Learning about Match Quality: Information Flows and Labor Market Outcomes

Gonul Sengul*

Central Bank of Turkey

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Abstract

Workers with lower skills have higher unemployment rates. This is because they are more likely to become unemployed, not because they are less likely to find a job. Thus, understanding the differences in probability of becoming unemployed between skill groups is crucial to understand the gap between their unemployment rates. This paper analyzes to what extent these differences come from variations in information frictions about the suitability of an employee for the job (match quality) by skill.

Keywords: Unemployment, Skill, Match Quality, Hiring Strategies, Search and Matching Models

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*Istanbul School of Central Banking, Central Bank of the Republic of Turkey. Email: Gonul.Sengul@tcmb.gov.tr.

Introduction

Low skill workers have higher unemployment rates compared to their higher skill counterparts, which is a result of their higher probability of separation, as shown by Layard et al. (1991), Nagypál (2007) and Kitao et al. (2011). This paper extends the aforementioned evidence and develops a search and matching model with employers' selection effort and learning that can account for this observation. The aim is to understand how much of the observed disparities in labor market outcomes of skill groups can be attributed to the differences in information flows in their labor markets. Although the importance of information in the labor market is long recognized (Stigler (1962)), its implications for skill groups is not well studied.

I use data from the Current Population Survey (CPS), between January, 1976 and December, 2007, on prime age males to document the skill differences in unemployment experiences. Over the sample period, low skill workers have, on average, twice the unemployment rate of high skill workers (see Table 1). High and low skill workers have average job finding probabilities of 32 and 36 percent, respectively, from 1976 to 2007. The difference in the job finding probability between skill groups is clearly not the reason behind the difference between their unemployment rates. Furthermore, low skill workers have approximately three times higher probability of becoming unemployed compared to high skill workers. The dispersion in the job separation probability by skill is the basis of the difference in unemployment rate these skill groups face.

There also exists differences in the recruiting efforts of firms. van Ours and Ridder (1992) use establishment level survey data from Netherlands that is conducted between 1986 and 1987 to document that employer search is selection among applicants. They find that "almost all vacancies are filled from a pool of applicants that is formed shortly after the posting of the vacancy. Hence, vacancy durations

should be interpreted as selection periods and not as search periods for applicants." ((van Ours and Ridder, 1992, pp 138)).[1] Barron et al. (1985) use data collected in the 1980 Employer Opportunities Pilot Project (EOPP) survey of employers to investigate effects of factors such as training and employer size on employer search. They find that employer search, measured by the number of applicants interviewed per offer, increases as the firm size and education and training requirements of the job increase. Barron and Bishop (1985) use the second wave of the EOPP survey that contains data for 1982 and document that as the firm size, training requirement, and the physical capital used on the job increase, so does the number of interviews conducted per offer. Barron et al. (1997) also find evidence suggesting that firms interview more candidates per offer as the required training level, education, and the prior experience of the worker increase.[2] More recently, Pinoli (2008) uses two datasets from Great Britain to analyze how firms collect information about the quality of workers; screening ex-ante vs. monitoring on-the-job. The results suggest that workers with temporary contracts are monitored more closely and screened less ex-ante compared to employees hired on a permanent contract, which is especially true for low-level occupations. Pellizzari (2011) employs British data to find that firms putting more effort into recruitment end up with better quality matches with higher wages and lower turnover.

This paper proposes an explanation that can generate the differences in unemployment rates across skill groups that is consistent with their flow rate differences and analyzes the extent of its success. In doing so, the paper also provides an explanation for higher selection effort of firms to hire high skill workers. The explanation builds on the fact that the firm-worker match is "an experience good, whose char-

[1] See also van Ours and Ridder (1993).

[2] Also can see Barron et al. (1987), Burdett and Cunningham (1998), Brencic (2009), and Behrenz (2001) and references therein.

acteristics are initially uncertain, and are gradually revealed over time by output performance" (Moscarini (2005), p.481). However, an employment relationship is not purely an experience good, it is also an inspection good, i.e., something can be learned about the match quality of potential employees beforehand. Firms' hiring decisions are based on the information they acquire from the applicant pool and information they acquire depends on the effort they put into selection. If firms inspect more prospect employees, their probability of finding a suitable worker for the job increases. Hence these employment relationships are more likely to be of desired quality, and thus less likely to be terminated.

This mechanism is modeled in a discrete time infinite horizon labor search and matching model with high skill and low skill workers. For each skill type, an employment relationship between a firm and a worker can be of either good or bad quality. Good quality matches are expected to produce higher output than bad quality matches and bad quality matches are undesirable. Match quality is unknown when the employment relationship is formed and it is learned over time through observing the output.

When a firm with a vacancy meets an unemployed worker the parties receive information regarding the probability of this match being of good quality. Based on this information (probability), they decide whether to form the employment relationship. To model the selection channel, I assume that the information prospect firm-worker pairs receive can be drawn from one of two available distribution: a "basic" distribution and a "better" distribution. The better distribution first order stochastically dominates the basic distribution. Hence it is more likely to deliver good quality matches. Firms can invest in this better technology paying an additional cost. Firms decide which distribution to use when they open a vacancy.

I calibrate the model to the U.S. economy to quantitatively asses the ability of the mechanism provided in this paper to explain the separation rate disparity across

skill. The model delivers that high skill firms select the "better" distribution in equilibrium. Hence more high skill firms get high quality matches, resulting in a lower job separation rate. The model can account for around half of the separation rate differences across skill groups. Moreover, difference in job finding probability across high and low skill workers is small. Consistent with the data, the unemployment rate differences across skill groups is mostly due to differences in their separation probabilities.

Hiring policies are used to answer some other facts regarding labor markets. Pries and Rogerson (2005) analyze differences in labor and job turnovers between the U.S. and the Europe. The differences in labor market policies of these economies generate differences in hiring policies of firms. Tasci (2006) looks at firms' hiring policies over the business cycle and proposes changes in hiring behavior over the cycle as another mechanism to increase the response of the key aggregate labor market variables to productivity shocks.[3] Villena-Roldan (2012) analyzes implications of recruitment selection on unemployment duration and re-employment wages in a model with heterogenous workers.

To my knowledge, there are only two other papers that propose an explanation for the difference in job separation probabilities across skill, which are complements to this paper.[4] Moscarini (2003) quantifies the match specific capital and analyzes its implications for wage inequality. In the model, low skill workers have a comparative disadvantage in market work (lower wedge between productivity and opportunity cost of work). Thus, they do not tolerate mismatches and separate to

[3]Wolthoff (2014) develops a search and matching model with number of interviews and characterizes the equilibrium. Bull et al. (1987) proposes a mechanism in which a worker quality is inherent and intermediaries (recruitment firms) can find able workers more efficiently. Stevens (2004) analyses firms' hiring strategies in a matching model with wage posting and on-the-job search, finding that firms can offer contracts where wages increase with tenure.

