Essays on Macroeconomics of Labor Markets

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Abstract

This dissertation explores job matching process in the labor market and its implications for job match quality. The first chapter develops a theory of a firm's recruitment activities where the firm optimally chooses the quality of its workforce through worker selection, and studies its policy implications. The second chapter studies the cyclical behavior of match quality using a micro-level dataset.

In the first chapter, I incorporate worker selection into a random matching model with multi-worker firms. Unlike the standard random matching model, the worker selection model is compatible with establishment-level behavior of the hires-to-vacancy ratio, which (i) steeply rises with the employment growth rate, (ii) falls with establishment size, and (iii) rises with worker turnover rate. I calibrate the worker selection model to match the salient features of the U.S. labor market and compare it with the standard matching model without worker selection. I show that accounting for these patterns has both aggregate and firm-level implications for labor market policies. A hiring subsidy reduces aggregate unemployment substantially in the worker selection model, whereas the reduction in aggregate unemployment is very small in the standard model. Similarly, a firing tax reduces aggregate unemployment more in the worker selection model. At the firm level, labor market policy changes have a relatively bigger impact on fast growing and high worker turnover firms in the worker selection model. In contrast, the standard model implies that slowly growing and low worker turnover firms are affected relatively more by labor market policy changes. The existing empirical evidence supports the predictions of the worker selection model about the firm-level effects of labor market policies.

In the second chapter, I study the cyclical behavior of employment duration, a proxy for match quality. Models with on-the-job search predict that jobs created during a recession have shorter spells, because workers are more likely to accept low-quality jobs during a recession. In contrast, models with endogenous separation predict that jobs created during a recession endure longer, because firms contact a larger group of applicants and are able to hire high-quality workers. I test these competing predictions using data from the National Longitudinal Survey of Youth 1979 cohort. I estimate a proportional hazard model under the assumption that job terminations due to different reasons are competing risks. My results support the predictions of both models with on-the-job search and endogenous separation. A higher unemployment rate at the start of an employment relationship increases the probability that the worker quits to take or look for another job, but it decreases the probability the firm fires the worker. The net effect of these opposing forces on the overall duration of the employment is negative, but small, implying that match quality is weakly pro-cyclical. Furthermore, an increase in the current unemployment rate reduces the probability that the job spell ends by the worker's quit decision, but it increases the probability that the firm fires the worker. These findings are consistent with pro-cyclical quits and counter-cyclical firings.

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Chapter 1

Worker Selection, Hiring and Vacancies

1.1 Introduction

The impact of the Great Recession between 2007 and 2009 on the U.S. labor market was severe. The unemployment rate sharply increased at the onset of the recession, reaching as high as 10%, and still remains well above its pre-recession level. The gradual response of the unemployment rate has led to a debate about how to implement labor market policies to combat high U.S. unemployment rate. Currently, the most popular approach to labor market analysis in macroeconomic context is to use the framework of the Diamond-Mortensen-Pissarides (DMP) random matching model. While the standard DMP model is successful in many dimensions, it implies that the hires-to-vacancy ratio is constant across establishments. This implication is incompatible with the data. In the U.S., the hires-to-vacancy ratio at the establishment level (i) rises steeply with employment growth rate, (ii) falls with employer size, and (iii) rises with worker turnover rate. I extend the standard DMP model to resolve this discrepancy between the data and the theory and show that accounting for these patterns has important consequences for labor market policy analysis.

I incorporate worker selection into a random matching model where multi-worker firms hire among a pool of applicants. In response to idiosyncratic productivity shocks, firms post vacancies and are randomly matched to unemployed workers according to an aggregate matching function. Unlike the standard DMP model, not all of the matches are hired. Instead, firms go through a costly evaluation process of applicants before making a hiring decision. I model this worker selection process by allowing firms to partially observe the match quality of the applicants, set a minimum hiring standard, and hire only the applicants who satisfy this threshold. As firms select workers differently, the hires-to-vacancy ratio varies by establishment. The calibrated model accounts for all three patterns of the hires-to-vacancy ratio observed in the data.

Accounting for these patterns of the hires-to-vacancy ratio has both aggregate and firm-level policy implications. For example, when firms are subsidized for hiring new workers, the decline in unemployment rate is about seven times larger in the worker selection model. At the firm level, a hiring subsidy shifts the employment growth distribution to the right in both models, but most of this shift occurs in the right tail of the employment growth distribution in the worker selection model. Moreover, the worker selection model implies that firms that have initially high worker turnover rates experience a relatively larger decline in the worker turnover rates after a firing tax. In contrast, the standard model predicts that the worker turnover rate decreases more at firms with initially lower worker turnover rates. The firm-level implications of the worker selection model are consistent with the empirical evidence from the literature.

The cross sectional patterns of the hiring-vacancy ratio are documented in Davis, Faberman and Haltiwanger (2012), henceforth DFH, where the authors use establishment-level data from the Job Openings and Labor Turnover Survey (JOLTS).

Building upon the cross sectional patterns of the hires-to-vacancy ratio, they argue that firms heavily rely on other instruments in addition to vacancies as they hire new workers. This paper adds worker selection as a new instrument for recruiting new workers. Such an extension 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 applicants. The standard deviation of the time spent per hire for evaluating applicants is 17.16 hours. These numbers imply that per-hire cost of recruitment is on average 4.3% of the quarterly wage of a newly hired worker and varies across firms.[1] I interpret this variation in firms' recruitment costs as evidence for worker selection introduced in this paper.

I motivate the idea of worker selection by introducing worker heterogeneity in the form of unobserved match-specific quality shocks. Firms first choose the number of vacancies and randomly matched with unemployed workers. Then, each vacancy-worker pair draws a match-specific quality shock which determines the productivity of a worker at the hiring firm. When increasing employment, firms now face a trade-off between the quantity and the quality of workers. Given a fixed number of vacancies, a firm would add fewer workers if it wanted to hire high quality workers. The decision for the hiring standard depends on how the quality and quantity margins interact.

Worker selection explains how the model generates the three patterns of the hires-to-vacancy ratio documented above. 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 hires-to-vacancy ratio. Second, as the firm size increases, the employment growth rate decreases and vacancies are filled at a slower rate. This mechanism generates a

[1]See Silva and Toledo (2009) and Hagedorn and Manovskii (2008).

negative relationship between the firm size and the hires-to-vacancy ratio. Finally, a firm that has initially set a lower hiring standard lays off a larger fraction of the current recruits in the near future, which implies a positive relationship between the hires-to-vacancy ratio and the worker turnover rate. The calibrated model accounts for all of the three patterns of the hires-to-vacancy ratio at the same time.

The model in this paper links existing models of worker selection to those with multi-worker firms to account for the cross-sectional patterns in the hires-to-vacancy ratio. 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 either have a vacant position or are employed with only one worker. Mortensen and Pissarides (2001), Pries and Rogerson (2005), Villena-Roldan (2008) and Merkl and van Rens (2013) are examples of worker selection models of this kind.[2] On the other hand, extensions to the standard DMP model assume workers are identical and, therefore, imply that firms indiscriminately hire all the workers they match. Then, for any firm, the job filling rate is determined by the aggregate matching function and is independent of individual firm's characteristics. Consequently, there is no firm-level variation in the hires-to-vacancy ratio in these models. Examples of papers with multi-worker firms are relatively new in the literature and include Cahuc, Marque and Wasmer (2008), Elsby and Michaels (2010), Acemoglu and Hawkins (2013) and Fujita and Nakajima (2013). One exception is the paper by Helpman, Redding and Itskhoki (2012), which studies the worker selection with multi-worker firms. However, their setup is static and does not account for the regularities in JOLTS studied in this paper. I extend their framework to a dynamic setting with some modifications.

When matching is not random, the hires-to-vacancy ratio may vary at firm level even without worker heterogeneity. For example, Kaas and Kircher (2011) build a directed search model, where firms attract workers by posting wages. Posting wages

[2] Villena-Roldan (2008) differs from the others by allowing firms to meet multiple workers. However, firms are still restricted to hire at most one worker.

adds another competitive element into the labor market: firms that want to grow faster post higher wages in the market, attract more workers and fill vacancies at a higher rate. This generates a positive relationship between the hires-to-vacancy ratio and the employment growth rate. The worker selection and directed search models are complementary to each other in the way they model firm's search activities. In the directed search model, firms' search activities are at the extensive margin, i.e. firms can affect the total number of applicants by posting different wages. In contrast, firms in the worker selection model search at the intensive margin, i.e. firms can search for better workers within a pool of applicants.

Another notable difference between the worker selection and directed search models is that worker selection model can account for the cross-sectional behavior of the worker turnover rate. In the directed search model, faster growing firms hire more workers and hence experience a higher worker turnover rate. However, all of the growing firms separate from workers at a constant rate by assumption.[3] Therefore, the relationship of the hires-to-vacancy ratio to the worker turnover rate is only a restatement of its relationship to the employment growth rate. On the contrary, the separation rate is not constant in the worker selection model. The worker selection model asserts that firms that fill vacancies at a faster rate experience a higher separation rate, because they hire proportionally more low-quality workers. Since the job filling rate is positively related to employment growth rate, the worker selection model predicts that the separation rate steadily rises in the cross section moving from stable to growing firms. According to the findings of DFH, separation rate increases from 1% to 5% as employment growth rate rises from 0% to 25% in the cross section, which supports the prediction of the worker selection model.[4]

[3]To be precise, the authors consider only the equilibrium in which wage contracts specify a constant separation rate for all of the workers within a firm.

[4]Matching the establishment-level behavior of worker turnover is novel to the worker selection model introduced in this paper. This feature of the model distinguishes it not only from the directed search model, but also from other models with establishment-level variation in the hires-to-vacancy ratio that assume a constant separation rate in expanding firms. See DFH for a discussion of other

In the policy analysis section, I use the calibrated model to examine the aggregate and firm-level effects of a hiring subsidy and a firing tax. A hiring subsidy is a per-hire payment made to firms that hire new workers. A firing tax is a payment collected from firms for each worker they fire. To highlight the impact of worker selection, I compare the results obtained from the worker selection model to those obtained from the standard DMP model with homogeneous workers calibrated to match the same targeted moments.

A hiring subsidy and a firing tax affect the aggregate labor market outcomes differently with and without worker selection. For example, if employers are paid half of the average wage of a newly hired worker, the unemployment rate in the worker selection model falls by half of a percentage point. In contrast, the standard DMP model is not very optimistic about the effects of the hiring subsidy on the unemployment rate. The decline in unemployment rate in response to an equivalent subsidy in the standard DMP model is one-seventh the size of the decline in the worker selection model. While a firing tax increases the aggregate unemployment rate only slightly in the standard DMP model, the effect in the worker selection model is about ten times larger.

The worker selection and the standard DMP models also produce different results about the aggregate hires-to-vacancy ratio. In the standard DMP model, changes in the aggregate hires-to-vacancy ratio in response to policy changes are unambiguous, because the direction of the change is solely determined by the aggregate matching function. However, in the worker selection model, firms also respond to the policy changes by adjusting their hiring standards, which changes the aggregate hires-to-vacancy ratio in the opposite direction. The net effect on the aggregate hires-to-vacancy ratio depends on which of the quality and quantity margins dominates the effect of the other. For example, in response to a hiring subsidy the aggregate hires-

models that can potentially account for the behavior of the hires-to-vacancy ratio.

to-vacancy ratio unambiguously falls in the standard DMP model due to increased number of total vacancies. In the worker selection model, a hiring subsidy also makes firms less picky about potential hires, which tends to increase the aggregate hires-to-vacancy ratio. When the hiring subsidy is small, the quality margin dominates the quantity margin and the aggregate hires-to-vacancy ratio rises. As the size of the hiring subsidy increases, the aggregate hires-to-vacancy ratio starts to decline as the quantity margin dominates the quality margin. Similarly, a firing tax increases the aggregate hires-to-vacancy ratio in the standard DMP model due to decreased number of total vacancies. In the worker selection model, a firing tax also induces firms to be more picky about the workers as they have to now pay an additional cost for hiring a low-productive worker. I find that the aggregate hires-to-vacancy ratio declines with a firing tax.

Both models produce similar results regarding the effect of these policies on aggregate output net of labor adjustment costs. A firing tax always reduces net output, because too few firms produce in equilibrium due to increased labor adjustment costs. On the other hand, a hiring subsidy can increase net output. However, if the hiring subsidy becomes too large, firms start replacing existing workers with new workers and experience very large worker turnover rates. Further increases in the hiring subsidy eventually reduces net output, because firms incur large adjustment costs, but contribute only a little to the aggregate output.

Earlier papers that used matching models to analyze labor market policies are silent about the effects of labor market policies on firms with different characteristics. Using a multi-worker setting in this paper, I provide new insights about the firm-level effects of labor market policies. Contrary to the predictions of the standard DMP model, worker selection makes fast growing and large worker turnover firms respond relatively more to changes in labor market policies.

A hiring subsidy creates incentives for hiring new workers and shifts the employment growth distribution to the right in both models. However, a hiring subsidy in the standard DMP model has a relatively bigger impact on employment at slowly growing firms, while the opposite is true in the worker selection model.[5] Therefore, a hiring subsidy shifts the employment growth distribution out in the right tail in the worker selection model. The implication of the worker selection model is consistent with the findings of Perloff and Wachter (1979). They argue that The New Jobs Tax Credit of the stimulus package in 1977 shifted the employment growth distribution of the firms who knew about the subsidy program to the right relative to those who did not know about the program. They further argue that most of this shift occurred in the right tail of the distribution.

In response to a firing tax, the worker selection model predicts that worker turnover rates falls relatively more at firms with initially high worker turnover rates. Conversely, the standard DMP model predicts that the effect of a firing tax on the worker turnover rate is larger at firms with initially lower worker turnover rates. In a cross-country comparison, Haltiwanger, Scarpetta and Schweiger (2010) show that firms in the industries and size classes that require more often employment changes are affected relatively more from hiring and firing restrictions. This evidence is consistent with the predictions of the worker selection model about the effects of a firing tax.

The paper is organized as follows. Section 1.2 describes the worker selection model and Section 1.3 characterizes the equilibrium. I calibrate the model in Section 1.4 and discuss my findings in Section 1.5. Section 1.6 presents the results from the counterfactual policy experiments with a hiring subsidy and a firing tax. The last section concludes.

[5]Some low productive firms even grow at a slower rate after a hiring subsidy, because hiring is more costly due to increased number of aggregate vacancies.

1.2 The Worker Selection Model

1.2.1 Overview

The economy is populated by risk-neutral workers, the measure of which is normalized to 1, and a large number of risk-neutral entrepreneurs. Time is discrete and the discount factor for both the workers and the entrepreneurs is β. Each entrepreneur runs a firm which produces a single good. Hereafter, I refer to firms and entrepreneurs interchangeably. There are no aggregate shocks and the focus is on the steady state equilibrium.

In any period, a worker is either employed or unemployed. An employed worker receives a wage income, but there is no on-the-job-search. An unemployed worker searches for a job; if he cannot find a job, he is engaged in home production and receives b. 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 by 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. Productivity shocks are large enough to ensure that none of the firms optimally chooses to become inactive at any point in time.

1.2.2 Recruiting New Workers

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.

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

$$M(U,V) = (U^{-\zeta} + V^{-\zeta})^{-\frac{1}{\zeta}}. \tag{1.1}$$

U and V are total number of unemployed workers and vacancies, respectively. $\zeta > 0$ 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. $q(\theta)$ is derived from the matching function as follows:

$$q(\theta) = \frac{M(U,V)}{V} = (1+\theta^{\zeta})^{-\frac{1}{\zeta}}. \tag{1.2}$$

Similarly, $M(U,V)/U = \theta q(\theta)$ is the probability a worker meets a vacancy.[6] In the sequel, I drop θ and simply write q for notational purposes.

