Rational Inattention in Hiring Decisions *

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Abstract

This paper provides an information-based theory of match efficiency. Rationally inattentive firms have limited capacity to process information and cannot perfectly determine suitable applicants for production. As losses from hiring the wrong worker are amplified in a recession, firms seek to be more selective in their hiring. Unable to obtain sufficient information about applicants, firms err on the side of caution and accept fewer applicants in order to avoid unsuitable workers. Pro-cyclical acceptance rates form a wedge between meeting and hiring rates, corresponding to match efficiency. Unlike the standard search model, our model accounts for fluctuations in measured match efficiency.

Keywords: Rational Inattention, Hiring Behavior, Screening Costs, Match Efficiency, Composition of Unemployed
JEL Codes: D8, E32, J63, J64

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1 Introduction

The Great Recession was marked by a severe spike in unemployment rates as well as a tripling in the ratio of unemployed job-seekers for each job opening. Despite this sharp increase in the number of job-seekers per vacancy, employers frequently complained that they were unable to find suitable workers to fill their vacancies.[1] This has led many commentators to argue that match efficiency declined during the Great Recession. In this paper, we provide an information-based theory of match efficiency. In particular, we show how the changing aggregate state and composition of job-seekers over the business cycle affects the hiring decisions of firms which in turn drives movements in match efficiency over the business cycle.

We consider a standard search and matching model in which workers permanently differ in their ability. A firm's profitability is affected by an aggregate productivity shock, a worker's ability and a match-specific component. A worker's ability is perfectly observable to the worker and to her current employer, but not to a new firm which may want to hire the worker. These new firms can conduct interviews to learn about the suitability of the worker, and given the information they have processed about the job-seeker, reject applicants who are below the bar. Match efficiency is defined as the firm's acceptance rate of a worker and is distinct from the rate at which a firm contacts a worker. The acceptance rate of firms depends on how much information firms acquire as well as the costliness of making a mistake in hiring the wrong worker. In our model, firms are *rationally inattentive* and have a limited capacity to process information about an applicant. When firms face a lot of uncertainty regarding the set of job-seekers they encounter, they need to process more information about the job-seeker to determine her suitability for production.

The losses associated with hiring an unsuitable worker and the uncertainty surrounding the pool of unemployed job-seekers vary over the business cycle. When aggregate productivity is high, firms are willing to hire almost any worker except those deemed to be very poor matches. During a recession, firms require a worker who can compensate for the fall in aggregate productivity. Since the losses from hiring an unsuitable worker are larger during a recession, firms seek to acquire more information about the job-seeker to determine her suitability for production. Firms, however, do not have infinite information processing capacity and, conditional on hiring, their limited capacity to decipher their job applicant's suitablity for production increases the firm's incidence of making a mistake. Given their less informative signals about the job-seeker, firms err on the side of caution and reject applicants

[1] *"Even with unemployment hovering around 9%, companies are grousing that they can't find skilled workers, and filling a job can take months of hunting."* (Cappelli, 2011) in Wall Street Journal on October 24, 2011.

more often in the downturn to avoid the costly mistake of hiring the wrong worker. Overall, firms' attempt to avoid the mistake of hiring unsuitable workers (false positives) leads them to reject a larger fraction of suitable workers (false negatives).

These higher rejection rates in turn cause the distribution of unemployed job-seekers to become more varied. When firms reject job-seekers more often on average due to their lack of precise information, they inadvertently reject high ability workers along with other ability types. This causes not only the average quality of the pool of unemployed job seekers to increase but also has the effect of elevating the uncertainty that the firm faces regarding these job-seekers. Higher uncertainty about job applicants reinforces the firms' need for more precise information to determine the viability of job candidates. With information-constrained firms, this higher uncertainty translates into even higher rejection rates which weigh on match efficiency and reduce the amount of meetings that are successfully converted into hires.

The increased selectivity in hiring and retaining workers during recessions is well supported in data. A large literature has argued that the quality of the unemployment pool improves during a recession as better quality workers enter or remain in unemployment during downturns (See for example, Kosovich (2010), Lockwood (1991), Nakamura (2008) and Mueller (2015) among others.Our paper contributes to the existing literature and argues that selective hiring standards in a recession not only induce a rise in the average quality of the unemployment pool but also cause a corresponding increase in the firm's uncertainty over the types of job-seeker she would meet. This increase in uncertainty during a recession further hampers firms' recruitment efforts during a downturn despite an improvement in the average quality of the unemployment pool.

It is well known that in standard full information search and matching models, hiring does not fall much in recessions resulting in a muted response of unemployment. An improvement in the job-seeker quality makes firms even less inclined to reduce job creation, exacerbating the employment volatility puzzle (See (Shimer, 2005)). Our paper resolves these issues. Crucially, the lack of precise information and the increased cost of making a type I error (hiring the wrong worker) during a downturn raises the rejection rate of all job-seekers despite the improvement in average quality of the unemployment pool. Our numerical exercise shows that a 3% drop in aggregate productivity causes match efficiency to decline by about 1% in the model with rational inattention but generates negligible response in the full information model. In response to a severe recession where productivity declines by ten percent, match efficiency dives by 10% in the model with rational inattention and only completely recovers 50 months after the shock. In contrast, match efficiency in the full information model dives on impact but rebounds and actually rises above its steady state level by the third month as higher average quality of the unemployed counteracts the lower aggregate productivity in the economy.

The idea that recruiting strategies may change over the business cycle is not a new one. Using data from JOLTS and CPS, Figure 1 replicates the findings as in Davis et al. (2013) and shows how the implied job-filling rate from a standard constant returns to scale matching function with match efficiency assumed to be constant at 1, diverged significantly from its empirical counterpart, the vacancy yield.[2] We add to this graph the computed match efficiency which is the residual variation in hires not accounted for by unemployed job-seekers and vacancies posted. The divergence between the implied job-filling rate from the standard matching function and the vacancy yield coincides with the fall in computed matching efficiency. An influential paper by Davis et al. (2012) suggests that the divergence between the two rates is due to changes in recruiting intensity by firms. Recruiting intensity - a catch-all term for the other instruments and screening methods firms use to increase their rate of hires - fell dramatically during the Great Recession and has been a critical drag on hiring rates. In this paper, we offer a theory of recruiting intensity which is based on firms' limited ability to process information and consequently, their ability to distinguish viable job candidates. In a recession, the desire for more information about the worker causes the information processing constraint of firms to bind more, raising the shadow cost of information and making it harder to distinguish between different types of applicants. This inability to distinguish between job candidates causes recruiting intensity to be low in the sense that firms accept a lower fraction of applicants.

Several recent papers have also tried to examine and decompose the forces driving the decline in match efficiency. Gavazza et al. (2014) consider how financial frictions, firm entry and exit together with the firm's choice of recruiting intensity can account for the drop in match efficiency. Closely related to our paper, Sedlacek (2014) considers a full-information model in which firms are differentially selective over the business cycle due to the presence of firing costs. Barnichon and Figura (2015) focus on how the composition of job-seekers (in terms of short and long term unemployed) and dispersion in local labor market conditions can help explain the variation in matching efficiency over time. In contrast, our proposed mechanism offers insight as to how constraints on information processing and uncertainty regarding the pool of the unemployed can cause hiring rates to stall and vacancy yields to falter despite the large number of job-seekers available for each vacancy.

Our paper also speaks to a large literature which argues that firms use unemployment duration as an additional tool to evaluate the suitability of a worker. Some recent papers such as Kroft et al. (2013), Eriksson and Rooth (2014) and Oberholzer-Gee (2008) among others

[2] The vacancy yield is defined as the ratio of hires to vacancies.

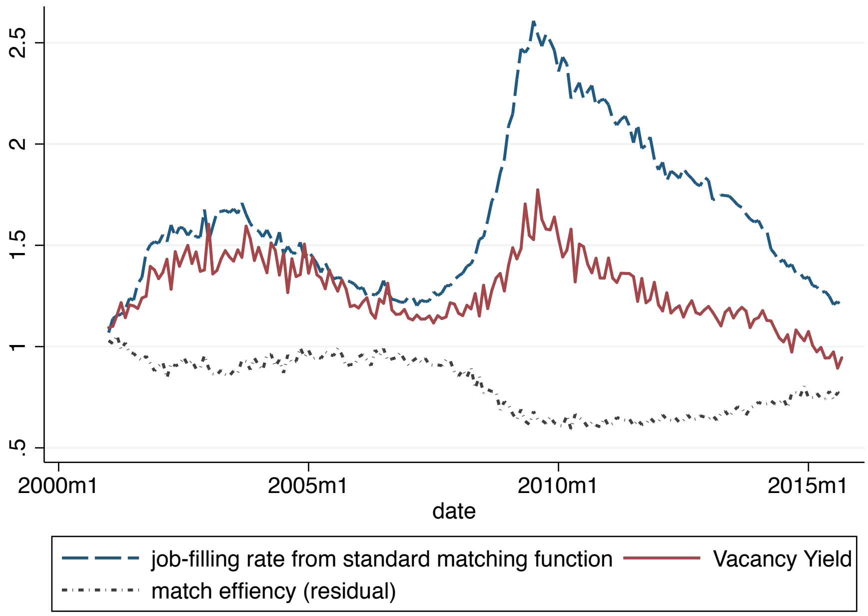


Figure 1: Vacancy Yield and Match Efficiency as computed from JOLTS and CPS

conduct resume audit studies and find evidence of negative duration dependence. Given a level of screening, unemployment duration conveys some information about the applicant. Firms are less likely to call back workers who have been unemployed for longer. Unemployment duration as an indicator of worker quality, however, weakens during a recession. In our model, unemployment duration lengthens during a recession for two reasons. First, firms post fewer vacancies during recessions and this lowers the rate at which workers meet firms. Second, to avoid making Type I errors, firms accept fewer applicants. Both these forces lower the job finding rate, causing unemployment duration to be a noisier indicator of the worker's type. In line with findings by Kroft et al. (2013) who show that call-back rates exhibit a gentler decline with unemployment duration in areas with weak economic conditions, our model qualitatively replicates the gentler decline in the relative job-finding rates of workers across different durations in recessions relative to booms. In our model, the relative job-finding rate of individuals more than 6 months unemployed to those one month unemployed is 5% higher in a recession than in a boom. By construction, such dynamics are impossible in a full-information model since the unemployment duration provides no additional information about a worker.

Our paper also relates to recent literature that examines how rational inattention can affect workers' and firms' search behavior. Cheremukhin et al. (2014) consider how the costliness of processing information can affect the degree of sorting between firms and workers. While their paper demonstrates how rational inattention can lead to equilibrium outcomes that lie between random matching and directed search, we instead focus on a different question and ask how the time-varying cost of making a mistake and the distribution of the unemployed can affect firms' hiring behavior. Briggs et al. (2015) consider how rational inattention can rationalize the occurrence of increased labor mobility and participation amongst older workers late in their working life. Because we are focused on firms' hiring behavior, our paper instead considers the information processing problem of the firm as opposed to the worker. Bartos et al. (2016) directly measure attention choice and show that amount of attention allocation to a job candidate varies over their types (ethnicity).

Finally, our paper also relates to the literature that looks at applicant and interview strategies. Recent work by Lester and Wolthoff (2016) shows how the presence of screening costs can affect the allocation of heterogeneous workers to firms of varying productivity. Given a cost of interviewing workers, the authors consider a directed search environment and find that the optimal posted contract must specify both a wage and a hiring policy. Unlike our paper, Lester and Wolthoff (2016) treat the cost of information as given while the implicit cost of processing information in our model is key to explaining the evolution of match efficiency over the business cycle.

The rest of this paper is organized as follows: Section 2 introduces the model with rational inattention in an otherwise standard random search framework. Section 3 discusses our calibration approach. Section 4 documents our results while Section 5 concludes.

2 Model

We use a standard Diamond-Mortensen-Pissarides model of labor-market frictions. The model is formulated in discrete time. We describe the economic agents that populate this economy.

Workers The economy consists of a unit mass of workers. These workers are risk neutral and discount the future at a rate β. Each worker i has a permanent productivity-type given by $z_i \in \mathcal{Z}$. The exogenous and time-invariant distribution of worker-types is given by $\Pi_z(z)$ which has full support over $\mathcal{Z}$. Workers can either be employed or unemployed. All unemployed workers produce $b > 0$ as home-production. Unemployed workers are further distinguished by their duration of unemployment, denoted by τ.

Firms We define jobs as a single firm-worker pair. The per-period output of a job is given by production function $F(a, z, e) = aze$ where a is the level of aggregate productivity and z is the worker's type and e is a match-specific shock. Aggregate productivity a follows an exogenous mean-reverting stationary process. When a firm and worker meet, they draw match-specific shock $e \in \mathcal{E}$ which is independent of the aggregate state and the worker's type, and which stays constant throughout the duration of the match. All draws of the match-specific shock are i.i.d and drawn from a time-invariant distribution $\Pi_e(e)$. The presence of a match-specific shock allows for high productivity workers, i.e. high z type workers, to be deemed as bad matches if they draw a low e shock. Likewise, low productivity workers can still be considered suitable hires so as long they draw a sufficiently high e.

Labor Market A firm that decides to enter the market must post a vacancy at a cost $\kappa > 0$. The measure of firms in operation at any date t is determined by free-entry. Search is random and a vacancy comes into contact with a worker at a rate q_t. This contact rate depends on the total number of vacancies and job-seekers according to a constant returns to scale matching technology $m(v_t, l_t)$ where v_t is the number of vacancies posted and l_t is the number of job seekers. In our model, job-seekers consist of the unemployed and workers who are newly separated from their job at the beginning of the period. Wages are determined by Nash-Bargaining between the firm and worker. For simplicity, we assume that the firm has all the bargaining power and thus, makes each worker a take-it-or-leave-it wage offer of b every period.

So far the model is identical to a standard Diamond-Mortensen-Pissarides search model and the timing of the model is summarized in Figure 2. As can be seen in the timeline, we deviate from the standard model by assuming that a firm cannot observe the effective productivity, ze, of the applicant at the time of meeting. The firm can, however, choose how much information to acquire about the worker's effective productivity, ze. We refer to this process as an *interview*. We assume that the firm can perfectly identify the worker's type once production has taken place. We allow a firm to fire a worker ex-post if she turns out to be unsuitable for the job. Prior to production, however, the firm has to interview the worker to reduce the uncertainty it faces about the worker's effective productivity ze. Given the information revealed in the interview, the firm decides whether or not to hire a worker. The following sections characterize the hiring strategy of a firm.

