Search and Nonwage Job Characteristics

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ABSTRACT

This paper quantifies the importance of nonwage job characteristics to workers by estimating a structural on-the-job search model. The model generalizes the standard search framework by allowing workers to search for jobs based on both wages and job-specific nonwage utility flows. Within the structure of the search model, data on accepted wages and wage changes at job transitions identify the importance of nonwage utility through revealed preference. The estimates reveal that utility from nonwage job characteristics plays an important role in determining job mobility, the value of jobs to workers, and the gains from job search.

I. Introduction

Nonwage job characteristics are important determinants of job mobility and choice. Important nonwage job characteristics include employer provided health insurance (Gruber and Madrian 2004), employer provided retirement benefits, flexible hours (Altonji and Paxson 1992), paid vacation, occupational choice (Goddeeris 1988), risk of injury or death (Thaler and Rosen 1975), commuting time (White 1988), onsite amenities, or a whole host of other, possibly intangible or heterogeneously valued,[1] job characteristics. Despite their importance, there is relatively little research that estimates search models with nonwage job characteristics and studies

1. See Bhaskar and To (1999) and Bhaskar, Manning, and To (2002).

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their effect on job choice and mobility decisions. The bulk of the empirical search literature assumes that the wage captures the entire value of a job and the literature that does account for nonwage job characteristics typically focuses on a single job characteristic. For example, Blau (1991), Bloemen (2008), Flabbi and Moro (2010), and Gørgens (2002) estimate models with hours or hours flexibility, Dey and Flinn (2005, 2008) estimate models with health insurance provision, and Sullivan (2010) estimates a model with occupational choice. Instead of focusing on a single observable job characteristic, we estimate a structural search model that allows workers to derive utility from their aggregate valuation of all the nonwage characteristics of a particular job.

The goals of this paper are to estimate the total value that workers place on the nonwage attributes of their jobs and to quantify the importance of nonwage factors in determining individual labor market dynamics. To accomplish this, we estimate a search model which augments the standard income maximizing on-the-job search framework (Burdett 1978) by including utility from nonwage job characteristics. In the model, employed and unemployed workers search across jobs that offer different wages and levels of nonwage utility. When a worker and firm meet, the worker receives a wage offer and also observes a match-specific nonwage utility flow that represents the net value that this particular worker places on all the nonwage job characteristics present at the job. Search frictions are present because both job offers and layoffs occur randomly, and because both wages and nonwage match values are modeled as random draws from a distribution that is known to the worker. Following a large fraction of the empirical search literature, we adopt a stationary, partial equilibrium framework.[2] As in the canonical on-the-job search model, wage growth occurs as workers climb a job ladder by moving to higher wage jobs. A novel feature of the model is that it also allows workers to benefit from moving to jobs that offer higher nonwage utility. Depending on the importance of the nonwage side of the model, basing conclusions about the value of job mobility solely on wages could give a misleading view of the gains to job search and mobility. Estimating the structural model is a direct way of quantifying the importance of the wage and nonwage channels in determining the total gains to mobility over the career.

The structural parameters are estimated by simulated minimum distance using the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97). The estimates reveal that workers place a substantial value on nonwage job characteristics, and also show that nonwage utility flows vary widely across different worker-firm matches. More specifically, workers who are searching for a job face slightly more dispersion in job-specific nonwage utility flows than in wage offers. Simulations performed using the estimated model reveal that increases in the utility derived from nonwage job characteristics account for approximately one-half of the total gains from job mobility. This result indicates that standard models of on-the-job search—which are based solely on wages—are missing a key determinant of the value of jobs, the causes of worker mobility, and the gains from job search.

Our use of the nonwage match value as an aggregate measure of the nonwage value of a job is primarily motivated by the goal of estimating the total nonwage value of jobs to workers. In addition, four observations about the information available in

2. See, for example, Flinn (2002), Jolivet, Postel-Vinay, and Robin (2006), Bloemen (2008) and Dey and Flinn (2008).

standard sources of labor market data on the employer provided benefits, tangible job characteristics, and intangible job characteristics that differentiate jobs are relevant. First, important employer provided benefits such as health insurance and retirement plans are imperfectly measured.[3] Second, information about many tangible job characteristics, such as risk of injury or commuting time, is frequently unavailable. Third, measures of intangible job characteristics such as a worker's evaluation of his supervisor, which may be significant determinants of the value of a job to a worker, are typically completely absent. Fourth, and perhaps most importantly, it is likely that workers have heterogeneous preferences over the employer provided benefits and tangible and intangible job characteristics that differentiate jobs. With these facts in mind, rather than attempting to estimate the value of specific job characteristics, we estimate the net value of all nonwage job characteristics to a worker using the nonwage match value.