In the second stage, each worker matched with a firm draws an unobserved match-specific quality shock, x_i, from a uniform distribution between 0 and 1. The match-specific quality shock determines whether the worker will be productive or unproductive at the hiring firm conditional on being hired. Specifically, 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 engage in a costly process where it evaluates the applicants and infer about their

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

true match-specific quality. I model this process by allowing firms to choose a hiring standard, $p \in [0,1]$, and hire only the worker that satisfy this minimum threshold. Firms observe the match-specific quality of an applicant up to p. If an applicant's match-specific quality is greater than p, it is still unobserved, but known to be greater than p.

Total selection costs have the following quadratic form:

$$C_s(p, qv) = \frac{c_s}{2} \exp\left(\frac{c_p}{2} p^2\right) (qv)^2. \tag{1.3}$$

This functional form assumes that worker selection technology exhibits decreasing returns to scale in the number of applicants captured by the quadratic term: given p, the marginal cost of selection is increasing in the number of applicants. It also assumes that this marginal cost is increasing in the hiring standard set by the firm. The interpretation is that worker selection is time-consuming and as the hiring standard goes up the interviewer spends more time to distinguish high quality workers from low quality ones. The exponential form in p satisfies three conditions. First, it is greater than zero at $p = 0$, which prevents firms to choose p close to zero, post enormous amount of vacancies and converge to their long-run employment level in a short period of time. Second, the derivative of this function with respective p is zero at $p = 0$. This property of the exponential function guarantees an interior solution for p. Finally, it is log-convex, which guarantees that the dynamic programming problem of a hiring firm is concave.

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 existing workers and the 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 for his outside option, i.e. 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.[7] The firm identifies those workers during the worker selection process.

1.2.3 Firms' Problem

Since firms are subject to idiosyncratic productivity shocks, 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 existing worker is more productive than any potential new worker and adjustment is costly. Moreover, the problem of a hiring firm includes an additional control variable, p. Therefore, I write down the dynamic problem of a hiring and firing firm separately. I allow for a corner solution for the firing firm when it neither hires nor fires any worker.

Let $\Pi^h(n, \varepsilon)$ and $\Pi^f(n, \varepsilon)$ denote the value of a hiring and firing firm, respectively. Let also $\Pi(n, \varepsilon) = \max(\Pi^h(n, \varepsilon), \Pi^f(n, \varepsilon))$. Given the timing of events in a period, total number of hires at a firm posting v vacancies are equal to $qv(1-p)$, but only $qv(1-p^\gamma)/\gamma$ will be productive and retained by the firm next period. Hence, employment at a hiring firm evolves over time according to the following equation:

$$n' = (1-\lambda)n + qv(1-p^\gamma)/\gamma. \tag{1.4}$$

[7] Some of the newly hired workers will have negative value to the firm. However, due to costly selection, the firm does not attempt to find those workers in the applicant pool.

I assume that incumbent workers lose their jobs at the beginning of the period with probability λ and can search for a new job in the current period.

An active firm has access to a Cobb-Douglas production function which depends on the number of *productive* workers employed in the current period: $A\varepsilon n'^{\alpha}$. Note that the production function accounts for the fact that new recruits are employed in the current period.

Let $w^n(n', \varepsilon)$ and $w^p(n', \varepsilon, p)$ denote wages paid to existing workers and new recruits, respectively. I conjecture and verify later that both wages depend on the total number of productive workers and firm productivity. In addition, the hiring standard affects the wage payment to the new workers as it determines the expected productivity of a randomly selected new hire. This specification is later verified in the wage bargaining section.

The following summarizes the dynamic programing problem of a hiring firm:

$$\begin{aligned}\Pi^h(n, \varepsilon) = \max_{n', p \in [0,1], v \geq 0} \quad & -c_v v - \frac{c_s}{2} \exp\left(\frac{c_p}{2} p^2\right) (qv)^2 + A\varepsilon n'^{\alpha} \\ & -qv(1-p)w^p(n', \varepsilon, p) - (1-\lambda)nw^n(n', \varepsilon) \\ & +\beta(1-\delta)E_{\varepsilon'|\varepsilon}[\Pi(n', \varepsilon')], \end{aligned} \tag{1.5}$$

subject to (1.4).

Let d denote total firings. Then, employment at a firing firm evolves according to:

$$n' = (1-\lambda)n - d. \tag{1.6}$$

The dynamic programing problem of a firing firm is as follows:

$$\Pi^f(n, \varepsilon) = \max_{n', d \geq 0} \quad A\varepsilon n'^{\alpha} - n'w^n(n', \varepsilon) + \beta(1-\delta)E_{\varepsilon'|\varepsilon}[\Pi(n', \varepsilon')], \tag{1.7}$$

subject to (1.6).

1.2.4 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. I describe how they are related to each other further below. The value function of an existing worker employed at a firm with n workers and productivity ε is:

$$V^n(n,\varepsilon) = w^n(n',\varepsilon) + \beta((1-\delta)((1-\lambda)E_{\varepsilon'|\varepsilon}[V^n(n',\varepsilon')] + \lambda\tilde{V}^u) + \delta\tilde{V}^u), \quad (1.8)$$

where n' is the firm's optimal decision for employment and depends on current size, n, and productivity, ε, of the firm. The worker takes n' as given. The interpretation is standard: an existing worker receives $w^n(n',\varepsilon)$ this period. With probability $(1-\delta)(1-\lambda)$, he is employed at the same firm and enjoys the expected value of employment. Otherwise, he receives $\tilde{V}^u$. Note that the expected value of employment is over the productivity shocks and accounts for the change in firm's employment.

Let $g(p) = \frac{1-p^\gamma}{\gamma(1-p)}$ be the probability that a randomly selected new hire is productive. Then, the value function of a newly hired worker is:

$$\begin{aligned} V^p(n,\varepsilon) = \quad & w^p(n',\varepsilon) + \beta(g(p)((1-\delta)((1-\lambda)E_{\varepsilon'|\varepsilon}[V^n(n',\varepsilon')] + \lambda V^u) \quad (1.9) \\ & +\delta V^u) + (1-g(p))V^u). \end{aligned}$$

Note that the continuation value of a newly hired worker depends on the hiring standard set by the firm this period, p, and is taken as given by the worker. The functional equation above is otherwise same with (1.8).[8] Finally, V^u and $\tilde{V}^u$ are related according to:

$$V^u = \quad b + \beta\tilde{V}^u, \quad (1.10)$$

[8]In fact, (1.8) can be thought as the limiting case of (1.9) as $p \to 1$.

and

$$\tilde{V}^u = \theta q \int_{\mathscr{E},\mathscr{N}} \frac{g_v(n,\varepsilon)\left((1-g_p(n,\varepsilon))V^p(n,\varepsilon)+g_p(n,\varepsilon)V^u\right)}{\int_{\mathscr{E},\mathscr{N}} g_v(\tilde{n},\tilde{\varepsilon})d\Gamma(\tilde{n},\tilde{\varepsilon})} d\Gamma(n,\varepsilon) + (1-\theta q)V^u, \tag{1.11}$$

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 $\mathscr{N}$ and $\mathscr{E}$ 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.

1.2.5 Wage Bargaining

To determine wages, I adopt the bargaining solution in Stole and Zwiebel (1996). They describe a dynamic game where the firm negotiates the wage payment in pair-wise bargaining sessions with its employees in an arbitrary order. If an agreement is reached between the worker and the firm during a bargaining session, the firm continues bargaining with the next worker. Otherwise, the worker leaves the firm and the bargaining process resumes with *all* the remaining workers. Each bargaining session is the limiting case of the offer-counteroffer game between the firm and the worker described in Binmore et al. (1986). In this offer-counteroffer bargaining game, each time the worker rejects an offer, there is an exogenous probability, $(1-\phi)h$, that the negotiations break down. Similarly, each time the firm rejects an offer, the negotiations break down with probability ϕh. As $h \to 0$, they split the joint surplus net of outside options such that the worker receives ϕ fraction of it. If there is only one worker, the solution is the Nash bargaining solution with ϕ being the workers' bargaining power. For the firm, the surplus is continuing the bargaining process with one less worker. When labor is continuous, the solution to the wage function implies a split of the *marginal* surplus and outside option of the worker according to bargaining powers.

The bargaining game in Stole and Zwiebel (1996) assumes that workers are the same with respect to their productivities. In the worker selection model, existing and new workers differ in size and productivity and are potentially paid different wages. The firm negotiates with $(1-\lambda)n$ existing workers and $qv(1-p)$ potential workers. The productivity of existing workers is 1 and the productivity of selected applicants is $g(p)$. Let me define *total* surplus to the firm at the bargaining stage as $D(\tilde{n}, r, p, \varepsilon)$, where $\tilde{n} = (1-\lambda)n$ and $r = qv(1-p)$. At the bargaining stage, vacancy posting and worker selection costs are sunk. Hence, from the firms problem, one obtains total surplus as follows:

$$
\begin{aligned}
D(\tilde{n}, r, p, \varepsilon) = \quad & A\varepsilon(\tilde{n} + g(p)r)^{\alpha} - w^{n}(\tilde{n} + g(p)r, \varepsilon)\tilde{n} \\
& -w^{p}(\tilde{n} + g(p)r, \varepsilon)r + \beta(1-\delta)E_{\varepsilon'|\varepsilon}[\Pi(\tilde{n} + g(p)r, \varepsilon)].
\end{aligned}
\tag{1.12}
$$

Note that n' is equal to $\tilde{n} + g(p)r$. The marginal surplus to the firm from an existing worker is the partial derivative of the total surplus with respect to $\tilde{n}$, $D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon)$. The marginal surplus to the firm from a potential worker is similarly given by $D_r(\tilde{n}, r, p, \varepsilon)$. Then, the solution to the bargaining problem satisfies the following conditions:

$$
\phi D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon) = (1-\phi)(V^{n}(n', \varepsilon) - V^{u}), \tag{1.13}
$$

and

$$\phi D_{\tilde{r}}(\tilde{n}, r, p, \varepsilon) = (1-\phi)(V^p(n', \varepsilon) - V^u). \tag{1.14}$$

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

$$w^n(n', \varepsilon) = \frac{\alpha\phi}{1-\phi+\alpha\phi} A\varepsilon n'^{\alpha-1} + (1-\phi)\Omega, \tag{1.15}$$

and

$$w^p(n', \varepsilon, p) = g(p)\frac{\alpha\phi}{1-\phi+\alpha\phi} A\varepsilon n'^{\alpha-1} + (1-\phi)\Omega, \tag{1.16}$$

where Ω is:

$$\Omega = (1-\beta)V^u - (\lambda + \delta - \lambda\delta)((1-\beta)V^u - b). \tag{1.17}$$

The derivations are available in Appendix A.1. The wage functions are similar to ones obtained in other papers featuring random matching with multi-worker firms, e.g., Acemoglu and Hawkins (2013), Elsby and Michaels (2012) and Cahuc, Marque and Wasmer (2008). The solution for the wage equation in Stole and Zwiebel (1996) implies sharing of the worker's outside option and the weighted average of infra-marginal products of labor. The solution above preserves this property except that it now includes additional terms to the worker's outside option due to timing assumption. 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 $V^n(n', \varepsilon) = V^u$. This is implied by equation (1.13). Finally, as I conjectured, both wage functions depend only on the total number of productive workers and not separately on the number of productive and unproductive workers. This result is not surprising given that both groups enter the production function linearly.

1.2.6 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:

$$\Gamma(N,E) = \int_{N,E}\left[\int_{\mathscr{N},\mathscr{E}} f(\varepsilon'|\varepsilon)\mathcal{I}(n' = g_{n'}(n,\varepsilon))d\Gamma(n,\varepsilon)\right]dn'd\varepsilon'), \tag{1.18}$$

where $N \subset \mathscr{N}$ and $E \subset \mathscr{E}$, $g_{n'}(n,\varepsilon)$ 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 which is 1 if the condition is satisfied and 0 otherwise.

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

$$E_\varepsilon(\Pi(0,\varepsilon)) = c_e. \tag{1.19}$$

A formal definition of recursive stationary equilibrium is available in Appendix A.2. Two equilibrium outcomes, the measure of firms and the total number of unemployed workers seeking for jobs, are not specified in the definition of the recursive competitive equilibrium and 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:

$$V = \mu\int_{\mathscr{N},\mathscr{E}} g_v(n,\varepsilon)d\Gamma(n,\varepsilon),$$
$$U = 1-(1-\lambda-\delta)\mu\int_{\mathscr{N},\mathscr{E}} nd\Gamma(n,\varepsilon) + \mu\int_{\mathscr{N},\mathscr{E}} g_f(n,\varepsilon)d\Gamma(n,\varepsilon),$$

where $g_f(n,\varepsilon)$ is the policy function from the firing firm's optimization problem. Recall market tightness is $\theta = V/U$. Using the equilibrium value of θ and the calculated decision rule for firings, one can obtain the equilibrium value of μ. Plugging μ in the second equation above, equilibrium unemployment is determined.

1.3 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:

$$\begin{aligned}\Pi^h(n,\varepsilon) = \max_{n',p\in[0,1],v\geq 0} \quad & -c_v v - \frac{c_s}{2}\exp\left(\frac{c_p}{2}p^2\right)(qv)^2 + \frac{1-\phi}{1-\phi+\alpha\phi}A\varepsilon n'^{\alpha} \\ & -(1-\phi)\Omega\left((1-\lambda)n + (1-p)qv\right) \\ & +\beta(1-\delta)E_{\varepsilon'|\varepsilon}[\Pi(n',\varepsilon')], \end{aligned} \tag{1.20}$$

subject to (1.4).

1.3.1 Optimal Decision for the Hiring Standard

In (1.20), when $\gamma = 1$, any worker from the unemployment pool is productive. Hence, firms optimally choose to hire every worker they match, i.e. $g_p(n,\varepsilon) = 0$ for all (n,ε). In this case, the model reduces to the standard DMP model with multi-worker firms. In general, replacing qv from (1.4) into the firm's problem in (1.20) and taking the derivative with respect to p implies:

$$\begin{aligned}&(1+(\gamma-1)p^{\gamma}-\gamma p^{\gamma-1})((1-\phi)\Omega \\ &= \gamma p^{\gamma-1}cv/q + \frac{c_s}{2}\exp\left(\frac{c_p}{2}p^2\right)\gamma\Delta\left(\frac{1}{1-p^{\gamma}}\right)^2(c_p p(1-p^{\gamma}) + 2\gamma p^{\gamma-1}),\end{aligned} \tag{1.21}$$

where $\Delta = n' - (1 - \lambda)n$ is the net change in employment.[9] In other words, the decision for the optimal hiring standard is a solution to static problem given Δ. The LHS in (1.21) 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 wages 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. The RHS, on the other hand, is strictly increasing in p and equal to 0 when $p = 0$. This term is the marginal cost of increasing the hiring standard: as a hiring firm increases the hiring standard, the marginal cost of selection increases not only because the selection costs are larger when p is larger, but also because the firm has to post more vacancies to satisfy a given level of Δ. I plot these curves for $\Delta = 1$ in Figure 1 using the calibrated parameter values.[10] As implied by LHS and RHS being monotone, the solution to p is interior and unique.

[Figure 1 about here.]

Now, consider an increase in Δ, i.e. the firm grows faster. This shifts the marginal cost curve up and leaves the marginal benefit unchanged. Such a change is depicted in Figure 1. Given the initial size of the firm, the optimal choice for p falls with employment growth. Hence, if the firm grows faster, it fills vacancies faster and attain a high hires-to-vacancy ratio. However, this result is conditional on the initial and next period's employment. The cross sectional patterns of the job filling rate depends on the optimal decision for employment in the next period, which I analyze in the next section.