[4]Kitao et al. (2011) calibrate their model to match inflow and outflow rates for low and high skill workers, they do not provide an explanation.

unemployment more often than the high skill workers.[5]

Nagypál (2007) focuses on the difference in levels and the standard deviations of unemployment rate across skill. Nagypal explains that the existence of match specific capital (information about the quality of a match) for high skill workers and the lack of such capital for low skill workers make low skill employment relations more vulnerable to adverse idiosyncratic shocks. She uses a matching model with firms employing both high and low skill workers, and with uncertainty regarding match quality for high skill jobs. Firms' decisions to terminate a high skill match, when faced with an adverse idiosyncratic shock, depends on the accumulated information about the quality of that match. Nagypal constructs a numerical example to show that differences in learning about the match quality can generate differences in unemployment rates.

The rest of the paper is organized as follows. The next section extends the empirical evidence on skill differences in unemployment experiences. Section 2 lays out the model. The equilibrium of the model is defined and analyzed in section 3. Section 4 presents the quantitative results and is followed by concluding remarks.

1 Data

I use the CPS data from January 1976 to December 2007 to document the skill differences in unemployment rate.[6] I focus on prime age (between 25 and 54) males

[5]Bils et al. (2012) develops a model in which workers differ in their market human capital and valuation of non-market time to investigate the success of search and matching models in capturing employment fluctuations. In their model workers with lower market comparative advantage have higher separation probabilities as well.

[6]The CPS is a monthly survey of about 50,000 households. It is the primary source of information on the labor force characteristics of the U.S. population. The CPS is conducted by the Bureau of the Census for the Bureau of Labor Statistics. The web site for the Survey is: http://www.census.gov/cps. The data can be downloaded from http://www.nber.org/data/cps_basic.html.

since they have the strongest labor market attachment among labor market participants. Results for the overall labor force are displayed in the appendix. Following the standard definition for "skill" in the literature, I use education level as a proxy. Workers without a four year college degree are low skill workers while those with at least 16 years of education (a four-year college degree) are high skill workers.

I calculate the unemployment rate as the ratio of the number of the unemployed in a particular month to the size of the labor force in that month for each skill group. In computing the job finding probability and the job separation probability, I follow the methodology used in Shimer (2012) and Elsby et al. (2009).[7] The job finding probability in a given month measures the likelihood of a worker finding a job within that month. The job separation probability measures the likelihood of employed workers becoming unemployed within that month.

Table 1: Unemployment Rate and Worker Flows

	Unemployment Rate	**Job Finding Probability**	**Separation Probability**
Low-skill*	.058	.36	.026
	(.02)	(.06)	(.004)
High-Skill	.023	.32	.009
	(.006)	(.07)	(.002)

Flow Averages over Monthly CPS Data (prime age [25−50] males), February 1976 - Dec 2008. *: Workers with no college degree.

Table 1 summarizes unemployment experiences by skill groups. Between January 1976 and December 2007, low skill workers experienced an average unemployment rate of 5.6 percent whereas high skill workers faced a 2.3 percent unemployment rate. Moreover, low skill workers had a slightly better chance of finding

[7] I discuss this methodology in more detail in the appendix.

jobs than their high skill counterparts. The data reveal that low skill workers have higher unemployment rates due to higher job separation probabilities. Figures A.1, A.2, A.3 illustrate the skill differentials in unemployment rates and job finding and separation probabilities of skill groups over time.[8]

These facts are robust to different specifications of the data. I analyze the unemployment rate difference between skill groups that is not due to lay-offs. The CPS collects data on the reason for unemployment after 1994. Over the period of 1994 to 2007, the average unemployment rate (counting those who are laid-off as unemployed) is 4.9 percent for low skill workers, and 2.1 percent for high skill workers. If we do not count laid-off workers as unemployed, and look only at unemployment for reasons other than lay-offs, the average unemployment rate is 3.9 and 1.9 percent for low skill and high skill workers, respectively. Clearly, not counting laid-offs as unemployed reduces low skill unemployment more. However, the relative number of lay-offs among low skill workers, compared to high skill workers, is not large enough to account for the differences in unemployment rates.

Data facts presented above are also robust to the cutoff for the definition of skill. Redefining high skill workers as workers with at least some college education (instead of a four-year college degree) changes quantitative results slightly, but not enough for the gap to go away or decrease significantly. Moreover, the gap in the unemployment rate and the job separation probability is significant for finer categories of education.

The skill differences in unemployment experiences are also documented by other authors. Mincer (1991) uses the Panel Study of Income Dynamics data on male labor force participants and finds that higher levels of education reduce the risk of unemployment. He also finds that the difference in the incidence of unemployment is more important than the difference in unemployment durations for ed-

[8] All figures are quarterly averages of the monthly data.

ucational differences in unemployment. Nagypál (2007) uses March Supplements and Displaced Worker Supplements of the CPS and finds differences in unemployment rate by education. Moreover, Nagypál (2007) documents that the differences in unemployment duration by education are not large enough to account for the differences in unemployment rates. Layard et al. (1991) use managerial vs. manual occupations to show that higher unemployment rate of manual occupations is mostly due to their higher separation rates.

2 Model

To analyze the question posed above, I use a labor search and matching model with two types of workers: high skill and low skill. The skill type is exogenous and each type has a total mass normalized to one. Moreover, there are high skill and low skill jobs which can employ only the workers of the same skill type. Firms are free to choose the type of jobs they want to create. I assume that there is no other interaction between skill types.

Within each skill group, firms and workers are ex-ante identical. Workers can be unemployed or employed, and there are filled and vacant jobs. A firm can employ at most one worker. All agents are risk neutral and they discount the future at a rate β. A production unit in the model is a firm-worker pair (match hereafter). A match between a firm and a worker can be of either good or bad quality. The quality of the match is unknown when it is formed and it is learned over time through the realized output.

The output produced by a match is $y_j = \bar{y}_j + \epsilon_j$, where $j \in \{hs,\ ls\}$ is the skill type and $i \in \{g,\ b\}$ is the quality. Note that the output a match produces depends on the skill type of the firm-worker pair as well as the quality of the match. The match output is composed of a deterministic part, $\bar{y}_j \in \{y_j^b, y_j^g\}$, and a stochastic

part, ϵ_j. Good quality employment relationships are expected to produce higher output than bad quality matches within a skill group, i.e., $y_j^g > y_j^b,\ \forall\ j \in \{hs, ls\}$.