This paper contributes to a growing literature that demonstrates the importance of accounting for imperfect information, search frictions, and dynamics when estimating the value of nonwage job characteristics. Hwang, Mortensen, and Reed (1998), Dey and Flinn (2005, 2008), and Gronberg and Reed (1994) all discuss the problems caused by using a static framework to analyze nonwage job characteristics in a dynamic labor market. More recently, Bonhomme and Jolivet (2009) estimate the value of a number of observed job characteristics using a search model. We take a different approach by estimating the total nonwage value of jobs using the nonwage match value, rather than attempting to identify the value of specific characteristics. Becker (2010) develops a model that focuses on incorporating nonwage utility into the equilibrium wage bargaining framework of Postel-Vinay and Robin (2002) and applying the model to unemployment insurance.

Nonwage utility flows are of course not observed by the econometrician so identification is an important concern. The on-the-job search model provides a natural framework for using data on wages, job acceptance decisions, and employment durations to infer the value that workers place on nonwage job characteristics. Broadly speaking, the intuition behind the identification of the model is that since a standard income maximizing search model is nested within the utility maximizing search model, the importance of nonwage job characteristics is identified by the extent to which an income maximizing model fails to explain the moments used in estimation. More specifically, observed patterns of job mobility and wage changes at transitions between jobs are particularly informative about the importance of nonwage job characteristics. To give a concrete example, a key moment matched during estimation is the proportion of direct job-to-job transitions where workers choose to accept a decrease in wages.[4] Wage declines at job transitions occur frequently: In the NLSY97 data, reported wages decline for more than one-third of direct transitions between jobs. Taking the structure of the model as given, this type of transition indicates through revealed preference that a worker is willing to accept lower wages in exchange for higher nonwage utility at a specific job.

3. For example, in the 1979 and 1997 cohorts of the NLSY, information is available about whether or not employers offer benefits such as health insurance but there is no information about takeup of benefits, dollar amount of the employer and employee contributions, or plan quality.

4. Throughout the paper, direct transitions refer to transitions between jobs that occur without an intervening spell of unemployment.

During estimation, we are careful to account for the two alternative explanations for observed wage decreases at direct transitions between jobs that have dominated the empirical search literature up to this point. Ignoring either of these possible explanations during estimation would lead to an upward bias in the estimated importance of nonwage utility. The first explanation is that if a job ends exogenously, a worker might choose to move directly to a lower-paying job to avoid unemployment, if this option is available.[5] The second explanation is that measurement error in wages might cause some transitions between jobs that are actually accompanied by wage increases to be erroneously shown as wage decreases in the data.[6] Our model allows for both of these explanations, and also adds a third possible explanation: A worker could choose to move from a high-wage job to a lower-wage job that offers a higher level of nonwage utility.

We incorporate the involuntary direct transitions into the model by allowing existing jobs to end involuntarily (from the perspective of the worker) in the same time period that a job offer is received from a new employer. The probability that this event occurs is identified using NLSY97 data that identifies direct job-to-job transitions that begin with involuntary job endings. Existing research has not used this type of data to identify involuntary direct transitions between employers.

We account for measurement error in wages by estimating a parametric model of measurement error jointly along with the other parameters of the model. Although at first glance it might appear that measurement error in wages and match-specific nonwage utility are observationally equivalent, Section IV.D of this paper demonstrates that they actually have very different implications for the simulated moments used to estimate the model. More specifically, although measurement error and nonwage utility can both account for observed wage decreases at job transitions, neither feature on its own is capable of simultaneously explaining the extent of variation in wages, the amount of wage growth over the career, and the frequency of wage declines at direct job transitions in the NLSY97.

