JOB SEARCH, BARGAINING, AND WAGE DYNAMICS

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ABSTRACT. What are the sources of rapid wage growth during a worker's early career? To address this question, I construct and estimate a model of strategic wage bargaining with on-the-job search to explore three different components of wages: general human capital, match-specific capital, and outside option. Workers search for alternative job opportunities on the job and accumulate human capital through learning-by-doing. As the workers find better job opportunities, the current employer has to compete with outside firms to retain them. This between-firm competition improves the outside option value of the worker, which results in wage growth on the job even when productivity remains the same. The model is estimated by a simulated minimum distance estimator and data from the NLSY 79. The parameter estimates are used to simulate counterfactuals. The results indicate that the improved value of outside option raises wages of ten-year-experienced workers by 13%, which accounts for about a quarter of the wage growth during the first ten years of career. I also find that human capital accumulation affects wage profile not only because it directly changes labor productivity, but also because it alters job search behavior due to low future productivity.

1. INTRODUCTION

Wages of young workers grow rapidly. For example, a typical male high-school graduate in the U.S. can expect 55% of wage growth during the first ten years of his permanent transition to the labor market. This early wage growth accounts for about two thirds of the entire wage growth over the lifetime. Given that new entrants to the labor market can look forward to about 40 years of work, this fact implies that a major part of wage growth occurs in a relatively short period of time. The objective of the paper is to empirically understand the sources of wage growth of young workers.

One standard interpretation is based on the accumulation of human capital. Workers learn skills more quickly while they are young. The rapid wage growth can be interpreted as a direct conse- quence of the rapid accumulation of human capital. Another explanation is job turnover. Young

workers change jobs frequently. Workers start their careers without detailed knowledge about the nature of their jobs or where they can find better jobs. They gradually find a better place to work. Wages grow when a worker finds a better job and switches from the current job to a new job. Topel and Ward (1992) find that about a third of early career wage growth can be explained by job switching. This paper considers another source of wage growth: the value of outside option of workers. This effect can increase wages even when a worker stays with the same employer and productivity remains the same.

In the model employed workers are occasionally contacted by firms other than the current employer. When the value of the offer is better than that of the current employment contract, the worker wants to quit the current job to accept the offer. However, the current employer may be willing to pay the worker a higher wage to retain him. In this way, offers from outside firms improve the bargaining position of a worker when he renegotiates wages with the current employer. Wages can grow due to an increase in outside option value, even when productivity remains the same. A worker is in a position of renegotiation, because rent from a match exists due to search frictions. Workers do not have alternative job opportunities in hand, while firms are not able to immediately find new workers that replace the current employees. Finding an alternative partner who is as good as the current partner is more difficult when agents are heterogeneous, because the agents similar to the current partner can be scarce in the market. This labor market friction is a source of the rent from a worker-firm match.

Understanding the sources of wage growth is important for active labor market policies. If a large fraction of wage growth is due to the labor market frictions, policies that attempt to accelerate matching process will have significant effect on individual wages. Public Employment Services that assist job search not only reduce unemployment, but also enhance the wage growth of employed workers.

To consider the effects of outside option value, match quality, and human capital accumulation on wages, I develop and estimate a model of on-the-job search with strategic bargaining. The model is based on a continuous-time search model in which unemployed and employed workers search for jobs that are characterized by idiosyncratic match quality. On the one hand, employed workers accumulate human capital through learning-by-doing. On the other hand, they occasionally receive job offers from new potential employers. When the match quality with a new potential employer is high enough, a bargaining game begins among three-players: the worker, the current employer, and a new potential employer who attempts to recruit him. In this three-player bargaining, a worker first bargains with a firm that is strategically chosen by the worker. He then bargains with the other firm if the bargaining with the first firm is not successful. The worker exploits these multiple job opportunities and uses a firm as a threat in bargaining with another firm. Wages grow over

the duration of a job, not only because workers accumulate human capital, but also because they receive job offers, which improves their value of outside option.[1]

My work is related to the paper by Postel-Vinay and Robin (2002) that analyzes wage dispersion in France using a model of on-the-job search with counteroffers. Although their model has some similar features to my model, they focus on wage distribution in a stationary equilibrium, instead of wage dynamics. To address the question of sources of wage growth, my model departs from their previous contributions in two ways. First, the model allows for productivity growth of workers through learning-by-doing. The productivity growth contributes to wage growth, because it increases not only the value of a match, but also the value of outside option such as unemployment. The intuition is that experienced workers are more likely to get employed and that they would have higher value of a match if they are employed. My empirical results suggest that the growth of worker productivity actually explains the largest part of wage growth. Second, wage renegotiation following idiosyncratic productivity shocks is considered in this paper. The model by Postel-Vinay and Robin (2002) does not predict any wage decreases on the job and it assumes exogenous destruction of a match. In contrast, in my model productivity shocks may cause a wage decrease on the job and a separation endogenously occurs if a match becomes inefficient due to negative productivity shocks. The price of these extensions is that an explicit solution to the equilibrium wage and its distribution are too complicated to be derived analytically because of nonstationarity. I use a numerical solution for simulation and estimation of the model. These extensions are important to match the observed dynamics of wages and worker flows.

The main contribution of the paper is to empirically explore the effect of labor market frictions on wages of young workers. The structural parameters of the model are estimated by a simulated minimum distance estimator using a sample of white male high school graduates from the National Longitudinal Survey of Youth 1979. The parameter estimates are used to simulate three counterfactuals. The first exercise evaluates the effect of the improved outside option value on wages. I find that wages of ten-year-experienced workers would be 13% lower, if their outside option is unemployment, not the employer with the second best match. This result indicates that the effect of the improved value of outside option is substantial and it accounts for about 25% of the observed wage growth during the first ten years. In the second simulation, labor market friction is shut off so that workers are able to find the best matches immediately. In the absence of frictions, wage growth is solely driven by the accumulation of human capital. In this simulation, wages grow by 30% during the first ten years of their careers, which implies that only about 60% of the observed wage growth reflects the accumulation of human capital. The third simulation imposes that human capital does not grow. I find that human capital accumulation affects wage profile not only because

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[1]Barron, Berger, and Black (2005) provide empirical analysis for counteroffers using the data from the 2001 Small Business Administration Survey. They find that factors that are likely to raise match rents indeed increase the likelihood that a firm will extend a counteroffer to an employee with a competing offer. This empirical evidence supports the theoretical argument in this paper.

it directly changes labor productivity, but also because it alters job search behavior. A lack of human capital accumulation reduces the value of a match, and thus, it increases the reservation match quality. As a result, the initial wage in the career is raised by 15%, but wages grow only by 15% in the first ten years. The mean unemployment duration is also increased by 20%. The results suggest that human capital accumulation has important implication on job search and that they should be considered together.

The plan of the paper is as follows. The following section reviews the related literature. The theoretical model is presented in section 2. Section 3 describes the data. The estimation strategy is detailed and the results are presented in section 4. To evaluate the effect of human capital and labor market frictions on wages, the parameter estimates are used to simulate counterfactuals in section 5. Section 6 concludes. Proofs and technical details are gathered in appendices.

2. THE MODEL

2.1. **Setup.** I consider the labor market for infinitely lived *ex ante* heterogeneous workers and *ex post* heterogeneous firms. Both the workers and the firms are risk neutral, have the same interest rate r, and have complete access to the capital market. Workers are heterogeneous with respect to innate ability γ_0 and general human capital h. Innate ability is fixed for each individual's lifetime, while general human capital grows with work experience. Both are precisely observed by all agents in the economy.

Unemployed workers receive utility value b, including both pecuniary and non-pecuniary unemployment benefits, and meet a firm at a rate of λ_0. Employed workers receive a flow wage payment w and produce a flow output y. They are also contacted by firms other than the current employer at a rate of λ. When a worker is contacted by a firm, match quality θ and an idiosyncratic shock to the match ϵ_θ are drawn from distributions with CDFs F and G, respectively. Both θ and ϵ_θ are bounded above $\theta_{MAX}, \epsilon_{\theta,MAX}$ and below $\theta_{MIN}, \epsilon_{\theta,MIN}$. All workers and firms precisely observe the values of the match quality θ and the idiosyncratic shock ϵ_θ. The accumulation of match-specific human capital is captured by a stochastic growth of match quality. This modeling saves the amount of computation because no additional state variable such as tenure is used, although an alternative (and more common) way is that match-specific capital grows with tenure. The match quality grows from θ to $\theta^+(\theta)$ at the Poisson rate of $\delta_1(\theta)$. The idiosyncratic shock changes occasionally at the Poisson rate of δ.

Firms are *ex post* heterogeneous in the sense that match quality varies across firms. However, they are *ex ante* homogeneous because neither workers nor firms know their match quality until they meet. A match is exogenously destroyed at a rate δ_0 due to family problem, health problem, and etc.

General human capital is accumulated through learning-by-doing while workers are employed and it does not depreciate. This implies that human capital does not change while workers are

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unemployed. Hence I have $h(t + a) \geq h(t) \ \forall a > 0$ where t is the index for time and equality holds only when workers are unemployed from period t to period $t + a$. I also assume that human capital does not grow once it reaches a certain level $\bar{h} < \infty$.

The output y produced by a worker-firm match is strictly increasing in innate ability γ_0, general human capital h, match quality θ, and idiosyncratic shock to the match ϵ_θ. For example, the production function can take a multiplicative form $y = \exp(\gamma_0 + \gamma_1 h + \gamma_2 h^2) \cdot \theta \cdot \epsilon_\theta$ where $\gamma_1 > 0$ and $\gamma_2 < 0$.

The assumption that all workers meet firms at the same rate and draw match quality from the common distribution may seem restrictive, because high-skilled workers should receive more job offers and face a better distribution of job opportunities. This observation is plausible and it is also true in the model. The intuition is that I distinguish between meeting rates (λ and λ_0) and offer rates. In the model, the high-skilled workers receive more job offers than the low-skilled workers when they meet the same number of firms. Firms are less likely to employ unskilled workers because they are unproductive. Moreover, high-skilled workers face a better distribution of job opportunities, even though all workers have the common match quality distribution F. To see this, consider the distribution of productivity of a match, rather than the distribution of match quality. The distribution that high-skilled workers face is better than that for low-skilled workers in the sense of first order stochastic dominance because the productivity is increasing in innate ability and human capital. For example, if the production technology is additive in workers' skill and match quality, workers' skill shifts the productivity distribution to the right.[2]

2.2. **Wage Bargaining.**

2.2.1. *Bilateral bargaining between an unemployed worker and a firm.* Unemployed workers receive unemployment benefit b and meet a firm at the Poisson rate of λ_0. When an unemployed worker meets a firm, the match quality θ and idiosyncratic shock ϵ_θ to the match are randomly determined. The worker and the firm bargain over an employment contract given all relevant information such as skill and match quality. Once the contract is signed, the firm pays a constant flow of wage w and the worker supplies flow of labor service until the contract is renegotiated or separation occurs. The contract is renegotiable with mutual consent. Also, workers can quit a job and firms can fire workers at any time. The contract also expires when the employee negotiates an employment contract with a third party firm. This assumption implies that the worker cannot be re-employed by the current employer under the current contract when he bargains with a third party firm and the bargaining fails. This assumption does not imply that workers are fired because of a bargaining with outside firms, but it means that the incumbent firm is not bound by the existing

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[2]Strictly speaking, the value of a job is not measured by the productivity at the time when a worker and a firm meet. But, as I will see below, the value of a job is strictly increasing in the initial productivity and the argument here still works.

contract. As it will be shown below, in equilibrium the worker bargains with outside firms only when he actually leaves the current employer.

I use a strategic approach to describe the bargaining process, rather than employing an axiomatic Nash bargaining solution. One advantage of this approach is that it clarifies the bargaining process. The bargaining environment is similar to Binmore (1987) in the sense that the proposer of an offer at each bargaining round is randomly chosen by nature. The worker and the firm are allowed to quit bargaining to look for another partner. However, to do so, the agent must wait for the offer from the other agent. The bargaining might break down into disagreement at the Poisson rate s because of exogenous factors such as the worker's family emergency. For simplicity, I assume that a worker and a firm bargain in artificial time so that the worker and the firm discount payoffs from the bargaining by a different interest rate ρ from that used for production, which is r. The bargaining takes the following steps over an infinite horizon. I assume that a worker and a firm accept an offer when they are indifferent.

(1) Nature determines the proposer at the beginning of each round. The worker makes an offer with probability β, while the firm makes an offer with probability $1 - \beta$.

(2) The respondent has the following three options.
   - Accept the offer and start production.
   - Reject the offer and look for other potential partners.
   - Reject the offer, but wait for the next round after time Δ elapses. The bargaining may break down with the probability $s\Delta$ before they reach the next round (go back to step 1.)

The probability β that the worker makes an offer is the measure of the worker's bargaining power. The intuition is that agents with high bargaining power take the initiative during the bargaining process. Thus, when a worker has high bargaining power, the offers are made more frequently from the worker's side.

Let $\Theta = \{\theta, \epsilon_\theta\}$ be the vector of match quality and idiosyncratic shock to the match. The continuation values of employed workers and firms are denoted by $U(h, \Theta, w)$ and $V(h, \Theta, w)$, respectively. Let $U_0(h)$ be the continuation value for unemployed workers. I omit the innate ability γ_0 in the notation, because it is constant over time. The firms' value of a vacancy is zero because of the free entry condition. I find it convenient to define the joint value $J(h, \Theta)$,

$$J(h, \Theta) = U(h, \Theta, w) + V(h, \Theta, w).$$

Observe that w does not change the joint value J, although it certainly changes the allocation. This will be clear when I see the condition for job turnover and the equilibrium payoffs in the case of job turnover, which are both independent of wages.

Lemma 2.1. *The following outcome of the bilateral bargaining between an unemployed worker and a firm is obtained when $\Delta \to 0$ and $\rho \to 0$.*

1. $J(h, \Theta) < U_0(h)$: If the match is inefficient, they immediately separate to look for other potential partners. The resulting payoffs are $\{U_0(h), 0\}$.

2. $J(h, \Theta) \geq U_0(h)$: If the match is efficient, they sign a contract immediately and the resulting payoffs are

$$\{U(h, \Theta, w), V(h, \Theta, w)\} = \{\beta J(h, \Theta) + (1-\beta)U_0(h), \ (1-\beta)(J(h, \Theta) - U_0(h))\}.$$

Proof. See appendix C. □

This is a fairly standard result in bargaining problems. From the viewpoint of axiomatic Nash bargaining solution, one interpretation is that the worker's threat point is U_0 and the firm's threat point is 0. They split the surplus $J - U_0$ and the worker takes his fraction of β as well as U_0. The contract is signed only when the match is efficient.

2.2.2. *Multilateral bargaining between a worker and two firms.* Employed workers are contacted by firms other than the current employer at a rate λ. When a worker meets a firm, the worker draws a match quality with the new firm and an idiosyncratic shock to the match. The outcome is precisely observed by the worker, the new firm, and the incumbent firm. The bargaining procedure among three players is the following:

(1) The worker decides whether or not to initiate bargaining. If he decides not, the challenger firm leaves and the current contract remains effective. If he decides to initiate bargaining, the worker chooses which firm to start with first.

(2) The bargaining starts between the worker and the firm that is chosen by the worker in the previous step.

  (a) Nature determines the proposer at the beginning of each round. The worker makes an offer with probability β, while the firm makes an offer with probability $1 - \beta$.

  (b) The respondent has the following three options.

   • Accept the offer and start production.

   • Reject the offer to look for other potential partners. If this is chosen, the firm leaves and the worker starts bargaining with the remaining firm.

   • Reject the offer, but wait for the next round (go back to step 2-a) after time Δ elapses. The bargaining may break down with probability $s\Delta$ before they reach the next round. If this occurs, the firm leaves and the worker starts bargaining with the other firm.

