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How much do Workers Search?*

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In this paper, I consider four determinants of wages: productivity, workers' bargaining power, competition between employers due to on-the-job search, and search intensity by workers. Workers can increase their job offer arrival rate through costly search. Employers take into consideration the search intensity choices of their employees when the two parties jointly set wages. Using a Nash bargaining model with on-the-job search and wage renegotiation, I quantify the search intensity of workers, for both unemployed and employed. I estimate the structural model using the 2001 panel of the Survey of Income and Program Participation (SIPP) from the US, together with supplementary information from the American Time Use Survey (ATUS). The empirical results show that search intensity weakly declines as the worker gets a wage rise from her current job. But direct job-to-job transition does not necessarily imply higher wage and lower search intensity on the new job. Indeed, simulation suggests that, there are cases where workers on high-productivity jobs are most inclined to search, but the social returns to job search is highest in workers on low-productivity jobs. In this sense, the labor market equilibrium may not be socially efficient.

Key Words: Search intensity; Wage determination; Bargaining; On-the-job search.
JEL Classification Numbers: J30, J64, E24.

1. INTRODUCTION

Studies on search intensity with on-the-job search have assumed exogenous wage offer distribution and constant wage on a job. Mortensen et al (2005) explicitly specify search cost and job offer arrival rate as functions of search intensity. Through the use of matched employer-employee data, they accomplish to isolate the search cost parameter from the offer arrival rate parameter, even if search intensity is not directly observed in

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the data. In Bloemen (2005), the data are from the worker side only but nevertheless contain various indicators for search intensity. Examples of these indicators are, whether the worker is searching seriously, and how many times the worker has applied for a job in the past two months. A common theoretical prediction of these two studies is that search intensity strictly decreases with wage.[1] This argument about search intensity becomes invalid, though, if productivity on the job is heterogeneous and if wage change on a job is allowed. On-the-job search puts employers into competition for the worker's service because a formed job match always carries a positive rent in the presence of labor market search frictions. If an employed worker is contacted by a potential employer, it is in his current employer's interest to retain the worker through wage increase,[2] and the maximum amount of wage a job can offer is its productivity. Therefore, worker's on-the-job search behavior carries the effect of both wage and productivity.

On the other hand, in the presence of on-the-job search, models that explore the determination of wage have largely ignored the effect of search intensity on wage setting. In the on-the-job search model of Shimer (2006) with heterogeneous firms, firms contact the worker at the same rate, and the model implies that higher-productivity firms pay higher wages.[3] Eckstein and Wolpin (1995) allow for search intensity to influence wage bargaining between firms and unemployed workers, buts search intensity by employed workers is not considered. Cahuc et al (2006) attribute wage formation to three determinants: productivity, worker's bargaining power, and inter-firm competition resulting from on-the-job search. In their framework, offer arrival rate is constant across employees and so only the job's productivity determines the worker's rate of leaving the job. However, as argued in the previous paragraph, worker's incentive to search for outside offers depends on wage and productivity. The firm can use wage as a tool to control the worker's search intensity. Worker's ability to vary search intensity on-the-job, and thus offer arrival rate, needs to be reflected in wage setting.

This paper studies the search behavior of both unemployed workers[4] and employed workers. Search intensity is modeled as a determinant of wage,

[1]See the survey paper by Rogerson et al (2005).

[2]Burdett and Coles (2003) consider a model where firms post wage-tenure contracts. Worker's wage increases with his tenure at the firm. Both unemployed workers and employed workers search, but they cannot vary their search intensity.

[3]The findings in this paper are different. Higher-productivity jobs do not pay higher wages to prevent workers from searching because, by assumption, the hazard rate associated with leaving a high-productivity job is low.

[4]There is a large literature on the search intensity of unemployed workers. Mortensen and Pissarides (1999) and Pissarides (2000) use a general equilibrium model to show how unemployment rate and search effort are endogenously determined. Yashiv (2000) finds that a rise in the replacement rate lowers search effort and leads to higher unemployment. Pavoni and Violante (2007) develop a model in which unemployed worker's search effort

along with the three determinants in Cahuc et al (2006). Empirical work on search intensity is sparse,[5] mainly because of lack of search intensity index[6] in most datasets. In the 2001 panel of the Survey of Income and Program Participation (SIPP), which is used for estimation in this paper, only unemployed workers were asked whether or not they were searching. Search information for employed workers, who are of particular interest in this paper, is missing. Since search intensity is a vague scalar that is unobserved in the SIPP data, I am not able to separately identify search cost scale parameters and offer arrival rate parameters. Aggregate information on search intensity from the 2003 American Time Use Survey[7] (ATUS) makes the model identifiable.

According to the 2003 ATUS, 91.76% of unemployed prime-age white males were in active search during a week, yet this number is only 21.45% for employed prime-age white males who were just out of unemployment. At the same time, among those who search, the average time spent on search is 167.57 minutes per day for the unemployed and 160 minutes per day for the employed who were just out of unemployment. Clearly, the difference between unemployed workers and employed workers is on the extensive margin — to search or not to search, not on the intensive margin — how much to search. Indeed, only 3.5% of all employed workers spent a positive amount of time on search during a week. But Bowlus et al (2001) find that 44% of job transitions among young males were direct job-to-job moves in the National Longitudinal Survey of the Youth (NLSY). In order to reconcile these facts, I incorporate a fixed search cost, and allow the offer arrival rate to be positive if employed workers choose not to search.

The outline of the paper is as follows. In the next section I develop a theoretical model with search intensity being a determinant of wage. Section 3 contains data description. In Section 4 I present the empirical specification. Section 5 discusses the results. Efficiency issues resulting from the unobservability of search behavior are briefly addressed.[8] Section 6 concludes.

2. THEORY

Consider a continuous-time model with ex ante identical workers and identical firms. Agents are infinitely-lived and discount the future at rate ρ.

becomes less effective during unemployment as human capital depreciates. Yan (2011) studies optimal unemployment insurance with endogenous search.

[5]Echstein and ven den Berg (2007) survey the literature on empirical labor search.

[6]Gautier et al (2007) use the number of job applications sent out by the worker as the index for search intensity.

[7]Hamermesh et al (2005) provide a description of the ATUS data.

[8]See Hosis (1990) and Postel-Vinay and Robin (2004) for more detailed discussion of efficiency.

Assume the labor market is in a stationary equilibrium. Workers and firms come together via search. Upon meeting each other, the instantaneous match value, θ, also referred to as productivity in this paper, is observed by both parties. The data used for estimation in this paper come from the worker's side. Due to inability to access matched employer-employee data, I cannot decompose the instantaneous match value into worker's ability and firm's productivity (Cahuc et al, 2006). The distribution of θ is governed by a nondegenerate function $G(\theta)$. Each job dissolves at an exogenous Poisson rate η. The instantaneous income flow of being unemployed is denoted by b. This could be understood of either as the value of leisure, or home production. Both unemployed workers and employed workers meet potential employers through costly search. Let denote search intensity. s is normalized to be between 0 and 1. The cost of search is an increasing function $c(s)$, with $c(0) = 0$ and $c'(0) = 0$. Once employed, the worker earns a wage w and forgoes his home production value. The worker enjoys an instantaneous utility which equals $w - c(s)$ if employed, and $b - c(s)$ if unemployed. The firm's instantaneous profit is the sum of the profits from all its workers. Job offer arrives at a Poisson rate $\lambda(s)$,[9] so the worker can affect his job offer arrival rate by choosing search intensity. Given the same search intensity, the offer arrival rate for an unemployed worker may be different from the offer arrival rate for an employed worker. Since all workers are assumed to be ex ante identical, all unemployed workers search the same amount. Let s_0 stand for it. The search intensity chosen by employed workers may not be the same, since they earn different wages and productivities differ. I provide a detailed discussion on this point below.

