdot)$ is the lower incomplete gamma function[1].

This density is the pdf of a truncated gamma distribution with an upper bound $\overline{\lambda}$, scale parameter $\frac{1}{\tau}$, and shape parameter $n+1$. In the expression (Re. 1) and throughout the paper, we drop the tilde notation on λ to distinguish it from the actual encounter rate with suitability s, given by $\tilde{\lambda}_s$. One can derive a closed-form expression for the mean of this distribution, which turns out to be an important expression for the workers' value functions:

Result 2 *For a worker with labor market history summarized by n and τ, the instantaneous expectation of the offer arrival rate is given by*

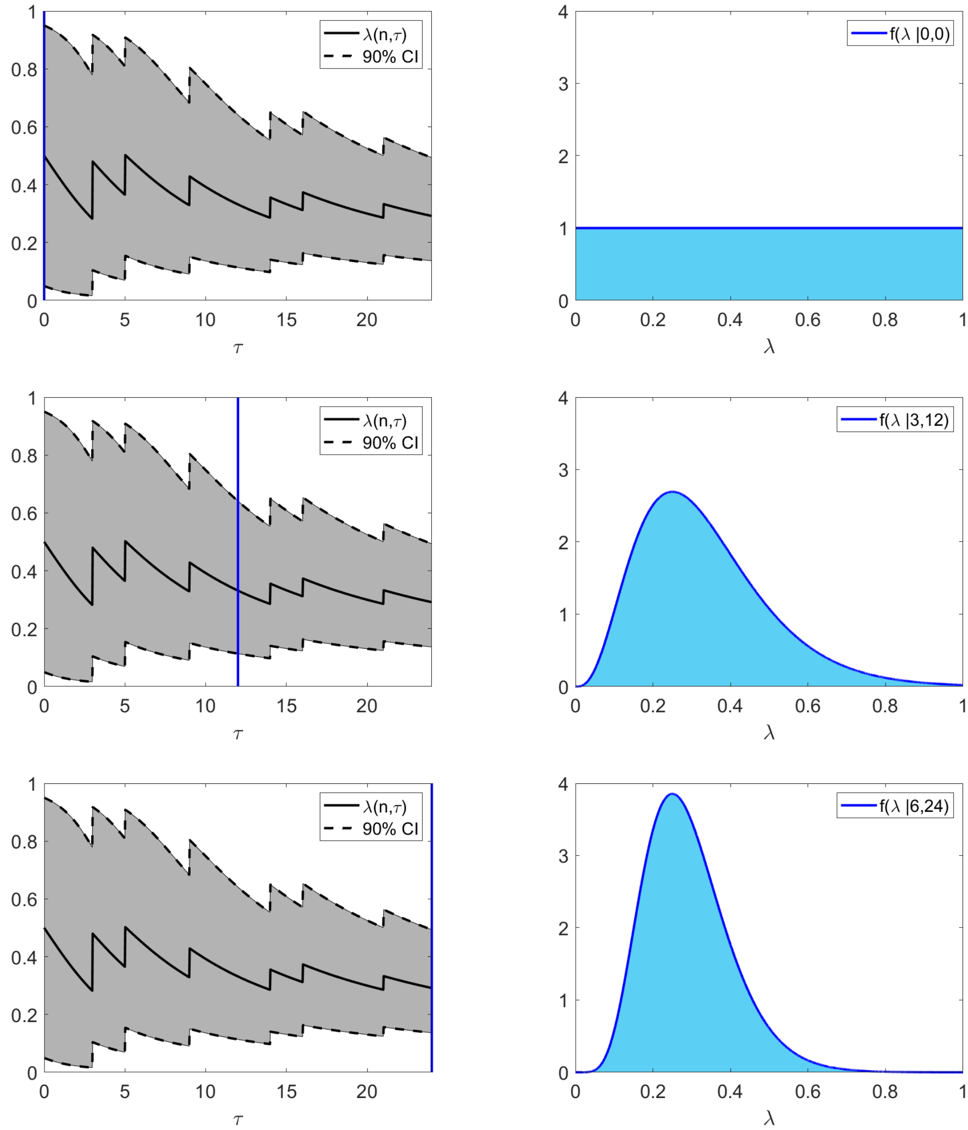
$$\begin{aligned}\lambda(n,\tau) &= \frac{1}{\tau}\left(\frac{\gamma(n+2,\tau\overline{\lambda})}{\gamma(n+1,\tau\overline{\lambda})}\right) \\ &= \frac{1}{\tau}(n+1) - \overline{\lambda}\left(\sum_{k=n+1}^{\infty}\frac{(\tau\overline{\lambda})^{(k-n)}}{(k-n)!}\right)^{-1}\end{aligned} \tag{Re. 2}$$

Result 2 is derived in Appendix A.2. The expression is comprised of two terms. The first is the inverse of the mean duration of each spell. Absent any prior information over the arrival rate the naive expectation would be this first term. However, contained in the worker's prior is a maximum value that the offer arrival rate can take, $\overline{\lambda}$. Thus this second boundary term incorporates this information into the worker's updating rule.

[1]The lower incomplete gamma function is defined as

$$\gamma(s,x) = \int_0^x t^{s-1}e^{-t}dt.$$

Figure 1: Illustration of a worker's updating rule



The left hand panel displays the evolution of the mean of the posterior density, with associated 90% credible intervals. Where the parameter $\overline{\lambda}$ has been fixed at unity. The right hand panel shows the evolution of the entire posterior density.

Figure 1 shows an example of how the posterior density, defined by (Re. 1) might evolve over time. This figure is initialized with a worker with $\tau = 0$ and $n = 0$. Thus, given Assumption 1 the mean of the posterior equal to $0.5\overline{\lambda}$, and the 5^{th} and 95^{th} percentile equal to $0.05\overline{\lambda}$ and $0.95\overline{\lambda}$, respectively. The sawtooth pattern of the mean of the posterior represents a worker becoming more pessimistic as time goes on without an offer, where τ increases and n stay constant with intermittent discrete upward jumps when offers arrive and n increases by one. As the worker spends more time in the market, the credible interval narrows and the posterior becomes more and more precise. While the specifics of the second panel of Figure 1 are unique to this arbitrary history, the general pattern in the figure holds universally. Workers' expectations over the arrival rate worsen in a continuous fashion with increasing τ and improve discontinuously with discrete jumps in n.

3.3 Value Functions

Simplifying the posterior in the fashion described in Result 1 allows us to write down the workers value functions. Let V_e and V_u denote the value functions of an employed and an unemployed worker respectively. An employed worker's value satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$(r + \delta + \eta)V_e(z, n, \tau) = w(z, n, \tau) + \delta V_u(n, \tau) + \eta \left[V_u(0, 0) - \chi\right] \quad (1)$$

Employed workers receive their wage until the match is terminated. If it is terminated by a δ-shock, they re-enter unemployment, retaining their information (n, τ). If the match is terminated by an η-shock, they also enter unemployment but in addition lose all of their information ($n = \tau = 0$), as they reallocate to an unknown market. Moreover, a market transition, voluntary or not, always incurs the mobility cost χ. Contained in equation (1) is no option for a worker to voluntarily switch markets. Although a worker can always decide to switch markets voluntarily at cost χ, they will never do so in employment, since their information set and the expected value of switching remains unchanged. Absent on-the-job-search no new information regarding the market is obtained while in employment, hence n and τ are fixed during an employment spell. A simple revealed preference argument shows that it would never be optimal for an employed agent to voluntarily switch markets. If a worker accepts a job at wage $w(z, n, \tau)$ given their information (n, τ), they must value employment at wage $w(z, n, \tau)$ over the option to switch, as otherwise they would value switching over staying unemployed under information (n, τ) and would have left their current market prior to meeting their employer.[2] Finally, in expression (1) no terms contain a tilde implying arguments are in expectation. Hence, the *true* suitability of a worker to the market plays no direct role in the value function.

We now turn to the value function of the unemployed which features learning. Since at any moment workers have the option to switch markets, the dynamic programming problem takes the form of an optimal stopping time problem. Let $\lambda(n, \tau)$ denote the posterior mean

[2]Formally, this argument is implied by the continuity of V_u in both arguments which can be shown from the Bellman equation using standard arguments.

of the encounter rate distribution. Then the value of an unemployed worker $V_u(\cdot)$ satisfies (2). A formal derivation of the value function is performed in Appendix A.3.

$$
\begin{aligned}
rV_u(n,\tau) = \max\Bigg\{ \Bigg(& b + \overbrace{\lambda(n,\tau)\mathbb{E}_z\left[\max\left(V_e(z,n+1,\tau) - V_u(n+1,\tau), 0\right)\right]}^{(1)} \\
& + \underbrace{\eta\left(V_u(0,0) - \chi - V_u(n,\tau)\right)}_{(2)} \\
& + \underbrace{\lambda(n,\tau)\left(V_u(n+1,\tau) - V_u(n,\tau)\right)}_{(3)} + \underbrace{\frac{\partial V_u(n,\tau)}{\partial \tau}}_{(4)} \Bigg), \\
& r(V_u(0,0) - \chi) \Bigg\}
\end{aligned}
\tag{2}
$$

Consider first the subset of the domain $\mathbb{N}_0 \times \mathbb{R}_+$ on which the worker does not voluntarily switch markets. In this case, the max operator in equation 2 selects the first of its two arguments. It is comprised of five components: A worker receives a flow value of b while unemployed. At an unknown rate $\tilde{\lambda}_s$, the worker encounters a firm and has the option to become employed. Since the true encounter rate $\tilde{\lambda}_s$ is unknown, the worker uses their posterior f to determine their expected value, integrating over all possible values of λ. This turns out to be identical to simply using the posterior mean as the arrival rate when computing the value function. Term (1) therefore captures the option value of employment. At the time of a job offer, the worker's information state changes and therefore so do the worker's beliefs. Therefore, both the value of employment and unemployment are compared at the new information state with $n+1$ encounters. Unemployed workers are subject to forced reallocation shocks, captured by term (2). Terms (3) and (4) correspond to the Bayesian updating rule. Every encounter causes the worker to positively update their posterior (term (3)) but time spent in unemployment without receiving offers leads to negative updating of the posterior (term (4)).

Now consider the subset of the domain on which the max operator selects the second argument, i.e. states in which the worker chooses to leave their market. Since suitability is idiosyncratic, each market looks identical to one another from the perspective of an uninformed worker. A worker thus reallocates to a randomly drawn new market with a prior over suitability defined by Assumption 1. The value associated with this option is $V_u(0,0) - \chi$.

Although the posterior distribution enters equation 2 only through the posterior mean, $\lambda(n,\tau)$ is by no means a sufficient statistic for the value function at (n,τ). This is because of the learning terms (3) and (4), which will generally play a larger role when n and τ are small and disappear as n and τ go to infinity. The presence of these learning terms means that the worker takes into account how their beliefs will change in the future given any possible labor market history they might experience. This sets our model apart from models using the "anticipated utility" framework (see e.g. Potter (2021)), a popular assumption that rules out such an internalization of belief changes to simplify computation.

As we show in appendix A.4, we can use the Nash bargaining assumption detailed in section 3.4 to write the right hand side of equation 2 solely as a function of V_u, n and τ. Appendix A.5.1 outlines how the resulting HJBVI can be written as the special case of a linear complementarity problem (LCP) for which fast solution methods are known. The corresponding solution yields optimal stopping times $T^\star(n)$ for each $n \in \mathbb{N}_0$, i.e. the total market unemployment duration at which a worker with n encounters decides to leave the market.