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

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

1.3.2 Optimal Decision for Employment

The previous section characterizes the optimal decision for p. When Δ is given, the optimal decision for p is independent of the production in the current period and the continuation value of the firm. This property of the optimal hiring standard allows me to characterize the adjustment cost function in terms of Δ given that p is optimally chosen. Let $C(\Delta)$ be the total cost to the firm from changing the employment from n to n'. It is the value function of the following minimization problem:

$$C(\Delta) = \min_{p\in[0,1]} \left\{ \frac{c_v}{q} \frac{\gamma\Delta}{1-p^\gamma} + \frac{c_s}{2} \exp\left(\frac{c_p}{2}p^2\right) \left(\frac{\gamma\Delta}{1-p^\gamma}\right)^2 + (1-\phi)\Omega\gamma\Delta\frac{1-p}{1-p^\gamma} \right\}. \tag{1.22}$$

I obtained the following results regarding the problem in (1.22). A detailed analysis is available in the Appendix A.3.

1. Let $\tilde{g}_p(\Delta)$ be the policy function in (1.22). Then, $\frac{d\tilde{g}_p}{d\Delta} < 0$, as discussed in the previous section.

2. $\frac{dC(\Delta)}{d\Delta} > 0$, i.e. the adjustment cost function is increasing.

3. $\frac{d^2C(\Delta)}{d\Delta^2} > 0$, i.e. the adjustment cost function is strictly convex. This result uses the fact that $\exp\left(\frac{c_p}{2}p^2\right)$ is log-convex in p.

The convexity of the adjustment cost function implies that 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 convexity of the adjustment cost function also determines the relationship of hires-to vacancy ratio to employment growth, firm size and worker turnover, *conditional* on productivity. It implies that an entrant firm gradually converges to its long-run size. Therefore, small firms post more vacancies, grows faster, fills vacancies faster and attain a higher hires-to-vacancy ratio. This establishes the relationship of the hires-to-vacancy ratio to employment growth and firm size. 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. This generates a positive relationship between the hires-to-vacancy ratio and the worker turnover rate. All of these three results about the behavior of the hires-to-vacancy ratio are conditional on productivity. Using the calibrated model, I show that these results also hold in the cross section.

1.4 Calibration

I calibrate the model to match the salient features of JOLTS documented in DFH. Unless otherwise stated, all the targeted moments are taken from their work. The parameter estimates are presented in Table 1.

[Table 1 about here.]

I choose a period to be equal to one week and I set the discount factor to match the quarterly interest rate of 1.12%. As in Acemoglu and Hawkins (2013) and Fujita and Nakajima (2013), I use 0.67 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. For worker's bargaining power, Shimer (2005) and Hagedorn and Manovskii (2008) use 0.72 and 0.052, respectively. Shimer (2005) justifies his choice for the bargaining parameter by relying on the Hosios condition, which does not apply in this paper. Hagedorn and Manovskii (2008) target the elasticity of wages with respect to productivity to calibrate worker's bargaining power. I use an intermediate value and assume equal bargaining power between the firm and the workers.

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

$$\log(\varepsilon_{t+1}) = \rho \log(\varepsilon_t) + \eta_t, \tag{1.23}$$

with $\eta_t \sim N(0, \sigma^2)$. For the persistence parameter, ρ, I use the estimate in Abraham and White (2006). They find the persistence of the idiosyncratic shocks to be 0.59 on an annual basis.[11] To represent this process on a weekly basis, I impose that firms get 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%.

There are three sources of worker-firm separation in the model. First, firms fire productive workers in response to a negative productivity shock, so 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. In JOLTS, the monthly job turnover rate is 3.0%, 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 JOLTS, separations due to reasons other than quits and lay-offs is 0.24%. I set λ to this value. 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. JOLTS excludes exiting firms. Accordingly, I set $\delta = 0.015/5 = 0.003$.

The value of b relative to the average worker productivity, Y/N, plays an important role in the context of the volatility puzzle. A higher value of the ratio of b to (Y/N)

[11] This value is the estimate without the firm fixed effects. To be consistent with the specification in (1.23), I use this value throughout the analysis. After controlling for the firm fixed effects, Abraham and White (2006) estimate the persistence parameter as 0.40. Changing the value of ρ this value does not affect the properties of the hires-to-vacancy ratio in the cross section.

tends to amplify the effects of productivity shocks in the standard DMP model. The values used in the literature lies between 0.4 and 0.955.[12] Following Mortensen and Nagypal (2007), I set the ratio of b to Y/N to 0.72.[13] Furthermore, I normalize the equilibrium value of Ω to 1 and choose A to satisfy this equilibrium value.

Note from equation (1.21) that, as the number of vacancies posted approaches zero, the optimal hiring standard approaches a value that is strictly less than 1. Given γ and V^u, the magnitude of c_v determines this upper bound for the optimal hiring standard. In the lowest worker turnover quintile, the daily job filling probability is equal to 0.011. A similar value is observed around the zero employment growth rate. In weekly terms, this is equal to 0.0745. Accordingly, I choose c_v so that the job filling probability is equal to 0.0745 in the model when total vacancies are equal to zero.

The daily job-filling rate in the data is 0.05. Hence, the probability of filling a vacancy in a week is 0.3017. The model counterpart of this value is $q(1 - \bar{p})$, where $\bar{p}$ is the average hiring standard set by the firms. Shimer (2005) estimates that the average job finding probability of a worker in a month is 0.45. In weekly terms, this is equal to 0.1388. In the model, this is given by $\theta q(1 - \bar{p})$. Dividing the latter by the former, I obtain $\theta = 0.4601$. To determine q, I use the fact from Roldan-Vilena (2008) 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 0.20. This is simply $(1 - \bar{p})$ in daily terms. Then, the daily probability that a firm meets a worker is $0.05/0.20 = 0.25$. On a weekly basis, this is equivalent to setting $q = 0.8665$. Using the calibrated values of θ and q, I find $\zeta = 1.6783$.

There are two parameters in the selection cost function to be calibrated: c_s and c_p. They determine how the quantity and quality margins are related. Hence, I choose

[12] See Shimer (2005) and Hagedorn and Manovskii (2008).

[13] Consistently with the discussion in Mortensen and Nagypal (2007), a smaller value of b attenuates the responses of labor market outcomes to aggregate productivity shocks.

these parameters value to match the average job filling rate and the average firm size. The job filling probability is calculated as 0.3017 in the previous paragraph. The average firm size in Business and Employment Dynamics (BED) is 21.6. I choose c_s and c_p to match these figures.

The last parameter to be calibrated is the fixed entry cost, c_e. I choose this value so that the expected value of an entrant is equal to zero in equilibrium.

1.5 Results

In this section, I present the results from the worker selection model regarding the cross sectional behavior of the hires-to-vacancy ratio. In their analysis, DFH construct a daily accounting model of establishment-level hiring dynamics and report estimates for the daily job filling rate, the theoretical counterpart of the hires-to-vacancy ratio. For comparability, I report the results for daily job filling rate from the worker selection model. My main finding is that the worker selection model accounts for about 30% of the variation of in the daily job filling rate observed in the data.

[Figure 2 about here.]

Figure 2 plots the daily job filling rate against the monthly employment growth rate bins from the worker selection model.[14] The job-filling rate near zero percent growth is around 2% and reaches 5% as the growth rate becomes about 5%. After this point, the response of the job-filling rate to employment growth becomes weaker, reaching only 6% at a 20% employment growth rate. The corresponding figures in the data are stronger: the job-filling rate is about 18% at a 20% employment growth rate.

[14] I construct the growth rate bins so that the share of vacancies are equal in each bin. This procedure creates narrower bins near the zero employment growth rate and progressively wider bins as the employment growth rate becomes larger. DFH constructs the growth rate bins in a similar fashion.

There are several possible explanations for this gap between the model and the data. First, there can be micro level randomness in the data. Some firms are lucky to find good candidates and therefore fill vacancies at a higher rate and grow faster. The maximum value that the daily job filling rate can take in the model is 25%, which happens when the hiring standard is set equal to zero. This natural bound constrains the firms from achieving a higher job-filling rate. Second, there might be increasing returns at the establishment level. For example, it may be easier to attract more workers when the firm has more open positions. Hence, firms that are posting more vacancies meet proportionally more workers. Such a feature is absent in the model. Finally, there might be other margins, e.g. wage posting and firms' search effort, that are not modeled in this paper. DFH provides an extensive discussion about these explanations.

To quantitatively evaluate the model, I calculate the elasticity of the daily job-filling rate with respect to the hires rate. The elasticity I calculated from the model is 0.24. From the data, DFH estimate this elasticity to be 0.82. These numbers imply that the model alone can account for about 30% of the variation in the growth rates. Further, DFH find that 0.04 of the 0.82 is due to increasing returns at the establishment level. In a simulation exercise, they also find that micro level randomness accounts for about 10% of the variation across the growth rate bins. These together imply that the worker selection can account for about 35% of the elasticity after controlling for scale and luck effects.

[Figure 3 about here.]

Figure 3 shows the relationship between the daily job filling rate and log firm size. Firm size is calculated as the average of the employment at the firm at the beginning and the end of the period. Since I do not directly target the firm size distribution, the firm sizes from the model are smaller than the firm sizes observed in the data. To make the size groups comparable to the data, I construct firm size bins such that log difference of average size in two consecutive bins are equal to those used in DFH. The daily job filling rate follows a hump-shaped pattern across the firm size bins, which is also present in the data. In the model, the job filling rate is about 6.5% at small firms, and decreases to 4.5% at medium and large firm sizes. The job-filling rate in the data goes from 6.6% down to 2.6% when moving from small establishments to large establishments. The job filling rate at large firms in the model stays high compared to the data.[15]

[Figure 4 about here.]

Finally, Figure 4 plots the daily job filling rate against monthly worker turnover quintiles.[16] Moving from low worker turnover rates to high turnover rates, the job filling rate rises from 1.5% to 8.0%. Similar numbers are present in the data as well, though the job-filling rate in the fifth quintile shoots up to 11.4% in the data.

1.6 Policy Analysis

Using the calibrated model in Section 1.4, 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. A firing tax is a one-time payment collected from firms for each worker they fire. To highlight the effects of worker selection, I calibrate the standard DMP model and compare the results from labor market policy changes to those from the worker selection model. To ensure that the two models are comparable, I modify the standard DMP model, which I describe next.

[15]The difference might reflect that large firms have cost advantages in recruiting new workers, e.g. an advanced human resources department. Introducing size dependent adjustment costs reduces the job filling rate at large firms, but increases it at small firms relative to the calculations in Figure 3.

[16]The plot in Figure 4 does not start from 0%, which shows that about 18% of the firms do not hire any worker in a given month.

1.6.1 Calibrating the 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. I calibrate the model in a way that it matches the same targeted moments with the worker selection model described in Section 1.4. However, the two models differ regarding the cross-sectional variation in the hires-to-vacancy ratio. Although both models target the same average job filling probability, the standard DMP model implies a constant hires-to-vacancy ratio at the firm level, because firms are not allowed to screen workers. This allows me to isolate the effects of worker selection.

In the worker selection model, firms contact workers with probability q but hire them with a smaller probability equal to $(1-p)q$. Firms optimally choose p, which is allowed to vary across firms. 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 hires-to-vacancy ratio varies only in the worker selection model.

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:

$$n' = (1-\lambda)n + (1-\bar{p})qv(1-p_\gamma). \tag{1.24}$$

p_γ now determines a common separation probability for newly hired workers. Comparing equation (1.24) and equation (1.4), $1 - p_\gamma$ in the standard DMP model corresponds to $\frac{1-p^\gamma}{\gamma(1-p)}$ in the worker selection model. Recall that I targeted the job turnover rate from JOLTS in Section 1.4 to calibrate γ. Similarly, I choose p_γ in the standard DMP model to match this target. While I search for the value of p_γ, I also change the value of c_s, A, σ and c_e. As in Section 1.4, c_s targets average firm size; A targets an equilibrium value of Ω equal to 1, σ is set to match the hires rate, and c_e satisfies the free entry condition. I maintain the restriction that $\frac{b}{Y/N} = 0.72$. I also drop c_p from the selection cost function while preserving its quadratic form in the the number of applicants. I set the value of c_v equal to the value obtained from the calibration of worker selection model. The precise treatment of this parameter does not change the conclusions of this section. Finally, I set all the remaining parameters equal to their corresponding values in Table 1. The values of the newly calibrated parameters are presented in Table 2.

[Table 2 about here.]

1.6.2 Wage Bargaining with a Hiring Subsidy and a Firing Tax

A hiring subsidy and a firing tax affect the wage bargaining outcome because these policy instruments 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 Stole-Zwiebel bargaining rules defined in equations (1.13) and (1.14) become

$$\phi(D_{\tilde{n}}(\tilde{n}, r, p, \varepsilon) + \tau) = (1 - \phi)(V^n(n', \varepsilon) - V^u), \tag{1.25}$$

and

$$\phi(D_{\tilde{r}}(\tilde{n}, r, p, \varepsilon) + s) = (1 - \phi)(V^p(n', \varepsilon) - V^u). \tag{1.26}$$

When a firm is paid s for hiring a new worker, the surplus to the firm from the newly hired worker increases by s. When a firm is forced to pay a firing tax of τ, the surplus to the firm from keeping an existing worker increases by τ as the firm avoids paying the firing tax. Following the same steps in the derivation of wages detailed in Appendix A.1, I show that the wage equations for existing and new workers become:

$$w^p(n', \varepsilon, p) = \quad g(p)\frac{\alpha\phi}{1-\phi+\alpha\phi}A\varepsilon n'^{\alpha-1} + (1-\phi)\Omega + \phi s, \tag{1.27}$$

where Ω is defined as in equation (1.17). One can obtain the wage equation for the standard DMP model after replacing $g(p)$ with $1 - p_\gamma$ in the equations above.

1.6.3 Effects of a Hiring Subsidy

I calculate the response of labor market outcomes to incremental increases in hiring subsidy.[17] Table 3 reports equilibrium labor market outcomes and total output net of adjustment cost from the worker selection and the standard DMP models. I also report the amount of subsidy as a fraction of the average wage of a newly hired worker for each model to compare the relative size of the subsidy between the two models.

[Table 3 about here.]

If a policymaker assesses the hiring subsidy using the standard DMP model, he will not be optimistic about the hiring subsidy in combating unemployment. When firms are subsidized about half of the average wage of newly hired worker, the decline in unemployment is only 0.08 percentage points. On the other hand, the worker selection model predicts that the same policy is a powerful tool to reduce unemployment. A hiring subsidy that is equal to the half of the average wage of a newly hired worker reduces the unemployment rate by 0.5 percentage points.

[17] I assume that government finances the hiring subsidy through a lump-sum tax on workers.

The aggregate hires-to-vacancy ratio responses are different between the two models. In the standard DMP model, the aggregate hires-to-vacancy ratio decreases with the hiring subsidy. Because the aggregate level of vacancies increases with the subsidy, the probability that a firm contacts a worker goes down due to increased market tightness. If firms can select workers, however, there is an additional effect on the hires-to-vacancy ratio through the optimal choice of the hiring standard. When firms are subsidized for hiring new workers, they become less picky about the workers as they are compensated for the loss due to hiring an unproductive worker. The combined effect on the hiring vacancy-ratio is ambiguous. Table 3 shows that the effect of the latter is greater than the former when the subsidy is small. When the subsidy becomes large, the hires-to-vacancy ratio starts to decline.