All productivities and wages are perfectly observed, but search intensity is not observed. Wages are formed via bargaining. Before proceeding to the bargaining process, let me introduce some notations. V^N denotes the value of unemployment to the unemployed worker. $V^e(w, s, \theta)$ stands for the value to an employed worker who is employed on a job with productivity θ and paid a wage w, conditional on his search intensity s. Let $V^f(w, s, \theta)$ be the value to the firm conditional on worker's search intensity. Based on (w, θ), the worker chooses his search intensity $s(w, \theta)$ optimally. Given this choice of search intensity, the unconditional value of employment to the worker is $V^E(w, \theta)$, and the unconditional value of a formed match to the firm is $V^F(w, \theta)$. I assume free entry of firms. So the value of an unfilled job to the firm is zero. The maximum wage the firm is willing to pay on a filled job is equal to the productivity θ. So $V^E(\theta, \theta)$ is the value to the

[9]This rate is assumed to be constant if search intensity is not considered, examples are Cahuc et al (2006) and Dey and Flinn (2005). These two studies do allow offer arrival rate to differ between employed and unemployed workers. For studies that consider search intensity, see Bloemen (2005) and Christensen et al (2005).

worker when he gets all the match surplus. A match is formed if and only if $V^E(\theta,\theta) \geq V^N$.

When an unemployed worker and a firm meet, wage is determined through Nash bargaining. The value of unemployment serves as the worker's threat point. The outcome of the bargaining is a wage $w = \phi_0(\theta)$, such that

$$V^E(\phi_0(\theta),\theta) = V^N + \beta[V^E(\theta,\theta) - V^N] = (1-\beta)V^N + \beta V^E(\theta,\theta) \quad (1)$$

where $\beta \in (0,1)$ is the worker's bargaining power.

When an employed worker on a job with productivity θ is contacted by another firm with which his productivity is θ', these two levels of productivity are observed by all three parties. The two firms enter a Bertrand game to bid for the worker's service. Since the total match surplus is higher in the firm where productivity is higher, the bidding process will make the worker end up with the higher-productivity job. If the worker's current job delivers the higher productivity and if the worker can threat to leave his current job using the potential job as a credible threat, his current employer may be willing to initiate a wage renegotiation with the worker and try to retain him. Assume renegotiation cost is zero. Formally, the outcome of the bidding process is:

Case 1. If $\theta' > \theta$, the worker quits his current job and moves to the other job.

Case 2. If $\theta' \leq w$, the worker keeps his current job and his wage stays the same.

Case 3. If $w < \theta' \leq \theta$, the worker renegotiates with his current employer and gets a wage rise.

In the above case 1, the current job serves as the threat point when the worker bargains with his new employer, whereas in case 3, the poaching firm constitutes the threat point. It is worth noting that the worker may accept a lower wage when he enters the new firm. Generally, the worker's wage $\phi(\theta',\theta)$ after the competition of two employers with $\theta' > \theta$ is determined by

$$\begin{aligned} V^E(\phi(\theta',\theta),\theta') &= V^E(\theta,\theta) + \beta[V^E(\theta',\theta') - V^E(\theta,\theta)] \\ &= (1-\beta)V^E(\theta,\theta) + \beta V^E(\theta',\theta') \end{aligned} \quad (2)$$

So the wage increase in the above case 3 is $\phi(\theta,\theta') - w$. This model setting implies a straightforward result: wage goes up gradually as job tenure with a particular employer increases.

Conditional on worker's search intensity, the firm's value is given by

$$\begin{aligned} V^f(w,s,\theta) &= (1+\rho\varepsilon)^{-1}\Big\{(\theta-w)\varepsilon+\eta\varepsilon\times 0+\lambda(s)\varepsilon G(w)\times V^f(w,s,\theta) \\ &\quad +\lambda(s)\varepsilon\int_w^\theta V^F(\phi(\theta,\tilde\theta),\theta)dG(\tilde\theta)+\lambda(s)\varepsilon\tilde G(\theta)\times 0 \\ &\quad +(1-\lambda(s)\varepsilon-\eta\varepsilon)V^f(w,s,\theta)+o(\varepsilon)\Big\} \end{aligned} \tag{3}$$

where ε is an infinitely small amount of time, $\lim_{\varepsilon\to 0}\frac{o(\varepsilon)}{\varepsilon}=0$, and $\tilde G(\cdot)=1-G(\cdot)$. The above equation says that the instantaneous profit of the firm is $\theta-w$. The firm's value can be driven to zero due to either an exogenous job separation, or a voluntary quit by the work. The firm's value stays the same if the worker does not renegotiate. If the worker renegotiates and gets a wage increase, the new wage contract $\phi(\theta,\tilde\theta)$ will deliver the firm a value of $V^F(\phi(\theta,\tilde\theta),\theta)$. Letting $\varepsilon\to 0$ and rearranging yields

$$V^f(w,s,\theta)=[\rho+\eta+\lambda(s)\tilde G(w)]^{-1}\left\{\theta-w+\lambda(s)\int_w^\theta V^F(\phi(\theta,\tilde\theta),\theta)dG(\tilde\theta)\right\} \tag{4}$$

The unconditional value of the firm is given by

$$V^F(w,\theta)=V^f(w,s(w,\theta),\theta) \tag{5}$$

where $s(w,\theta)$ is the worker's optimal choice of search intensity.

For the employed worker, the value of employment conditional on search intensity is

$$\begin{aligned} V^e(w,s,\theta) &= (1+\rho\varepsilon)^{-1}\Big\{(w-c(s))\varepsilon+\eta\varepsilon\times V^N+\lambda(s)\varepsilon G(w)\times V^e(w,s,\theta) \\ &\quad +\lambda(s)\varepsilon\int_w^\theta V^E(\phi(\theta,\tilde\theta),\theta)dG(\tilde\theta)+\lambda(s)\varepsilon\int_\theta V^E(\phi(\tilde\theta,\theta),\tilde\theta)dG(\tilde\theta) \\ &\quad +(1-\lambda(s)\varepsilon-\eta\varepsilon)V^e(w,s,\theta)+o(\varepsilon)\Big\} \end{aligned} \tag{6}$$

The worker's value changes if he becomes unemployed, or gets a wage rise, or moves to a new firm. The worker's value is unchanged if he stays with his current employer but does not get a wage increase, or if he is not contacted by any potential employer. After rearranging and taking limits, the above yields

$$\begin{aligned} V^e(w,s,\theta) &= [\rho+\eta+\lambda(s)\tilde G(w)]^{-1}\Big\{w-c(s)+\eta V^N \\ &\quad +\lambda(s)\int_w^\theta V^E(\phi(\theta,\tilde\theta),\theta)dG(\tilde\theta)+\lambda(s)\int_\theta V^E(\phi(\tilde\theta,\theta),\tilde\theta)dG(\tilde\theta)\Big\} \end{aligned} \tag{7}$$

Plugging in the rent-splitting rule for on-the-job search in equation (2) and rearranging, the above equation gives

$$\begin{aligned} V^E(w,s,\theta) &= [\rho+\eta+\lambda(s)\tilde{G}(w)]^{-1}\Big\{w-c(s)+\eta V^N \\ &+ \lambda(s)\int_w^\theta [(1-\beta)V^E(\tilde{\theta},\tilde{\theta})+\beta V^E(\theta,\theta)]dG(\tilde{\theta}) \\ &+ \lambda(s)\int_\theta [(1-\beta)V^E(\theta,\theta)+\beta V^E(\tilde{\theta},\tilde{\theta})]dG(\tilde{\theta})\Big\} \end{aligned} \quad (8)$$

Given (w,θ), the worker chooses his search intensity $s(w,\theta)$, so that

$$V^E(w,\theta) = \max_s V^e(w,s,\theta) \quad (9)$$

Similar to (6), the value of unemployment follows the following equation

$$\begin{aligned} V^N &= (1+\rho\varepsilon)^{-1}\Big\{(b-c(s_0))\varepsilon+\lambda(s_0)\varepsilon G(\theta^*)\times V^N \\ &+ \lambda(s_0)\varepsilon\int_{\theta^*} V(\phi_0(\tilde{\theta}),\tilde{\theta})dG(\tilde{\theta})+(1-\lambda(s_0)\varepsilon)V^N+o(\varepsilon)\Big\} \end{aligned} \quad (10)$$

where the unemployed worker's decision to enter employment is governed by a critical match value θ^*. The unemployed worker accepts a job offer with productivity greater than θ^* and rejects an offer with productivity less than θ^*. Using equation (1) and taking limits, the above equation can be rewritten as

$$V^N = \max_{s_0}[\rho+\lambda(s_0)\tilde{G}(\theta^*)]^{-1}\left\{b-c(s_0)+\lambda(s_0)\int_{\theta^*}[(1-\beta)V^N+\beta V^E(\tilde{\theta},\tilde{\theta})]dG(\tilde{\theta})\right\} \quad (11)$$

Note that all unemployed workers will search the same amount s_0.

