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Worker Selection, Hiring, and Vacancies†

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This paper incorporates worker selection into a random matching model with multi-worker firms. Unlike the standard Diamond-Mortensen-Pissarides (DMP) model, the extended model is compatible with cross-sectional behavior of vacancy yields, which rise with employment growth and worker turnover, but fall with establishment size. Using calibrated versions of the standard and worker selection models, I show that accounting for these patterns has quantitatively important policy implications. I also compare the worker selection and the directed search models. While both models account for these patterns equally well, they differ with regard to labor market policy. (*JEL* E24, J23, J63, J64)

Diamond-Mortensen-Pissarides (DMP) models are used extensively to study labor market flows and unemployment and to assess the effects of labor market policies on these outcomes. Standard versions of these models assume an aggregate matching function and imply that vacancy yields, the ratio of hires to vacancies, are identical in the cross section. Recent work by Davis, Faberman, and Haltiwanger (2013)—henceforth, DFH—finds systematic differences in vacancy yields in the cross section: they rise steeply with employment growth rate, fall with employer size, and rise with worker turnover rate. In this paper, I extend the standard DMP model to account for these differences and show that this has quantitatively important implications for labor market policies.

I modify the standard DMP model along two dimensions. First, I assume a decreasing returns to scale production technology. While this modification yields a well-defined firm distribution, it alone is not enough to generate cross-sectional variation in vacancy yields. Second, I modify the recruitment process by incorporating a worker selection mechanism. Unlike the standard DMP model, worker-firm pairs are differentiated by a match quality under this modification. By paying a cost, e.g., interviewing applicants, firms can partially observe the match quality of the applicants and selectively hire among them. I model this process by allowing

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firms to set a minimum hiring standard and hire only the applicants who satisfy this threshold. Firms' ability to change the hiring standard threshold generates firm-level variation in vacancy yields.

The cross-sectional patterns of vacancy yields from this extended model are consistent with the observed patterns in the Job Openings and Labor Turnover Survey (JOLTS) described in DFH (2013). These patterns are tightly related to the shape of the worker selection cost function. I derive this function using an auxiliary model in which already employed workers are used to produce recruitment services.[1] The resulting cost function is strictly convex in the number of applicants and the mechanism generating these cross-sectional patterns crucially relies on this property.[2] First, in a growing firm, the marginal cost of increasing the hiring standard is larger because a growing firm also posts more vacancies and contacts a larger group of applicants. Therefore, a growing firm fills vacancies faster by being less picky about new recruits and attains a higher vacancy yield. Second, as the firm size increases, the employment growth rate decreases and vacancies are filled at a slower rate, which generates a negative relationship between the firm size and the vacancy yield. Finally, a firm that has initially set a lower hiring standard lays off a larger fraction of the current recruits in the near future. This implies a positive relationship between the vacancy yield and the worker turnover rate.

For policy analysis, I study the effects of a hiring subsidy and a firing tax on labor market outcomes. In particular, these policies affect equilibrium unemployment through two channels. First, these policies change the hiring cost function either directly or through wage bargaining. Therefore, changes in these policies have a direct effect on the job finding probability of workers through firms' vacancy creation decisions. Second, these policies have an indirect effect on firm value, since an increase in the job finding probability also increases the search value of an unemployed worker. This indirect effect strengthens worker's bargaining position, reduces firm value and discourages firm entry. The unemployment rate is determined by these opposing forces in the equilibrium.

The ability to change hiring standards amplifies the effects of labor market policies. For example, firms lower their hiring standard thresholds after a hiring subsidy because they are compensated for the loss due to hiring a low-productive worker. This latter adjustment tends to strengthen the direct effect on job finding probability. Despite an increase in the job finding probability, the search value of an unemployed worker does not increase as much compared to the standard DMP model, because lower hiring standard thresholds create low quality matches, thereby mitigating the indirect effect on search value. Similarly, a firing tax makes firms become more picky as the cost of hiring a low productivity worker increases. This adjustment tends to reduce the job finding probability more in the worker selection model. However, the value of unemployment does not drop as much because higher hiring

[1] This modeling approach is consistent with microeconomic evidence regarding firms' hiring practices. Barron and Bishop (1985) report from the 1982 Employment Opportunities Pilot Project that company personnel spend on average 9.87 hours per hire to recruit, screen, and interview the applicants, with a standard deviation of 17.16 hours. See also Silva and Toledo (2009) and Hagedorn and Manovskii (2008).

[2] This property is obtained when there are decreasing returns to scale in the recruitment technology, e.g., interviewer's fatigue.

standard thresholds yield high quality matches and increases employment value to an unemployed worker. As a result of these disproportionate effects, the response of unemployment to changes in policies is bigger in the worker selection model.

Using calibrated versions of the worker selection and the standard DMP models, I show that these effects are also quantitatively important. When firms are subsidized for hiring new workers, the decline in the unemployment rate is about three times larger in the worker selection model. A firing tax increases the unemployment rate with worker selection, but equilibrium unemployment goes down when the worker selection channel is shut down.

This paper is closely related to work by Kaas and Kircher (2015), where the authors build a directed search model to explain the vacancy yields in the cross section. While the authors depart from the assumption of random search, I show that one can also account for these patterns in a model with random search. I carry out a detailed comparison of the two models and find two key results from this comparison. First, both models are able to account for the basic cross-sectional patterns reported in DFH (2013), but a distinguishing feature of the worker selection model is that higher vacancy yields are positively correlated with separations as in the data, whereas in their directed search model, separations are exogenously constant across firms. Second, the models have very different predictions for the effect of policies on unemployment. While changes in policies have a bigger impact on job finding probability in the worker selection model, their effect is bigger on the search value in the directed search model. Consequently, the unemployment rates move in opposite directions in these models in response to policy changes. The empirical literature is inconclusive about the effects of labor market policies on the unemployment rate. Thus, these differing predictions are at least not currently sufficient to help us decide which model is "better."

The model in this paper links existing models of worker selection to those with multi-worker firms. On the one hand, existing worker selection models are not suitable for studying the cross-sectional properties of hires and vacancies because they assume that firms are either vacant or employed with only one worker.[3] Pries and Rogerson (2005), Villena-Roldán (2012), Merkl and van Rens (2012), and Sedláček (2014) are examples of worker selection models of this kind.[4] On the other hand, extensions to the standard DMP model assume workers are identical and, therefore, imply that there is no firm-level variation in vacancy yields. Matching models with multi-worker firms have been around for a while, but not studied in an applied sense until recently. Examples include Bertola and Caballero (1994); Bertola and Garibaldi (2001); Cahuc, Marque, and Wasmer (2008); Elsby and Michaels (2013); Fujita and Nakajima (2016); Acemoglu and Hawkins (2014); and Coşar, Guner, and Tybout (2016).[5] This paper generates cross-sectional variation in vacancy yields

[3] To be precise, when the production technology features constant marginal productivity of labor, the equilibrium distribution of firms is not determined and can be represented by one worker firms. See, for example, Faia, Lechthaler, and Merkl (2014).

[4] Villena-Roldán (2012) differs from the others by allowing firms to meet multiple workers. However, firms are still restricted to hire at most one worker.

[5] One deviation from the previous studies with multi-worker firms, except Coşar, Guner, and Tybout (2016), is the generalization on the labor adjustment cost which depends on firm size in this paper. With this modification, incumbent workers affect the firm's labor adjustment costs in the next period and this generates a time inconsistency

by incorporating worker selection to a random matching model with multi-worker firms.[6]

The paper is organized as follows. Section I describes the worker selection model and Section II characterizes the equilibrium. Section III presents the cross-sectional patterns of vacancy yields from the calibrated model and compares them to the data and the standard DMP model. Section IV presents the results from the counterfactual policy experiments with a hiring subsidy and a firing tax. In Section V, I compare the directed search and worker selection models. The last section concludes.

I. Worker Selection Model

The economy is populated by risk-neutral workers with a unit measure and a large number of risk-neutral entrepreneurs. Time is discrete and the discount factor is β. Each entrepreneur runs a firm which produces a single good. Hereafter, I refer to firms and entrepreneurs interchangeably.

In any period, a worker is either employed or unemployed. An employed worker receives a wage income, but cannot search for a new job. An unemployed worker searches for a job; if he cannot find a job, he enjoys leisure and receives b. Savings are disallowed, so workers consume all of their income in the current period.

In any period, a firm can be either active or inactive. An active firm employs a measure of workers denoted by n. Firm productivity has an idiosyncratic component, ε. It evolves according to a Markov process, $F(\varepsilon' | \varepsilon)$, where I adopt prime notation to denote variables in the next period. The productivity process is common to all of the firms. An inactive firm can become active at the beginning of each period after paying a fixed entry cost, c_e. Upon entry, it draws its initial idiosyncratic productivity from the unconditional distribution of the same Markov process, $F_0(\varepsilon)$. Active firms become inactive with exogenous probability δ.

Recruiting new workers consists of three stages: vacancy posting, worker selection, and wage bargaining. The first and the last stages are common to the standard DMP matching model. The innovation of this paper is the introduction of the interim stage where firms selectively hire among a pool of applicants.

A. *Vacancy Posting*

In the first stage, firms post vacancies, v, to attract unemployed workers and pays c_v per vacancy. There are matching frictions in the labor market. The total number of matches in the economy is determined via an aggregate matching function, which has a constant elasticity of substitution form:

$$M(U,V) = (U^{-\zeta} + V^{-\zeta})^{-\frac{1}{\zeta}}, \tag{1}$$

problem. I address this issue by splitting the payment to an incumbent worker into a production wage paid in the current period and a promised payment for recruitment services in the next period contingent on firms' optimal decisions.

[6] Helpman, Itskhoki, and Redding (2008) study a static version of the worker selection model with multi-worker firms with a different focus. The employment dynamics differ substantially when firms make employment decisions in a dynamic setting.

where U and V are the total number of unemployed workers and vacancies, respectively. The parameter $\zeta > 0$ governs the degree of elasticity of substitution. Let $\theta = V/U$ be the market tightness. Then, a firm that posts v number of vacancies meets $q(\theta)v$ workers, where $q(\theta)$ is the probability that a vacancy meets a worker. Probability $q(\theta)$ is derived from the matching function as follows:

$$q(\theta) = \frac{M(U,V)}{V} = (1 + \theta^{\zeta})^{-\frac{1}{\zeta}}. \tag{2}$$

Similarly, $M(U,V)/U = \theta q(\theta)$ is the probability a worker meets a vacancy.[7] In the rest of the paper, I drop θ and simply write q for notational purposes.

B. *Match Quality Shock and Worker Selection*

In the second stage, each worker who is matched with a firm draws an unobserved match-specific quality shock, x_i, from a uniform distribution between zero and one. A worker with a match-specific quality x_i becomes productive at the hiring firm with probability $x_i^{\gamma-1}$, where $\gamma > 1$. Otherwise, the worker becomes unproductive. Both the firm and the worker learn the true productivity of the worker only after one period of employment. If a worker turns out to be unproductive, he leaves the firm.

Although the match-specific quality shock is unobserved at the time of hiring, the firm can infer the true match-specific quality of an applicant. I model this process by allowing firms to choose a hiring standard, $p \in [0,1]$, and hire only the workers that satisfy this minimum threshold.[8] However, this worker selection process is time-consuming and requires recruitment services. The unit cost of evaluating an applicant is equal to $\tilde{c}$. When a firm posts v vacancies, it meets qv applicants and needs $R = \tilde{c}qv$ units of recruitment services to evaluate these applicants.[9]

The recruitment services during the worker selection process correspond to the time spent by company personnel to screen, interview, and evaluate the applicants. Accordingly, each employed worker and entrepreneur are capable of producing recruitment services, r_i, from the final output, y_i, according to a Cobb-Douglas production technology: $r_i = y_i^{\tilde{z}}$, where i indexes the worker. I impose diminishing marginal product of the input to this production technology by restricting $\tilde{z} < 1$. This restriction captures the fatigue of the recruiter during the worker selection process. The interpretation is that the recruiter gets tired after screening each applicant and requires more input for evaluating the next applicant.

[7] Note that $\zeta > 0$ guarantees that both of the meeting probabilities lie in the interval [0,1].

[8] The worker selection mechanism in this paper is closest to Pries and Rogerson (2005), which build on the learning model of Jovanovic (1979). I deviate from their paper by revealing the type of the worker after one period, which allows me to avoid keeping track of the distribution of worker types at firm level.

[9] In the current setup, there is no direct cost of increasing the hiring standard threshold, but there is an indirect cost of increasing p associated with the cost of posting vacancies because a higher p leaves more of the posted vacancies unfilled. It could be argued that there are also direct costs of increasing the hiring standard threshold, e.g., identifying higher quality workers would require longer hours of interview with each applicant. In that case, the unit cost of worker selection would also increase with p. However, such an extension does not change the main conclusions of this paper. For the sake of simplicity, I ignore it in what follows.