The output net of adjustment costs initially increases with the hiring subsidy, but the increases in net output is less than 1% in each case. When the subsidy exceeds 0.4, output net of the adjustment costs starts declining in both models.

[Figure 5 about here.]

The effects of a hiring subsidy on employment growth rates in the cross section are qualitatively different in the worker selection and the standard DMP models. To highlight the impact of a hiring subsidy on employment growth rates, I divide employment growth rates into non-overlapping bins with the first bin including all of the shrinking firms. Since the firms are concentrated in low employment growth rate bins, I construct the growth rate bins so that the bins become progressively wider. I calculate monthly employment growth rates for each firm and place them into their corresponding employment growth rate bins. Then, I introduce a hiring subsidy equal to 0.1 and calculate the monthly employment growth rates. When I place the firms into their corresponding employment growth rate bins, I use the weights in the steady state stationary distribution without the subsidy. Finally, I calculate the cumulative distribution with and without the hiring subsidy for each model and plot the difference in Figure 5.

The cumulative distribution after the hiring subsidy evaluated at each employment growth rate is smaller than the corresponding value in the employment growth distribution without the subsidy for both models. A negative value in Figure 5 at all growth rates implies that the entire distribution of the employment growth shifted to the right. However, the effects on individual firms are different in the worker selection and the standard DMP models. The number of firms around zero employment growth decreases sharply in each model. The decline in the standard DMP model is larger, but becomes very quickly close to zero. This pattern implies that the hiring subsidy increases employment growth at slowly growing firms, but leaves the right tail of the distribution unaltered. In contrast, the decline in the number of firms around 0% employment growth rate is smaller in the worker selection, but approaches zero slowly relative to the standard DMP model. For the standard DMP model, Figure 5 implies that the increase in the number of firms with employment growth rate between 1% and 8% is roughly three times larger than the increase in the number of firms with more than 8% employment growth rate. The opposite is true for the worker selection model. In other words, most of the shift in the worker selection model occurs in the right tail of the employment growth distribution.

The difference between the two models stems from firms' ability to change the hiring standard in response to a hiring subsidy in the worker selection model. A hiring subsidy shifts the marginal cost of labor adjustment in a parallel fashion if firms cannot change the hiring standard. Because the production function is Cobb-Douglas, this 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 hiring standards in response to a hiring subsidy. The ability to select workers reduces the marginal cost of labor adjustment more at these firms. Hence, small and growing firms increase their employment more compared to large firms. The stronger response of the slow and growing firms causes the employment growth distribution to shift more in the right tail of the distribution.

Empirical evidence from the literature supports the predictions of the worker selection model. Perloff and Wachter (1979) analyze the effects The New Jobs Tax Credit of the stimulus package in 1977 on employment growth. Despite its complex structure, the tax credit program affects incremental hirings rather than total employment, and hence similar to the hiring subsidy experiment in this section. 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. According to their findings, the knowledge about the tax credit program shifts the employment growth distribution to the right and most of this shift occurs in the right tail of the distribution.

1.6.4 The Effects of a Firing Tax

Compared to a hiring subsidy, a firing tax has opposite effects on the equilibrium outcomes in both models, but the differences between the two models remain. The results from incremental increases in the firing tax are presented in Table 4 for worker selection and the standard DMP models.[18]

[Table 4 about here.]

An increase in the firing tax unambiguously increases the unemployment rate in both models, because the equilibrium mass of active firms decreases due to increased labor adjustment costs. However, the increase in the unemployment rate in the worker selection model is about ten times larger.

[18] I assume collected tax is distributed to workers as a lump-sum transfer.

The aggregate hires-to-vacancy ratio slightly increases in the standard DMP model, but declines in the worker selection model. Even when the firing tax doubles the average weekly wage of a newly hired worker, the increase in the hiring standard surpasses the increase in the aggregate contact probability. The dominant effect of the hiring standard reduces the aggregate hires-to-vacancy ratio.

Finally, net output decreases with the firing tax. There is not a simple Hosios condition that guarantees that the competitive equilibrium is socially optimal, but Tables 3 and 4 imply that subsidizing new hires is welfare improving over taxing firings. The reason for this outcome is that there are too few active firms in the competitive equilibrium and some workers are inefficiently employed at very large firms. A hiring subsidy increases net output not only by encouraging new firm entry, but also by causing very large firms to shed marginal workers who could be more efficiently employed at smaller firms.

[Figure 6 about here.]

The effects of a firing tax on worker turnover rates at the firm level are qualitatively different in the worker selection and the standard DMP models. To show the effects of a firing tax on worker turnover rates in the cross section, I divide the worker turnover rates into non-overlapping bins. As in the previous section, I start with narrower bins and make them progressively wider. First, I calculate monthly worker turnover rates for each firm without the firing tax and place them into their corresponding worker turnover bin. Then, I impose a tax of 0.1 in terms of the consumption good on firings and find the new monthly worker turnover rate for every firm. Finally, I calculate the change in the average worker turnover rate in each bin using the weights in the stationary distribution of the pre-policy steady state. I plot the difference in Figure 6. The left panel corresponds to the worker selection model and the right panel corresponds to the standard DMP model.

From Figure 6, the decrease in the worker turnover rate after a firing tax is larger at firms with initially higher worker turnover rate in the worker selection model. In contrast, the decrease in the worker turnover rate is larger at firms with initially lower worker turnover rates in the standard DMP model. The reason for the difference between the models is that a firing tax discourages firings at shrinking firms in the standard DMP model, but it has a relatively small effect on worker turnover rates in expanding firms. In the stationary distribution of the standard DMP model, shrinking firms are concentrated at low to medium worker turnover rate bins. In contrast, a firing tax reduces worker turnover rate relatively more at growing firms in the worker selection model. In response to a firing tax, growing firms increase their hiring standards to avoid paying a firing tax for a potentially low quality match. Therefore, worker turnover rates decline relatively more at high worker turnover firm in the worker selection model.

The predictions of the worker selection model is consistent with empirical evidence from the literature. Haltiwanger, Scarpetta and Schweiger (2010) use a 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. The graphs in Figure 6 confirms that the predictions of the worker selection model is consistent with the data.

1.7 Conclusion

In the U.S., the hires-to-vacancy ratio in the cross section (i) rises steeply with employment growth rate, (ii) declines with firm size, and (iii) increases with worker turnover rate. These patterns of the hires-to-vacancy ratio 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. Even extensions to the standard DMP model that allow firms to hire multiple workers fail to generate the cross-sectional variation in the hires-to-vacancy ratio due to the use of an aggregate matching function.

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 the hires-to-vacancy ratio. 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 inference 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 the hires-to-vacancy ratio are consistent with the data. Calibrated to the salient features of the U.S. labor market, the worker selection model accounts for about 30% of the variation in the hires-to-vacancy ratio across different growth rates. The remaining part can be explained by micro-level randomness, increasing returns to scale at establishment level, other mechanisms such as wage posting and firms' search effort.

In the policy analysis section, I analyze the effects of a hiring subsidy and a firing tax on labor market outcomes. The worker selection and the standard DMP models have different policy implications at both the aggregate and firm levels. The standard DMP model predicts that a hiring subsidy would reduce unemployment only slightly. However, the decline in the worker selection model is substantial: the unemployment rate would go down by half of a percentage points if firms are subsidized for half of the wages of a newly hired worker.

The worker selection model also gives new insights about how different firm groups are affected by labor market policies. The worker selection model implies that labor market policies have a bigger impact on employment dynamics at fast growing and high worker turnover firms, while the standard DMP model implies the opposite. Empirical evidence from the literature supports the predictions of the worker selection model.

Chapter 2

Employment Duration over the Business Cycles: Quits vs. Firings

2.1 Introduction

The duration of an employment relationship is a signal about its match quality and can be used to explore how business cycles affect match quality. High quality matches are likely to endure longer, while low quality matches dissolve relatively quickly. Therefore, match quality is pro-cyclical if jobs created during recessions have shorter spells and counter-cyclical otherwise.

However, the theoretical predictions about the direction of the cyclical behavior of match quality is unclear, because job seekers and hiring firms respond to labor market conditions in opposite directions. On one hand, the unemployment rate is high during a recession, and job seekers compete for a relatively small number of job openings. Models with on-the-job-search imply that increased competition among the job seekers causes unemployed workers to accept low-quality jobs and quit later to take or look for another job.[1] Hence, jobs ending due to workers' quit decisions tend

[1] See Mortensen (1994) for an application to U.S. data.

to be shorter. On the other hand, labor market conditions are favorable for hiring firms during a recession, because there are a relatively small number of hiring firms. Models with endogenous separation imply that favorable labor market conditions during a recession are likely to cause firms to hire high quality workers that remain at the hiring firm longer.[2] As a result, the aggregate labor market conditions at the start of a job have an ambiguous effect on employment duration.

In this paper, I empirically study the effects of aggregate labor market conditions on employment duration using data from the National Longitudinal Survey of Youth (NLYS) 1979 cohort. I use a proportional hazard model for job terminations, where I treat job terminations due to different reasons as competing risks. I am particularly interested in estimating the effects of unemployment rate separately for job terminations ended by a worker's quit decision to take or look for another job and those ended by the firm's firing decision.

I find that a high unemployment rate at the start of a job increases the probability that a worker quits his current job to take or look for another job, but it reduces the probability that a job spell ends by firm's firing decision. The overall effect of the unemployment rate at the start of a job on employment duration is negative, implying match quality is pro-cyclical. However, this effect is rather small. The median duration of a non-union job held by a 29 year-old white male with a high school degree falls from 44 weeks to only 42 weeks if the unemployment rate at the start of the job is one standard deviation above its sample mean.

Furthermore, aggregate data show that quits are pro-cyclical but firings are counter-cyclical.[3] These regularities in the aggregate data suggest that workers and firms with ongoing employment relationships also respond to current labor market conditions in opposite directions. Using the estimates from the proportional hazard model, I find

[2] See Mortensen and Pissarides (1994) and Sedlacek (2014).

[3] See Akerlof, Rose, and Yellen (1989) for a discussion. For an analysis of more recent data, see the Job Openings and Labor Turnover Survey Highlights (January 2014) report from The Bureau of Labor Statistics.

that an increase in the current unemployment rate reduces the probability that an already employed worker quits to take or look for another job, but it increases the probability that a job spell ends by firm's firing decision. These results are consistent with the aggregate behavior of quits and firings.

The main contribution of this paper is to utilize information about the reason for job terminations. The NLSY 1979 cohort includes detailed information about the reason why a job spell has ended. In particular, I observe job terminations due to a worker's quit decision specifically to take or look for another job and due to the firm's firing and lay-off decision. This feature of the data enables me to distinguish worker-initiated job terminations from firm-initiated job terminations.

Previous studies used the data from the NLSY 1979 cohort to estimate the cyclical behavior of job match quality, but these studies do not make a distinction among the cause-specific job terminations. For example, Bowlus (1995) and Mustre-del-Rio (2012) also find that match quality is pro-cyclical, but their estimates suggest a much stronger pro-cyclical behavior of match quality.

The inclusion of the causes for job terminations distinguishes my paper from the earlier studies for four reasons. First, it allows me to estimate the effects of labor market conditions separately on worker-initiated and firm-initiated job terminations. In models with on-the-job search, workers accept low-quality jobs during recessions, but they later quit to take or look for another job. The mechanism in the models with on-the-job search imply that job match quality is pro-cyclical and the cause of a job termination is more likely to be due to a worker's quit decision. In contrast, models with endogenous separation imply that only high quality matches are created during recessions. Therefore, match quality is counter-cyclical and the cause of job termination is more likely to be due to the firm's firing decision. Earlier studies do not make a distinction between quits and firings and try to estimate the *net* effect of these opposing forces described in these theoretical models. Instead, I estimate the effects of unemployment rate on quits and firings separately and find supporting evidence for *both* of these class of models. However, these opposing forces are of similar magnitude and cancel each other's effect.[4]

Second, earlier studies discarded job spells for females, because they are likely to quit their jobs due to personal concerns, e.g. pregnancy and child care, rather than professional concerns. Since I observe the specific reason for job terminations, I do not need to impose such a restriction to my sample.

Third, earlier studies also acknowledge that the current unemployment rate affects the duration of a job spell and controls for that to isolate the effect of the unemployment rate at the start of the job. However, as supported by the aggregate data, the effect of the unemployment rate on job termination decisions for workers and firms are in opposite directions. Without making a distinction among the job terminations according to their causes, the inclusion of the current unemployment rate on the right hand side causes the model to be misspecified.[5] Since I treat cause-specific job terminations as competing risks, my results do not suffer from this misspecification bias.

Finally, the inclusion of information about the reasons for job terminations necessitates a change in my estimation strategy. While the termination of a job is still the failure event in the proportional hazard model, it can occur due to several mutually exclusive reasons. For example, if a job spell ends by a worker's quit decision in the data, then a termination for the same job spell due to the firm's firing decision is never observed. In other words, each cause of job terminations is a competing risk for the other causes.

I estimate the hazard functions for job terminations under two different specifi-

[4]Kahn (2008) finds a similar result using a matched employer-employee data set and after controlling for firm fixed effects.

[5]To address this problem, Bowlus (1995) adds the square of the current unemployment rate as an explanatory variable. The coefficient estimate for the current unemployment in Mustre-del-Rio (2012) is insignificant.

cations. In the first specification, I estimate a proportional hazard model for each cause-specific event as in Cox (1972). This specification is similar to the standard application of Cox's proportional hazard model except that job terminations due to other reasons are treated as right-censored and handled as in the standard Cox proportional hazard model. Despite the similarities in implementation, the interpretation of the coefficient estimates are completely different when there are competing risks. While the proportionality assumption in Cox hazard model allows for inference solely based on the coefficient estimates, this is generally not possible when there are competing risks for the same failure event. For example, the probability of a job termination due to a worker's quit decision before a specific point in time depends on the survival probability of the job up to that point. However, the survival probability depends on all the cause-specific hazard functions, which makes the cause-specific job terminations interdependent. To facilitate inference from the cause-specific regressions, I calculate the probability of observing each cause-specific event, called the cumulative incidence function, using the estimates from all the cause-specific hazard estimations.

The second specification is based on an alternative method for cause-specific hazard regressions proposed by Fine and Grey (1999). They directly estimate a subhazard function, which counts job terminations due to other reasons in the risk set of the failure event rather than treating them as right-censored. An advantage of subhazard regressions is that, as in the standard Cox regression, inference can be made solely based on the coefficient estimates. Furthermore, potential bias in the coefficient estimates due to unobserved heterogeneity is less of a concern. I include only one randomly selected job spell for each individual in my sample. This sampling scheme produces unbiased coefficient estimates, although the baseline hazard is biased downward due to overrepresentation of longer job spells. While the potential bias due to unobserved heterogeneity is not an issue for inference from the subhazard regressions, it may potentially bias the estimates of the cumulative incidence functions from the cause-specific regressions, which uses the baseline hazard estimates in addition to coefficient estimates.

I provide estimation results from the subhazard regressions to address issues concerning unobserved heterogeneity in the cause-specific hazard regressions. The estimation results from both of the specifications are consistent with each other. However, cumulative incidence functions for the subhazard regressions are calculated from separately-run regressions and can potentially produce inconsistent results. For example, the sum of the probabilities of all possible cause-specific job terminations can potentially exceed one. An advantage of the cause-specific regressions over the subhazard regressions is that cumulative incidence functions are estimated simultaneously and robust to such inconsistencies.

In the next section, I describe the data set I use in this study. Section 2.3 describes the cause-specific and subhazard regressions. I present my estimation results from both of the specifications in Section 2.4. The last section concludes.