If the worker receives the total surplus of the match, he must be paid his marginal product θ, i.e. $w=\theta$. This will happen if the employed worker's productivity at the current firm and the poaching firm are the same. When this happens, there is no room for renegotiation because any wage above θ will make the worker's employer make negative profit. Equation (8) implies

$$\begin{aligned} Q(\theta) &\equiv V^E(\theta,\theta) = [\rho+\eta+\lambda(s(\theta,\theta))\tilde{G}(\theta)]^{-1} \quad (12) \\ &\times \left\{\theta-c(s(\theta,\theta))+\eta V^N+\lambda(s(\theta,\theta))\int_\theta[(1-\beta)V^E(\theta,\theta)+\beta V^E(\tilde{\theta},\tilde{\theta})]dG(\tilde{\theta})\right\} \end{aligned}$$

where $s(\theta,\theta)$ is the worker's optimal choice of search intensity when paid his productivity.

Since θ^* is the critical match value for the decision to enter employment, the following equation must hold

$$Q(\theta^*) \equiv V^E(\theta^*, \theta^*) = V^N \tag{13}$$

To characterize the equilibrium, I need to solve for the decision rules — wage, search intensity and the critical match value to exit unemployment. First I need to work on the system of equations (11), (12) and (13) and look for the "fixed-point" solution $\{Q(\theta), V^N\}$ and $\{\theta^*, s_0, s(\theta, \theta)\}$. When this is done, equation (8) can be written more explicitly, and I can derive equation (9) and the decision rule $s(w, \theta)$. The first wage after unemployment $\phi_0(\theta)$ can be obtained from the rent-splitting rule in equation (1). The wage for employed workers $\phi(\theta', \theta)$ is computed from equation (2). All this algebra is done numerically. I list my model specification below.

Productivity is assumed to be lognormally distributed, with mean μ and standard error σ.

The search cost function and offer arrival rate function follow Christensen et al (2005). In particular,

$$c(s) = c_0 + \frac{c_1 s^{1+(1/\gamma)}}{1 + (1/\gamma)} \quad \text{if} \quad s > 0 \tag{14}$$

where $c_0, c_1 > 0$ are scale parameters and γ is a curvature parameter. The worker will incur zero search cost if $s = 0$. My model specification is different from that in Christensen et al (2005) in that I include a fixed cost in equation (14). Therefore, my model incorporates both a discrete choice on whether to search or not, and a continuous choice on how much to search. According to the 2003 American Time Use Survey (ATUS), which I use as supplemental information in my estimation, there was not much difference in the time spent searching among people who searched a positive amount. But the fraction of people who searched among the employed, is much smaller than the fraction of people who searched among the unemployed. Indeed, for prime-age white males who were in the labor force, almost all unemployed workers spent some time on search during a week, but only 21.45% of employed workers spent some time on search during a week. Fixed cost of search is introduced to capture the heterogeneity of search behavior at the extensive margin in the ATUS data.

The offer arrival rate function is given by

$$\lambda(s) = \lambda_0 s \quad \text{if the worker is unemployed} \tag{15}$$

$$\lambda(s) = \overline{\lambda} + \lambda_1 s \quad \text{if the worker is employed} \tag{15$'$}$$

with $\lambda_0, \overline{\lambda}, \lambda_1 > 0$. In Christensen et al (2005), the offer arrival rate function for the employed does not have the parameter $\overline{\lambda}$. The inclusion of $\overline{\lambda}$ in my model is crucial because the ATUS data show that the fraction of employed workers who exerts positive search effort is small, yet another finding from the National Longitudinal Survey of the Youth (NLSY) (Bowlus et al, 2001) is that 44% job transitions do not involve an intervening period of unemployment, in other words, they result from on-the-job search. Without allowing for a positive arrival rate for employed workers who do not search, it's hard to reconcile the ATUS fact with the NLSY fact.

3. DATA

I use the 2001 panel of the Survey of Income and Program Participation (SIPP) to estimate the model.[10] Individuals in the SIPP are surveyed every four months, and the maximum length of the sample window for an individual is 36 month. The SIPP collects monthly information on earnings from various ways, wage rate, number of weeks worked, as well as demographic characteristics. Employment status in each week during the month is recorded. In addition, the SIPP contains information on whether the individual changed jobs, and also the starting and ending date of each job held during the sample period. Unemployment spells and job spells data can be derived from this piece of information. My estimation will be focused on a relatively homogenous group of people. To create my sample, I choose white males with at least a high school diploma, aged 25 to 64 and in the labor force. Individuals who reported school attendance and military service are dropped from my sample. I also exclude people who worked for his own business, and people who were on welfare programs such as Food Stamps and residential assistance.[11]

Descriptive statistics are summarized in Table 1. Among the 10096 individuals in my sample, 2067 had at least an unemployment spell, and 8029 did not experience unemployment during the sample period. On average, the length of the sample window[12] of those who had a period of unemployment is 1.4 weeks longer than those who had not. 980 of the

[10]Dey and Flinn (2005) use the 1996 panel of the SIPP to estimate a similar model. Since in my estimation the 2003 ATUS data are used as supplementary information, I choose the 2001 panel of the SIPP. The maximum length of the sample window in the 1996 panel is 48 months, and the maximum length of the sample window in the 2001 panel is 36 months. In terms of sample length, the 1996 panel is more preferable since individuals are followed for a longer period of time. But the 2001 panel is chosen in my estimation because I believe the arrival rate parameters may change over time, and I want to make my choice of the SIPP sample consistent with the search behavior of people in the 2003 ATUS.

[11]Individuals with missing data for wage or duration are excluded from the sample. To eliminate large outliers, I also drop individuals whose wage exceeds $140 per hour.

[12]I define the sample window in my sample to be the period starting from the time when the individual first entered the survey, until the time when he first dropped out of the survey.

2067 unemployment spells were right-censored, and the rest were ended by transition into employment. At the beginning of the first job after unemployment, those who had exactly one job were earning an average wage of $19.25 per hour. This wage rate was $16.95 for individuals who had at least two consecutive jobs following unemployment, and these people were paid were paid an average of $20.10[13] per hour at the start of their second job out of unemployment. Although in the data the average wage on the second job is bigger than the average wage on the first job, my theory does allow worker to accept a wage cut when he moves to the higher-productivity job, because he expects bigger wage increase in the future on the new job.

TABLE 1.

Summary statistics*

Table 1a. Characteristics of employment history

Type of history	Number of workers	Sample Window (weeks)
Full sample	10096	78.13
		(59.23)
Without an unemployment	8029	77.85
		(59.87)
With an unemployment	2067	79.21
		(56.67)

Table 1b. Characteristics of unemployment spells (2067 observations)

Type of transition	Number of workers	Spell Duration (weeks)
Right-censored	980	30.03
		(35.67)
To a job	1087	13.63
		(13.42)

Table 1c. Characteristics of the first wage on the first job,
for people with only one job (909 observations)

Type of transition	Number of workers	Accepted Wage	Spell Duration (weeks)
Whole sample	909	19.25	14.14
		(16.02)	(14.72)
Right-censored	243	15.38	19.91
		(10.39)	(20.40)
Renegotiation	589	21.37	11.75
		(18.13)	(11.53)
To unemployment	77	15.17	14.21
		(8.91)	(9.14)

[13]This number is shown in the last column of Table 1d.