(3) If the worker does not reach an agreement with the firm initially chosen, the worker starts bargaining with the remaining firm. The structure of the bargaining is exactly same as the one occurs between an unemployed worker and a firm.

The worker bargains with firms in order and the order is chosen by the worker. The intuition for this assumption is that a worker and two firms do not meet at the same bargaining table in reality. It is also plausible that the worker can schedule a job interview in a time convenient for him.

Let Θ_C and Θ_N be the vectors of match quality and idiosyncratic shocks to the match with the current employer and the new potential employer, respectively. In the following, I assume that the match with the current employer is efficient. This is actually true in equilibrium because no inefficient matches exist. Also, the worker prefers the current employer to the new potential employer and he prefers not bargaining when he is indifferent.

Lemma 2.2. *The following equilibrium outcome of the three-player bargaining is obtained when* $\Delta \to 0$ *and* $\rho \to 0$.

1. $J(h, \Theta_C) \geq J(h, \Theta_N)$ *and* $U(h, \Theta_C, w) \geq \beta J(h, \Theta_C) + (1 - \beta)[\beta J(h, \Theta_N) + (1 - \beta)U_0(h)]$: *the worker does not initiate bargaining. The worker stays with the current employer and the current contract remains effective.*

2. $J(h, \Theta_C) \geq J(h, \Theta_N)$ *and* $\beta J(h, \Theta_C) + (1 - \beta)[\beta J(h, \Theta_N) + (1 - \beta)U_0(h)] > U(h, \Theta_C, w)$: *the worker first bargains with the current employer. The outcome is that the worker stays with the current employer and he is promoted. The equilibrium payoffs of the worker and the current employer are*

$$\{U(h, \Theta_C, w), V(h, \Theta_C, w)\} = \{\beta J(h, \Theta_C) + (1 - \beta)[\beta J(h, \Theta_N) + (1 - \beta)U_0(h)],$$
$$(1 - \beta)[J(h, \Theta_C) - \beta J(h, \Theta_N) - (1 - \beta)U_0(h)]\}$$

3. $J(h, \Theta_N) > J(h, \Theta_C)$: *the worker first bargains with the new potential employer. The outcome is that the worker quits the current employer to take an offer from the new potential employer. The equilibrium payoffs of the worker and the new potential employer are*

$$\{U(h, \Theta_N, w), V(h, \Theta_N, w)\} = \{\beta J(h, \Theta_N) + (1 - \beta)[\beta J(h, \Theta_C) + (1 - \beta)U_0(h)],$$
$$(1 - \beta)[J(h, \Theta_N) - \beta J(h, \Theta_C) - (1 - \beta)U_0(h)]\}$$

Proof. See appendix C. □

Notice that the threat point of the bargaining with the new firm is the value of the match with the incumbent firm, which is positively correlated with the current wage. When a worker earns high wage, it is likely that he also has a good match quality. Thus the prediction of the model is consistent with the observed feature of the data in the sense that a high wage earner also receives a high wage in the new job.

Dey and Flinn (2005)and Cahuc, Postel-Vinay, and Robin (2006) also consider a similar bargaining problem. Dey and Flinn (2005) impose an axiomatic Nash bargaining solution assuming that the worker's threat point is the match value with the losing firm. Cahuc et al. (2006) consider this bargaining problem using a strategic model and find a particular bargaining procedure that can

support the assumption used by Dey and Flinn (2005). My approach here is to start with a relatively simple setup. I find that the worker's threat point is the payoff that the worker could obtain in the bilateral bargaining with the losing firm.[3]

2.2.3. *Renegotiation in response to a productivity shock.* An idiosyncratic productivity shock to a match ϵ_θ occasionally changes at a rate δ. The new shock is drawn independently from the previous shocks. Firms and workers may want to renegotiate the contract in response to the shock. The bargaining takes the following steps.

(1) Nature determines the proposer at the beginning of each round. The worker makes an offer with probability β, while the firm makes an offer with probability $1 - \beta$.
(2) The respondent has three options.
   - Accept the offer and continue the employment relationship under the new condition.
   - Reject the offer to quit the employment relationship.
   - Reject the offer and wait for the next round (go back to step 1) after time Δ elapses. The bargaining may break down before they reach the next round with probability Δs. When this actually occurs, they end up with the current contract. Separation does not occur.

Notice that when an exogenous breakdown of bargaining occurs, they still keep the employment relationship under the current contract. This comes from the assumption that the employment contract is not negotiable without mutual consent, which is widely observed in employment contract.[4] The intuition is the following. If they do not have a previous employment relationship, it is natural to separate when a breakdown occurs. But, if they have a previous relationship, it is also natural to end up with the original place when they fail to reach an agreement. The breakdown caused by an exogenous factor implies that both agents come back to the place before the bargaining is initiated. Separation is an outcome of decisions taken by agents, not a direct consequence of an exogenous breakdown.

Lemma 2.3. *The following outcome of renegotiation is obtained in response to a productivity shock when $\Delta \to 0$ and $\rho \to 0$.*

1. $J(h, \Theta) \geq U_0(h)$ and $V(h, \Theta, w) \geq 0$: When the match remains efficient and the participation constraint of the firm is still satisfied, they keep the current contract.

2. $J(h, \Theta) \geq U_0(h)$ and $V(h, \Theta, w) < 0$: When the match remains efficient but the firm's participation constraint is not satisfied, wage is cut so that the firm's participation constraint is satisfied with equality. The updated wage w^* gives agents the following payoffs,

$$\{U(h, \Theta, w^*), V(h, \Theta, w^*)\} = \{J(h, \Theta), 0\}.$$

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[3]Postel-Vinay and Turon (2006) consider how i.i.d. productivity shock generate persistent wage dynamics in a similar way to this paper.
[4]See Malcomson (1999) for a survey.

3. $J(h, \Theta) < U_0(h)$*: When the match becomes inefficient, separation occurs. The resulting payoffs are* $\{U_0(h), 0\}$*.*

Notice that the participation constraint of the worker does not get violated due to productivity shocks.

Proof. See appendix C. □

Notice that a positive productivity shock does not cause a renegotiation because it does not make a firm or a worker worse off and thus, the participation constraints do not get violated due to the shock. Also, the participation constraint of the worker does not get violated due to the shock unless it is already violated before the bargaining is initiated. Of course, this does not happen in equilibrium.

The wage dynamics presented here are different from those derived by an axiomatic Nash bargaining solution. In models with Nash bargaining, wages are continuously renegotiated so that the rent share is constant over time. On the contrary, wages are not renegotiated in my model when both a worker and a firm receive positive rent shares under the existing contract. When a small idiosyncratic shock reduces labor productivity, the firm wants to cut wages because the shock makes the firm worse off. However, the worker does not agree to such a modification of his contract. The firm can fire the worker if it wishes, but it does not want to do so because the firm still receives a positive profit under the existing contract. As a consequence, the existing contract remains effective. Next suppose that the firm earns a negative profit due to a shock, i.e., the participation constraint of the firm is violated. The firm wants to cut the wage, or fire the worker to avoid a negative profit. The worker is willing to accept wage cut, because his value of employment after wage cut is still better than the value of unemployment. The size of wage cut is made as small as possible so that the firm is indifferent between firing the worker and retaining the employment relationship.

Harris and Holmstrom (1982) find that this wage contract is optimal for risk-averse workers who cannot commit to remaining in the job. The intuition is that these wage dynamics minimize the fluctuation of wages given a lack of commitment, and thus they are preferred by risk-averse agents. Another interpretation is that the proposed wage dynamics minimize the deviation from the *ex ante* optimal wage dynamics in the case of full commitment. Although I assume that agents are risk-neutral for analytical simplicity, this argument is still applicable if workers are even slightly risk-averse.

Endogenous separation is an important property from empirical viewpoint. In the model, matches with high-skilled or experienced workers are more likely to survive negative productivity shocks than those with low-skilled or inexperienced workers. Matches are destroyed when they become inefficient. Workers who have high labor productivity are unlikely to become unemployed. This

prediction of the model is consistent with many empirical findings. These wage dynamics and worker mobility are useful for a quantitative analysis.[5]

2.3. **Value Function.** I have not discussed how value functions are defined in terms of the primitives of the model. The next proposition provides the existence and the uniqueness of the value functions.

Proposition 2.4. *The value functions U, V, U_0, and J are uniquely determined by the following contraction mappings. The value of unemployment U_0 is given by*

$$(r + \lambda_0)U_0(h) = b + \lambda_0 E_X \max[\beta J(h, X) + (1 - \beta)U_0(h), \ U_0(h)]$$

where X is a vector of the new match quality and idiosyncratic shock. The joint value of the match J is given by

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)J(h, \Theta)$$

$$= y(h, \Theta) + \lambda \Pr(J(h, X) > J(h, \Theta)) \cdot$$

$$E_X[\beta J(h, X) + (1 - \beta)\{\beta J(h, \Theta) + (1 - \beta)U_0(h)\}|J(h, X) > J(h, \Theta)]$$

$$+ \delta_0 U_0(h) + \delta_1(\theta)J(h, \Theta^+(\theta)) + \delta E_X \max[J(h, X), \ U_0(h)] + \dot{J}(h, \Theta).$$

The continuation value for the worker U and the continuation value for the firm V are given by

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)U(h, \Theta, w)$$

$$= w + \lambda E_X \max[\beta J(h, X) + (1 - \beta)\{\beta J(h, \Theta) + (1 - \beta)U_0(h)\},$$

$$\beta J(h, \Theta) + (1 - \beta)\{\beta J(h, X) + (1 - \beta)U_0(h)\}, \ U(h, \Theta, w)] + \delta_0 U_0(h)$$

$$+ \delta_1(\theta)U(h, \Theta^+(\theta), w) + \delta E_X \max[\min\{U(h, X, w), \ J(h, X)\}, \ U_0(h)] + \dot{U}(h, \Theta, w)$$

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)V(h, \Theta, w)$$

$$= y(h, \Theta) - w + \lambda \Pr(J(h, X) \le J(h, \Theta)) \cdot$$

$$E_X \min[(1 - \beta)\{J(h, \Theta) - \beta J(h, X) - (1 - \beta)U_0(h)\}, \ V(h, \Theta, w)|J(h, X) \le J(h, \Theta)]$$

$$+ \delta_1(\theta)V(h, \Theta^+(\theta), w) + \delta E_X \max[V(h, X, w), 0] + \dot{V}(h, \Theta, w).$$

Proof. The value of unemployment U_0 is determined by the following asset pricing equation,

$$(r + \lambda_0)U_0(h) = b + \lambda_0 E_X \max[\beta J(h, X) + (1 - \beta)U_0(h), \ U_0(h)]$$

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[5]Wages are assumed to be constant until renegotiation. Alternative assumption is that wage is a product of efficiency unit of labor and its price and that the price of efficiency unit of labor is constant until renegotiation. However, the model does not fit the observed patterns in the data. More specifically, the model does not match the employment hazard rate and the wage variance simultaneously. In this specification, all variations in productivity are translated into variations in wages. If I allow for endogenous separation and the model matches the observed employment hazard rate, the model generates too large wage variance compared with the observed wage variance. In contrast, my original specification in which agents negotiate wages fits both the employment hazard rate and the wage variance simultaneously, because productivity is not directly translated into wages. The detailed discussion and the simulation results are provided in the appendix.

where the first term on the right hand side is the flow of unemployment benefit and the second term captures the value when the worker meets a firm. Notice that there is no human capital accumulation while unemployed. Given J, the equation defines a contraction mapping for U_0.

The value of employment U is determined by the following asset pricing equation,

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)U(h, \Theta, w)$$

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\begin{aligned}
= \quad & w + \lambda E_X \max[\beta J(h, X) + (1 - \beta)\{\beta J(h, \Theta) + (1 - \beta)U_0(h)\}, \\
& \beta J(h, \Theta) + (1 - \beta)\{\beta J(h, X) + (1 - \beta)U_0(h)\}, \ U(h, \Theta, w)] + \delta_0 U_0(h) \\
& + \delta_1(\theta)U(h, \Theta^+(\theta), w) + \delta E_X \max[\min\{U(h, X, w), \ J(h, X)\}, \ U_0(h)] + \dot{U}(h, \Theta, w)
\end{aligned}
$$

where $\dot{U}$ is a time-derivative term, which is given by $\dot{U} = dU/dh \cdot dh/dt$. The second term on the right hand side captures the change of the continuation value when the worker is contacted by a firm other than the current employer. Specifically, the first element in the bracket is the value from job turnover, the second element is the value from being promoted, and the third element is the value of remaining in the current employment contract. The third term captures the value of exogenous separation. The value of the growth of match quality is captured by the fourth term. The fifth term captures the continuation value when an exogenous shock hits the match. The first element is the value of keeping the current contract, the second element is the value from renegotiation (wage cut), and the third element is the value from being fired (separation.) Given J and U_0, the recursive equation above defines a contraction mapping for U.
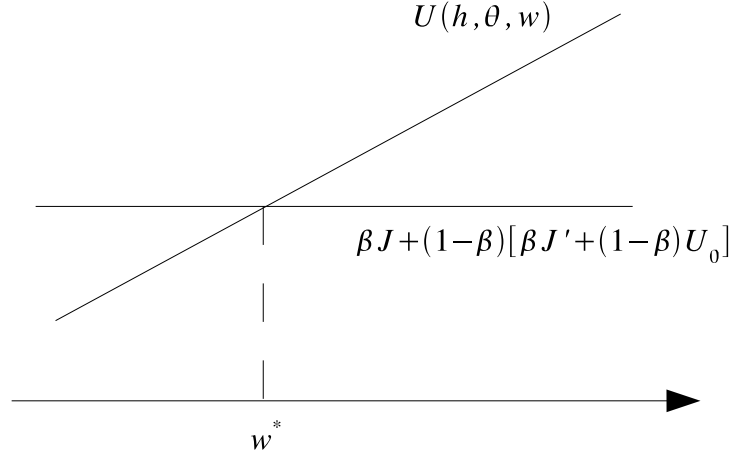
Similarly, the firm's value of filling a position is determined by the asset pricing equation,

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)V(h, \Theta, w)$$

$$
\begin{aligned}
= \quad & y(h, \Theta) - w + \lambda \Pr(J(h, X) \leq J(h, \Theta)) \cdot \\
& E_X \min[(1 - \beta)\{J(h, \Theta) - \beta J(h, X) - (1 - \beta)U_0(h)\}, \ V(h, \Theta, w) | J(h, X) \leq J(h, \Theta)] \\
& + \delta_1(\theta)V(h, \Theta^+(\theta), w) + \delta E_X \max[V(h, X, w), 0] + \dot{V}(h, \Theta, w).
\end{aligned}
$$

where $\dot{V}$ is a time-derivative term. The first term on the right hand side is the income from output, the second term is the labor cost, the third term captures the continuation value when the employee receives outside offers. The value of match quality growth is captured by the fourth term. The fifth term captures the continuation value when a productivity shock hits the match. In the third term, the first element is the value of promoting the employee to retain him and the second element is the value from remaining in the current contract. In the fourth term, the first element is the value when the contract remains the same and the second element is the value from firing (separation) or the value of employment when wage cut occurs. Given J, the Bellman equation defines a contraction mapping for V.