2.2 Data Description

I use data from the NLSY 1979 cohort in this study. A total of 12,686 individuals that were born between 1957 and 1964 participated in this survey. These individuals were interviewed annually from 1979 through 1994 and biennially thereafter until the survey ended in 2010. The data set I use in this study covers all the survey years.

The survey collects detailed information about each job a respondent holds or previously held. The structure of the survey enables me to create employment histories for all the individuals participating in the survey. I construct the data set for the employment duration analysis by linking each job across different survey years.[6] I

[6] I obtain some of the job-specific characteristics, e.g. job start and stop dates, from the Employer History Roster (Beta Version). This roster alleviates the more involved linking process across

measure the duration of a job spell in weeks. Some of the job spells are right-censored due to the finite horizon of the survey and loss of follow-up.

The explanatory variables include personal and job characteristics at the start of a job such as age, gender, race, education, and whether the job is protected by a union. I include unemployment rate at the start of the job, u_0, to account for the aggregate labor market conditions when the job is created. I also include the current unemployment rate, u_t, as a time-varying regressor to capture the on-going labor market conditions. I obtain data from the Bureau of Labor Statistics for the national unemployment rate. The time series is not seasonally adjusted so that it is consistent with the data from NLYS.

The NLSY 1979 also provides detailed information about the reason why a job spell ended. A detailed description of the reasons for job terminations is available in the Appendix. In particular, I observe whether the job ended due to the worker's quit decision to take or look for another job or due to the firm's firing decision. The theory predicts that workers and firms response to aggregate labor market conditions are different and the overall effect on the duration of a job spell is ambiguous. On one hand, workers are likely to accept low-quality jobs during recessions due to tight labor market conditions and quit later during booms to take or look for a better job. Workers' incentive to quit for a better job tends to reduce the duration of the job. On the other hand, firms hire among a larger applicant pool during recessions and can potentially form high-quality matches that endure longer. Hence, the duration of a job spell can be different for the jobs ending by the worker's quit decision and those ending by the firm's firing decision.

Using information about the reason why a job spell ended, I test these theoretical predictions in this paper. I expect both the starting and the current unemployment rate to affect quits and firings in opposite directions. While workers accept a low-

different survey years.

quality job and are more likely to quit when the starting unemployment rate is high, they are less likely to quit if the current unemployment rate is high. In contrast, firms tend to form better matches when the starting unemployment rate is high, but they are more likely to fire a worker when the current unemployment rate is high.

2.3 Estimation Strategy

The Cox proportional hazard model is widely applied to duration data when time to a failure event is of interest. In the analysis of employment duration, the failure event of interest is the termination of a job. In this paper, the failure event of interest is still the termination of a job. However, there are multiple causes of job terminations, and only the first of these causes for job termination, if any, is observed. In other words, each reason for job termination is a competing risk for the other reasons. In this section, I describe two alternative approaches proposed in the literature when there are competing risks: cause-specific hazard regressions and regression on a subhazard function.[7]

2.3.1 Cause-Specific Hazard Functions

Let the hazard function for job terminations be:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}. \tag{2.1}$$

The hazard function is the instantaneous probability that a job is terminated at time T conditional on surviving up to time t. Cox (1972) further imposes that the hazard function for job terminations, conditional on a set of explanatory variables at time t,

[7] Refer to Putter, Fiocco and Geskus (2006) for a general discussion.

$X(t)$, takes the following proportional form:

$$h(t|X(t)) = h_0(t)\exp(X(t)\beta), \tag{2.2}$$

where $X(t)$ are time-varying explanatory variables, β is a vector of parameters common across all job spells, and $h_0(t)$ is the baseline hazard. The baseline hazard is also common across all job spells, and its form is left unspecified. Cox (1972) describes a semi-parametric approach for obtaining estimates of the model parameters, $\hat{\beta}$, through the maximization of the following partial likelihood function:

$$\mathscr{L} = \prod_{i:C_i=1} \frac{h(t_i|X_i(t_i))}{\sum_{j:t_j\geq t_i} h_(t_i|X_j(t_i))} = \prod_{i:C_i=1} \frac{\exp(X_i(t_i))}{\sum_{j:t_j\geq t_i}\exp(X_j(t_i))}, \tag{2.3}$$

where $C_i = 0$ if the job spell is right-censored. Note that right-censored job spells enter the partial likelihood function only through the denominator. Further, the baseline hazard can be recovered non-parametrically after obtaining $\hat{\beta}$ even though it cancels from the estimating equation. The proportionality assumption implies that the hazard functions are strictly parallel and inference is possible solely based on $\hat{\beta}$. Specifically, a positive (negative) value of $\hat{\beta}$ implies that the probability of terminating a job increases (decreases) with an increase in the value of the explanatory variable.

A standard application of the Cox proportional hazard model can be misleading when there are competing events. The proportional hazard model in equation (2.2) assumes that the explanatory variables affect the probability of terminating a job in the same way regardless of its cause. However, the model is misspecified under such a restriction if the effect of one of the explanatory variables is different for each cause-specific job termination. In this study, a quit and a firing are competing events for job terminations, and the theory predicts that both the starting and current unemployment rate affect the probability of terminating a job due to quits or firings in opposite directions.

To empirically test for potentially different effects of the starting and current unemployment rates on the duration of a job, I define a separate hazard function for each cause-specific job termination. Formally, let k denote one of the K possible cause of job terminations. The hazard function for terminating a job due to reason k is:

$$h_k(t|X(t)) = h_{0,k}(t) \exp(X(t)\beta_k). \tag{2.4}$$

The specification in equation (2.4) is similar to the standard specification in equation (2.2) except that it is now separately defined for K different possible reasons for job terminations. Both the baseline hazard functions and the parameters are allowed to differ across different types of job terminations. β_k's can be estimated separately for each cause-specific hazard function by maximizing the partial likelihood function in equation (2.3). However, the occurrence of a competing event is treated as right-censored in each of these estimations.

2.3.2 Cumulative Incidence Functions and Inference

While the estimation procedure with cause-specific hazard functions is the same as with the standard Cox proportional hazard model, the interpretations of the parameter estimates are different. Because the distributions of time to a job termination for each cause-specific event are potentially dependent, the sign of the parameter estimates alone cannot determine the effect of a covariate on the duration of employment. When the hazard functions are estimated separately for each cause-specific job termination, the effect of a change in the variable of interest on a cause-specific job termination depends nonlinearly on baseline hazard functions and parameter estimates of the other cause-specific hazard functions.

To illustrate this point, let the baseline cumulative cause-specific hazard function be:

$$H_k(t) = \int_0^t h_k(s)ds. \tag{2.5}$$

Then, the probability of surviving from any event at time t is:

$$S(t) = \exp(-\sum_{k=1}^{K} H_k(t)). \tag{2.6}$$

The survival probability now depends on the baseline and parameter estimates not only from the hazard regression of the event of interest, but also from the hazard regressions of the other competing events. Further, the probability of failing from cause k before time t is:

$$I_k(t) = \int_0^t h_k(s)S(s)ds. \tag{2.7}$$

The probability in equation (2.7) is called the cumulative incidence function. The effect of a change in the starting and current unemployment rates can now be examined for quits and firings by constructing cumulative incidence functions for each event using the baseline and parameter estimates from the cause-specific hazard regressions.

2.3.3 Regression on a Subhazard Function

As an alternative to cause-specific hazard regressions, Fine and Gray (1999) propose a methodology that allows inference on cumulative incidence functions solely based on estimates of β. They define a subhazard function for the competing risk k as follows:

$$\bar{h}_k(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t \cup (T \leq t \cap K \neq k))}{\Delta t}. \tag{2.8}$$

The subhazard function shows the instantaneous probability of a job ending due to reason k conditional on surviving up to time t *or* ending before time t due to a reason other than k. As in Cox's proportional hazard model, Fine and Grey (1999) also assume that the subhazard function is proportional to a baseline hazard function:

$$\bar{h}_k(t|X(t)) = \bar{h}_{0,k} \exp(X(t)\beta_k). \tag{2.9}$$

The subdistribution hazard function in equation (2.9) can be estimated in a way that is analogous to equation (2.3). The only difference in the estimation procedure is in the treatment of the risk set. According to equation (2.8), job spells that have already ended due to another cause are still considered to be in the risk set for the competing risk k. Since these observations can potentially become right-censored and drop from the risk set, Fine and Grey (1999) weight them using the Kaplan-Meier estimate of the survivor function for the censoring distribution.

One of the advantages of the estimation strategy proposed by Fine and Grey (1999) is that inference can now be made solely based on $\hat{\beta}$. Note that the baseline cumulative incidence function and subhazard function for the competing risk k are related as follows:

$$\text{CIF}_k = 1 - \exp\left(-\int_0^t \bar{h}_k(s)ds\right). \tag{2.10}$$

The estimates of β have a similar interpretation to the standard Cox proportional hazard model. A positive (negative) value of $\hat{\beta}$ implies that the effect of increasing the value of the explanatory variable increases (decreases) the probability of terminating a job due to cause k.

In the next section, I implement both of these estimation methods using the duration data from NLSY 1979 cohort.

2.4 Results

2.4.1 Sample Restrictions

Following Bowlus (1995), I restrict the data set to include only private sector employment. Jobs that start before the individual completes all schooling or is younger than 16 years old are dropped from the sample. Further, jobs with missing job start and stop dates and those lasting less than two weeks are not included in the sample. Unlike Bowlus (1995), I still include females in my sample. Bowlus (1995) restricts the sample to only males on the grounds that females are likely to quit for reasons other than poor match quality, such as marriage, pregnancy, and childcare. The information about the reason for job terminations allows me to distinguish job terminations due to professional concerns from personal concerns. Therefore, I do not need to make such a restriction on my sample.

I define three reasons for job terminations for the empirical analysis: quits, firings, and other reasons. Models with on-the-job search imply that job spells are shorter for those jobs created during a recession because workers quit to take or look for a better job. Accordingly, quits due to reasons other than to take or look for another job are included in the other reasons category. Similarly, models with endogenous separation imply longer spells for jobs created during a recession, because these matches are expected to be high quality, and firms are less likely to fire these workers. Thus, firings include discharges and layoffs. Termination of temporary and seasonal jobs are included in the other reasons category, because these jobs are set for a fixed term regardless of match quality. Terminations due to closings are also included in the other reasons category since all jobs regardless of match quality are terminated with this type of job termination.[8]

The original data set consists of one observation per job and multiple spells for

[8]Inclusion of these type of job terminations in the firings category does not change the conclusions of this paper.

each individual. If there is an individual-specific unobserved component, the job spells for the same individual are potentially correlated and the estimates of β are biased. To address the concerns about unobserved heterogeneity, I randomly select one spell per individual. Bowlus (1995) points out that such a restriction on the sample produces unbiased estimates of β. However, the estimates for the baseline hazard functions are still biased, because longer spells are now overrepresented in the sample. Since cumulative incidence functions are constructed from the estimates of the baseline hazard functions, they are potentially biased too. While the bias in cumulative incidence function calculations is problematic for inference from the cause-specific hazard regressions, this is not a concern for the subhazard regressions because inference is possible solely based on the estimates of β.

2.4.2 Estimation Results

Table 5 presents the estimation results. The first three columns show the estimation results from the cause-specific hazard regressions for job terminations due to quits, firings, and other reasons, respectively. The last three columns show the results from the subhazard resgressions. The coefficients of interest are those for the unemployment rate at the start of the job spell, u_0, and throughout the duration of the job, u_t, for quits and firings.

[Table 5 about here.]

The effects of the explanatory variables can be directly inferred from the estimates of the subhazard regressions. The effect of u_0 is positive and statistically significant for the job spells ending by a worker's quit decision to take or look for another job. The positive sign implies that a high unemployment rate at the start of a job spell increases the probability that the worker is more likely to quit his current job. This result is consistent with the predictions of the models with on-the-job search.

Regarding the effects of u_0 on job spells ending by firm's firing decision, the sign of the coefficient from the subhazard regressions supports the predictions of the models with endogenous separation. In contrast to the job terminations due to quits, the sign of the coefficient for u_0 is negative and statistically significant. The negative coefficient implies that a high employment rate at the start of a job reduces the probability that a firm will fire the worker in the future.

In the aggregate data, the cyclical behavior of aggregate quits and firings are qualitatively different. While quits are strongly pro-cyclical, firings are counter-cyclical. This macro-level observation suggests that workers and firms also respond to u_t in opposite directions.[9] The negative coefficient for u_t from the subhazard regression for quits indicates that the probability that a job spell ends by a worker's quit decision is lower during recessions. In contrast, the coefficient estimate from the subhazard regression for firings is positive and statistically significant. The positive coefficient implies that the probability that a job spell ends by a firm's firing decision is higher during a recession. Both of these estimates are consistent with the cyclical behavior of quits and firings.

The results for the effect of u_t are crucial for isolating the effect of u_0, as the duration of a job spell is affected by the current cyclical fluctuations. Bowlus (1995) and Mustre-del-Rio (2012) both include the unemployment rate as an explanatory variable for the hazard regressions. However, the model suffers from misspecification bias if u_t has opposite effects on the decisions of workers and firms. In both of these papers, the coefficient estimate for u_t is statistically insignificant when it is added linearly to the model. To account for the cyclical patterns in quits and firings, Bowlus (1995) further adds the squared value of u_t to the right-hand side variables, and the estimates for the explanatory variables involving u_t becomes significant. By

[9] Employment-to-employment transitions are more likely to be induced by a worker, whereas employment-to-unemployment transitions are more likely to be induced by the firm. Similar to quits and firings, employment-to-employment transitions are pro-cyclical and employment-to-unemployment transitions are counter-cyclical. See Fallick and Fleishman (2004).

distinguishing job separations according to their causes, I separately identify the effects of current cyclical fluctuations on the duration of a job spell ended by quits and firings. The opposite signs for quits and firings support the discussion about the effect of u_t raised in Bowlus (1995).

2.4.3 Cumulative Incidence Functions

While the estimates from the subhazard regressions provide a direct inference on the effects of u_0 and u_t on quits and firings, using these estimates to make inferences about the overall duration of employment can be misleading. The subhazard functions for different reasons of job terminations are estimated separately, and the probability of job termination can potentially exceed one when the value of one of the explanatory variables is changed.[10]

To evaluate the overall behavior of employment duration, I use the coefficient estimates from the cause-specific hazard regressions. Note that the estimates of the coefficients from the cause-specific regressions alone are not informative about the effects of u_0 and u_t, although the signs agree with the estimates from the subhazard regressions. Therefore, I obtain the cumulative incidence functions for each job termination category using the coefficient and baseline hazard estimates from the cause-specific hazard regressions. By construction, the probability of job termination is less than unity at any point in time.

[Figure 7 about here.]

Figure 7 shows the cumulative incidence functions for each cause-specific job terminations. The cumulative incidence functions are drawn for a 29 year-old high-school graduate white male whose job is not protected by a union. The unemployment rate is set equal to the average value of the unemployment rate for the survey years, 6.10%,

[10]The probability of ending a job exceeds one after 150 weeks when the starting unemployment rate is one standard deviation above its sample mean.

and it is assumed to be equal to this value for all of the time periods from the start of the job. The plots for all three reasons are stacked so that the differences show the probability of observing the corresponding cause-specific job termination before time t. At any time t, the difference between the sum of cumulative incidence functions and one represents the survival probability. Thus, the median duration of a job is 44 weeks.

[Figure 8 about here.]

Figure 8 shows the effects of a change in u_0 on the cumulative incidence functions for quits, firings, and other reasons. In each plot, the solid curves show the cumulative incidence functions when u_0 is equal to its sample mean. The dashed and dotted curves correspond to the cumulative incidence functions when u_0 is one standard deviation, 1.46%, above or below its sample mean. The current unemployment rate is still kept at its average value for all of the remaining time periods.

