

# Rational Inattention in Hiring Decisions - Online Appendix\*

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## 1 Numerical Implementation

### 1.1 Constructing the sets $\mathcal{Z}$ and $\mathcal{E}$

This Appendix details how we construct the discrete sets  $\mathcal{Z}$  and  $\mathcal{E}$  from the continuous  $\text{Beta}(A, B)$  distributions used to calibrate the model. We only describe the process for constructing  $\mathcal{Z}$  as the same procedure is used to construct  $\mathcal{E}$ . In what follows, we denote the cumulative distribution of the  $\text{Beta}(A, B)$  distribution by  $\mathcal{F}(\cdot; A, B)$ .

1. Construct a sequence  $\{p_i\}_{i=1}^{n_z+1}$  where each  $p_1 = 0$ ,  $p_{n_z+1} = 1$  and for  $i \in \{2, \dots, n_z\}$   $p_i$  is given by:

$$p_i = i/n_z$$

where  $n_z$  denotes the cardinality of the set  $\mathcal{Z}$ .

2. Using the sequence  $\{p_i\}$  construct a sequence of intervals denoted  $\{m_i\}_{i=1}^{n_z+1}$  such that

$$m_i = \mathcal{F}^{-1}(p_i; A, B)$$

where  $\mathcal{F}^{-1}(\cdot; A, B)$  denotes the inverse cdf.

3. Next construct the sequence  $\{z_i\}_{i=1}^{n_z}$  as:

$$z_i = \frac{m_i + m_{i+1}}{2}, \text{ for } i \in \{1, \dots, n_z\}$$

The set  $\mathcal{Z}$  is just defined as  $\{z_1, \dots, z_{n_z}\}$  and the probability mass associated with each  $z_i$  is given by  $1/n_z$ .

### Implied Probability Distributions

Given our calibrated parameters for  $\{A_z, B_z, A_e, B_e\}$ , Figure 1a and 1b plot the implied probability density functions under these given parameters.

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\*The views expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the Federal Reserve Bank of New York or the Federal Reserve System.

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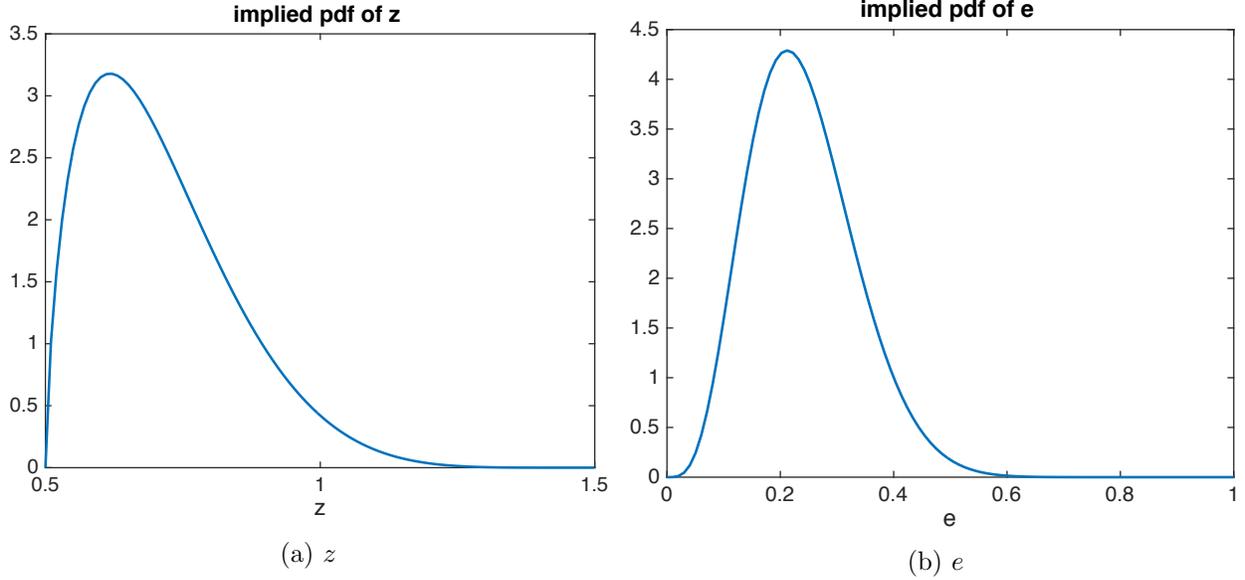


Figure 1: Implied probability distributions

## 1.2 Solving the model

We assume that firms observe a top-coded distribution of unemployment durations. Firms can observe the exact duration of unemployment  $\tau$  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:

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

and the evolution of the mass of unemployed workers of type  $z$  and unemployment duration  $\tau$  can be written as follows. For unemployment durations  $1 \leq \tau < \bar{\tau}$ , we can write the transition equation as:

$$u_t(z, \tau) = l_t(z, \tau - 1) \left\{ 1 - p(\theta[\sigma_t]) + p(\theta[\sigma_t]) \sum_e \pi_e(e) (1 - \gamma[z, e | \sigma_t, \tau - 1]) \right\}$$

while for  $\tau \geq \bar{\tau}$  we can write it as:

$$\begin{aligned} u_t(z, \tau \geq \bar{\tau}) &= l_t(z, \bar{\tau} - 1) \left\{ 1 - p(\theta[\sigma_t]) + p(\theta[\sigma_t]) \sum_e \pi_e(e) (1 - \gamma[z, e | \sigma_t, \bar{\tau} - 1]) \right\} + \\ & l_t(z, \bar{\tau}) \left\{ 1 - p(\theta[\sigma_t]) + p(\theta[\sigma_t]) \sum_e \pi_e(e) (1 - \gamma[z, e | \sigma_t, \bar{\tau}]) \right\} \end{aligned}$$

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.

## 1.3 Parameterization of Full Information model

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 addition, the full information model sets  $\chi$  to infinity, i.e. there is no fixed capacity processing constraint. Given the parameters governing the heterogeneity of workers, this leaves us with three parameters  $\{b, \delta, \kappa\}$  to recalibrate for the full information model. We target the unemployment rate, exit probability and 70% UI ratio to recalibrate these three parameters. Table 1 details used in the full information model.

Table 1: Model Parameters for Full Information

Inferred Parameters		
Parameter	Description	Value
$b$	home production	0.1429
$\delta$	exog. separation rate	0.0330
$\kappa$	vacancy posting cost	0.0850

A fully re-calibrated FI model would make comparison difficult as the two economies would not have the same unconditional distribution of workers (the distribution of  $z$ ) and the distribution of match quality  $e$ . This would change the surplus of a match and hence the hiring decisions. As a result it would be hard to identify if the differences in hiring decisions across the two models arose because of differences in information or because the differences in surplus induced by a different  $(z, e)$  distribution.

On the other hand, if one were to keep all parameters in the FI model the same as in the RI model except that now  $\chi = \infty$ , then the FI model would not have the same average unemployment rates or job-finding rates. This too complicates the comparison.

Thus, we choose to partially re-calibrate the FI model so that it has the same distribution of  $z$  and  $e$  as the RI model while also featuring the same average unemployment rate and job-finding rates.

## 2 Noisy Information

### 2.1 Model

Consider the following noisy information model where upon meeting a job-seeker, firms obtain a signal of the form Firm gets a signal of form

$$s = ze + \varsigma \varepsilon$$

where  $\varepsilon$  is an iid draw from a normal  $\mathcal{N}(0, 1)$  distribution. Let  $\varsigma$  be the parameter that governs the noisiness of the signal  $s$ . For a given aggregate state  $\sigma$  and unemployment duration  $\tau$  of the job-seeker, the firm chooses to hire whenever he receives a signal  $s \geq s^*(\sigma, \tau)$ .

Then the firm's problem can then be re-written as choosing the cut-off for signal  $s$  so as to maximize ex-ante firm surplus.

$$\max_{s^*} \sum_z \sum_e \left[ 1 - \Phi \left( \frac{s^* - ze}{\varsigma} \right) \right] \mathbf{x}(a, z, e) g(z, e \mid \sigma, \tau)$$

Taking first order conditions with respect to  $s$ , we have:

$$\sum_z \sum_e \phi \left( \frac{s^* - ze}{\varsigma} \right) \mathbf{x}(a, z, e) g(z, e \mid \sigma, \tau) \begin{cases} \leq 0 & \text{if } s^* = \infty \\ = 0 & \text{if } s^* \in (-\infty, \infty) \\ \geq 0 & \text{else} \end{cases}$$

where  $s^*$  is the cut-off for which the firm will always hire for signal values above this threshold. Observe that the probability of hiring a job-seeker of type  $(z, e, \tau)$  in aggregate state  $\sigma$  is given by:

$$\gamma^{noisy}(z, e | \sigma, \tau) = 1 - \Phi\left(\frac{s^*(\sigma, \tau) - ze}{\varsigma}\right) \quad (1)$$

and the average probability of hiring a worker of duration  $\tau$  is given by:

$$\mathcal{P}^{noisy}(\sigma, \tau) = \sum_z \sum_e \gamma^{noisy}(z, e | \sigma, \tau) g(z, e | \sigma, \tau) \quad (2)$$

Finally, match efficiency or the average probability of hiring any worker in state  $\sigma$  is given by:

$$\mathcal{P}^{noisy}(\sigma) = \sum_{\tau} g_{\tau}(\tau | \sigma) \mathcal{P}^{noisy}(\sigma, \tau)$$

## 2.2 Parameterizing $\varsigma$

To figure out the noise in the signal, we use the acceptance probabilities from the model, i.e. equations (1) and (2), and set  $\varsigma$  such that the amount of mutual information is equal to the fixed processing capacity  $\chi$  in the rational inattention model in steady state. In other words, we choose  $\varsigma$  such that the following equation is satisfied:

$$\chi = \mathcal{H}[\mathcal{P}^{noisy}(\sigma, \tau)] - \sum_z \sum_e H[\gamma^{noisy}(z, e | \sigma, \tau)] g^{noisy}(z, e | \sigma, \tau)$$

We keep all other parameters in the model the same as that for the RI model. Our calibration gives us  $\varsigma = 0.1259$ .