This specification of the recruitment technology is consistent with the empirical evidence on the cost of labor adjustment. To see this point, consider the total recruitment services, R, produced by a firm with n workers:

$$R = y_0^{\tilde{z}} + \int_0^n y_i^{\tilde{z}}\, di, \tag{3}$$

where the first term is the entrepreneur's contribution to recruitment services. Since all the workers and the entrepreneur are equally productive, cost minimization requires allocating an equal amount of the final output to each worker and the entrepreneur, i.e., $y_i = \bar{y}$. Plugging this solution in the equation above, the total amount of recruitment services produced becomes

$$R = (1 + n)\,\bar{y}^{\tilde{z}} = \tilde{c}qv. \tag{4}$$

The last equality follows from the fact that the firm can evaluate $\tilde{c}qv$ applicants with R units of recruitment services. According to equation (4), the amount of final output allocated to each worker is related to the number of applicants as follows:

$$\bar{y} = \left(\frac{\tilde{c}qv}{(1 + n)}\right)^{\frac{1}{\tilde{z}}}. \tag{5}$$

Hence, the total cost of worker selection is

$$C_s(qv, n) = (1 + n)\bar{y} = (1 + n)\left(\frac{\tilde{c}qv}{(1 + n)}\right)^{\frac{1}{\tilde{z}}}. \tag{6}$$

After replacing $z = 1/\tilde{z}$ and $c_s = z\tilde{c}^{1/\tilde{z}}$,

$$C_s(qv, n) = \frac{c_s}{z}\left(\frac{qv}{1 + n}\right)^{z}(1 + n). \tag{7}$$

The cost function in equation (7) is convex in the number of applicants, but exhibits economies of scale.[10] This specification of the cost function has found empirical support in the literature. Using aggregate level data from Colombia and a cost function specification similar to the one in (7), Coşar, Guner, and Tybout (2016) find evidence for convexity in the number of vacancies and economies of scale. Yashiv (2000) and Merz and Yashiv (2007) find support for strong convexity of the labor adjustment costs in the hiring rate for Israel and the United States, respectively. Blatter, Muehlemann, and Schenker (2012), using firm-level data from Switzerland, also find that average recruitment costs are increasing with the firm's hiring rate.

[10] Economies of scale stems from the fact that, with $\tilde{z} < 1$, larger firms are able to allocate resources for recruitment to workers with higher marginal product. A reduced form interpretation of the cost function in (7) is that large firms would develop a larger personnel department and screen the applicant at a lower marginal cost.

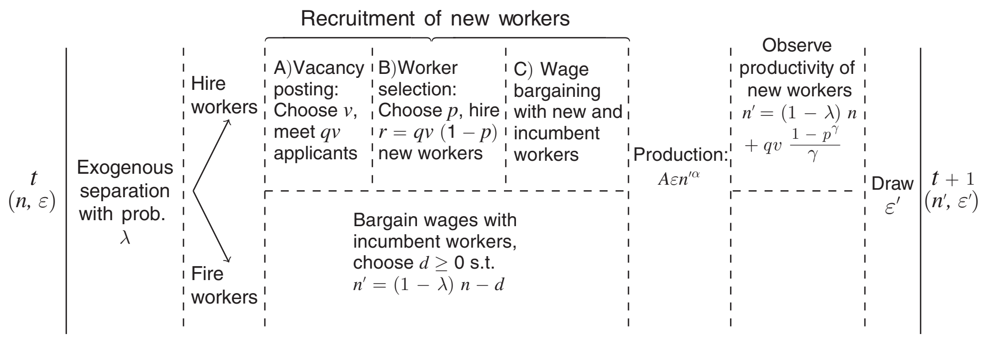

Figure 1. Timing of Events within a Period

The model presented in this section provides a micro foundation for these empirical findings.

Due to matching frictions in the labor market, a firm's current match with its workers generates bilateral monopoly rents. In the third stage, firms bargain over the wage with their incumbent workers and the successful workers in their applicant pool to split these rents. I describe wage bargaining formally below.

I refer to the second stage above as worker selection, because the wage bargaining process implies that a firm does not hire all the workers it matches. To see that, consider an applicant with $x_i = 0$. His contribution to output is zero in this period, and he leaves the firm at the end of the period. However, the firm has to compensate him for his outside option, i.e., the value of finding a job with a higher match quality. The total value of surplus from this match is negative and both parties mutually agree not to form an employment relationship. Furthermore, the value of a worker to the firm increases with x_i. Hence, there exists a reservation match-specific quality below which workers have negative value to the firm. The firm identifies those workers during the worker selection process.[11]

C. *Timing of Events, Law of Motion for Labor, and Production*

Figure 1 summarizes the timing of events within a period. The period begins with exogenous separation of incumbent workers with probability λ and ends with a new draw of productivity, ε'. For the interim stage, the recruitment process explained in the preceding section has certain implications for the law of motion for employment and production.

First, large firms that receive an adverse productivity shock may find it optimal to reduce employment. However, such a firm would never find it optimal to hire from the unemployment pool, because an incumbent worker is more productive than any potential new worker and labor adjustment is costly. Therefore, at the beginning

[11] I assume that if an applicant's match-specific quality is greater than p, it is still unobserved, but known to be greater than p. This assumption implies that the firm treats all the newly recruited workers similarly. The model would still be tractable if the firm knew the true productivity of each worker. Moreover, the wage bargaining process below implies that the firm would pay a different wage to every new worker, but total wages would be the same, leaving a firm's decision on v and p unchanged.

of the period, firms decide whether to hire additional workers depending on their current size and productivity. In Figure 1, firms' hiring and firing decisions are split to reflect this distinction.[12]

Second, production takes place after wage bargaining in both hiring and firing firms. Firms have access to a Cobb-Douglas production function, $A\varepsilon n'^{\alpha}$, where A and α are scale and curvature parameters, respectively. The production technology exhibits decreasing returns to production, i.e., $\alpha < 1$, which generates a well-defined firm distribution in equilibrium. A firm's production depends on the number of *productive* workers it employs in the current period. It is straightforward to see that the number of productive workers is equal to n' in a firing firm. Let d denote total firings. Then, employment at a firing firm evolves according to

$$n' = (1 - \lambda) n - d. \tag{8}$$

But, a firing firm produces after wage bargaining and firing d workers. So, n' is also the number of productive workers in the current period.

A more subtle point is that the production function above accounts for the fact that new recruits are employed in the current period. To see this point, note that not all workers are fully productive in a hiring firm. A hiring firm posts v vacancies, meets qv workers, and hires $r = qv(1 - p)$ of them. The expected productivity of a newly recruited worker is $g(p) = (1 - p^{\gamma})/(\gamma(1 - p))$. In other words, only $g(p)$ fraction of r newly recruited workers are fully productive. Then, the total number of productive workers in a hiring firm is $(1 - \lambda) n + rg(p)$. But, after production in the current period, the firm observes which of these newly recruited workers are unproductive and separates from them. So, the total number of productive workers in the current period is equal to n'. In terms of v and p, employment at a hiring firm evolves over time according to the following equation:

$$n' = (1 - \lambda) n + qv \frac{1 - p^{\gamma}}{\gamma}. \tag{9}$$

D. *Firms' Problem*

Let $J^h(n, \varepsilon)$ and $J^f(n, \varepsilon)$ denote the value of a hiring and firing firm, respectively, and $J(n, \varepsilon) = \max\{J^h(n, \varepsilon), J^f(n, \varepsilon)\}$. Let $w^e(p, n', n, \varepsilon)$ and $w^p(p, n', n, \varepsilon)$ denote wages paid to incumbent workers and new recruits, respectively, in terms of the firm's optimal decision on (p, n') and its current state (n, ε). The following summarizes the dynamic programming problem of a hiring firm:

$$\begin{aligned} J^h(n, \varepsilon) = \max_{n', p \in [0,1], v \geq 0} & -c_v v - \frac{c_s}{z}\left(\frac{qv}{1 + (1 - \lambda) n}\right)^{z} (1 + (1 - \lambda) n) \\ & - qv(1 - p)\, w^p(p, n', n, \varepsilon) - (1 - \lambda) n w^e(p, n', n, \varepsilon) \\ & + A\varepsilon n'^{\alpha} + \beta(1 - \delta)\, E_{\varepsilon'|\varepsilon}[J(n', \varepsilon')], \end{aligned} \tag{10}$$

[12] I allow for a corner solution for the firing firm when it neither hires nor fires any worker.

subject to (9). A hiring firm incurs a labor adjustment cost given by the first two terms in (10). At the time of hiring, there are $(1 - \lambda)n$ workers available for producing recruiting services and this adjustment is reflected above. The firm also receives revenue from production in the current period net of wage payments and the expected discounted continuation value.

Similarly, let $w^f(n', n, \varepsilon)$ be the wage paid at shrinking firms. Then, the dynamic programming problem of a firing firm is as follows:

$$(11) \qquad J^f(n, \varepsilon) = \max_{n', d \geq 0} \; A\varepsilon n'^{\alpha} - n' w^f(n', n, \varepsilon) + \beta(1 - \delta) E_{\varepsilon'|\varepsilon}[J(n', \varepsilon')],$$

subject to (8). A firm can costlessly fire workers and produce with the remaining workers in the current period. It also receives the expected discounted continuation value.

E. *Worker's Value Functions*

Let $\tilde{V}^u$ and V^u denote the value of unemployment at the beginning of the period and after the labor market closes, respectively. The value function of an incumbent worker employed at a firm with n workers and productivity ε is

$$(12) \qquad V^e(n, \varepsilon) = w^e(p, n', n, \varepsilon) + \beta\Big(E_{\varepsilon'|\varepsilon} \varphi^e(n', \varepsilon') V^e(n', \varepsilon') + \big(1 - \varphi^e(n', \varepsilon')\big) V^u\Big),$$

where $\varphi^e(n', \varepsilon')$ is the retention probability of an incumbent worker in the next period. If the firm does not fire workers in the next period, $\varphi^e(n', \varepsilon')$ is simply equal to $(1 - \lambda)(1 - \delta)$. The worker takes firm decisions, n' and p, as given. The interpretation is standard: an incumbent worker receives $w^e(p, n', n, \varepsilon)$ this period. With probability $\varphi^e(n', \varepsilon')$, he is employed at the same firm and enjoys the expected value of employment, which is over the productivity shocks and accounts for the change in firm's employment. Otherwise, he is unemployed for one period and receives V^u.

Similarly, the value function of a newly hired worker is

$$(13) \qquad V^p(n, \varepsilon) = w^p(p, n', n, \varepsilon) + \beta\Big(E_{\varepsilon'|\varepsilon} \varphi^p(p, n', \varepsilon') V^e(n', \varepsilon') + \big(1 - \varphi^p(p, n', \varepsilon')\big) V^u\Big),$$

where $\varphi^p(p, n', \varepsilon')$ is the retention probability of a newly recruited worker in the next period and depends on the hiring threshold set by the firm, p. If the firm does not fire workers in the next period, $\varphi^p(p, n', \varepsilon')$ is equal to the probability of being a productive worker at the hiring firm, $g(p)$, multiplied by $(1 - \lambda)(1 - \delta)$. The functional equation above is otherwise the same as (12).[13] Finally, V^u and $\tilde{V}^u$ are related according to

$$V^u = b + \beta \tilde{V}^u, \tag{14}$$

and

$$\tilde{V}^u = \theta q \int_{\mathcal{E},\mathcal{N}} \frac{g_v(n,\varepsilon)\big((1 - g_p(n,\varepsilon))V^p(n,\varepsilon) + g_p(n,\varepsilon)V^u\big)}{\int_{\mathcal{E},\mathcal{N}} g_v(\tilde{n},\tilde{\varepsilon})\, d\Gamma(\tilde{n},\tilde{\varepsilon})}\, d\Gamma(n,\varepsilon) + (1 - \theta q)V^u, \tag{15}$$

where $g_v(n,\varepsilon)$ and $g_p(n,\varepsilon)$ are solutions to the hiring firm's optimization problem, Γ is a probability measure of firms over (n, ε), and $\mathcal{N}$ and $\mathcal{E}$ are sets of all possible realizations of n and ε, respectively. At the beginning of the period, an unemployed worker matches with a vacancy with probability θq. Conditional on a match, he receives the expected value of the outcome of the selection process: with probability $(1 - g_p(n,\varepsilon))$ he is employed and enjoys the value of being employed at a firm with n workers and productivity ε. Otherwise, he is unemployed and receives V^u. The probability that he matches with a firm of size n and productivity ε is weighted by the firm's share of vacancies in total vacancies. Finally, with probability $(1 - \theta q)$, he does not find a match and receives V^u.

F. *Wage Bargaining*

The approach in Stole and Zwiebel (1996) is standard in the literature to determine wages in multi-worker settings with frictional labor markets. They describe a dynamic game where the firm negotiates the wage payment in pairwise bargaining sessions with its employees in an arbitrary order. If an agreement is reached, the firm continues bargaining with the next worker. Otherwise, the worker leaves the firm and the bargaining process resumes with *all* of the remaining workers. Stole and Zwiebel (1996) show that the solution to the wage function implies a split of the *marginal* surplus and outside option of the worker according to bargaining powers.

There are two challenges to adopt this solution in the current setup. First, incumbent and new workers differ in size and productivity, and they are potentially paid different wages. The firm negotiates with $(1 - \lambda)n$ incumbent workers and $qv(1 - p)$ successfully selected workers. The productivity of an incumbent worker is 1 and the expected productivity of a new worker is $g(p)$. The differences in productivity and size require keeping track of the new and incumbent workers separately.