I follow Pries and Rogerson (2005) in modeling the learning about the match quality. As such, the stochastic term ϵ_j is assumed to be uniformly distributed over the interval $[-\tilde{\epsilon}_j, \tilde{\epsilon}_j]$, where $\tilde{\epsilon}_j > \frac{y_j^g - y_j^b}{2}$. Under this assumption, when worker and the firm in an employment relationship observe the output, they ascertain the true quality of the match with probability $\pi_j = \frac{y_j^g - y_j^b}{2\tilde{\epsilon}_j}$, or continue with the same beliefs about the quality of the match (i.e., all-or-nothing learning).[9] Observe that the stochastic term ϵ_j depends only on the skill type of the match and it determines the speed of ex-post learning. If, for instance, $\pi_j = 1$, then parties learn the match quality after observing the first period of output as there would not be any output value which both a good and a bad quality match could have produced.

In the model, unemployed workers and vacant jobs find each other via a function that endogenously determines workers' and firms' meeting probabilities. I assume that matching markets are segregated, so that there is a separate matching market (function) for each skill type. Since there is no interaction across skill, I drop the skill subscript. The $M(u, v)$ function, generically named as the matching function, takes the numbers of unemployed workers (u) and vacant jobs (v) and determines the number of meetings between these parties (M). The number of meetings determines the probability that an unemployed worker meets a vacancy ($h_w = M(u, v)/u$) and the probability that a vacant job meets a worker ($h_f = M(u, v)/v$).

When a firm with a vacancy meets an unemployed worker, the parties learn the

[9] Note that if $y_j < y_j^g - \tilde{\epsilon}_j$, parties know that the match must be of bad quality, while $y_j > y_j^b + \tilde{\epsilon}_j$ indicates a good quality match. Hence, the probability that the match quality reveals, π_j, is

$$\pi_j = 1 - P(y_j^g - \tilde{\epsilon}_j < y_j^i + \epsilon_j < y_j^b + \tilde{\epsilon}_j) = 1 - \frac{y_j^b + \tilde{\epsilon}_j - y_j^g + \tilde{\epsilon}_j}{2\tilde{\epsilon}_j} = \frac{y_j^g - y_j^b}{2\tilde{\epsilon}_j}.$$

probability of this match being of good quality, γ, and decide whether to form the employment relationship. The probability of a good quality match, γ, is drawn from either a "basic" distribution Γ or from a "better" distribution Ω. These distributions are defined over the unit interval and have the standard properties of a cdf. Moreover, Ω first order stochastically dominates Γ, i.e., in expectation, the better distribution is more likely to yield a good quality match than the basic distribution. Firms choose which distribution to employ when they open the vacancy. The better distribution comes at a cost κ.

Once the match is formed, the firm and the worker observe the level of output and learn the match quality with probability π.[10] If the worker-firm pair learns that the match is of good quality, they stay attached until hit by an exogenous separation shock. If the match is revealed to be of bad quality, the parties unanimously decide to separate. I assume that $y^b \leq b$ and $y^g > b$ (for each skill type). Under this assumption bad quality matches are not profitable in equilibrium.

2.1 Bellman Equations

I start by formalizing the firm's decision problem. Let $\lambda \in \{0, 1\}$ denote the firm's selection effort such that $\lambda = 1$ if the firm selects the better distribution and $\lambda = 0$ if the firm chooses the basic distribution. The value of a vacancy is the discounted value of expected profits, net of the cost of creating the vacancy.

$$V = -c + \max_{\lambda \in \{0,1\}} \Big\{ -\lambda\kappa + \beta(1-h_f)V + \beta h_f \Big[\lambda \int J(\gamma) d\Omega(\gamma) + (1-\lambda) \int J(\gamma) d\Gamma(\gamma) \Big] \Big\}, \tag{1}$$

[10] Recall that π can differ across skill.

where h_f is the probability that the firm meets a worker and $J(\gamma)$ is the value of the firm when in a match which is of good quality with probability γ. Note that the firm pays a vacancy cost c regardless of its selection effort. Equation (2) formalizes the problem of a firm that is in a match with a worker.

$$\begin{aligned} J(\gamma) = \max \Big\{ & V,\, E(y|\gamma) - w(\gamma) + \beta\delta V \\ & + \beta(1-\delta)\Big[\pi\big(\gamma J(1) + (1-\gamma)J(0)\big) + (1-\pi)J(\gamma)\Big]\Big\}, \end{aligned} \tag{2}$$

where δ is the exogenous probability of job destruction, $w(\gamma)$ is the wage the firm pays, and $E(y|\gamma)$ is the expected value of output, which is defined as $E(y|\gamma) = y^g\gamma + y^b(1-\gamma)$.

The firm compares the expected discounted value of profits from producing output with the current worker to the discounted present value of separating from the worker (being vacant). The value the firm gets from producing is the sum of the current period profit, which is the expected value of output produced net of the wage paid to the worker, and the discounted value of being in a match with the same worker in the subsequent period, if the match survives.

Workers face a choice problem that is similar to that of firms', except for the choice of selection effort. Let U be the value of unemployment to a worker, and $W(\gamma)$ be the value of being in a match with a firm where γ is the probability that the match is of good quality. If a worker is unemployed, she gets the unemployment income, b, for the current period. With probability $1 - h_w$ the worker does not meet any firms, and thus continues to be unemployed in the subsequent period. The worker meets a firm with probability h_w and gets the expected value from being in a match with that firm. The equation below states this sequence of events:

$$U = b + \beta(1-h_w)U + \beta h_w\Big[\lambda \int W(\gamma)d\Omega + (1-\lambda)\int W(\gamma)d\Gamma\Big], \tag{3}$$

where λ is the equilibrium choice of selection effort. Note that the expected value the worker gets from being in a match with a firm depends on the selection effort firms choose.

The formal statement of a worker's decision problem when she is in a match is as follows:

$$W(\gamma) = \max\Big\{U,\, w(\gamma) + \beta\delta U + \beta(1-\delta)\Big[\pi\big(\gamma W(1) + (1-\gamma)W(0)\big) + (1-\pi)W(\gamma)\Big]\Big\}. \tag{4}$$

The worker needs to decide between being unemployed and being in a match which is of good quality with probability γ . If the worker chooses to be in the match, she receives a wage and continues to get a value which depends on the quality of the match in the subsequent period and whether the match survives the risk of destruction. If she separates, she gets the value of being unemployed, U.

2.2 Wage Determination and Worker Flows

Wages are determined according to the Nash bargaining rule, where workers' bargaining power is μ. The wage rate that solves the bargaining problem is such that a worker gets a constant (μ) fraction of the net value generated by the worker-firm union. It is a weighted average of the expected output the match will produce and the worker's outside option, which is the value of unemployment. After some algebra, one can show that

$$w(\gamma) = \mu\big[y^g\gamma + y^b(1-\gamma)\big] + (1-\mu)(1-\beta)U. \tag{5}$$

The Nash bargaining assumption guarantees the unanimity of the separation or

match formation decision. That is because parties bargain over the net surplus of the match, and if the surplus is positive (negative) they decide to form the match (separate). Hence there is no inconsistency across parties in decision making.