Finally I solve the value function J. Combining the worker's value function U and the firm's value function V, I find the joint value function J,

FIGURE 2.1. Equilibrium Wage Determination

$$(r + \lambda + \delta_0 + \delta_1(\theta) + \delta)J(h, \Theta)$$

$$= \; y(h, \Theta) + \lambda \Pr(J(h, X) > J(h, \Theta)) \cdot$$

$$E_X[\beta J(h, X) + (1 - \beta)\{\beta J(h, \Theta) + (1 - \beta)U_0(h)\}|J(h, X) > J(h, \Theta)]$$

$$+ \delta_0 U_0(h) + \delta_1(\theta)J(h, \Theta^+(\theta)) + \delta E_X \max[J(h, X), \; U_0(h)] + \dot{J}(h, \Theta).$$

Notice that the joint value J is independent of wages as I mentioned at the beginning of the section, because the wage only affects the allocation, not the size of the rent. This Bellman equation defines a contraction mapping for J given U_0. $\qquad\qquad\square$

The equilibrium wage is set so that the worker's continuation value $U(h, \Theta, w)$ equals his payoff from the bargaining. Suppose that the wage is determined through bargaining among three players, and that the type-Θ firm wins and the type-Θ' firm loses. The equilibrium wage w^* satisfies

$$U(h, \Theta, w^*) \;=\; \beta J(h, \Theta) + (1 - \beta)[\beta J(h, \Theta') + (1 - \beta)U_0(h)].$$

This equilibrium wage determination process is illustrated in figure 2.1. The payoff in three-player bargaining is drawn as a horizontal line because it is not a function of the wage. The continuation value for a worker U is strictly and monotonically increasing in wage w. This should be clear from the Bellman equation shown above. The equilibrium wage is uniquely determined so that the continuation value for the worker equals the payoff obtained from the bargaining, which occurs at the intersection seen in figure 2.1. I find it intractable to derive an explicit solution to the equilibrium wage w^*. The wage is numerically derived in the following empirical sections.

3. DATA

3.1. **Sampling Criteria.** The data are taken from the National Longitudinal Survey of Youth (NLSY) 1979 which includes information on the weekly work history of individuals from 1978

through 2002. The survey consists of individuals who were 14-21 years old as of January 1, 1979. There are some advantages from using the NLSY to analyze career. First, the NLSY has a rich work history. In particular, more than one job is recorded in a survey year. Young workers frequently switch jobs and having more than one job in a year is not uncommon. To understand how young workers build their careers, it is important to record job switching as accurately as possible. Second, the survey period covers the initial transition to the labor market. I am particularly interested in the wages and labor mobility of young workers. The NLSY focuses on this part of the life cycle.

I use a sample of white male high school graduates for the following reasons. First, I consider the labor market to be heterogeneous across race, sex, and education. Second, this is the largest demographic group if I take a subset of individuals in terms of the conditions given in the first point. Third, this group is the most commonly used for wage and worker mobility analysis in the literature and thus, my results can be compared to the previous contributions to some extent.

Following Farber and Gibbons (1996), I limit my sample to jobs that were held after an individual first made a primary commitment to become a full-time worker. I say that an individual has made a long-term transition to the labor market if he works in full-time jobs for six or more quarters during three years after graduating. A full-time job is defined as a job that consists of 30 or more hours per week worked. I also omit self-employed jobs and jobs without pay. Details of the construction of the data set are contained in appendix D. The final sample consists of 9,462 observations for 662 individuals and 3,882 full-time jobs.

3.2. **Variable Definitions.**

3.2.1. *Wages.* Hourly wages are computed by dividing weekly earnings by hours worked per week. If earnings or hours per week worked are recorded on a monthly or an annual basis, I convert them to weekly data. Wages are deflated by the monthly consumer price index of the year of 2004.

3.2.2. *Job-to-Job Transition Indicator.* I say that an individual makes a job-to-job transition if (1) he stays unemployed or has a part-time job for three weeks or less before he starts working for a new job and (2) he leaves the job voluntarily. Otherwise, I say that an individual changes jobs via non full-time employment. For example, if a worker is unemployed for four weeks between jobs, I say that he changes jobs via non full-time employment. Bowlus, Kiefer, and Neumann (2001) define job-to-job transition as the condition (1) only. But condition (2) is also relevant for my analysis because between-firm competition must occur in the model whenever job-to-job transition occurs.

4. ESTIMATION

4.1. **Solution and Simulation Method.**

4.1.1. *Empirical Specification.* I allow for worker heterogeneity in terms of productivity. The productivity of a type i worker who has h years of experience, match quality θ, and an idiosyncratic productivity shock ϵ_θ is given by

$$(4.1) \qquad y_i(h, \theta, \epsilon_\theta) \quad = \quad \exp(\gamma_{0,i} + \gamma_1 h + \gamma_2 h^2 + \gamma_3 h^3 + \gamma_4 h^4) \cdot \theta \cdot \epsilon_\theta.$$

The distribution of individual types is assumed to have two support points: low-skilled and high-skilled. I normalize the low-skilled type as $\gamma_{0,LOW} = 0$. The parameters to be estimated are the support point for high-skilled type $\gamma_{0,HIGH}$ and its weight p_{HIGH}. The sampling distribution of match quality is assumed to be lognormal, $\ln\theta \sim N(\mu, \sigma_\theta^2)$. I discretize match quality into M support points so that each point is equally distant. Let θ_m be the match quality at the m-th level ($1 \leq m \leq M$). When the match quality with the current employer is θ_m, match quality grows θ_{m+1} at the Poisson rate $\delta_1(\theta_m)$,

$$\delta_1(\theta_m) \quad = \quad \delta_{1a} + \delta_{1b}m \;\; if \; 1 \leq m < M$$
$$0 \;\; otherwise.$$

The distribution of productivity shocks is assumed to have two support points: bad state and good state. Because it is imposed that $E\epsilon_\theta = 1$ for normalization, I only have to estimate the support point of bad state $\epsilon_{\theta,BAD}$ and its weight p_{BAD}. I also assume wages are measured with error but this error is unbiased relative to the true log wage $\ln w^*$,

$$\ln w \quad = \quad \ln w^* + \epsilon$$
$$\epsilon \quad \sim \quad N(0, \sigma_\epsilon^2)$$

where $\ln w$ is the observed wage. This measurement error is necessary for estimation because I will match not only the conditional mean of wages, but also the conditional variance of wages. The interest rate r is set to 0.075. The parameter for bargaining power β is fixed[6] at 0.5 for identification purpose, which will be discussed in the section 4.4.

4.1.2. *Model Implementation.* The model is numerically solved using a contraction mapping in discretized state space. Match quality is discretized to 20 levels. They are equally distant and their weights are given by the method proposed by Kennan (2004). The lowest match quality is at 2.5% quantile and the highest is at 97.5% quantile. Wages are discretized to 35 levels. The lowest hourly wages on the grid is $1.0 and the highest is $45.0. This grid turns out not to be restrictive because any simulated wage is on either of these boundaries in the estimation. For a numerical solution of a continuous time model, the model must be converted into a discrete time model. The length of a decision period is assumed to be a quarter (13 weeks.) This relatively fine grid is especially relevant while agents are young, because they change jobs frequently and have multiple jobs during a year. If I use a year as a decision period, I would lose more information about the early careers

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[6]As an additional result, I also estimated this parameter. The results can be found in the appendix.

of young workers. All events described by Poisson process with the rate a in the continuous time model are approximated by a Bernoulli process with the rate $a\Delta h$ where Δh (= 0.25) is the length of the period in the discretized model. Each individual is simulated for K (= 10) times from his first transition to the labor market until his first exits from the labor market or the survey ends.

It is important to match the length of survey and the length of simulation so that I can re-generate the actual sampling process. Suppose I am interested in the conditional mean wage given ten years of experience. If the agents are simulated for ten years, more productive workers are likely to be included in the simulated sample of workers with ten years of experience, because high-skilled workers tend to be more experienced. On the contrary, if the simulation length is as long as one hundred years, probably all types of workers will be included in the simulated sample of workers with ten years of experience. Due to the sampling mechanism, the conditional mean wage will be higher in the former simulated sample. The simulation length can affect the auxiliary model parameter estimates and thus, matching it with the survey length is important in the estimation.

4.2. **Model Estimator.** The parameters of the model are estimated by a simulated minimum distance estimator, which is closely related to the simulated method of moments, the efficient method of moments, and indirect inference.[7] The model is simulated to generate an artificial data set of employment history and wage path. This simulated data is summarized by descriptive statistics such as hazard rate of job and unemployment, wage growth rate, and wage variance. These summary statistics of simulated data are compared with the corresponding statistics of actual data. The objective of estimation is to look for structural parameters that give the best fit. Summary statistics used in a simulated minimum distance estimator are called auxiliary parameters. Auxiliary parameters are often moments of data, but they can be parameters of a reduced form model. For example, coefficients of a wage regression are used as auxiliary parameters.

There are a few reasons to use simulated minimum distance estimator to estimate the model. First, implementation is straightforward. For example, maximum likelihood is computationally too demanding for my model because it requires me to integrate out serially correlated unobserved state variables. In particular, the match quality in one job is correlated with those in other jobs. The match quality with an alternative job opportunity is also correlated over time, even when the worker does not change jobs. In addition, idiosyncratic shocks also need to be integrated out, because they change only occasionally. Second, I directly match the important features of the data. By looking at the gap between auxiliary parameter of the data (i.e., summary statistics of the data) and their simulated counterparts, I can tell which features of the data the model fails to fit.

The simulated minimum distance estimator minimizes the criterion function that is defined as the weighted average of the squared distance between the sample auxiliary parameters and the corresponding simulated auxiliary parameters. Let ϕ be the vector of structural parameters. The vector of sample auxiliary parameter estimated from the NLSY is denoted by $\hat{\rho}$. The vector of

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[7]See Carrasco and Florens (2002) for a survey.

simulated auxiliary parameter computed from a simulated data set with K simulations is denoted by ρ_K. The simulated minimum distance estimator $\hat{\phi}$ is defined as

$$\hat{\phi} = \arg\min_{\phi}[\rho_K(\phi) - \hat{\rho}]'W[\rho_K(\phi) - \hat{\rho}]$$

where W is a positive definite matrix. The variance of the estimated structural parameters is minimized when the weighting matrix W is the inverse of the covariance matrix of the auxiliary parameters. Notice that an auxiliary parameter is a function of structural parameters. The choice of auxiliary parameters affects efficiency and they should be good descriptions of the data. One interpretation is that I see the data through the "lens" of a descriptive statistical model. When the optimal weighting matrix W^* is used, the covariance matrix for the structural parameters is given by

$$Var(\hat{\phi}) = (1 + 1/K)\left[\frac{\partial g'(\phi)}{\partial \phi}W^*\frac{\partial g(\phi)}{\partial \phi}\right]^{-1}$$

where $W^* = Var(\hat{\rho})^{-1}$, $g(\phi) = \rho(\phi) - \hat{\rho}$, and K is the number of simulation.

4.3. **Auxiliary Models.** The auxiliary parameters that describe employment history data are hazard rates of full-time job spells $\{p_{J,t}\}_{t=1}^{40}$, full-time employment spells $\{p_{F,t}\}_{t=1}^{40}$, and non full-time employment spells $\{p_{N,t}\}_{t=1}^{5}$. Non full-time employment includes part-time employment and unemployment. A spell of non full-time employment ends if a worker finds a new full-time job. The hazard rate of non full-time employment captures the transition from unemployment or part-time employment to full-time employment. A spell of full-time employment ends if a worker loses a full-time job and gets unemployed or switches to a new part-time job. Thus, the hazard rate of full-time employment captures the transition from full-time employment to unemployment or part-time employment. Lastly, a spell of full-time job ends if a worker loses full-time employment status or he switches to another full-time employment. The hazard rate of full-time job captures the job-to-job transition as well as a transition to non full-time employment. Quarterly hazard rates of full-time job spells (up to 40 quarters), full-time employment spells (up to 40 quarters), and non full-time employment spells (up to 5 quarters) are nonparametrically estimated by a Kaplan-Meier estimator using both censored and non-censored spells. The length of the periods is chosen so that roughly 90% of spells die during that time interval. For example, the hazard rate of a full-time job at quarter t is given by

$$p_{J,t} = \frac{N_t}{\sum_{\tau \geq t}(N_\tau + N_{\tau+1}^C)}$$

where N_t is the number of jobs that end at quarter t and N_t^C is the number job spells that are censored at quarter t.

The auxiliary parameters that describe the wage data are the average log wage conditional on general work experience, within-job wage growth rate, and within-individual wage growth rate.

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Let w_{ijt}, GX_{ijt} and TN_{ijt} be log wage, experience, and tenure of individual i when he works for employer j in period t. Following Murphy and Welch (1990), the average log wage conditional on general work experience is estimated by OLS with quartic term,

$$w_{ijt} = \beta_{0,OLS} + \beta_{1,OLS}GX_{ijt} + \beta_{2,OLS}GX^2 + \beta_{3,OLS}GX^3 + \beta_{4,OLS}GX^4 + \epsilon_{ijt}$$

where ϵ_{ijt} is a statistical error. The coefficients β_{OLS} and the residual variance σ^2_{OLS} are used as the auxiliary parameters. This auxiliary model provides a parametrically estimated conditional mean and variance of log wage given experience. Notice that the estimated coefficients should not be interpreted as returns to experience because of endogeneity. In particular, experience and unobserved innate ability are positively correlated. This motivates me to estimate within-individual wage growth rate using a fixed effect model.

Denote the average log wage and experience of individual i by $\overline{w}_i$ and $\overline{GX}_i$. Let $\tilde{w}_{ijt} = w_{ijt} - \overline{w}_i$ be the deviation of log wage from the average over the entire job history of individual i. I also define the averages and the deviations for GX and ϵ in a similar way. The fixed effect model for within-individual wage growth is given by

$$\tilde{w}_{ijt} = \beta_{1,FE}\widetilde{GX}_{ijt} + \beta_{2,FE}\widetilde{GX^2}_{ijt} + \beta_{3,FE}\widetilde{GX^3}_{ijt} + \beta_{4,FE}\widetilde{GX^4}_{ijt} + \tilde{\epsilon}_{ijt}.$$

Notice that I use wage variation within individual job histories to identify returns to experience. The coefficients β_{FE} and the residual variance σ^2_{FE} are used as the auxiliary parameters. The residual variance of this fixed effect estimator σ^2_{FE} is expected to be smaller than the residual variance of the OLS σ^2_{OLS}, because the individual fixed effect is eliminated in this model. Thus, the difference between two is useful to identify the dispersion of individual innate ability.

The estimated returns to experience include both within-job wage growth and the wage growth through job switching. To understand the wage growth structure more deeply, I estimate within-job wage growth using a fixed effect estimator. Denote the average log wage and tenure of individual i at job j by $\overline{\overline{w}}_{ij}$ and $\overline{\overline{TN}}_{ij}$. Let $\tilde{\tilde{w}}_{ijt} = w_{ijt} - \overline{\overline{w}}_{ij}$ be the deviation of log wage from the average over the duration of job j. I also define the averages and the deviations for other variables such as TN and ϵ in a similar way. The fixed effect model for within-job wage growth is given by

$$\tilde{\tilde{w}}_{ijt} = \beta_{1,OJFE}\widetilde{\widetilde{TN}}_{ijt} + \beta_{2,OJFE}\widetilde{\widetilde{TN^2}}_{ijt} + \beta_{3,OJFE}\widetilde{\widetilde{TN^3}}_{ijt} + \beta_{4,OJFE}\widetilde{\widetilde{TN^4}}_{ijt} + \tilde{\tilde{\epsilon}}_{ijt}.$$

4.3.1. *Estimates of Auxiliary Parameters.* The estimated hazard rates are plotted in figure 4.1 through 4.3. Some selected numbers are also presented in table 1 for detailed information. The quarterly hazard rate of non full-time employment at the first quarter is 0.51. It decreases to 0.46 in the fifth quarter. The estimates imply that the average time to find a full-time job is about 2 quarters. The quarterly hazard rate of full-time employment at the first quarter is 0.16. It quickly decreases in the first few years and drops to 0.05 at the tenth quarter. The rates seem to be stable around 0.03 after the fifteenth quarter. The hazard rate of full-time job at the first quarter is 0.20, which is higher than the employment hazard rate because some jobs end with job-to-job switching.