Second, the continuation values enter the bargaining problem and create a time inconsistency problem. To see this point, consider an incumbent worker who bargains over his marginal surplus to the firm. There are two sources of surplus to the

[13] In fact, (12) can be thought as the limiting case of (13) as $p \to 1$.

firm: production in the current period and savings from selection costs in the *next* period.[14] If the surplus from both of these sources are paid in the current period, then the firm has an incentive to deviate from its planned recruitment decision in the next period.[15] To address this time inconsistency problem, I split the wage payment to incumbent workers into two components: a payment from production services, and a future payment due to recruitment services *contingent* on firms' optimal decision in the next period.

Formally, let $w^n(n', \varepsilon)$ and $w^r(p, n', n, \varepsilon)$ be the wage payments to incumbent workers for production and recruitment services, respectively. The function $w^p(p, n', \varepsilon)$ is similarly defined as the wage payment to the new worker from his production services in the current period. Production wages depend on n', because vacancy posting and worker selection costs are sunk at the bargaining stage, and production is a function of n'. Further, let $D(\tilde{n}, r, p, \varepsilon)$ be the *total* surplus to the firm at the bargaining stage, where $\tilde{n} = (1 - \lambda)n$ and $r = qv(1 - p)$. From the firm's problem,

$$D(\tilde{n}, r, p, \varepsilon) = A\varepsilon(\tilde{n} + g(p)r)^{\alpha} - w^n(\tilde{n} + g(p)r, \varepsilon)\tilde{n} - w^p(p, \tilde{n} + g(p)r, \varepsilon)r + \beta(1 - \delta) E_{\varepsilon'|\varepsilon}[J(\tilde{n} + g(p)r, \varepsilon)]. \tag{16}$$

The wage payment for recruitment services enters equation (16) through the continuation value. The marginal surplus to the firm from an incumbent worker is the partial derivative of the total surplus with respect to $\tilde{n}$, $D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon)$. Similarly, the marginal surplus to the firm from a potential worker is given by $D_r(\tilde{n}, r, p, \varepsilon)$. The solution to the bargaining problem satisfies the following conditions:

$$\phi D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon) = (1 - \phi)(V^e(n, \varepsilon) - V^u) \tag{17}$$

and

$$\phi D_{\tilde{r}}(\tilde{n}, r, p, \varepsilon) = (1 - \phi)(V^p(n, \varepsilon) - V^u), \tag{18}$$

where ϕ is the worker's bargaining power.

Using these two conditions, along with the firm's problem and workers' value functions, I obtain the wages from production for each group as follows:

$$w^n(n', \varepsilon) = \frac{\alpha\phi}{1 - \phi + \alpha\phi} A\varepsilon n'^{\alpha-1} + (1 - \phi)(b + \Omega) \tag{19}$$

and

$$w^p(p, n', \varepsilon) = g(p)\frac{\alpha\phi}{1 - \phi + \alpha\phi} A\varepsilon n'^{\alpha-1} + (1 - \phi)(b + \Omega), \tag{20}$$

[14] The latter would vanish if the worker selection costs were independent of the firm's size.
[15] A simple two-period model in the online Appendix illustrates this point further.

where Ω is expected surplus from job search. Note that Ω is endogenously determined in equilibrium and can be expressed as $\beta(\tilde{V}^u - V^u)$ in terms of the worker's value function.

The wage payment for recruitment services is given by

$$(21) \qquad w^r(p, n'; n, \varepsilon) = (z - 1)\frac{c_s}{z}\left(\frac{\gamma(n' - (1-\lambda)n)}{1 - p^{\gamma}}\right)^z \times [(1-\lambda)n]^{-\frac{1}{\phi}} B\left(\frac{(1-\lambda)n}{1 + (1-\lambda)n}, \frac{1}{\phi}, z - \frac{1}{\phi}\right),$$

where $B(x, a, b) = \int_0^x t^{a-1}(1-t)^{b-1}\,dt$ is the incomplete beta function. The details of the derivation are available in Appendix A.

The wage payments from production are similar to ones obtained in other papers featuring random matching with multi-worker firms, e.g., Acemoglu and Hawkins (2014), Elsby and Michaels (2013), and Cahuc, Marque, and Wasmer (2008). The solution implies sharing of the worker's outside option, $(b + \Omega)$, and the weighted average of infra-marginal products of labor. The wages at a non-hiring firm (firing or no-action) is the same as $w^n(n', \varepsilon)$. Further, wages at a firing firm are such that $V^e(n', \varepsilon) = V^u$ as implied by equation (17).[16]

The deviation from the other papers is the existence of a separate wage payment for recruitment services. This wage payment results from the dependence of the labor adjustment costs on the current size of the firm and it would be equal to zero otherwise, e.g., $z = 1$. In that regard, the current model is an extension to these papers and allows for dependence on firm size in labor adjustment costs.

G. *Recursive Stationary Equilibrium*

Two more conditions are needed to define the recursive stationary equilibrium. First, $\Gamma(n, \varepsilon)$ must be consistent with firms' optimal decision for employment at the steady state. Hence, it satisfies

$$(22) \qquad \Gamma(N, E) = \int_{N,E}\left[\int_{\mathcal{N},\mathcal{E}} f(\varepsilon'|\varepsilon)\mathcal{I}(n' = g_{n'}(n, \varepsilon))\, d\Gamma(n, \varepsilon)\right] dn'\, d\varepsilon',$$

where $N \subset \mathcal{N}$ and $E \subset \mathcal{E}$, $g_{n'}(n, \varepsilon)$ is the policy function for next period's employment, $f(\varepsilon'|\varepsilon)$ is the density function of the Markov process governing the idiosyncratic shock process, and $\mathcal{I}$ is an indicator function that is one if the condition is satisfied and zero otherwise.

Second, the recursive stationary equilibrium satisfies a free entry condition:

$$(23) \qquad E_{\varepsilon}(J(0, \varepsilon)) = c_e.$$

[16]For the bargaining solution in Stole and Zwiebel (1996), there is no simple condition, as in Hosios (1990), that guarantees efficiency. Firms may under-employ or over-employ depending on labor adjustment costs. See Acemoglu and Hawkins (2014) for a discussion.

A formal definition of the recursive stationary equilibrium is available in the online Appendix. Two equilibrium outcomes, the measure of firms and the total number of unemployed workers seeking jobs, can be calculated from other endogenous variables as follows. Let μ denote the mass of firms in equilibrium. Then, total vacancies and total unemployed workers are

$$V = \mu \int_{\mathcal{N},\mathcal{E}} g_v(n,\varepsilon)\, d\Gamma(n,\varepsilon)$$

and

$$U = 1 - \mu \int_{\mathcal{N},\mathcal{E}} n\, d\Gamma(n,\varepsilon) - \mu \int_{\mathcal{N},\mathcal{E}} g_r(n,\varepsilon) \left(1 - \frac{1 - [g_p(n,\varepsilon)]^{\gamma}}{\gamma(1 - g_p(n,\varepsilon))}\right) d\Gamma(n,\varepsilon),$$

where $g_r(n,\varepsilon)$ is the total hires from the firm's optimization problem. The second integral in the second equation above accounts for the fact that unproductive workers cannot search in the subsequent period. Recall that market tightness is $\theta = V/U$. Using the equilibrium value of θ and the calculated decision rules, one can obtain the equilibrium value of μ. Plugging μ in the second equation above, equilibrium unemployment is determined.

II. Characterization of Equilibrium

Heterogeneity in firms' recruiting practices is the main focus of this paper. Therefore, I analyze the problem of a hiring firm in this section. The problem of a firing firm is rather standard. Inserting the wage functions in the hiring firm's optimization problem, the dynamic programming problem becomes

$$\text{(24)}\quad J^h(n,\varepsilon) = \max_{n', p \in [0,1], v \geq 0} -c_v v - \frac{c_s}{z}(qv)^z \Psi((1-\lambda)n) + \frac{1-\phi}{1-\phi+\alpha\phi} A\varepsilon n'^{\alpha}$$
$$- (1-\phi)(b+\Omega)\big((1-\lambda)n + (1-p)qv\big)$$
$$+ \beta(1-\delta)\, E_{\varepsilon'|\varepsilon}[J(n',\varepsilon')],$$

with

$$\Psi(x) = (1+x)^{1-z} + (z-1)\, x^{1-\frac{1}{\phi}} B\left(\frac{x}{1+x}, \frac{1}{\phi}, z - \frac{1}{\phi}\right)$$

and subject to (9).

A. *Optimal Decision for the Hiring Standard*

The decision for the hiring standard threshold can be characterized as a solution to a labor adjustment cost minimization problem. Let $\Delta = n' - (1-\lambda)n$ denote the net change in employment and $C(\Delta, n)$ denote the total cost to the firm from changing employment from n to n'. Replacing qv from (9) and collecting all the labor costs in the firm's problem in (24) yield $C(\Delta, n)$ as the solution to the following cost minimization problem:

$$(25)\quad C(\Delta, n) = \min_{p \in [0,1]} \frac{c_v}{q}\frac{\gamma\Delta}{1-p^{\gamma}} + \frac{c_s}{z}\left(\frac{\gamma\Delta}{1-p^{\gamma}}\right)^{z}\Psi((1-\lambda)n) + (1-\phi)(b+\Omega)\left((1-\lambda)n + (1-p)\frac{\gamma\Delta}{1-p^{\gamma}}\right).$$

The optimal decision for p is the solution to the static problem in (25) for given Δ and n, which is independent of the production in the current period and the continuation value of the firm. The first-order condition characterizing optimal p is[17]

$$(26)\quad (1-\phi)(b+\Omega)\left(1+(\gamma-1)p^{\gamma}-\gamma p^{\gamma-1}\right) = \gamma p^{\gamma-1}\left(\frac{c_v}{q} + c_s\left(\frac{\gamma\Delta}{1-p^{\gamma}}\right)^{z-1}\Psi((1-\lambda)n)\right).$$

The left-hand side (LHS) of (26) is strictly decreasing in p and is equal to 0 when $p = 1$. This term is the marginal benefit from increasing the hiring standard: as a firm increases the hiring standard, it avoids paying the outside option to the workers who are more likely to be unproductive in the next period. However, this gain diminishes with p as the firm has to post more vacancies to satisfy a given level of Δ.[18] The right-hand side (RHS), on the other hand, is strictly increasing in p, is equal to 0 when $p = 0$, and tends to infinity as $p \to 1$. This term is the marginal cost of increasing the hiring standard: as a firm increases the hiring standard, the marginal cost of selection increases because the firm has to post more vacancies to satisfy a given level of Δ. This marginal cost also decreases with firm size, because $\Psi'(x) < 0$.[19] As implied by LHS and RHS being monotone, the solution to p is interior and unique.

Consider an increase in Δ for given n, i.e., the firm grows faster. This increases the marginal cost of increasing p, but leaves the marginal benefit unchanged. As a result, the optimal choice for p falls. In other words, if the firm grows faster, it fills vacancies faster and attains a high vacancy yield. However, this result depends on the firm size and the level of employment adjustment in the current period. The next section characterizes the optimal decision of employment over time.

B. *Optimal Decision for Employment*

In the problem in (25), $C(\Delta, n)$ has the following properties:

(i) $\frac{\partial C(\Delta,n)}{\partial \Delta} = C_{\Delta}(\Delta, n) > 0$ and $\frac{\partial C(\Delta,n)}{\partial n} = C_n(\Delta, n) < 0$, i.e., the adjustment cost function is increasing in Δ and decreasing in n;

[17] The common term $\frac{\gamma\Delta}{(1-p^{\gamma})^2}$ is factored out.

[18] The cross-sectional properties of p would follow as long as the outside option of the worker is positive.

[19] Since the factored out term includes Δ, these curves represent marginal benefit and cost from increasing the hiring standard *per* net employment change.

(ii) the adjustment cost function is strictly convex in (Δ, n).

A detailed analysis is available in Appendix B. Because the labor adjustment cost function is convex, the dynamic programming problem of a hiring firm is concave and the first-order condition with respect to n' is necessary and sufficient for optimal employment in the next period. The problem of a hiring firm can be written in a compact form as follows:

$$(27) \quad J^h(n,\varepsilon) = \max_{n' \geq (1-\lambda)n} -C(n' - (1-\lambda)n, n) + \frac{1-\phi}{1-\phi+\alpha\phi} A\varepsilon n'^{\alpha} + \beta(1-\delta)E_{\varepsilon'|\varepsilon} J(n', \varepsilon').$$

The first-order condition with respect to n' is

$$(28) \quad -C_{\Delta}(n' - (1-\lambda)n, n) + \frac{1-\phi}{1-\phi+\alpha\phi}\alpha A \varepsilon n'^{\alpha-1} + \beta(1-\delta)E_{\varepsilon'|\varepsilon} J'(n', \varepsilon') \leq 0,$$

with equality when $n' > (1-\lambda)n$. The policy function $g_{n'}(n,\varepsilon)$ in the problem (27) determines how the firm adjusts its employment over time.

The convexity of the adjustment cost function implies that an entrant firm gradually converges to its long-run size. Conditional on productivity, small (and young) firms post more vacancies, grow faster, fill vacancies faster, and attain a higher vacancy yield. This establishes the relationship of the vacancy yield to employment growth and firm size.[20] Small firms also experience larger worker turnover rates because they set lower hiring standards and separate from the newly hired workers in the next period with a greater likelihood.[21] This generates a positive relationship between the vacancy yield and the worker turnover rate. All three results about the behavior of the vacancy yield are conditional on productivity. Using the calibrated model, I show that these results also hold in the cross section.