Note that at any period there will be two types of employment relationships; those matches that are known to be of good quality and those with unknown quality. Let e_t^g and e_t^n denote the number of workers with good and unknown quality matches, respectively. Unknown quality matches in the subsequent period are the current period unknown quality matches that survive and stay unknown and the newly-formed matches.

$$e_{t+1}^n = e_t^n(1-\delta)(1-\pi) + h_w E(X) u_t, \tag{6}$$

where h_w is the worker's probability of meeting a firm, X is the decision rule about match formation and $E(X)$ is the expected probability of being in an acceptable match. The decision rule for whether to form a match will be a cutoff rule. As such, only the good quality match probabilities that are above the cutoff value, call it γ^*, will result in employment relationships. Hence,

$$E(X) = \lambda \int_{\gamma^*} d\Omega + (1-\lambda) \int_{\gamma^*} d\Gamma. \tag{7}$$

The number of workers who have known (good) quality matches in the subsequent period is the sum of the current period good quality matches that survive and the current period unknown quality matches that survive and turn out to be of good quality.

$$e_{t+1}^g = (1-\delta)e_t^g + e_t^n(1-\delta)\pi E(\gamma|X), \tag{8}$$

where $E(\gamma|X)$ is the expected probability of good quality match conditional on

match formation. More formally:

$$E(\gamma|X) = \lambda \frac{\int_{\gamma^*} \gamma d\Omega}{\int_{\gamma^*} d\Omega} + (1-\lambda) \frac{\int_{\gamma^*} \gamma d\Gamma}{\int_{\gamma^*} d\Gamma}. \tag{9}$$

Unemployment evolves according to the following equation:

$$u_{t+1} = e_t^g \delta + u_t(1 - h_w E(X)) + e_t^n(\delta + (1-\delta)\pi(1 - E(\gamma|X))) \tag{10}$$

At every period, there is exit from unemployment as $f_w E(X)$ fraction of them become employed. Entry to unemployment has two sources: a constant fraction of good (known) quality employment relationships get hit by an exogenous separation shock and a fraction of jobs with unknown quality matches separate due to an exogenous shock or learning that the quality of the match is bad.

Observe that a higher speed of learning increases the endogenous separations of unknown quality matches, therefore increasing unemployment. A higher conditional expected value increases the fraction of unknown quality matches that are of good quality, reducing endogenous separations.

3 Equilibrium

This section describes the equilibrium of the economy and the optimal selection effort. It is more convenient to work with surplus equations, the total net value of a match, rather than the value of a match to the firm and to the worker. Let $S(\gamma)$ be the net value a match generates: $S(\gamma) = W(\gamma) - U + J(\gamma) - V$. Substituting

equations (2) and (4) into this equation for $J(\gamma)$ and $W(\gamma)$ yields

$$S(\gamma) = \max\left\{0,\ \frac{E(y|\gamma) + \beta(1-\delta)\pi(\gamma S(1) + (1-\gamma)S(0)) - (1-\beta)(U+V)}{1-\beta(1-\delta)(1-\pi)}\right\}. \tag{11}$$

Moreover, the surplus from a match that is known to be good, and bad, quality is:

$$S(1) = \max\left\{0,\ \frac{y^g - (1-\beta)(U+V)}{1-\beta(1-\delta)}\right\}, \qquad S(0) = \max\left\{0,\ \frac{y^b - (1-\beta)(U+V)}{1-\beta(1-\delta)}\right\}.$$

The assumption that $y^b = b$ makes workers and firms prefer separation to staying in a bad quality match, hence bad quality matches are terminated in equilibrium and $S(0) = 0$.[11] Moreover, the assumption that $y^g > b$ is needed to assure a positive match surplus from good quality matches so that there is employment in equilibrium ($S(1) > 0$).

Definition: The steady state equilibrium, for each skill, is a list $\{v, u, \lambda, e^g, e^n, \gamma^*, w(\gamma), J(\gamma), V, W(\gamma), U, X, h_w, h_f\}$ such that

- $\{V,\ J(\gamma),\ U,\ W(\gamma)\}$ satisfy equations (1), (2), (3) and (4).
- There is free entry and hence vacancies earn zero profits ($V = 0$).
- $w(\gamma)$ satisfies equation (5) (it is the solution to the Nash bargaining problem).
- Match formation decision rule X is such that

$$X = \begin{cases} 1, & \gamma \ \geq\ \gamma^* \\ 0, & \gamma \ <\ \gamma^* \end{cases}$$

[11] As shown later in the section, in equilibrium $V = 0$ and $(1-\beta)U$ is the sum of b and another term. Hence, $y^b = b$ guarantees that $y^b - (1-\beta)(U+V) < 0$.

where γ^* is such that $S(\gamma^*) = 0$,

$$0 = \frac{E(y|\gamma^*) + \beta(1-\delta)\pi\gamma^* S(1) - (1-\beta)U}{1-\beta(1-\delta)(1-\pi)}.$$

- Employment stocks are such that

$$\begin{aligned}
\delta e^g &= e^n(1-\delta)\pi E(\gamma|X), \\
e^n &= (1-\delta)e^n(1-\pi) + f_w E(X)u, \\
u &= (1-f_w E(X))u + e^n(\delta + (1-\delta)\pi(1-E(\gamma|X))) + e^g\delta.
\end{aligned}$$

- λ is the solution to the optimization problem described in equation (1).

Since vacancies earn zero profit in equilibrium, we can rewrite equation (1) as follows:

$$C(\lambda) = \beta h_f(1-\mu)\Big[\lambda \int S(\gamma)d\Omega + (1-\lambda)\int S(\gamma)d\Gamma\Big],$$

making use of the fact that $J(\gamma) = (1-\mu)S(\gamma)$. For notational convenience $C(\lambda) = c + \lambda\kappa$. Moreover, the equation for value of unemployment, (3), can be rewritten as

$$(1-\beta)U = b + \beta h_w \mu\Big[\lambda \int S(\gamma,\lambda)d\Omega + (1-\lambda)\int S(\gamma)d\Gamma\Big] = b + \theta\frac{C(\lambda)\mu}{(1-\mu)},$$

where $\theta = v/u$ is the market tightness and it governs the firm's and the worker's meeting probabilities. We can rewrite the surplus function as:

$$S(\gamma) = \max\left\{0,\ \frac{E(y|\gamma) + \beta(1-\delta)\pi\gamma S(1) - b - \theta C(\lambda)\frac{\mu}{(1-\mu)}}{1-\beta(1-\delta)(1-\pi)}\right\}. \tag{12}$$

First, notice that surplus is increasing in γ. Since surplus from a bad quality match ($\gamma = 0$) is zero, and surplus from a good quality match ($\gamma = 1$) is positive, and surplus is increasing in γ, there is a threshold probability of a good quality match, γ^*, such that firms and workers are indifferent between the match and their outside options, i.e. $S(\gamma^*) = 0$. Using equation (12), the threshold value is formally defined as

$$\gamma^* = \frac{(1-\beta)U - y^b}{y^g - y^b + \beta(1-\delta)\pi S(1)}. \tag{13}$$

The threshold probability of a good quality match depends negatively on the speed of learning about the match quality. As firms and workers learn about the match quality faster, the expected profit from a prospective match increases, making the marginal firm-worker pair have positive match surplus. Hence, threshold value for an acceptable match goes down. Also note that as the productivity difference between good and bad quality matches increase, threshold value also increases for the same reason.