Consider now the firm's problem. A matched firm receives the flow output of a match minus the wage until termination. By free entry, the value to the firm of any match is zero after termination (as the value of a vacancy is zero). Therefore, the value of a filled match is given by (3). Notice again the *true* suitability of the worker for the market does not feature in the value function. We assume that the firm also does not observe the true s, just whether the worker is suitable for this particular job. However, since wages depend on the worker's beliefs, even if the firm were to know s it would not change the value of the match.

$$(r + \delta + \eta)J(z, n, \tau) = z - w(z, n, \tau) \tag{3}$$

Given V_u, we can therefore write the joint surplus $S(z, n, \tau) := V_e(z, n, \tau) + J(z, n, \tau) - V_u(n, \tau)$ of a match as

$$(r + \delta + \eta)S(z, n, \tau) = z - (r + \eta)V_u(n, \tau) + \eta \left[V_u(0, 0) - \chi\right]$$

Hence, surplus is positive when

$$z > z^\star(n, \tau) := (r + \eta)V_u(n, \tau) - \eta \left[V_u(0, 0) - \chi\right] \tag{4}$$

$z^\star(n, \tau)$ is the minimum productivity draw necessary for an encounter to become a match. The formula determining this threshold is intuitive - at the threshold, the value of unemployment in flow units must equal z adjusted for the possibility of forced reallocation shocks. $z^\star$ turns out to be an important statistic. For one, it is a sufficient statistic for computing wages. Moreover, since we assume that $z \sim \text{Pareto}(1, \alpha)$, the probability of a match given an encounter is given by $\max\{1, z^\star(n, \tau)\}^{-\alpha}$.

3.4 Wages

We assume that wages are set by Nash bargaining. In our environment, neither the firm nor the worker know the true market environment for the worker. Instead the information set is limited to (n, τ) which we assume is observable to both parties. While the assumption that (n, τ) is observable to the firm is not completely innocuous, we argue that two features of the environment are sufficient for this information being revealed even in a private information setting. First, τ has to be public information. We deem this assumption reasonable, as in reality unemployment duration in a given market is generally observable during the job application process. Second, we assume that a worker has access to a technology that allows them to credibly prove any past encounter to the firm. Since a higher n strengthens the worker's bargaining position, they will always have an incentive to communicate all encounters to any prospective employer. However, the firm will require proof of every encounter, since a higher n deteriorates their position. In equilibrium, the worker will communicate and submit proof for every true encounter. Under this assumption, the co-operative Nash bargaining game therefore mirrors the standard, full information cases with disagreement points $(V_u(n, \tau), 0)$. In appendix A.7 we show that, given a solution for $z^\star$, wages are affine in productivity z.

$$w(z, n, \tau) = \beta z + (1 - \beta) z^\star(n, \tau) \tag{5}$$

3.5 Worker Distributions

In appendix A.6, we show that given the matching thresholds $z^\star(n, \tau)$, the distributions $u(n, \tau, s)$ and $e(n, \tau, s)$ can be found as the solution to a system of differential equations which can be solved numerically by iterating over values of n: First, for $n = 0$ and $\tau < T^*(0)$,

$$\begin{aligned} &\partial_\tau u(0, \tau, s) = -(\tilde{\lambda}_s + \eta) u(0, \tau, s) \\ \implies\ &u(0, \tau, s) = u(0, 0, s) \cdot \exp(-(\tilde{\lambda}_s + \eta)\tau) = \mu \cdot \exp(-(\tilde{\lambda}_s + \eta)\tau) \end{aligned} \tag{6}$$

where μ is the number of entrants in each market (which can be found using the condition that population must integrate to one). Then, for $n \geq 1$, $\tau < T^*(n)$, the employment distribution can be characterized as a solution to a set of linear non-homogeneous ODEs given the solution for $n-1$:

$$e(n,\tau,s) = \mathbb{I}(\tau < T^*(n-1))P(z \geq z^*(n,\tau))\frac{\tilde{\lambda}_s}{\delta+\eta}u(n-1,\tau,s) \tag{7}$$

$$\partial_\tau u(n,\tau,s) = \Bigg[\mathbb{I}(\tau < T^*(n-1))\left(P(z < z^*(n,\tau)) + P(z \geq z^*(n,\tau))\frac{\delta}{\delta+\eta}\right)\cdot \tilde{\lambda}_s u(n-1,\tau,s)\Bigg] - (\tilde{\lambda}_s+\eta)u(n,\tau,s) \tag{8}$$

with boundary conditions $u(n,0,s) = 0\,\forall n \geq 1$. After solving the system of differential equations, the aggregate unemployment rate is computed as

$$\overline{u} = \sum_{n'=0}^{\infty}\int_0^{T^\star(n)}\int_0^1 u(n',\tau',s')d\tau' ds'.$$

3.6 Free Entry

To close the model we now consider the free entry condition. Using equations 3 and 5, the value of a match to a firm is given by

$$(r+\delta+\eta)J(z,n,\tau) = (1-\beta)z - (1-\beta)z^\star(n,\tau) \tag{9}$$

The value of posting a vacancy to a firm is given by V_v.

$$rV_v = -\kappa + \overline{\lambda}_f\left(\frac{1}{\overline{u}}\right)\sum_{n'=0}^{\infty}\int_0^{T^\star(n)}\int_0^1\left(s'u(n',\tau',s')\left(\int_{\max\{1,z^\star(n+1,\tau)\}}^{\infty}J(z,n+1,\tau)d\Gamma(z) - V_v\right)\right)d\tau' ds'$$

To keep a vacant position open requires a flow cost κ. The aggregate contact rate of workers to firms — both the suitable and unsuitable potential employees, is defined as $\overline{\lambda}_f$. Upon meeting a worker, they may or may not be suitable, and will vary in their labor market history summarized by n and τ. The unsuitable workers provide no value to the firm. The labor market history is of consequence to the firm as it will determine the bargained wage, given by (5). The ideal candidate from a firm's perspective would be a suitable worker who believes, with some precision, that they are in a poor market. This worker will be more likely hired, having a lower threshold productivity, and for a given productivity will command a lower wage.

Free entry of firms implies that firms continue to enter until the value of doing so is zero, $V_v = 0$. Substituting the free entry condition into the value of a vacancy and following analogous steps to those of appendix A.4 for the value of a match to the firm yields expression

(10).

$$\kappa = \overline{\lambda}_f \left(\frac{1}{\overline{u}}\right) \sum_{n'=0}^{\infty} \int_0^{T^\star(n)} \int_0^1 \left(s' u(n', \tau', s') \int_{\max\{1, z^\star(n+1,\tau)\}}^{\infty} J(z, n+1, \tau) d\Gamma(z) \right) d\tau' ds' \quad (10)$$

$$\text{where} \int_{\max\{1, z^\star(n+1,\tau)\}}^{\infty} J(z, n+1, \tau) d\Gamma(z) = \begin{cases} \frac{1-\beta}{r+\delta+\eta} \left(\frac{\alpha}{\alpha-1} - z^\star(n,\tau)\right) & \text{for } z^\star(n,\tau) < 1 \\ \frac{1-\beta}{r+\delta+\eta} \left(\frac{1}{\alpha-1}\right) z^\star(n,\tau)^{1-\alpha} & \text{for } z^\star(n,\tau) \geq 1 \end{cases}$$

The suitability parameter directly enters in the free entry condition. This is because workers with low suitability will still encounter firms and thereby congest the market without producing matches. This leads to an important source of misallocation: Without *ex ante* information on which markets they are suitable for, workers spend a lot of time in unsuitable markets. This drives down match efficiency for all workers, causing a decline in job posting incentives that leads to a lower job encounter rate $\bar{\lambda}$ in general equilibrium.

Finally, the worker and firm contact rates are determined by a constant returns to scale Cobb-Douglas matching function $m(\overline{u}, \overline{v}) = Au^{\omega}\overline{v}^{(1-\omega)}$, where $\overline{v}$ is the aggregate measure of vacancies. Therefore, the maximum worker contact rate is computed as $\overline{\lambda} = m(\overline{u}, \overline{v})/\overline{u}$ and given by (11). Given constant returns to scale and identical markets, it is isomorphic to think of the matching function as defined at the market rather than aggregate level.

$$\overline{\lambda} = A^{\frac{1}{\omega}} \overline{\lambda}_f^{\frac{\omega-1}{\omega}}. \quad (11)$$

3.7 Equilibrium

We are now ready to define an equilibrium in the baseline model:

Definition 1 *A* ***baseline equilibrium*** *is a tuple* $(V_e(\cdot), V_u(\cdot), J(\cdot), z^\star(\cdot), w(\cdot), u(\cdot), e(\cdot), \overline{\lambda}, \overline{\lambda}_f)$ *such that*

1. *The value functions solve their Bellman equations* (V_e, J) *or the HJBVI* (V_u) *(equations 1, 2 and 3)*

2. *Productivity thresholds are set according to equation 4*

3. *Wages are set according to Nash bargaining (equation 5)*

4. *The employment distributions* $u(\cdot)$ *and* $e(\cdot)$ *solve the Kolmogorov Forward Equations (equations 6, 7 and 8)*

5. *Free entry pins down* $\overline{\lambda}$ *and* $\overline{\lambda}_f$ *(equations 10 and 11)*

4 The Full Information Model

To assess the effects of the informational friction, we compare our economy to one with full information. To this end, we construct what we term the "full information model". This model is set up to fully mirror the baseline model with one important difference: We assume that at any point every worker is fully informed about their suitability in every market. There is no uncertainty about the underlying arrival rate of jobs, only about the realization of the Poisson process. In this environment, there is no need for workers to keep track of the information state (n, τ). Under full information, a worker will always choose the market they are most suitable for, $s = 1$. In equilibrium, every worker will thus be suitable for all jobs in their market and the Poisson arrival rate of jobs to unemployed workers is $\bar{\lambda}$. Hence, the model collapses along two dimensions. First, because the information state becomes irrelevant, second, because market suitability is always one.