Table 1d. Characteristics of the first wage on the first job, for people with two or more jobs (178 observations)

Type of transition	Number of workers	Accepted Wage (job 1)	Spell Duration (weeks)	Accepted Wage (job 2)
Whole sample	178	16.95	11.50	20.10
		(15.61)	(12.75)	(24.72)
No Renegotiation	112	16.62	12.71	19.37
		(14.82)	(14.53)	(24.01)
Renegotiation	66	17.49	9.44	21.33
		(16.98)	(8.65)	(26.03)

* Standard errors are in parentheses.

4. EMPIRICAL SPECIFICATION

The theoretical model in Section 2 is estimated using the method of simulated maximum likelihood. In this section I derive the likelihood function. As is often noted in empirical analysis of labor market dynamics, the initial condition problem often arises as a difficult problem, due to left-censoring of longitudinal survey data. According to the theoretical model, since entry into unemployment sets a worker's employment dynamics for a brand-new start, it is essential to track the worker from an unemployment spell. Based on my model and a set of primitive parameters, I can simulate the labor market outcome of each worker who experiences at least one unemployment spell during the sample period. Those workers are the main focus of my discussion of the likelihood function. For them, I will use the following information to do the estimation: the length of the sample window, T; the length of the unemployment spell, whether it censored or not, t^u; the wage at the beginning of the first job following unemployment, w_1; the wage at the beginning of the second job following unemployment, w_2; and the length of the spell for which w_1 lasts, which I denote by t_1. For the rest of the workers in the sample, who is employed all the time through the survey period, I will utilize their sample length information to construct their contribution to the complete likelihood function. Before proceeding to detailed discussion, let me introduce some notations (following Dey and Flinn, 2005). Let Ψ take the value 1 if the worker is unemployed for some time during the sample period and 0 otherwise. Denote by $\omega(T)$ the probability that the worker is observed to have at least one unemployment spell, i.e. $\omega(T) = P(\Psi = 1|T)$. I assume this probability is a function of the sample length T only.

To construct the complete likelihood function, I need an econometric specification to link the observed wages to the wages simulated from the model. Measurement error assumption achieves this goal. Namely, for every true wage w, there is an observed wage $\tilde{w}$ which satisfies

$$\ln(\tilde{w}) = \ln(w) + \varepsilon \tag{16}$$

Where ε is a random variable which is normally distributed with mean zero and standard error σ_ε, and is independently and normally distributed. Denote by $f(\tilde{w}|w)$ the conditional distribution function of observed wage given the true wage corresponding to the measurement error specification above. As mentioned in Dey and Flinn (2005), measurement error in the first place acts to reflect the fact that survey data contain a non-negligible amount of mismeasurement. Secondly, the measurement error assumption smoothes away any zero-probability event in the maximum likelihood estimation. In addition to these two points, this measurement error specification captures the part of wage that cannot be explained by the theoretical model in this paper.

Next I derive the expression of $P(\Psi = 1|T) = \omega(T)$, the probability that a worker is observed to be unemployed at some time during the sample period with length T. Letting u be the fraction of workers who are unemployed at any point in time and normalizing the size of the worker force to be one, in an infinitesimal amount of time ε, unemployment inflow is $(1-u)\eta\varepsilon$, and unemployment outflow is $u\lambda_0 s_0 \tilde{G}(\theta^*)\varepsilon$. Assume the labor market is in a stationary equilibrium, in which flow into unemployment equals flow out of unemployment, then

$$(1-u)\eta = u\lambda_0 s_0 \tilde{G}(\theta^*) \tag{17}$$

Or,

$$1-u = \frac{\lambda_0 s_0 \tilde{G}(\theta^*)}{\eta + \lambda_0 s_0 \tilde{G}(\theta^*)} \tag{18}$$

People who do not experience unemployment during the sample period are those who are employed when the sample window begins, and who do not enter unemployment throughout the sample period. Since the hazard rate into unemployment, which equals the job separation rate η, is constant over time, the probability that a worker does not experience unemployment during the sample period of length T is $(1-u)\exp(-\eta T)$. So that

$$1-\omega(T) = \frac{\lambda_0 s_0 \tilde{G}(\theta^*)}{\eta + \lambda_0 s_0 \tilde{G}(\theta^*)} \exp(-\eta T) \tag{19}$$

Put Equivalently,

$$\omega(T) = 1 - \frac{\lambda_0 s_0 \tilde{G}(\theta^*)}{\eta + \lambda_0 s_0 \tilde{G}(\theta^*)} \exp(-\eta T) \tag{19$'$}$$

The above two equations are the probabilities of not having an unemployment spell and having an unemployment spell during the sample period, respectively. Equation (19) is the contribution to the complete likelihood by people with $\Psi = 0$. The rest of this section is devoted to deriving the likelihood functions for people with $\Psi = 1$.

Workers who spend some in the unemployment state for some time during the sample period, i.e. those who with $\Psi = 1$, can be categorized into three groups. Group 1 consists of workers whose unemployment spell is right-censored. For this group, I utilize the information of their unemployment spell length when forming the likelihood function. Group 2 is composed of workers who have exactly one job after unemployment. They may either enter another unemployment period following this job, or their employment on this job is still ongoing when the sample period concludes. The information that is used for this group is: the spell length of unemployment, the wage at the beginning of the first job out of unemployment, and the spell length of this initial wage on the first job. The last group contains workers who have at least two jobs in a row after the unemployment spell. I define the likelihood contribution of this group with respect to unemployment duration, the duration of the first wage after unemployment, and the wages paid at the onset of the first and second jobs. Largely, the discussion that follows is analogous to the corresponding part in Dey and Flinn (2005). But their paper abstracts from search intensity variations over the spell of a job, so job offer arrival rate is constant over the spell of the job, although wage may change due to wage renegotiation. Unlike their model, search intensity in my model changes when the worker gets a wage promotion after renegotiating with the worker's current employer, and thus job offer arrival rate also changes. As a result, the hazard rate associated with a job is no longer constant over time, whereas the hazard rate associated with a particular wage on the job is constant over time, so that I need to use duration information for a wage instead of duration information for a job.

4.1. Unemployment only

This subsection considers workers who have not found a job when the sample window closes. Since offer arrival rate is zero if search effort is zero, unemployed workers have to search a positive amount s_0 in order to get a job offer. The hazard rate out of unemployment is defined as

$$h^u = \lambda_0 s_0 \tilde{G}(\theta^*) \tag{20}$$

The density of unemployment duration (t^u) is

$$f^u(t^u) = h^u \exp(-h^u t^u) \tag{21}$$

Because the hazard rate associated with unemployment is constant, equation (20) holds for every group 1 individual, no matter whether I observe the beginning of the unemployment spell or not. The likelihood function for this group of workers is given by

$$L^1(t^u, \Psi = 1|T) = \omega(T)\exp(-h^u t^u) \tag{22}$$

4.2. One job only

Since it is analytically impossible to write a closed-form likelihood function for workers who have at least one job after unemployment, I employ the simulated maximum likelihood method. For each worker with only one job following unemployment, I simulate R random draws for the worker's productivity on the first job. Specifically, assume the productivity has a lognormal distribution with mean μ and standard error σ. The lognormal distribution is a commonly used assumption in the literature with an exogenous wage distribution. To simulate the productivity I randomly draw a number ζ_1 from a distribution that is uniformly distributed over the interval $[0, 1]$. The productivity on the first job follows a truncated lognormal distribution, truncated from below by the lowest acceptable productivity θ^*. So the productivity is given by

$$\theta_1(\zeta_1) = \exp(\mu + \sigma\Phi^{-1}(1 - \Phi\left(\frac{\ln(\theta^*) - \mu}{\sigma}\right)(1 - \zeta_1))) \tag{23}$$

I then obtain the "true" wage associated with this productivity based on the decision rules implied by the model.