3.1 Optimal Selection Effort

As noted before, the surplus function (equation 12) is linearly increasing in γ. Thus, we can write $S(\gamma) = S^{'}(\gamma - \gamma^*)$, $\forall \gamma \geq \gamma^*$, where

$$S^{'} = \frac{y^g - y^b}{1 - \beta(1-\delta)(1-\pi\gamma^*)}.$$

We can rewrite a firm's selection choice in hiring using the surplus function as follows:

$$\max_{\lambda \in \{0,1\}} \Big\{ -C(\lambda) + \beta h_f (1-\mu) S^{'} \Big[\lambda \int (\gamma - \gamma^*) d\Omega + (1-\lambda) \int (\gamma - \gamma^*) d\Gamma \Big] \Big\}.$$

A firm, for given equilibrium values of γ^* and h_f, chooses the better selection technology if

$$\frac{\beta h_f(1-\mu)(y^g - y^b)}{1-\beta(1-\delta)(1-\pi\gamma^*)}\Big(\int(\gamma-\gamma^*)d\Omega - \int(\gamma-\gamma^*)d\Gamma\Big) > \kappa$$

Notice that a larger productivity gap between good and bad quality matches, a higher $(y^g - y^b)$, increases the value of a good quality match, thus making returns from putting in more effort go up. Also notice that as the speed of learning decreases, $S^{'}$ increases. With slower speed of learning firms' losses from a possible bad quality match go up as firms would realize the loss and terminate the relationship slower. Hence, returns to a higher probability of good quality match increases, incentivizing firms to choose better selection technology.

4 Implications for Labor Market Outcomes

This section discusses model's implications for tenure profiles, wages and unemployment. Let f be the job finding probability. It is a function of the probability of meeting a firm and the expected value of having an acceptable match. Formally, f in the model is:[12]

$$f = h_w\Big(\lambda\int_{\gamma^*} d\Omega + (1-\lambda)\int_{\gamma^*} d\Gamma\Big), \tag{14}$$

where h_w is the probability of meeting a firm and it is a function of the market tightness (vacancy to unemployment ratio). Market tightness is determined by the free entry condition and its value depend on whether firms select the better technology.

[12]Similarly, vacancy filling rate, q is

$$q = h_f\Big(\lambda\int_{\gamma^*(\lambda)} d\Omega + (1-\lambda)\int_{\gamma^*} d\Gamma\Big).$$

Note that the speed of learning does not directly affect the job finding rate while selection effort does so through optimal match formation probability, ($E(X) = \lambda \int_{\gamma^*} \gamma d\Omega + (1-\lambda) \int_{\gamma^*} d\Gamma$), does. If firms choose the better selection technology, for a given threshold value, they are more likely to have an acceptable match. However the equilibrium value of firms' effort choice in hiring affects the threshold value for an acceptable match as well. Selecting the better technology ($\lambda = 1$) increases γ^*. This is because workers' outside options depend on the firms' selection behavior. As firms increase their effort in hiring, they have better prospects of matches, and thus they can offer higher wages, which increases workers' outside options. When workers' outside options increase, the marginal worker and firm will not be indifferent anymore since the net surplus for this match will be lower. Hence, the threshold value would go up. Not only selection effort, but also the market tightness affects the threshold value. As we cannot determine how equilibrium market tightness changes with skill, we cannot determine whether the threshold for high skill is higher in equilibrium or not. Hence, we cannot compare job finding rates across skill without quantitative analysis.

The other important determinant of unemployment is separation probability, (s). It is defined as the ratio of separations to employment. Using the employment stock equations in section 3, the separation rate is

$$s = \delta \frac{\delta + (1-\delta)\pi}{\delta + (1-\delta)\pi E(\gamma|\gamma^*)}.$$

Increase in the speed of learning increases the job separation probability. This is because learning about the match quality faster makes bad quality matches not last long, increasing endogenous separations. Separation rate depends negatively on conditional expected value of a good quality match as higher conditional probability implies a higher fraction of new matches to be of good quality, reducing endogenous

separations.

After some algebra using the employment equations, the unemployment rate u will be

$$u = \frac{s}{f+s}.$$

As we cannot determine how job finding and separation probabilities change with skill, model's implication for unemployment rate disparity is also qualitatively ambiguous. The next section calibrates the model to analyze the extend of its ability to explain the unemployment and separation rate disparities across skill.

A higher speed of learning affects tenure directly, as most of the bad quality matches are sorted out in the earlier periods of employment. Thus one expects the empirical hazard rate to be higher at the beginning, and then decline fast. Selection technology also changes the hazard rate. With better selection there are less endogenous separations, reducing the hazard rate at earlier tenures. As selection only affects tenure profile through endogenous separations, its effect diminishes over the course of employment.

Recall the wage equation (equation (5)):

$$w(\gamma) \quad = \quad \mu\big(\gamma y^h + (1-\gamma)y^l\big) + (1-\mu)(1-\beta)U.$$

Workers start to work for a wage that depends on the probability of the match being of good quality. As production takes place, if the parties learn the true match quality the worker either looses her job or gets a wage raise. Note that workers will not get any further raise after they learn that they are in a good quality match.

5 Quantitative Analysis

To explore the effects of speed of learning and selection effort on labor market outcomes, I carry out the following quantitative exercise. I start by assigning values from the literature to parameters common in these models. In doing so, I use moments of low skill workers when calibrating model parameters that are the same for both groups. Moreover, I search over equilibrium where low skill firms do not use the better selection technology to be able to calibrate the vacancy cost and the basic distribution parameter. Whether high skill firms use the better selection technology or not is determined endogenously.

The model period is one month, which implies a discount factor $\beta = 0.9967$ to get an annual interest rate of 4 percent. Observe that multiplying C, y^g, y^b, and b by the same number does not change the solution to the equation system. Thus, I normalize y^b to 1 for both skill types. I also set $b = y^b$, following Pries and Rogerson (2005), which is sufficient for the bad quality matches to be terminated in equilibrium. I use the Cobb-Douglas form for the matching function: $M = Au^{\alpha}v^{1-\alpha}$. This functional form is widely used in the literature and is supported by empirical evidence (see Petrongolo and Pissarides (2001) for a survey on matching function). α is the elasticity of matching function with respect to unemployment and is set to 0.36 as estimated in Cooper et al. (2007). Workers' bargaining power is generally set equal to α, which is also done here.[13]

Speed of learning governs the duration of employment as slower speed of learning implies flatter employment hazard rate. I calibrate the speed of learning parameter for low skill workers to match the survival probability of a job to its second year in equilibrium. I use tenure supplement files of the Current Population Survey and find this probability to be 0.046.[14] This implies that, on average, the quality of

[13]It is so done to satisfy the Hosios condition (Hosios (1990)).