2.1 Hiring Strategy of the Firm

Consider a firm that has posted a vacancy knowing the level of aggregate productivity, a, and the distribution of (z, e) type job-seekers for each duration length τ. The hiring strategy of a firm can be described as a two-stage process. (i) In the *first-stage*, given that the firm can observe the applicant's unemployment duration, the firm must devise an information strategy which can roughly be described as specifying how much information the firm would

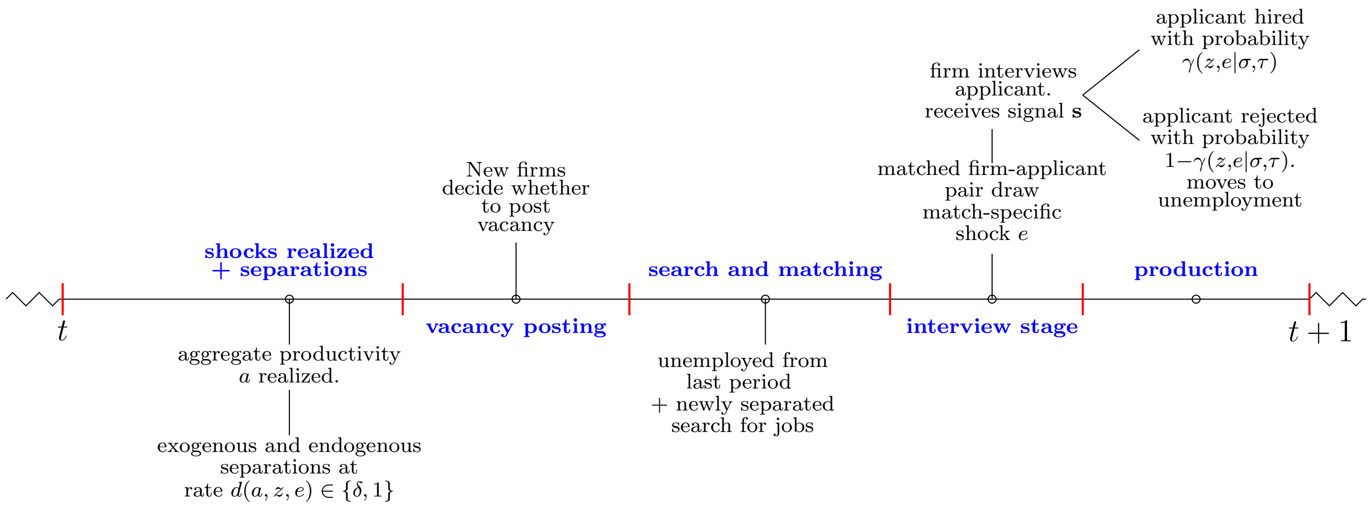


Figure 2: Timeline

like to process about the worker-type z and the match-specific productivity e. This first stage ends with the firm receiving signals about the worker's productivity. (ii) In the *second-stage*, based on the information elicited from the interview, the firm must then decide whether to *reject* or *hire* the applicant. Next, we characterize the firm's hiring strategy starting from the second stage problem.

2.1.1 Second-stage Problem

Let σ denote the set of aggregate state variables of the economy which will be fleshed out later. In the meantime it is sufficient to know that σ contains information about the level of aggregate productivity and the joint distribution of effective productivity (z, e) and unemployment duration τ in the pool of job-seekers. Further denote $G(z, e \mid \sigma, \tau)$ as the conditional distribution of (z, e) types given that the aggregate state is σ and the firm meets a worker of duration τ. We assume that firms observe aggregate variables costlessly and hence, $G(\cdot \mid \sigma, \tau)$ corresponds to the prior a firm has about an applicant's type conditional on σ and τ.

In the second-stage, the firm has already chosen an information strategy and received signals $\mathbf{s}$ about each type (z, e) applicant who had been unemployed for τ periods prior to meeting the firm. Denote the joint-posterior belief of the firm about this applicant's ability z and match-specific shock e by $\Gamma(z, e \mid \mathbf{s}, \sigma, \tau)$. Given this posterior belief, the firm's problem is to decide whether to *hire* or *reject* the applicant. If the firm chooses to reject the worker, she gets a payoff of zero. However, depending on the combination of (z, e), the payoff from hiring an applicant can vary. Denote the payoff from hiring an applicant of effective productivity ze (when the aggregate productivity is a) by $\mathbf{x}(a,z,e)$. Since the firm does not observe z or e when meeting the applicant, this payoff is a random variable. The proposition below summarizes the second stage decision problem:

Proposition 1 (Second-Stage Decision Problem of a Firm)**.** *Given the posterior about the applicant $\Gamma(z, e \mid \mathbf{s}, \sigma, \tau)$, the firm hires the applicant iff*

$$\mathbb{E}_\Gamma[\mathbf{x}(a,z,e)] > 0$$

and rejects the applicant otherwise. Thus, the value of such a firm can be written as:

$$J\left(\Gamma(\cdot \mid \mathbf{s}, \sigma, \tau)\right) = \max\Big\{0, \mathbb{E}_\Gamma\left[\mathbf{x}(a,z,e)\right]\Big\}$$

Proof. A firm can always reject a candidate and ensure a payoff of at least 0. Thus, the firm chooses to hire only if the expected payoff from hiring a worker is larger than 0. $\square$

2.1.2 First-stage Problem

The first stage of the hiring strategy requires the firm to choose an information strategy to determine the applicant's effective productivity. We model the limited information processing capacity as an entropy-based channel capacity constraint as posited in the seminal paper by Sims (2003). In other words, firms are limited by the information they can process and thus, may not be able to determine an applicant's type with certainty. As is standard in the rational inattention literature, we measure uncertainty about the type in terms of entropy and the reduction of uncertainty as mutual information.

Definition 1. *Consider a random variable $X \in \mathcal{X}$ with prior density $p(x)$. Then the entropy can be written as:*

$$H(X) = -\sum_{x\in\mathcal{X}} p(x) \ln p(x)$$

Consider a information strategy under which an agent acquires signals $\mathbf{s}$ about the realization of X. Denote the posterior density of the random variable X as $p(x \mid \mathbf{s})$. Then, the mutual information between the prior and the posterior is given by:

$$\mathcal{I}\Big(p(x), p(x \mid \mathbf{s})\Big) = H(X) - \mathbb{E}_\mathbf{s} H\left(X \mid \mathbf{s}\right)$$

This can be interpreted as a measure of reduction in uncertainty about X by virtue of getting signals $\mathbf{s}$.

From this definition, a choice of the information strategy can be thought of as the firm asking an applicant a series of questions to reduce its uncertainty about the worker's type. Every additional question provides the firm with incremental information which helps it make a more informed decision as to whether to accept or reject an applicant in the second-stage. However, each additional question also consumes the finite information capacity a firm possesses. An entropy-based measure is natural in our setting as information flow measured in terms of reduction in entropy is proportional to the expected number of questions needed to implement an information strategy and reflects the comprehensiveness of an interview.[3] We are now ready to describe the firm's information strategy and thus its first stage problem.

Recall that conditional on meeting a worker with unemployment duration τ in aggregate state σ, the firm's prior about the workers effective productivity is given by the distribution $G(z, e \mid \sigma, \tau)$. Through the interview, firms can choose to receive signals $\mathbf{s}$ in order to update her belief about worker-productivity z and match-specific shock e of the applicant. More informative signals consume more channel capacity than less informative ones. The following definition characterizes an information strategy of the firm

Definition 2 (Information Strategy)**.** *The information strategy of a firm who has met a worker with unemployment duration τ (when the aggregate state of the economy is given by σ) is given by a joint distribution of signals $\mathbf{s}$ and types, $\Gamma(z, e, \mathbf{s} \mid \sigma, \tau)$ such that:*

$$G(z, e \mid \sigma, \tau) = \int_{\mathbf{s}} d\Gamma(z, e, \mathbf{s} \mid \sigma, \tau) \tag{1}$$

Equation (1) simply requires that a firm's priors and posteriors are consistent with each other. A consequence of this consistency requirement is that the firm is only free to choose $\Gamma(\mathbf{s} \mid z, e, \sigma, \tau)$. Thus, an information strategy can be thought of as a firm choosing what set of signals to observe when it has met a particular type of worker. Following a large literature on rational inattention, we assume that firms cannot process unlimited amounts of information (See for example Sims (2003), Mackowiak and Wiederholt (2009)). In particular, we assume that the maximum amount of information that a firm can process in a period is constrained by a finite channel capacity $\chi > 0$. We can then write the constraint on the information processed by firms as:

$$\mathcal{I}(G, \Gamma \mid \sigma, \tau) = H(G(\cdot \mid \sigma, \tau)) - \mathbb{E}_s H\left(\Gamma(\cdot \mid \mathbf{s}, \sigma, \tau)\right) \leq \chi \tag{2}$$

where $\mathcal{I}$ refers to the information that a firm receives by way of observing signals $\mathbf{s}$ and corresponds to the reduction in entropy after observing signals. In equation (2), $H(G)$ is the

[3] For details, see the coding theorem (Shannon, 1948) and Matejka and McKay (2015).

firm's initial uncertainty given the distribution $G(z, e \mid \sigma, \tau)$ and $\mathbb{E}_{\mathbf{s}} H\left(\Gamma(\cdot \mid \mathbf{s}, \sigma, \tau)\right)$ is the firm's residual uncertainty after obtaining signals about the worker. The constraint implies that firms have limited attention and thus there is a limit to the informativeness of the signals that firms can choose. The extent to which the attention constraint (2) binds in a firm's decision depends not just on the informativeness of the signals that the firm chooses but also on the distribution of workers $G(\cdot \mid \sigma, \tau)$. It is important to note that this distribution G is determined in equilibrium and varies with the business cycle. As such, how much the information processing constraint binds for the firm also depends on the business cycle. The Proposition below summarizes the first-stage problem of the firm.

Proposition 2 (First-Stage Problem of a Firm)**.** *Denote the joint pmf associated with G as g. Then the firm's first-stage problem involves choosing an information strategy to maximize ex-ante payoffs from the second-stage for each unemployment duration τ:*

$$\mathbf{V}(\sigma, \tau) = \max_{\Gamma \in \Delta} \sum_{z} \sum_{e} \int_{s} J\left[\Gamma(\cdot \mid \mathbf{s}, \sigma, \tau)\right] d\Gamma(\mathbf{s} \mid z, e, \sigma, \tau) g(z, e \mid \sigma, \tau) \tag{3}$$

subject to:

$$\mathcal{I}(\Gamma, G \mid \sigma, \tau) \leq \chi \tag{4}$$

where $\mathcal{I}$ is defined in (2).

The firm's first stage problem consists of her ex-ante payoff for each (z, e) worker given signals $\mathbf{s}$, this is given by $J\left[\Gamma\left(\cdot \mid \mathbf{s}, \sigma, \tau\right)\right]$. Since the firm does not know which worker she would meet and therefore which signal she would receive, the firm's payoff is a weighted sum over the signals $d\Gamma\left(\mathbf{s} \mid z, e, \sigma, \tau\right)$ and job-seekers, $g\left(z, e \mid \sigma, \tau\right)$ she encounters. The problem of the firm specified in Proposition 2 is not trivial to solve as it allows firms to choose signals of any form.[4] Fortunately, the problem above can be reformulated into a more tractable form. Rather than solving for the optimal signal structure, following Matejka and McKay (2015), we instead solve the identical but transformed problem in terms of choosing state-contingent choice probabilities and the associated payoffs.

Let $\mathcal{S}$ be the set of signals that lead the firm to take the action *hire* for an applicant of type (z, e) of duration τ in aggregate state σ. Denote the induced probability of hiring a (z, e)-type worker with unemployment duration τ in aggregate state σ by $\gamma\left(z, e \mid \sigma, \tau\right)$. This induced probability is defined as the probability of drawing a signal in $\mathcal{S}$ conditional

[4]Notice that the problem of the firm is not a Linear-Quadratic problem and hence the optimal choice of signals is not linear-gaussian. See Sims (2003, 2006) for more details.

on being a (z, e) worker with unemployment duration τ:

$$\gamma(z, e \mid \sigma, \tau) = \int_{s \in \mathcal{S}} d\Gamma(s \mid z, e, \sigma, \tau)$$

Similarly, we can define the average probability of hiring a worker of duration τ in state σ as the average induced probability of hiring over the entire pool of job-seekers of that particular unemployment duration:

$$\mathcal{P}(\sigma, \tau) = \sum_z \sum_e \gamma(z, e \mid \sigma, \tau) g(z, e \mid \sigma, \tau)$$

The following Lemma presents the reformulated problem in terms of these choice probabilities:

Lemma 1 (Reformulated First-Stage Problem)**.** *The problem in Proposition 2 is equivalent to the transformed problem below:*

$$\mathbb{V}(\sigma, \tau) = \max_{\gamma(z,e|\sigma,\tau) \in [0,1]} \sum_z \sum_e \gamma(z, e \mid \sigma, \tau) \mathbf{x}(a, z, e) g(z, e \mid \sigma, \tau) \tag{5}$$

subject to:

$$\mathcal{I}(\mathcal{P}, G \mid \sigma, \tau) = \mathcal{H}(\mathcal{P}) - \sum_z \sum_e \mathcal{H}\Big(\gamma(z, e \mid \sigma, \tau)\Big) g(z, e \mid \sigma, \tau) \quad \leq \quad \chi \tag{6}$$

where $\mathcal{H}(x) = -x \ln x - (1 - x) \ln(1 - x)$.

Proof. The proof is very similar to Appendix A of Matejka and McKay (2015). □

Intuitively, the LHS of (6) measures the information flow based on the optimal signal choices but written instead in terms of choice probabilities. This equivalence follows from the fact that the information flow is a strictly convex function, implying that a firm optimally associates each action with a particular signal. Receiving multiple signals that lead to the same action is inefficient as the additional information acquired is not acted upon and uses up limited channel capacity which could have otherwise been used to make better decisions. The transformed problem in Lemma 1 is more tractable than the original problem. The proposition below characterizes the optimal information strategy of a firm.

Proposition 3 (Optimal Information Strategy)**.** *Under the optimal information strategy, the firm chooses a set of signals which induces the firm to hire a worker of productivity-type z and match-specific shock e with unemployment duration τ in aggregate state σ with* *probability $\gamma(z, e \mid \sigma, \tau)$ which can be written as:*

$$\gamma\left(z, e \mid \sigma, \tau\right) = \frac{\mathcal{P}\left(\sigma, \tau\right) e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma,\tau)}}}{1 + \mathcal{P}\left(\sigma, \tau\right)\left[e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma,\tau)}} - 1\right]} \tag{7}$$

where $\lambda(\sigma, \tau)$ is the multiplier on the channel capacity constraint and represents the shadow-value of reducing uncertainty by one nat. Consequently, the unconditional probability that a firm hires an applicant of duration τ after meeting her is implicitly defined by:

$$1 = \sum_z \sum_e \frac{e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma,\tau)}}}{1 + \mathcal{P}\left(\sigma, \tau\right)\left[e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma,\tau)}} - 1\right]} g(z, e \mid \sigma, \tau) \tag{8}$$

Proof. See Appendix A.1 □

2.1.3 What affects hiring decisions?

Equation (7) reveals an important feature of the information strategy. Consider two applicants with the same match-specific shock e and duration τ, but with worker-productivity z_1 and z_2 where $z_1 > z_2$. Then the optimal information strategy implies the following:

$$\log \frac{\gamma\left(z_1, e \mid \sigma, \tau\right)}{1 - \gamma\left(z_1, e \mid \sigma, \tau\right)} - \log \frac{\gamma\left(z_2, e \mid \sigma, \tau\right)}{1 - \gamma\left(z_2, e \mid \sigma, \tau\right)} = \frac{\mathbf{x}(a, z_1, e) - \mathbf{x}(a, z_2, e)}{\lambda(\sigma, \tau)} \tag{9}$$

The equation above implies that the firm chooses signals such that the induced odds-ratio of accepting a more-productive applicant relative to a less productive applicant is proportional to the difference in the payoffs from hiring the two types of workers. In this sense, the firm chooses signals so as to reduce the incidence of making a Type II error. For more productive candidates, the firm chooses signals that lead him to accept the productive applicant more often on average. Furthermore, equation (9) implies that the higher the shadow value of information λ, the less likely a firm is to process information distinguishing different productivity workers. This is reflected in a smaller odds ratio. As the shadow value of information becomes very large and firms are starved of information, firms are increasingly unable to distinguish between different types of applicants and the difference between $\gamma(z, e \mid \sigma, \tau)$ gets increasingly smaller between (z, e) pairs. In the limit as $\lambda \to \infty$, the firm optimally chooses to set $\gamma(z, e \mid \sigma, \tau)$ to be the same for all (z, e) types. Since $\lambda \to \infty$ implies that the firms posterior belief about an applicants type is the same as its prior, the firm either accepts all applicants or rejects all of them. In other words, $\gamma(z, e \mid \sigma, \tau)$ is either 1 or 0 for all (z, e) realizations for a given τ.