Since I observe the termination of the unemployment spell for group 2 workers, the likelihood of the completed unemployment spell is as follows

$$u^u \exp(-h^u t^u) \tag{24}$$

Let $s_1(\theta_1)$ stand for the search intensity at the beginning of the first job out of unemployment, and $\lambda(s_1)$ stand for the job offer arrival rate at the beginning of the first job out of unemployment respectively, where $\lambda(s_1) = \overline{\lambda} + \lambda_1 s_1(\theta_1)$, and for simplicity I have suppressed θ_1 in the expression $\lambda(s_1)$.

The worker can exit the wage at the beginning of the first job out of unemployment w_1 through three ways: first, by exogenous job separation with rate η; secondly, by encountering a potential firm and getting a wage rise. This second way happens with rate

$$h_1(\theta_1) = \lambda(s_1)(\tilde{G}(w_1) - \tilde{G}(\theta_1)), \tag{25}$$

and finally, by encountering a potential firm and moving to the new firm with rate

$$h_2(\theta_1) = \lambda(s_1)\tilde{G}(\theta_1) \tag{26}$$

If the duration associated with the wage at the beginning of the first job out of unemployment t_1 is right-censored, then the likelihood for the rth random draw is

$$\begin{aligned} &L^2(t^u, \tilde{w}_1, t_1, \Psi = 1|\zeta_1(r), T) \\ =&\omega(T)h^u \exp(-h^u t^u)\exp(-(\eta + h_1 + h_2)t_1)f(\tilde{w}_1|w_1) \end{aligned} \tag{27}$$

If the worker gets a wage change before the sample period ends, then the likelihood for the rth random draw is given by

$$\begin{aligned} &L^2(t^u, \tilde{w}_1, t_1, \Psi = 1|\zeta_1(r), T) \\ =&\omega(T)h^u h_1 \exp(-h^u t^u)\exp(-(\eta + h_1 + h_2)t_1)f(\tilde{w}_1|w_1) \end{aligned} \tag{27$'$}$$

This is because the likelihood contribution for the completed spell associated with the second way of exiting w_1 is $h_1 \exp(-h_1 t_1)$, and the likelihood contribution for the incomplete spell associated with the first and third ways of exiting w_1 is $\exp(-(\eta + h_2)t_1)$.

If the worker's first wage out of unemployment lasts until the worker is unemployed again, then the likelihood contribution for the completed spell associated with the first way of exiting w_1 is $\eta \exp(-\eta t_1)$, and the likelihood contribution for the incomplete spell associated with the second and third ways of exiting w_1 is $\exp(-(h_1 + h_2)t_1)$. So in this case, the likelihood for the rth random draw is as follows

$$\begin{aligned} &L^2(t^u, \tilde{w}_1, t_1, \Psi = 1|\zeta_1(r), T) \\ =&\omega(T)h^u \eta \exp(-h^u t^u)\exp(-(\eta + h_1 + h_2)t_1)f(\tilde{w}_1|w_1) \end{aligned} \tag{27$''$}$$

Averaging over the likelihood function from all random draws of ζ_1 will yield the unconditional likelihood function for each individual with only one job following unemployment, i.e.

$$L^2(t^u, \tilde{w}_1, t_1, \Psi = 1|T) = \sum_{r=1}^{R} L^2(t^u, \tilde{w}_1, t_1, \Psi = 1|\zeta_1(r), T) \tag{28}$$

4.3. Two or more job spells

When the worker's employment history involves two consecutive job spells following unemployment, in setting up the likelihood function, I utilize the wages when the first and the second job start. Not considering the third job and beyond does not generate a large information loss because the maximum length of the sample window is 36 months for the 2001 panel of the SIPP data, and few workers has more than two consecutive jobs after a spell of unemployment. In addition to the wage information, I also employ information on the unemployment duration and the spell length of the first wage out of unemployment. To reduce computational burden, I do not incorporate duration of the wage at the onset of the second job.

I obtain the productivities on the first and second jobs by simulation. As in Section 4.2, the productivity $\theta(\zeta_1)$ on the first job is given by equation (23). Since the worker moves to a new job only when the new job yields a higher productivity than the old one, the productivity on the second job comes from a truncated lognormal distribution with lower truncation point given by $\theta_1(\zeta_1)$. To simulate the productivity on the second job, for each individual who has at least two jobs, I draw a pseudo-random number ζ_2 from the uniform distribution over the range $[0, 1]$, and I do the random draw R times. The productivity at the second job is given by

$$\theta_2(\zeta_1, \zeta_2) = (\mu + \sigma\Phi^{-1}(1 - \Phi\left(\frac{\ln(\theta_1(\zeta_1)) - \mu}{\sigma}\right)(1 - \zeta_2))) \tag{29}$$

The decision rules implied by the structural model will give the "true" wage associated with the productivities on the first and the second jobs corresponding to these random draws.

For those workers whose wage on the first job has never changed when they accept the second job, the likelihood contribution for the completed spell due to the third way of exiting w_1 is $h_2 \exp(-h_2 t_1)$, and the likelihood contribution for the incomplete spell due to the first and second ways of exiting w_1 is $\exp(-(\eta + h_1)t_1)$. The likelihood function corresponding to the productivities $(\theta_1(\zeta_1), \theta_2(\zeta_1, \zeta_2))$ is thus

$$\begin{aligned} & L^3(t^u, \tilde{w}_1, t_1, \tilde{w}_2, \Psi = 1 | \zeta_1(r), \zeta_2(r), T) \qquad (30) \\ = \ & \omega(T) h^u h_2 \exp(-h^u t^u) \exp(-(\eta + h_1 + h_2)t_1) f(\tilde{w}_1 | w_1) f(\tilde{w}_2 | w_2) \end{aligned}$$

Lastly, for those workers whose wage on the first job has changed before they accept the second job, the likelihood contribution for the completed spell due to the second way of exiting w_1 is $h_1 \exp(-h_1 t_1)$, and the likelihood contribution for the incomplete spell due to the first and third ways of exiting w_1 is $\exp(-(\eta + h_2)t_1)$. The likelihood function corresponding to the productivities $(\theta_1(\zeta_1), \theta_2(\zeta_1, \zeta_2))$ is

$$\begin{aligned} & L^3(t^u, \tilde{w}_1, t_1, \tilde{w}_2, \Psi = 1 | \zeta_1(r), \zeta_2(r), T) \qquad (30') \\ = & \omega(T) h^u h_1 \exp(-h^u t^u) \exp(-(\eta + h_1 + h_2)t_1) f(\tilde{w}_1 | w_1) f(\tilde{w}_2 | w_2) \end{aligned}$$

Similar to the discussion at the end of Section 4.2, after averaging over all random draws for the individual worker, the unconditional likelihood function is given by the following equation

$$L^3(t^u, \tilde{w}_1, t_1, \tilde{w}_2, \Psi = 1|T) = \sum_{r=1}^{R} L^3(t^u, \tilde{w}_1, t_1, \tilde{w}_2, \Psi = 1|\zeta_1(r), \zeta_2(r), T) \tag{31}$$

4.4. Estimation and identification issues

Combining the analysis in the above three subsections, the complete likelihood function for the whole sample is

$$\begin{aligned} L \; = \; & \prod_{i \in I_1} L^1(t_i^u, \Psi_1 = 1|T_i) \prod_{i \in I_2} L^2(t_i^u, \tilde{w}_{1,i}, t_{1,i}, \Psi_1 = 1|T_i) \\ \times \; & \prod_{i \in I_3} L^3(t_i^u, \tilde{w}_{1,i}, t_{1,i}, \tilde{w}_{2,i}, \Psi_i = 1|T_i) \prod_{i \in I_4} P(\Psi_1 = 0|T_i) \end{aligned} \tag{32}$$

where the sets of individuals with unemployment only, with one job, and with two or more jobs following unemployment are denoted by I_1, I_2, and I_3 respectively. I_4 represents the set of individuals without an unemployment spell during the sample period.