TABLE 1. Sample Hazard Rates

Quarter	Full-time Job		Full-time Employment		Non Full-time Employment	
	Estimates	Std. Dev.	Estimates	Std. Dev.	Estimates	Std. Dev.
1	0.200	0.008	0.155	0.008	0.512	0.020
5	0.108	0.007	0.083	0.007	0.462	0.068
10	0.065	0.007	0.051	0.007		
20	0.045	0.008	0.025	0.006		
30	0.049	0.011	0.036	0.009		
40	0.034	0.011	0.022	0.008		
No. of Spells	3898		2541		680	

Note: The hazard rates are estimated by the Kaplan-Meier estimator. Non full-time employment includes part-time employment and unemployment. The standard deviation of the estimated hazard rates is obtained by a nonparametric bootstrap with blocking for time dimension at the individual level. The number of replications in bootstrap is 10,000. The survival rate of full-time jobs and full-time employment at 40th quarter is 0.07 and 0.14, respectively. The survival rate of non full-time employment at 5th quarter is 0.04.

Similar to the full-time employment hazard rate, the job hazard rate decreases quickly in a first few years and it drops to 0.07 at the tenth quarter. The pattern found here is very similar to the one reported by Farber (1999).

The estimated sample auxiliary parameters for wages are presented in table 2. The first two columns are the OLS estimates. The results imply that the average initial log wage is 2.1 (= $8.1) and the average log wage with ten years experience is 2.6 (= $13.6.) The next two columns present the regression estimates for within-individual wage growth. The results imply that the average annual return to experience in the first ten years is 0.054. Also notice that the residual variance is smaller than that of OLS, because individual effect is eliminated in this model. The last two columns show the regression estimates for within-job wage growth. The results imply that the average annual wage growth rate on the job is 0.033. Again, the residual variance is smaller than those from OLS and within-individual wage regressions, because both individual and employer fixed effects are eliminated.

The distance between the sample auxiliary parameters and the simulated counterparts is optimally weighted by the estimated variance-covariance matrix of the sample auxiliary parameters. I estimate it by a nonparametric bootstrap with 10,000 replications. To preserve the dependent structure of the data, I sample individuals with blocking over the time dimension. If a particular individual i is selected, his entire wage and employment history are included in the sample. There are some advantages using a bootstrap to estimate the optimal weighting matrix. First, I can avoid small sample bias for second order moments as is pointed out by Altonji and Segal (1996). Second, analytical solutions to covariance between auxiliary parameters can be complex. But I can estimate it through simulation. The estimated standard deviations are presented in table 1 and 2. Third, no update of the weighting matrix is necessary. This simplifies computation.

TABLE 2. Sample Auxiliary Parameters

	OLS		Within-Individual		Within-Job	
	Estimates	Std. Dev.	Estimates	Std. Dev.	Estimates	Std. Dev.
Intercept	2.086	0.019				
Exp/10	1.122	0.118	1.190	0.111		
Exp^2/100	-0.997	0.214	-1.094	0.199		
Exp^3/1000	0.485	0.145	0.539	0.131		
Exp^4/10000	-0.084	0.032	-0.096	0.029		
Ten					0.555	0.092
Ten^2/100					-0.265	0.205
Ten^3/1000					0.030	0.159
Ten^4/10000					0.012	0.039
Var. of Residual	0.206	0.009	0.118	0.006	0.066	0.005
R-squared	0.169		0.240		0.114	
D.F.	9444		8784		5841	

Note: Log of hourly wages deflated by 2004 price are regressed on experience (Exp) or tenure (Ten.) Eighteen observations of hourly wages are higher than $100 and they are excluded from regressions. The fixed effect estimator is used to estimate within-individual wage growth and within-job wage growth. The standard deviation is obtained by a nonparametric bootstrap with blocking for time dimension at the individual level. The number of replications in bootstrap is 10,000.

The number of auxiliary parameters is 101 (40 from the full-time job hazard rate, 40 from the full-time employment hazard rate, 5 from the non full-time employment hazard rate, 6 from the OLS wage regression, 5 from the fixed effect model for on-the-job wage growth, 5 from the fixed effect model for overall wage growth.) The simulated minimum distance estimator $\hat{\phi}$ is formally given by

$$\hat{\phi} = \arg\min_{\phi}[\rho_k(\phi) - \hat{\rho}]'W^*[\rho_K(\phi) - \hat{\rho}]$$

where

$$\phi = \{\gamma_1, \gamma_2, b, \lambda_0, \lambda, \delta_0, \delta, \gamma_{0,HIGH}, p_{HIGH}, \epsilon_{\theta,BAD}, p_{BAD}, \alpha, \theta_{MIN}, \sigma_{\epsilon}\}$$
$$\rho = \left\{\{p_{J,t}\}_{t=1}^{40}, \{p_{F,t}\}_{t=1}^{40}, \{p_{N,t}\}_{t=1}^{5}, \beta_{OLS}, \sigma_{OLS}^2, \beta_{FE}, \sigma_{FE}^2, \beta_{OJFE}, \sigma_{OJFE}^2\right\}$$
$$W^* = Var(\hat{\rho})^{-1}.$$

Remember that $\hat{\rho}$ is the sample auxiliary parameter estimated by the observed sample.

4.4. **Identification.** Flinn and Heckman (1982) show that search models are underidentified if only unemployment duration and initial accepted wages are used. Because employment duration and the subsequent wages after the initial accepted wages are also used in the estimation, I might be able to fully identify the model. However, identification through such information is not fully studied.[8] Thus, following Flinn and Heckman (1982), I impose three parametric assumptions to

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[8]Barlevy (2005) finds nonparametric identification conditions for a search model without bargaining.

satisfy the recoverability condition to assure the identification of the structural parameters. The additional information such as employment duration and wages other than the initial ones improves the efficiency of the estimator. First, I fix the annual discount rate r at 0.075. They show that it is not separately identified from the value of unemployment benefit b. Second, the match quality distribution is assumed to be lognormal. This shape restriction is necessary to identify the fraction of unaccepted match quality, and thus the rate at which an unemployed worker meets a firm. In other words, the reason for unemployment cannot be decomposed into the reservation match quality and job availability without this shape restriction. Third, the bargaining power of workers β is set to 0.5, because it is weakly identified without additional structure.[9] Intuitively, it is difficult to distinguish the bargaining power from the size of the 'pie.' These parametric assumptions are commonly used in the literature such as paper by Dey and Flinn (2005).

Although the model is identified using the parametric assumptions, it is probably worthwhile to intuitively discuss the identification of the bargaining effect on wages. For simplicity, let us suppose that the match-specific capital (e.g. tenure effect) does not grow on the job. More general case will be discussed below. Consider two groups of workers with same general work experience. Workers in the first group have worked for years in the same employer, and thus their tenure is long. Workers in the second group were unemployed, but they have just found a new job. The bargaining position and the match quality of workers in the former group are expected to be high, because they stay with the same employer for years for good match quality and because they should have received many job offers from outside on the job. Thus, the wage growth of these workers is solely driven by the accumulation of general human capital. On the other hand, on-the-job wage growth of workers with zero tenure is also driven by the change in bargaining position. The difference in the average on-the-job wage growth between two groups identifies the wage growth through bargaining. Notice that workers in both groups are highly experienced, because long tenure implies high labor market experience. Nevertheless, the estimated effect of bargaining can be applied to inexperienced workers, because the match quality distribution and the rate at which a worker meets a firm are same across workers with different experience, which is also a common identification assumption in the search literature.

When match-specific capital grows over time, its effect on wages must be taken into account in order to identify the bargaining effect on wages. This effect may not be negligible for workers with zero tenure, while it probably has little effect for workers with long tenure. The growth of match-specific capital is included in the model so that match quality with the current employer stochastically grows. This productivity component is identified using job-to-job transition rate. When the growth of match quality is fast, job turnover rate is strongly decreasing in tenure (i.e., the slope of job hazard rate will be steep.) The contribution of this component to wage growth

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[9]Cahuc et al. (2006) address the identification of bargaining parameters using employer-employee matched data.

is derived from the model, because it explicitly relates productivity to wages. Thus, the effect of bargaining on wage growth is still identified by comparing the two groups.

4.5. **Estimation Results.** The estimation results are presented in table 3. The objective function is minimized by simulated annealing.[10] A worker's productivity grows by 30% during the first ten years of his career through accumulation of general human capital. Notice that this is not the entire productivity growth of a typical worker with ten years work experience, because the productivity also grow through match quality change. The value of unemployment benefit amounts to $5.2 per hour in 2004 dollar. This value is lower than the minimum wage during early 80s, which was between about $7.00 and $5.50. Those who do not have a full-time job meet 3.2 firms during a year. Full-time job holders are contacted by 1 firm during a year. Notice that these numbers are not same as the number of offers actually made by firms. In many cases, they immediately separate because they realize they do not have a good match quality as soon as they meet. The match quality distribution is assumed to be lognormal. The mean and the standard deviation of log of match quality are 0.44 and 0.44, which implies that the mode of the distribution is 0.83. The lowest possible match quality in the estimated model is 0.95, which is 5th out of 20 levels of the discretized match quality. So only the right side of the mode affects the behavior of agents. The medians of match quality of workers with zero, five, and ten years of experience are 1.95 (13th), 2.79 (17th), and 3.05 (18th), respectively. The means of match quality of workers with zero, five, and ten years of experience are 2.01, 2.86, and 2.94, respectively. Match quality grows once in every five years if a five-year-experienced worker has the median match quality. When match quality changes, it improves by 9% (calculated by taking log difference.) Given these estimates, the average annual match quality growth rate is about 2%. A negative productivity shock occurs once in every 1.5 years. This negative shock causes a significant productivity drop. When a worker-firm match is in a bad state, their output is almost zero. Also a match is destroyed due to an exogenous shock once in 8.6 years. The proportion of high-skilled workers is 39% and they are 61% more productive than low-skilled workers, which implies that the distribution of worker types is skewed to the left. Lastly, the lowest wage and the highest wage in the simulation are $4.59 and $39.6, respectively. This implies that my wage grid is not restrictive, because the grid covers wages between $1.00 and $45.00.

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[10]Fortran software is provided by Goffe, Ferrier, and Rogers (1994) in netlib.org.

TABLE 3. Parameter Estimates

Parameter		Notation	Estimates	Std. Dev.
Human Capital		γ_1	0.382	0.075
		γ_2	-0.198	0.087
		γ_3	0.097	0.032
		γ_4	-0.014	0.003
Unemp. Benefit		b	5.167	0.540
Poisson Rate	Unemp.	λ_0	3.197	0.133
	Emp.	λ	1.024	0.065
	Separation	δ_0	0.117	0.004
	Match Q. Change	δ_{1a}	0.474	0.052
		δ_{1b}	-0.016	0.003
	Prod. Shock	δ	1.776	0.086
Type Dist.	High-skilled	$\gamma_{0,HIGH}$	0.614	0.039
	Weight	p_{HIGH}	0.389	0.143
Shock Dist.	Bad	$\epsilon_{\theta,BAD}$	-2.686	0.288
	Weight	p_{BAD}	0.385	0.020
Match Q. Dist.	Mean	μ	0.440	0.088
	Std. Dev.	σ_θ	0.436	0.037
Measurement Error		σ_ϵ	0.282	0.012

Interest Rate: $r = 0.075$
Bargaining Power: $\beta = 0.5$
No. of Moment Conditions: 101
Function Value at the Minimum: 214.901

Note: The coefficients of production function are denoted by γ. The hourly value of unemployment compensation measured in 2004 dollar is b. The annual arrival rate of an offer for those who do not have a full-time job is λ_0. The annual offer arrival rate on the full-time job is λ. The annual arrival rate of an exogenous separation is δ_0. The parameters for the annual rate of match quality change are δ_{1a} and δ_{1b}. The annual arrival rate of productivity shock is δ. The support point for high-skilled individuals and its weight are denoted by $\gamma_{0,HIGH}$ and p_{HIGH}. The support point for low-skilled workers are normalized to zero. The support point for bad (negative) shock and its weight are $\epsilon_{\theta,BAD}$ and P_{BAD}. Those for good (positive) shock are $\epsilon_{\theta,GOOD}$ and P_{GOOD}. I impose a restriction that the mean of the shock be one for normalization. The location and the scale parameter of match quality distribution, which is lognormal, are μ and σ_θ, respectively. The standard deviation of measurement error is σ_ϵ.

4.6. **Model Fit.**

4.6.1. *Hazard Rates.* The sample hazard rates and simulated hazard rates are plotted in figures 4.1, 4.2, and 4.3. The results indicate that the model captures the basic features of the hazard rates. The apparent duration dependence of the non full-time employment hazard rate is driven by heterogeneity in innate ability and human capital. High-skilled workers and experienced workers receive more job offers. However, the model does not have duration dependence here, because human capital does not depreciate while workers are unemployed.

TABLE 4. Sample and Simulated Auxiliary Parameters (Hazard Rate)

Quarter	Full-time Job		Full-time Employment		Non Full-time Employment	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
1	0.200	0.168	0.155	0.127	0.512	0.476
5	0.108	0.099	0.083	0.070	0.462	0.453
10	0.065	0.066	0.051	0.044		
20	0.045	0.047	0.025	0.034		
30	0.049	0.043	0.036	0.029		
40	0.034	0.045	0.022	0.032		

The hazard rate of full-time employment is declining because of both duration dependence and heterogeneity. Workers accumulate human capital through learning-by-doing. This process makes a worker-firm match more and more productive. As a consequence, the transition rate from full-time employment to unemployment (or part-time employment) decreases over time. Matches are heterogeneous in terms of the innate ability and the experience of the worker and the match quality. Because less efficient matches are destroyed by negative productivity shocks, the selection mechanism generates declining hazard rate over time.

The full-time job hazard rate decreases over time for a similar reason, but there is one important difference because this includes job-to-job transition. Observe that human capital and innate ability do not affect the job-to-job transition rate, because these are transferable across jobs. However, a worker is more likely to separate from the match and switch to a new job if the match quality is low. This is another source that generates a declining hazard rate.