The parameter estimates reveal that the variation in nonwage utility flows across worker-firm matches is slightly greater than the variation in wage offers. This implies that there are substantial gains to workers from job search based on nonwage factors. Although the parameter estimates provide direct evidence on the importance of the nonwage side of the model, perhaps a more informative way of examining the implications of the utility maximizing search model is to study simulated data generated by the estimated model. In these data, nonwage utility accounts for 23 percent of the total variation in the one-period utility flows that workers receive from employment. On average, measuring the value of a job using only the wage substantially understates the true value of a job to a worker. More specifically, in 85 percent of all jobs in the simulated data, workers value the nonwage characteristics of their job greater than the mean offered value of nonwage job characteristics. The fact that workers receive below mean nonwage utility flows in only 15 percent of accepted job offers

5. For example, Jolivet, Postel-Vinay, and Robin (2006) assume that all direct job-to-job transitions accompanied by wage decreases are the result of simultaneous job endings and mobility to new jobs.
6. Flinn (2002) adopts this approach, and Wolpin (1992) allows for both measurement error in wages and simultaneous exogenous job endings and outside job offers.

shows that although utility maximizing workers in the model are perfectly willing to accept higher wages in exchange for undesirable job characteristics, the search model reveals a strong tendency for workers to sort into jobs with nonwage job characteristics that they are willing to pay for. The above average nonwage value of jobs is generated by two features of the search environment. First, the reservation utility strategy followed by unemployed agents implies that the accepted job offers observed in the simulated data are truncated from below. Second, on-the-job search implies that workers climb both wage and nonwage utility ladders as they move between employers.

The search model with nonwage job characteristics has important implications for the study of compensating differentials. Previously, papers such as Hwang, Mortensen, and Reed (1998) and Gronberg and Reed (1994) make the point that in general, estimates of compensating differentials will be biased unless search frictions are taken into account. Our primary contribution to this line of research is to use the estimated structural search model to obtain a direct estimate of the magnitude of the bias caused by estimating compensating differentials using a static framework. Standard hedonic regression approaches to valuing nonwage job characteristics implicitly assume that workers are free to select an optimal job from a perfectly known labor market hedonic wage curve. In contrast, the simulated data from our model contain a sample of wages and nonwage utility received by workers who must search for jobs in a dynamic labor market due to imperfect information about available job opportunities. When we estimate a standard hedonic regression using these data, the estimated marginal-willingness-to-pay for nonwage job characteristics is biased downward by approximately 50 percent from the true value used to generate the data.

This application of the model offers an explanation for the fact that empirical support for the theory compensating differentials is relatively weak, despite a vast literature on estimating these differentials. The intuition behind the downward bias in estimated compensating differentials is that in a search model, the only information provided by accepted pairs of wages and nonwage utility is that they exceed a reservation utility threshold. In this setting, they do not directly reveal the marginal willingness to pay for nonwage job characteristics as they would in a static, frictionless, perfect information world where workers maximize utility subject to a given labor market hedonic wage locus.

In the following section, we develop a partial equilibrium model of on-the-job search with nonwage utility. In Section III, we discuss the data set used to estimate our model and in Section IV we discuss our econometric methodology and some important identification issues. Section V presents our parameter estimates and discusses the effect of nonwage utility on labor market outcomes. Section VI concludes.

II. The Search Model with Utility from Nonwage Job Characteristics

This section presents the search model used to estimate the importance of nonwage utility. The model is set in discrete time. Agents maximize the discounted sum of expected utility over an infinite time horizon in a stationary environment. In each time period, individuals occupy one of two states: employment or unemployment.[7] Agents randomly receive job offers while unemployed and employed, and the employed face a constant risk of exogenous job loss.[8] When a job ends exogenously, there is no chance of recall. For ease of exposition, this section describes the decision problem facing a single agent. However, we allow for person-specific unobserved heterogeneity when estimating the model (Section IV).

A. Preferences and job offers

The utility received by an employed agent is determined by the log-wage, w, and the match-specific nonwage utility flow, ξ. The one-period utility from employment is

$$(1) \quad U(w,\xi) = w + \xi,$$

where both w and ξ are specific to a particular match between a worker and employer, and are constant for the duration of the match. A job offer consists of a random draw of (w,ξ) from the distribution $F(w,\xi)$, which is a primitive of the model. Although with this functional form, the saving decision is no longer irrelevant as it is with the linear utility functions that are commonly adopted in search models, it has the desirable property that the marginal utility of the wage declines as the wage increases—this is particularly important for our application because the tradeoff between wages and nonwage utility is central to the workers' mobility decisions. While explicitly allowing savings in our model would be of interest in its own right, it is beyond the scope of our current exercise and we leave it as an extension for future research.