The resulting model turns out to be the baseline DMP model, replicated infinitely many times along an irrelevant dimension m, which we can drop from the notation. This is an elegant feature of our baseline model: When the informational friction is removed, the resulting model is simply the standard search model under free entry. The resulting HJB equations are

$$(r + \bar{\lambda} + \eta)V_u = b + \bar{\lambda}\mathbb{E}_z[\max\{V_e(z), V_u)\}] + \eta(V_u - \chi) \tag{12}$$

$$(r + \delta + \eta)V_e(z) = w(z) + \delta V_u + \eta(V_u - \chi) \tag{13}$$

$$(r + \delta + \eta)J(z) = z - w(z) \tag{14}$$

Further, as shown in appendix A.8, the equilibrium is characterized by

$$z^\star = b + \kappa\frac{\beta}{1-\beta}\frac{\bar{\lambda}}{\bar{\lambda}_f} \tag{15}$$

$$w(z) = \beta z + (1-\beta)z^\star \tag{16}$$

$$u = \frac{\delta + \eta}{\delta + \eta + \max\{1, z^\star\}^{-\alpha}\bar{\lambda}} \tag{17}$$

$$e = 1 - u \tag{18}$$

$$\bar{\lambda}_f \mathbb{E}_z[J(z)] = \kappa \tag{19}$$

which allows us to write the following equilibrium definition for the case of full information:

Definition 2 *A* ***full information equilibrium*** *is a tuple* $(V_e(\cdot), V_u(\cdot), J(\cdot), z^\star(\cdot), w(\cdot), \overline{u}, e(\cdot), \bar{\lambda}, \bar{\lambda}_f)$ *such that*

1. *The value functions solve their Bellman equations (equations 12, 14 and 13)*

2. *Productivity thresholds are set according to equation 15*

3. *Wages are set according to Nash bargaining (equation 16)*

4. *Employment e and unemployment u are given by equations 17 and 18*

5. *Free entry pins down $\bar{\lambda}$ and $\bar{\lambda}_f$ (equations 19 and 11)*

5 Calibration and identification

We now turn to the calibration of the model. For the purpose of computing welfare gains, we use the same calibration for both the baseline and the full information model. This calibration is such that we match targets in the baseline model. For the purpose of comparing implications for frictional wage dispersion (section 6.2.2) and when studying the aggregate shock (section 7) we re-calibrate the full information model to hit the same targets as the baseline model. Appendix A.9 displays the corresponding calibration table.

In total, there are 10 parameters to calibrate, listed in Table 3. Our calibration strategy intentionally side-steps using moments that force us to commit to a clear delineation of labor markets in the data. Instead, for some parameters, we find corresponding aggregate moments for which we have clear data counterparts or literature estimates and target those moments. For others, we simply impose standard values.

We calibrate 5 parameters externally: We set the interest rate to a value of 5% annually. The monthly separation rate is 2% of which we attribute two thirds to reallocative separations, which corresponds roughly to the share of separations that are quits in the JOLTS data[3]. We set the matching function elasticity with respect to the number of unemployed to 0.3, following Borowczyk-Martins et al. (2013). Finally, we normalize $A = 1$, which simply pins down the scale of vacancies but has no other allocative consequences.

There are 5 remaining parameters that are calibrated internally. We follow the convention to calibrate b by targeting the replacement rate, defined as the ratio of b over the mean wage in the economy, $\bar{w} = \int_0^1 \sum_{n=0}^{\infty} \int_0^T \star(n) \frac{e(n,\tau,s)}{\int \sum_{\tilde{n}=0}^{\infty} \int e(\tilde{n},\tilde{\tau},\tilde{s})\, d\tilde{\tau} d\tilde{s}} \mathbb{E}_z \left[w(z,n,\tau) \right] d\tau ds$. We calibrate to a replacement rate of 0.4, which is a typical value used in the literature, for example in Shimer (2005). We can pin down κ by imposing a realistic unemployment rate, which we set to

[3] This is consistent with our interpretation that η-shocks can be thought of as preference shocks that sufficiently incentivize reallocation. The same argument is made in Alvarez and Shimer (2011) to calibrate a similar parameter in a model in which workers switch across industry.

5%. There are 3 remaining parameters for which the calibration targets are somewhat more intricate.

First, consider the reallocation cost χ. Since workers will always switch markets if the suspected net payoff is larger than χ, the parameter determines how pessimistic worker beliefs have to be to induce switching. The parameter χ therefore directly determines the most pessimistic belief workers hold in the economy. In our model, the most pessimistic belief manifests in the lowest wage paid. A natural calibration target in our context is therefore the ratio of the average wage to the lowest wage paid in the economy (which occurs in every market)[4]. This "mean-min ratio" of wages has been the subject of study in the literature since it was pointed out in Hornstein et al. (2011) that standard labor market models often fail to generate it. We take our calibration target to be 1.64, which we take from row (6) of Table 1 in Hornstein et al. (2007). The fact that our model is able to match this moment sets it apart from many standard search models, a point we will return to in the succeeding section.

The second remaining parameter to calibrate, β, governs the share of surplus appropriated by workers. We pin it down by using estimates of the pass-through elasticity of wages with respect to productivity shocks. When β is high, so is the pass-through rate, i.e. productivity increases lead to higher wage increases. Vice versa, a low β leads to a low pass-through rate. We use the result from Lamadon et al. (2022) who estimate this elasticity to be equal to 0.13 on average. In our application, it is very easy to find the harmonic mean of the elasticity of wages with respect to productivity:

$$\begin{aligned}\mathbb{E}_z\left[\varepsilon(z,n,\tau)^{-1}\right] =&\mathbb{E}_z\left[\left(\frac{d\log w(z,n,\tau)}{d\log z}\right)^{-1}\right] = \mathbb{E}_z\left[\left(\frac{\partial w(z,n,\tau)}{\partial z}\right)^{-1}\frac{w}{z}\right]\\ =&\mathbb{E}_z\left[\beta^{-1}\left(\beta+(1-\beta)\frac{z^\star(n,\tau)}{z}\right)\right] = \mathbb{E}_z\left[1+\frac{1-\beta}{\beta}\frac{z^\star(n,\tau)}{z}\right]\\ =&1+\frac{1-\beta}{\beta}\frac{\alpha}{1+\alpha}\frac{z^\star(n,\tau)}{\max\{1,z^\star(n,\tau)\}} = 1+\frac{1-\beta}{\beta}\frac{\alpha}{1+\alpha}\min\{1,z^\star(n,\tau)\}\end{aligned}$$

so we impose a β that generates the correct harmonic mean $\bar{\varepsilon}$ of the pass-through elasticity in our economy, i.e. $\bar{\varepsilon} = \left(\int_0^1 \sum_{n=0}^\infty \int_0^{T^\star(n)} \frac{e(n,\tau,s)}{\int\sum_{\tilde{n}=0}^\infty \int e(\tilde{n},\tilde{\tau},s)d\tilde{\tau}d\tilde{s}} \mathbb{E}_z\left[\varepsilon(z,n,\tau)^{-1}\right] d\tau ds\right)^{-1} = 0.13$.

Finally, α is calibrated to match the rate at which workers encounter jobs. This is equivalent to calibrating to the acceptance rate of jobs, since we calibrate to the unemployment rate and therefore implicitly impose the job finding rate. Intuitively, when α goes to infinity, all jobs are accepted and, conversely, when α goes to one, none are. We hit a target

[4] In our baseline economy, employment-weighted average of market-specific mean-min ratios is equal to the economy-wide mean-min ratio.

Symbol	Parameter description	Value	Target	Value
r	Interest rate	0.05/12		
δ	Separation rate into same market	$0.02 \cdot \frac{1}{3}$		
η	Reallocation rate into new market	$0.02 \cdot \frac{2}{3}$		
ω	Matching function elasticity	0.3		
A	Matching efficiency	1.0		
b	Flow value of unemployment	0.418	Replacement rate $\frac{b}{\overline{w}}$	0.4
α	Pareto parameter of prod. dist.	5.76	Encounter rate	0.5
χ	Reallocation cost	23.3	Mean-min ratio	1.64
β	Worker bargaining power	0.11	Wage-prod. pass-through	0.13
κ	Vacancy posting cost	1.61	Unemployment rate	0.05

Table 3: Parameters and calibration targets

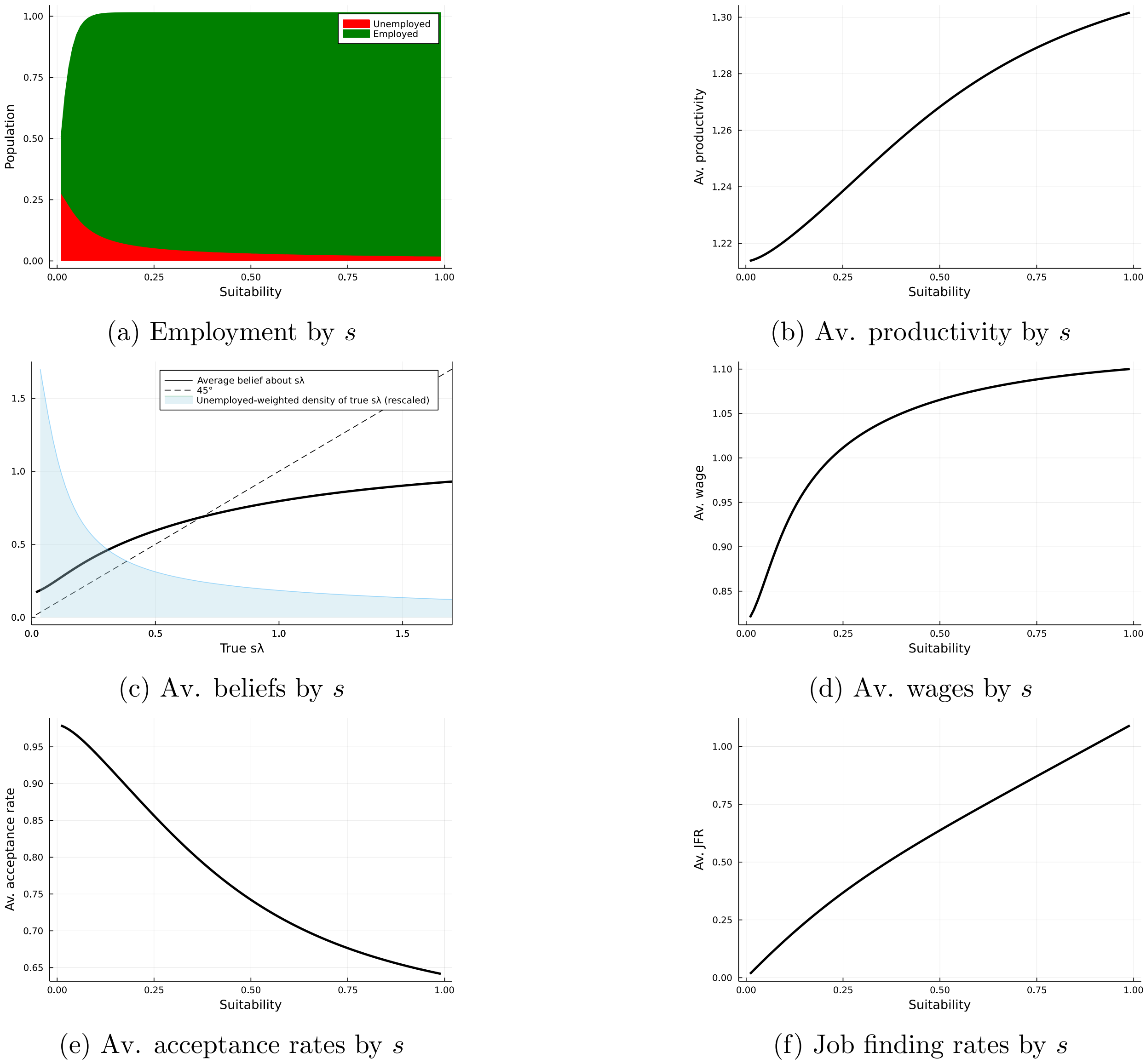
encounter rate of 0.5, in accordance with the average monthly number of offers for a typical unemployed worker as reported in Faberman et al. (2022).