III. Vacancy Yields in the Cross Section

This section starts with a discussion of mapping the worker selection model to the data. Then, I calibrate the worker selection model based on the mapping rule developed in this section. Later, I present the results from the calibrated worker selection model regarding the cross sectional behavior of vacancy yields and compare them to DFH's (2013) calculations from JOLTS as well as the standard DMP model. I describe the set up and calibration of the standard DMP model further below.

[20] Since the cost of labor adjustment is negatively related to the size of the firm, it is possible that very small firms choose a smaller value of Δ. Nonetheless, Δ eventually reaches zero due to decreasing returns to scale in production. In the calibrated model, these very small firms still attain higher employment growth rates despite lower values of Δ.

[21] Note that worker selection mechanism also implies a positive relationship between employment growth and worker turnover rates. From a screening standpoint, high-growth hiring is more costly since the firm trades off quality for quantity of the new hires.

A. *Mapping between the Data and the Model*

The way vacancies are measured in JOLTS and the worker selection model are not exactly the same, but they are related. Vacancies are measured in JOLTS as a stock of open positions that remain unfilled at the end of a given month. In the model, the choice of v corresponds the total vacancy stock at the beginning of the week that a firm is willing to fill. To map the model to the data, let $v^{u}_{\tau,t}$ and $v^{f}_{\tau,t}$ be the stock of unfilled vacancies and the flow of new vacancies in week τ of month t, respectively. Then, these two variables are related to each other as follows:

$$v^{u}_{\tau,t} = \big(1 - q_{\tau,t}(1 - p_{\tau,t})\big)\big(v^{u}_{\tau-1,t} + v^{f}_{\tau,t}\big). \tag{29}$$

Note that $v^{u}_{\tau,t}$ corresponds to the measure of vacancies in JOLTS, whereas vacancies in the model are equal to the sum of unfilled vacancies at the end of the previous week and the new flow of vacancies in this week, $v^{u}_{\tau-1,t} + v^{f}_{\tau,t}$. Then, equation (29) provides a mapping between the model and the data. In a stationary equilibrium, the job filling probability and total vacancy postings are constant. Moreover, aggregation over firms yields that the stock of total vacancies that remain unfilled at the end of the previous month, V^{u}_{t-1}, is equal to $(1 - q(1 - p^{-}))V$, where $\bar{p}$ is the average hiring standard. Assuming that there are four weeks in a month, total hires in a month, h_t, is given by $4q(1 - \bar{p})V$. Finally, the vacancy yield, defined as in DFH (2013), is

$$\frac{h_t}{V^{u}_{t-1}} = \frac{4q(1 - \bar{p})}{1 - q(1 - \bar{p})}. \tag{30}$$

I use this mapping rule to calculate the vacancy yields below.

B. *Benchmark Calibration*

My calibration strategy relies on matching the salient features of JOLTS data documented in DFH (2013). Unless otherwise stated, all of the targeted moments are taken from their work. The parameter estimates are presented in Table 1.

I choose a period to be equal to one week and set the discount factor to match the quarterly interest rate of 1.12 percent. As in Acemoglu and Hawkins (2014) and Fujita and Nakajima (2016), I use 0.677 for the curvature of the Cobb-Douglas production function. This value is commonly used in the real business cycle literature and is a lower bound when decreasing returns are due to factors other than labor that are fixed.

The cross-sectional behavior of vacancy yields is sensitive to the choice of the curvature parameter of the selection cost function, z. As a benchmark case, I assume a cubic function and set $z = 3$. In the online Appendix, I change the value of this parameter to see the response of vacancy yields in the cross section. The scale parameter, c_s, targets an equilibrium value of aggregate vacancy yield equal to 1.3.

The matching function elasticity, ζ, governs the relationship in equation (2) between the probability that a vacancy is matched with a worker, q, and market tightness, θ. To pin down its value, I choose the target values of q and θ in equilibrium

TABLE 1—CALIBRATED PARAMETERS OF THE WORKER SELECTION MODEL (*benchmark weekly model*)

Parameter		Target	Value
β:	Discount factor	Quarterly interest rate: 1.12%	0.999
α:	Production curvature	RBC literature	0.677
z:	Selection cost, curvature	Benchmark	3.000
c_s:	Selection cost, scale	Aggregate vacancy yield, 1.3	3.423
ζ:	Matching elasticity	$q = 0.827$ and $\theta = 0.567$ in equilibrium	1.699
ρ:	Persistence of shocks	Abraham and White (2006)	0.590
σ:	Dispersion of shocks	Hires rate, 3.4%	0.156
γ:	Success probability, $x^{\gamma-1}$	Job turnover rate, 3.0%	2.451
λ:	Exogenous separation	Separation rate at 0% employment growth	0.223%
δ:	Exogenous exit	1/6 of job destruction	0.075%
b:	Value of leisure	Normalization	0.947
ϕ:	Workers' bargaining power	Ratio of b to Y/N, 0.73	0.391
c_v:	Flow cost of vacancy	Vacancy yield at low turnover firms, 0.1	3.288×10^{-4}
A:	Aggregate productivity	Average firm size, 20	3.243
c_e:	Fixed entry cost	Free entry condition in (23)	3,307.912

as follows. First, given that the aggregate vacancy yield is 1.3, the mapping rule in (30) implies that the probability of filling a vacancy in a week is 0.245. The model counterpart of this value is $q(1 - \bar{p})$. To determine q separately from $(1 - \bar{p})$, I use the fact from Villena-Roldán (2012) that firms interview, on average, five applicants before filling an open position. This value implies that, conditional on being matched, the daily probability that a firm hires a worker is 0.200. This is simply $(1 - \bar{p})$ in daily terms. Then, the daily probability that a firm meets a worker is 0.222. This latter implies that q is equal to 0.827 in weekly terms. Second, Shimer (2005) estimates that the average job finding probability of a worker in a month is 0.450. In weekly terms, this is equal to 0.139. In the model, this is given by $\theta q(1 - \bar{p})$. Dividing this value by the job filling probability yields $\theta = 0.567$. Using the equilibrium values of θ and q, I find $\zeta = 1.699$ from equation (2).

The idiosyncratic productivity process approximates an AR(1) process:

$$\log(\varepsilon_{t+1}) = \rho \log(\varepsilon_t) + \eta_t, \quad (31)$$

with $\eta_t \sim N(0, \sigma^2)$. For the persistence parameter, ρ, I use the estimate in Ábrahám and White (2006). They find the persistence of the idiosyncratic shocks to be 0.590 on an annual basis. To represent this process on a weekly basis, I impose that firms receive a productivity shock with probability 1/52 in a given week. I choose the variance of the shocks to match a hires rate of 3.4 percent.

There are three sources of worker-firm separation in the model. First, firms fire productive workers in response to a negative productivity shock. Thus, separations due to firings are driven by the productivity process. Since separations are equal to hires in a stationary equilibrium, I account for this type of separation by setting σ to match the hires rate. Second, some of the newly hired workers leave the firm next period if they turn out to be unproductive. The probability that a worker with the average match-quality will be productive next period depends on γ. All else equal, when γ becomes larger, a larger fraction of the newly hired workers leave the firm next period. Hence, a larger value of γ implies a larger difference between the worker turnover rate, which is the sum of hiring and separation rates, and the job turnover rate, which is the sum of *net* job creation and destruction rates. Davis, Faberman and Haltiwanger (2006) report that the monthly job turnover rate is 3.0 percent in JOLTS, less than half of the worker turnover rate. Since the hires rate is already targeted, I choose γ to match the monthly job turnover rate. Finally, separations occur exogenously with probability λ or due to firm exit with probability δ. In the model, λ is the separation probability of a fully productive worker. In JOLTS, firms with no employment growth lose 0.891 percent of its workforce in a month due to reasons other than layoff and discharges. I set λ to one-fourth of this value to match this figure on a weekly basis. Consistent with the evidence from Davis, Haltiwanger, and Schuh (1996), I choose δ so that one-sixth of job destruction is due to firm exit. The monthly job destruction rate in JOLTS is 1.5 percent, but JOLTS excludes exiting firms. So, I target a monthly exit rate that is equal to 0.3 percent and set $\delta = 0.075$ percent.

I normalize the value of leisure, b, in a way that makes the sum of b and Ω, the surplus from job search, equal to one in equilibrium.[22] I target an equilibrium value of Ω so that the ratio of b to average productivity, (Y/N), is equal to 0.73, which corresponds to the calibrated value of leisure in Mortensen and Nagypál (2007). I choose the value of a worker's bargaining power, ϕ, to satisfy the equilibrium value of Ω that is consistent with this figure.

To calibrate the flow cost of vacancy, c_v, I use the relationship in equation (26). As the number of vacancies posted approaches zero, the optimal hiring standard approaches a value that is strictly less than 1 and the magnitude of c_v determines this upper bound for the optimal hiring standard. In the lowest worker turnover quintile, the vacancy yield is around 0.1. A similar value is observed around the zero employment growth rate. Accordingly, I choose c_v so that the vacancy yield is equal to 0.1 in the model when a hiring firm's vacancy postings approaches zero from above.

There are two more parameters to be calibrated: the technology scale parameter, A, and the fixed entry cost, c_e. Faberman and Nagypál (2008) report that the average establishment size in JOLTS is 20. I choose A to match this value. Finally, I choose c_e so that the free entry condition in equation (23) is satisfied, i.e., the expected value of an entrant is equal to the fixed entry cost in equilibrium.

C. *Standard DMP Model*

As in the worker selection model, the standard DMP model I describe in this section assumes decreasing returns to scale production technology and allows firms to hire multiple workers. The main difference from the worker selection model is that firms are not allowed to optimize over the hiring standard threshold, but it is constant across firms by assumption. This restriction allows me to isolate the effects of worker selection. To make these models comparable, I calibrate the standard DMP model in a way that it matches the targeted moments with the worker selection model as closely as possible. This requires some modifications to the standard DMP model.

[22] Normalizing $(b + \Omega)$ is computationally easier to implement than normalizing b or Ω individually.

First, firms contact workers with probability q in the worker selection model, but hire them with a smaller probability equal to $(1 - p)q$. In the standard DMP model, the contact probability coincides with the job filling probability, because workers are identical and firms indiscriminately hire all of the workers they contact. To create a gap between the contact and the job filling probabilities as in the worker selection model, I introduce an exogenous parameter, $\bar{p}$, to the standard DMP model. I set the value of $\bar{p}$ equal to the average value of the hiring standard in the calibrated worker selection model so that the job filling probability becomes $(1 - \bar{p})q$ in the standard DMP model. This modification makes the average job filling probability the same between the two models, but the firm-level vacancy yield varies only in the worker selection model.

Second, the choice of hiring standard also affects the probability of separation in the next period through the value of γ. Define a new parameter p_γ in the standard DMP model such that the law of motion becomes

$$n' = (1 - \lambda)n + (1 - \bar{p})qv(1 - p_\gamma). \tag{32}$$

The parameter p_γ now determines a common separation probability for newly hired workers. Comparing equations (32) and (9), $(1 - p_\gamma)$ in the standard DMP model corresponds to $g(p)$ in the worker selection model. Recall that I targeted the job turnover rate from JOLTS in Section IIIB to calibrate γ. Similarly, I choose p_γ in the standard DMP model to match this target.

Regarding the calibration of the remaining parameters, note that the modifications above reduce degrees of freedom. In the benchmark calibration, the selection cost function parameters, c_v and c_s, targeted aggregate vacancy yield and the vacancy yield at lowest worker turnover firms. In the standard DMP model, the former moment is targeted by $\bar{p}$ and the latter moment coincides with the former since worker selection is not allowed.

To address these issues, I first set the value of b equal to the value obtained from the calibration of worker selection model and choose ϕ so that $b/(Y/N) = 0.73$ as before. This makes all the units relative to b comparable between the models. I set the value of c_v equal to the value obtained from the calibration of the worker selection model and choose the value c_s so that the cost per hire is the same from both models. As in the benchmark calibration, A targets average establishment size, σ is set to match the hires rate, and c_e satisfies the free entry condition. Finally, I set all of the remaining parameters equal to their corresponding values in Table 1. The values of the newly calibrated parameters are presented in Table 2.