The structure of the search and matching process in the model labor market is as follows. When a worker and firm randomly meet, the worker receives a wage offer. At the same time, the worker observes the complete bundle of nonwage job characteristics present at the firm. These characteristics include employer provided benefits (health insurance), tangible job characteristics (risk of injury, commuting time), and intangible job characteristics (friendliness of coworkers). Based on his preferences, which may be heterogeneous across agents, the worker determines the net value of the nonwage job characteristics present at this firm (ξ).[9] The worker then decides whether or not to accept the job offer. Once a job offer is accepted, the wage and nonwage component of the offer remain constant for the duration of the job spell.[10] Because our primary goal is to estimate the total importance of nonwage job characteristics to workers, which is captured by ξ, we do not attempt to determine how much of the variation in nonwage

7. Following the majority of the search literature, the model does not distinguish between unemployment and nonparticipation in the labor market.
8. The terms exogenous job endings and layoff are used interchangeably in the remainder of the paper.
9. One specific nonwage job characteristic that is likely to be reflected in ξ is hours of work. (See Blau 1991 and Bloemen 2008 for search models which focus on hours.) However, the utility function shown in Equation 1 is separable in its two arguments, which rules out interactions between w and ξ—which may be important in a model where hours of work are explicitly modeled. Also, it is worthwhile to note that we restrict our analysis to full-time jobs (Section III) so hours only vary in our sample to the extent that they vary within full-time jobs. The primary advantage of our separable utility function is that it provides a straightforward, tractable framework for thinking about how workers evaluate jobs that differ in (w, ξ). It is also consistent with existing literature on search with nonwage amenities such as Dey and Flinn (2005). Of course, it is less general than other possible functional forms.
10. Section III explains that the assumption of constant wages within jobs is broadly consistent with the NLSY97 data used to estimate the model.

utility is due to firm level variation in nonwage job characteristics versus preference heterogeneity.[11]

B. Unemployed search

Unemployed agents search for jobs, which arrive randomly with probability λ_u. Since w and ξ are additively separable in the utility function, it is convenient to define the agent's decision problem in terms of total utility, $w + \xi$, where $U(w,\xi) \equiv U$ and U is distributed as $H(U)$. Note that the distribution function $H(\cdot)$ is not a primitive of the model and is derived from the joint distribution function for log-wages and nonwage utility. In particular, if the joint distribution is $F(w, \xi)$ then $H(U) = \int_{-\infty}^{\infty} F_{w|\xi}(U - \xi|\xi) f_\xi(\xi) d\xi$ where $f_{w|\xi}$ is the cumulative conditional wage distribution and f_ξ is the unconditional probability density function for ξ. The discounted expected value of lifetime utility for an unemployed agent is

$$(2) \quad V^u = b + \delta[\lambda_u E\max\{V^u, V^e(U')\} + (1-\lambda_u)V^u],$$

where b is the one-period utility flow from unemployment, which reflects the value of unemployment benefits and leisure, and δ is the discount factor. The term $V^e(U')$ represents the expected discounted value of lifetime utility for an agent employed in a job with utility level U'.

The optimal search strategy for an unemployed agent is a reservation utility strategy, which is analogous to the reservation wage strategy found in income maximizing search models. The rule is to accept any job offer which offers a one-period utility flow greater than the reservation level, U^*, and reject all other offers. Appendix 1 presents the formal derivation of U^*. This stationary unemployed search problem assumes away duration dependence in unemployment spells. A large empirical literature examines duration dependence in unemployment spells.[12] In the NLSY97 data used to estimate the model, the hazard rate out of unemployment is approximately constant so the constant exit rate assumed by the model is broadly consistent with the data.[13]

C. On-the-job search

In each time period, with probability λ_e an employed agent receives a job offer from an outside firm. The worker may accept the job offer, or reject it and continue working for his current employer. Job matches end with exogenous probability λ_l. When a job ends for this reason, the worker is forced to become unemployed. With probability

11. We leave decomposing the sources of variation in match-specific nonwage utility as an interesting, although difficult, extension for future research. Empirical work along these lines would require detailed data on the complete set of nonwage job characteristics valued by workers along with sufficiently high mobility rates between jobs with different characteristics to identify preference heterogeneity. In addition, data on the firm side of the market, ideally matched worker-firm data, would be useful to control for unobserved, firm-specific variation in working conditions and job amenities.