The model is estimated by maximizing the likelihood expression in equation (32). I use $R = 500$ as the number of random draws for each individual worker with at least one job following unemployment. I set the bargaining power parameter of the worker at 0.25. This is the estimation result of Dey and Flinn (2005). In accordance with Dey and Flinn (2005), who estimate a similar job search model using the 1996 panel of the SIPP data, the discount rate is fixed at an annualized rate of 0.08. One unit of time is a week The distribution of productivity is assumed to be lognormally distributed with mean μ and standard error σ.

The primitive parameters to be estimated are $(\eta, b, \lambda_0, \overline{\lambda}, \lambda_1, \gamma, \mu, \sigma, \sigma_\varepsilon)$. Standard errors of the estimated parameters are obtained via bootstrapping. I do not attempt to estimate the bargaining power parameter since I do not have firm-side information. Even if I could estimate the bargaining power parameter along with other primitive parameters using the aggregate information on the labor's share as a fraction of total revenue, as done by Dey and Flinn (2005), it would be computationally difficult to characterize the steady-state of the economy given the complication of my model. This complication arises from the fact that the worker in my model can choose his search intensity on the job, and thus the job offer arrival rate is not constant across employed workers, nor is it constant across time for each individual worker. The model estimated by Dey and Flinn (2005) abstracts from endogenous search intensity, and job offer arrival rate is constant.

The SIPP does not have an accurate measurement for search intensity. The survey only contains questions like whether an unemployed worker searches or not. With this sparse information on search intensity, I cannot separate the set of offer arrival rate parameters $(\lambda_0, \overline{\lambda}, \lambda_1)$, from the scale parameters in the search cost function (c_0, c_1). The same labor market outcome can be the result of either an economy with big offer arrival rate parameters, or an economy with small search cost scale parameters. Christensen et al. (2005) discuss a similar identification problem when they use Danish data to estimate an on-the-job search model with exogenous wage distribution. Thanks to the availability of the recent American Time Use Survey (ATUS) data, I am able to isolate the scale parameters in the search cost function from the job offer arrival rate parameters. In particular, I have two additional pieces of information from the 2003 ATUS[14]: during a week, 21.45% of employed workers spent some time on search, and the average time to search among employed workers who searched was 95.48% of the average time to search among unemployed workers. The scale parameters (c_0, c_1) are chosen such that the maximum likelihood estimates for equation (32) yields an equilibrium which is consistent with the above two facts from the 2003 ATUS. Because the model involves a discrete choice on search and this causes non-smoothness, I do not attempt to obtain the standard errors for the estimates of the search cost scale parameters.

5. RESULTS

The simulated maximum likelihood estimates are reported in Table 2. One unit of time is a week. The worker who chooses to search incurs a fixed cost of \$4.84 per hour. The instantaneous value of not working is \$4.97 per hour. The exogenous job separation rate implies that, on average, a job is destroyed after 10.5 years. Since my model estimates generate a search intensity of one for the unemployed in equilibrium, an unemployed workers gets a job offer every 4 months. On the other hand, if an employed worker chooses not to search, it takes him 13.7 months to wait for a potential new employer to contact him. In the 2003 American Time Use Survey (ATUS), among those who searched, the average time spent on search on each day was 118.59 minutes for the employed white males, and 167.57 minutes for the unemployed white males. This implies that in equilibrium, the average search intensity of employed workers who search is 118.59/167.57, or 0.708. So, the average waiting time between two job offers is 11.2 months, for those who search on-the-job. The offer arrival rate for the employed, if not searching, is significantly positive. This reconciles the seemingly two conflict facts: 44% job transitions are found

[14]Appendix discusses the facts from the ATUS.

to be direct job-to-job transition in the National Longitudinal Survey of the Youth (Bowlus et al, 2001), but only 3.5% of employed workers spent time on search during a week in the 2003 ATUS.

The standard error of the logarithm of the measurement error in log wage is comparable to that in Dey and Flinn (2005), this means there is not much in the wage data that cannot be explained by my model. The standard error of the curvature parameter in the search cost function is sufficiently small, thus it is safe to conclude that the search cost function is convex.

TABLE 2.

Simulated maximum likelihood estimates

Parameter	Estimate	Standard Error
Scale parameter in the search cost function, c_1	10	
Fixed cost of search, c_0	4.8445	
Exogenous job separation rate, η	0.0018	0.00009
Instantaneous value of home production, b	4.9681	0.4735
Marginal offer arrival rate for the unemployed, λ_0	0.0571	0.0026
Fixed offer arrival rate for the employed, $\overline{\lambda}$	0.0171	0.0035
Marginal offer arrival rate for the employed, λ_1	0.0053	0.0010
Curvature parameter in the search cost function, γ	0.5146	0.0781
Mean of $\ln(\theta)$, μ	3.1481	0.2421
Standard error of $\ln(\varepsilon)$, σ	0.6788	0.0361
Standard error of $\ln(\varepsilon)$, σ_ε	0.6375	0.0537
$\ln L$	−16747	

Durations are measured in weeks. Pecuniary terms are in dollars per hour. Standard errors are obtained via bootstrapping.

I compute the decision rules and labor market outcomes based on the estimates in Table 2. These are presented in Table 3. The critical productivity value for the unemployed to enter employment is \$19.65 per hour. 60% job offers are accepted by unemployed workers. Accounting for measurement error in wages, on average, workers earn \$17.64 per hour at the beginning of their first job out of unemployment. The two moments, the fraction of workers who search when they are at the start of their first job, and their average search intensity relative to that of the unemployed, are comparable to the 2003 ATUS data. Note that the 2003 ATUS data show that 21.45% of newly-employed workers searched, but my model yields 23.33%, somewhat higher than that in the 2003 ATUS. This is understandable since in the 2003 ATUS 91.76% of unemployed workers were in active search, while my model suggests that all unemployed workers search. The smaller fraction of people who search in the 2003 ATUS, as compared to my model findings, could be due to reporting error in the 2003 ATUS.

TABLE 3.

Estimated labor market outcomes

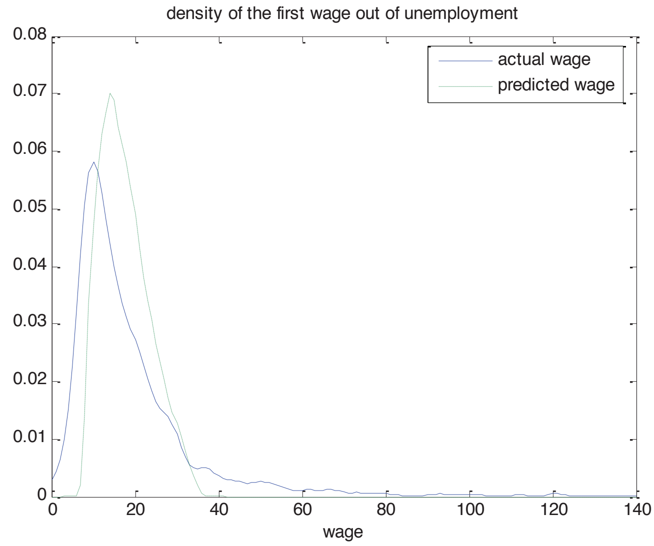
Parameter	Estimate	Data
Critical match productivity for the acceptance of employment, θ^*	19.6458	
Probability match is accepted out of unemployment	0.6000	
Weekly unemployment rate	0.0499	
Mean of first wage out of unemployment	17.6404	18.8695
Fraction of employed who search, at the start of their first job out of unemployment	0.2333	0.2145
Average search intensity of the employed, at the start of their first job out of unemployment, relative to that of the unemployed, conditional on search	0.9500	0.9548

Base on the estimates in Table 2. Critical match productivity for the acceptance of employment and the mean of first wage out of unemployment are in dollars per hour, where the latter takes into consideration of measurement error. The last two rows of the last column come from the 2003 American Time Use Survey.