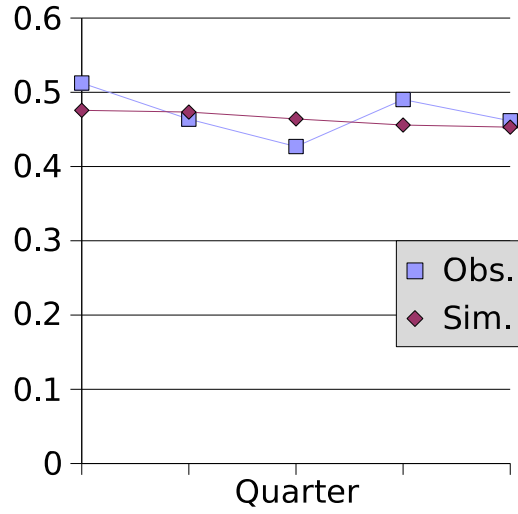FIGURE 4.1. Non Full-time Employment Hazard Rate
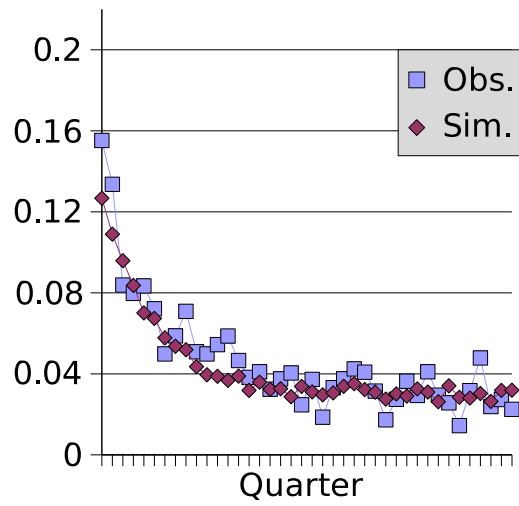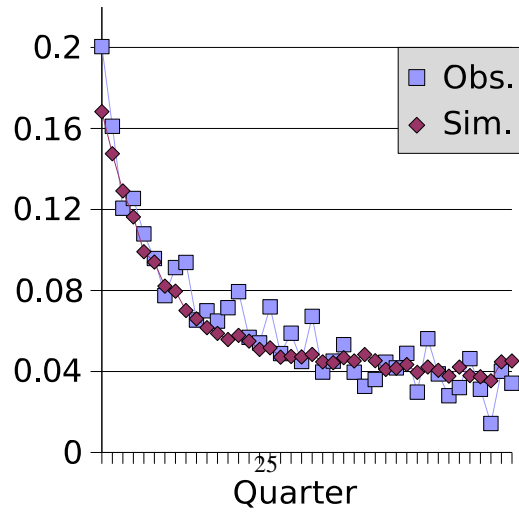

FIGURE 4.2. Full-time Employment Hazard Rate

FIGURE 4.3. Full-time Job Hazard Rate

4.6.2. *Wages.* The sample and simulated auxiliary parameters of wage regression are presented in table 5. The prediction of average low wage given experience is reasonably close to the data, as is shown in figure 4.4. The difference between the simulation and the observation is 0.02 when experience is ten years. Notice that the slope quickly decreases around the point where experience is five years. This feature cannot be captured by wage regression if only linear and quadratic terms are used, which is also emphasized by Murphy and Welch (1990). The prediction of average within-individual wage growth rate also captures the basic features of the data (see figure 4.5), although the simulated wage growth path is less concave than the observation. The model generates a similar wage growth path to the simulation, partly because human capital accumulation function includes a quartic term. The difference between the simulated path and the observation is largest at five years of experience and it is 0.03. Figure 4.6 presents within-job wage growth rate. The model captures the basic patterns of on-the-job wage growth. However, the simulated on-the-job wage growth path is less concave than the observation: the simulated wage growth is slower than the observed wage growth when tenure is short, while it is too fast when tenure is long. A possible explanation for the gap between the model and the observation is that match quality distribution and the rate at which a worker meets a firm are assumed to be the same across workers with different experience and tenure. If inexperienced workers (or workers with short tenure) meet firms more frequently than experienced workers (or workers with long tenure), the wages of inexperienced workers will grow more rapidly, which helps the model fitting the observed on-the-job wage growth path.

TABLE 5. Sample and Simulated Auxiliary Parameters (Wage Regression)

	OLS		Within-Individual		Within-Job	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
Intercept	2.086	2.107				
Exp/10	1.122	1.054	1.190	1.043		
Exp^2/100	-0.997	-0.886	-1.094	-0.869		
Exp^3/1000	0.485	0.444	0.539	0.436		
Exp^4/10000	-0.084	-0.086	-0.096	-0.087		
Ten					0.555	0.390
Ten^2/100					-0.265	0.011
Ten^3/1000					0.030	-0.065
Ten^4/10000					0.012	0.014
Var. of Residual	0.206	0.207	0.118	0.117	0.066	0.072

Note: Hourly log-wages are regressed on experience (EXP) or tenure (TEN). For the detailed information on the results for sample auxiliary parameter estimation, see table 2.
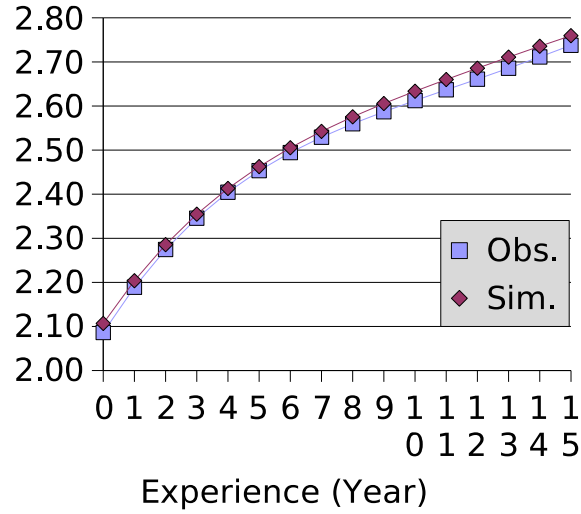
FIGURE 4.4. Average Log-wage by Experience

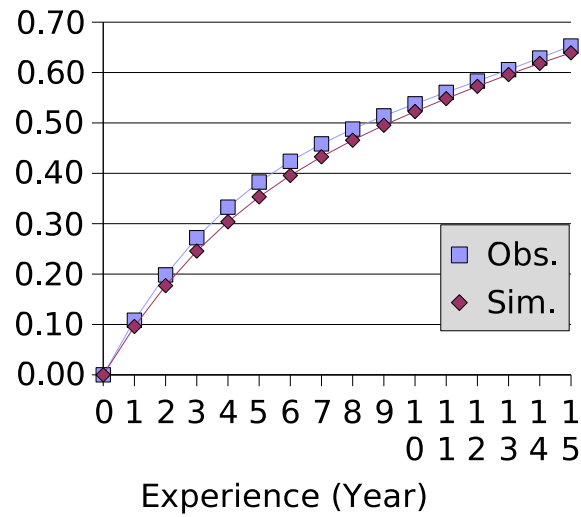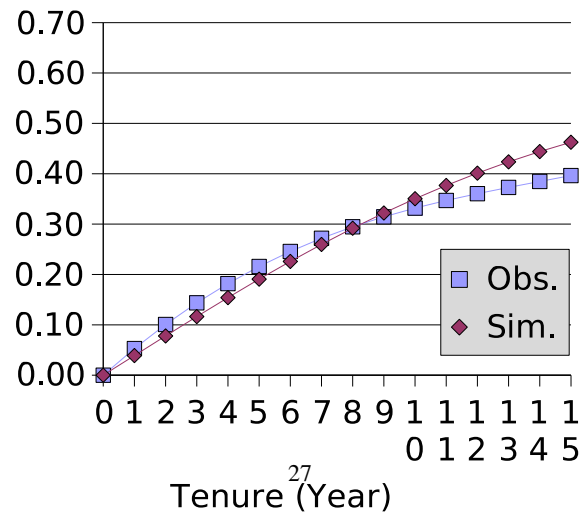FIGURE 4.5. Within-Individual Wage Growth Rate

FIGURE 4.6. Within-Job Wage Growth Rate

5.1. **Is Improving Outside Option Important?** The most interesting feature of the model is that not only labor productivity, but also the value of outside option changes over time and contributes to wage growth. The effect of the outside option value on wages can be evaluated by comparing wages with a counterfactual wage when the outside option is unemployment. The actual (predicted) wage profile and the counterfactual wage profile are presented in figure 5.1. At the initial wage (zero experience) the actual and the counterfactual wages are same because the actual outside option at the initial wage is unemployment. However, workers quickly improve their outside options, particularly for the first five years. The actual wage is 11% higher than the counterfactual wage when workers have five years of experience. Although the growth rate slows down, wages continue to grow due to the improved value of outside option; they are 13% higher when experience is ten years. Because wages grow by about 50% during the first ten years, the improved value of outside option can account for about a quarter of this wage growth. This simulation exercise indicates that improving outside option substantially contributes to wage growth of young workers.

5.2. **Reducing labor market frictions.** Another empirical question of the paper is what the effect of the labor market frictions on wages is. Due to the labor market frictions, workers have to search for better jobs and outside options, and bargain wages. In the absence of frictions, workers are able to immediately find the best match and an alternative job opportunity which is as good as the best one. Thus, the wage growth is solely driven by the growth of human capital in this economy. By comparing the actual wage profile with the counterfactual wage profile in the absence of frictions, I

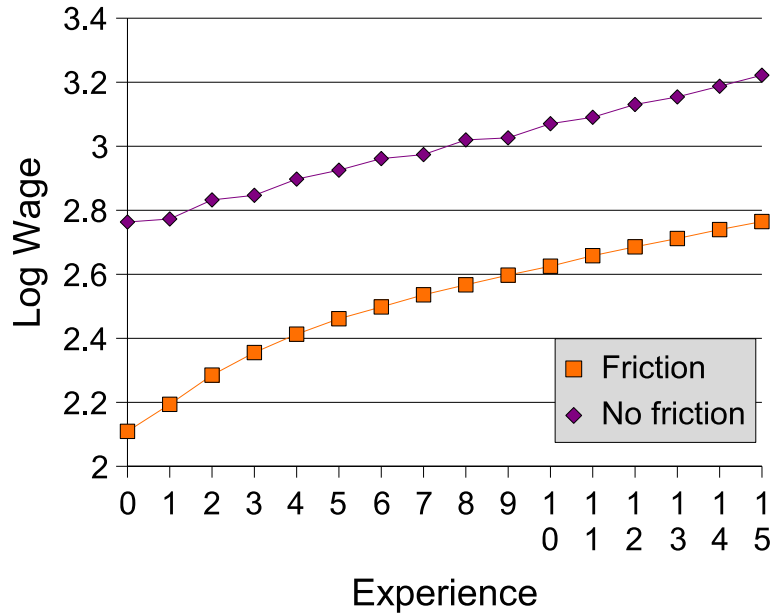FIGURE 5.1. Wage Profile When Outside Option is Unemployment
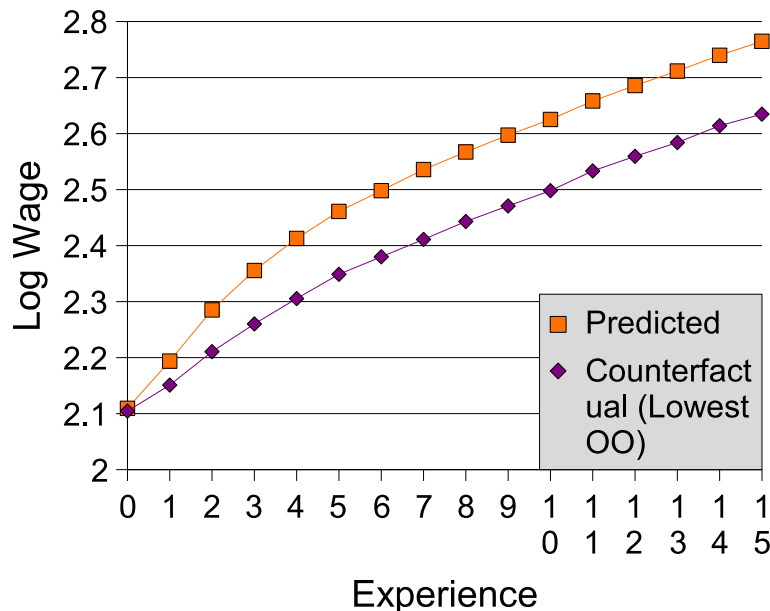
FIGURE 5.2. Log-Wage Profile in a Labor Market with Few Frictions.

can quantify the effect of the labor market frictions on wages. Since the simulation of the model is carried out in a discrete time model, it is impossible to simulate an economy with absolutely zero friction. But it is still worth simulating an economy with the feasibly lowest possible frictions.

To implement the idea, the model is parameterized in the following way. First, workers always have the best match quality with all firms. This "best" match quality is at the 97.5% quantile in the estimated underlying match quality distribution and the idiosyncratic productivity shock is in a good state. In the simulation of the estimated model, 18.6% of workers have this match quality when they have ten years of work experience. Second, workers meet one firm in every quarter regardless of their employment status. So the parameters are set so that $\lambda_0 = \lambda = 4$. Remember that Poisson processes are approximated by the corresponding Bernoulli processes and that the decision period is a quarter. This parameterization implies that the probability that a worker and a firm meet in a quarter is 1. Third, workers do not lose a job. In a labor market without frictions, workers are able to find a job immediately even if they lose one. To bring about this situation in a discrete time model, the parameters are set so that $\delta_0 = \delta = 0$. All other parameters remain the same as the estimated model.

The simulated wage profiles are presented in figure 5.2. There are two interesting features. First, the wage growth in the frictional labor market is more rapid than the wage growth without frictions. In the absence of frictions, wage growth is solely driven by the growth of human capital. To the contrary, in a frictional labor market, workers are improving their match quality and the value of outside option, which also increases their wages. The wage gap between two wage profiles is

quickly decreasing during the first six years by 20% (measured by log difference) and the remaining gap is not reduced after that. Because the observed wage growth rate during the first ten years is about 50%, labor market frictions account for about 40% of the observed wage growth during this period. This estimate is greater than the number claimed by Topel and Ward (1992), which is 30%, because they do not take into account the effect of the improved value of outside option. The second interesting feature of the comparison of two wage profiles in figure 5.2 is that the wage gap remains unfilled even after ten years of job search. This is explained by the average productivity of worker-firm matches. In a labor market without frictions, workers are always assigned to the best match. But, in a frictional labor market, workers are occasionally taken away from a job due to productivity shocks even if they once find the best match quality. Thus, the average match quality in a frictional labor market is strictly lower than the best match quality even after several years of job search.

5.3. **No Human Capital Growth.** Yet another counterfactual is simulated to examine the effect of human capital accumulation on wages and job search behavior. In this simulation, workers do not accumulate their human capital, which has two implications. First, wages grow slowly because only job search and bargaining improve the continuation value for workers. Second, the reservation match quality is increased because a lack of human capital growth reduces the value of a worker-firm match. As a result, unemployment spells become longer than those in the standard case. This counterfactual experiment is implemented by setting $\gamma_i = 0$ for $i = 1, \cdots, 4$. All other parameters remain the same as the estimated model.
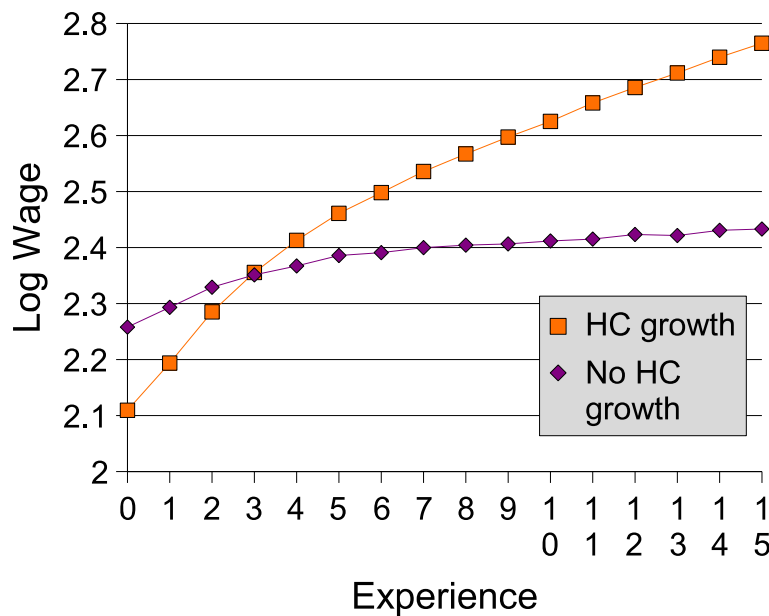

FIGURE 5.3. Log-Wage Profile with No Human Capital Growth.

TABLE 6. Log-Wage Profile with No Human Capital Growth.

	Experience	0	5	10	15
Average	HC growth	2.109	2.461	2.625	2.765
	No HC growth	2.258	2.386	2.412	2.433
	No HC growth (+27%)	2.472	2.624	2.658	2.675
Low-skill	HC growth	1.894	2.230	2.393	2.528
	No HC growth	2.059	2.168	2.187	2.196
	No HC growth (+27%)	2.253	2.390	2.423	2.438
High-skill	HC growth	2.453	2.821	2.986	3.118
	No HC growth	2.575	2.724	2.758	2.766
	No HC growth (+27%)	2.821	2.989	3.024	3.033

Note: In the third row (No HC growth, +27%) of each skill level, the innate productivity of workers are increased by 27%.