Lemma 2 (Information Strategy with Costless Information)**.** *Given any distribution of $G(z,e)$, if $\chi \geq H(G)$, then firms are able to replicate the hiring decisions that would have arisen under full information. Consequently, the induced probability of hiring a particular type of worker (z,e) with duration τ under the optimal information strategy is given by:*

$$\gamma(z, e \mid \sigma, \tau) \;=\; \begin{cases} 1 & \textit{if } \mathbf{x}(a,z,e) \geq 0 \\ 0 & \textit{else} \end{cases} \tag{10}$$

Proof. See Appendix A.2. □

The above Lemma implies that if the firm's information processing constraint does not bind, the firm can ascertain the worker-productivity z and match-specific productivity e and this scenario corresponds to the full-information case. In this case, the payoff from hiring an applicant is non-random and the firm accepts an applicant only if $\mathbf{x}(a,z,e) \geq 0$. Interestingly, even with full-information, $\mathcal{P}(\sigma) < 1$ if some applicants have $\mathbf{x}(a,z,e) < 0$. Thus, relative to the standard search and matching model, worker heterogeneity can result in a wedge between the contact rate and the job-filling rate for firms.

The Static Limit In order to further uncover the forces that affect a firm's hiring decision, we make some simplifying assumptions. We start by considering the static limit of the model in which $\beta = 0$. We also shut-down the match-quality e dimension of heterogeneity and assume that there are two types of workers $z_H > z_L$ in proportion $\alpha \geq 0.5$ and $1-\alpha$ respectively. In this case, the hiring decision of a firm can be written as a solution to the following problem:

$$\Pi(a) = \max_{(\gamma_H,\gamma_L)\in[0,1]^2} \alpha\gamma_H \mathbf{x}(a,z_H) + (1-\alpha)\gamma_L \mathbf{x}(a,z_L)$$

s.t.

$$\mathcal{H}\Big(\mathcal{P}(a)\Big) - \alpha\mathcal{H}(\gamma_H) - (1-\alpha)\mathcal{H}(\gamma_L) \leq \chi \tag{11}$$

where $\mathbf{x}(a,z) = az - b$ and $\mathcal{P}(a) = \alpha\gamma_H + (1-\alpha)\gamma_L$ denotes the unconditional probability that the firm hires an applicant when aggregate productivity is a.

We start by assuming that aggregate productivity $\frac{b}{z_H} < a < \frac{b}{z_L}$. Given this assumption, $\mathbf{x}(a,z_H) > 0 > \mathbf{x}(a,z_L)$ and a firm would only choose to hire the z_H worker if it could identify her. Figures 3a and 3b graphically depicts the hiring decisions of a firm for different values for χ. The firm's unconstrained choice is the south-east corner $(\gamma_H = 1, \gamma_L = 0)$. The level of χ determines how close a firm's decision can be to the unconstrained choices. For

$\chi < -\alpha \ln \alpha - (1-\alpha)\ln(1-\alpha) \equiv \overline{\chi}$, the unconstrained choice is not feasible given the limited channel capacity. The shaded area in Figure 3a shows the feasible choices for a firm with channel capacity such that $0 < \chi < \overline{\chi}$. Notice that hiring everyone, $\gamma_H = \gamma_L = 1$, hiring no one $\gamma_H = \gamma_L = 0$, and in general not discriminating between the types $\gamma_H = \gamma_L \in [0, 1]$ is always feasible but not necessarily optimal. Overall, the problem reveals that trying to distinguish between applicant types is costly in terms of using up channel capacity. Choices close to the diagonal require less channel capacity but correspond to less informative signals. Figure 3b shows that if the firm is unable to process any information, then the only feasible choices lie along the diagonal where $\gamma_H = \gamma_L$. In other words, the firm is unable to choose an information strategy which allows it to distinguish the different types of applicants. In fact, in this case, the firm can only choose a strategy in which he is equally likely to hire a z_H and z_L type.

The parallel blue lines are the iso-profit curves which are increasing in the south-east direction. The highest profit is achieved at the point $(\gamma_H = 1, \gamma_L = 0)$. Given this fact, it is obvious that the optimal choice of (γ_H, γ_L) must lie on the south east frontier of the feasible set which implies that the optimal choice satisfies $\gamma_H \geq \gamma_L$. Next, notice that in an interior solution, the optimal choices of γ_H and γ_L satisfy:

$$\frac{\alpha \mathbf{x}(a, z_H)}{(1-\alpha)\mathbf{x}(a, z_L)} = \frac{\alpha \left[\mathcal{H}'\Big(\alpha\gamma_H + (1-\alpha)\gamma_L\Big) - \mathcal{H}'(\gamma_H)\right]}{(1-\alpha)\left[\mathcal{H}'\Big(\alpha\gamma_H + (1-\alpha)\gamma_L\Big) - \mathcal{H}'(\gamma_L)\right]}$$

which corresponds to the tangency between the iso-profit curves and the constraint function.[5] The firm would like to choose the highest γ_H and lowest γ_L possible. However, while trying to increase γ_H, the firm is forced to choose a higher γ_L so as to stay within the feasible set. Thus, the information processing constraint limits the amount by which firms are able to distinguish between the z_H and z_L applicant and graphically forces choices to be closer to the diagonal. In fact, in the extreme case with $\chi = 0$, the capacity constraint forces choices to lie exactly on the diagonal and the firm is forced to choose $\gamma_H = \gamma_L = \gamma$. The optimal choices in this case is characterized by a *bang-bang* solution with firms choosing $\gamma = 1$ and hiring any applicant applicant, if $\alpha\mathbf{x}(a, z_H) + (1-\alpha)\mathbf{x}(a, z_L) \geq 0$ (depicted by the intersection of the solid blue and red lines in Figure 3b , otherwise they choose $\gamma = 0$ and reject all applicants (depicted by the intersection of the dashed blue line and red line in figure 3b).

[5]The LHS is the slope of the iso-profit curve while the RHS is the slope of the constraint set.

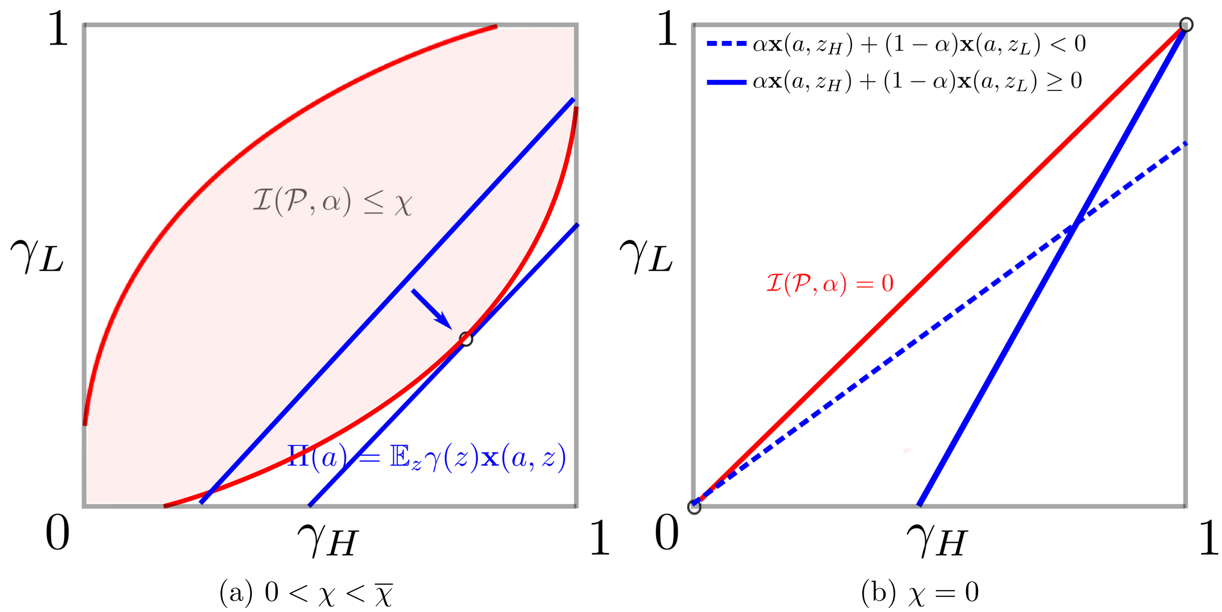


Figure 3: Optimal Hiring Decisions

How does a fall in aggregate productivity affect optimal choices? Next, we explore how a fall in aggregate productivity - *a recession* - affects hiring decisions.[6] Notice that a change in a does not affect the set of feasible choices since the information processing constraints is unaffected. However, as can be seen in Figure 4a,[7] a fall in a does affect the slope of the iso-profit curves making them flatter.[8] The outcome is that the firm becomes more selective in hiring and reduces the probability of accepting both z_H and z_L types with the optimal choice shifting to the south-west. In order to understand why this is the case, it is important to notice that a fall in a lowers the profit the firm makes by hiring a z_H applicant and increases the loss that the firm makes if it hires a z_L applicant. Since making a mistake and hiring a z_L worker is now costlier, and since at the same time hiring a z_H applicant is also less attractive, the firm chooses to increase hiring standards and reduce the acceptance probability for both types and thus the unconditional probability $\mathcal{P} = \alpha\gamma_H + (1-\alpha)\gamma_L$ of hiring an applicant also falls. As we explain in subsequent sections, this fall in $\mathcal{P}$ corresponds to a fall in match-efficiency in our model. The Lemma below formalizes this notion while Figure 4b graphically depicts how the optimal choices of $\gamma_H(a)$, $\gamma_L(a)$ and $\mathcal{P}(a)$ are affected by changing a.

Lemma 3 (Comparative Statics)**.** *Under a firm's optimal information strategy, both* $\gamma_H(a)$

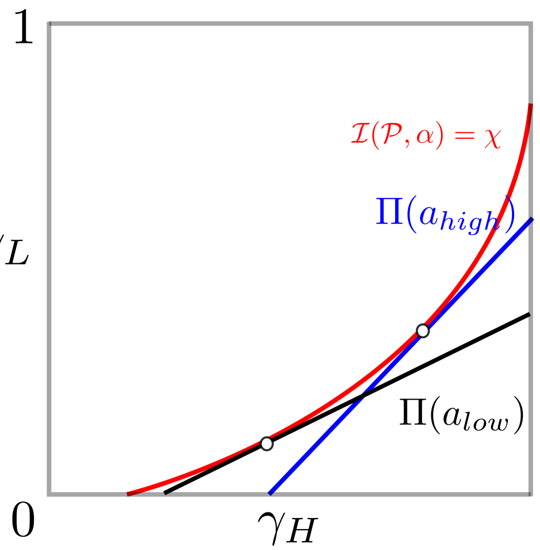
[6] We still assume that the lower value of a lies in the interval $[\frac{b}{z_H}, \frac{b}{z_L}]$.

[7] Since the optimal choices of γ_H and γ_L lie on the south-east frontier of the constraint set, we omit drawing the north-west frontier in Figures 4a and 5b to avoid cluttering up the figures.

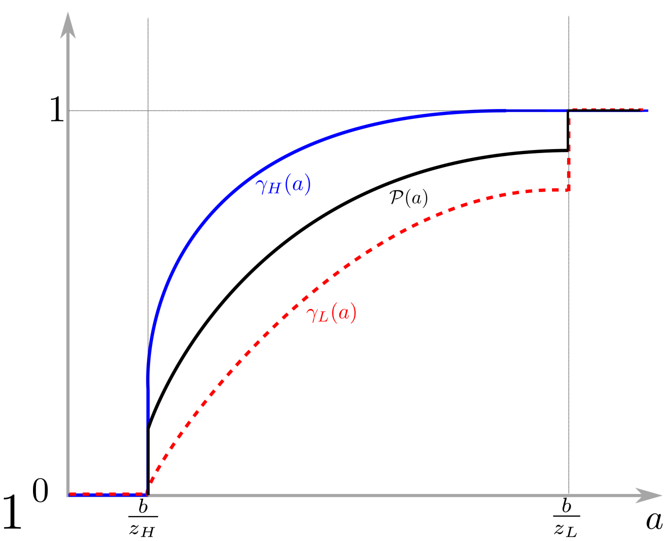
[8] It is straightforward to see that $\frac{\mathbf{x}(a,z_H)}{\mathbf{x}(a,z_L)} = \frac{az_H - b}{az_L - b}$ is decreasing in a.

and $\gamma_L(a)$ are increasing in a. Consequently, the unconditional probability of accepting an applicant $\mathcal{P}(a)$ is increasing in a.