6 Results

6.1 Summary of model output

Figure 2 summarizes the allocations produced by the calibrated model by displaying the employment distribution as well as averages of variables by worker suitability s. The job finding rate is the product of the contact rate ($s\overline{\lambda}$) and the acceptance rate (given by panel (e)), and is increasing in suitability. Consequently, since separations are fixed across markets, the unemployment rate declines with s. The population is increasing in s as unemployed workers, on average, leave bad markets when their estimates of market conditions become sufficiently pessimistic. Productivity and wages are increasing in s, since the more suitable workers have more encounters and can be more selective about which encounters to accept - this can be verified by the fact that the average acceptance rate - the ratio of matches per encounter - in each market is also falling in s.

The figure demonstrates that the model endogenously generates biased beliefs. Workers in bad markets are overly optimistic while workers in good markets are overly pessimistic. This pattern of beliefs in consistent with the findings of Mueller et al. (2021). Irrespective of their true suitability, a worker enters each market with the same prior. If a worker is unsuitable for some specific market and s is close to zero, their posterior mean will converge to the truth from above and hence will on average be larger than the true encounter rate. The reverse argument follows for a worker with high suitability, who is on average overly pessimistic.



(a) Employment by s

(b) Av. productivity by s

(c) Av. beliefs by s

(d) Av. wages by s

(e) Av. acceptance rates by s

(f) Job finding rates by s

Figure 2: Allocations in the baseline model

6.2 Model implications

The calibrated model provides us with three consequences of incorporating an information friction in an otherwise standard labor search model, which we believe are worthy of discussion. First, a natural consequence of our model is declining starting wages with the duration of an unemployment spell. This is of consequence to a recent literature evaluating the cost of job loss which typically attribute this relationship to depreciation of human capital while in unemployment. Second, unlike the canonical search model, our calibrated model can generate a level of frictional wage dispersion that is consistent with data. Third, the model highlights new sources of inefficiencies which we document. Overall welfare losses of misinformation are large, and account for more than a third of total output.

6.2.1 Wage dependence on duration

There is a burgeoning literature that attempts to explain the persistence in the cost of job loss through the lens of a search model of the labor market. A common feature of Ortego-Marti (2016), Burdett et al. (2020), Flemming (2020), and Jarosch (2021) is that when in unemployment a worker loses human capital. The extent of the *scarring effect* of unemployment in all four papers is disciplined by a regression akin to (20).

$$\log\left(w_{it}^{0}\right) = \beta_0 + \beta_1 \text{dur}_{it} + \beta_2 \log\left(w_{it}^{P}\right) + \varepsilon_{it} \tag{20}$$

The specification takes the newly employed and regresses the log starting wage on the duration of unemployment and a measure of previous wages. While the first wage following an unemployment spell can be, on average, lower than a typical wage through the job ladder (Jarosch (2021)) or wage-tenure contracts (Burdett et al. (2020)), there is nothing present in these models other than human capital depreciation that would generate a sensitivity with respect to the duration of the unemployment spell. Consequently, the existence of a mechanism omitted from these studies explaining the phenomenon would lead to inaccuracy in the calibration of human capital depreciation.

In the framework presented here, absent any human capital depreciation, there is a mechanism that generates a negative relationship between unemployment duration and re-employment wages. As a worker spends time in unemployment, assuming they have not turned down wage offers, their perception of their labor market opportunities deteriorates. Over time the worker becomes more pessimistic and is willing to accept lower and lower productivity jobs. Further, their outside option falls, and hence the same productivity job will lead to a lower bargained wage. The equivalent specification to (20) in Flemming (2020) estimates a monthly value of β_1 for the US labor market at -0.03.[5] If one interprets this as being entirely driven by human capital loss in unemployment, then it implies it would take less than two years in unemployment for one's human capital to halve. Simulating worker histories from the baseline model we run the regression specification in (20), using the worker's previous wage as the right hand side variable. Our estimate of β_1 is -0.02. In comparison with the regression in Flemming (2020), the results suggest that the rate of human capital depreciation is over-stated by a factor of three.

[5]This number is taken from column 3 of Table 1. A monthly number is obtained my multiplying the weekly estimate of -0.007 by 4.33.

6.2.2 Degree of Frictional Wage Dispersion

Hornstein et al. (2011) document the inability of the canonical search model to generate the degree of frictional wage dispersion seen in the data. To understand this, under full information a worker's reservation wage $\underline{w}$ is the wage to which they are indifferent between employment and unemployment. One can then decompose the degree of wage dispersion potentially generated, measured as the ratio of the reservation wage to the mean wage in the economy as the sum of the replacement rate and a worker's search option. Since the search option increases in the mean wage, for *reasonable* values of the replacement rate the model is unable to generate a substantial difference between the minimum acceptable wage and the mean. Implementing this decomposition on the calibrated full information model yields the following.

$$\underbrace{\frac{\underline{w}}{\mathbb{E}(w)}}_{\text{min-mean ratio 96\%}} = \underbrace{\frac{b}{\mathbb{E}(w)}}_{\text{rep. rate 40\%}} + \underbrace{\frac{\beta}{\mathbb{E}(w)}\tilde{\lambda}\int S(z')^{+}d\Gamma(z')}_{\text{search option 56\%}}$$

There have been several recent papers that highlight mechanisms that facilitate a search model generating a greater degree of wage dispersion. Broadly speaking, the strategies for generating more dispersion come in one of two forms: ether reducing the value associated with unemployment; or alternatively, reducing the search option value. An example of the former, Ortego-Marti (2016) includes human capital depreciation in unemployment, hence a worker will accept a lower wage offer to preserve future human capital. Alternatively, Bradley and Gottfries (2021) derive a model in which opportunities arrive akin to stock-flow matching and the employed endogenously draw wage offers from a distribution that stochastically dominates that of the unemployed. This leads to less of an option value for the unemployed. In our model, within a market the search option is fixed and the perceived value of unemployment only changes with changing beliefs. To understand the novel mechanism of our model, consider the following decomposition of the calibrated baseline model.

$$\underbrace{\frac{\underline{w}}{\mathbb{E}(w)}}_{57\%} = \underbrace{\frac{b}{\mathbb{E}(w)}}_{\text{rep. rate 40\%}} + \underbrace{\frac{\beta}{\mathbb{E}(w)}\lambda(0,0)\int S(z',1,0)^{+}d\Gamma(z')}_{\text{search option 54\%}} \underbrace{-(r+\eta)\frac{\chi}{\mathbb{E}(w)}}_{\text{information friction -39\%}}$$
$$+\underbrace{\frac{1}{\mathbb{E}(w)}\left(\lambda(0,0)\left(V_u(1,0)-V_u(0,0)\right)+\frac{\partial V_u(0,0)}{\partial\tau}\right)}_{\text{learning option 2\%}}$$

The reservation wage $\underline{w}$, is the lowest acceptable wage.[6] This wage corresponds to the reser-

[6]Note that since the bargained wage of the lowest productivity exceeds $\underline{w}$ the reservation wage is non-

vation wage of a worker indifferent between remaining in their market and switching. The replacement rate, as a consequence of the calibration, is identical across both decomposition exercises. The perceived search option varies with workers beliefs, here the reference group are those newly entering a market, and the value is similar in both the full information and the baseline model. The final two terms are novel to this paper. First, the learning option which plays little role captures that by simply remaining in unemployment, your value will change through learning. This will either increase discretely with job offers or deteriorate smoothly with the absence of offers. It is the term labeled information friction which allows the model to generate the level of frictional wage dispersion in the data. The size of the cost of mobility determines how long a worker is willing to stay in what they perceive as a market with a low job finding rate. As $\chi \to \infty$ a worker will never leave a market and hence even if they believe the job finding rate to be zero, and thus there is no option value they will remain fixed. It is thus this heterogeneity in beliefs, that governs the heterogeneity in acceptable wages.

Since the parameter χ allows the model to match frictional wage dispersion a natural question to answer is, whether the calibrated parameter value of χ that generates the degree of frictional wage dispersion estimated by Hornstein et al. (2007) is sensible. Table 3 gives the calibrated switching cost at 23.3. Given a mean monthly wage of 1.04, this corresponds to a switching cost of approximately 22 months of average earnings. This is quite low, when compared with the structural microeconometric literature that estimates the cost of switching markets. Kennan and Walker (2011) estimates the cost of switching across geographic space at $312,000 and Artuç et al. (2010) estimates the cost of a worker switching industry at 13 times their annual earnings on average.

6.2.3 Welfare loss of the informational friction

Efficiency in the canonical search model is governed by the level of vacancies. Since the matching function is typically assumed concave in the level of vacancies, posting an additional vacancy exerts a negative *congestion* externality on the labor demand side of the market. The constrained efficient allocation is reached in the knife-edge case when the elasticity of the matching function with respect to unemployment coincides with the worker bargaining power, the Hosios (1990) condition. In a setting with learning, this efficiency condition breaks down. Rather than examine a general equilibrium constrained efficiency condition, we focus on the inefficient decisions that are made by workers behind a veil of ignorance. They are: (i) jobs are accepted that should be rejected and vice-versa; (ii) workers stay in markets they should leave and leave markets in which they should stay. Our concept of what

binding and thus the *potential* min-mean ratio exceeds the targeted *true* value in the calibration.

a worker *should* do, is the decision they would take were their suitability s for their current market to be revealed to them.

Consider a worker with duration τ in a market with suitability s who has accumulated n offers. The expected arrival rate of job offers is given by $\lambda(n, \tau)$. As n and τ go to infinity a worker becomes certain of the market they are in, that is that $\lambda(n, \tau)$ converges in probability to the true market arrival rate $\tilde{\lambda}_s$.

$$\operatorname*{plim}_{\tau\to\infty\ ,\ n\to\infty} \lambda(n, \tau) = \tilde{\lambda}_s$$

To evaluate workers' decisions we take the limit in equation (2) as τ and n go to infinity.

$$(r+\eta)\tilde{V}_u(s) = \max \left\langle b + \tilde{\lambda}_s \mathbb{E}_z \left[\max\left(\beta \tilde{S}(z,s), 0\right)\right] + \eta(V_u(0,0) - \chi)\ ,\ (r+\eta)(V_u(0,0) - \chi) \right\rangle$$

The worker has two threshold strategies to deduce: (i) a productivity cutoff $z^\star(s)$, above which jobs are accepted; and (ii) a market cutoff $s^\star$, which determines whether they wish to stay in the market. These objects are derived in Appendix A.10. Computing these for workers in the baseline model we can get a sense for where worker decisions are inefficient. The shares of these inefficient decisions are reported in Table 4.

Table 4: Workers Inefficient Decisions

	Job Offers	Market Switching
Incorrect rejections/stayers	5.3%	31.6%
Incorrect acceptances/movers	9.9%	2.6%
Total Welfare Loss	36.3%	

The top panel uses the optimal thresholds computed in Appendix A.10, where it is assumed workers have certainty over the market they are in with the equilibrium outcomes of the model. The total welfare loss associated with the information friction compares welfare in the baseline model with welfare in the full information model using the parameters from Table 3.

The moment that stands out most from Table 4 is the share of workers who remain in a market, but would switch if they were informed about the true arrival rate. This corresponds to almost a third of all unemployed workers. In an ideal world, the first panel of Figure 2 should have no mass left of the marginal market. Workers remain there because of overly optimistic views of the market. Finally, we evaluate the welfare loss of the informational friction. We obtain it by computing a welfare measure in the baseline model and the full information model using the parameters in Table 3. In a model with distorted beliefs, a welfare definition is not obvious. Should one maximize expected or realized benefits?