To see how my model fits the data, in Figure 1 I plot the kernel density of predicted wage and actual wage at the beginning of the first job out of unemployment. The figure demonstrates that the coincidence of my model prediction with the data is not due solely to the inclusion of measurement error in my estimation. Because of the big computational burden associated with characterizing the steady-state, I do not examine the models fit in the steady-state.

The decision rules at the beginning of the first job following unemployment are presented in Figure 2 and Figure 3. As can be seen from Figure 2, wage is a U-shaped curve. Job turnover rates on low-productivity jobs are high. The fact that workers on low-productivity jobs are paid higher wages than on medium-productivity jobs reflects the incentive of employers with low-productivity jobs to retain their employees through high wage, which makes workers search less. It should be noted that employers' share of total revenue on low-productivity jobs is already low when they hire workers out of unemployment, so the chance of their employee's getting a wage rise is also low. Turning to the comparison of the wages paid by high-productivity jobs and medium-productivity jobs, I can see that as productivity passes a threshold, wages increase with productivity. This is because productivity starts to dominate in the determination of wage. Figure 3 depicts search intensity at the beginning of the first job out of unemployment. Workers on low-productivity jobs do not search because they are paid high wages to refrain from searching and leaving their current jobs. Workers on high-

FIG. 1. The actual wage distribution is based on the 2001 panel of the SIPP. The predicted wage is based on the estimates in Table 2 and incorporates measurement error.



productivity jobs are paid low, but their potential of getting large wage increases in the future is high. So search is worthwhile.

Figure 4 and Figure 5 display the wage and search intensity on the new job when the worker switches jobs. As can be seen from Figure 4, the worker may be willing to accept a lower wage when he moves to another firm. This is because the new job is associated with a higher productivity and the room for renegotiation may be bigger. Figure 5 suggests that the worker may increase his search intensity, both on the extensive margin — from not search to search, and on the intensive margin — to search more. This is in accordance with the above analysis since higher-productivity jobs are the ones where the room for wage renegotiation is big.

In Figure 6 and Figure 7, I depict the wage and search intensity after renegotiation. Given that the worker stays with his current employer, his wage rise after renegotiation will be bigger if the productivity of the last job that serves as the threat point is bigger. This is consistent with the theory part. Search intensity after renegotiation is a weakly decreasing function of the potential firm's productivity, which means that the worker searches less and less as his wage increases during the time he stays with his employer.

In summary, the previous findings demonstrate that worker's search intensity weakly decreases as his wage increases, conditional on his productivity. But when the worker moves to a job with higher productivity, his

FIG. 2. Predicted wage is based on the estimates in Table 2 and incorporates measurement error.

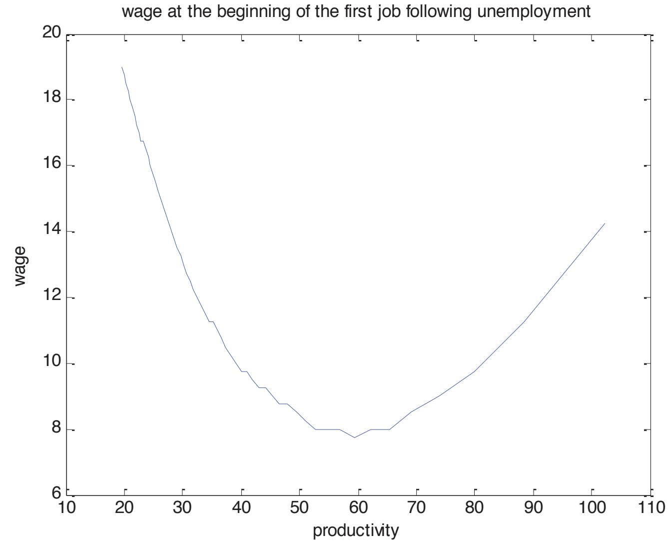
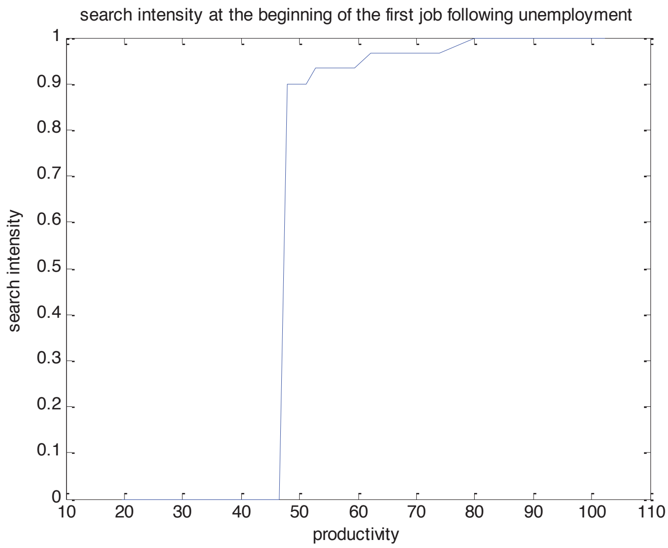
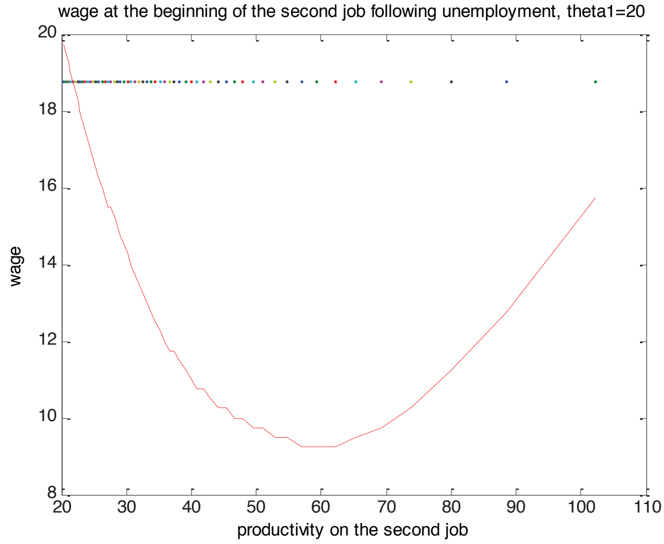


FIG. 3. Predicted search intensity is based on the estimates in Table 2.



search intensity may increase. A natural question may arise: does switching jobs generate any inefficiencies due to increased search intensity on the

FIG. 4. Predicted wage is based on the estimates in Table 2 and incorporates measurement error. Productivity on the first job is 20 dollars per hour. The dashed line represents wage at the beginning of the first job following unemployment. The solid line represents wage at the beginning of the second job following unemployment.

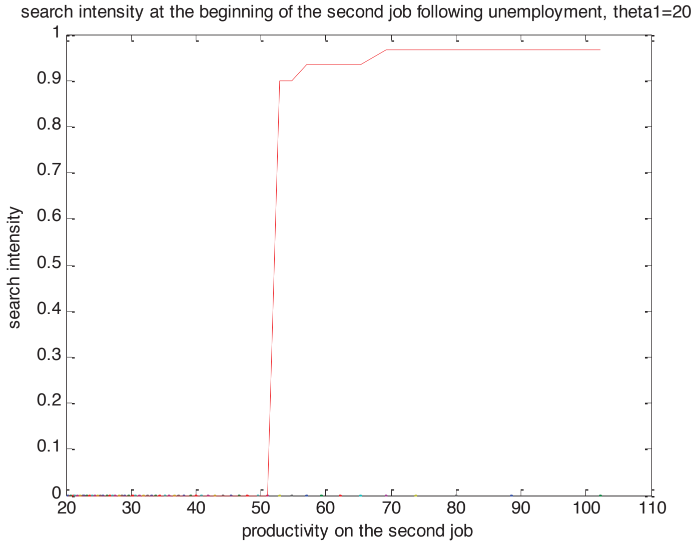


new job? As is already known that wage renegotiation does not lead to inefficiencies because search intensity is weakly lower after renegotiation while productivity stays the same. To study the efficiency issues associated with job change, I define the net match surplus as the difference between productivity and worker's search cost, i.e., $\theta - c(s)$. Using my model estimates, I compute the net match surplus before and after job change for all job-to-job transitions. I find that no job-to-job transition involves a decrease of the net match surplus. Therefore, there is some social gain in moving workers from low-productivity to high-productivity jobs. However, my simulation suggests that in some cases, it is workers on high-productivity jobs who are most inclined to search, but the social returns to job search is highest in workers on low-productivity jobs. In this sense, the labor market equilibrium is not socially efficient.