Proof. See Appendix A.3. □



(a) Change in aggregate productivity a



(b) $\gamma_H, \gamma_L, \mathcal{P}$ as a function of a

Figure 4: Changes in Hiring decisions with a

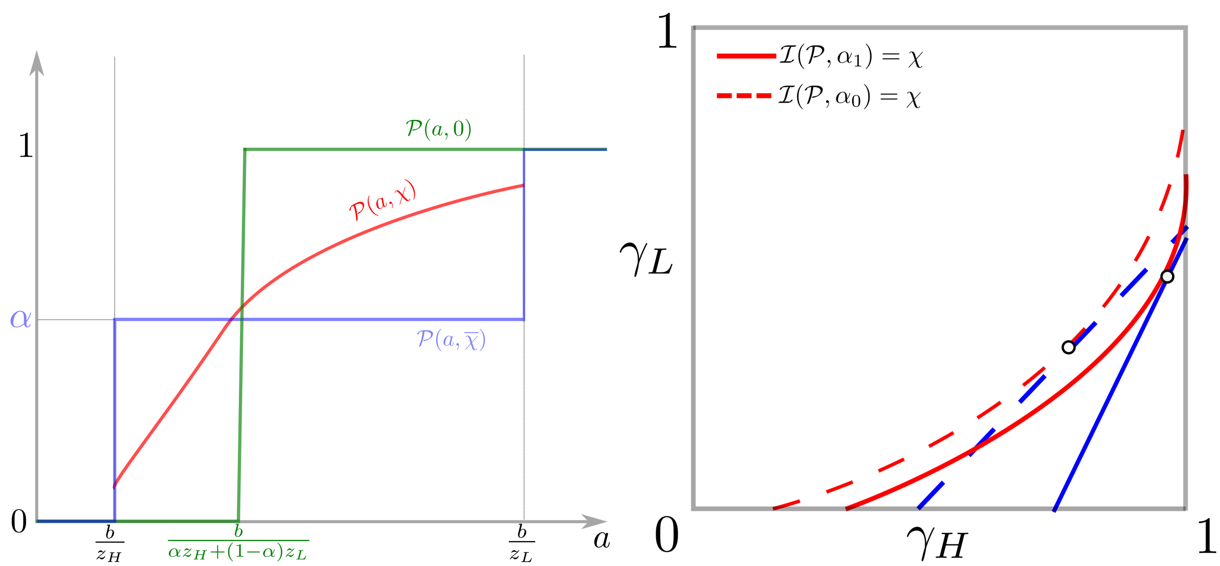
Figure 5a shows that the optimal hiring probability $\mathcal{P}(a)$ responds more to changes in aggregate productivity in an environment where firms are informationally constrained. The blue line denotes the optimal $\mathcal{P}_{FI}(a)$ under full information. In this case, the firm can always correctly identify the true type of an applicant and thus, never makes a mistake in hiring. Thus, for any $\frac{b}{z_H} < a < \frac{b}{z_L}$, the firm always rejects the L type applicant, $\gamma_L(\frac{b}{z_H} < a < \frac{b}{z_L}) = 0$ and hires the H type, $\gamma_H(\frac{b}{z_H} < a < \frac{b}{z_L}) = 1$. As a result, the optimal $\mathcal{P}_{FI}(a)$ can be written as:

$$\mathcal{P}_{FI}(a) = \begin{cases} 0 & \text{if } a < b/z_H \\ \alpha & \text{if } b/z_H \leq < b/z_L \\ 1 & \text{ else} \end{cases}$$

Notice that in the range $\frac{b}{z_H} < a < \frac{b}{z_L}$, $\mathcal{P}'_{FI}(a) = 0$, i.e. small changes in the full information regime do not result in any change in the unconditional acceptance probability of hiring a worker. In contrast, the red curve in figure 5a depicts that even small changes in a can have large effects on match efficiency in the rational inattention model, $\mathcal{P}(a)$.[9] Overall, $\mathcal{P}'(a)$

[9]See Section 2.2.2 for details.

is larger when the firm is informationally constrained relative to the full information case, demonstrating that match efficiency responds relatively more when firms are informationally constrained.[10]



(a) Effect of χ on $\mathcal{P}(a)$

(b) Effect of changing α on γ_H, γ_L

Figure 5: Match Efficiency

How does a change in the distribution of job-seekers affect optimal choices? Next, we investigate how a change in α, the distribution of applicants, affects hiring decisions. Unlike a, an increase in α which corresponds to the fraction of z_H types in the population, affects both the slope of the indifference curve and the constraint set. Figure 5b shows that an increase from $\alpha_0 \geq 0.5$ to $\alpha_1 > \alpha_0$ makes the iso-profit curves steeper since there are more z_H types in the population (the solid line curves represent the case with α_1 while the dashed ones correspond to α_0 case). At the same time, an increase in α also reduces the entropy or uncertainty associated with the distribution of applicant types (also equal to the prior beliefs a firm has about an applicant). Recall that the entropy associated with the prior is given by $-\alpha \ln \alpha - (1-\alpha)\ln(1-\alpha)$ is the largest for $\alpha = 0.5$. Thus, the firm's uncertainty regarding his job applicant is at its maximum whenever $\alpha = 0.5$. For $\alpha \in [0.5, 1]$, an increase in α lowers the initial uncertainty and allows the firm to be less constrained in processing more precise information to lower his posterior uncertainty compared to the case with a lower α.

[10]The green line corresponds to the case with no information processing capacity $\chi = 0$. This line has an infinite slope at $a = \frac{b}{\alpha z_H + (1-\alpha) z_L}$ implying that small declines in a around this point could lead to large changes in $\mathcal{P}(a)$ causing it to fall from 1 to 0. No such change would occur in the full information case.

This can be seen from the fact that the south-east frontier of the feasible choices shifts down with a larger α. Overall, this makes it easier for the firm to distinguish between the two type of applicants and thus raise γ_H. Notice that in the figure γ_L is also higher but in expectation this still leads to higher profits since there are more z_H types in the population.

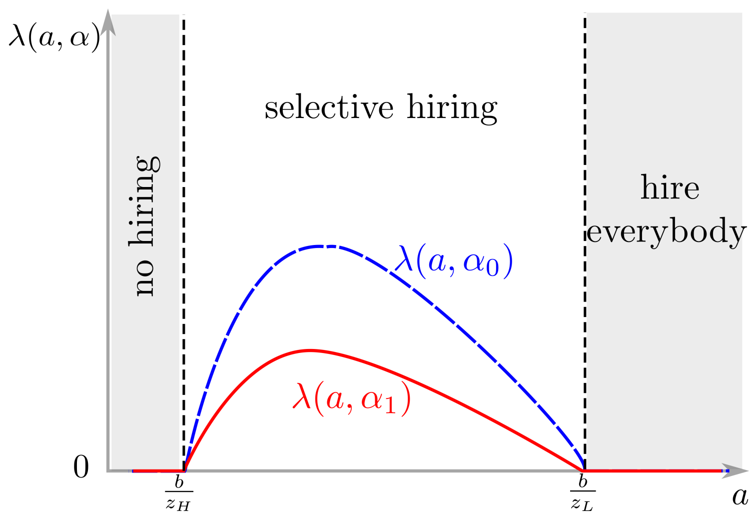


Figure 6: Shadow value of additional information

Shadow value of additional information The discussion above did not mention how the shadow value of information, λ interacted with the changes in aggregate productivity a or the distribution α. We start by analyzing the change in productivity. It is important to notice that even though a change in a does not directly affect the set of feasible choices it does change the shadow value of an additional unit of information which is given by the multiplier on the constraint. Moreover, the relationship between $\lambda(a)$ and a is non-monotonic. Figure 6 shows that for large enough falls in productivity (below $\frac{b}{z_H}$), hiring either type of applicants becomes unprofitable for the firm and at this level of aggregate productivity, the optimal choices are $\gamma_H = \gamma_L = 0$. In this case, the firm is certain that it does not want to hire any of the applicants and thus there is no value from being better able to distinguish between workers. Similarly, for a level of aggregate productivity $a > \frac{b}{z_L}$, hiring either z_H or z_L workers results in positive profits and thus, a firm is willing to hire any applicant $\gamma_H = \gamma_L = \mathcal{P} = 1$. Since either worker brings the firm positive surplus, the firm does not derive further benefit from distinguishing between types and $\lambda = 0$. However, for levels of aggregate productivity in the region $[\frac{b}{z_H}, \frac{b}{z_L}]$, hiring a z_L type worker leads to losses and λ is positive in this range as the firm would like to be able to identify and avoid hiring a type z_L worker. Equation (7) shows that when the shadow value of information is high, holding other things fixed, a firm lowers its acceptance probability. Consequently, the red curve with $\alpha_1 > \alpha_0$ lies below the below the blue curve. With a larger fraction of H types, the shadow value of information for a firm is relatively lower since (i) the firm is less likely to meet a low type worker in the first place and (ii) with a less uniform distribution, the feasible set of choices of γ_H, γ_L is larger as discussed above. Overall, both these forces imply that with $\alpha_1 > \alpha_0$, the shadow value of information is weakly lower (see Figure 6).

While in this static case, the distribution of job-seekers is given exogenously, in the dynamic model that follows, this distribution endogenously evolves over the business cycle. For example, as we show in subsequent sections, a large recession which precipitates an increased inflow into unemployment on impact makes it extremely costly for the firm to hire the wrong worker. In such a scenario, the firm wants to attain more precise information but fails to acquire this information due to his finite processing capacity constraint. This causes firms to raise hiring standards to avoid hiring the wrong worker and thus, lowers the unconditional probability that a firm hires an applicant it meets, leading to a fall in match-efficiency. When the recession is small, and does not result in an increased inflow into the pool of unemployed on impact, a lower aggregate productivity is still enough to lower the unconditional probability of hiring $\mathcal{P}$ as discussed above. While this does not simultaneously affect the uncertainty about the pool of job-seekers, it does so dynamically and can lead to higher uncertainty about the pool of job-seekers in the future, slowing down hiring in the recovery.

2.2 Closing the Model

With the hiring strategy characterized, all that remains is to close the model. This entails specifying how equilibrium meeting rates are determined.

2.2.1 Value of a Firm

Given our assumption that the worker's type is revealed after one period of production, the firm's payoff to hiring a worker of type (z, e), $\mathbf{x}(a, z, e)$, can be written as:

$$\mathbf{x}(a, z, e) = F(a, z, e) - b + \beta \mathbb{E}_{a'|a} \left[1 - d(a', z, e)\right] \mathbf{x}(a', z, e) \tag{12}$$

where

$$d(a, z, e) = \begin{cases} \delta & \text{if } \mathbf{x}(a, z, e) \geq 0 \\ 1 & \text{else} \end{cases}$$

and δ is the exogenous rate of separation. Since firms learn the worker's productivity perfectly after production, endogenous separations may also occur if after production the value of match cannot be sustained. Notice that the actual payoff to the firm does not depend on an applicant's unemployment duration but depends on her true effective productivity.

2.2.2 Free Entry Condition

The total number of firms that post vacancies in a particular period is determined by a free-entry condition. This condition pins down the equilibrium market-tightness and hence, the rate at which firms and workers meet. Denote $g_\tau(\tau \mid \sigma)$ as the probability mass of job-seekers of duration τ given aggregate state σ, i.e., define $g_\tau(\tau \mid \sigma)$ as:

$$g_\tau(\tau \mid \sigma) = \sum_z \sum_e g(z, e, \tau \mid \sigma)$$

Then from the free-entry condition, we have:

$$\kappa \geq q(\theta) \sum_\tau \mathbb{V}(\sigma, \tau) g_\tau(\tau \mid \sigma)$$

$$\left[\kappa - q(\theta) \sum_\tau \mathbb{V}(\sigma, \tau) g_\tau(\tau \mid \sigma)\right] \theta = 0 \tag{13}$$

where $\mathbb{V}(\sigma, \tau)$ denotes the value of a firm from hiring a worker of duration τ and is defined in equation (5). Since we assume random search, it is clear that, θ, the labor market-tightness only depends on the aggregate state as summarized by σ. Further, we can now decompose the job-filling rate into two components. The free entry condition pins down the first component, $q(\theta) = \frac{m(v,l)}{v}$, which is the rate at which a firm meets a job-seeker. We refer to this as the *contact rate*. The second component that affects a firm's hiring rate of a worker of duration τ is given by the firm's acceptance rate, $P(\sigma, \tau)$. Formally, we can now express the aggregate job-filling rate in our model as the product of these two components:

$$\text{Job-filling rate} = \underbrace{q(\theta)}_{\text{contact rate}} \times \mathcal{P}(\sigma)$$

where $\mathcal{P}(\sigma) = \sum_\tau g_\tau(\tau \mid \sigma)\mathcal{P}(\sigma, \tau)$ is the average (across all durations) unconditional acceptance probability and is our measure of match efficiency. Notice that there now exists a wedge between the job-filling rate and the rate at which a firm meets a worker. This wedge arises because a firm can choose to reject an applicant after interviewing the applicant.[11]

[11] As explained earlier, this wedge also potentially exists in the model with no information processing constraints because of the presence of worker heterogeneity. The shadow cost of information affects the size

Correspondingly, our measure of the job-finding rate is the product of the rate at which a worker meets a firm, $p(\theta) = \frac{m(v,l)}{l}$, and the average acceptance rate of the firm.

2.3 Composition of job seekers over the business cycle

Thus far, we have shown how the firm's hiring problem works for a given distribution $G(z, e, \tau)$. The firm's choice of information strategy, crucially depends on the prior distribution of job-seekers $G(z, e \mid \sigma, \tau)$. We now address how the firm's prior over the distribution of job-seekers is formed.

At this point, it is now essential to define the state variables σ for this economy. At any date t, the economy can be fully described by $\sigma_t = \{a, n_{t-1}(z, e), u_{t-1}(z, \tau)\}$ where $n_{t-1}(z, e)$ is the measure of employed (z, e) individuals at the end of last period and $u_{t-1}(z, \tau)$ is the measure of unemployed individuals of type z and of duration τ by the end of last period. The aggregate state σ is always known to the firm at the start of each period. Knowing the aggregate state, the firm can always compute the prior distribution of workers who have been unemployed for τ periods.

The aggregate laws of motion for each type of worker are known by all firms. In particular, the evolution of the mass of job-seekers of duration τ with worker productivity z in period t can be written as:

$$l_t(z, \tau) = \begin{cases} \sum_e d(a, z, e) n_{t-1}(z, e) & \text{if } \tau = 0 \\ u_{t-1}(z, \tau) & \text{if } \tau \geq 1 \end{cases} \tag{14}$$

The first part of equation (14) refers to job-seekers of type z with zero unemployment duration. These job-seekers of duration zero are the fraction of employed workers at the end of last period, $t-1$, who were either endogenously or exogenously separated from their firms at the beginning of the current period, t. The second line in equation (14) refers to all the unemployed of type z and duration τ at the end of the last period. By construction, all unemployed individuals at the end of a period have duration $\tau \geq 1$. To see this, consider the law of motion for the mass of unemployed individuals with productivity z and duration τ. This is given by:

$$u_t(z, \tau) = l_t(z, \tau - 1) \left\{ 1 - p\left[\theta(\sigma_t)\right] + p\left[\theta(\sigma_t)\right] \sum_e \pi_e(e) \left(1 - \gamma\left[z, e \mid \sigma, \tau - 1\right]\right) \right\}, \forall \tau \geq 1 \tag{15}$$

The first term on the RHS of Equation (15) refers to all job-seekers of duration $\tau - 1$ at the

and cyclicality of this wedge.

beginning of the period who have productivity z. With probability $1 - p\,[\theta(\sigma)]$, a job-seeker of type z and duration $\tau - 1$ fails to meet a firm and remains unemployed. With probability $p\,[\theta(\sigma)]$, the worker meets a firm, draws match productivity e with probability $\pi_e(e)$, but is rejected with probability $(1 - \gamma\,[z, e \mid \sigma, \tau - 1])$ and remains unemployed. Note if a job-seeker fails to find a job within a period, her duration of unemployment must increase by 1 period. As such, all $l_t(z, \tau - 1)$ job-seekers who fail to be hired by the end of period t form the mass of unemployed $u_t(z, \tau)$ at the end of period t.