12. Card, Chetty, and Weber (2007) provide a survey of the literature on unemployment durations, with a focus on evidence of spikes in the exit rate from unemployment at the time of UI benefit exhaustion.

13. More specifically, the hazard rate out of unemployment is approximately constant for the first 16 months of an unemployment spell. Beyond 16 months, the hazard rate begins to increase, although the hazard rate is imprecisely estimated in this range because there are very few extremely long unemployment spells in the data.

λ_{le}, a worker's current job exogenously ends and he receives a job offer from a new employer in the same time period. When this happens, the worker can accept the new offer or become unemployed. Finally, with probability $(1 - \lambda_e - \lambda_l - \lambda_{le})$ the job does not end exogenously and no new offers are received, so the worker remains in his current job.

The discounted expected value of lifetime utility for a worker who is currently employed in a job with utility level U is

$$(3) \quad V^e(U) = U + \delta[\lambda_e E\max\{V^e(U), V^e(U')\} + \lambda_l V^u + \lambda_{le} E\max\{V^u, V^e(U')\} + (1 - \lambda_e - \lambda_l - \lambda_{le})V^e(U)].$$

The first term within the square brackets in Equation 3, $\lambda_e E\max\{V^e(U), V^e(U')\}$, represents the expected value of the best option available in the next time period for an employed individual who receives a job offer from a new employer.[14] The second bracketed term, $\lambda_l V^u$, corresponds to the case where a job exogenously ends and the worker is forced to enter unemployment. The third bracketed term, $\lambda_{le} E\max\{V^u, V^e(U')\}$, represents the case where the worker is laid off but also receives a job offer from a new employer. The final bracketed term represents the case where the worker is neither laid off nor receives an outside job offer.

In this stationary search environment, optimal decisions for employed agents are based on comparisons of one-period utility flows. When an employed agent receives an offer from an outside firm but does not experience an exogenous job ending, a simple reservation utility strategy is optimal. Because $V^e(U)$ is increasing in U, the rule is to accept the offer if it offers greater utility than the current job $(U' > U)$, and reject the offer otherwise $(U' \leq U)$. If a worker's job exogenously ends and he receives a new job offer at the same time, which occurs with probability λ_{le}, the situation is identical to the one faced by an unemployed agent who receives a new job offer. As a result, he will choose to accept or reject the offer based on the unemployed reservation utility level U^*.

In the remainder of the paper, we will refer to direct job-to-job transitions that occur as the result of a simultaneous layoff and job offer as "involuntary" transitions between employers. This terminology reflects the fact that although a direct job-to-job transition occurs, the worker's previous job ended involuntarily (exogenously). For agents in the model, voluntary and involuntary transitions are fundamentally different types of job mobility. When a voluntary job-to-job transition occurs, utility increases $(U' > U)$. In contrast, when an involuntary transition occurs, the new job offer is preferable to unemployment $(U' > U^*)$, but it may be the case that total utility is lower than the previous job that exogenously ended $(U' < U)$.

III. Data

We use the 1997 rather than the venerable 1979 cohort of the NLSY to estimate our model for two reasons. First, the NLSY97 is more representative of cur-

14. The value function reflects the fact that in this model it is never optimal for a worker to quit a job and enter unemployment.

rent labor market conditions. Second, the NLSY97 design team incorporated lessons from the NLSY79 and has a more consistent methodology (Pergamit et al. 2001).

The NLSY97 is a nationally representative sample of 8,984 individuals who were between the ages of 12 and 16 on December 31, 1996. Interviews have been conducted annually since 1997. The NLSY97 collects extensive information about labor market behavior and educational experiences that provide the information needed to study the transition from schooling to employment, early career mobility between employers, and the associated dynamics of wages. Individuals enter the estimation sample when they stop attending high school. The information from the annual interviews is used to construct a weekly employment record for each respondent.