6. CONCLUDING REMARKS

This paper extends the Cahuc et al (2006) framework in that I allow for worker's search intensity to be a determinant of wage, besides the three determinants in their model: productivity, worker's bargaining power, and on-the-job search. Workers choose their search intensity, and thus their job

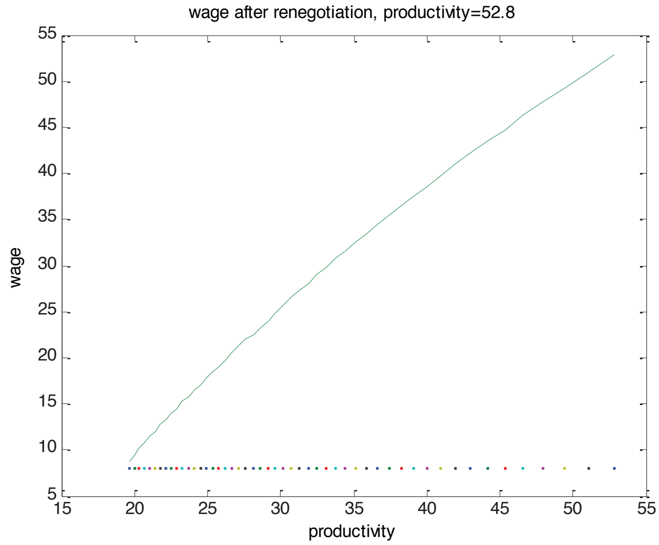
FIG. 5. Predicted search intensity is based on the estimates in Table 2. Productivity on the first job is 20 dollars per hour. The search intensity at the beginning of the first job following unemployment is zero.



offer arrival rate, based on their current wage and productivity. Employers take account of the search intensity choice of workers when they bargain over wage with workers. I explicitly write the search cost function and the job offer arrival rate function that both depend on search intensity. Parameters in these functions are structurally estimated along with other primitive parameters. By supplementing workers' employment history data with aggregate search intensity information from the 2003 American Time Use Survey, I overcome the identification difficulty of isolating the scale parameters in the search cost function from the job offer arrival rate parameters. I find that search intensity is weakly negatively related to wage, conditional on productivity. However, moving from low-productivity jobs to high-productivity jobs is not always associated with a decrease in search intensity. Meanwhile, higher-productivity jobs are not necessarily associated with higher wages.

Unlike previous empirical studies of search intensity, my estimation includes a fixed cost of search. With this nonconvexity in the search cost function, the model can be easily reconciled with the following facts found in the ATUS: a small fraction of employed workers choose to search while almost all unemployed workers search, yet there is only a moderate difference in the average time spent on search between employed workers and unemployed workers, conditional on search.

FIG. 6. Predicted wage is based on the estimates in Table 2 and incorporates measurement error. Productivity on the current job is 52.8 dollars per hour. The horizontal axis is the productivity of the job that serves as the threat point when the worker renegotiates with the current employer. The dashed line represents wage at the beginning of the current job following unemployment. The solid line represents wage after renegotiation.



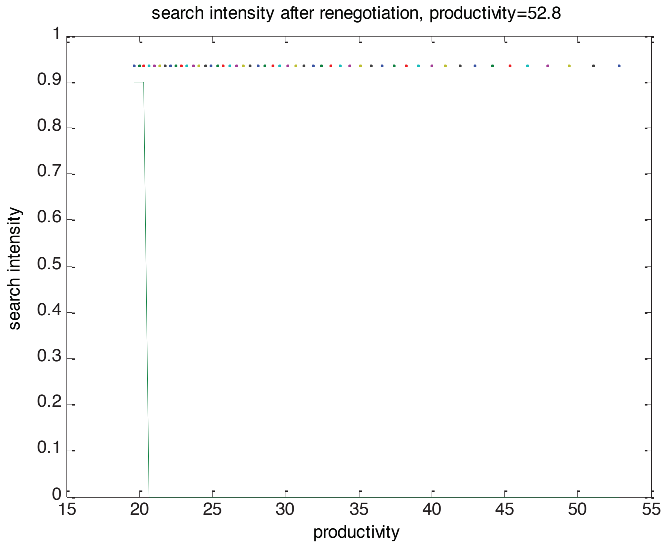
All employers are assumed to match outside offers when another employer contacts the worker and competes with the current employer for the worker's service. Actually, in a model like this (Postel-Vinay and Robin, 2004), the firm may choose to match or not to match outside offers by comparing its expected profit using these two different wage policies. The resulting labor market equilibrium may be one where some firms match and some not. Computational difficulty limits my ability to characterize firms' expected profit in the steady-state. Addressing this issue is on my future research agenda.

APPENDIX A

A brief description of the 2003 American Time Use Survey (ATUS) data

The American Time Use Survey (ATUS) provides information on how Americans spend their time. Participating households are randomly drawn from the recent sample of the Current Population Survey (CPS). All adults within a household have the same chance of being selected to participate in the ATUS. The interviewee is asked to report his/her activities from 4 AM

FIG. 7. Predicted search intensity is based on the estimates in Table 2. Productivity on the current job is 52.8 dollars per hour. The horizontal axis is the productivity of the job that serves as the threat point when the worker renegotiates with the current employer. The dashed line represents search intensity at the beginning of the current job following unemployment. The solid line represents search intensity after renegotiation.



through 4 AM of the following day, and these activities are classified into several categories. There is a subcategory named "job search and interviewing". The sum of all the minutes that fall into this subcategory gives the individual's total time spent on job search. In order to circumvent the need to characterize the steady-state of the search model in this paper, I only look at the facts from the ATUS that describes the search behavior of unemployed workers and employed workers who are on their first job out of unemployment. The 2003 ATUS respondent file contains information on whether the respondent is employed, or unemployed, or out of the labor force when the ATUS was conducted. The ATUS-CPS file has data on the employment status and demographic characteristics of the ATUS respondent. The ATUS-CPS data were collected 2 to 5 months before the ATUS interview. I extracts the moments used in the estimation in the following way. First, white males aged 25-64 in the ATUS-CPS file are selected. To avoid the serious initial condition problem, I only focus on the subsample of people who were unemployed in the ATUS-CPS file. I assume if someone in this subsample had a job when the ATUS interview was conducted, then that job was his first job out of unemployment, and he had not got a wage change since he got that job. This assumption is plausible since the em-

ployment information from the ATUS-CPS file is only 2 to 5 months ahead of that of the ATUS respondent file. Looking at the subsample described above, 3.39% of employed workers were searching a positive amount on a day, and 30% of unemployed workers were searching on a day. Translating this daily information into weekly, the fraction of employed workers who were searching during a week is $1-(1-0.039)^7 = 0.2145$, while the fraction of unemployed workers who were searching during a week is $1-(1-0.3)^7 = 0.9176$. The latter fraction, 0.9176, is close to one. This validates my theory that all unemployed workers search. Among workers who searched, on average, employed workers spent 160 minutes per day on search, and unemployed workers spent 167.57 minutes per day to search for jobs. Using time spent on search as the proxy for search intensity, conditional on search, the average search intensity of employed workers relative to that of unemployed workers was 160/167.57=0.9548. The two moments, the fraction of employed people who searched and the search intensity of employed workers relative to that of unemployed workers, are used as supplementary information to identify the primitive parameters.

For a more detailed description of the ATUS data, see Hamermesh et al (2005).

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