There are two interesting features in the simulated log wage profiles in figure 5.3. First, the initial wages are increased by 15% if human capital does not grow. This high initial wages are consequences of a high reservation match quality. Remember that the continuation value for the worker is proportional to the sum of the current wage and the expected future income gains as shown in proposition 2.4. When human capital does not grow, the value of a match is reduced for a given level of match quality. Because the value of unemployment changes little, workers have to wait for a higher match quality to start a job. Since the initial match quality is high, there is not much room for the match quality to be improved through on-the-job search. This high reservation match quality and a lack of human capital accumulation decrease the expected future income gains. When the changes of continuation value for the worker are small and the expected future income gains decrease a lot, the current wage has to increase. In other words, when workers cannot expect high income in the future, they must be compensated by a high wage today. This is why the initial wages are higher when human capital does not accumulate.

Second, wages grow slowly in the absence of human capital growth. Specifically, wages grow only by 15% on average during the first ten years of careers (see table 6.) This is partly due to my specification of multiplicative production technology, but a high reservation match quality is also the reason. When workers start with a high match quality, there is not much room to improve match quality through job search. These explanations also account for the difference in wage growth rate between low-skilled workers and high-skilled workers. High-skilled workers are not only more productive, but also have a lower reservation match quality than low-skilled workers, as shown in table 7.

The reservation match quality is raised not only because of low labor productivity today (except for the very first job), but also because of low labor productivity in the future. Individuals work to receive the returns from production. Another reason for working is that they invest on human capital.[11] To assess the effect of low future productivity on the current reservation match quality,

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[11]Imai and Keane (2004) estimates labor supply elasticity from this viewpoint.
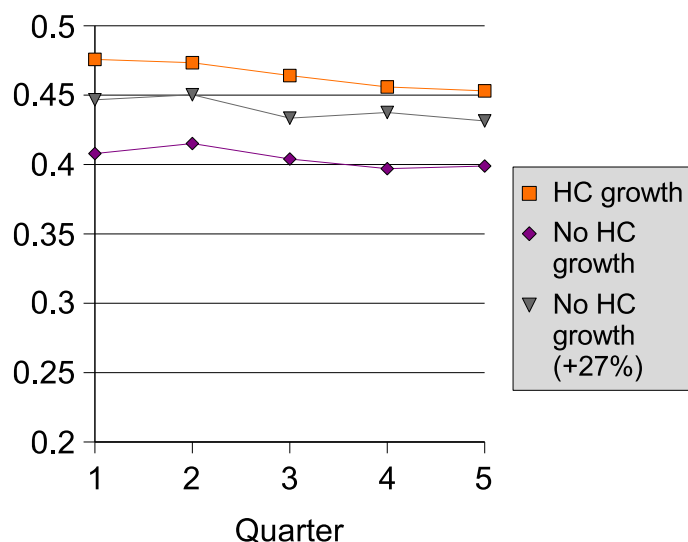
TABLE 7. Reservation Match Quality.

		Bad Shock	Good Shock
Low-skill	HC growth (GX = 0)	2.128 (14)	1.134 (7)
	HC growth (GX = 10)	2.329 (15)	1.240 (8)
	No HC growth	2.548 (16)	1.357 (9)
	No HC growth (+27%)	2.329 (15)	1.240 (8)
High-skill	HC growth (GX = 0)	1.945 (13)	0.947 (5)
	HC growth (GX = 10)	1.945 (13)	1.036 (6)
	No HC growth	2.128 (14)	1.134 (7)
	No HC growth (+27%)	2.128 (14)	1.134 (7)

Note: The reservation match quality depends on the state of idiosyncratic shock. The ranks in the discretized match quality space are in parenthesis (20 is the highest.) In the fourth row (No HC growth, +27%) of each skill level, the innate productivity of workers are increased by 27%.

a counterfactual is simulated imposing that worker's innate productivity be increased by 27%, which amounts to ten years of experience. The reservation match qualities for each specification are presented in table 7. The current productivity at the first job is same in the simulation with human capital growth (the first row) and in the simulation without human capital growth (the third row.) So the difference in the reservation match quality is explained by the difference in future productivity. With a lack of human capital growth, the reservation match quality for both types of workers is increased by 18% (measured by log difference) when idiosyncratic shock is in good state. However, this effect of future productivity is weakened in ten years. Notice that the current productivity of ten-year-experienced workers is same in the simulation with human capital growth (the second row) and in the simulation with no human capital growth and 27% productivity raise (the fourth row.) The reservation match quality for low-skilled workers is same as that in the simulation with human capital accumulation. High-skilled workers now have 9% higher reservation match quality. Because the speed of human capital accumulation slows down as workers become experienced, the effect of future productivity at ten-year-experience is weaker than that in the first job.

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FIGURE 5.4. Unemployment Hazard Rate

Note: In the simulation of "No HC growth (+27%)", the innate productivity of workers are increased by 30%.

The increased reservation match quality also results in a longer unemployment duration. In the standard simulation with human capital growth, the predicted unemployment hazard rate in the first quarter is 0.48. But it decreases to 0.41 if human capital does not accumulate. In my simulations, the average unemployment duration increases from 2.1 quarters to 2.5 quarters.

Through this simulation exercise I find that human capital accumulation affects wage growth not only by its direct effect on the current labor productivity, but also by its indirect effect on job search behavior due to low future productivity.

6. CONCLUSION

The main contribution of this paper is to investigate wage dynamics using a model of wage bargaining with on-the-job search. This is a departure from the conventional wage growth literature in the sense that I consider a new component of wage growth: the improved value of outside option. The model improves on previous work in two respects: it allows for productivity growth, and it deals with wage renegotiation following productivity shocks. These changes make the model analytically complex and the equilibrium wage is numerically solved rather than using the explicit wage solution used in previous work. However, the first change allows me to examine the effect of general human capital growth, which makes a substantial contribution to wage growth. I find that human capital accumulation affects wage profile by changing job search behavior as well as labor productivity itself. The model also generates a wage decrease on the job and endogenous separation due to productivity shocks. Both of these are necessary to match the observed wage dynamics and worker mobility.

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The model captures important features of wage dynamics and worker mobility in the NLSY 79. The empirical results show that the contributions of job search and bargaining to wage growth is significant. The improved value of outside option accounts for about a quarter of the observed wage growth during the first ten years. This paper also quantifies the effect of human capital on wage growth and search behavior. Without human capital accumulation, the reservation match quality is increased by 18%, which results in 15% higher initial wage and only 15% of wage growth in the first ten years. The results suggest a tight relationship between human capital accumulation and job search.

This paper provides a detailed econometric model of bargaining with on-the-job search that allows for rich forms of heterogeneity and time-varying productivity components. Nevertheless, there are important extensions that will be addressed in the future work. First the role of fellow workers in wage bargaining is ignored. Large firms can easily replace their employees from their internal labor market. Thus, the bargaining position of the worker tends to be low in larger firms. Second, parametric assumption for match quality distribution is strong. The assumption of lognormality is common in the literature, but there are a number of possible alternative assumptions. Nonparametric identification might be possible using the idea of record statistics, which is proposed by Barlevy (2005) for a job search model without bargaining.

APPENDIX A. ALTERNATIVE BARGAINING ASSUMPTION

In this paper wages are assumed to be constant until renegotiation. However, this is not the only possible assumption. Alternative assumption is that wage is a product of efficiency unit of labor and its price and that the price of efficiency unit of labor is constant until renegotiation. In this alternative specification, wages grow over time without renegotiation as workers accumulate their human capital. Let q be the price of efficiency unit of labor and y be the labor productivity. The flow wage payment is then $w = qy$. In bargaining, the price is set so that the continuation value of the worker coincides with the equilibrium payoff in the bargaining. Suppose that the wage is determined through bargaining among three players, and that the type-Θ firm wins and the type-Θ' firm loses. The equilibrium price q^* satisfies

$$U(h, \Theta, q^*) = \beta J(\Theta, h) + (1 - \beta)[J(\Theta', h) + (1 - \beta)U_0(h)].$$

Similar to the result presented in figure 2.1, this equilibrium price q^* is also determined uniquely.

One advantage of this specification is that wage decomposition is straightforward. Assuming the production technology is given by equation (4.1), wages can be decomposed as

$$\ln w = \gamma_{0,i} + \gamma_1 h + \gamma_2 h^2 + \gamma_3 h^3 + \gamma_4 h^4 + \theta + \epsilon_\theta + \ln q(h, \Theta, \Theta')$$

where q only captures the effect of change in outside option value. For normalization, the lowest price $\underline{q}$ is set 0.01 and the highest price $\bar{q}$ is set 1.00, because price and labor productivity are not separately identified.

TABLE 8. Parameter Estimates

Parameter		Notation	Estimates	Std. Dev.
Human Capital		γ_1	0.483	0.049
		γ_2	-0.243	0.045
		γ_3	0.086	0.020
		γ_4	-0.011	0.004
Unemp. Benefit		b	7.894	0.863
Poisson Rate	Unemp.	λ_0	3.950	0.502
	Emp.	λ	1.236	0.091
	Separation	δ_0	0.158	0.004
	Match Q. Change	δ_{1a}	1.237	0.080
		δ_{1b}	-0.027	0.004
	Prod. Shock	δ	0.509	0.068
Type Dist.	High-skilled	$\gamma_{0,HIGH}$	0.591	0.063
	Weight	p_{HIGH}	0.618	0.094
Shock Dist.	Bad	$\epsilon_{\theta,BAD}$	-1.080	0.130
	Weight	p_{BAD}	0.148	0.020
Match Q. Dist.	Mean	μ	1.439	0.117
	Std. Dev.	σ_θ	0.361	0.029

Interest Rate: $r = 0.05$
Bargaining Power: $\beta = 0.5$
No. of Moment Conditions: 101
Function Value at the Minimum: 524.5206

Note: The coefficients of production function are denoted by γ. The hourly value of unemployment compensation measured in 2004 dollar is b. The annual arrival rate of an offer for those who do not have a full-time job is λ_0. The annual offer arrival rate on the full-time job is λ. The annual arrival rate of an exogenous separation is δ_0. The parameters for the annual rate of match quality change are δ_{1a} and δ_{1b}. The annual arrival rate of productivity shock is δ. The support point for high-skilled individuals and its weight are denoted by $\gamma_{0,HIGH}$ and p_{HIGH}. The support point for low-skilled workers are normalized to zero. The support point for bad (negative) shock and its weight are $\epsilon_{\theta,BAD}$ and P_{BAD}. Those for good (positive) shock are $\epsilon_{\theta,GOOD}$ and P_{GOOD}. I impose a restriction that the mean of the shock be one for normalization. The location and the scale parameter of match quality distribution, which is lognormal, are μ and σ_θ, respectively.

A.1. **Estimation Results.** The estimation results are presented in table 8. A worker's productivity grows by 30% during the first ten years of his career through accumulation of general human capital. This estimated human capital accumulation process is similar to that in the original model. The value of unemployment benefit amounts to $7.9 per hour in 2004 dollar. Those who do not have a full-time job meet 3.95 firms during a year. Full-time job holders are contacted by 1.24 firms during a year. The match quality distribution is assumed to be lognormal. The mean and the standard deviation of log of match quality are 1.44 and 0.36. The estimated mean of log match quality is much larger than the original counterpart, but this is due to normalization. A productivity shock occurs once in every 2 years. When a worker-firm match is in a bad state, their output is

TABLE 9. Sample and Simulated Auxiliary Parameters (Hazard Rate)

Quarter	Full-time Job		Full-time Employment		Non Full-time Employment	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
1	0.200	0.092	0.155	0.038	0.512	0.460
5	0.108	0.081	0.083	0.037	0.462	0.428
10	0.065	0.067	0.051	0.040		
20	0.045	0.057	0.025	0.042		
30	0.049	0.047	0.036	0.036		
40	0.034	0.051	0.022	0.039		

reduced by 66%. But this negative shock is smaller than that of the original model, which reduces productivity by 93%. This difference is the most significant one between the original model and the alternative model. I will discuss its implication in the next subsection. Also a match is destroyed due to an exogenous shock once in 6.32 years. The proportion of high-skilled workers is 39% and they are 61% more productive than low-skilled workers, which implies that the distribution of worker types is skewed to the left.

A.2. **Model Fit.** The sample hazard rates and the simulated hazard rates are plotted in figures A.1, A.2, and A.3. The simulated non full-time employment hazard rate presents the downward trend. It is 0.46 at the first quarter and it declines to 0.43 in the fifth quarter. The level of the non full-time employment hazard rate and the trend are similar to the observed patterns in the data. However, the simulated employment hazard rate does not fit to the data quite well. In particular, the simulated hazard rate does not have a downward trend: it is around 0.04 in all periods. Because the annual Poisson rate for the exogenous separation is about 0.16, no endogenous separations occur in my simulation. This simulation result implies that the estimated model does not have sufficiently large negative productivity shock to generate endogenous separation. However, if the model had a larger negative productivity shock, it would drive too much fluctuation in wages, because all changes in productivity translate into wages in this alternative specification. More specifically, the residual variance in wage regressions would be too high, if a larger negative productivity shock existed. Unless exogenous separation rate is directly related to work experience, the model cannot match both the employment hazard rate and the wage variance at the same time if I assume agents negotiate the price of efficiency unit of labor.

The simulated job hazard rate presents a downward trend. But the slope is less steep than the observed counterpart. Because the workers with low match quality are more likely to make job turnover, the simulated job-to-job transition rate is decreasing in job tenure, which results in a downward job hazard rate. However, the slope is not steep enough because the model does not generate transitions from employment to unemployment.

The sample and simulated auxiliary parameters of wage regression are presented in table 10. The simulated variance of residual in each wage regression is close to the observed counterpart.
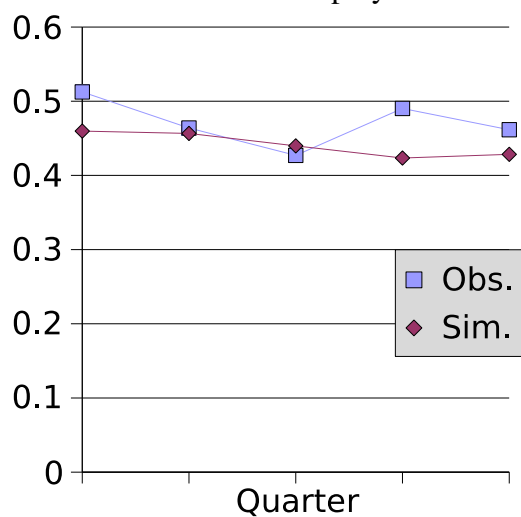
FIGURE A.1. Non full-time employment Hazard Rate

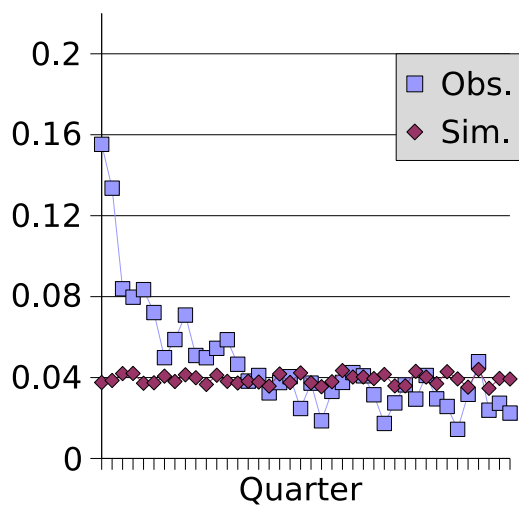FIGURE A.2. Full-time Employment Hazard Rate
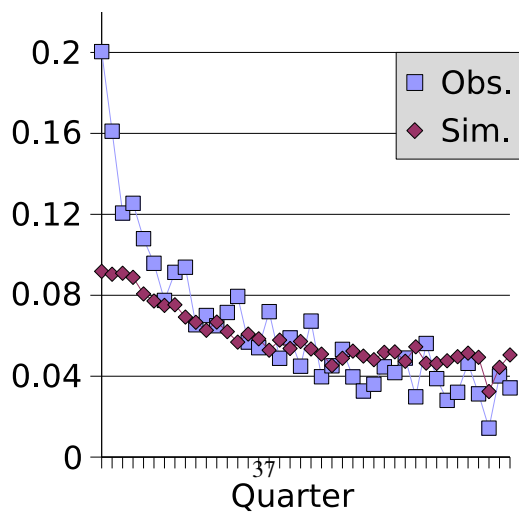

FIGURE A.3. Full-time Job Hazard Rate

TABLE 10. Sample and Simulated Auxiliary Parameters (Wage Regression)

	OLS		Within-Individual		Within-Job	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
Intercept	2.086	2.076				
Exp/10	1.122	1.303	1.190	1.298		
Exp^2/100	-0.997	-1.220	-1.094	-1.222		
Exp^3/1000	0.485	0.580	0.539	0.592		
Exp^4/10000	-0.084	-0.097	-0.096	-0.104		
Ten					0.555	0.716
Ten^2/100					-0.265	-0.455
Ten^3/1000					0.030	0.123
Ten^4/10000					0.012	-0.002
Var. of Residual	0.206	0.195	0.118	0.109	0.066	0.067

Note: Hourly log-wages are regressed on experience (EXP) or tenure (TEN). For the detailed information on the results for sample auxiliary parameter estimation, see table 2.