## 2.3 Computing Error Probabilities

To compute the error probabilities in the RI model vs. the noisy information model. We first calculate the probability that for a job-seeker of  $(z, e, \tau)$  type, the firm incorrectly chooses to accept as opposed to reject the job-seeker. In other words, we calculate the probability of making a Type 1 error for a job-seeker of type  $(z, e, \tau)$  as:

$$Pr(\text{Type 1 error} | z, e, \tau, \sigma) = \gamma^j(z, e | \sigma\tau) Pr(\gamma^{FI}(z, e | \sigma, \tau) == 0)$$

where  $j \in \{\text{noisy}, \text{RI}\}$  indicates the model of interest. The average probability of making a Type 1 error is then given by:

$$Pr(\text{Type 1 error} | \sigma) = \sum_{\tau} \sum_z \sum_e Pr(\text{Type 1 error} | z, e, \tau, \sigma) g^j(z, e | \tau, \sigma) g_{\tau}^j(\tau)$$

Similarly, we define the probability that a firm incorrectly chooses to reject a job-seeker of type  $(z, e, \tau)$  that is suitable for hiring as the following:

$$Pr(\text{Type 2 error} | z, e, \tau, \sigma) = [1 - \gamma^j(z, e | \sigma\tau)] Pr(\gamma^{FI}(z, e | \sigma, \tau) == 1)$$

where  $j \in \{\text{noisy}, \text{RI}\}$  again represents the model of interest. The average probability of making a Type 2 error is then given by:

$$Pr(\text{Type 2 error} | \sigma) = \sum_{\tau} \sum_z \sum_e Pr(\text{Type 2 error} | z, e, \tau, \sigma) g^j(z, e | \tau, \sigma) g_{\tau}^j(\tau)$$

### 3 Additional Graphs

#### 3.1 Recovery in aggregate productivity

Figure 2a shows how quickly aggregate productivity recovers after a 5% shock.

#### 3.2 Isolating the response of $\mathcal{P}$ w.r.t. $a$

In this exercise, we treat the distribution of job-seekers as exogenous and impose the steady state distribution of job-seekers. Figure 2b shows how much lower measured matching efficiency would be in percentage terms relative to steady state (y-axis) with respect to different values of  $a$  (x-axis) keeping the distribution of job-seekers fixed.

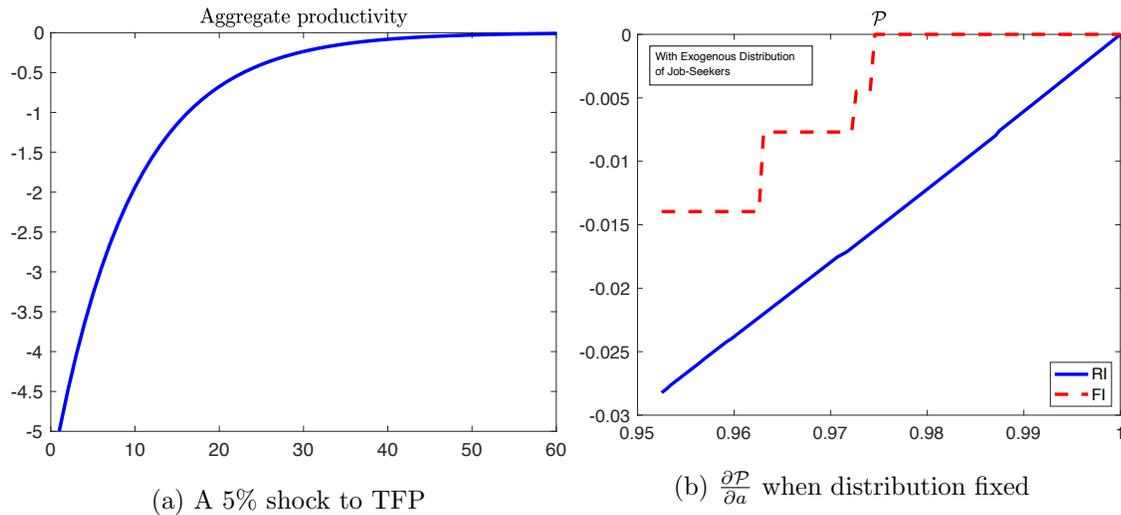


Figure 2: Misc. graphs

Without any change in the distribution of job-seekers, the FI model predicts that  $\mathcal{P}$  would fall by about 1.5% with respect to a 5% productivity shock while the RI model observes a larger decline of about 3%.