[14]The data is from Center for Economic and Policy Research (2012)ter for Economic and Policy

a match is revealed in 10 months for low skill workers ($\pi_{ls} = 0.1$). I set the exogenous destruction rate δ to be 25 % of the low skill job separation rate, following Davis and Haltiwanger (1990) and Davis and Haltiwanger (1998).[15]

There is scarce evidence regarding the distribution of the match quality. As wage distribution resembles log-normal (Moscarini (2005)), I assume that the match quality distribution is log-normal with scale parameter -2.[16] I target low skill job separation rate to calibrate the standard deviation of the basic distribution. The average job separation probability among low skill workers is 0.026 between 1967 and 2007. Given that δ is 25 % of the low skill job separation rate ($\delta = 0.0065$), targeting separation rate of 0.026, requires a conditional expected value of 0.2. Moreover, I target the job finding rate to calibrate the vacancy cost, as will be discussed in the next paragraph. Since the match surplus is linear in good quality match probability and $y^b = b$, targeting both the separation rate (hence conditional expected probability of good quality match) and the job finding rate implies a specific value for the cutoff probability. The standard deviation of the basic distribution is calibrated to deliver the required conditional expected value of the good quality match probability for this cutoff value.

Matching efficiency parameter (A) is set so that in equilibrium market tightness for low skill workers is 1. This also implies that workers' and firms' meeting probabilities are the same. Choice of A rescales the equilibrium market tightness value for low skill workers while leaving the findings of this paper unchanged. Hence, I follow the strategy Pries and Rogerson (2005) use to pin down this parameter. I target the wage gap between the highest and the lowest earner in low skill sector

Research. I use the average of 1998, 2000 and 2004 for prime age male employees in nonagricultural private sector. I exclude the data for 2002 as it is right after the 2001 recession in the USA.

[15]They report that shut downs account for 25% of job destruction.

[16]The value of the cutoff and the conditional expected probability require a left-skewed density function, which requires a negative scale parameter as we re-scale the distribution to the unit interval.

to calibrate y^g_{ls}. The ratio of the highest to the lowest wage in low skill sector is set to be 1.33 in the steady state, following Topel and Ward (1992).[17] As mentioned earlier, I calibrate the vacancy cost parameter to match the average job finding probability, which is 36 percent between 1967 and 2007. I jointly calibrate these three parameters to get the targeted moments. The values of all parameters are reported in Table 2.

Table 2: Parameter Values

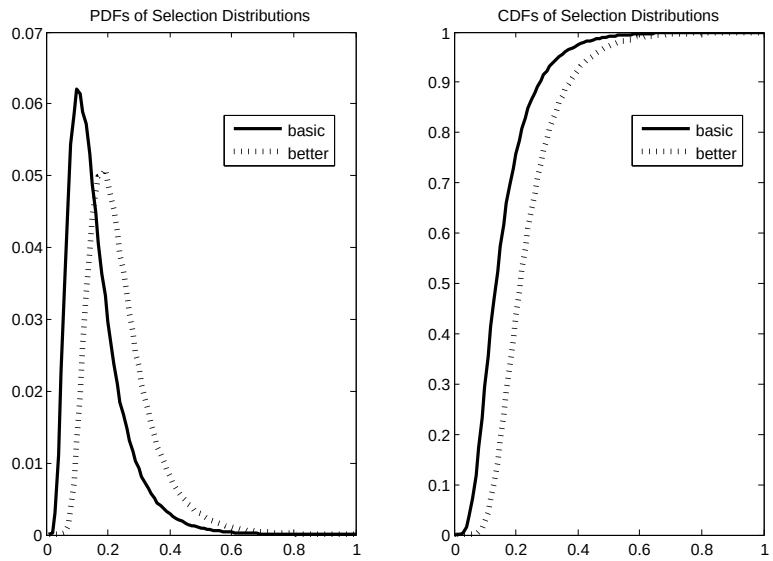
Parameter	**Value**	**Definition**
β	0.997	discount factor
μ	0.36	workers' bargaining power
α	0.36	Matching function parameter, match elasticity
A	0.554	Matching function parameter, match efficiency
δ	0.0065	Exogenous fraction of job destructions
y^b_{ls}	1	bad-quality output, low skill
b_{ls}	y^b_{ls}	unemployment income, low skill
π_{ls}	0.1	low-skilled learning speed
π_{hs}	0.059	high-skilled learning speed
y^b_{hs}	1	bad-quality output, high skill
b_{hs}	y^b_{hs}	unemployment income, high skill
c	1.82	Vacancy creation cost
κ	2.55	Selection cost parameter
y^g_{ls}	2.77	good-quality output, low skill
y^g_{hs}	5.27	good-quality output, high skill
σ_Γ	0.558	Basic distribution, std. error

To quantify the selection technology distribution and its cost, I proceed as follows: Barron and Bishop (1985) compute to cost of hiring for different occupations using a survey conducted in 1982. Cost of hiring for a managerial position is around 2.4 times of the cost of hiring a blue collar worker. I set $\kappa = 1.4c$ so that the differ-

[17] Topel and Ward (1992) report that one third of wage growth during the first 10 years of tenure is due to job changes. Following Pries and Rogerson (2005), I use this statistic to calibrate the good quality match output.

ence in total cost with and without selection is that large. I assume that the better distribution is the empirical distribution of the maximum order of n draws from the basic distribution.[18] Note that for any $n > 1$, the better distribution first order stochastically dominates the basic distribution. n determines how much "better" the better distribution is; as n increases, so does the mean of the better distribution, albeit rather slowly. I set n to the highest possible number such that low skill firms choose not to use the better technology for the given κ value.[19] The model delivers $n = 3$.[20] Figure 1 shows the basic and the better distributions for the calibrated standard error parameter.

Figure 1: Equilibrium Distributions



Given the selection cost and distribution parameters, I jointly calibrate the re-

[18]Hence, Ω is the distribution we get if we draw n random γ values from the basic distribution and choose the maximum γ, $\Omega(\gamma) = n\Gamma(\gamma)^{n-1}\gamma(\gamma)$.

[19]Recall that calibration strategy is such that low skill firms do not use the better technology.