Since there are no distortions in the beliefs in the full information model, to create as fair a comparison as possible we assume a social planner would want to maximize realized benefits. Since workers are risk-neutral, maximizing total welfare is equivalent to the maximizing flow values. Total welfare is defined by Ω below. The four terms represent the sum of the flow benefit received by the unemployed, the output produced by the employed, net of vacancy and market switching costs.

$$\Omega := b\overline{u} + \int_0^1 \sum_{n=1}^{N} \int_0^{T^\star(n)} e(n,\tau,s)\mathbb{E}\left[z|z \geq z^\star(n,\tau)\right] d\tau ds - \kappa\overline{v} - \chi\left(\eta + \int_0^1 \sum_{n=0}^{N} u(n, T^\star(n), s)ds\right)$$

Using this definition, the overall welfare loss associated with the information friction is computed at 36.3%. We can further decompose this result: First, part of the welfare gain comes from the fact that workers, once informed, make better decisions. Under full information, they know which jobs to accept or reject, and are able to sort into the market they are most suitable for. Second, part of the welfare gains arises from the general equilibrium response. Unsuitable workers congest their market - they encounter many jobs they are not suitable for, thus crowding out other workers. Once worker sorting improves, the vacancy posting incentive of firms rises. This leads to higher market tightness, improving productivity and reducing unemployment.

We can perform this decomposition by holding market tightness in the full information equilibrium at the level of the baseline equilibrium and computing the welfare gain. The resulting number represents the partial equilibrium effect, the residual represents the general equilibrium effect. We find that both effects account for a substantial share of the welfare improvement with 25.1% (PE) and 8.9% (GE) respectively. The large share of the partial equilibrium effect coupled with the large share of workers making incorrect decisions resonates with the findings of Belot et al. (2022). In a randomized field experiment in the UK, Belot et al. find inexpensive job advice that informs workers about occupation with high labor demand can increase job finding probabilities by between 20% and 40%.

7 Aggregate Shock

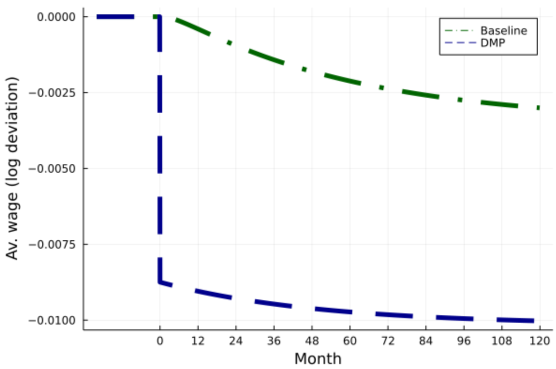
The final exercise of the paper is to understand the implications of worker learning on wages and employment over the business cycle. In calibration of canonical models of macro-labor there exists a dissonance between generating sufficient wage dispersion in the cross-section, and sufficient volatility in employment in the time-series. We have shown in section 6.2.2 that in the presence of learning we can overcome the problems documented by Hornstein et al. (2011) and generate sufficient frictional wage dispersion without relying on a large and negative replacement rate. When one introduces aggregate shocks into such models a similar obstacle arises. As pointed out by Shimer (2005) these models will ordinarily fail in generating enough volatility in employment over the business cycle. One resolution to the so called *puzzle* is to follow the *small surplus* calibration of Hagedorn and Manovskii (2008) and set the replacement rate close to one. This then begs the question: with an intermediate value for the replacement rate, can our learning model simultaneously generate dispersion in wages and employment volatility over the cycle?

A commonly proposed propagation mechanism is to impose wage rigidity onto the canonical labor search model (see for example Hall (2005), Hall and Milgrom (2008), or Pissarides (2009)). If the wages of new hires are rigid, such that they vary little over the business cycle, then hiring costs remain high in downturns and the wage is unable to smooth firm recruitment over the cycle. Although the baseline model presented is derived in steady-state, one can imagine that in our framework, wage rigidity would emerge naturally out of steady-state. Given an unforeseen shock to the economy, rather than observing it, workers learn through experience about the new state of the world. In the model, wages are the solution to a Nash bargaining protocol. The bargaining outcome depends on beliefs which respond sluggishly, and hence so too will wages. A similar mechanism is present in Menzio (2022). In Menzio's framework a share of workers are fully informed of the aggregate shock and operate under rational expectations. A complementary share has stubborn beliefs, believing aggregate productivity is fixed at its unconditional mean. The existence of agents with stubborn beliefs prevents wages from fully adjusting and propagates employment fluctuations in a way akin to our setting.

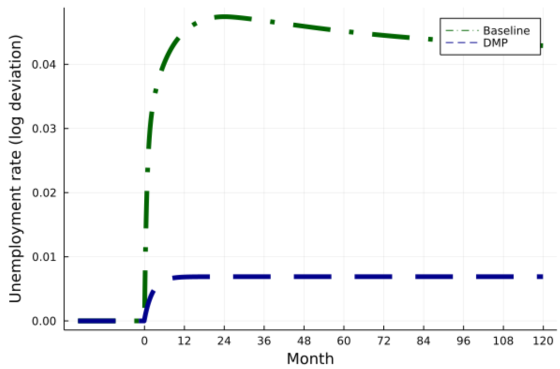
To examine the volatility of employment and rigidity of wages in the model we consider a permanent and unanticipated shock to the cost of posting a vacancy. We calibrate the shock as a 5% increase in the parameter κ. In the baseline model the shock is not observed, but rather agents update their beliefs over job offer arrival rates and the economy becomes informed gradually about the new state of the world. One should consider the response analyzed to be a short run response to shocks, since worker's prior distribution is assumed fixed. Recall, that the full information model corresponds to the canonical DMP model. We further assume that full information extends to the shock process, and although the shock is unanticipated, once it happens agents are fully informed over its impact.

Series for wages, productivity and unemployment of the two models are presented in Figure 3. The response of the full information model is well understood. Market tightness, vacancies divided by unemployment, jumps immediately to its new lower steady-state level. Consequently, the wages of new hires also move discontinuously to a new lower level. The

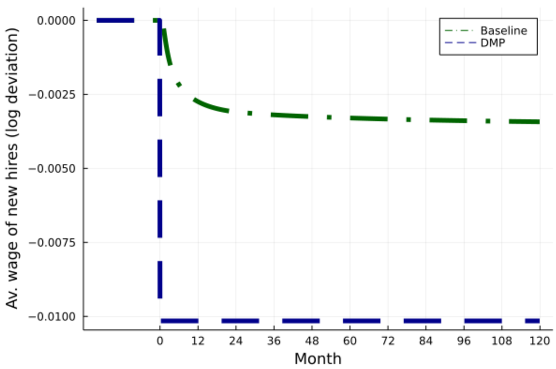
Figure 3: Transition dynamics in response to a one-time permanent shock to κ



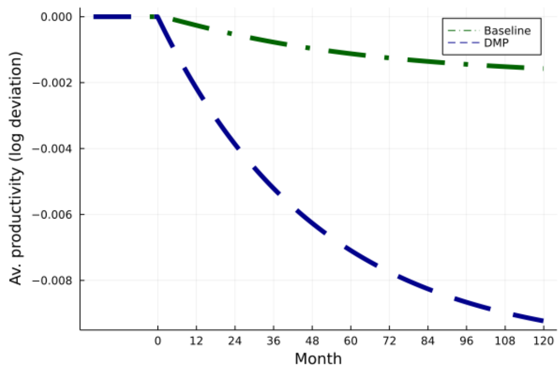
(a) Wages



(b) Unemployment



(c) Wages (new hires)



(d) Productivity

impact on aggregate wages, unemployment, and productivity is more protracted. Existing matches continuously re-negotiate wages, and hence we see an immediate drop on impact in aggregate wages. However, with a larger vacancy cost there are fewer job offers and the unemployed are thus less discerning in which jobs to accept, thus lowering their reservation productivity threshold $z^{\star}$. This leads to a further fall in aggregate wages and a decline in labor productivity.

By contrast, in the baseline model the new state of the world is understood through workers learning. Following a hike in the cost of posting a vacancy there are fewer vacancies, because of the free entry condition. However, the reduction in job offers is not immediately apparent to the unemployed who learn slowly from experience in unemployment. As workers learn more about the market, they are willing to accept a lower wage and thus after a point unemployment begins to decline. Since workers are slow to learn, the impact on employment is much larger than in the baseline model. The cost of a firm hiring increases by the same amount in both specifications, but under full information this is somewhat compensated by lower wages, and thus dampening the cycle. In the baseline model, at the point of impact workers are uninformed and hence their perceived employment opportunities are unchanged despite the fall in labor demand. This results in larger changes in employment. The same impact can be seen in productivity. In the full information model workers immediately drop their reservation wage and thus productivity drops substantially. In the baseline model it takes time for reservation wages to adjust, and thus productivity moves far less.

8 Conclusion

This paper presents a tractable model to understand the importance of learning in a search theoretic model of the labor market. A worker's labor market history becomes consequential for decisions in the present. Tractability is retained as one's history can be full characterized by two sufficient statistics. Strikingly, the model reconciles features of the data that are typically missing in macro labor models. In particular, the model consistent with data produces: the pattern of bias implied by worker's labor market expectations; falling starting wages with the duration of an unemployment spell; and the level of cross-sectional frictional wage dispersion.

The cost of misinformation is large. In a hypothetical world in which all agents are fully informed, the economy would grow by approximately one third. Most economic losses originate from workers making *wrong* decisions because of limited information. Thus, even in partial equilibrium, large welfare improvements can be made by informing unemployed workers. We believe a model of this type can help tailor such an intervention in the labor market, and this could prove to be a fruitful future research agenda. Finally, we show following an unanticipated shock to the economy our baseline model generates an order of magnitude more propagation to employment than a full information economy. Since learning is protracted, wage rigidity arises endogenously and hiring costs do not adjust as much over the cycle, leading to larger employment fluctuations.