Similarly, we can define the law of motion for the employed of each type (z, e) as:

$$n_t(z, e) = [1 - d(a_t, z, e)]\, n_{t-1}(z, e) + p(\theta(\sigma_t))\pi_e \sum_{\tau=0}^{\infty} \gamma(z, e \mid \sigma, \tau) l_t(z, \tau) \tag{16}$$

The first term on the RHS of Equation (16) are the fraction of employed workers at the end of last period of (z, e) type who are not separated from the firm. Across all durations of job-seekers of type z, a fraction $p(\theta)$ meet a firm and draw match specific productivity e with probability $\pi_e(e)$. Conditional on their duration of unemployment, τ, they are then hired by the firm after the interview with probability $\gamma(z, e \mid \sigma, \tau)$. Finally, the sum of employed and unemployed workers of type z must equal to the total number of workers of type z in the economy.

$$\sum_{\tau} u_t(z, \tau) + \sum_{e} n_t(z, e) = \pi_z(z)$$

Given the law of motion for the employed and unemployed of each type and duration, we can now construct the probability masses of each type in the economy. We define the probability mass of job-seekers of type z conditional on τ as:

$$g_z(z \mid \sigma, \tau) = \frac{g_{z,\tau}(z, \tau \mid \sigma)}{g_\tau(\tau \mid \sigma)} \equiv \frac{l_t(z,\tau)/l_t}{l_t(\tau)/l_t} = \frac{l_t(z, \tau)}{l_t(\tau)}\ ,\ \forall \tau \geq 0 \tag{17}$$

where $g_z(z \mid \sigma, \tau)$ is defined simply as the share of job-seekers of duration τ who are of type z. $l_t(\tau)$ is the mass of job-seekers of duration τ, i.e. $l_t(\tau) = \sum_z l_t(z, \tau)$, while l_t is the total mass of job-seekers, i.e. $l_t = \sum_\tau l_t(\tau)$. Since the match-specific productivity e is drawn independently of z and any past realizations each time a worker matches with a firm, the joint probability mass of drawing a worker of type (z, e) from the pool of job-seekers is simply given by $g_z(z \mid \sigma, \tau)\pi_e(e)$, i.e.

$$g(z, e \mid \sigma, \tau) = g_z(z \mid \sigma, \tau)\pi_e(e)$$

As this is an environment with random search, a firm's prior about any workers type (z, e)

given τ is simply given by the joint distribution $G(z, e \mid \sigma, \tau)$. This concludes the description of the model. In the next section, we proceed to discuss the numerical exercises we perform with our model.

3 Numerical Exercise

We discipline the parameters of the model using data on the aggregate flows of workers in the US labor market. The length of a period in our model is a month. Thus, we set $\beta = 0.9967$ which is consistent with an annualized risk free rate of about 4%. We assume that the rate at which a worker meets a firm $p(\theta)$ takes the form of $p(\theta) = \theta(1+\theta^{\iota})^{-1/\iota}$ which ensures that the probability of a worker meeting the firm is bounded between 0 and 1. We set ι to be 0.5 as standard in the literature.[12] We assume that the production function takes the following form $F(a, z, e) = a \times z \times e$, and that $\log(a)$ follows an AR(1) process:[13]

$$\log a_t = \rho_a \log a_{t-1} + \sigma_a \varepsilon_t \ , \ \varepsilon_t \sim N(0, 1) \tag{18}$$

We set the persistence $\rho_a = 0.9$. We set the standard deviation $\sigma_a = 0.0165$ as in Shimer (2005).

The remaining parameters are chosen to minimize the distance between moments from the simulated data and their empirical counterparts. In particular, we use the following moments to discipline our model. To govern the amount of separations in the economy, we target an employment to unemployment transition rate (EU) of 3%. This is the average exit probability in the data over the period of 1950-2016.[14] This implies that the average tenure of a worker lasts roughly 2.8 years. In the model, we define the EU rate in period t as the share of employed people at the end of $t-1$ who are unemployed at the end of period t. As in Hall (2009) and in Fujita and Moscarini (2013), we set b such that it is equal to 70% of output. Following Jarosch and Pilossoph (2016), we assume that the unobserved worker fixed effect, z, is drawn from a discretized Beta distribution, i.e. $z \sim Beta(A_z, B_z) + 0.5$ while the match quality shock is drawn from the Beta distribution $e \sim Beta(A_e, B_e)$.[15] Since the vacancy posting cost, κ, the capacity processing constraint, χ and the parameters governing heterogeneity amongst workers and matches, $\{A_z, B_z, A_e, B_e\}$ affect the rate at which workers find jobs, we use information on the aggregate unemployment rate and the

[12] See for example Menzio and Shi (2011).

[13] Wherever it is necessary, we approximate the stochastic process of a with a seven-state Markov process using the algorithm specified in Tauchen (1986). In the simulation, we use the continuous process.

[14] We calculate the exit probabilities as in Shimer (2012).

[15] Specifically we set the number of worker productivity types to be $n_z = 7$ and the number of match-specific shocks to $n_e = 15$.

relative job-finding rates across workers of different unemployment duration to govern these parameters. We also target an aggregate unemployment rate of about 5.8%, which is the average unemployment rate in the data over the period 1950-2016.

Resume audit studies suggests that firms use unemployment duration to screen workers and that the observed unemployment duration across workers possesses some information about their underlying productivity. As such, we use data on unemployment duration and unemployment-to-employment transitions (UE) from the Current Population Survey (CPS). As in Kroft et al. (2016) and Jarosch and Pilossoph (2016), we conduct a weighted non-linear least squares regression on the relative job-finding rate against unemployment duration of the following form:

$$\frac{\mathrm{UE}(\tau)}{\mathrm{UE}(1)} = \pi_1 + (1-\pi_1)exp(-\pi_2\tau)$$

where τ is the duration of unemployment, and $\frac{\mathrm{UE}(\tau)}{\mathrm{UE}(1)}$ is the average job-finding rate of an unemployed individual of duration τ relative to an unemployed individual with 1 month of unemployment duration. We target this relative job-finding rate in the data and cluster all those who are more than 9 months unemployed into a single bin.

Note that the heterogeneity in individual fixed productivity z and match-specific productivity e are crucial for generating the decline in relative job-finding rates across unemployment spells. If the only form of heterogeneity across matches arose from match-specific productivity, the relative job-finding rate of a job-seeker across different unemployment durations would essentially be flat since in that scenario the worker's type is of no consequence to production and since match-specific productivity is an i.i.d. draw at the time of meeting that is independent of worker's type and past matches. If, instead, the only form of heterogeneity stemmed from workers' fixed productivity types, then the relative job-finding rates in the data would be strictly declining in duration and should not exhibit any flattening out with respect to individuals with higher unemployment duration. The presence of the two types of heterogeneity, z and e, drives the convex shape in the relative job-finding rates. We use this feature in relative job-finding rates to discipline our choice of parameters regarding the heterogeneity in z and e.

In summary, we have 8 parameters to estimate $\{\chi, \kappa, \delta, b, A_z, B_z, A_e, B_e\}$ and we target 11 moments: the average monthly separation rate, the aggregate unemployment rate, unemployment benefits worth 70% of output and the relative job-finding rate for unemployment spells greater than one month. Tables 1 summarizes both the fixed and inferred parameters.

The model is able to match the moments in data very well. Under the parametrization, home production is 68.3% of average output (the target was 70% of average output). The

Table 1: Model Parameters

Fixed Parameters

Parameter	Description	Value	Source
β	discount factor	0.9967	annualized interest rate of 4%
σ_a	std. dev. of a	0.0165	Shimer (2005)
ρ_a	autocorr. of a	0.9	Shimer (2005)
ι	matching function elasticity	0.5	Menzio and Shi (2010)

Inferred Parameters

Parameter	Description	Value
b	home production	0.2581
δ	exog. separation rate	0.0078
κ	vacancy posting cost	0.0001
χ	capacity processing constraint (in nats)	0.1118
A_z	shape parameter - worker ability	1.3451
B_z	shape parameter - worker ability	8.5290
A_e	shape parameter - match productivity	1.9975
B_e	shape parameter - match productivity	7.3234

model generates an average EU rate of 1.8%[16] compared to the targeted 3%. Also, the model is generates an average unemployment rate of 5.9%. Figure 7 shows the estimated relative job-finding rates from the data and the model implied counterpart. The model does a fairly good job at replicating the relative job finding rates but under-predicts the relative job-finding rates for workers who are long-term unemployed. The drop-off in the model's implied relative job-finding rates for individuals unemployed for nine months or more reflects the fact that we have clustered these individuals with unemployment duration greater than equals to nine months into one bin.

The shadow cost of processing information In steady state, the average shadow value firms put on having 1 more unit of uncertainty reduced, i.e. $\lambda = \sum_\tau g_\tau(\tau)\lambda(\tau)$ is given by $\lambda = 0.42$. The shadow value can be interpreted in terms of how much output a firm is willing to give up for one more unit of information. Survey evidence on turnover and recruitment costs suggests that the cost of hiring is not trivial. Using data from the California Establishment Survey, Dube et al. (2010) report that the average cost per recruit is about 8% of annual wages. Hamermesh (1993) reports that a 1979 national survey suggests that

[16]This includes both exogenous and endogenous separations

Figure 7: Relative Job finding rates by duration of unemployment

depending on the occupation, hiring costs range from \$680 to \$2200 dollars. In our model, the shadow value of having one more unit of information is equivalent to 13% of annual wages. Thus, while we do not have direct measures of the expenditure on information, our model gives some suggestion of how much firms value information in their hiring practices.

4 Results

4.1 What happens in recessions?

As our first exercise, we simulate a recession as a two standard deviation fall in aggregate productivity relative to steady state and compare the responses of the model with rationally inattentive firms (RI) to responses of the full information model (FI). All results are presented in terms of log deviations. For the full information economy, we assume that firms have no constraints on the amounts of information they can process, i.e. $\chi \to \infty$. In other words, firms are able to process unlimited amounts of information and are able to determine an applicant's type exactly.

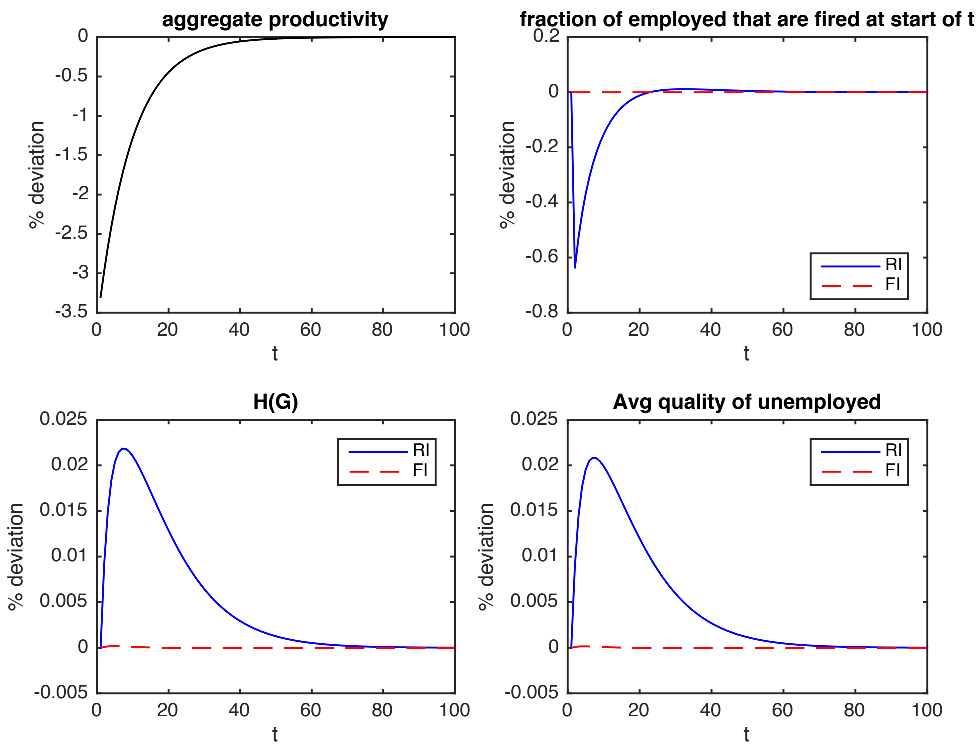


Figure 8: Decline in Hiring Due to 2 Std Dev. Drop in TFP Responsible for Increase in $H(G)$ and Average Quality of Unemployed in RI model

The top left panel of Figure 8 plots the path of aggregate productivity in our experiment while the top right panel shows how the firing margin responds to a two standard deviation drop in productivity. We measure the firing margin as the fraction of employed individuals from last period who are newly separated at the start of the current period. On impact, both the FI and RI model do not show any change in the firing margins, implying that despite the fall in aggregate productivity, the set of workers hired in the prior period before the shock are still profitable to retain in the current period.[17] For a moderate downturn, any impact in our calibrated model to unemployment rates comes from the hiring margin and not from a sudden spike in separation rates. In addition, the firing margin in the RI model actually declines relative to steady state in subsequent periods, indicating that outflows from employment are declining faster relative to the stock of employed at the start of the period.

[17]This result is due to the discreteness of types in our model. For larger shocks, the firing margin is triggered and the distribution of types in the unemployment pool changes on impact. We illustrate this outcome in Section 4.2

We elaborate below how this phenomenon stems largely from the fact that when firms in the RI model reject job-seekers more often on average, they reduce the amount of firings due to mistakes in hiring the wrong candidate.

The bottom panels of Figure 8 shows how uncertainty (as measured by entropy) and average quality of the unemployment pool rise with a lag following a moderate downturn in the RI model. Since firing margins did not change on impact, the hiring margin of firms in response to the adverse shock is entirely responsible for the rise in uncertainty and the average quality in the pool of unemployed. In a downturn, firms require a productive worker to compensate for the fall in aggregate productivity to stay profitable. As such, firms would like to be selective in hiring and require more information about a job-seeker in order to determine her suitability in production. In the RI model, firms are constrained in terms of how much information they can process and as such, are unable to attain more information on their job applicant. The lack of more precise information about job applicants leads firms to reject unemployed job-seekers more often to avoid the costly mistake of hiring the wrong worker during a downturn. This, in turn, has the effect of elevating uncertainty in the next period as firms who do a poor job of filtering out applicants today leave behind a more varied pool of unemployed job-seekers for tomorrow. As a result, the uncertainty that the firm faces regarding the pool of unemployed job-seekers, $H(G)$, rises with a lag. Average quality of the unemployed also rises as higher and more indiscriminate rejection imply that some high ability job-seekers are inadvertently rejected and released into the unemployment pool.

Figure 9 breaks down how each additional round of inadequate screening amplifies and propagates the uncertainty surrounding unemployed job-seekers of τ duration. On impact (i.e. $t = 1$), uncertainty does not rise since there was no change in firing on impact and hiring decisions today only affect the pool of unemployed tomorrow. In $t = 2$, however, uncertainty rises for all job-seekers of any duration since at the end of the first period firms rejected applicants more often on average. Furthermore, Figure 9 demonstrates that each additional round of inadequate screening further raises the uncertainty surrounding a particular cohort of unemployed job-seekers going forward. Higher entropy is recorded for job-seekers with six months unemployment duration in $t = 7$ which are the remainder of the group of zero duration job-seekers at $t = 1$.