[20]This is a plausible value as the average number of interviews reported by Barron and Bishop (1985) is around 4. For the n value used, the mean of better distribution is 0.24, while the mean of the basic distribution is 0.16.

maining high skill parameters. As such, I target the ratio of the expected wages across skill to be 1.77 to calibrate y^g_{hs}. The average ratio of the median usual weekly earning of college graduates to high school graduates is 1.77 from 2000 to 2013.[21] The implied value is $y^g_{hs} = 1.9y^g_{ls}$. This output gap implies a productivity gap of 1.83 across skill. The average productivity gap between high and low skill sectors is reported to be 79 percent in Acemoglu and Zilibotti (2001), and Kitao et al. (2011) set output gap between high and low skill workers to 2. Similar to speed of learning for low skill, I calibrate the speed of learning parameter for high skill workers to match the survival rate of a job the first year in equilibrium. This implies that, on average, the quality of a match is revealed in 17 months for high skill workers ($\pi_{hs} = 0.059$).

Steady state outcomes implied by the model for high and low skill workers using parameter values discussed above are displayed in Table 3. Columns two and three display the labor market outcomes for the benchmark economy. Low skill firms do not use the better technology by construction and their labor market values are used to pin down many of the model parameters. The model's success lies in its ability to generate the differences across high and low skill labor market outcomes. High skill firms do choose to use the better selection technology in equilibrium. As a result, they have lower separation probabilities than their low skill counterparts. The model can explain around half of the difference across skill groups in their separations. The job finding probability among high skill workers is 0.35 in the model. Even though this is slightly higher than the data value of 0.32, it is not much different from the job finding probability of low skill workers. Hence the unemployment rate disparity across skill is due to differences in separation probabilities in the model,

[21] The data is median usual weekly earnings (second quartile) of full time employed wage and salary workers who are male and 25 years and over from the CBS and it is reported by BLS (id numbers LEU0252918500 and LEU0252917300).

which is consistent with the data.

Low skill workers are more likely to separate from their jobs at earlier tenure stages than high skill workers. Right panel of Figure 2 shows that a lower fraction of low skill jobs survive to the second year, compared to high skill ones. The gap closes as tenure increases, as the quality of the most of the jobs are learned by that time, which leaves the exogenous separation as the only source. Moreover, wage inequality among high skill workers is higher compared to that of low skill workers (high skill workers experience higher wage increases).

Table 3: Main Results

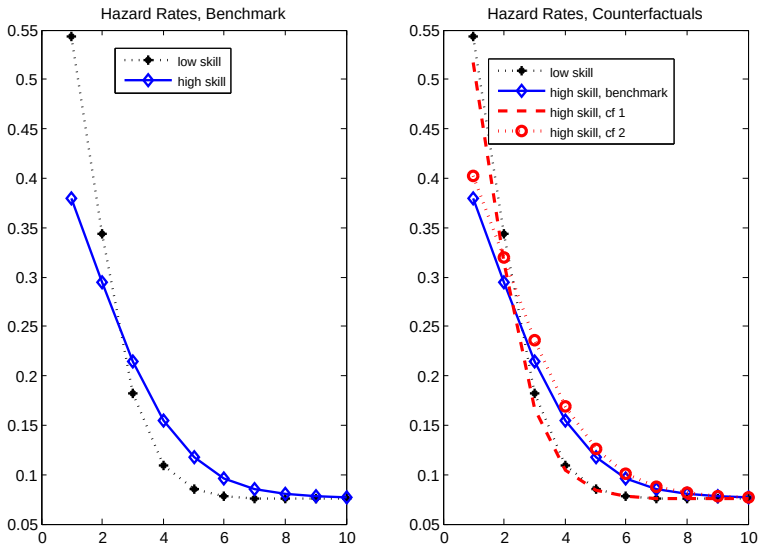
	Low skill	High skill		
		Benchmark	Counterfactual 1	Counterfactual 2
λ	0	1	0	0
θ	1	1.08	2.71	2.41
γ^*	0.109	0.192	0.14	0.16
s	**0.026**	**0.018**	**0.023**	**0.020**
f	**0.36**	**0.35**	**0.46**	**0.35**
u	0.067	0.048	0.048	0.053
$\omega(1)/\omega(\gamma^*)$	1.33	1.41	1.44	1.45
$E(X)$	0.65	0.60	0.46	0.36
$E(\gamma\|X)$	0.20	0.29	0.23	0.25
f_w	0.554	0.592	1	0.973
$S(1)$	0.46	0.62	0.48	0.60
$E(\omega(\gamma))_{hs}/E(\omega(\gamma))_{ls}$		1.77	1.75	1.67
$E(y_{hs})/E(y_{ls})$		1.83	1.87	1.77

$S(1)$: Survival probability of a job to the second year. $E(y_{hs})/E(y_{ls})$: productivity gap between high and low skill sectors.
Counterfactual 1: Speed of learning among high skill jobs is the same as it is for the low skill jobs. Counterfactual 2: Better technology is not available.

Total vacancy cost (cost of vacancy creation and selection) is higher for high skill jobs. If measured in terms of expected wages a worker gets, vacancy cost in low skill jobs is approximately around 6.5 weeks' wages, while the total cost in

high skill jobs is equivalent of 8.8 weeks' pay. Increase in vacancy cost with the skill requirements of a job is supported by the empirical evidence (see Blatter et al. (2012) and references therein).[22]

Figure 2: Completed Tenure Profiles by Skill; Model



There are two channels in the model that generate the differences across skill in their flows into unemployment. The first one is the difference is in the speed at which match quality is revealed and the second one is the selection technologies used by firms with different skill types. Match quality is revealed slower for high skill jobs. I conduct the following counterfactual exercise to see its effect on the model outcomes. I compute outcomes for the high skill workers assuming that their speed of learning is the same as that of low skill workers. Fourth column in Table 3 shows the results. First, notice that high skill firms do not choose to use

[22]In a recent study, Blatter et al. (2012) find that average hiring costs are between 10 to 17 weeks of wages using Swiss establishment level surveys from 2000 and 2004. They report that around 30 percent of this hiring cost is associated with recruitment costs. The rest is due to costs associated with the lower productivity during the adaptation period of the worker to the job.

the better technology. As a result, their job separation probability is much bigger than its benchmark value. Moreover, high skill workers experience much higher job finding rates, contradicting the data. If high and low skill workers were to have the same speed of learning, their tenure profiles would resemble each other (see the second panel of Figure 2).

To see the effect of better selection technology in generating the differences in outcomes of skill groups, I also do a counterfactual exercise where the better technology is not available. This exercise does not affect low skill workers' outcomes as their equilibrium distribution is the basic one. High skill firms, on the other hand, get affected significantly. Under this counterfactual (fifth column in Table 3) there is still separation rate difference across skill groups, but it is less than the benchmark case. High skill separations are still lower because their learning speed is lower and their cutoff probability is higher. We do not observe a significant change in job finding rate. This is because high skill workers' probability of meeting a job is higher, but their probability of being in an acceptable match is lower. Because total vacancy cost is much lower in this counterfactual compared to the benchmark, where firms also pay selection cost, there are more vacancies, resulting in higher meeting probabilities for workers. As shown in the second panel of Figure 2, lack of better selection decreases the survival rate of a job at the beginning of the tenure. Also note that without better selection, even though the output gap between good and bad quality matches is the same as in the benchmark, wage gap across skill is significantly lower.