We select a particular subset of the NLSY97 in order to minimize unnecessary complications in estimating our model. Women are excluded for the usual reason of avoiding the difficulties associated with modeling female labor force participation. Similarly, in order to avoid issues relating to household search, men who are ever married during the sample period are excluded. Moreover, we use data from interviews up to the 2006 interview and we select workers who have never attended college because low-skilled workers with little work experience can be expected to have little or no bargaining power and hence conform best to our wage-posting model. Thus we focus on young, unmarried, low-skilled men who are at the beginning of their careers. As is standard in the empirical search literature, individuals who ever serve in the military or are self-employed are excluded from the sample. Because the maximum age that an individual could reach during the sample period is only 26 years, our results should be viewed as applying to young workers who tend to be quite mobile during this early phase of their career. Whether the results generalize to older workers, or different cohorts of workers, is an open question.

The NLSY97 provides a weekly employment record for each respondent that is aggregated into a monthly[15] labor force history for the purposes of estimation. First, each individual is classified as unemployed or employed full-time[16] for each month depending on whether more weeks were spent employed or unemployed during the month.[17] Next, employed individuals are assigned a monthly employer based on the employer that the worker spent the most weeks working for during the month. The monthly wage is the one associated with the monthly employer. The monthly employment record contains a complete record of employment durations, direct transitions between employers that occur without an intervening spell of unemployment, transitions into unemployment, and the growth in wages resulting from mobility between employers.

Since the importance of nonwage job characteristics is identified in part by job-to-job transitions, we are careful to differentiate between those that are voluntary and those that are not. To identify involuntary job-to-job transitions we use the stated reason that a worker left their job. We consider "layoffs," "plant closings," "end of

15. For tie-breaking purposes, we use a five-week month.
16. We classify full-time employment as 15 or more hours per week. Individuals working less than 15 hours per week are classified as unemployed. In our data, unemployment spells involving part-time work make up only 5.3 percent of all unemployment spells.
17. Nonparticipation and unemployment are considered to be the same state for the purposes of aggregating the data.

a temporary or seasonal job," "discharged or fired," or "program ended" to be involuntary. While these data may be somewhat noisy, we are reassured by the summary statistics that show that direct transitions we classify as strictly involuntary are more likely to result in a wage decline (Table 1). In addition, on average, workers who make involuntary transitions between employers experience nearly a 2 percent decline in wages. In contrast, wages increase on average by 8 percent at all transitions between employers.

The final issue worthy of discussion regarding the data is the treatment of within-job variation in wages. In the NLSY97, when a job persists across survey interviews, which occur approximately one year apart, a new measurement of the wage is taken. If a job does not last across interview years, only the initial measurement of the wage is available. In principle, it would be possible to allow for within-job variation in wages using these data. However, as discussed by Flinn (2002), jobs with observed wage changes are not a random sample from the population, so there are difficult selection issues that must be confronted when estimating an on-the-job wage process using these data. Even more importantly for our purposes, since the NLSY97 is still a relatively short panel, the majority of jobs do not persist across survey years. For these jobs, it is impossible to observe on-the-job wage growth; we only observe a single wage for 72 percent of all jobs in our data. To be precise, for our estimation sample we are unable to reject the null hypothesis that mean wage growth is zero within job spells.[18] Given these features of the data, there is little hope of precisely estimating an on-the-job wage growth process. As a result, we restrict wages to be constant within job spells for the purposes of estimation. When multiple wages are reported for a particular job, we use the first reported wage as the wage for the entire job spell. Moreover, for our application, with our focus on young, unskilled workers during the highly mobile, early stage of their career, constant wages within jobs does not seem unrealistic.

A. Descriptive statistics

This section highlights the key characteristics of the data used to estimate the importance of nonwage job characteristics in determining employment outcomes. It is convenient to describe the labor market histories in the data and the data generated by the search model in terms of employment cycles, as in Wolpin (1992). An employment cycle begins with unemployment and includes all of the following employment spells that occur without an intervening unemployment spell. When an individual enters unemployment, a new cycle begins. In the remainder of the paper, whenever a job is referred to by number, it represents the position of the job within an employment cycle.

Table 1 shows the means and standard deviations of key variables from the sample of the NLSY97 used in this analysis. There are 980 individuals in the data who remain in the sample for an average of 54.2 months, and these people experience an average

18. Mean wage growth is computed using the first and last wage present for each job in the NLSY estimation sample. The null hypothesis that mean wage growth equals zero cannot be rejected at the 5 percent level.