In contrast, the rise in uncertainty and average quality of the unemployed relative to its steady state in the FI model is negligible. Because firms can exactly observe and process the effective productivity of the worker, they do not make mistakes in their hiring decisions and exactly screen out the job-seekers who provide them with negative surplus. Thus, for moderate shocks that do not change the firing margin of firms, there is no demonstrable change

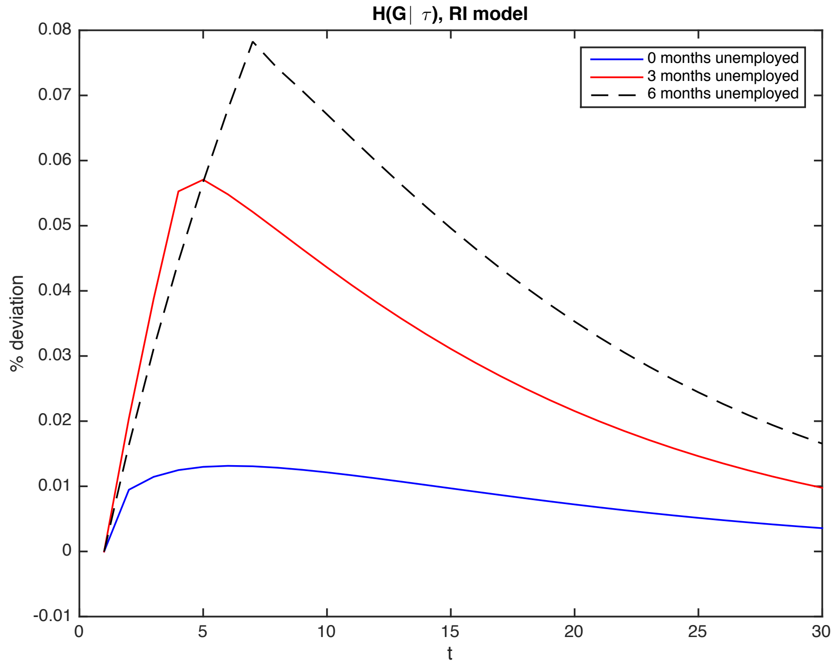


Figure 9: Inadequate Screening Propagates Increase in Uncertainty

in uncertainty or the average quality of the unemployed in the FI model since applicants who should be hired are not mistakenly rejected and released back into the unemployment pool.

The initial fall in aggregate productivity and subsequent increase in uncertainty drive movements in unemployment, job-finding rates and match efficiency in the RI model but generate negligible response in the FI model. The leftmost four cells and the rightmost four cells of of Figure 10 show these responses in the RI and FI model respectively. The top leftmost panel of Figure 10 shows the average shadow value firms place on having an additional unit of uncertainty reduced which we measure as $\lambda(\sigma) = \sum_\tau g_\tau(\tau \mid \sigma)\lambda(\tau, \sigma)$. When aggregate productivity falls, firms want more information to guide their hiring decisions but are unable to attain and process this additional information. As such, the shadow value of information rises by 2.5% on impact. The lack of precise information at a time when firms value information more, in turn translates into lower acceptance rates as firms seek to avoid hiring the wrong worker. The cell in the second column and top row of Figure 10 shows how the average acceptance rate, $\mathcal{P}(\sigma)$, which is our measure of match efficiency, falls by close to 1% in the RI model. In contrast, the top rightmost panel of Figure 10 shows that match efficiency changes by a negligible amount in the FI model. Again this lack of change in the FI model relative to its steady state arises precisely because 1) firms' firing standards

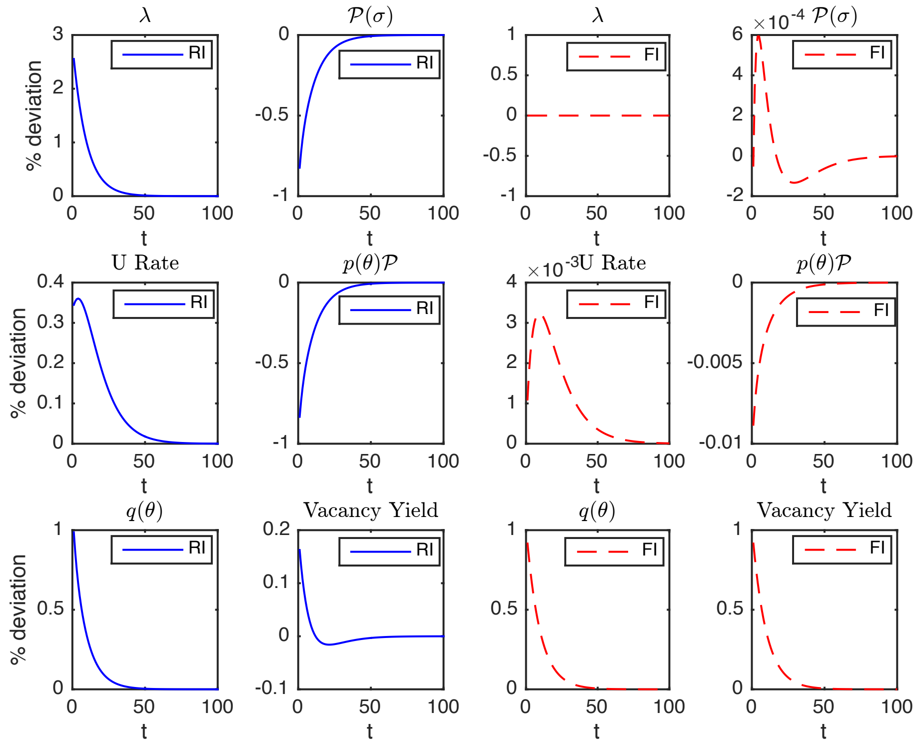


Figure 10: Response of Key Labor Market Variables in RI (left) and FI (right) models

did not change in response to a moderate downturn and 2) firms can perfectly observe the worker's type, allowing him to hire exactly the same set of workers he found suitable to hire prior to the recession.

The shock's impact on match efficiency in turn affects unemployment and job-finding rates in the economy. In the RI model, the unemployment rate rises by close to 0.35% while the job-finding rate, measured as $p(\theta)\mathcal{P}(\sigma)$, falls by about 0.8%.[18] In contrast, the unemployment rate rises by a mere 0.003% in the FI model. The differential response of match efficiency with respect to a moderate downturn is the primary factor behind the different unemployment experiences between the two models.

Although the drop in aggregate productivity was not enough to trigger a change in firms' retention decisions, the decline nonetheless reduces the value of creating a vacancy. When aggregate productivity falls, the value of a vacancy declines and fewer firms enter the labor market, causing $q(\theta)$ to rise as in the bottom first and third cell in Figure 10. Importantly,

[18] While these numbers may seem small, it reflects that our model suffers from the usual Shimer puzzle issues, i.e. that the labor search model is unable to generate enough volatility to match the fluctuations in the data. This is despite the fact that we give firms the ability to make take-it-or-leave-it offers in *both* the rational inattention and full information model. Nonetheless, despite firms offering take-it-or-leave-it wage offers, the FI model fares much worse in predicting the response of unemployment to moderate downturns.

the bottom rightmost panel of Figure 10 reveals that vacancy yield in the FI model exactly mirrors the rise in $q(\theta)$. In contrast, the RI model predicts a muted increase in vacancy yields in response to a shock. The latter occurs as job-filling rates are a combination of both the contact rate and the acceptance rate. In the RI model, the fall in acceptance rates during a recession mitigates the rise in $q(\theta)$. These differential responses in vacancy yield in the RI and FI model are reminiscent of Figure 1 where the standard full information labor search model with constant match efficiency predicts a much higher vacancy yield than its empirical counterpart.

4.1.1 How Does Uncertainty Affect the Firm's Problem?

To show how the changing uncertainty over the composition of job-seekers compounds the firm's hiring problem, we do an alternative exercise where the economy observes a two standard deviation drop in productivity in period 1 and remains at this lower productivity level for 6 consecutive months. While we hold fixed the aggregate productivity at a lower level for 6 periods, the composition of the unemployed continues to evolve with the hiring decisions of the firm each period.

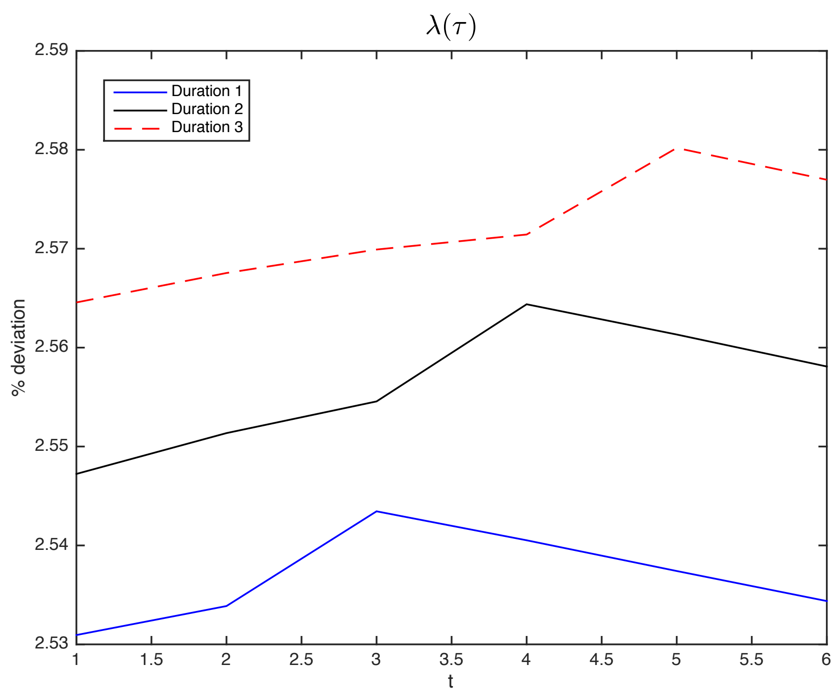


Figure 11: Additional Increase in Shadow Value Due to Rise in Uncertainty

The rise in uncertainty for a moderate downturn in the first six months is smaller than the decline in aggregate productivity. Average uncertainty, $H(G)$, increases to a peak of

0.02% by $t = 6$ while aggregate productivity is set to remain 3% lower than its steady state level for all $t < 7$. As such, most of the impact on λ for the moderate shock comes from changes in a. Nonetheless, the rise in uncertainty does contribute to raising the shadow value of information. Figure 11 shows the evolution of the shadow value of information and uncertainty for job-seekers with 1 to 3 months unemployment duration for the periods $1 \leq t \leq 6$. At $t = 4$, uncertainty amongst the group of job-seekers with 3 months unemployment duration is five percent higher than its steady state level.[19] This increase in uncertainty contributes to an additional 0.02% in the shadow value of information for job-seekers of 3 months unemployment duration from its initial spike at $t = 1$, highlighting the fact that poor filtering of the job applicants by firms elevates the amount of uncertainty amonst the unemployed and further compounds the firm's information problem.

Having described how the firm's information problem is affected in a moderate recession, we next discuss how a severe recession affects firms' hiring decisions and the overall impact on match efficiency.

4.2 What Happens in Severe Recessions?

To mimick a severe recession, we hit the economy with a ten percent fall in aggregate productivity. Figure 12 shows the response of the RI and FI model to a ten percent decline in aggregate productivity. The second cell in the top row of Figure 12 shows that in response to a severe negative shock, the fraction of employed individuals that are separated at the beginning of the period now spikes on impact. Notice that the spike in firing in the FI model is larger than the increase in firing for the RI model. This reflects that in steady state, firms and employed workers in the FI model only undergo exogenous separations since firms in the FI model never hire a worker who is unsuitable for production. In contrast, in the RI model, firings include both exogenous and endogenous separations since firms can make mistakes in hiring the wrong workers. As a result, the differential increase in the fraction of employed individuals separated at the time of the shock arises as the two models do not have the same base.

Because the firing margin is triggered in a severe recession, the average quality of the unemployed in both models rises on impact. This is in line with observations by Mueller (2015) who after controlling for individual characteristics, finds that the composition of the unemployed shifts towards high quality types during a recession. Note that the percentage increase in the average quality of the unemployed is higher in the FI model. Since firms in the RI model in steady state can still make a mistake and reject a high ability worker, the

[19] Note that job-seekers with 3 months unemployment duration in $t = 4$ were part of the unemployed job-seekers with zero duration at the time the initial shock hits the economy, $t = 1$.

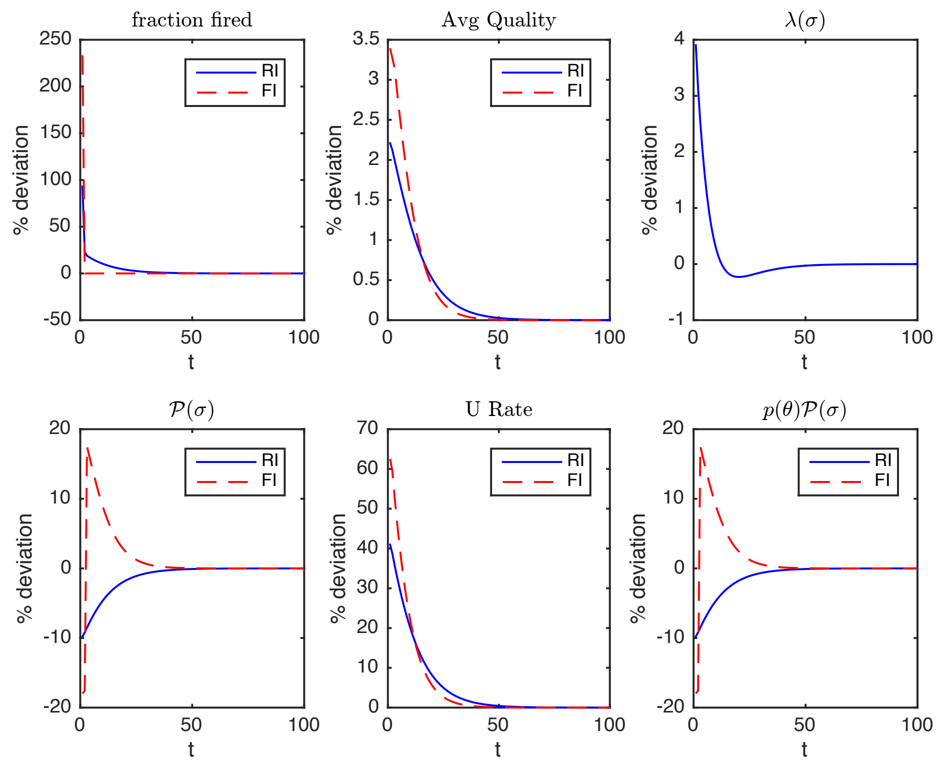


Figure 12: Response to a Severe Recession

pool of unemployed is more varied in the RI model. As such, the differential response in average quality reflect that the steady state average quality of the unemployed are different between the two models.

As per the results in the moderate recession, firms' concern about hiring the wrong worker during a downturn becomes more severe the more adverse the shock. As such, in response to a 10% decline in TFP, the average shadow value of information rises by 4%. Again, the rise in λ reflects that firms would like more precise information about the worker but are unable to attain that information. As a result of this coarser information, match efficiency in the rational inattention model falls by close to 10%.

In contrast, match efficiency behaves very differently in the FI model. On impact, match efficiency in the FI model falls by close to 20%. However, in subsequent periods, i.e. $t \geq 3$, match efficiency recovers and actually increases 20% relative to steady state in the FI model. This rise in match efficiency stems from the counteracting effects of a higher average quality of the unemployed. Individuals that form the set of duration zero job-seekers in $t = 1$ are those that were affected by the firm's firing decision on impact of the shock. As the economy recovers, the higher average quality of the unemployed of duration zero who were not re-employed at the end of $t = 1$ mitigates the lower aggregate productivity. Since the remainder of duration zero job applicants in $t = 1$ who did not manage to find a job within period $t = 1$ now form a larger share of the unemployment pool going forward, and since firms perfectly observe worker's types in the FI model, firms accept more often relative to steady state. The combination of recovering TFP and higher average quality of the unemployment pool lead average job finding rates, as given by $p(\theta)\mathcal{P}(\sigma)$, and average match efficiency to rebound and rise above their steady state level in the FI model.