D. *Results*

Figure 2 plots vacancy yield against monthly employment growth rates. The calculations from JOLTS are obtained from DFH (2013). In JOLTS, the vacancy yield is relatively stable at shrinking firms, but it sharply increases as we move to positive employment growth rates, reaching from a half at around 0 percent employment growth rate to six at 30 percent. To see how sizable these differences are, consider how quickly vacancies are filled at around 0 percent and 30 percent employment

TABLE 2—CALIBRATED PARAMETERS OF THE STANDARD DMP MODEL (*weekly model*)

Parameter		Target	Value
$\bar{p}$:	Hiring probability	Aggregate vacancy yield, 1.3	0.703
c_s:	Selection cost, scale	Cost per hire from benchmark calibration, 5.527%	0.748
σ:	Dispersion of shocks	Hires rate, 3.4%	0.155
p_γ:	Success probability, $(1-p_\gamma)$	Job turnover rate, 3.0%	0.291
ϕ:	Workers' bargaining power	Ratio of b to Y/N, 0.73	0.412
A:	Aggregate productivity	Average firm size, 20	3.245
c_e:	Fixed entry cost	Free entry condition in (23)	3,222.183

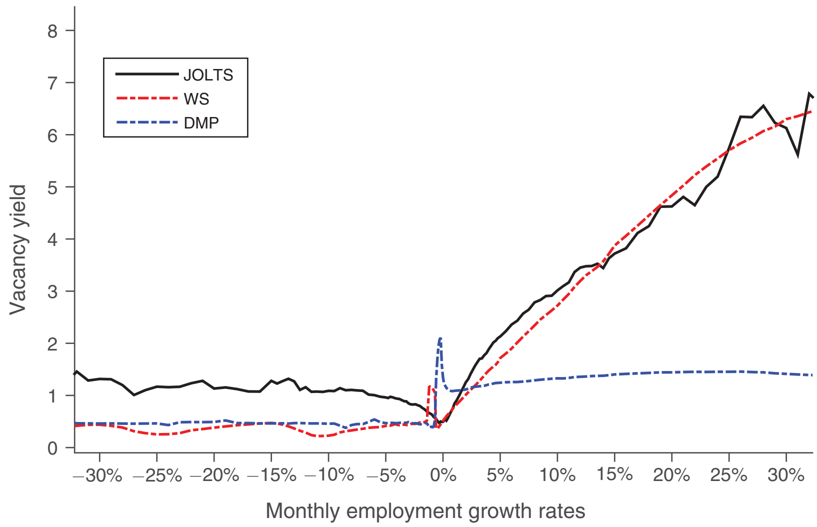

FIGURE 2. VACANCY YIELD AND EMPLOYMENT GROWTH: A COMPARISON ACROSS WORKER SELECTION AND STANDARD DMP MODELS, AND THE DATA

Notes: The data from the models are generated from the stationary distribution of the corresponding model with $z = 3$. WS and DMP stand for worker selection and standard DMP models, respectively.

Source: JOLTS data is taken from DFH (2013).

growth rates. Based on the mapping rule in (30), the corresponding weekly job filling probabilities are 0.111 and 0.600, respectively. In other words, it takes about nine weeks to fill a vacancy at around 0 percent employment growth rate while it takes only about a week and a half to fill a vacancy at 30 percent employment growth.

To compare the cross-sectional patterns from JOLTS to the calibrated models, I applied the procedure described in DFH (2013) to the data generated from each model. The variation in vacancy yields in the standard DMP model is a result of the pure time aggregation effect discussed in DFH (2013). The plot from the standard DMP model is flat, reflecting a moderate time aggregation effect.[23] The worker selection model, on the other hand, generates a pattern that is very close to the data.

[23] There is a spike at around $-\lambda$ percent employment growth rate. These are the firms that start the period above their long-run sizes with a small number of vacancies. Through the end of the month, they hire new workers to

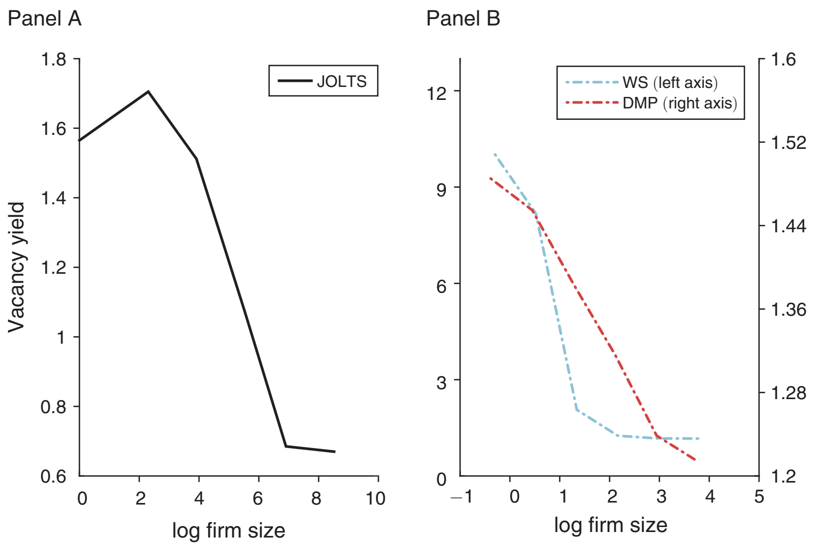

Figure 3. Vacancy Yield and Firm Size: A Comparison across Worker Selection and Standard DMP Models, and the Data

Notes: The data from the models are generated from the stationary distribution of the corresponding model with $z = 3$. WS and DMP stand for worker selection and standard DMP models, respectively. At panel B, vacancy yield from the worker selection model is measured on the left axis and vacancy yield from the standard DMP model is measured on the right axis.

Source: JOLTS data is taken from DFH (2013).

Figure 3 shows the relationship between vacancy yield and log firm size. Panel A is drawn based on the calculations of DFH (2013) from JOLTS data and panel B is drawn using the simulated data from the worker selection and the standard DMP models. Firm size is calculated as the average of employment at the beginning and the end of the period. Since I do not directly target the firm size distribution, the firm sizes from the models are smaller than the firm sizes observed in the data. To make the size groups comparable, I construct six firm size bins such that the log difference of average size in two consecutive bins are equal, which roughly holds for the size classification in DFH (2013). As shown in panel B, the vacancy yield decreases with firm size in both models, but the levels are larger in the worker selection model, measured on the left axis, than those in the standard DMP model, measured on the right axis.

To understand the difference in levels, recall that high vacancy yields at small firm sizes are driven by highly productive and fast growing firms. At intermediate firm sizes, a majority of the firms are close to their long-run sizes, grow at slower rates, and, hence, have lower vacancy yields. Compared to the data, fast growing firms are more concentrated at low employment levels in the worker selection model, and this explains the gap in Figure 3. There is also an inverse relationship in the standard DMP model, measured on the right axis, because the time aggregation effect is bigger at fast growing firms as in Figure 2.

replace some of the workers leaving after an exogenous separation shock. Since these firms start with a very small number of vacancies, vacancy yield is big at these firms.

TABLE 3—VACANCY YIELD AND WORKER TURNOVER: A COMPARISON ACROSS WORKER SELECTION AND STANDARD DMP MODELS, AND THE DATA

	Hires rate	Separation rate	Vacancy yield	Employment share (percent)
JOLTS				
No turnover	0.000	0.000	0.000	24.4
First quintile	0.517	0.560	0.290	15.1
Second quintile	1.330	1.238	0.490	15.1
Third quintile	2.395	2.249	0.787	15.1
Fourth quintile	4.493	4.288	1.433	15.1
Fifth quintile	13.527	12.989	3.077	15.1
Worker selection				
Low turnover	0.798	0.937	0.465	50.7
First quintile	1.123	1.009	0.550	9.8
Second quintile	1.567	1.083	0.641	9.8
Third quintile	2.846	1.354	0.879	9.8
Fourth quintile	5.995	2.804	1.404	9.8
Fifth quintile	17.369	16.963	3.175	9.8
Standard DMP				
Low turnover	1.253	1.256	1.304	59.5
First quintile	1.724	1.394	1.142	8.1
Second quintile	3.225	1.846	1.092	8.1
Third quintile	5.631	2.992	1.172	8.1
Fourth quintile	10.512	4.031	1.261	8.1
Fifth quintile	17.161	17.724	1.348	8.1

Note: The data from the models are generated from the stationary distribution of the corresponding model.

Source: JOLTS data is taken from DFH (2013).

Finally, Table 3 shows the statistics for worker turnover bins from the data and the models. In JOLTS, there are firms with no worker turnover in a month, but each firm has some worker turnover in both models due to exogenous separation shocks. To make worker turnover categories comparable, I create a bin from the models, which includes firms with very low worker turnover rates. These are largely firms with no employment growth. In JOLTS, the employment share of firms with no employment growth is 31.5 percent. Firms with no worker turnover are also in this group with an overall employment share equal to 24.4 percent. In other words, firms with no employment growth rate employ roughly half of the labor force in the first quintile generated from JOLTS. Accordingly, I set the employment share of this first bin with low turnover worker so that half of the labor in the first quintile is employed by firms with no employment growth.

Moving from low worker turnover rates to high turnover rates, the vacancy yield in JOLTS rises from 0.290 to 3.077. A positive relationship emerges from the worker selection model and vacancy yield levels are very close to those in JOLTS. However, vacancy yields in the standard DMP model show a U-shaped pattern. There is not much variation across worker turnover bins either. The values are around 1.3, which is the aggregate vacancy yield targeted in calibration.

Overall, the worker selection model accounts for the cross-sectional patterns of vacancy yields in JOLTS quite well. In the next section, I show that accounting for these patterns has first-order implications for labor market policy and that these implications are quantitatively significant.

IV. Policy Analysis

Using the calibrated version of the worker selection and standard DMP models, I examine the effects of a hiring subsidy and a firing tax on aggregate and firm-level employment decisions. A hiring subsidy is a one-time payment made to firms for each worker they hire, whereas a firing tax is a one-time payment collected from firms for each worker they fire. I assume that government finances the hiring subsidy through a lump-sum tax levied on every worker regardless of their employment status. Similarly, I assume the collected firing tax is distributed to the workers in a lump-sum fashion.

A. *Wage Bargaining under Labor Market Policy*

In both models, the bargaining outcome changes because both policies affect the surplus to the firm and the workers. Let s and τ denote a hiring subsidy and a firing tax, respectively, measured in terms of the consumption good. Then, the bargaining rules defined in equations (17) and (18) for the worker selection model become

$$\phi(D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon) + \tau) = (1 - \phi)(V^e(n, \varepsilon) - V^u) \tag{33}$$

and

$$\phi(D_{\tilde{r}}(\tilde{n}, r, p, \varepsilon) + s) = (1 - \phi)(V^p(n, \varepsilon) - V^u). \tag{34}$$

Since a firing tax increases the cost of firing, firms are willing to accept a smaller surplus to keep an incumbent worker. Equivalently, the surplus to the firm from keeping an incumbent worker increases by τ as the firm avoids paying the firing tax.[24] Note that τ does not enter directly the bargaining rule for a potential hire, because there is not an ongoing employment relationship at the time of the first meeting, and the firm is not obligated to pay the firing tax. However, the surplus to the firm from the newly hired worker increases by s. With these policy parameters, the production wages for incumbent and new workers become

$$\begin{aligned} w^n(n', \varepsilon) = {} & \frac{\alpha\phi}{1 - \phi + \alpha\phi} A\varepsilon n'^{\alpha - 1} + (1 - \phi)(b + \Omega) \\ & + \phi\tau(1 - \beta(1 - \delta)(1 - \lambda)) \end{aligned} \tag{35}$$

and

$$\begin{aligned} w^p(p, n', \varepsilon) = {} & g(p)\frac{\alpha\phi}{1 - \phi + \alpha\phi} A\varepsilon n'^{\alpha - 1} + (1 - \phi)(b + \Omega) \\ & + \phi s - \phi\tau\big(1 - g(p)\big(1 - \beta(1 - \lambda)(1 - \delta)\big)\big), \end{aligned} \tag{36}$$

[24] More formally, the surplus to the firm from an incumbent worker becomes

$$\lim_{\epsilon \to 0} \frac{D(\tilde{n}, \cdot) - (D(\tilde{n} - \epsilon, \cdot) - \tau\epsilon)}{\epsilon} = \lim_{\epsilon \to 0} \frac{D(\tilde{n}, \cdot) - (D(\tilde{n} - \epsilon, \cdot))}{\epsilon} + \tau = D_{\tilde{n}}(\tilde{n}, \cdot) + \tau.$$

TABLE 4—EFFECTS OF HIRING SUBSIDY ON EQUILIBRIUM: A COMPARISON BETWEEN THE WORKER SELECTION AND STANDARD DMP MODELS

	Hiring subsidy (percent of b)					
	0.000	1.000	2.000	3.000	4.000	5.000
Unemployment rate (percent)						
Worker selection	5.759	5.749	5.739	5.729	5.720	5.710
Standard DMP	5.759	5.756	5.752	5.749	5.746	5.743
Job finding prob. (percent change)						
Worker selection	0.000	0.451	0.917	1.391	1.880	2.361
Standard DMP	0.000	0.199	0.412	0.626	0.841	1.057
Ω (*percent change*)						
Worker selection	0.000	0.007	0.015	0.022	0.029	0.036
Standard DMP	0.000	0.008	0.015	0.023	0.030	0.038
μ (*percent change*)						
Worker selection	0.000	0.004	0.007	0.011	0.014	0.017
Standard DMP	0.000	−0.003	−0.006	−0.008	−0.011	−0.014

Note: Percent changes are calculated relative to the equilibrium without hiring subsidy.

while recruitment wages are unaffected.[25] One can obtain the wage equation for the standard DMP model after replacing $g(p)$ with $(1 - p_\gamma)$ in the equations above. The wage equations in (35) and (36) are intuitive. At the time of the hiring, the worker shares the subsidy and the cost of firing depending on the survival probability. In subsequent periods, he receives the firing tax back conditional on retention.

B. *Effects of a Hiring Subsidy*

I calculate the response of labor market outcomes to incremental increases in hiring subsidy as a fraction of the value of leisure, b, which is normalized to the same value in both models. Table 4 reports equilibrium labor market outcomes from each model.