A Appendix

A.1 Proof of Result 1

Let X be the duration of time a worker waits for a job offer. Given job offers arrive according to a Poisson process with rate λ. The waiting time for an offer is exponential, and given Assumption 1, the prior over lambda is uniform on $[0, \overline{\lambda}]$. Thus if a worker has received n offers in the market, and is currently unemployed, they have $n+1$ data points to infer the value of λ with $(x_1, ...x_n, x_{n+1})$. Where for $i = \{1, 2, ...n\}$, x_i is an uncensored job offer waiting time, and x_{n+1} is the time lapsed without a job offer in their current unemployment spell. Implementing Bayes' rule and defining $\boldsymbol{x} := (x_1, ...x_n)$ yields

$$f(\lambda|\boldsymbol{x}, x_{n+1}) = \left(\frac{f(\boldsymbol{x}|\lambda)}{f_{\boldsymbol{x}}(\boldsymbol{x})}\right)\left(\frac{1 - F(x_{n+1}|\lambda)}{1 - F_x(x_{n+1})}\right)\pi(\lambda) \propto \left(\prod_{i=1}^{n} f(x_i|\lambda)\right)(1 - F(x_{n+1}|\lambda))\,\pi(\lambda)$$

where,

$$\begin{aligned}
\prod_{i=1}^{n} f(x_i|\lambda) &= \prod_{i=1}^{n} \lambda e^{-\lambda x_i} \\
(1 - F(x_{n+1}|\lambda)) &= e^{-\lambda x_{n+1}} \\
\pi(\lambda) &= \frac{1}{\overline{\lambda}} \quad \text{for } \lambda \in [0, \overline{\lambda}] \\
&= 0 \quad \text{otherwise.}
\end{aligned}$$

So,

$$\begin{aligned}
f(\lambda|\boldsymbol{x}, x_{n+1}) &\propto \left(\prod_{i=1}^{n} f(x_i|\lambda)\right)(1 - F(x_{n+1}|\lambda))\,\pi(\lambda) \\
&\propto \lambda^n e^{-\lambda \sum_{i=1}^{n+1} x_i} \quad \text{for } \lambda \in [0, \overline{\lambda}]
\end{aligned}$$

Hence the posterior only depends on the total duration of unemployment $\tau := \sum_{i=1}^{n+1} x_i$ and the number of job offers accumulated n. Thus rather than having $n+1$ state variables to infer the posterior of λ, the worker need only keep track of the number of offers they have received n and the total length of time spent in unemployment $\tau := \sum_{i=1}^{n+1} x_i$. Rewriting the posterior density in terms of these two sufficient statistics yields

$$f(\lambda|n, \tau) = \mathcal{C}\lambda^n e^{-\lambda\tau} \quad \text{for } \lambda \in [0, \overline{\lambda}].$$

Where $\mathcal{C}$ is the constant of integration, to pin down the constant $\mathcal{C}$, we ensure the posterior density integrates to one. Hence,

$$\frac{1}{\mathcal{C}} = \int_0^{\overline{\lambda}} \lambda^n e^{-\lambda\tau} d\lambda$$
$$\frac{1}{\mathcal{C}} = \tau^{-n} \int_0^{\overline{\lambda}} (\lambda\tau)^n e^{-\lambda\tau} d\lambda$$

Define $u = \lambda\tau$, $du = \tau d\lambda$

$$\tau^{-n} \int_0^{\overline{\lambda}} (\lambda\tau)^n e^{-\lambda\tau} d\lambda = \tau^{-n-1} \int_0^{\tau\overline{\lambda}} u^n e^{-u} du$$

The lower incomplete gamma function is defined as,

$$\gamma(s, x) = \int_0^x t^{s-1} e^{-t} dt$$

and hence,

$$\frac{1}{\mathcal{C}} = \tau^{-n-1} \gamma(n+1, \tau\overline{\lambda}).$$

Finally, substituting the constant of integration back into the posterior density yields

$$f(\lambda|n,\tau) = \frac{\tau^{n+1}}{\gamma(n+1, \tau\overline{\lambda})} \lambda^n e^{-\lambda\tau} \quad \text{for } \lambda \in [0, \overline{\lambda}]$$

This is a truncated gamma distribution with shape parameter $n+1$ and scale parameter $1/\tau$.

A.2 Proof of Result 2

The mean of the posterior for a worker with labor history summarized by τ and n is given by

$$\lambda(n,\tau) = \int_0^{\overline{\lambda}} \lambda f(\lambda|n,\tau) d\lambda$$
$$= \frac{\tau^{n+1}}{\gamma(n+1, \tau\overline{\lambda})} \int_0^{\overline{\lambda}} \lambda^{n+1} e^{-\lambda\tau} d\lambda$$

Define $u = \lambda\tau$, hence $du = \tau d\lambda$

$$\int_0^{\overline{\lambda}} \lambda^{n+1} e^{-\lambda\tau} d\lambda = \frac{1}{\tau^{n+1}} \int_0^{\tau\overline{\lambda}} u^{n+1} e^{-u} \frac{1}{\tau} du$$
$$= \frac{1}{\tau^{n+2}} \gamma(n+2, \tau\overline{\lambda})$$

Substituting back in gives the mean of the posterior as,

$$\lambda(n,\tau) = \frac{1}{\tau} \frac{\gamma(n+2, \tau\overline{\lambda})}{\gamma(n+1, \tau\overline{\lambda})}$$

The following recurrence relation of the incomplete gamma function is given on page 262 of Abramowitz and Stegun (1970).

$$\gamma(s+1, x) = s\gamma(s,x) - x^s e^{-x}$$

so,

$$\gamma(n+2, \tau\overline{\lambda}) = (n+1)\gamma(n+1, \tau\overline{\lambda}) - \left(\tau\overline{\lambda}\right)^{n+1} e^{-\tau\overline{\lambda}}$$

Hence substituting expression above into our expression for the mean yields,

$$\lambda(n,\tau) = \underbrace{\frac{1}{\tau}(n+1)}_{\text{unbounded mean}} - \tau^n \underbrace{\left(\frac{\overline{\lambda}^{n+1} e^{-\tau\overline{\lambda}}}{\gamma(n+1, \tau\overline{\lambda})} \right)}_{\text{boundary term}}$$

This can be simplified further, exploiting that $n+1$ is a positive integer. Since for s a positive integer, the upper incomplete gamma function $\Gamma(s,x)$ can be written as

$$\Gamma(s,x) = (s-1)! e^{-x} \sum_{k=0}^{s-1} \frac{x^k}{k!}$$

Or alternatively, the lower incomplete gamma function,

$$\gamma(s,x) = (s-1)! \left(1 - e^{-x} \sum_{k=0}^{s-1} \frac{x^k}{k!} \right)$$
$$\implies \quad \gamma(n+1, \tau\overline{\lambda}) = n! \left(1 - e^{-\tau\overline{\lambda}} \sum_{k=0}^{n} \frac{(\tau\overline{\lambda})^k}{k!} \right)$$

$$\lambda(n,\tau) = \underbrace{\frac{1}{\tau}(n+1)}_{\text{unbounded mean}} \underbrace{- \frac{\tau^n}{n!}\bar{\lambda}^{n+1}\left(\frac{1}{e^{\tau\bar{\lambda}} - \sum_{k=0}^{n}\frac{(\tau\bar{\lambda})^k}{k!}}\right)}_{\text{boundary term}}$$

The denominator of the boundary term is the n^{th} order Taylor remainder of $e^{\tau\bar{\lambda}}$. Hence the posterior mean can be simplified further to

$$\begin{aligned}\lambda(n,\tau) &= \frac{1}{\tau}(n+1) - \bar{\lambda}\left(\frac{(\tau\bar{\lambda})^n}{n!}\right)\left(\sum_{k=n+1}^{\infty}\frac{(\tau\bar{\lambda})^k}{k!}\right)^{-1} \\ &= \frac{1}{\tau}(n+1) - \bar{\lambda}\left(\sum_{k=n+1}^{\infty}\frac{(\tau\bar{\lambda})^{(k-n)}}{(k-n)!}\right)^{-1}\end{aligned}$$

A.3 Derivation of the HJB equation for the unemployed

Assuming that the time interval Δ is small enough such that,

$$\Delta\eta - \int_{\tau}^{\tau+\Delta}\int_{0}^{\infty}\lambda f(\lambda|n,\tau')d\lambda d\tau' < 1$$

Then a discrete time representation of the value function is,

$$\begin{aligned}V_u(n,\tau) = \Delta b + \frac{1}{1+r\Delta}\Bigg[&\left(\int_{\tau}^{\tau+\Delta}\int_{0}^{\infty}\lambda f(\lambda|n,\tau')\Big(V_u(n+1,\tau') + \mathbb{E}_z\left[\max\left(\beta S(z,n+1,\tau'),0\right)\right]\Big)d\lambda d\tau'\right) \\ &+ \Delta\eta V_u(0,0) + \left(1 - \Delta\eta - \int_{\tau}^{\tau+\Delta}\int_{0}^{\infty}\lambda f(\lambda|n,\tau')d\lambda d\tau'\right)V_u(n,\tau+\Delta)\Bigg] + o(\Delta)\end{aligned}$$

Where $o(\Delta)$ encompasses terms that go to zero faster than Δ, for example workers getting more than one job offer in a period Δ. Define $\lambda(n,\tau)$ as the mean of the posterior density such that, $\lambda(n,\tau) = \int_0^\infty \lambda f(\lambda|n,\tau)d\lambda$. Hence the HJB equation simplifies to,

$$\begin{aligned}V_u(n,\tau) = \Delta b + \frac{1}{1+r\Delta}\Bigg[&\left(\int_{\tau}^{\tau+\Delta}\lambda(n,\tau')\Big(V_u(n+1,\tau') + \mathbb{E}_z\left[\max\left(\beta S(z,n+1,\tau'),0\right)\right]\Big)d\tau'\right) \\ &+ \Delta\eta V_u(0,0) + \left(1 - \Delta\eta - \int_{\tau}^{\tau+\Delta}\lambda(n,\tau')d\tau'\right)V_u(n,\tau+\Delta)\Bigg]\end{aligned}$$

Multiply both sides by $(1 + r\Delta)$ and rearranging yields,

$$
\begin{aligned}
(1 + r\Delta)\, V_u(n,\tau) = \Delta b\,(1 + r\Delta) + &\left(\int_\tau^{\tau+\Delta} \lambda(n,\tau')\Big(V_u(n+1,\tau') + \mathbb{E}_z\left[\max\left(\beta S(z,n+1,\tau'),0\right)\right]\Big) d\tau' \right) \\
&+ \Delta\eta V_u(0,0) + \left(1 - \Delta\eta - \int_\tau^{\tau+\Delta} \lambda(n,\tau')d\tau'\right) V_u(n,\tau+\Delta) \\
rV_u(n,\tau) = b\,(1 + r\Delta) + &\frac{1}{\Delta}\left(\int_\tau^{\tau+\Delta} \lambda(n,\tau')\Big(V_u(n+1,\tau') - V_u(n,\tau)\Big) d\tau' \right) \\
&+ \frac{1}{\Delta}\left(\int_\tau^{\tau+\Delta} \lambda(n,\tau')\mathbb{E}_z\left[\max\left(\beta S(z,n+1,\tau'),0\right)\right] d\tau' \right) + \eta\left(V_u(0,0) - V_u(n,\tau)\right) \\
&+ \frac{1}{\Delta}\left(1 - \Delta\eta - \int_\tau^{\tau+\Delta} \lambda(n,\tau')d\tau'\right)\left(V_u(n,\tau+\Delta) - V_u(n,\tau)\right)
\end{aligned}
$$

Finally, taking the limit as $\Delta \to 0$ gives the HJB equation for the value of unemployment as,

$$
\begin{aligned}
rV_u(n,\tau) = b + \lambda(n,\tau)\left(V_u(n+1,\tau) - V_u(n,\tau)\right) + \lambda(n,\tau)\mathbb{E}_z\left[\max\left(\beta S(z,n+1,\tau),0\right)\right] \\
+ \eta\left(V_u(0,0) - V_u(n,\tau)\right) + \frac{\partial V_u(n,\tau)}{\partial \tau}
\end{aligned}
$$

A.4 Rewriting the value function

The Nash bargaining assumption allows us to write

$$
\mathbb{E}_z\left[\max\left(V_e(z,n+1,\tau) - V_u(n+1,\tau),0\right)\right] = \mathbb{E}_z\left[\max\left(\beta S(z,n,\tau),0\right)\right]
$$