This spike in match efficiency in $t = 3$ does not occur in the model with rational inattention. Although the average quality of the unemployed improves, the firm in the RI model still cannot process its desired amount of information to determine if the job applicant is suitable to hire. Since the losses to hiring the wrong worker in a severe recession are even greater, the firm rejects applicants at an even higher rate than what was observed for a moderate recession. Thus, despite improving average quality of the unemployment pool, the inability of firms in the RI model to process more information and determine the viablity of the job candidate causes acceptance rates to remain depressed. As such, match efficiency in the RI takes longer to recover.

While the full information model observes a larger spike in unemployment rates in response to a large recession on impact, the FI model cannot sustain high unemployment rates over long periods of time. This is precisely because match efficiency in the FI model recovers and rises above its steady state level in $t = 3$ due to improvements in the average quality of the unemployed. In contrast, the rational inattention model generates more persistence in unemployment rates. By the 45th month, unemployment rates in the FI model have fully returned back to their steady state levels while unemployment rates in the RI model remain 0.7% higher than their steady state.

Overall, the impulse response functions show that the RI model generates propagation properties that better fit the data than the FI model. In response to smaller shocks, the RI model observes a rise in unemployment rates and a decline in match efficiency while the FI model observes negligible change. In response to large shocks, the improvement in the average quality of the unemployed mitigates the decline in aggregate productivity in the FI model and predicts a rise in match efficiency after the third period. In contrast, the RI model observes persistently low match efficiency. We now examine how well simulated match efficiency from the rational inattention model fits actual match efficiency in the data.

4.3 Comparisons with data

4.3.1 Model vs. Data - Match Efficiency

Having described how the model responds in both moderate and severe recessions, we now assess how well match efficiency in our model with rationally inattentive firms compares to actual match efficiency in the data. To back out match efficiency in the data, we assume the same matching function as in our model. We define (log) match efficiency ξ_t as :

$$\ln \xi_t = \ln m_t - \ln \left(\frac{u_t v_t}{(u_t^{\iota} + v_t^{\iota})^{1/\iota}} \right)$$

We use data on total non-farm hires from JOLTS as our measure of matches, m, and data on the total non-farm job postings and total unemployed for our measures of v and u respectively. As per our calibration, we set $\iota = 0.5$ and back out the natural log of match efficiency, ξ, as the residual to the above equation. We detrend this measure of match efficiency by regressing against a cubic time trend.

To assess our model's ability to replicate match efficiency as in the data, we use information on unemployment rates for the coverage period of JOLTS, i.e. 2000m12 - 2016m12, and apply a particle filter to the model to infer the underlying sequence of aggregate productivity shocks that would generate the same unemployment realizations as in the data. In order to keep the comparison fair, we calibrate the FI model such that the moments from the FI model matches the targets we used to calibrate our benchmark RI model.[20]. Next, we apply a particle filter[21] to back out the sequence of shocks required for the model to replicate unemployment rates as in the data. We use the unemployment rate as the observable and assume that:

$$u_t^{data} = u_t^{model} + e_t$$

where we treat $e_t \sim N(0, \sigma_e^2)$ as measurement error.

The left panel of Figure 13 demonstrates the models' ability to match unemployment rates as in the data. Noticeably, the FI model struggles to match unemployment rates as in the data and the particle filter attributes most of the deviations from the mean unemployment rate to measurement error e_t. This is not surprising since our earlier impulse response exercises showed that the unemployment rate in the FI model barely responds to moderate TFP shocks and only rises in response to severe downturns. Further, the FI model was unable to sustain persistently low job-finding rates during severe downturns. The introduc-

[20]This in principle gives it the same chance as the RI model to match the data. For the calibrated parameters used in the full information model, please see the appendix C

[21]The application of the particle filter closely follows Fernandez-Villaverde et al. (2016). We thank Pablo Cuba-Borda for helping us implement the particle filter.

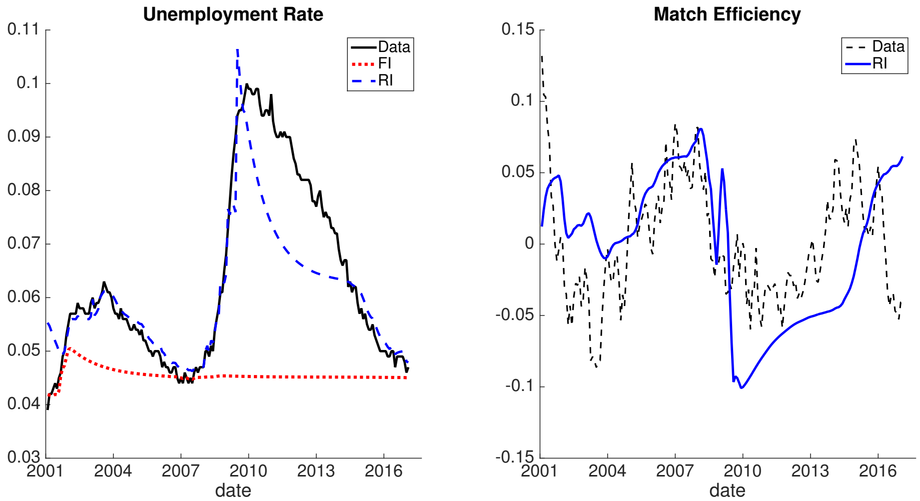


Figure 13: Data vs. Model: Unemployment Rates and Match Efficiency

tion of heterogeneity in the FI standard labor search model exacerbates the Shimer puzzle as improving quality in the pool of unemployed serves to counteract some of the decline in aggregate productivity, causing the FI model to at best predict v-shaped labor market recoveries in response to sharp downturns. As such, it is not surprising that the FI model fails at matching the unemployment rate data. In contrast, the model with rational inattention is able to match unemployment rates fairly well. Unlike the FI model, unemployment rates in the RI model move in response to both small and large shocks. In addition, our earlier impulse response exercises suggested that the RI model is also capable of generating more propagation in job-finding rates and the unemployment rate than the model with full information.

The RI model is also able to replicate match efficiency in the data fairly well and matches the turning points in the data. Note that while we used information on unemployment to infer the implied shocks needed to generate such an unemployment series in our model, we did not use any information on match efficiency to characterize the sequence of shocks. The right panel of Figure 13 shows the model's ability to replicate match efficiency in the data.[22]

Because, the particle filter in the context of the FI model could not even match unemployment rates in the data, instead attributing the changes in unemployment to measurement error, the filtered changes in productivity and hence, match efficiency are negligible. Thus, we do not show its performance here against match efficiency in the data. We check for whether our implied match efficiency from either model is significantly different from match

[22]In Appendix C, we feed the filtered productivity series from the rational inattention model into the full information model and compare the Full information model-generated series of match efficiency with that in data. The fit is very poor.

efficiency in the data by running separate Kolmogorov-Smirnov tests. We find that for the RI model, we cannot reject the hypothesis that the our model's implied match efficiency is drawn from the same distribution as the match efficiency in the data. For the FI model, we find that the Kolmogorov-Smirnov test rejects the hypothesis that the match efficiency implied by the FI model is drawn from the same distribution as the data.[23] Hence, we find support for the claim that the model with rational inattention is a better fit for explaining match efficiency movements in the data.

4.4 Duration of unemployment as signal of quality

In reality, firms elicit some information from observable worker-characteristics to gain additional information about a worker before conducting an interview. From the point of view of the firm, this allows them to conduct a less rigorous interview compared to a situation where such additional information is not avaialable. One such characteristic which has recently garnered a lot of attention is *unemployment duration*. We use the model to ask whether the duration of unemployment is a less informative signal about the applicant's type in a recession.

To see why the duration of unemployment is informative about a worker's type, note that the failure of an applicant to find employment can be either because she did not meet a firm or conditional on meeting a firm, she did not pass the interview. Furthermore, the failure to clear the interview could be because of various reasons: (i) a worker could fail an interview if she was actually of low ability, (ii) or she was of high-ability but drew a low match-specific shock, or (iii) the firm mistakenly rejects a worker since it may be acquiring very imprecise signals about the worker at periods when it wants more information to avoid hiring unsuitable workers. Whenever the capacity processing constraint binds less and effect (iii) is mild, the longer the job-seeker has been unemployed, the more likely it is that she is a low-productivity type.

Our model suggests that duration as an indicator of worker quality is a weaker signal during recessions. As recessions are periods where the value of the firm declines, less firms post vacancies and the overall rate at which a worker contacts a job is lower. A lower meeting rate by itself already implies that the pool of long term unemployed job-seekers is more likely to be more varied in a recession since higher ability job-applicants have a harder time finding a job. Moreover, rational inattention suggests an additional force that further dilutes the quality of duration as a signal of workers' ability. In our model, firms want more

[23]The p-value for the rational inattention model is 0.4255 implying that the null hypothesis that the two series are drawn from the same distribution cannot be rejected. In contrast, the p-value for the full information model is given by 3.9e-14.

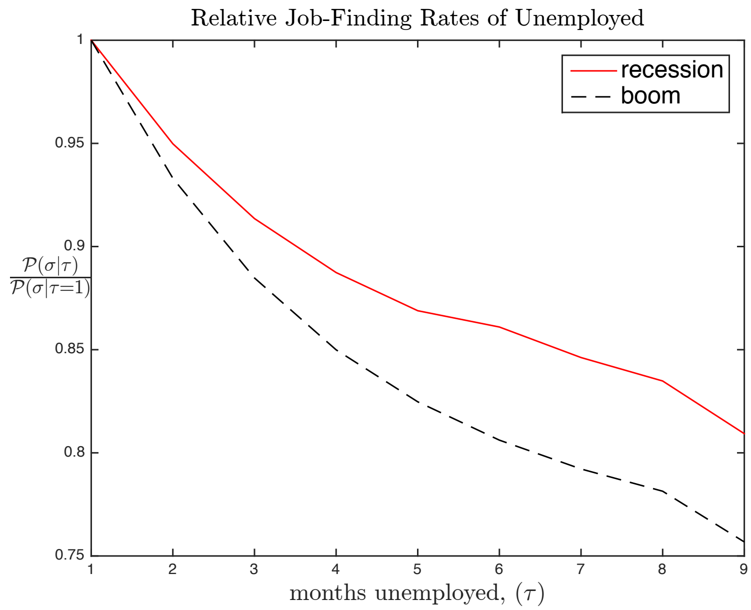


Figure 14: Relative Job Finding Rate of Job-seekers by Duration of Unemployment τ.

information about the job-applicant during recessions. The inability to attain and process this information causes them to lower their acceptance rates and reject applicants more often to avoid hiring an unproductive worker and making a type 1 error. These lower acceptance rates compound the lower meeting rates of job-seekers and raise the likelihood of a longer unemployment spell for all job-seekers of varying quality. As such, duration becomes a poorer signal of a job applicant's true productive ability during a recession.

Figure 14 shows the relative job-finding rates of unemployed job-seekers relative to a job-seeker with 1 month unemployment duration across normal times and severe recessions. While both curves slope downwards and reflect the fact that firms believe the pool of long-term unemployed is largely composed of lower ability types, the rate at which the relative job-finding rates decline with duration differs across the business cycle. In normal times, the job-finding rate of job-seekers 6 months unemployed is about 20% lower than that of a job-seeker with an unemployment spell of 1 month. In a severe recession, however, the job-finding rate of an individual with 6 months unemployment duration is about 15% lower than in a boom. These results are consistent with the findings of Kroft et al. (2013) who find that there is less stigma attached to longer durations of unemployment spells in areas with depressed economic activities.

5 Discussion

Thus far, we have shown how a model of rational inattention can rationalize the movements in match efficiency over the business cycle. In this section, we argue that an alternative model of costly information acquisition such as that of a fixed cost of acquiring information generates movements in match efficiency inconsistent with that observed in the data.

Consider the alternative model where firms in each period choose whether to acquire information about the job applicant. If they choose to acquire information, all information about the applicant is revealed to the firms after they've paid a fixed cost. In such a setting, the acceptance rate of firms would be similar to that generated by the full information model. As firms value information more in a recession, they are willing to pay the fixed cost during downturns, and learn perfectly the applicant's type upon acquiring information. As such, firms always perfectly screen out the correct candidates for production and match efficiency behaves as in the full information model. Fixed costs of acquiring information, when activated, present an additional cost of creating a vacancy and merely act toward further depressing vacancy posting and raising the contact rate of firms.

An alternative method of generating selective hiring would be to consider a model of noisy information. One common application[24] has firms observing a signal that is a combination of the worker's quality and some noise, both of which are normally distributed. Firms can choose how noisy a signal to obtain or choose a cut-off for which they are willing to hire. We argue that our model captures these same features (firms must choose an information strategy which in turn influences their probability of hiring a worker), and has the added feature of allowing firms to choose the least costly information structure to maximize lifetime profits. As per Sims (2006), gaussian posterior uncertainty is optimal only when the loss function is linear-quadratic. Restricting the information structure to be normal imposes additional costs on firms' processing capacity and prevents firms from designing more cost-effective information strategies.

One important aspect we abstracted from in this paper was wage-setting. Rather than explicitly acquiring information about applicants, firms could potentially use contracts to incentivize applicants to reveal their true types, thus, circumventing the constraints posed by the firm's limited information processing capacity. While the use of contracts to separate different ability workers does potentially help overcome the limited processing capacity of the firm, it requires the firm to give up informational rents in order to incentivize applicant to reveal their types truthfully. Thus, depending on how constrained firms are in terms of channel capacity, they may or may not choose to use contracts. Furthermore, in a setting

[24]See for example Jovanovic (1979))

with multiple worker types, firms may not be able to design contracts to perfectly separate types. In such settings, firms may still choose to explicitly acquire information. The choice of when to issue separating contracts or pooling contracts and screen workers thereafter likely depends on the firm's prior uncertainty over the pool of workers and therefore the shadow cost of information, both of which are changing over the business cycle. We leave this for future research.

6 Conclusion

We present a novel channel through which firms' hiring standards affect fluctuations in match efficiency. The key insight is the presence of a tight link between match efficiency, firms' hiring strategies and the composition of unemployed job-seekers. In particular, we show that selective hiring during a downturn causes not only the average quality of the pool of unemployed job-seekers to increase but also raises the uncertainty firms have regarding applicants going forward. Recessions are periods where firms want more precise information about an applicant to avoid hiring the wrong worker. Failure to get more precise information leads firms to reject job-seekers more often and these lower acceptance rates correspond to declines in match efficiency. Further, lack of adequate screening by firms in filtering out suitable workers for production today leads to elevated uncertainty in the pool of unemployed tomorrow. The link between hiring decisions today and the composition of the unemployed tomorrow provide a different propagation mechanism for initial shocks to affect and amplify unemployment rates tomorrow. In addition, our proposed mechanism offers insight as to how the changes in the composition of the unemployment pool caused hiring rates to stall and vacancy yields to falter despite the large number of job-seekers available for each vacancy.