The cumulative incidence functions constructed from the cause-specific hazard regressions are consistent with the results from the subhazard regressions. When u_0 is equal to its sample mean, the probability of quitting a job is equal to 0.225 at the median employment duration. This probability increases to 0.288 if u_0 is one standard deviation above its sample mean and decreases to 0.173 when u_0 is one standard deviation below. Firings respond to changes in u_0 in the opposite direction. At the median employment duration, the probability of firing a worker decreases from 0.094 to 0.085 when u_0 is one standard deviation above its sample mean. This probability increases to 0.102 when u_0 is one standard deviation about its sample mean. The behavior of job terminations are similar to those due to firings. At the median employment duration, the probability of terminating a job due to reasons other than quits and firings is equal to 0.173. This probability decreases to 0.137 when u_0 is above its sample mean and increases to 0.215 when u_0 is below its sample mean.

The overall effect of these opposing forces on the duration of a job spell is ambiguous. Taken together with job terminations due to other reasons, the overall effect of u_0 on the duration of employment is negative but small. The duration of employment decreases from 44 weeks to 42 weeks if u_0 is one standard deviation above its sample mean and it increases by only one week when u_0 is one standard deviation below its sample mean. Duration of employment is used as a proxy for match quality in the literature. Therefore, these findings suggest that match quality is weakly pro-cyclical.

[Figure 9 about here.]

Similar results hold for the effects of u_t. Figure 9 shows the change in the cumulative incidence functions for cause-specific job terminations after a change in u_t. In each plot, the solid curves show the cumulative incidence functions when u_t is equal to its sample mean. The dashed and dotted curves correspond to the cumulative incidence functions when u_t is permanently one standard deviation above or below its sample mean for all the periods after the job spell has started.

Changes in u_t affect the cumulative incidence functions constructed from the cause-specific hazard regressions in the same direction implied by the coefficient estimates from the subhazard regressions. At the median employment duration, the probability of quitting a job decreases from 0.225 to 0.187 if u_t is permanently increased by one standard deviation above its sample mean and increases to 0.268 when u_t is permanently one standard deviation below its sample mean. Unlike quits, the probability of being fired increases with u_t as implied by the subhazard regressions. At the median employment duration, the probability of firing a worker increases from 0.094 to 0.116 when u_t is permanently one standard deviation above its sample mean, but it decreases to 0.075 when u_t is permanently one standard deviation below its sample mean. The response of job terminations due to other reasons is similar to the response of firings. At the median employment duration, the probability of terminating a job due to a reason other than quits and firings increases from 0.173 to 0.198

when u_t is permanently above its sample mean, but it decreases to 0.149 when u_t is permanently below its sample mean.

2.5 Conclusion

Workers and firms respond to labor market conditions at the start of the employment relationship in opposite directions. In models with on-the-job search, job seekers have an incentive to take a low-quality job during a recession due to increased competition among the job seekers. The workers' incentive to take low-quality jobs implies that jobs created during a recession are likely to have shorter spells. In contrast, models with endogenous separation imply that hiring firms can potentially form better matches because they hire workers from a bigger applicant pool. Therefore, jobs created during a recession are likely to have longer spells. The net effect of these opposing forces on the duration of employment is a priori ambiguous.

In this paper, I empirically test for these theoretical predictions of the effects of labor market conditions on the duration of employment. Using data from NLYS 1979 cohort, I estimate a proportional hazard model under the assumption that different causes of job terminations are competing risks. I use information about the reason why a job spell has ended to distinguish job terminations due to a worker's quit decision from job terminations due to a firm's firing decision. Making a distinction between quits and firings is the main contribution of this paper, because it allows me to test separately for *both* of these opposing forces rather than estimating their *net* effect on the duration of employment.

Two methods have been widely used in the literature to estimate hazard models when there are competing risks. I apply both of these methods in this paper and they produce consistent results. I find that an increase in the unemployment rate at the start of an employment relation increases the probability that the worker quits his job to take or look for another job, but it reduces the probability that the firm fires the worker. These results support both the models with on-the-job search and the models with endogenous separation. Furthermore, the net effect of these opposing forces on the duration of employment is negative. Previous papers in the literature using the NLSY 1979 cohort also find a negative effect, but I find this effect to be much smaller. When the unemployment rate at the start of the employment relationship is one standard deviation above its sample mean, the median duration of a non-union job held by a 29 year-old white male with a high school degree decreases from 44 weeks to 42 weeks. These results suggest that match quality is weakly pro-cyclical.

Pro-cyclical quits and counter-cyclical firings imply that the responses of workers and firms in ongoing employment relationships to current labor market condition also move in opposite directions. My estimates from the proportional hazard model are also consistent with this aggregate behavior. The probability that a job spell ends with worker's quits decision decreases if the current unemployment rate is high. In contrast, the probability that a job spell ends with firm's firing decision is higher when the economy is in recession. The opposite response of quits and firings to the current unemployment rate supports the discussion in Bowlus (1995) about the non-linear response of the employment duration to the current unemployment rate.

My results provide useful empirical evidence for developing theoretical models of labor markets. While jobs created during recessions are on average low quality, this result does not necessarily imply that the predictions of the models with endogenous separation are negligible. Instead, both mechanisms find empirical support and are equally important for theoretical models studying the cyclical behavior of match quality.

Appendix A

Technical Appendix

A.1 Derivation of Wage Functions

The derivation of the wage functions exploits the fact that the continuation values for the firm and the workers cancel each other from the first order condition for n' and the envelope condition. Let $J(n', \varepsilon) = E_{\varepsilon'|\varepsilon}\Pi_{n'}(n', \varepsilon')$. From (1.12), the marginal value of an existing and potential worker are:

$$D_{\tilde{n}}(.) = \alpha A \varepsilon {n'}^{\alpha-1} - (w^n)'(.)\tilde{n} - w^n(.) - (w^p)'(.)r + J(.), \tag{A.1}$$

and

$$\begin{aligned} D_r(.) = \; & g(p)\alpha A \varepsilon {n'}^{\alpha-1} - g(p)(w^n)'(.)\tilde{n} - g(p)(w^p)'(.)r - w^p(.) \\ & + g(p)J(.), \end{aligned} \tag{A.2}$$

where $(w^n)'(.)$ and $(w^p)'(.)$ are the derivatives of the wage functions with respect to n'. Rearranging the bargaining solution in (1.13), I get:

$$(1-\phi)(w^n(.) - \Omega + \beta(1-\delta)(1-\lambda)[E_{\varepsilon'|\varepsilon}V^n(n',\varepsilon') - V^u]) \\ = \phi(\alpha A\varepsilon n'^{\alpha-1} - (w^n)'(.)\tilde{n} - w^n(.) - (w^p)'(.)r + J(.)), \tag{A.3}$$

where Ω is defined in (1.17). First, I show that $J(n',\varepsilon) = \beta(1-\delta)(1-\lambda)[E_{\varepsilon'|\varepsilon}V^n(n',\varepsilon') - V^u])$. To see that, re-write the dynamic problem of a hiring firm before inserting the wage functions and after replacing the constraint in equation (1.4):

$$\Pi^h(n,\varepsilon) = \max_{n',p\in[0,1]} \; -\frac{c_v}{q}\frac{\gamma(n'-(1-\lambda)n)}{1-p^\gamma} - \frac{c_s}{2}\exp\left(\frac{c_p}{2}p^2\right)\left(\frac{\gamma(n'-(1-\lambda)n)}{1-p^\gamma}\right)^2 \\ +A\varepsilon n'^{\alpha} - (1-\lambda)nw^n(n',\varepsilon) - \frac{(1-p)\gamma(n'-(1-\lambda)n)}{1-p^\gamma}w^p(n',\varepsilon) \\ +\beta(1-\delta)E_{\varepsilon'|\varepsilon}\Pi(n',\varepsilon'). \tag{A.4}$$

The first order condition for n' is:

$$-\frac{c_v}{q}\frac{\gamma}{1-p^\gamma} - c_s\exp\left(\frac{c_p}{2}p^2\right)\left(\frac{\gamma}{1-p^\gamma}\right)(n'-(1-\lambda)n) \\ +\alpha A\varepsilon n'^{\alpha-1} - (1-\lambda)n(w^n)'(.) - \frac{(1-p)\gamma}{1-p^\gamma}w^p(.) - \frac{(1-p)\gamma(n'-(1-\lambda)n)}{1-p^\gamma}(w^p)'(.) \\ +\beta(1-\delta)E_{\varepsilon'|\varepsilon}\Pi_{n'}(n',\varepsilon') = 0. \tag{A.5}$$

Next, conditional on hiring, the envelope condition implies:

$$\Pi_{n'}(n',\varepsilon) = (1-\lambda)\left(\frac{c_v}{q}\frac{\gamma}{1-p^\gamma} + c_s\exp\left(\frac{c_p}{2}p^2\right)\left(\frac{\gamma}{1-p^\gamma}\right)^2(n'-(1-\lambda)n)\right) \\ +(1-\lambda)\left(-w_n(.) + \frac{(1-p)\gamma}{1-p^\gamma}w^p(.)\right). \tag{A.6}$$

Replacing the first line in (A.6) from (A.5) and substituting for $\tilde{n}$ and r, one obtains:

$$\Pi_{n'}(n', \varepsilon) \quad = (1-\lambda)D_{\tilde{n}}(.). \tag{A.7}$$

If the firm is neither hiring nor firing, (A.7) holds by definition. Finally, if the firm is firing workers, then the marginal surplus of an existing worker is equal to 0. Equivalently, $\Pi_{n'}(n', \varepsilon) = 0$. Hence, (A.7) is trivially satisfied. From the definition of $J(.)$ and using (A.7), one gets $J(n) = \beta(1-\delta)(1-\lambda)D_{\tilde{n}}(.)$, which further implies $J(n', \varepsilon) = \beta(1-\delta)(1-\lambda)[E_{\varepsilon'|\varepsilon}V^n(n', \varepsilon') - V^u])$ by (1.13).

The bargaining equations now can be written as follows:

$$\phi\left(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(.)\tilde{n} - (w^p)'(.)r\right) \quad = (1-\phi)(w^n(.) - \Omega), \tag{A.8}$$

and

$$g(p)\phi\left(\alpha A \varepsilon n'^{\alpha-1} - (w^n)'(.)\tilde{n} - (w^p)'(.)r\right) \quad = (1-\phi)(w^n(.) - \Omega). \tag{A.9}$$

Multiplying (A.8) by $g(p)$ and subtracting from (A.9) implies:

$$(w^p)(.) = g(p)(w^n)(.) + (1-g(p))\Omega. \tag{A.10}$$

After taking the derivative with respective to n' and plugging this back in (A.1), I obtain the following first order differential equation in n':

$$w^n(.) + \phi n'(w^n)'(.) = \phi\alpha A \varepsilon n'^{\alpha-1} + (1-\phi)\Omega. \tag{A.11}$$

The solution to this differential equation is given by (1.27). The constant of integration is set to zero so that $n'w(.) \to 0$ as $n' \to 0$. The wage equation for newly hired workers can be obtained from (A.10).

A.2 Recursive Stationary Equilibrium

Definition 1. (Recursive Stationary Equilibrium) The recursive stationary equilibrium consists of value function for firms, $\Pi(n, \varepsilon)$; a set of decision rules for vacancies, hiring standard, firings and employment, $g_v(n, \varepsilon)$, $g_p(n, \varepsilon)$, $g_f(n, \varepsilon)$ and $g_{n'}(n, \varepsilon)$; value functions for employed workers, $V^n(n, \varepsilon)$ and $V^p(n, \varepsilon)$; wage functions, $w^n(n', \varepsilon)$ and $w^p(n', \varepsilon, p)$; market tightness and aggregate matching probability, θ and q; value of unemployment at the beginning and bargaining stages, $\tilde{V}^u$ and V^u; and a stationary distribution firms across productivities and employment, $\Gamma(n, \varepsilon)$, such that:

1. θ and q are related according to (1.2).
2. Firm's Optimization: Given q, $w^n(n', \varepsilon)$ and $w^p(n', \varepsilon, p)$, the set of decision rules, $g_v(n, \varepsilon)$, $g_p(n, \varepsilon)$, $g_f(n, \varepsilon)$ and $g_{n'}(n, \varepsilon)$, solve firms' problem described by equations (1.4), (1.5), (1.6) and (1.7).
3. Worker Value Functions: Given θq, $w^n(n', \varepsilon)$, $w^p(n', \varepsilon, p)$ and firms' decision rules, $g_v(n, \varepsilon)$, $g_p(n, \varepsilon)$, and $g_{n'}(n, \varepsilon)$, value functions for workers, $V^n(n, \varepsilon)$, $V^p(n, \varepsilon)$, $\tilde{V}^u$ and V^u, satisfy equations (1.8), (1.9), (1.10) and (1.11).
4. Wage Bargaining: The wage equations, $w^n(n', \varepsilon)$ and $w^p(n', \varepsilon, p)$, satisfy (1.12), (1.13) and (1.14).
5. Free-entry condition in (1.19) holds.
6. Consistency: The stationary distribution $\Gamma(n, \varepsilon)$ is consistent with the firm's decision rules and satisfies (1.18).

A.3 Properties of the Adjustment Cost Function

As in the text, let $\Delta = (n' - (1 - \lambda)n)$. We are seeking the optimal choice for p given Δ to minimize total cost of adjustment. For brevity, let $f(p) = \frac{1}{1-p^{\gamma}}$ and

$h(p) = c_p \exp\left(\frac{c_p}{2}p^2\right)(f(p))^2$. Note that the natural logarithm of $h(p)$, $f(p)^2$ and $c_p \exp(p^2)$ are all convex. I use this observation to show the convexity of $C(\Delta)$. The minimization problem of the firm is:

$$C(\Delta) = \min_{p\in[0,1]} \gamma\Delta\left((\Omega + c_v/q)f(p) - \Omega f(p)p + h(p)\Delta\right)$$

Let $\Upsilon(p,\Delta)$ denote the objective function of the problem above. I have already established in the text that the solution is interior and unique. Then, the first order condition (FOC) and the second order condition (SOC) are:

$$\begin{aligned} \Upsilon_p(p,\Delta) &= 0 \\ \Upsilon_{pp}(p,\Delta) &> 0 \end{aligned}$$

Totally differentiating the FOC, one obtains:

$$p'(\Delta) = \frac{dp}{d\Delta} = -\frac{\Upsilon_{p\Delta}}{\Upsilon_{pp}} = -\frac{h'(p)\Delta}{\Upsilon_{pp}} \leq 0$$

The last inequality follows from the SOC. Further, the cost function satisfies:

$$C(\Delta) = \Upsilon(p(\Delta),\Delta)$$

Taking the derivative with respect to Δ:

$$C'(\Delta) = \Upsilon_p p'(\Delta) + \Upsilon_\Delta$$

By the FOC, the first term is zero. Hence:

$$C'(\Delta) = (\Omega(1-p) + c_v/q)f(p) + 2h(p)\Delta > 0$$

Finally, differentiating the expression for $C'(\Delta)$ yields:

$$C''(\Delta) = \Upsilon_p p''(\Delta) + \Upsilon_{p\Delta} p'(\Delta) + \Upsilon_{\Delta\Delta}$$

By the FOC, the first term is zero. Rearranging the terms and replacing for $p'(\Delta)$ yields:

$$C''(\Delta) = \Upsilon_{\Delta\Delta} - \frac{\Upsilon_{p\Delta}^2}{\Upsilon_{pp}}$$

By the SOC, the adjustment cost function is convex iff $\Upsilon_{\Delta\Delta}\Upsilon pp - \Upsilon_{p\Delta}^2 \geq 0$. This requires:

$$\Delta(\Omega(1-p) + c_v/q)f''(p) - 2\Omega f'(p)))2h(p)\Delta$$
$$+\Delta 2(\Delta)^2 h''(p)h(p) - \Delta^3(h'(p))^2 \geq 0$$

The first term is positive from the definition of $f(p)$. A sufficient condition for the second term to be positive is that $h(p)h''(p) - (h'(p))^2 \geq 0$. This condition is also satisfied by log-convexity of $h(p)$.