Table 1
Descriptive Statistics: NLSY97 Data

	Job Number Within Cycle		
	Job 1	Job 2	Job 3
Mean log-wage	1.979	2.038	2.061
Standard deviation of log-wage	0.425	0.458	0.457
Mean employment spell duration[a]	8.939	9.271	9.738
Number of observations	2614	940	382

	Type of Employer Switch	
	All	Involuntary
Pr(wage decrease) at job-to-job move	0.364	0.460
Mean Δw at job-to-job switch[b]	0.081	–0.017
Median Δw at job-to-job switch	0.074	0.000
Mean Δw at job-to-job switch $\lvert \Delta w > 0$	0.359	0.322
Median Δw at job-to-job switch $\lvert \Delta w > 0$	0.231	0.211
Mean Δw at job-to-job switch $\lvert \Delta w < 0$	–0.327	–0.345
Median Δw at job-to-job switch $\lvert \Delta w < 0$	–0.163	–0.206

	All Jobs
Mean unemployment spell duration	5.908
Mean number of cycles per person[c]	2.878
Standard deviation of number of cycles per person	1.793
Mean total work experience at end of sample period[d]	40.010
Fraction of job-to-job transitions that are involuntary	0.151
Number of people	980
Mean number of months in sample per person	54.153

Notes: a. All durations are measured in months.
b. Δw represents the change in the wage at a job-to-job transition.
c. An employment cycle begins with the first job after an unemployment spell, and includes all subsequent jobs that begin without an intervening unemployment spell.
d. This is the across-person mean of total work experience in the final time period. The final time period is either the end of the sample timeframe or the final time period before an observation is truncated due to missing data.

of 2.88 employment cycles. The top section of the table shows that as individuals move between employers within an employment cycle, the average wage and employment duration increase.[19] The middle section of the table shows that although mean wages increase as individuals move directly between jobs, conditional on switching employers without an intervening unemployment spell there is a 36 percent chance that an individual reports a lower wage at his new job.[20] For individuals who report that the direct transition between employers was involuntary, the mean wage change is negative, and the probability of a wage decrease rises to 46 percent. Measurement error in wages certainly accounts for some fraction of the observed wage decreases at voluntary transitions between employers. However, the prevalence of these wage decreases and the increased probability of observing a wage decline at an involuntary transition both suggest a role for nonwage job characteristics in determining mobility between jobs.

We conclude our analysis of the data with a discussion of the extent to which two important features of the search model are consistent with the patterns found in the NLSY97 data. First, the model assumes that workers who experience an involuntary job ending draw new job offers from the same distribution as unemployed workers. In reality, it may be the case that workers receive prior notice of job endings, and respond by increasing their on-the-job search effort. Because search effort is unobserved, we compare the observable characteristics of jobs that begin with an involuntary job ending to those of jobs that begin with a transition from unemployment. In the NLSY97 data, the average log-wage on jobs that begin with an involuntary job-to-job transition is only 0.005 lower than the average wage on jobs that begin with a transition from unemployment. Similarly, on average, a job that begins with an involuntary transition lasts only two weeks less than a job that begins with a transition from unemployment. Based on these statistics, assuming that the unemployed and involuntarily displaced draw job offers from the same distribution seems to be broadly consistent with the data. Second, the omission of general human capital implies that in the model, wages will not grow across employment cycles. In the NLSY97 data, the mean growth in wages between Job 1 in Employment Cycle 1 and Job 1 in Employment Cycle 2 is 0.1396 with a t-statistic of 0.2889. While the magnitude of this wage growth appears to be large, it is not statistically distinguishable from zero.

IV. Estimation

The parameters of the model are estimated by simulated minimum distance (SMD). This section begins by specifying the distributional assumptions about the job offer distribution, measurement error in wages, and unobserved heterogeneity needed to estimate the model. Then it explains how the simulated data is generated, describes the estimation algorithm, and discusses identification.

19. Statistics are not reported for more than three jobs within a cycle because only a very small number of people have four or more consecutive jobs without entering unemployment.

20. This number is consistent with existing estimates of the fraction of direct employer-to-employer transitions that involve a wage decrease. Bowlus and Neumann (2006) report that 40 percent of direct transitions involve a wage decrease in the NLSY79.