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APPENDIX

A Proofs

A.1 Proof of Proposition 3

Without loss of generality, we suppress the dependence of the firm's problem on τ, the duration of unemployment for simplicity. The reformulated first-stage problem in Lemma 1 can be expressed as the following Lagrangian:

$$\begin{aligned}
\mathcal{L} \;=\; & \sum_z \sum_e \gamma(z,e \mid \sigma)\mathbf{x}(a,z,e)g(z,e \mid \sigma) \\
& -\lambda(\sigma)\Bigg[-\mathcal{P}(\sigma)\log\mathcal{P}(\sigma) - [1-\mathcal{P}(\sigma)]\log[1-\mathcal{P}(\sigma)] \\
+ \; & \sum_z \sum_e \Big\{ \gamma(z,e \mid \sigma)\log\gamma(z,e \mid \sigma) + [1-\gamma(z,e \mid \sigma)]\log[1-\gamma(z,e \mid \sigma)] \Big\} g(z,e \mid \sigma) - \chi \Bigg] \\
& + \sum_z \sum_e \zeta(z,e \mid \sigma)\gamma(z,e \mid \sigma)g(z,e \mid \sigma) - \sum_z \sum_e \mu(z,e \mid \sigma)\left(\gamma_i(z,e \mid \sigma) - 1\right) g(z,e \mid \sigma)
\end{aligned}$$

where $\zeta(z,e)$ and $\mu(z,e)$ are the multipliers on the non-negativity constraint and the upper bound of 1 respectively. Taking first order conditions with respect to $\gamma(z,e \mid \sigma)$:

$$\mathbf{x}(a,z,e) - \lambda(\sigma)\left[-\ln\frac{\mathcal{P}(\sigma)}{1-\mathcal{P}(\sigma)} + \ln\frac{\gamma(z,e \mid \sigma)}{1-\gamma(z,e \mid \sigma)}\right] + \zeta(z,e \mid \sigma) - \mu(z,e \mid \sigma) = 0 \quad (19)$$

with complementary slackness conditions

$$\mu(z,e \mid \sigma)\left[1-\gamma(z,e \mid \sigma)\right] = 0 \quad (20)$$

$$\zeta(z,e \mid \sigma)\gamma(z,e \mid \sigma) = 0 \quad (21)$$

Thus, as long as $0 < \gamma(z,e \mid \sigma) < 1$, it must be the case that $\zeta(z,e \mid \sigma) = \mu(z,e \mid \sigma) = 0$ and $\gamma(z,e \mid \sigma)$ can be written as:

$$\gamma(z,e \mid \sigma) = \frac{\mathcal{P}(\sigma)e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma)}}}{1-\mathcal{P}(\sigma)\left[1-e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma)}}\right]} \quad (22)$$

Summing across (z,e) and dividing both sides by $\mathcal{P}(\sigma)$, one can show that:

$$1 = \sum_z\sum_e \frac{e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma)}}}{1-\mathcal{P}(\sigma)\left[1-e^{\frac{\mathbf{x}(a,z,e)}{\lambda(\sigma)}}\right]} g(z,e \mid \sigma) \quad (23)$$

A.2 Proof of Lemma 2

For $\chi > H(G)$, the shadow value of an additional nat, $\lambda = 0$. Evaluating (7) for (z,e) combinations such that $\mathbf{x}(a,z,e) < 0$ in the limit as $\lambda \to 0$ yields:

$$\lim_{\gamma\to 0}\gamma\left(z,e \mid \sigma\right) = \lim_{\lambda\to 0}\frac{\mathcal{P}\left(\sigma\right)e^{\frac{\mathbf{x}(a,z,e)}{\lambda}}}{1+\mathcal{P}\left(\sigma\right)\left[e^{\frac{\mathbf{x}(a,z,e)}{\lambda}}-1\right]} = 0$$

Next, consider an applicant (a,z) such that $\mathbf{x}(a,z,e) \geq 0$. If the firm hired this worker, the firm would surely have positive per-period profits. Then under the optimal information strategy, this applicant is hired with probability 1.

$$\lim_{\chi\to\infty}\gamma\left(z,e \mid \sigma\right) = \lim_{\lambda\to 0}\frac{\mathcal{P}\left(\sigma\right)e^{\frac{\mathbf{x}(a,z,e)}{\lambda}}}{1+\mathcal{P}\left(\sigma\right)\left[e^{\frac{\mathbf{x}(a,z,e)}{\lambda}}-1\right]} = \lim_{\lambda\to 0}\frac{\mathcal{P}\left(\sigma\right)\mathbf{x}(a,z,e)e^{\frac{-\mathbf{x}(a,z,e)}{\lambda^2}}}{\mathcal{P}\left(\sigma\right)\mathbf{x}(a,z,e)e^{-\frac{\mathbf{x}(a,z,e)}{\lambda^2}}} = 1$$

where the second equality follows from L'Hospital's Rule.

A.3 Proof of Lemma 3

Let $\gamma_H(a)$ and $\gamma_L(a)$ denote the optimal choices when aggregate productivity is given by a. Differentiating (11) with respect to aggregate productivity a yields:[25]

$$[\mathcal{H}'(\mathcal{P}) - \mathcal{H}'(\gamma_H)]\,\alpha \frac{\partial \gamma_H(a)}{\partial a} + [\mathcal{H}'(\mathcal{P}) - \mathcal{H}'(\gamma_H)]\,(1-\alpha)\frac{\partial \gamma_L(a)}{\partial a} = 0 \tag{24}$$

We also know that the optimal choices of $\gamma_H(a)$ and $\gamma_L(a)$ satisfy the first order conditions:

$$\mathbf{x}(a, z_i) = \lambda(a)\,[\mathcal{H}'(\mathcal{P}) - \mathcal{H}'(\gamma_i(a))]\ \ ,\ i \in \{H, L\} \tag{25}$$

where $\lambda(a)$ is the multiplier on the constraint (11) and denotes the shadow value of an additional unit of channel capacity. Using this, we can rewrite equation (24) as:

$$\frac{\gamma_H'(a)}{\gamma'_L(a)} = -\frac{(1-\alpha)\,\mathbf{x}(z_L, a)}{\alpha \mathbf{x}(z_H, a)} \tag{26}$$

Recall that since we assumed that $a \in \left[\frac{b}{z_H}, \frac{b}{z_L}\right]$, $\mathbf{x}(a, z_H) \geq 0$ and $\mathbf{x}(a, z_L) \leq 0$ for any a in this range. This implies that $\gamma_H'(a)$ and $\gamma_L'(a)$ are the same sign. It remains to show that the sign is positive. To see this, notice that that the optimal choices are characterized by:

$$\frac{\mathbf{x}(a, z_H)}{\mathbf{x}(a, z_L)} = \frac{\mathcal{H}'(\mathcal{P}) - \mathcal{H}'(\gamma_H)}{\mathcal{H}'(\mathcal{P}) - \mathcal{H}'(\gamma_L)}$$

In the relevant range of a, the LHS is a negative number. Also, when a goes up marginally, the LHS becomes a larger negative number. Suppose $\gamma_H(a)$ and $\gamma_L(a)$ were decreasing in a. Then the RHS must be a smaller negative number since the feasible set of choices is a convex set following from the properties of entropy which implies a contradiction. Thus, we have shown that the optimal choices of $\gamma_H(a)$ and $\gamma_L(a)$ are increasing in a in the range $a \in \left[\frac{b}{z_H}, \frac{b}{z_L}\right]$.

Now consider the range $a < \frac{b}{z_H}$. In this range, both the H and L type applicant yield negative profits if hired ($\mathbf{x}(a, z_L) < \mathbf{x}(a, z_H) < 0$ and thus, the firm does not hire any applicants. In this range of aggregate productivity, $\gamma_H(a) = \gamma_L(a) = 0$ and thus is constant (weakly increasing) in a. Similarly, if the level of aggregate productivity is very high, $a > \frac{b}{z_L}$, both H and L type applicants generate positive profits for the firm and $\gamma_H(a) = \gamma_L(a) = 1$ in this range and thus, is weakly increasing in a.

Since the unconditional probability of accepting a particular type of applicant is just a

[25] This condition holds as long as the constraint holds with an equality at the optimum which is always the case since we assumed that $\chi < \overline{\chi}$.

convex combination of $\gamma_H(a)$ and $\gamma_L(a)$, it is straightforward to see that $\mathcal{P}(a) = \alpha\gamma_H(a) + (1 - \alpha\gamma_L(a)$ is increasing in a.

B Numerical Implementation

We assume that firms observe a top-coded distribution of unemployment durations. Firms can observe the exact duration of unemployment τ as long as $0 \leq \tau < \bar{\tau}$. For all worker unemployed for a duration of at least $\bar{\tau}$, the firm cannot see the exact duration of unemployment but knows that the duration is at least $\bar{\tau}$. Then the transition equations for this top-coded model can be written as:

$$l_t(z,\tau) = \begin{cases} \int_e d(a_t, z, e) n_{t-1}(z,e) & \text{if } \tau = 0 \\ \\ u_{t-1}(z,\tau) & \text{if } 1 \leq \tau < \bar{\tau} \\ \\ u_{t-1}(z,\bar{\tau}) & \text{if } \tau \geq \bar{\tau} \end{cases} \tag{27}$$

$$u_t(z,\tau) = \begin{cases} l_t(z,\tau-1)\Big\{1 - p\left(\theta[\sigma_t]\right) + p\left(\theta[\sigma_t]\right)\sum_e \pi_e(e)(1 - \gamma\left[z, e \mid \sigma_t, \tau-1\right])\Big\} & \text{if } 1 \leq \tau < \bar{\tau} \\ \\ l_t(z,\bar{\tau}-1)\Big\{1 - p\left(\theta[\sigma_t]\right) + p\left(\theta[\sigma_t]\right)\sum_e \pi_e(e)(1 - \gamma\left[z, e \mid \sigma_t, \bar{\tau}-1\right])\Big\} + \\ l_t(z,\bar{\tau})\Big\{1 - p\left(\theta[\sigma_t]\right) + p\left(\theta[\sigma_t]\right)\sum_e \pi_e(e)(1 - \gamma\left[z, e \mid \sigma_t, \bar{\tau}\right])\Big\} & \text{if } \tau \geq \bar{\tau} \end{cases} \tag{28}$$

We use this top-coded model in our numerical exercises. For the purpose of our numerical exercises we set $\bar{\tau} = 9$ months. Thus, we label all individuals who have been unemployed for more than 9 months into one group.

C Parameterization of Full Information model

Full Information Impulse Response

Figure 15 documents how the full information model responds to a 2 standard deviation drop in TFP. This is the case where we set $\chi = \infty$ and all other parameters are kept the same as the rational inattention model. As highlighted in the main text, the model exhibits little to no response in unemployment rates or aggregate job-finding rates.

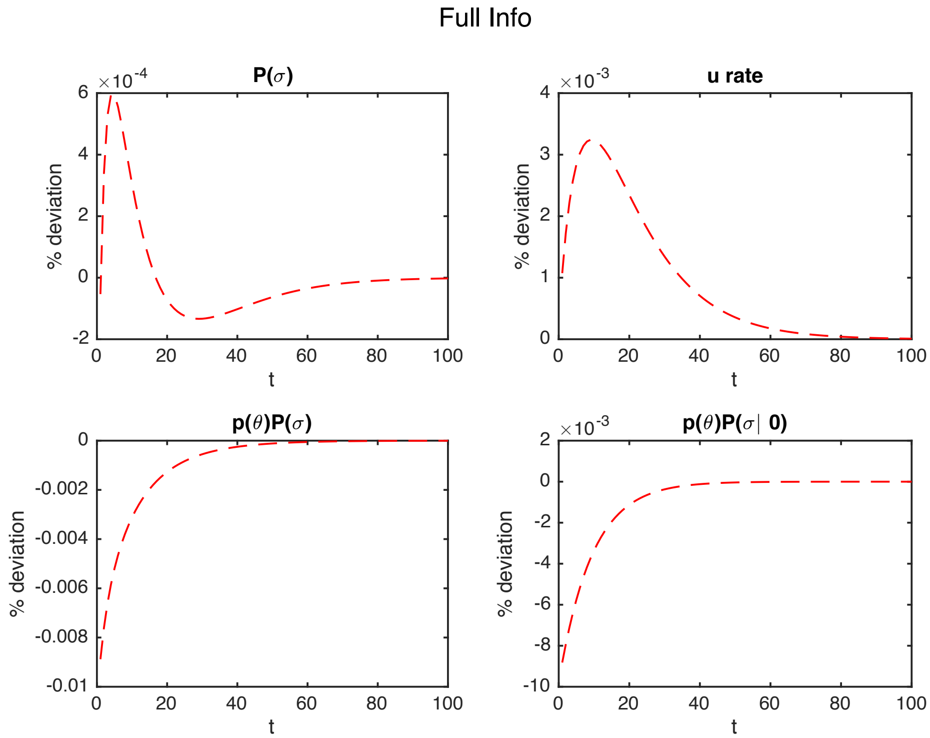

Figure 15: Response of full information model to 2 standard deviation decline in TFP

Parameters used for Full Information Model in Particle Filter Exercise

We re-calibrate the full information model such that the simulated moments from the full information model match our target moments. We keep fixed the parameters governing the heterogeneity of workers and match specific productivity as in the rational inattention model. This implies that the unconditional distribution of individuals have the same effective productivity, ze, as in the rational inattention model. In additional, the full information model sets χ to infinity, i.e. there is no fixed capacity processing constraint. Table 2 details used in the full information model.

Robustness check

To see if the full information model can replicate the match efficiency in the data, we do an additional check and feed in the TFP series filtered from the rational inattention model.

Table 2: Model Parameters for Full Information

Inferred Parameters		
Parameter	Description	Value
b	home production	0.2894
δ	exog. separation rate	0.0029
κ	vacancy posting cost	0.0281
A_z	shape parameter - worker ability	1.3451
B_z	shape parameter - worker ability	8.5290
A_e	shape parameter - match productivity	1.9975
B_e	shape parameter - match productivity	7.3234

Recall that when we used the inferred TFP series filtered from the full information model, the full information model did poorly in replicating unemployment rates. Thus, we try an alternative exercise where we feed the TFP series implied from the rational inattention model into the full information model. Figure 16 shows the performance of the full information model. In this case, the full information in response to large shocks over-predicts the response of match efficiency relative to the data.

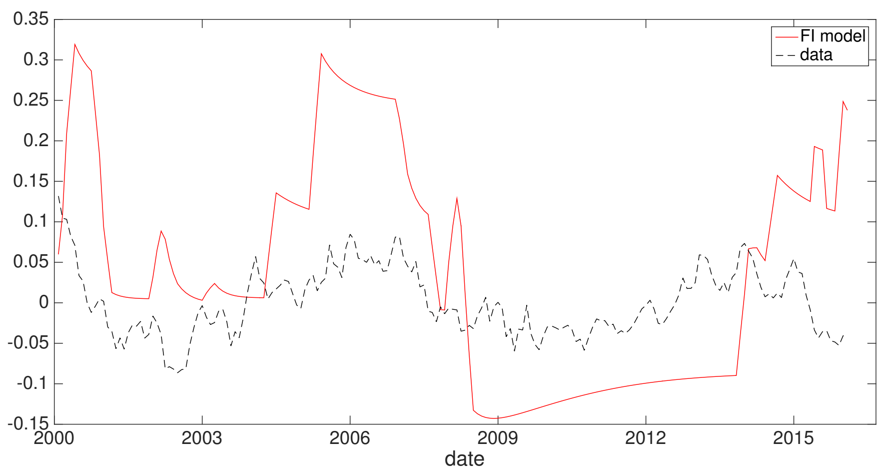

Figure 16: Data vs. Full Information Match Efficiency