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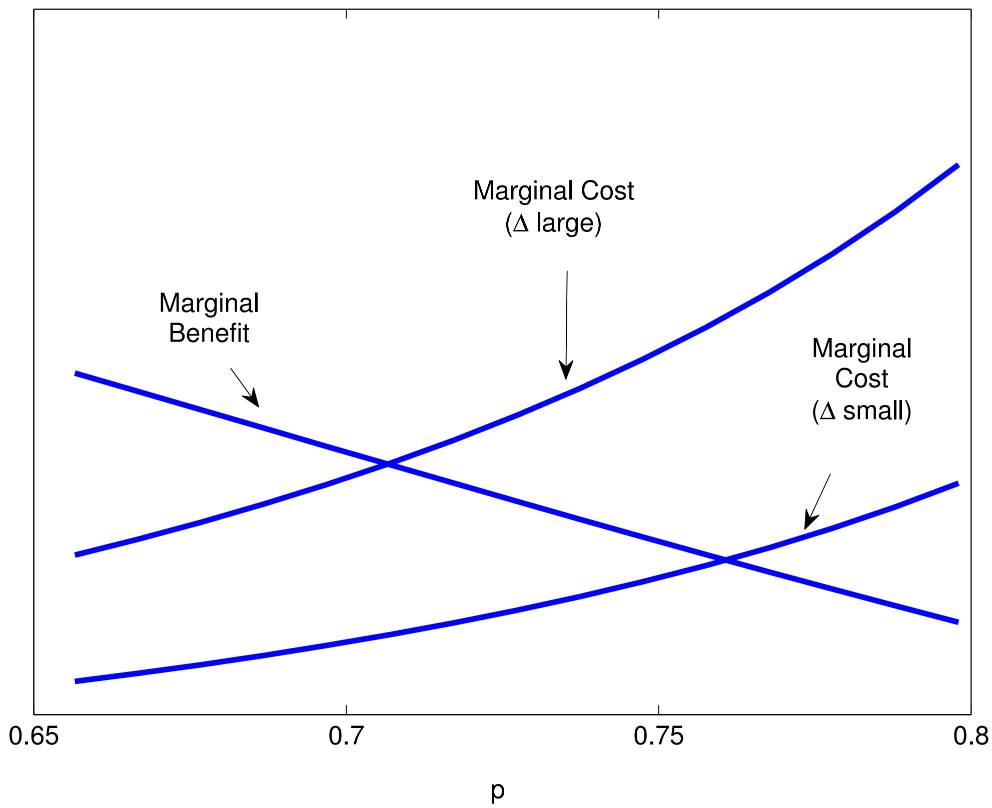

Figure 1: Optimal Choice for the Hiring Standard: An increase in the net change in employment, Δ, shifts the marginal cost curve for the hiring standard, p. As a result, the optimal p becomes smaller.

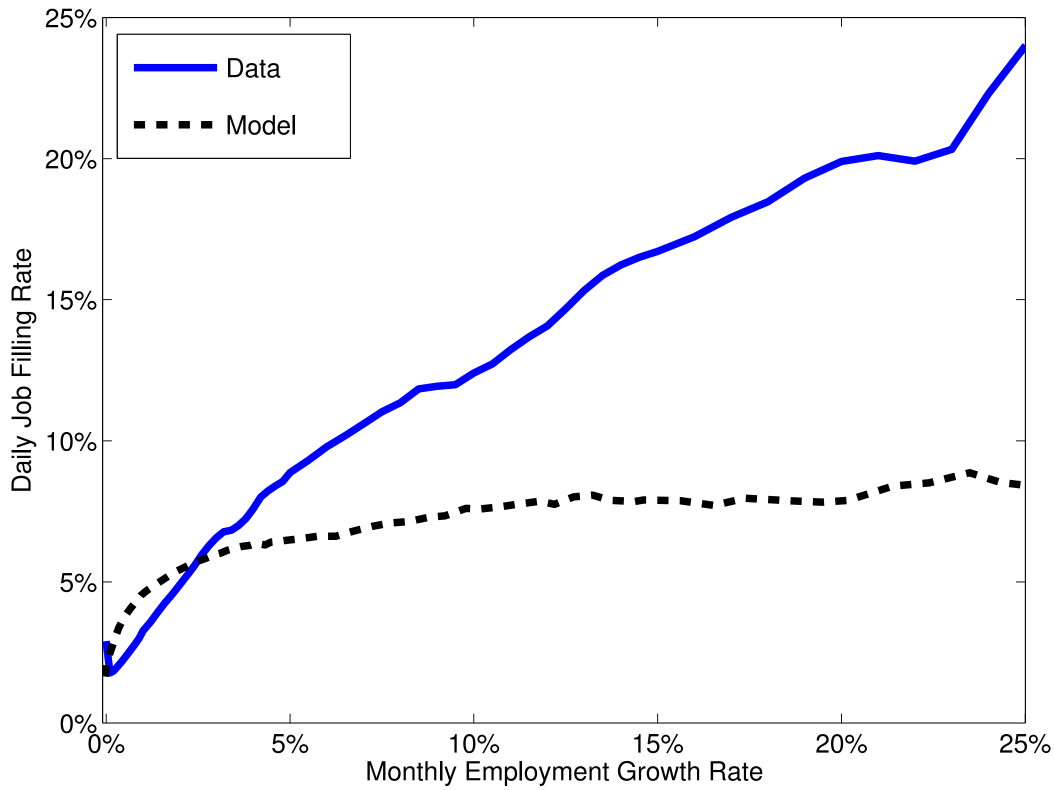

Figure 2: The Cross Sectional Relationship between Employment Growth Rate and Daily Job Filling Rate: The solid line corresponds to the calculations from the simulated model. The dashed line shows the pattern observed in the data. The calculations from the data are obtained from Davis, Faberman and Haltiwanger (2013).

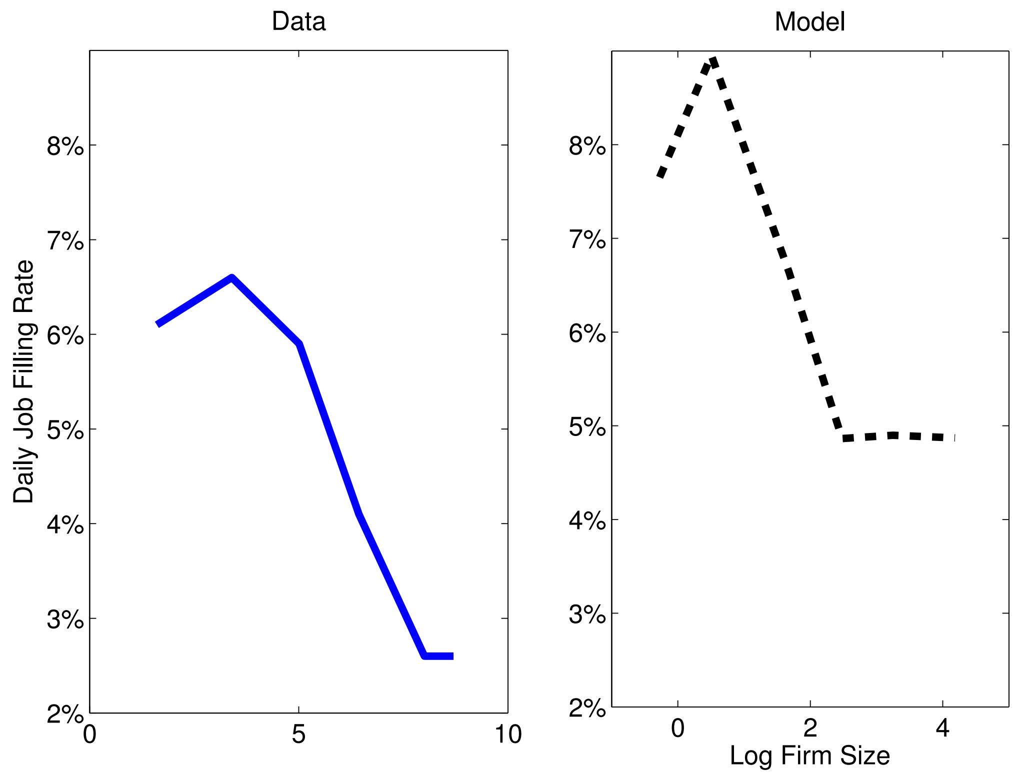

Figure 3: The Cross Sectional Relationship between Firm Size and Daily Job Filling Rate: The solid line corresponds to the calculations from the simulated model. The dashed line shows the pattern observed in the data. The calculations from the data are obtained from Davis, Faberman and Haltiwanger (2013).

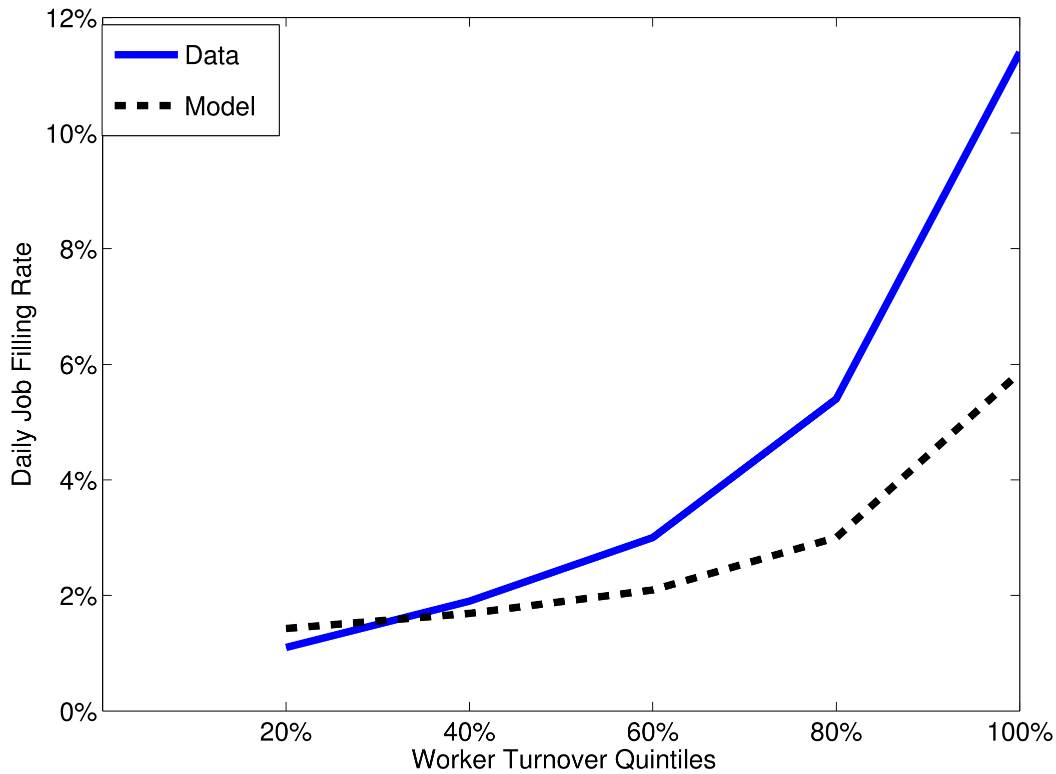

Figure 4: The Cross Sectional Relationship between Worker Turnover Rate and Daily Job Filling Rate: The solid line corresponds to the calculations from the simulated model. The dashed line shows the pattern observed in the data. The calculations from the data are obtained from Davis, Faberman and Haltiwanger (2013).

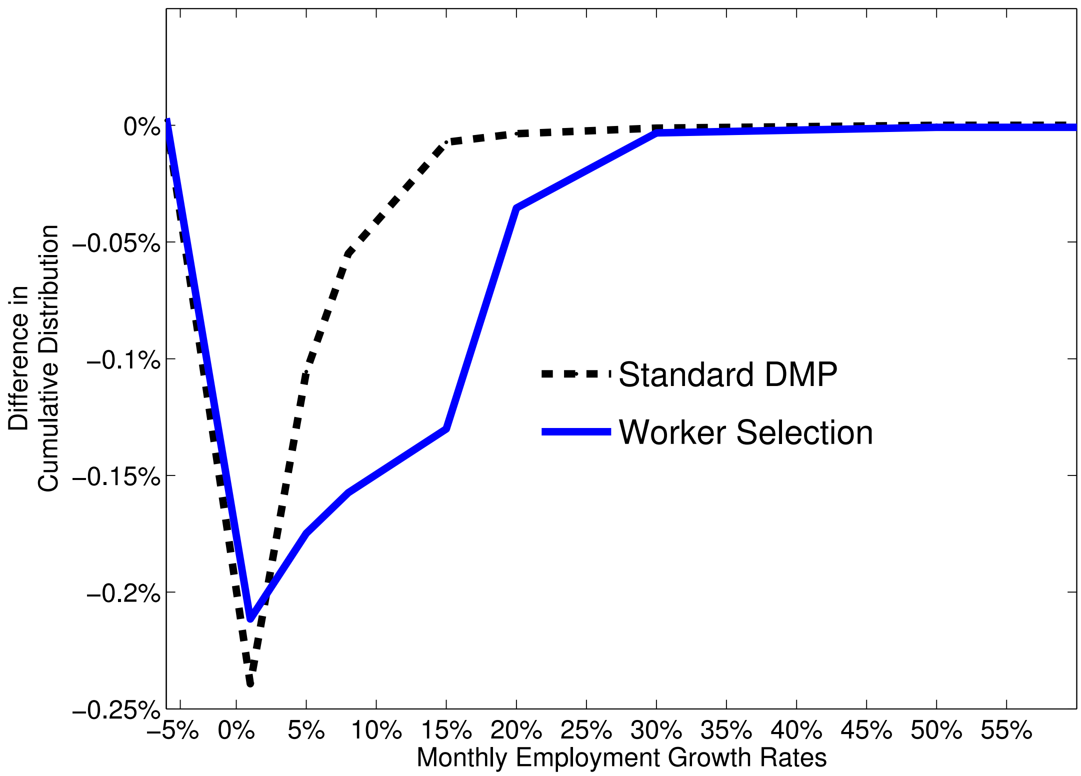

Figure 5: The Firm-Level Effect of a Hiring Subsidy: The figure shows the difference in the cumulative distribution of monthly employment growth rates in response to a hiring subsidy equal to 0.1 units of consumption good. The solid/dashed line corresponds to the worker selection/standard model.