If a policymaker assesses the hiring subsidy policy using the standard DMP model rather than the worker selection model, he will not be optimistic about the hiring subsidy in combating unemployment. An incremental increase in the hiring subsidy equal to one percent of b reduces the unemployment rate only by 0.003 percentage points in the standard DMP model, compared to 0.010 percentage points in the worker selection model.[26] The three-fold difference is due to the response of the worker selection margin to the hiring subsidy in addition to vacancies.

To understand how this margin increases the effectiveness of the hiring subsidy, note that there are two channels through which the hiring subsidy affects the unemployment rate in both models. On the one hand, the hiring subsidy creates a direct incentive for posting more vacancies. This incentive effect increases equilibrium

[25] Note that the lump-sum amounts drop out of the equation describing the surplus to a worker as they are paid regardless of the worker's employment status. Therefore, they do not show up in the wage equations.

[26] This result is true for low levels of subsidy. When the subsidy becomes large, the unemployment rate increases as firms start replacing incumbent workers with new workers to receive the subsidy.

market tightness, θ, and the job finding probability of workers, which tends to lower the unemployment rate. On the other hand, a higher job finding probability increases the search value, Ω, which increases production wages and labor adjustment costs. This latter indirect effect tends to increase the unemployment rate by reducing firm value and discouraging firm entry.[27] Overall, the former effect dominates the latter and the unemployment rate goes down in equilibrium in both models. However, the ability to select workers diminishes the effect of the hiring subsidy on Ω. Firms in the worker selection model become less picky about the workers, i.e., p goes down, as they are compensated for the loss due to hiring an unproductive worker. A lower p reduces the retention probability of a newly hired worker in the next period, which dampens the search value. Compared to the standard DMP model, the search value in the worker selection model increases less leading to a bigger drop in the unemployment rate.[28]

The effects of a hiring subsidy on employment growth rates in the cross section are also different. To highlight the impact of a hiring subsidy on employment growth rates, I construct employment growth rate bins as in Section IIID and place firms in my sample into their corresponding employment growth rate bins. Then, I introduce a hiring subsidy equal to three percent of b in each model and calculate the new employment growth rates for each firm. Using the weights in the steady state stationary distribution without the subsidy, I calculate a new employment growth rate for each bin. In Figure 4, I plot the change in employment growth rates across employment growth rate bins after the hiring subsidy.

In both models, the employment growth rates increase with the hiring subsidy at all employment growth rates, but the effect of the hiring subsidy extends more through the high employment growth rates in the worker selection model. The difference between the two models stems from the fact that a hiring subsidy shifts the marginal cost of labor adjustment in a parallel fashion if firms cannot change p. Because the production function exhibits diminishing marginal product of labor, the hiring subsidy induces a larger increase in employment at larger firms, which tend to have lower employment growth rates. However, when firms can select workers, small and growing firms lower their marginal cost of labor adjustment further by reducing p. The ability to reduce the marginal cost allows small and growing firms to increase their employment more in the worker selection model.

Hiring subsidy programs that are similar to the one studied in this section are rare, because most of the hiring subsidy programs in the United States target specific disadvantaged groups.[29] Despite its complex structure, The New Jobs Tax Credit stimulus package in 1977, a federal tax credit program aimed at increasing private employment, is an exception in that it was non-categorical, like the hiring subsidy policy in this section. Perloff and Wachter (1979) analyze the effects of this tax credit program on employment growth and find that the tax credit program shifted the employment growth distribution to the right, and most of this shift occurred

[27] Higher Ω also induces firing at large firms, but changes are similar across models.

[28] Shutting down the entry and exit margin in the worker selection model, i.e., $\delta = 0$, changes the effect of the hiring subsidy on job finding probability and Ω, but the overall effect on unemployment rate is similar to the model with free entry.

[29] See Neumark (2012) for a discussion of tax credit programs in the United States.

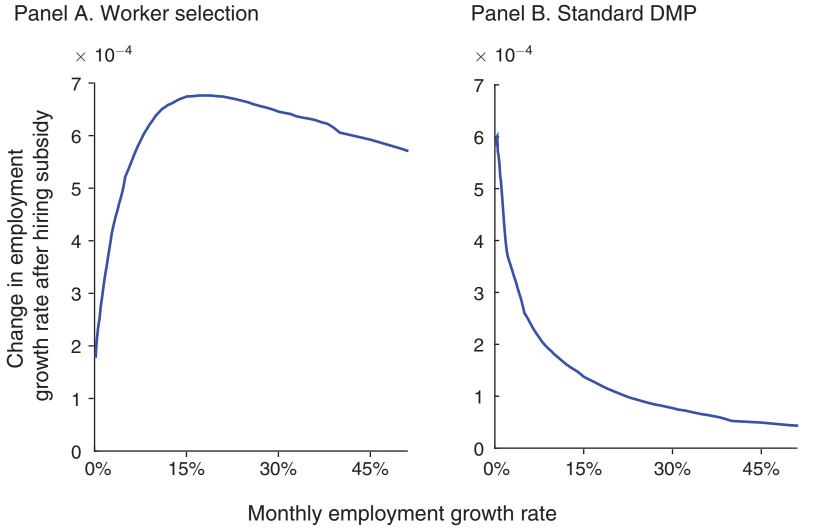

FIGURE 4. CHANGE IN EMPLOYMENT GROWTH AFTER A HIRING SUBSIDY: A COMPARISON BETWEEN THE WORKER SELECTION AND STANDARD DMP MODELS

Notes: The level of the hiring subsidy is set equal to three percent of the value of leisure in each model. The stationary equilibrium distribution without the hiring subsidy is used to weight the observations in each employment growth rate bin.

in the right tail of the distribution.[30] In Figure 4, the positive responses to the hiring subsidy imply that the employment growth rate distribution shifts right in both models. However, only in the worker selection model does the employment growth distribution shift more in the right tail of the distribution due to the stronger response of the slow and growing firms.[31]

C. *Effects of a Firing Tax*

The results from incremental increases in the firing tax are presented in Table 5. The unemployment rate increases with an increase in firing tax in the worker selection model because firms select workers more carefully with the increased cost of adjustment depressing job finding rates. However, the unemployment rate goes down when this channel is shut down as in the standard DMP model. In that case, the job search value, Ω, decreases enough to encourage more firm entry. The relatively smaller decline in Ω in the worker selection model stems from the fact that increased hiring standards imply a bigger retention probability and positively affect the search value for unemployed workers.

[30] Perloff and Wachter (1979) use a follow-up survey to the subsidy program which enables them to distinguish firms that knew about the program from those who did not. They use this knowledge information to identify the effects of the subsidy on employment growth.

[31] Perloff and Wachter (1979) argue that there were some practical problems in implementing the tax credit program, e.g., the program was too complicated to understand, a large number of firms were not aware of the program, and some thought that they were ineligible for the program although they were actually eligible. Therefore, the impact on unemployment in the worker selection model might be bigger than reality due to these practical problems not modeled in this paper.

Table 5—Effects of Firing Tax on Equilibrium

	Firing tax (percent of b)					
	0.000	5.000	10.000	15.000	20.000	25.000
Unemployment rate (percent)						
Worker selection	5.759	5.792	5.827	5.861	5.895	5.929
Standard DMP	5.759	5.758	5.756	5.754	5.752	5.751
Job finding prob. (percent change)						
Worker selection	0.000	−1.845	−3.572	−5.212	−6.773	−8.263
Standard DMP	0.000	−0.714	−1.389	−2.029	−2.648	−3.253
Ω *(percent change)*						
Worker selection	0.000	−0.019	−0.039	−0.059	−0.079	−0.099
Standard DMP	0.000	−0.019	−0.039	−0.058	−0.077	−0.097
μ *(percent change)*						
Worker selection	0.000	−0.002	−0.008	−0.019	−0.033	−0.050
Standard DMP	0.000	0.028	0.052	0.073	0.091	0.108

Note: Percent changes are calculated relative to the equilibrium without a firing tax.

Table 6—Cross-Sectional Effect of a Firing Tax on Worker Turnover

	Hires rate (percent change)	Separation rate (percent change)	Worker turnover (percent change)
Worker selection			
Low turnover	−0.041	−0.008	−0.049
First quintile	−0.105	−0.020	−0.125
Second quintile	−0.128	−0.029	−0.157
Third quintile	−0.204	−0.065	−0.269
Fourth quintile	−0.352	−0.267	−0.619
Fifth quintile	−0.710	−0.814	−1.524
Standard DMP			
Low turnover	−0.375	−0.109	−0.484
First quintile	−0.552	−0.161	−0.713
Second quintile	−0.383	−0.114	−0.497
Third quintile	−0.276	−0.198	−0.474
Fourth quintile	−0.185	−0.081	−0.266
Fifth quintile	−0.178	−0.465	−0.643

Note: Percent changes are calculated relative to the equilibrium without a firing tax.

The firing tax also has cross-sectional implications on worker turnover that differ across the models. Table 6 shows the change in the worker turnover rate after a firing tax equal to 15 percent of the flow value of leisure, b.

In the worker selection model, both the hires and separation rates, and hence the worker turnover rate, decrease more after the firing tax at firms with initially high worker turnover rates. While the firing tax reduces the separation rate at the highest worker turnover category in the standard DMP, there is no particular pattern in the change in worker turnover rates.

Haltiwanger, Scarpetta, and Schweiger (2014) use harmonized data on job creation and job destruction from emerging and developed countries and estimate the effects of hiring and firing regulations on job reallocation rates. Using a difference-in-difference approach, they find that firms in the industries and size classes that require more frequent employment changes, e.g., technological changes, are affected relatively more from hiring and firing restrictions. This finding supports the predictions of the worker selection model regarding the cross-sectional effects of the firing tax on worker turnover.

V. A Comparison between the Worker Selection and Directed Search Models

Kaas and Kircher (2015) develop a directed search model where multi-worker firms post wage contracts to hire workers in response to idiosyncratic productivity shocks. Depending on firm size and productivity, firms may decide to fill open positions at different rates. They show that the cross-sectional patterns of the vacancy yield from the directed search model are consistent with the data. To highlight the differences, I compare my results to the directed search model that provides an alternative explanation for the cross-sectional patterns of the vacancy yield observed in the data. I sketch an outline of the model here and refer the reader to the original paper for details. I keep the notation similar to the worker selection model to facilitate a direct comparison.

A. *Overview*

A distinctive feature of the directed search model is that the equilibrium is efficient and can be calculated from a social planner's problem. Let Ω be the social value of the worker. Then, the Bellman equation for a hiring firm is[32]

$$J^h(n,\varepsilon) = \max_{n',\, q\in[0,1],\, v\geq 0} -c_v v - \frac{c_s}{z}\left(\frac{v}{1+(1-\lambda)n}\right)^z (1+(1-\lambda)n) + A\varepsilon n'^{\alpha} - bn' - \Omega\left((1-\lambda)n + \frac{v}{\theta(q)}\right) + \beta(1-\delta)E_{\varepsilon'|\varepsilon}J(n',\varepsilon'), \tag{37}$$

subject to

$$n' = (1-\lambda)n + qv. \tag{38}$$

Here, q is the probability of filling a vacancy and $\theta(q)$ is the market tightness as a function of q derived from a matching function such as the one in equation (1). Different from the worker selection model, the social planner can assign each firm a different number of unemployed workers per vacancy and fill vacancies with different probabilities at these firms. In doing so, the social planner is constrained by the common matching technology, $\theta(q)$, and the resource constraint on labor force for which the shadow value is Ω.

[32] Deviating from the original paper, I allow for the newly hired worker to work in the current period as in the worker selection model.

Apart from the constant separation probability, λ, and wage setting structures, there is a relatively straightforward relationship between the directed search and the worker selection models, which enables a direct comparison between these models. In particular, in a competitive equilibrium, Ω becomes equal to the search value of an unemployed worker as in the worker selection model, and its value in equilibrium is determined via a free entry condition as in equation (23). One wage setting mechanism that supports this equilibrium is that newly recruited workers receive a hiring bonus in the first period, and $(b + \Omega)$ for subsequent periods before separating from the firm. I calibrate the directed search model in the next section in light of these observations.

B. *Calibration*

I set the value of leisure, b, equal to its value from the benchmark calibration for the worker selection model. I target an equilibrium value of Ω, which makes the ratio of b to average wage equal to the value of the same ratio from the benchmark calibration. I target the ratio of b to average wage rather than average productivity because the latter is bounded from above by α, the curvature parameter in the production function.[33] As in the benchmark calibration, c_s targets the aggregate vacancy yield, c_v targets the vacancy yield at low worker turnover firms, A targets average establishment size, σ is set to match the hires rate, and c_e satisfies the free entry condition. There is no endogenous separation at hiring firms in equilibrium in the directed search model. So, the calibration does not target the job turnover rate. I also adjust the value of λ to reflect the separation rate at 0 percent employment growth rate. Finally, I use the matching function specification in Kaas and Kircher (2015), which introduces k as a scale parameter as follows:

(39) $$M(U,V) = (kU^{-\zeta} + V^{-\zeta})^{-\frac{1}{\zeta}}.$$

As in Kaas and Kircher (2015), I calibrate k and ζ to match the weekly job finding probability, $\theta q(\theta)$, equal to 0.139, and its elasticity with respect to θ equal to 0.28. These values are calibrated at $\theta = 0.566$, as in the benchmark calibration.

Table 7 shows the calibrated parameter values for the directed search model. All the remaining parameter values are set equal to their counterparts in the worker selection model in Table 1.