6 Concluding Remarks

It is well documented that high skill workers have lower unemployment rates. Data also show that the reason behind lower rates of unemployment among high skill

workers is their lower probability of job separation. This paper proposes an explanation for the unemployment rate disparities across skill groups that is consistent with the determinants of the disparity: Information regarding the quality of a worker-firm match is more valuable for high skill jobs than it is for low skill jobs. This is because quality of the match is revealed slowly in high skill employment relationships and the gap between good and bad quality match outputs is larger. As a result high skill firms put in more selection effort to hire the right worker for the job, reducing separations.

I use a search and matching model with two types of workers: high skill and low skill. For each skill type, an employment relationship between a firm and a worker can be of either good or bad quality. Good quality matches are expected to produce higher output than bad quality matches within a skill group. I assume that the bad quality matches are not profitable, regardless of the skill type. Moreover, output gap between a good and a bad quality match can be different for each skill. The quality of the match is initially unknown and it is learned over time by observing the output. Shocks to output are such that firms either learn the match quality or continue with the same beliefs. Furthermore, these shocks differ by skill, implying different speeds of learning about the match quality for high and low skill matches.

The calibration exercise shows that high skill firms do choose to invest in a better selection technology. As a result, separations among high skill workers is around half of the separations observed in low skill jobs. The model also delivers job finding probability differences across skill that is comparable to the data. Hence, the most of the unemployment rate disparity in the model is from differences in separation probabilities across skill. Counterfactual analyses show that better selection by high skill firms not only amplifies the effect of lower speed of learning on separation, but also brings the model closer to the data in other dimensions.

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A

A.1 Computing Job Finding and Separation Rates

I use the CPS Basic data from January 1976 to December 2008. The sample is male labor force participants who are older than 24 and younger than 55. Let (L_t^{nc}) L_t^c be the number of workers who (do not) have a four-year college degree in period t. Let (U_t^{nc}) U_t^c be the number of unemployed workers who (do not) have a four-year college degree in period t. Similarly, define U_t^{s-c} (U_t^{s-nc}) as the number of workers who are unemployed for less than 5 weeks (short-term unemployed) and who (do not have) have a four-year college degree in period t.

The CPS survey had a redesign in 1994, which affected the number of short term unemployed workers after the redesign. To make data pre and post redesign era, I

do the following correction as suggested by Elsby, Michaels, and Solon (2009). For each skill group, I multiply the short-term unemployment numbers of post-design era by the era's average of the ratio of short-term share for the first and fifth rotation groups to the full samples's short term share. So, let $S_t = \frac{U_t^s}{U_t}$ be the short-term share of the all sample and let $S_t^{15} = \frac{u_t^{s15}}{u_t^{15}}$ be the short-term share for 1st and 5th rotation groups. Moreover, let $S_t^s = \frac{S_t^{15}}{S_t}$. We want to find the average S_t^s and multiply overall short term series by this number. Then, I seasonally adjust L_t, U_t, and U_t^s using Eviews' implementation of the Census Bureau's X-12 procedure.

Now, one can calculate job finding and separation probabilities using these time series data. Observe that the total number of unemployed in the current month is the sum of the number of workers who were unemployed in previous month and didn't find a job and the number of workers who were employed last month and unemployed in the current month (short-term unemployed).

$$U_{t+1} = (1 - F_t)U_t + U_{t+1}^s$$

where F_t is the probability of finding a job within a month. From this identity, one can back up the job finding probability as $F_t = 1 - \frac{U_{t+1} - U_{t+1}^s}{U_t}$. Then, job finding rate will be $f_t = -log(1 - F_t)$.

Finding job separation probability is not as straightforward. For this we need to use the following evolution equation for unemployment over time. Let s_t be the job separation rate for month t. Then, unemployment moves

$$\frac{du_t}{dt} = (1 - u_t)s_t - f_t u_t = -(s_t + f_t)(u_t - u_t^*) \tag{A.1}$$

where

$$u_t^* = \frac{s_t}{s_t + f_t}$$

If we solve the differential equation (A.1) for u_t under the assumption that s_t, f_t, and the labor force is constant across two consecutive surveys, and forward it one month we get

$$u_{t+1} = u_t^* + (u_t - u_t^*)e^{-(s_t+f_t)}$$

One can solve this equation for s_t and calculate job separation probability S_t as $S_t = 1 - e^{-s_t}$.

Figure A.1: Unemployment Rates by Skill Groups

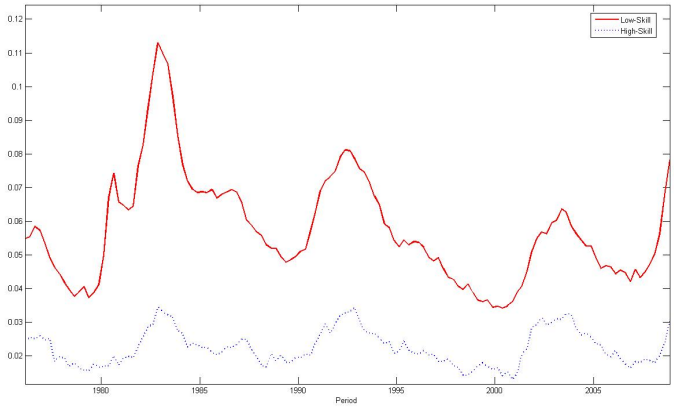

Figure A.2: Job Finding Probabilities by Skill Groups

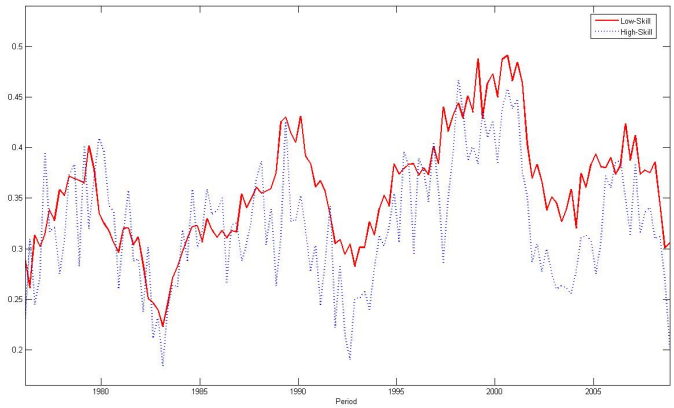

Figure A.3: Job Separation Probabilities by Skill Groups