The prediction of average log wage given experience is reasonably close to the data, as is shown in figure A.4. The difference between the simulation and the observation is 0.03 when experience is ten years. The prediction of average within-individual wage growth rate also captures the basic features of the data (see figure A.5), although the simulated wage growth rate is faster than the observation. The difference between the simulated path and the observed path is largest at seven years of experience and it is 0.03. Figure A.6 presents within-job wage growth rate. Similarly, the simulated on-the-job wage growth rate is faster than the observation. The gap at five years of tenure is 0.04.

A.3. **Wage Growth Decomposition.** The estimated parameters are used for wage growth decomposition. Because wage is a product of efficiency unit of labor and its price, log wage at period t can be written as

$$\ln w_t = \gamma_0 + \gamma_1 h_t + \gamma_2 h_t^2 + \gamma_3 h_t^3 + \gamma_4 h_t^4 + \theta_t + \epsilon_{\theta,t} + \ln q(h_t, \Theta_t, \Theta_t')$$

where $\Theta_t = (\theta_t, \epsilon_{\theta,t})$ is a pair of match quality and productivity shock for the employer and Θ' is that for the potential employer. Let $w_{h,t} = \gamma_1 h_t + \gamma_2 h_t^2 + \gamma_3 h_t^3 + \gamma_4 h_t^4$ be the contribution of general human capital to log wage. Similarly, the contributions of match specific capital Θ and the price of efficiency unit of labor q to log wage are denoted by $w_{\Theta,t} = \theta_t + \epsilon_{\theta,t}$ and $w_{q,t} = \ln q_t$, respectively. The wage growth rate from period t to period $t + 1$ can be decomposed into the general human capital effect, the match specific capital effect, and the price effect:

$$\ln w_{t+1} - \ln w_t = \Delta w_{h,t} + \Delta w_{\Theta,t} + \Delta w_{q,t}.$$

The results of a wage growth decomposition are summarized in table 11. The average simulated wage growth rate for the first ten years is 0.57, which is only 0.03 higher than the observation. The growth of general human capital explains the largest part of the wage growth and it accounts for

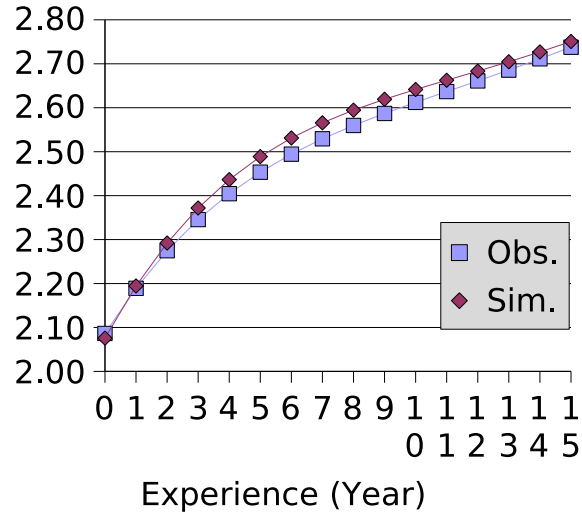FIGURE A.4. Average Log-wage by Experience

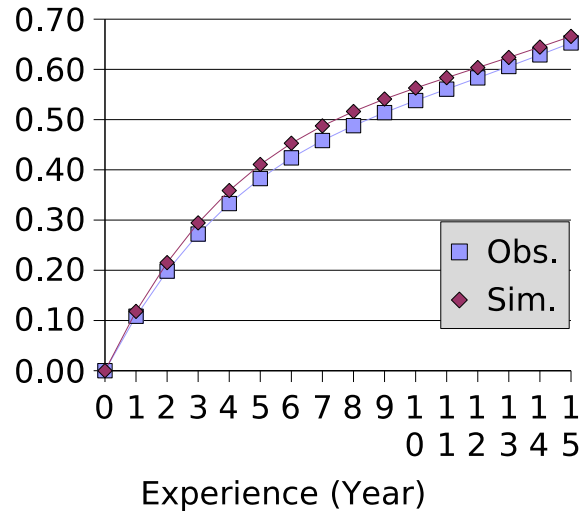Experience (Year)

FIGURE A.5. Within-Individual Wage Growth Rate

Experience (Year)

FIGURE A.6. Within-Job Wage Growth Rate

Tenure (Year)

39
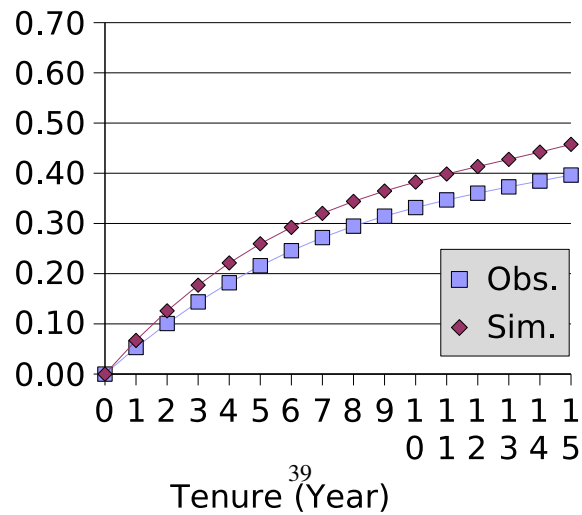
TABLE 11. Wage Growth Decomposition

Experience	Total	General	Specific	Price
0	0.000	0.000	0.000	0.000
5	0.414	0.193	0.220	0.001
10	0.575	0.318	0.249	0.009
15	0.692	0.418	0.259	0.014

about 55% of the observed wage growth. The second largest component of wage growth is match specific human capital, which accounts for 43% of the observation. The price effect is quite small and it accounts for 2% only.

A.4. **Remark.** I have examined alternative specification in which agents negotiate the price of efficiency unit of labor, rather than wage. Although this specification provides a straightforward wage growth decomposition, the model does not fit the observed patterns in the data. More specifically, the model does not match the employment hazard rate and the wage variance simultaneously. In this specification, all variations in productivity are translated into variations in wages. If I allow for endogenous separation and the model matches the observed employment hazard rate, the model generates too large wage variance compared with the observed wage variance. In contrast, my original specification in which agents negotiate wages fits both the employment hazard rate and the wage variance simultaneously, because productivity is not directly translated into wages.

APPENDIX B. ADDITIONAL ESTIMATION RESULTS

For the main results of the paper, the bargaining power parameter is fixed at 0.5. To be able to estimate the bargaining power in a reliable way, employer side information should be used. But, it is not included in the NLSY. Nevertheless, I also estimate the parameters including bargaining power to see how other parameter estimates but bargaining power are affected. The results are summarized in table 12. The estimated bargaining power is 0.48, which is close to the parameterized value of 0.5. Hence, other parameter estimates are also close to those in the main results.

TABLE 12. Parameter Estimates

Parameter		Notation	Estimates	Std. Dev.
Human Capital		γ_1	0.457	0.059
		γ_2	-0.383	0.078
		γ_3	0.165	0.031
		γ_4	-0.004	0.002
Unemp. Benefit		b	5.586	0.629
Poisson Rate	Unemp.	λ_0	3.369	0.212
	Emp.	λ	1.091	0.087
	Separation	δ_0	0.107	0.004
	Match Q. Change	δ_{1a}	0.088	0.018
		δ_{1b}	-0.001	0.001
	Prod. Shock	δ	2.090	0.108
Type Dist.	High-skilled	$\gamma_{0,HIGH}$	0.524	0.031
	Weight	p_{HIGH}	0.507	0.124
Shock Dist.	Bad	$\epsilon_{\theta,BAD}$	-2.541	0.271
	Weight	p_{BAD}	0.391	0.024
Match Q. Dist.	Mean	μ	0.496	0.035
	Std. Dev.	σ_θ	0.527	0.081
Measurement Error		σ_ϵ	0.281	0.013
Bargaining Power		β	0.482	0.049
Interest Rate: $r = 0.075$				
No. of Moment Conditions: 101				
Function Value at the Minimum: 201.944				

APPENDIX C. PROOFS

C.1. **Proof of Lemma 2.1.**

Proof. First notice that a worker and a firm care only about the present value of income and that the timing of the payment does not actually matter because they are risk-neutral, have a common discount rate, and have access to capital markets. For analytical simplicity, I consider a lump-sum payment W to the worker that gives him the same value as the contract based on the constant flow payment w. In each bargaining round, the following recursive equations for reservation values hold,

$$W_1 = \max\left[\frac{1}{1+\rho\Delta}\left[s\Delta U_0 + (1-s\Delta)\{\beta W_2 + (1-\beta)W_1\}\right],\ U_0\right]$$

$$J - W_2 = \max\left[\frac{1}{1+\rho\Delta}\left[(1-s\Delta)\{\beta(J-W_2) + (1-\beta)(J-W_1)\}\right],\ 0\right]$$

where I omit the arguments of the value functions U_0 and J for notational simplicity. The first equation says that the worker is indifferent between accepting the payment W_1 and the maximum of the following: waiting for the next round after the time Δ elapsed and quitting the bargaining to

look for other potential partners. The second equation says that the firm's reservation payment is W_2.

(1) $J \geq U_0$: In this case, the match is efficient and there is surplus to be split. Solving the system of linear equations and letting Δ go to zero, I find

$$W_1 = W_2 = \beta J + \frac{s}{s+\rho}(1-\beta)U_0.$$

I can interpret the worker's threat point $s/(s+\rho) \cdot U_0$ as the worker's payoff when the worker and the firm perpetually disagree. When agents are patient during the bargaining, i.e. $\rho \to 0$, I find that $W_1 = W_2 = \beta J + (1-\beta)U_0$. In equilibrium, the proposer makes an offer $\beta J + (1-\beta)U_0$ and it is accepted immediately. The payoffs of the worker and the firm are $\{U, V\} = \{\beta J + (1 - \beta)U_0, (1-\beta)(J-U_0)\}$.

(2) $J < U_0$: The match is inefficient in this case. When the worker is the proposer, he asks for U_0 or more and the firm rejects this to look for other workers. When the firm is the proposer, it asks 0 or more for the profit and the worker rejects this to look for other firms. In any case, they immediately separate. The payoffs are $\{U_0, 0\}$. $\qquad \square$

C.2. **Proof of Lemma 2.2.**

Proof. I solve the problem by backward induction. Without loss of generality, I assume the match quality with firm A is at least as good as the match quality with firm B, i.e., $J(h, \Theta_A) \geq J(h, \Theta_B)$. Suppose that the worker bargains with firm A first. Then the worker bargains with firm B in stage 3. Because this bargaining is exactly same as the bilateral bargaining between an unemployed worker and a firm, the equilibrium payoff of the worker is given by

$$U_3(\Theta_B) = \max[\beta J(\Theta_B) + (1-\beta)U_0, U_0]$$

where U_3 is the equilibrium payoff the worker earns in this subgame.

Next consider the subgame in stage 2. The following recursive equations for reservation values are satisfied

$$W_1 = \max\left[\frac{1}{1+\rho\Delta}\left[s\Delta U_3(\Theta_B) + (1-s\Delta)\{\beta W_2 + (1-\beta)W_1\}\right], \ U_3(\Theta_B), \ U_0\right]$$

$$J - W_2 = \max\left[\frac{1}{1+\rho\Delta}\left[(1-s\Delta)\{\beta(J-W_2) + (1-\beta)(J-W_1)\}\right], \ 0\right].$$

Remember that the worker will bargain with firm B if this bargaining fails. If $\beta J(\Theta_A) + (1-\beta)[\beta J(\Theta_B) + (1-\beta)U_0] \geq U_3(\Theta_B)$, the worker and the firm reach an agreement immediately as $\Delta, \ \rho \to 0$. The worker receives $\beta J(\Theta_A) + (1-\beta)[\beta J(\Theta_B) + (1-\beta)U_0]$ and the firm receives $(1-\beta)[J(\Theta_A) - \{\beta J(\Theta_B) + (1-\beta)U_0\}]$ in this subgame. If $\beta J(\Theta_A) + (1-\beta)[\beta J(\Theta_B) + (1-\beta)U_0] < U_3(\Theta_B)$, the respondent rejects the offer and the worker starts bargaining with the other firm and receives $U_3(\Theta_B)$.

Next suppose that the worker chooses to bargain with firm B first. By a similar argument to that in the previous paragraph, the worker's payoff in the subgame is $\max[\beta J(\Theta_B) + (1-\beta)[\beta J(\Theta_A) + (1-\beta)U_0], \ \beta J(\Theta_A) + (1-\beta)U_0, \ U_0]$.

Because $J(\Theta_A) > J(\Theta_B)$ by assumption, the worker chooses to bargain with firm A first. If the equilibrium payoff in this subgame exceeds the value of the current contract, the worker starts the bargaining. Otherwise, he lets the challenger firm go. □

C.3. **Proof of Lemma 2.3.**

Proof. The proof is basically same as the one for the lemma 2.1. The only difference is the payoff when bargaining breaks down. The following recursive equations for reservation values are satisfied

$$W_1 = \max\left[\frac{1}{1+\rho\Delta}\left[s\Delta U + (1-s\Delta)\{\beta W_2 + (1-\beta)W_1\}\right], \ U_0\right]$$

$$J - W_2 = \max\left[\frac{1}{1+\rho\Delta}\left[s\Delta V + (1-s\Delta)\{\beta(J-W_2) + (1-\beta)(J-W_1)\}\right], \ 0\right]$$

where U and V are the values under the current contract for the worker and the firm, respectively.

(1) $J \geq U_0$ and $V \geq 0$: The match is efficient and both agents' participation constraints are not binding. Solving the system of linear equations, I find $W_1 = W_2 = U \cdot s/(s+\rho)$ as $\Delta \to 0$. As a firm and a worker become more patient, i.e. $\rho \to 0$, the worker's equilibrium payoff is U, while the firm's payoff is V. They eventually end up with the current contract.