C. *Vacancy Yields in the Directed Search Model*

Figure 5 plots vacancy yields against monthly employment growth rates. Both the worker selection and the directed search models show a pattern similar to the data.[34]

[33] To see this point, consider an equilibrium in which Ω is very close to zero. This would happen, for example, when the entry cost is large. If this is the case, the wages are close to b, unemployment rate is small, and the workers' income share is close to α. Consequently, the ratio of b to average productivity is close to α. As Ω becomes large, the ratio of b to average productivity becomes small.

[34] Although the vacancy yields are similar, the hires, separation, and vacancy rates are different. In particular, the separation rate at growing firms increases with employment growth rate in the worker selection model due to

Table 7—Calibrated Parameters of the Directed Search Model (*weekly model*)

Parameter		Target	Value
k:	Matching function, scale	$\theta q(\theta) = 0.139$ at $\theta = 0.566$ in equilibrium	4.306
ζ:	Matching elasticity	Elasticity of $\theta q(\theta) = 0.28$ at $\theta = 0.566$ in equilibrium	0.906
σ:	Dispersion of shocks	Hires rate, 3.4%	0.217
λ:	Exogenous separation	Separation rate at 0% employment growth	0.295%
c_s:	Selection cost, scale	Aggregate vacancy yield, 1.3	10.354
c_v:	Flow cost of vacancy	Vacancy yield at low turnover firms, 0.1	2.352×10^{-4}
A:	Aggregate productivity	Average firm size, 20	3.505
c_e:	Fixed entry cost	Free entry condition in (23)	5,430.445

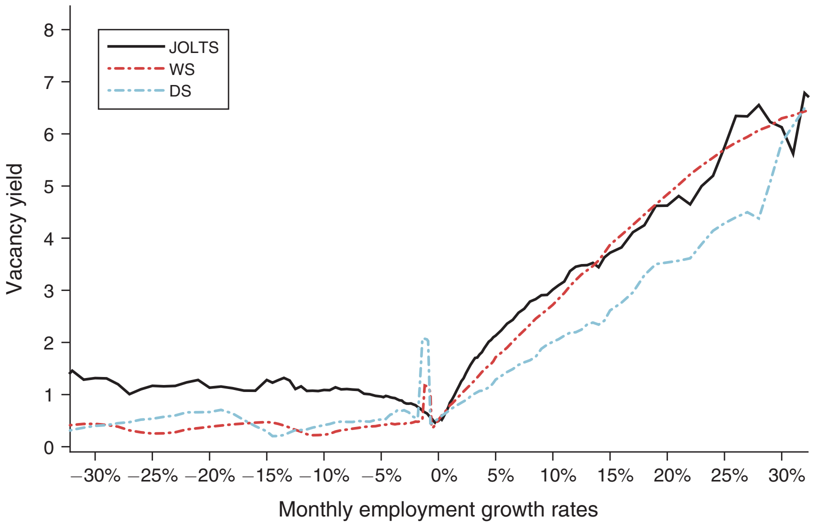

Figure 5. Vacancy Yield and Employment Growth: A Comparison across Worker Selection and Directed Search Models, and the Data

Notes: The data from the models are generated from the stationary distribution of the corresponding model with $z = 3$. WS and DS stand for worker selection and directed search models, respectively.

Source: JOLTS data is taken from DFH (2013).

The levels are also comparable to the data with the worker selection model being closer under benchmark calibration.[35] Moreover, both models display a negative relationship between firm size and vacancy yield as shown in Figure 6. However, the levels are much higher compared to the data for small-sized firms as in Section IIID. Finally, Table 8 shows the relationship between vacancy yield and monthly worker turnover rates in the directed search model. The results in Table 8 are comparable to the ones in Table 3. A positive relationship emerges from both the worker selection and directed search models, but they differ in the pattern of hires and separation rates. Both hires and separation rates monotonically increase with worker turnover

low hiring standard threshold set initially. A similar pattern is present in the data, but the difference is large as firms in the model learn the true productivity of a worker rather quickly. See the online Appendix for details.

[35] Increasing the value of z makes the relationship stronger in both models. See the online Appendix for details.

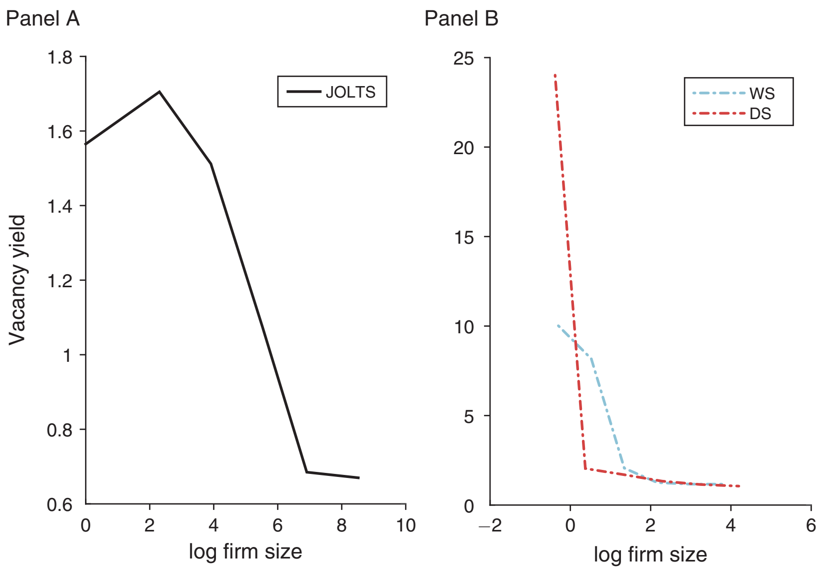

Figure 6. Vacancy Yield and Firm Size: A Comparison across Worker Selection and Directed Search Models, and the Data

Notes: The data from the models are generated from the stationary distribution of the corresponding model with $z = 3$. WS and DS stand for worker selection and directed search models, respectively.

Source: JOLTS data is taken from DFH (2013).

Table 8—Vacancy Yield and Monthly Worker Turnover in the Directed Search Model

	Directed search			
	Hires rate	Separation rate	Vacancy yield	Employment share (percent)
Low turnover	0.981	1.180	0.529	61.6
First quintile	1.290	1.180	0.557	7.7
Second quintile	1.693	1.180	0.620	7.7
Third quintile	3.114	1.180	0.836	7.7
Fourth quintile	7.670	2.058	1.505	7.7
Fifth quintile	20.621	20.953	4.016	7.7

Note: The data from the model are generated from the stationary distribution.

rate in JOLTS. A positive correlation between hires and separation rates is endogenously generated in the worker selection model because fast growing firms also lose workers with greater probability since they set a lower hiring standard threshold. In contrast, the separation rate in the directed search model is equal to the exogenous separation probability across the first three quintiles of worker turnover bins, even though the hires rate increases.

Overall, the worker selection and directed search models capture the relationship between employment growth and vacancy yield quite well, but they differ in terms of worker turnover behavior. The next section studies how these models differ regarding labor market policy.

TABLE 9—EFFECTS OF HIRING SUBSIDY ON EQUILIBRIUM

	Hiring subsidy (percent of b)					
	0.000	1.000	2.000	3.000	4.000	5.000
Unemployment rate (percent)						
Worker selection	5.759	5.749	5.739	5.729	5.720	5.710
Directed search	7.857	7.860	7.862	7.865	7.868	7.871
Job finding prob. (percent change)						
Worker selection	0.000	0.451	0.917	1.391	1.880	2.361
Directed search	0.000	0.054	0.107	0.162	0.216	0.271
Ω *(percent change)*						
Worker selection	0.000	0.007	0.015	0.022	0.029	0.036
Directed search	0.000	0.144	0.288	0.432	0.576	0.719
μ *(percent change)*						
Worker selection	0.000	0.004	0.007	0.011	0.014	0.017
Directed search	0.000	−0.007	−0.014	−0.021	−0.029	−0.036

Note: Percent changes are calculated relative to the equilibrium without hiring subsidy.

D. *Labor Market Policy in the Directed Search Model*

In the directed search model, I redefine the social planner's problem in a way that takes the government policies as given. I then calculate the equilibrium. I maintain the assumption that government finances the hiring subsidy through a lump-sum tax and distributes revenue from the firing tax to the workers in a lump-sum fashion. Despite the similarities in the patterns of vacancy yields, the worker selection and the directed search models differ with regard to labor market policy.

Effects of a Hiring Subsidy.—Table 9 reports equilibrium labor market outcomes from the calibrated models after incremental increases in hiring subsidy. As before, the hiring subsidy is measured as a fraction of the value of leisure, b, which is normalized to the same value in both models. While a hiring subsidy decreases the unemployment rate in the worker selection model, an incremental increase in the hiring subsidy equal to one percent of b increases the unemployment rate by 0.003 percentage points in the directed search model. Unlike the worker selection model, the effect of the hiring subsidy on worker's search value, Ω, is large enough to offset the direct incentive effect on vacancies. As a result, the unemployment rate goes up in equilibrium with the hiring subsidy.[36]

The cross-sectional effects of the hiring subsidy are also different across the two models. Figure 7 plots change in employment growth rates after a hiring subsidy against monthly employment growth rates. In the directed search model, the effect of the hiring subsidy is positive only for relatively stable firms and becomes negative for firms growing faster than 40 percent in a month. In contrast, the hiring subsidy has a positive impact on every growing firm in the worker selection model.

[36]The unemployment rate in the directed search model is higher than the other models, because the job finding probability, weighted by vacancy posting at each firm, is bigger in the directed search model.

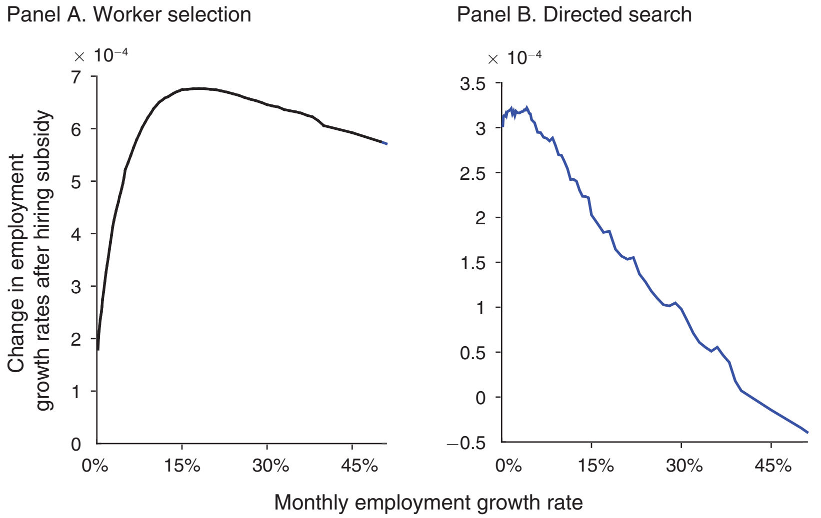

Figure 7. Change in Employment Growth after a Hiring Subsidy

Notes: The level of the hiring subsidy is set equal to three percent of the value of leisure in each model. The stationary equilibrium distribution without the hiring subsidy is used to weight the observations in each employment growth rate bin.

This asymmetric impact on employment growth rates in the directed search model stems from the fact that the hiring subsidy enters the social planner problem linearly. The social planner has an incentive to hire more workers with the subsidy, but he does so at relatively stable firms where the marginal cost of adjustment is low enough to make the hiring subsidy beneficial. Because there is a resource constraint on the labor force, he also shifts some of the unemployed workers from fast growing firms to relatively stable firms. This reallocation slows down the employment growth rate at fast growing firms.

Effects of a Firing Tax.—The results from incremental increases in the firing tax are presented in Table 10. Unlike the worker selection model, the unemployment rate decreases after the firing tax in the directed search model. Despite a smaller negative effect of the firing tax on job finding probabilities in the directed search model, the equilibrium search value, Ω, drops more than the worker selection model. This latter effect increases firm value and encourages firm entry. In equilibrium, the mass of firms rises in the directed model compared to the worker selection model.

Intuitively, for a given level of Ω, the social planner would keep some unproductive workers at very large firms after the firing tax. However, as these firms exit the market after an exogenous shock, the social planner would assign more of these unemployed workers to relatively smaller and fast growing firms. This allocation increases vacancy yields at these firms and the value of a potential entrant while depressing the search value of workers due to increased competition for a relatively small number of vacancies. This latter indirect effect turns out be big enough to lower unemployment rate in equilibrium.

TABLE 10—EFFECTS OF FIRING TAX ON EQUILIBRIUM

	Firing tax (percent of b)					
	0.000	5.000	10.000	15.000	20.000	25.000
Unemployment rate (percent)						
Worker selection	5.759	5.792	5.827	5.861	5.895	5.929
Directed search	7.857	7.836	7.817	7.797	7.778	7.760
Job finding prob. (percent change)						
Worker selection	0.000	−1.845	−3.572	−5.212	−6.773	−8.263
Directed search	0.000	−0.173	−0.337	−0.496	−0.647	−0.794
Ω *(percent change)*						
Worker selection	0.000	−0.019	−0.039	−0.059	−0.079	−0.099
Directed search	0.000	−0.325	−0.652	−0.976	−1.300	−1.624
μ *(percent change)*						
Worker selection	0.000	−0.002	−0.008	−0.019	−0.033	−0.050
Directed search	0.000	0.041	0.081	0.116	0.151	0.184

Note: Percent changes are calculated relative to the equilibrium without a firing tax.