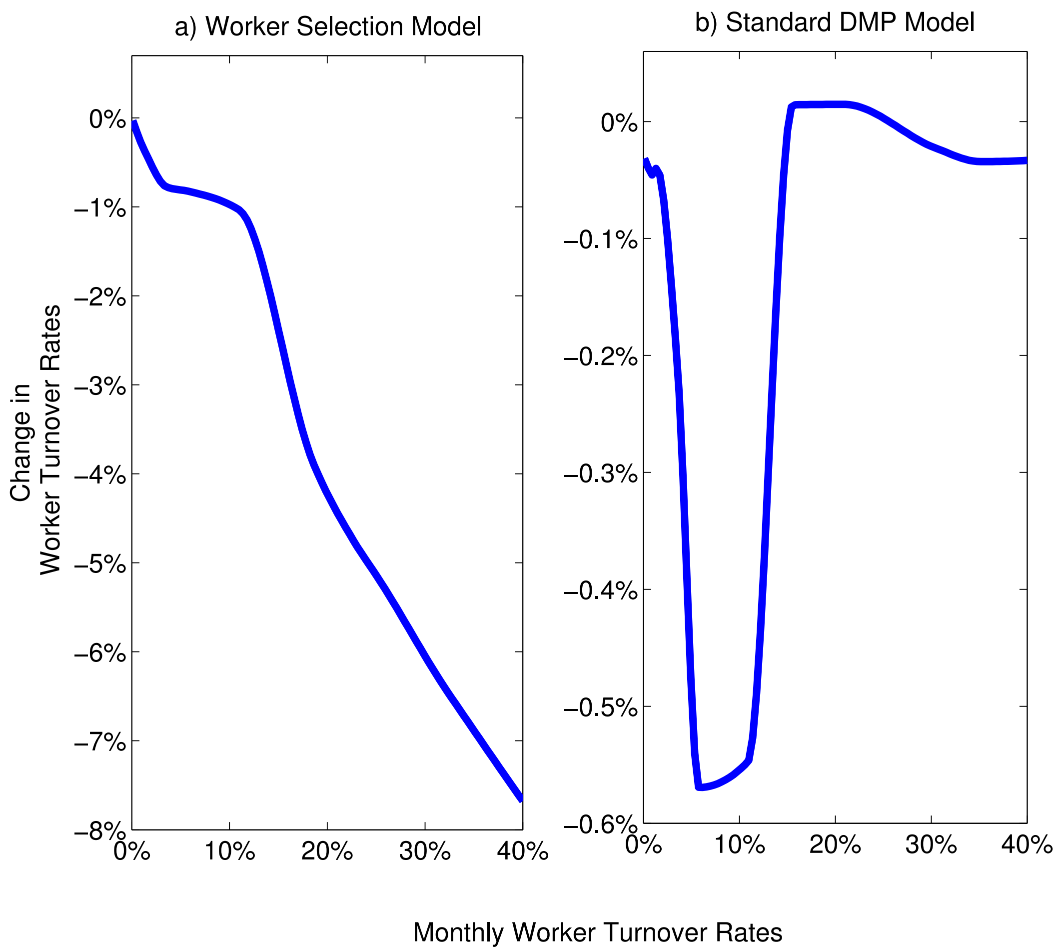

Figure 6: The Firm-Level Effect of a Firing Tax: Panel a) and Panel b) shows the changes in the worker turnover rates in response to a firing tax equal to 0.9 units of consumption goods across worker turnover rate bins from the worker selection and the standard models, respectively.

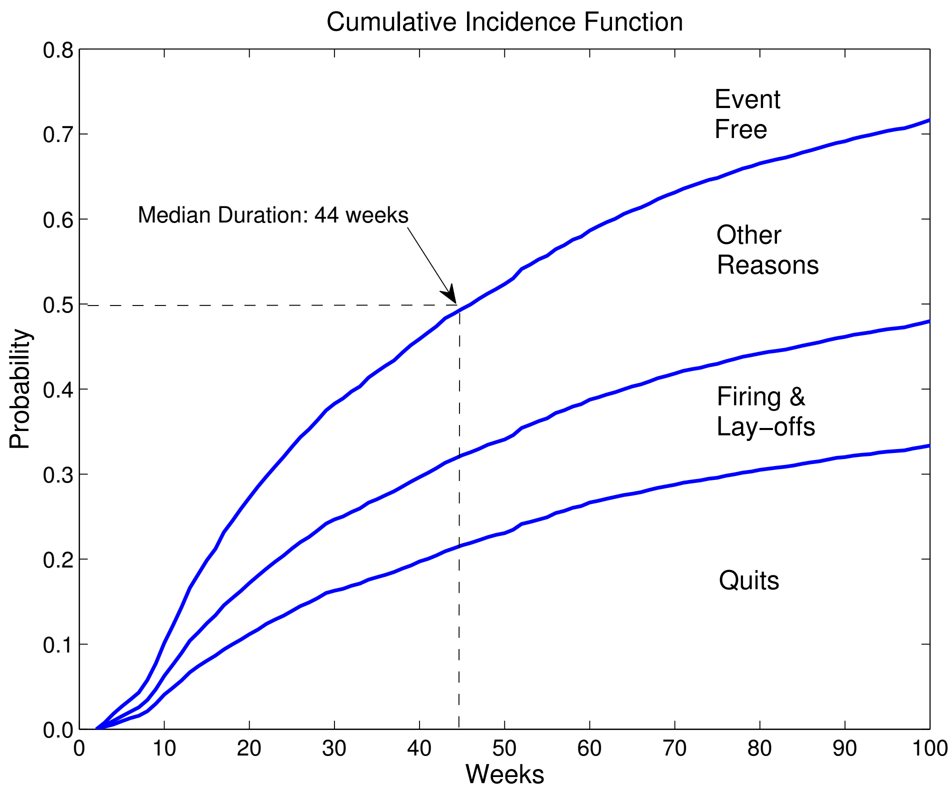

Figure 7: Cumulative Incidence Functions for Quits, Firings, and Other Reasons: The cumulative incidence functions are stacked so that the distance between two curves represents the probabilities of the different events.

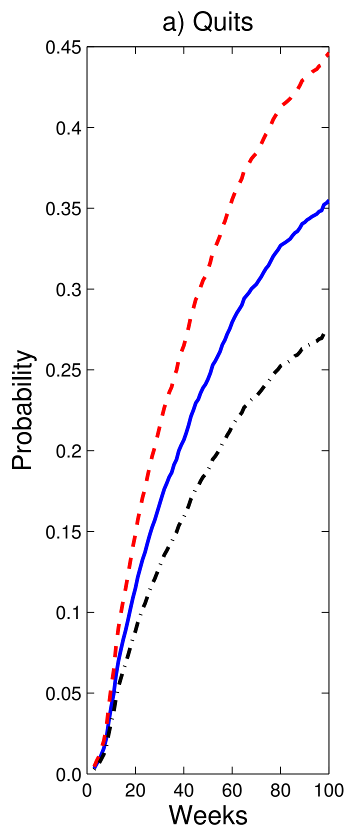

Figure 8: Changes in Cumulative Incidence Functions in Response to a Change in u_0: Panels a, b, and c show cumulative incidence functions for quits, firings, and other reasons, respectively. Solid line represents the cumulative incidence functions when the unemployment rate at the start of the employment relationship is set equal to its sample mean. Dash/dash-dot lines show the responses of cause-specific job terminations to a one standard deviation increase/decrease in the unemployment rate at the start of the employment relationship. The current unemployment rate is kept at the sample mean value for all the preiods.

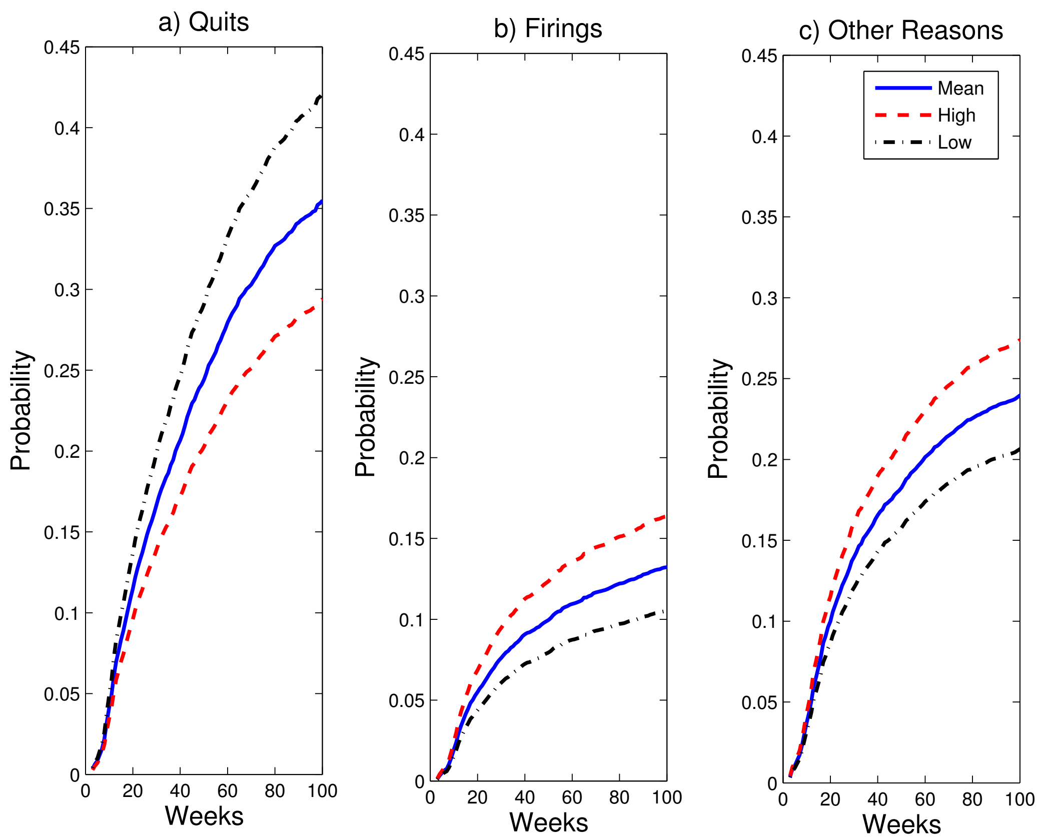

Figure 9: Changes in Cumulative Incidence Functions in Response to a Change in u_t: Panels a, b, and c show cumulative incidence functions for quits, firings, and other reasons, respectively. Solid line represents the cumulative incidence functions when the current unemployment rate is set equal to its sample mean. Dash/dash-dot lines show the responses of cause-specific job terminations to a one standard deviation permanent increase/decrease in the current unemployment rate.

Parameter	Meaning	Value
β	Discount factor	0.9996
ϕ	Bargaining power	0.5000
α	Production function curvature	0.6777
ρ	Persistence of idiosyncratic shocks	0.5900
σ	Dispersion of idiosyncratic shocks	0.1730
γ	Success probability parameter	4.0944
λ	Exogenous separation probability	0.0006
δ	Exogenous exit probability	0.00075
b	Value of leisure	0.9220
c_v	Flow cost of vacancy	0.0058
ζ	Matching function parameter	1.6783
c_s	Selection cost- quantity margin	0.0465
c_p	Selection cost- quality margin	1.6404
A	Aggregate productivity	3.3070
c_e	Fixed entry cost	3154.6083

Table 1: Calibrated Parameters of the Worker Selection Model (Weekly)

Parameter	Meaning	Value
$\bar{p}$	Hiring probability parameter	0.6519
p_γ	Success probability parameter	0.4540
σ	Dispersion of idiosyncratic shocks	0.1714
b	Value of leisure	0.9222
c_s	Selection cost	0.0481
A	Aggregate productivity	3.3094
c_e	Fixed entry cost	3155.7578

Table 2: Calibrated Parameters of the Standard DMP model (Weekly)

	Subsidy Levels in Consumption Good					
	0.000	0.100	0.200	0.300	0.400	0.500
% of average w^p						
Worker Selection	0.00%	11.54%	21.99%	31.50%	40.22%	48.14%
Standard DMP	0.00%	11.49%	21.72%	30.90%	39.18%	46.70%
Unemployment Rate						
Worker Selection	5.35%	5.25%	5.12%	4.98%	4.87%	4.79%
Standard DMP	5.35%	5.34%	5.32%	5.31%	5.29%	5.28%
Hires-to-vacancy ratio						
Worker Selection	0.302	0.311	0.321	0.331	0.337	0.325
Standard DMP	0.302	0.301	0.300	0.299	0.297	0.295
Contact Prob(q)						
Worker Selection	0.867	0.863	0.858	0.851	0.840	0.802
Standard DMP	0.867	0.863	0.861	0.858	0.854	0.848
Hiring Standard(p)						
Worker Selection	0.652	0.640	0.626	0.612	0.599	0.595
Standard DMP	0.652	0.652	0.652	0.652	0.652	0.652
Net Output (% change)						
Worker Selection	0.000%	0.020%	0.047%	0.067%	0.084%	0.068%
Standard DMP	0.000%	0.019%	0.031%	0.040%	0.049%	0.053%

Table 3: The Effects of Hiring Subsidy on Equilibrium: The amount of the hiring subsidy is measured in consumption good.

	Firing Tax Levels in Consumption Good					
	0.000	0.100	0.300	0.500	0.700	0.900
% of average w^p						
Worker Selection	0.00%	12.84%	43.44%	83.22%	137.26%	215.21%
Standard DMP	0.00%	12.97%	44.64%	87.23%	147.54%	239.63%
Unemployment Rate						
Worker Selection	5.35%	5.47%	5.70%	5.91%	6.12%	6.33%
Standard DMP	5.35%	5.36%	5.39%	5.42%	5.45%	5.48%
Hires-to-vacancy ratio						
Worker Selection	0.302	0.294	0.280	0.269	0.258	0.249
Standard DMP	0.302	0.302	0.304	0.306	0.307	0.309
Contact Prob(q)						
Worker Selection	0.867	0.871	0.878	0.884	0.889	0.895
Standard DMP	0.867	0.863	0.861	0.858	0.854	0.848
Hiring Standard(p)						
Worker Selection	0.652	0.663	0.681	0.697	0.710	0.722
Standard DMP	0.652	0.652	0.652	0.652	0.652	0.652
Net Output (% change)						
Worker Selection	0.000%	-0.050%	-0.146%	-0.248%	-0.351%	-0.456%
Standard DMP	0.000%	-0.025%	-0.089%	-0.157%	-0.228%	-0.301%

Table 4: The Effects of a Firing Tax on Equilibrium: The amount of the firing tax is measured in consumption good.

	Cause-Specific Hazard			Subhazard		
Variable	Quits	Firings	Other	Quits	Firings	Other
u_0	.157*	-.052*	-.134*	.344*	-.101*	-.214*
	(0.017)	(.022)	(.018)	(.021)	(.030)	(.024)
u_t	-.104*	.138*	.090*	-.360*	.151*	.116*
	(.017)	(.020)	(.0166)	(.024)	(.029)	(.023)
HS	.086	-.269*	-.148*	.189*	-.227*	-.056
	(.063)	(.068)	(.054)	(.063)	(.067)	.055
COL	.063	-1.337*	-.627*	.379*	-1.063*	-.355*
	(.076)	(.129)	(.078)	(.076)	(.129)	(.078)
AGE	.661*	.071	.024	.541*	-.072*	-.101*
	(.046)	(.039)	(.024)	(.045)	(.033)	(.022)
SQAGE	-.012*	-.002*	-.001*	-.010*	.001*	.001*
	(.000)	(.001)	(.000)	(.000)	(.001)	(.000)
NWHITE	.082	.325*	.061	.026	.277*	-.000
	(.043)	(.055)	(.042)	(.043)	(.054)	(.042)
GEN	-.150*	-.299*	.347*	-.176*	-.330*	.408*
	(.041)	(.056)	(.040)	(.041)	(.055)	(.040)
UNION	-.473*	-.084	-.608*	-.187*	.267*	-.374*
	(.055)	(.061)	(.055)	(.053)	(.061)	(.054)
Occurrence:	2522	1416	2542	2522	1416	2542
# of observations: 7655						
# of right-censored observations: 1175						

Table 5: Estimation Results from Cause-Specific and Subhazard Regressions: UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%.