The expected surplus expression can be written as

$$
\begin{aligned}
\mathbb{E}_z\left[\max\left(\beta S(z,n,\tau),0\right)\right] =& \frac{\beta}{r+\delta+\eta}\left[\frac{\alpha}{1-\alpha} z^{-\alpha+1}\right]_{\max(z^\star(n,\tau),1)}^{\infty} - \beta\frac{r+\eta}{r+\delta+\eta} V_u(n,\tau)\left(\frac{1}{\max(z^\star(n,\tau),1)}\right)^{\alpha} \\
&+ \beta\frac{\eta}{r+\delta+\eta}\left(V_u(0,0) - \chi\right)\left(\frac{1}{\max(z^\star(n,\tau),1)}\right)^{\alpha} \\
=& \frac{\beta}{r+\delta+\eta}\Bigg(\frac{\alpha}{\alpha-1}\max\left(z^\star(n,\tau),1\right)^{-\alpha+1} - (r+\eta)V_u(n,\tau)\max(z^\star(n,\tau),1)^{-\alpha} \\
&+ \eta(V_u(0,0) - \chi)\max(z^\star(n,\tau),1)^{-\alpha}\Bigg)
\end{aligned}
$$

When $z^\star(n,\tau) < 1$ and all worker-firm meetings form matches,

$$
\mathbb{E}_z\left[\max\left(\beta S(z,n,\tau),0\right)\right] = \frac{\beta}{r+\delta+\eta}\left(\frac{\alpha}{\alpha-1} - (r+\eta)V_u(n,\tau) + \eta V_u(0,0)\right)
$$

When the productivity threshold binds and $z^\star(n,\tau) \geq 1$ then

$$\begin{aligned}
\mathbb{E}_z\left[\max\left(\beta S(z,n,\tau),0\right)\right] &= z^\star(n,\tau)^{-\alpha}\frac{\beta}{r+\delta+\eta}\left(\frac{\alpha}{\alpha-1}z^\star(n,\tau)-(r+\eta)V_u(n,\tau)+\eta(V_u(0,0)-\chi)\right)\\
&= z^\star(n,\tau)^{-\alpha}\frac{\beta}{r+\delta+\eta}\left(\frac{\alpha}{\alpha-1}z^\star(n,\tau)-z^\star(n,\tau)\right)\\
&= z^\star(n,\tau)^{1-\alpha}\frac{\beta}{r+\delta+\eta}\left(\frac{1}{\alpha-1}\right)\\
&= \frac{\beta}{r+\delta+\eta}\left(\frac{1}{\alpha-1}\right)\left((r+\eta)V_u(n,\tau)-\eta(V_u(0,0)-\chi)\right)^{1-\alpha}
\end{aligned}$$

Substituting back into the unemployed value function equation (2) yields an expression for $V_u(n,\tau)$ as an expression of model primitives and V_u, n and τ.

$$\begin{aligned}
(r+\eta)V_u(n,\tau) = b+\lambda(n,\tau)\frac{\beta}{r+\delta+\eta}\Bigg[&\mathbb{1}(z^\star(n+1,\tau)<1)\\
&\left(\frac{\alpha}{\alpha-1}-(r+\eta)V_u(n+1,\tau)+\eta(V_u(0,0)-\chi)\right)\\
&+\mathbb{1}(z^\star(n+1,\tau)\geq 1)\left(\frac{1}{\alpha-1}\right)\left((r+\eta)V_u(n+1,\tau)-\eta(V_u(0,0)-\chi)\right)^{1-\alpha}\Bigg]\\
&+\lambda(n,\tau)\left(V_u(n+1,\tau)-V_u(n,\tau)\right)+\eta(V_u(0,0)-\chi)+\frac{\partial V_u(n,\tau)}{\partial\tau}
\end{aligned}$$

A.5 Computational appendix

The following outlines the exact computation of the value function for an unemployed worker. The unemployed worker's value function is the one part of the model for which the solution requires some numerical finesse. In contrast, the rest of the model is fairly standard and the numerical details for those parts of the model are not reported here.

A.5.1 Solving the value function of an unemployed worker

The value function of an unemployed worker is given by

$$rV_u(n,\tau) = \max\Bigg\{\Bigg(b + \lambda(n,\tau)\mathbb{E}_z\left[\max\left(V_e(z,n+1,\tau) - V_u(n+1,\tau),0\right)\right] \\ + \eta\left(V_u(0,0) - \chi - V_u(n,\tau)\right) \\ + \lambda(n,\tau)\left(V_u(n+1,\tau) - V_u(n,\tau)\right) + \frac{\partial V_u(n,\tau)}{\partial \tau}\Bigg), \\ r(V_u(0,0) - \chi)\Bigg\}$$

We can rewrite this equation as

$$\min\Bigg\{(r+\eta)V_u(n,\tau) - \Bigg(b + \lambda(n,\tau)\mathbb{E}_z\left[\max\left(V_e(z,n+1,\tau) - V_u(n+1,\tau),0\right)\right] + \eta S \\ + \lambda(n,\tau)\left(V_u(n+1,\tau) - V_u(n,\tau)\right) + \frac{\partial V_u(n,\tau)}{\partial \tau}\Bigg), V_u(n,\tau) - S\Bigg\} = 0 \tag{21}$$

where $S = [V_u(0,0) - \chi]$. To transform the equation into a fixed point equation solely dependent on V_u and parameters, we further need the following identity:

$$\mathbb{E}_z\left[\max\left(V_e(z,n+1,\tau) - V_u(n+1,\tau),0\right)\right] \\ = \begin{cases} \frac{\beta}{r+\delta+\eta}\left(\frac{\alpha}{\alpha-1} - (r+\eta)V_u(n+1,\tau) + \eta S\right) & \text{if } z^\star(n+1,\tau) < 1 \\ \frac{\beta}{r+\delta+\eta}\left(\frac{1}{\alpha-1}\right)\left((r+\eta)V_u(n+1,\tau) - \eta S\right)^{1-\alpha} & \text{if } z^\star(n+1,\tau) \geq 1 \end{cases}$$

where $z^\star(n,\tau) = (r+\eta)V_u(n,\tau) - \eta S$.

Given χ, the solution strategy consists of looping over different outside values S to find the value of S that yields the desired equality $S = [V_u(0,0) - \chi]$. In what follows, we can thus treat S as given.[7]

Within each loop, for a given S, the solution strategy is recursive, starting from a sufficiently high value of $n = \bar{N}$. We assume that, once the a worker reaches $\bar{N}$, both n and τ are fixed forever. By standard arguments, this assumption does not matter as long as $\bar{N}$ is sufficiently large. However, it provides a natural solution for V_u at $n = \bar{N}$. In our application, we choose $\bar{N} = 70$ and verify that a numerically negligible number of agents ever reach this part of the state space. For any τ, $V_u(\bar{N},\tau)$ solves

[7] In practice, when calibrating the model, it can be easier to treat S as a parameter instead of χ, and then set χ accordingly once S has been calibrated. This avoids a loop.

$$\min\Bigg\{(r+\eta)V_u(\bar{N},\tau)-\Bigg(b+\lambda(\bar{N},\tau)\mathbb{E}_z\left[\max\left(V_e(z,\bar{N},\tau)-V_u(\bar{N},\tau),0\right)\right]+\eta S\Bigg),$$
$$V_u(\bar{N},\tau)-S\Bigg\}=0$$

This yields a solution for $n=\bar{N}$. As shown below, for any n, we can then write the HJBVI for $V_u(n,\cdot)$ as a linear complementarity problem (LCP) given the solution for $V_u(n+1,\cdot)$.

To do this, we start by discretizing and rewriting equation 21 to fit the following format:

$$0=\min\{Lv-z,v-S\}$$

Discretizing the differential term in the standard manner (i.e. using finite differences), it is easy to rewrite the problem in this way, where v is a vector capturing the discretized version of $V_u(n,\cdot)$ and any terms involving $n+1$ are treated as known. Concretely, we choose a fine, uniformly spaced grid for τ, which we denote g_τ.[8]

Now, the discretized version of equation 21 can be written in the above format by setting

$$L=(\rho+\eta)\cdot I-\begin{pmatrix}-\frac{1}{d\tau}-\lambda(n,g_{\tau,1}) & \frac{1}{d\tau} & 0 & \dots & 0\\ 0 & -\frac{1}{d\tau}-\lambda(n,g_{\tau,2}) & \frac{1}{d\tau} & \dots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\end{pmatrix}$$

and letting z collect all remaining terms.

In a second step, one can rewrite the problem once more as

$$0=\min\{Lx+q,x\}$$

where $x=v-S$ and $q=-z+LS$. This is the well-known linear complementarity problem (see Dantzig and Cottle (1968)) to which there exist fast solvers.

Casting the problem in this way allows for rapid computation of $V_u(n,\cdot)$ given a solution for $V_u(n+1,\cdot)$ and therefore enables computation of $V_u(\cdot,\cdot)$ on its entire domain, given S. Finding the correct S solving $S=[V_u(0,0)-\chi]$ is then a matter of a simple one-dimensional fixed-point search.

[8]In our application, $g_{\tau,2}-g_{\tau,1}=d\tau=0.1$, so for example v_1, v_2 and v_3 denote $V_u(n,0), V_u(n,0.1)$ and $V_u(n,0.2)$ respectively. $g_{\tau,3001}=300$ is our largest grid point. We again verify that only a negligible number of agents ever encounter this boundary.

A.6 Kolmogorov Forward Equations

Since the entry rate in all markets is the same, we can denote it as μ and find μ ex post by using the fact that the population has to integrate to one. Recall that

- Job offers are taken whenever $z \geq z^*(n, \tau)$
- The true job finding rate in a market is given by $\tilde{\lambda}_s$
- Workers exogenously reallocate to new markets at rate η and reallocate endogenously whenever they reach $\tau = T^*(n)$

Denote by $e(n, \tau, s)$ and $u(n, \tau, s)$ the mass of employed and unemployed workers in information state (n, τ) and market m. For given n, $\tau < T^*(n)$, the stationary distribution satisfies:

$$0 = \mathbb{I}(\tau < T^*(n-1))P(z \geq z^*(n,\tau))\tilde{\lambda}_s u(n-1,\tau,s) - (\delta+\eta)e(n,\tau,s)$$
$$0 = \mathbb{I}(\tau < T^*(n-1))P(z < z^*(n,\tau))\tilde{\lambda}_s u(n-1,\tau,s) + \delta e(n,\tau,s) - (\tilde{\lambda}_s+\eta)u(n,\tau,s) - \partial_\tau u(n,\tau,s)$$

with absorbing boundaries at $\tau = T^*(n)$. For $n = 0$ and $\tau < T^*(0)$,

$$\partial_\tau u(0,\tau,s) = -(\tilde{\lambda}_s+\eta)u(0,\tau,s)$$
$$\implies u(0,\tau,s) = u(0,0,s)\cdot\exp(-(\tilde{\lambda}_s+\eta)\tau) = \mu\cdot\exp(-(\tilde{\lambda}_s+\eta)\tau)$$