TABLE 11—THE CROSS-SECTIONAL EFFECT OF A FIRING TAX ON WORKER TURNOVER IN THE DIRECTED SEARCH MODEL

	Directed search		
	Hires rate (percent change)	Separation rate (percent change)	Worker turnover (percent change)
Low turnover	−0.100	−0.000	−0.100
First quintile	−0.158	−0.000	−0.158
Second quintile	−0.153	−0.000	−0.153
Third quintile	−0.161	−0.001	−0.162
Fourth quintile	−0.158	−0.124	−0.282
Fifth quintile	−0.134	−0.396	−0.530

Note: Percent changes are calculated relative to the equilibrium without a firing tax.

The cross-sectional implications on worker turnover also differ between these models. Table 11 shows the change in the worker turnover rate in the directed search model after a firing tax equal to 15 percent of the flow value of leisure, b. The results are comparable to Table 6. Similar to the standard DMP model, there is no particular pattern in the change in worker turnover rates in the directed search model.

The worker selection and the directed search models can both capture the observed cross-sectional patterns in vacancy yields. However, they differ substantially with regard to policy analysis. There is mixed empirical evidence about the effects of labor market policies on unemployment rate. In particular, the employment protection laws, which can be thought of as the empirical counterpart of the firing tax, can have ambiguous effects on the unemployment rate depending on the data and the specification of the empirical model.[37] Given existing empirical evidence,

[37] There are a number of studies about the effects of employment protection laws on unemployment. See, for example, Nickell (1997), Blanchard and Portugal (2001), and Kahn (2010).

it is still an open question as to which model is better suited for examining labor market policy effects on unemployment.

VI. Conclusion

In the United States, vacancy yields in the cross section show systematic differences which are incompatible with the standard DMP model. The reason for the failure of the standard DMP model is due to the use of an aggregate matching function, which postulates that all of the firms fill vacancies at a common rate. I extend the standard DMP model to allow firms to selectively hire multiple workers among a pool of applicants to account for the firm-level behavior of vacancy yields. I motivate selection of workers by introducing match-specific quality shocks to the model, which determine the productivity of a worker at the hiring firm and can only be partially observed at the time of hiring. Firms recruit, screen, and interview applicants to make inferences about the match-quality of the potential hires. I model this selection mechanism by allowing firms to choose a minimum quality threshold below which applicants are not hired. Firms can fill vacancies at different rates by adjusting their hiring standards, and this mechanism generates cross-sectional variation in vacancy yields that are consistent with the data.

Using calibrated versions of these models, I show that accounting for these patterns has quantitatively important implications for labor market policy. While a hiring subsidy reduces the unemployment rate substantially in the worker selection model, the standard DMP model predicts that a hiring subsidy would reduce unemployment only slightly. At the firm level, the worker selection model implies that a hiring subsidy has a bigger impact on employment growth at fast growing firms, while the standard DMP model implies the opposite. Moreover, a firing tax increases the unemployment rate only in the worker selection model as firms hire workers more selectively. At the firm level, the firing tax has bigger impact on high worker turnover firms. Although there is not agreement on the effects of labor market policy on the level of unemployment, empirical evidence from cross-country studies supports the predictions of the worker selection model regarding the firm-level implications of labor market policy.

The worker selection model is an alternative to the directed search model studied in Kaas and Kircher (2015) to account for the cross-sectional patterns of the vacancy yield. Calibrated in a similar fashion, both models capture the cross-sectional patterns in vacancy yield well. These two models, however, differ with regard to labor market policy. While the unemployment rate decreases in the worker selection model after a hiring subsidy, the directed search model predicts that a hiring subsidy would increase the unemployment rate. Similarly, these models predict a change in the unemployment rate in opposite directions after a firing tax. Although both models capture the cross-sectional pattern of the vacancy yield equally well, the existing empirical evidence is not sufficient to determine which model is better suited for labor market policy.

Appendix

A. *Derivation of Wage Functions*

The marginal surplus of an incumbent and a newly hired worker are obtained from (16) as follows:

$$D_{\tilde{n}}(\cdot) = \alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)\tilde{n} - w^n(\cdot) - (w^p)'(\cdot)r$$
$$+ \beta(1-\delta)E_{\varepsilon'|\varepsilon}J'(\cdot);$$

$$D_{\tilde{r}}(\cdot) = g(p)\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)g(p)\tilde{n} - (w^p)'(\cdot)g(p)r - w^p(\cdot)$$
$$+ g(p)\beta(1-\delta)E_{\varepsilon'|\varepsilon}J'(\cdot),$$

where $n' = \tilde{n} + g(p)r$. Arguments of the functions are suppressed to keep the notation simple. The terms $(w^n)'(\cdot)$, $(w^p)'(\cdot)$, and $J'(\cdot)$ are derivatives of these functions with respect to n'. Similarly, surplus to an incumbent and a new worker are obtained from equations (12) through (15) as follows:

$$V^e(\cdot) - V^u = w^n(\cdot) - b - \Omega + \beta E_{\varepsilon'|\varepsilon}\big[\varphi^e(\cdot)\big(w^r(\cdot) + V^e(\cdot) - V^u\big)\big];$$

$$V^p(\cdot) - V^u = w^p(\cdot) - b - \Omega + \beta E_{\varepsilon'|\varepsilon}\big[\varphi^p(\cdot)\big(w^r(\cdot) + V^e(\cdot) - V^u\big)\big].$$

Note that recruitment wages are paid in the next period conditional on employment. From the Stole-Zwiebel bargaining rules, one obtains the following equations relating the marginal surplus to the workers' surplus:

$$\text{(A1)} \quad \phi\big(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)\tilde{n} - w^n(\cdot) - (w^p)'(\cdot)r + \beta(1-\delta)E_{\varepsilon'|\varepsilon}J'(\cdot)\big)$$
$$= (1-\phi)\big(w^n(\cdot) - b - \Omega + \beta E_{\varepsilon'|\varepsilon}[\varphi^e(\cdot)(w^r(\cdot) + V^e(\cdot) - V^u)]\big)$$

and

$$\text{(A2)} \quad \phi g(p)\bigg(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)\tilde{n} - (w^p)'(\cdot)r - \frac{w^p(\cdot)}{g(p)} + \beta(1-\delta)E_{\varepsilon'|\varepsilon}J'(\cdot)\bigg)$$
$$= (1-\phi)\big(w^p(\cdot) - b - \Omega + \beta E_{\varepsilon'|\varepsilon}\big[\varphi^p(\cdot)\big(w^r(\cdot) + V^e(\cdot) - V^u\big)\big]\big).$$

The next step is to determine how the continuation values affect wages. First, if a firm fires incumbent workers in the next period, then $J'(\cdot) = 0$ by the envelope condition. Similarly, the remaining workers get their outside option so that $V^e(\cdot) = V^u$. Since the firm is not hiring any workers, $w^r(\cdot) = 0$ as well. So, regardless of $\varphi^e(\cdot)$, continuation values drop out from the Stole-Zwiebel equations. When the firm is neither hiring nor firing, $J'(\cdot) = (1-\lambda)D_{\tilde{n}}$ from the definition of the marginal surplus of an incumbent worker above. Further, $w^r(\cdot) = 0$, $\varphi^e(\cdot) = (1-\lambda)(1-\delta)$, and $\varphi^p(\cdot) = g(p)(1-\lambda)(1-\delta)$ since the firm is neither hiring nor firing. Thus, continuation values for both the incumbent and new workers satisfy the bargaining rules and cancel each other out, because the firm and the incumbent worker share the surplus according to the same rule in the next period. Overall, if the firm is not hiring, the following system of differential equations summarizing the wages for incumbent and new workers is obtained:

$$\phi\big(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)\tilde{n} - (w^p)'(\cdot)r\big) + (1-\phi)(b+\Omega) - w^n(\cdot) = 0;$$

$$g(p)\phi\big(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(\cdot)\tilde{n} - (w^p)'(\cdot)r\big) + (1-\phi)(b+\Omega) - w^p(\cdot) = 0.$$

Equations in (19) and (20) solve the system of differential equations above. I impose a boundary condition such that total wage payments goes to zero so that the constant of integration is equal to zero.

If the firm is hiring, the envelope condition implies

$$J'(\cdot) = (1-\lambda)\left\{D_{\tilde{n}} - (w^r)'(\cdot)\tilde{n} - w^r(\cdot) + (z-1)\frac{c_s}{z}\left(\frac{\gamma\Delta}{(1-p^\gamma)(1+\tilde{n})}\right)^z\right\},$$

where $(w^r)'(\cdot)$ is the derivative of the recruitment wage function with respect to $\tilde{n}$. The last term in the equation above is the cost savings of the marginal worker to the firm during the worker selection process. As with production, the firm and the workers share this surplus according to their bargaining powers. The bargaining protocol is such that the firm and the workers agree on a wage payment for recruiting services to be paid in the next period contingent on the firm's recruitment policies. This bargaining protocol avoids the time inconsistency problem as it does not assume any particular employment decision in the next period, which would potentially affect the firm's employment decision in the current period. Taking the recruitment wage function as given, the firm optimizes over p and Δ in the next period.

Plugging the envelope condition above back into equations (A1) and (A2) yields the following differential equation for recruitment wages in addition to the production wages:

$$\phi\left((z-1)\frac{c_s}{z}\left(\frac{\gamma\Delta}{(1-p^\gamma)(1+\tilde{n})}\right)^z - (w^r)'(\cdot)\tilde{n}\right) - w^r(\cdot) = 0.$$

The solution to the differential equation above is

$$w^r(\cdot) = (z-1)\frac{c_s}{z}\left(\frac{\gamma\Delta}{1-p^\gamma}\right)^z \int_0^1 s^{\frac{1-\phi}{\phi}}\left(\frac{1}{1+ns}\right)^z ds,$$

after setting the constant of integration equal to zero. Moreover, changing $1/(1+\tilde{n}s)$ in the integral above with $(1-t)$ such that $t \in [0, \tilde{n}/(1+\tilde{n})]$ yields the wage equation in (21).

B. *Properties of the Labor Adjustment Cost*

For brevity, let $\Delta\Upsilon(p,\Delta,n)$ be the objective function of the cost minimization problem in (25) with

$$\Upsilon(p,\Delta,n) \;=\; \left((1-p)(b+\Omega)+\frac{c_v}{q}\right)h(p)+\frac{c_s}{z}\Delta^{z-1}h^z(p)\Psi((1-\lambda)n),$$

where $h(p) = \gamma/(1-p^{\gamma})$. Note that $\Upsilon_{p\Delta} > 0$, $\Upsilon_{pn} < 0$, and $\Upsilon_{\Delta n} = \Upsilon_{n\Delta} < 0$ from the properties of $h(p)$ and $\Psi((1-\lambda)n)$. By the first-order condition (FOC) and the second-order condition (SOC), the following relationships hold:

$$\Delta\Upsilon_p(p,\Delta,n) \;=\; 0;$$

$$\Delta\Upsilon_{pp}(p,\Delta,n) \;>\; 0.$$

Totally differentiating the FOC with respect to Δ implies

$$p_\Delta \;=\; -\frac{\Upsilon_{p\Delta}}{\Upsilon_{pp}} \;>\; 0.$$

The inequality follows from the SOC. Similarly, totally differentiating with respect to n yields

$$p_n \;=\; -\frac{\Upsilon_{pn}}{\Upsilon_{pp}} \;<\; 0.$$

Further, the cost function satisfies

$$C(\Delta,n) \;=\; \Delta\Upsilon(p(\Delta,n),\Delta,n).$$

Taking the derivative with respect to Δ gives

$$C_\Delta \;=\; \Delta(\Upsilon_p p_\Delta + \Upsilon_\Delta) \;>\; 0,$$

since the first term in parentheses is equal to zero by FOC. Similarly, taking the derivative with respect to n gives

$$C_n \;=\; \Delta(\Upsilon_p p_n + \Upsilon_n) \;<\; 0.$$

In other words, the cost function is increasing in Δ and decreasing in n. The strict convexity of $C(\Delta,n)$ in Δ and n follows from the positive definiteness of the Hessian matrix. To see that, note that the following relationships hold for the cross partial derivatives:

$$C_{\Delta\Delta} \;=\; \Upsilon_\Delta + \Delta(\Upsilon_{p\Delta}p_\Delta + \Upsilon_{\Delta\Delta}) \;>\; 0$$

$$C_{nn} \;=\; \Upsilon_{pn}p_n + \Upsilon_{nn} \;>\; 0$$

$$C_{n\Delta} = \Upsilon_{pp} p_n p_\Delta + \Upsilon_{p\Delta} p_n + \Upsilon_{n\Delta} < 0$$

$$C_{\Delta n} = \Upsilon_{pp} p_\Delta p_n + \Upsilon_{pn} p_\Delta + \Upsilon_{\Delta n} < 0.$$

The first inequality uses the fact that $\Delta \Upsilon_{\Delta\Delta} = (z-2)\Upsilon_\Delta$ and $z > 1$. It follows that $C_{\Delta\Delta} C_{nn} - C_{n\Delta} C_{\Delta n} > 0$, which is a sufficient condition for strict convexity of $C(\Delta, n)$ in Δ and n.

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