(2) $J \geq U_0$ and $V < 0$: The match remains efficient, but the firm's participation constraint is not satisfied. Then I have $J - W_2 = 0$. Thus, the worker accepts a wage cut so that the firm's participation constraint is just binding.

(3) $J < U_0$: The match becomes inefficient after the negative shock. They immediately separate to look for other potential partners. □

APPENDIX D. DETAILS OF DATA SET CONSTRUCTION

D.1. **Weekly Job Information.** First I collect information about each job. In particular, I am interested in (1) the start week of the job, (2) the end week of the job, (3) wages, and (4) hours worked per week. To determine the start and the end week of a job, I collect information from the most recent survey. I use white male high school graduates in this analysis. High school graduates are defined as individuals who have high school diploma but did not pursue further formal education until the most recent survey year. There are 950 white male high school graduates in my sample and they had 10,128 jobs in total. Because an individual may have a job for more than one survey year, I have multiple observations for each job. I have 24,565 observations in my sample. To reduce the initial condition problems, I need information about the transition from school to work. I omit individuals who graduated high school before January 1978, which is earlier than the first survey year. This condition leaves me 18,114 observations for 685 individuals and

7,780 jobs. Because I am interested in jobs after the transition to labor market is made, I omit jobs that ended before graduating. I have 16,364 observations for 684 individuals and 6,555 jobs after imposing this condition. Next I omit self-employment jobs and jobs without pay. Then I have 15,695 observations for 684 individuals and 6,417 jobs.

I determine whether a job is full-time or not by taking the average hours over all observations for each job. A full-time job is defined to be a job that individuals work at for 30 hours per week or more. The number of hours per week worked is topcoded so that it does not exceed 96 hours before the average is calculated. My model precludes a transition between part-time and full-time without changing employer. I expect that this does not cause a serious bias, because more than 90% of jobs (5,914 jobs) did not have such switching. Omitting all part-time jobs, I have 13,686 observations for 678 individuals and 5,388 full-time jobs in the sample.

D.1.1. *Dual Jobs.* Several individuals have more than one job at the same time. In particular, there are some short term full-time jobs that are started and ended while an individual holds a primary full-time job. I omit these short term jobs for two reasons. First, these jobs may be misclassified as full-time because individuals are unlikely to have two or more full-time jobs. Second, even if they are correctly classified, those secondary jobs are temporary and less important for an individual's career. There are 601 secondary jobs and the median duration of a job is 17 weeks (the mean duration is 34 weeks.) On the other hand, there are 4,787 primary jobs and the median duration of a job is 51 weeks (the mean duration is 126 weeks.)

Some jobs are started before old jobs are ended. To reconcile the gap between the data and the model, I move the start week of a job, while the end week of a job is not edited. If there are two jobs that have overlapping periods, I assume that the second job started right after the first job is ended. There are 250 jobs (about 5% of all jobs) of which start weeks have to move. The median change is 15 weeks (mean is 34 weeks.)

After all the operations described above, I have 12,846 observations for 678 individuals and 4,787 jobs. The information is used to construct a quarterly job array in the followings.

D.1.2. *Job-to-Job Transition Indicator.* As is mentioned in the main text, I say that an individual makes a job-to-job transition if (1) he spends three weeks or less before he starts working for a new job and (2) he leaves the job voluntarily. Otherwise, I say that an individual changes jobs via non full-time employment. Under this definition, I find that 1,612 jobs are started as job-to-job transitions, while 2,480 jobs are not. If I change the search duration from three weeks to two weeks, 1,461 jobs are started as job-to-job transition. If I change the search duration from three weeks to four weeks, 1,694 jobs are started as job-to-job transition.

D.2. **Quarterly Work History Array.** Using the information constructed in the previous subsection, I construct a quarterly work history array for each individual. A quarter consists of 13 weeks. The quarterly labor force status of an individual is determined by the labor force status of the first

TABLE 13. The number of observations.

Restriction	# of persons	# of jobs	# of obs.
High-school	950	10128	24565
Graduate after 1978	685	7780	18114
Jobs after graduation	684	6555	16364
Non self-employed	684	6417	15695
Full-time jobs	678	5388	13686
Primary jobs	678	4787	12846
After the transition	662	3882	9462

week in a given quarter. This implicitly assumes that the labor force status does not change during a quarter, although it may for some short term jobs. It is true that I could avoid this discretization bias by making the decision period shorter, but that may cause another problem. Weekly work history data would contain more noise. As Neal (1999) points out, NLSY work history file includes measurement errors. As I make the decision period shorter, I may pick up every noise contained in the data. Aggregating the weekly information to quarter may moderate the bias. In addition, using shorter decision period can be computationally expensive and make my estimation intractable.

D.2.1. *Entry and Exit from the Full-time Labor Market.* I trace each individual from his initial long-term transition to the full-time labor market until he exits from the full-time labor market or the survey ends. The definition of an initial long-term transition to the full-time labor market is similar to that of Farber and Gibbons (1996). I consider an individual has made this transition if he works for six or more quarters during three years.

Exit from the full-time labor market occurs when an individual does not work at a full-time job for three years or more. If this is observed in the data, I record his separation from a job and drop the information after that. Re-entry to the full-time labor market is not included in my sample, because I do not have any information about when individuals re-entered the labor market, i.e., the time job search is re-started.

D.2.2. *Wages.* Hourly wages are computed by dividing weekly earnings by hours worked per week. If those are not recorded on a weekly basis, such as monthly or annual, I convert them to weekly data. Wages are deflated by monthly CPI (the average in 2004 is set to 100.) If an individual had a job that ended before the interview week, I use the wage is observed in the last week of the job. Otherwise, I use the wage observed in the interview week. In both cases, I assume that the wage is constant during the quarter that includes the week when wage is observed. When I need to move the starting date of the job as I explained above, the wage observation is also moved. I keep the link between employment record and corresponding wage observations.

D.3. **Variables for Auxiliary Models.** My auxiliary parameters are hazard rates and conditional mean and variance of wage given experience and tenure. To compute the auxiliary parameters, I

need full-time job spells, full-time employment spells, non full-time employment spells, wages, and the corresponding experience and tenure.

D.3.1. *Job spells, Full-time Employment spells, and Non Full-time Employment spells.* Using the quarterly work history array made above, I construct full-time job spells, full-time employment spells, and non full-time employment spells. A full-time job spell ends when an individual switches to a new job or loses full-time employment status (his new status is non full-time employment.) On the other hand, a full-time employment spell ends only when an individual does not have a full-time job any more. Thus, the difference between job spells and employment spells is whether they include job-to-job transitions. A non full-time employment spell ends if an individual who does not have a full-time job finds a new full-time job.

D.3.2. *Work Experience.* All individuals start their career with zero experience and zero tenure, regardless of their actual experience recorded in original NLSY work history file. I construct these variables using only my quarterly work history array. It is important to make my variables consistent with my model. Otherwise I would be unable to interpret the data in terms of my model. As it is assumed in my theoretical model, experience does not depreciate. So, experience is the cumulative number of quarters that an individual had a full-time job in the past.

D.4. **Sensitivity Checks.** One major concern is a potential bias introduced by ignoring all part-time job experience. I constructed another quarterly work history array that includes part-time jobs. The differences from the original array are the following. First, if individuals have both a full-time job and a part-time job in a given week, only the full-time job is recorded in *weekly* work history array. Then I convert it to a quarterly array. Second, I assume part-time experience accounts for a half of full-time experience.

Using this quarterly work history array I construct two different measures of work experience: one includes both full-time and part-time job experience, and another includes full-time job experience only. The paths of the two different measures are reported in figure D.1. If I include part-time jobs, the average work experience is 7.4 years ten years after graduating, while it is 6.9 years if I do not include part-time jobs. Even 20 years after graduating, the difference is small and it is 0.8 years. This result suggests that the bias from ignoring part-time jobs is negligibly small.

I also present the proportion of all jobs that are part-time in figure D.2. Part-time jobs are quite common among the young. About a half of job holders worked in part-time jobs right after graduating. After a year, the proportion of all jobs that are part-time quickly drops to 23% and it continues to decrease. This pattern is consistent with the result found by Klerman and Karoly (1994). This result implies that part-time jobs are common only within a couple of years after graduating.

FIGURE D.1. The difference in work experience when part-time jobs are not counted.
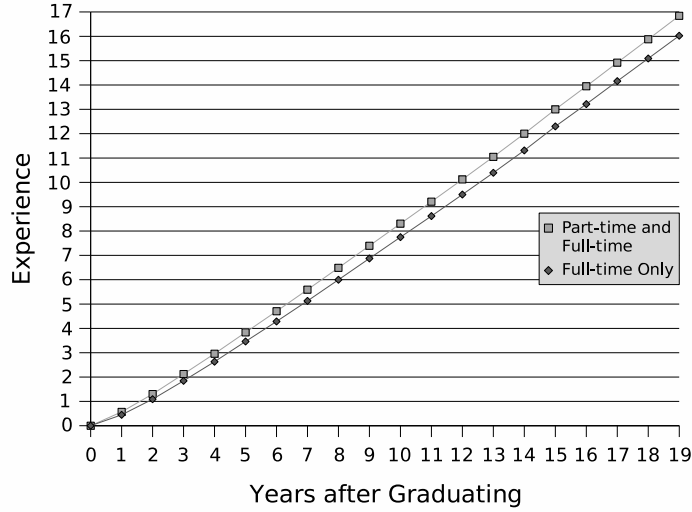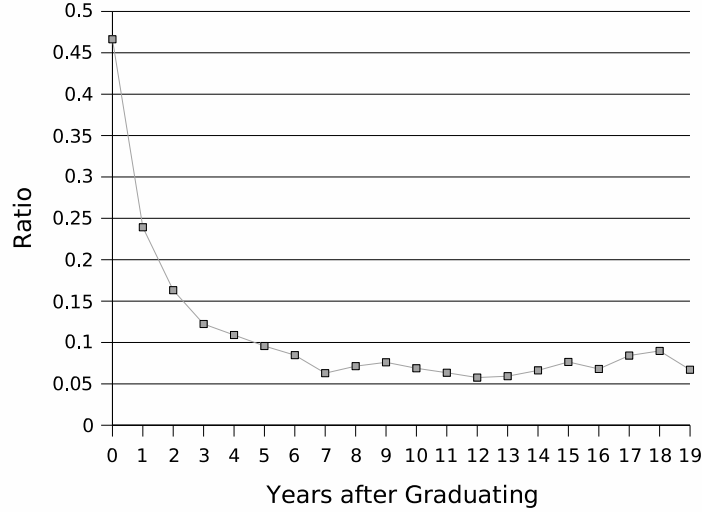

FIGURE D.2. Ratio of Part-time Jobs

APPENDIX E. NUMERICAL ISSUES

E.1. **Optimal Weighting Matrix.** The optimal weighting matrix used in a simulated minimum distance estimator is given by the covariance matrix of the sample auxiliary parameters. I first introduce some notations. Let $W_i = \{w_{i,t}\}_{t=1}^{T_i}$ be the wage history of individual i from the initial period ($t = 1$) to the last period included in my sample ($t = T_i$.) Although subscripts for a job are omitted, this wage history includes wages in different jobs. Let $d_i^J = \{d_{i,j}^J\}_{j=1}^{J_i}$ be the vector of job spells that individual i have worked at. The number of jobs that individual i had in my sample is denoted by J_i. Let $d_i^F = \{d_{i,k}^F\}_{k=1}^{F_i}$ be the vector of full-time employment spells for individual i where F_i is the number of full-time employment spells of individual i. Let $d_i^N = \{d_{i,l}^N\}_{l=1}^{N_i}$ be

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the vector of non full-time employment spells for individual i where N_i is the number of non full-time employment spells of individual i. Finally, let $D_i = \{W_i, d_i^J, d_i^F, d_i^N\}$ be the work history of individual i and let $D = \{D_i\}_{i=1}^N$ be the whole sample.

The covariance matrix of the sample auxiliary parameters is estimated using nonparametric bootstrap with blocking at the individual level. Specifically, I draw D_i for N times with replacement. This is important to preserve the dependent structure of the data. For example, I assume that wages are serially correlated due to the individual fixed effect and the employer fixed effect. Another example is that full-time job spells and full-time employment spells are positively correlated, because a long job spell necessarily implies a long employment spell. Also, the model predicts that wages and job spells are positively correlated, because workers with high match quality earn high wages and they are likely to remain in the job longer.

The B-th bootstrapped data set D_B is used to compute the auxiliary parameters $\hat{\rho}_B$. I replicate the bootstrap for 1,000 times and compute the covariance matrix of the auxiliary parameters. Although this computation takes about an hour for a 2-GHz CPU machine, it is worth doing because the estimated covariance matrix can be used for many different specifications of the structural model. This is very useful because I have to estimate models with different prefixed parameters such as bargaining power parameter β for sensitivity checks.

There are a few reasons that a nonparametric bootstrap should be used to estimate the optimal weighting matrix. First, this matrix can be computed even when the analytical form is very complex. One such example is the covariance between the coefficients of wage regression (e.g., β_{OLS}) and the hazard rates (e.g., $p_{J,t}$.) However I can still compute it through simulation in a straightforward way. Second, the weighting matrix does not have to be updated over during the iteration in the estimation of structural parameters. This reduces the computational burden.

E.2. **Minimizing the Objective Function Value.** The objective function is not smooth in the structural parameters, because actions of simulated agents are discrete such as whether or not to change jobs. The equilibrium wages of agents are also chosen from the discretized wage grid. Suppose a simulated agent does not change his action if I change the structural parameter values from ϕ to $\phi + \epsilon$, but he changes the action if I further change the parameter to $\phi + 2\epsilon$. This discrete response makes the objective function non-smooth through the auxiliary parameters. It is true that this non-smoothness vanishes as the number of simulations is increased up to infinity, but there are limitations for computational time and for computer memory to store actions of simulated agents. I could not make the objective function smooth enough to use a quasi-Newton method.

For the minimization of the objective function, I use a simulated annealing.[12] The method is robust to a non-smooth objective function and it works well for my model. Alternative algorithm that can be used for a non-smooth function is the Nelder-Mead simplex method. But, it converges to one of local minima, presumably because the surface of the objective function is too noisy. This

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[12]Goffe et al. (1994) implemented a Fortran software that is downloadable from http://www.netlib.org.

problem still happens when the number of simulation is 100, but I could not increase it given my computational resources. The additional advantage of simulated annealing is that it searches for the global minimum. The global optimum can be found as the number of iteration goes to infinity. The main disadvantage is that simulated annealing often requires several ten thousands of iterations to achieve convergence. In particular, about 50,000 iterations are needed for my model, which takes me three days.

E.3. **Standard Deviation of the Structural Parameters.** Non-smoothness of the objective function is also problematic when I estimate asymptotic standard deviations of the structural parameters, because Jacobian of the objective function has to be computed. Remember that the objective function is not differentiable due to discontinuous responses of simulated agents. The most formal method for this problem is to use a nonparametric bootstrap. However, it would take me a year for about 100 replications, which is not tractable. A practical solution here is to compute the Jacobian using a finite difference method with assuming smoothness. This should work well when the number of simulations is large enough, because the discontinuity vanishes as the number of simulations is increased to infinity. If this is not the case, the estimated standard deviations can be extremely small particularly when the step size for derivative is small. The reason is that the finite difference method captures a noise on the surface of the objective function and that the absolute value of the computed derivative is very large.

Different step sizes are tested to see how the estimated standard deviations change. As a reference point, the final step size of simulated annealing is used because it reflects the surface of the objective function around the minimum. I will also check the validity of the method in a little informal way. I will estimate the structural parameters using nonparametric bootstrap with a small number of replications, say, ten times. This should not be used to make a formal inference for the estimates. But it is worth doing to compare the results obtained by a finite difference method and those obtained by a bootstrap. If these two sets of results are very different, a different step size should be used.

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