For $n \geq 1$, the employment distribution can be characterized as a solution to a set of linear non-homogeneous ODEs given the solution for $n-1$:

$$\begin{aligned} e(n,\tau,s) =& \mathbb{I}(\tau < T^*(n-1))P(z \geq z^*(n,\tau))\frac{\tilde{\lambda}_s}{\delta+\eta}u(n-1,\tau,s) \\ \partial_\tau u(n,\tau,s) =& \mathbb{I}(\tau < T^*(n-1))\left(P(z < z^*(n,\tau)) + P(z \geq z^*(n,\tau))\frac{\delta}{\delta+\eta}\right)\tilde{\lambda}_s u(n-1,\tau,s) \\ &-(\tilde{\lambda}_s+\eta)u(n,\tau,s) \end{aligned}$$

with boundary conditions $u(n,0,s)=0\,\forall n\geq 1$. It is easy to solve this by integrating factor method and write this in closed form. For $\tau < T^*(n-1)$:

$$\begin{aligned}
&(\tilde{\lambda}_s+\eta)e^{(\tilde{\lambda}_s+\eta)\tau}u(n,\tau,s)+e^{(\tilde{\lambda}_s+\eta)\tau}\partial_\tau u(n,\tau,s)\\
&=e^{(\tilde{\lambda}_s+\eta)\tau}\mathbb{I}(\tau<T^*(n-1))\left(P(z<z^*(n,\tau))+P(z\geq z^*(n,\tau))\frac{\delta}{\delta+\eta}\right)\tilde{\lambda}_s u(n-1,\tau,s))\\
\implies u(n,\tau,s)&=\int_0^\tau e^{(\tilde{\lambda}_s+\eta)(\tilde{\tau}-\tau)}\left(P(z<z^*(n,\tilde{\tau}))+P(z\geq z^*(n,\tilde{\tau}))\frac{\delta}{\delta+\eta}\right)\tilde{\lambda}_s u(n-1,\tilde{\tau},s)d\tilde{\tau}\\
&\forall n\geq 1,\tau\leq T^*(n-1)\\
u(n,\tau,s)&=e^{-(\tilde{\lambda}_s+\eta)(\tau-T^*(n-1))}u(n,T^*(n-1),s)\quad \forall n\geq 1, T^*(n-1)<\tau\leq T^*(n)
\end{aligned}$$

This establishes that $u(n,\tau,s)$ (and therefore $e(n,\tau,s)$) can be computed recursively.

A.7 Wages in the baseline model

$$\begin{aligned}
(r+\delta+\eta)V_e(z,n,\tau)&=w(z,n,\tau)+\delta V_u(n,\tau)+\eta(V_u(0,0)-\chi)\\
(r+\delta+\eta)\left(V_e(z,n,\tau)-V_u(n,\tau)\right)&=w(z,n,\tau)-(r+\eta)V_u(n,\tau)+\eta(V_u(0,0)-\chi)\\
(r+\delta+\eta)S(z,n,\tau)&=z-(r+\eta)V_u(n,\tau)+\eta(V_u(0,0)-\chi)
\end{aligned}$$

So, by Nash bargaining,

$$\begin{aligned}
w(z,n,\tau)-(r+\eta)V_u(n,\tau)+\eta V_u(0,0)&=\beta z-(r+\eta)\beta V_u(n,\tau)+\eta\beta(V_u(0,0)-\chi)\\
w(z,n,\tau)&=\beta z+(1-\beta)\left((r+\eta)V_u(n,\tau)-\eta(V_u(0,0)-\chi)\right)
\end{aligned}$$

A.8 Full Information Model

The Bellman equations are:

$$\begin{aligned}
(r+\delta+\eta)V_e(z)=&w(z)+\delta V_u+\eta\left(V_u-\chi\right)\\
(r+\delta+\eta)J(z)=&z-w(z)\\
=&b+\tilde{\lambda}\mathbb{E}\left[\max\left\{\beta S(z),0\right\}\right]-\eta\chi\\
=&b+\tilde{\lambda}\beta\int_{z^\star}S(z')d\Gamma(z')-\eta\chi\\
rV_v=&-\kappa+\tilde{\lambda}_f\int_{z^\star(t)}J(z')d\Gamma(z')
\end{aligned}$$

Free entry implies $V_v = 0$, hence,

$$\begin{aligned}
\frac{\kappa}{\tilde{\lambda}_f} &= \int_{z^\star(t)} J(z')d\Gamma(z') \\
\frac{\kappa}{\tilde{\lambda}_f} &= (1-\beta)\int_{z^\star(t)} S(z')d\Gamma(z') \\
\beta \int_{z^\star(t)} S(z')d\Gamma(z') &= \frac{\kappa}{\tilde{\lambda}_f}\left(\frac{\beta}{1-\beta}\right)
\end{aligned}$$

and

$$\begin{aligned}
S(z) &= V_e(z) - V_u + J(z) - V_v \\
(r+\delta+\eta)S(z) &= z - b - \tilde{\lambda}\beta \int_{z^\star} S(z')dz' \\
&= z - b - \kappa \frac{\tilde{\lambda}}{\tilde{\lambda}_f}\left(\frac{\beta}{1-\beta}\right) \\
&= z - b - \kappa\theta\left(\frac{\beta}{1-\beta}\right)
\end{aligned}$$

where θ is market tightness. Threshold productivity $z^\star$ is such that $S(z^\star) = 0$ and hence,

$$z^\star = b + \kappa\theta\left(\frac{\beta}{1-\beta}\right)$$

Moreover,

$$\begin{aligned}
(r+\delta+\eta)\int_{z^\star}^{\infty} S(z')d\Gamma(z') &= \int_{z^\star}^{\infty} z' - b - \kappa\theta\left(\frac{\beta}{1-\beta}\right) d\Gamma(z') \\
&= \frac{1}{\alpha-1}\left(b + \kappa\theta\left(\frac{\beta}{1-\beta}\right)\right)^{1-\alpha}
\end{aligned}$$

Expressing in terms of firm value,

$$\int_{z^\star}^{\infty} J(z')d\Gamma(z') = \left(\frac{1}{r+\delta+\eta}\right)\left(\frac{1-\beta}{\alpha-1}\right)\left(b + \kappa\overline{\theta}\left(\frac{\beta}{1-\beta}\right)\right)^{1-\alpha}$$

Hence we have one non-linear equation that pins down market tightness, given by

$$\kappa = A\theta^{-\omega}\left(\frac{1}{r+\delta+\eta}\right)\left(\frac{1-\beta}{\alpha-1}\right)\left(b + \kappa\theta\left(\frac{\beta}{1-\beta}\right)\right)^{1-\alpha}$$

This delivers an equation for tightness in steady state that can be used for easy computation of the steady state equilibrium and to find market tightness before and after an unanticipated, permanent shock.

We now derive the wage equation in the full info case. By Nash bargaining,

$$(r+\delta+\eta)(V_e(z)-V_u)=\beta S(z)$$

and thus wages satisfy

$$w(z)-(r+\eta)V_u+\eta(V_u-\chi)=\beta(z-z*)$$

Since

$$(r+\delta+\eta)S(z)=z-(r+\eta)V_u+\eta(V_u-\chi)$$

it follows that $z^\star=(r+\eta)V_u+\eta(V_u-\chi)$ and hence

$$w(z)=\beta z+(1-\beta)z^\star$$

Finally, the steady state employment and unemployment rates follow directly from the equilibrium condition

$$0=\partial_t u_t=(\delta+\eta)(1-u_t)-\max\{1,z^\star\}^{-\alpha}\bar{\lambda}u_t$$

A.9 Calibration table of the full information model

Symbol	Parameter description	Value	Target	Value
r	Interest rate	$0.05/12$		
δ	Separation rate into same market	$0.02\cdot\frac{1}{3}$		
η	Reallocation rate into new market	$0.02\cdot\frac{2}{3}$		
ω	Matching function elasticity	0.3		
A	Matching efficiency	1.0		
b	Flow value of unemployment	0.446	Replacement rate $\frac{b}{\bar{w}}$	0.4
α	Pareto parameter of prod. dist.	3.85	Encounter rate	0.5
χ	Reallocation cost	23.3	Irrelevant (= baseline χ)	23.3
β	Worker bargaining power	0.106	Wage-prod. pass-through	0.13
κ	Vacancy posting cost	14.3	Unemployment rate	0.05

Table 5: Parameters and calibration targets

A.10 Revelation of the market m

In this appendix we derive the value function for workers were the true suitability s revealed to them. The value functions are absent any uncertainty, hence we follow the nomenclature of the paper and denote the value functions with a tilde. Since the agent is now perfectly informed about the market we can drop the n and τ state variable and replace with suitability s. Put differently, as the agent becomes more and more informed, as one tends n and τ to ∞, the expected arrival rate $\lambda(n, \tau)$ tends in probability to its true value $\tilde{\lambda}_s$. Thus the value an unemployed worker is the sum of the flow value b and the option value of finding employment, plus the probability they switch market and once again become uninformed.

$$(r + \eta)\tilde{V}_u(s) = b + \tilde{\lambda}_s \mathbb{E}_z \left[\max \left(\beta \tilde{S}(z, s), 0 \right) \right] + \eta(V_u(0, 0) - \chi)$$

Similarly, for matched firms and employed agents the value functions are given by the expressions below.

$$\begin{aligned} r\tilde{V}_e(z, s) &= w(z, s) + \delta(\tilde{V}_u(s) - \tilde{V}_e(z, s)) + \eta(V_u(0, 0) - \chi) \\ (r + \delta + \eta)\tilde{J}(z, s) &= z - w(z, s) \end{aligned}$$

Summing these three value functions, recalling that under free entry, the value to a open vacancy is zero gives the surplus of a match.

$$(r + \delta + \eta)\tilde{S}(z, s) = z - (r + \eta)\tilde{V}_u(s) + \eta(V_u(0, 0) - \chi)$$

The exercise is to compute what workers *should* do, were they to know the suitability of their market. Hence, we are looking for two equilibrium conditions. First, given a market s which jobs should one accept. This will be pinned down by a threshold productivity $z^\star(s)$. For $z > z^\star(s)$, the surplus function $\tilde{S}(z, s) > 0$. Second, when should a worker switch markets? We define this as a threshold offer arrival rate, such that for markets where $\tilde{\lambda}_s < \tilde{\lambda}^\star$, a worker would rather switch.

The threshold productivity is such that

$$z > z^\star(s) := (r + \eta)\tilde{V}_u(s) - \eta(V_u(0, 0) - \chi).$$

After some algebra one can simplify the expression for $z^\star(s)$. If the worker accepts all offers and the threshold is non-binding, the value for $z^\star(s)$ is inconsequential and given by

$$z^\star(s) = \left(\frac{r+\delta+\eta}{r+\delta+\eta+\tilde{\lambda}_s\beta}\right)\left(b+\tilde{\lambda}_s\beta\frac{\alpha}{\alpha-1}\right).$$

However, if the threshold is binding it is the solution to the fixed point below.

$$z^\star(s) = b+\tilde{\lambda}_s\beta\left(\frac{1}{r+\delta+\eta}\right)\left(\frac{1}{\alpha-1}\right)z^\star(s)^{1-\alpha}$$

The final equilibrium condition to determine is the threshold market switching condition, $\tilde{\lambda}^\star$. $s^\star$ is defined as the marginal market and is defined such that a worker is indifferent between switching and staying.

$$\tilde{V}_u(s^\star) = V_u(0,0)-\chi$$

After some rearranging,

$$z^\star(s^\star) = r(V_u(0,0)-\chi)$$

Finally, given a binding productivity threshold

$$\tilde{\lambda}^\star = \frac{(\alpha-1)(r+\delta+\eta)\left(r(V_u(0,0)-\chi)-b\right)}{\beta z^\star(s^\star)^{1-\alpha}}$$

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