A. Distributional assumptions

1. The wage offer distribution

Estimating the model requires specifying the distribution $F(w,\xi)$, which is a primitive of the model.[21] We assume that log-wage offers and match-specific utility flows are independent, and normally distributed,[22]

(4) $F(w,\xi) \sim \Omega(w)\Psi(\xi)$

(5) $\Omega(w) \sim N(\mu_w,\sigma_w)$

(6) $\Psi(\xi) \sim N(0,\sigma_\xi)$

Note that our normalization of the mean nonwage utility offer to zero is an innocuous assumption because, as in any discrete choice model, utility flows are only identified relative to a base choice. We normalize the employment nonwage utility flow to zero and estimate b, the nonpecuniary utility flow from unemployment.[23]

2. Measurement error in wages

A large literature surveyed by Bound, Brown, and Mathiowetz (2001) finds that wages in typical sources of microeconomic data are measured with error. We account for measurement error by assuming that the relationship between the log-wage observed in the data and the true log-wage is $w^o = \mathrm{w} + \varepsilon$, where w^o is the observed log-wage, w is the true log-wage, and $\varepsilon \sim N(0,\sigma_\varepsilon)$ represents measurement error in wages that is independent of the true wage.[24] The parameter σ_ε is estimated jointly along with the other parameters in the model. Section IV.D discusses how the extent of measurement error in wages is separately identified from the importance of nonwage utility. The addition of measurement error in wages to the model does not change the optimization problem faced by agents because optimal decisions are based on true wages, not observed wages. However, measurement error impacts the simulated data used to estimate the model.

3. Accounting for unobserved heterogeneity

The search model presented in Section II assumes that all individuals are *ex ante* identical at the start of their careers, which implies that all differences in wages and employment outcomes are driven by randomness in the labor market. Although the

21. We do not attempt to endogenize the job offer distribution because our primary goal in this paper is to quantify the relative importance of nonwage utility for workers, taking the offer distribution as given. Developing a tractable partial equilibrium model allows us to focus directly on this issue, as in much of the existing literature that uses search models to quantify the monetary gains to search and mobility (Jolivet, Posel-Vinay, and Robin 2006; Flinn 2002; Sullivan 2010).

22. The latter part of Section IV.D discusses the assumed independence of w and ξ within the context of identification.

23. An observationally equivalent model instead normalizes b to 0 and allows the mean nonwage utility offer to be a free parameter.

24. Accounting for measurement error in this way is standard in the search literature. See, for example, Stern (1989), Wolpin (1992), and Eckstein, Ge, and Petrongolo (2009).

sample of workers from the NLSY97 used in estimation consists of a fairly homogeneous group in terms of observable characteristics, it is possible that there are permanent differences between workers that are unobserved to the econometrician. In general, ignoring unobserved heterogeneity during estimation will lead to biased parameter estimates if unobserved heterogeneity is actually present.

In this application, the specific concern is that ignoring unobserved differences between workers could lead to an overstatement of the importance of nonwage utility. For example, suppose that a worker remains in a job with a wage in the bottom 5 percent of the wage distribution over the entire sample period. If workers are assumed to be homogeneous, then the model will tend to explain the long duration of this low-wage job as a situation where the worker has a large draw of ξ, so he is willing to remain in the low-wage job because it provides a high level of utility. However, if there is heterogeneity across workers in ability, low-ability workers could choose to remain in jobs that offer low wages relative to the overall wage distribution because these jobs are actually high paying relative to their personal (low-ability) wage distribution.

We account for person-specific unobserved heterogeneity in ability by allowing the mean of the wage offer distribution (μ_w) to vary across workers. Heterogeneity in preferences for leisure is captured by allowing the one-period utility flow from unemployment (b) to vary across workers. In addition, we allow the job offer arrival rates while unemployed (λ_u) and employed (λ_e), the layoff probability (λ_l), and the simultaneous layoff-offer probability (λ_{le}) to vary across workers to allow for the possibility that workers face different amounts of randomness in job offer arrivals and exogenous job endings.[25] Equation 8 shows that variation in these primitive parameters across workers leads to heterogeneity in the reservation utility level, U^* across workers. Following Keane and Wolpin (1997), and a large subsequent literature, we assume that the joint distribution of unobserved heterogeneity is a mixture of discrete types. Assume that there are J types of people in the economy, and let p_j represent the proportion of type j in the population. The parameters of the distribution of unobserved heterogeneity, $\{\mu_w(j), b(j), \lambda_u(j), \lambda_l(j), \lambda_e(j), \lambda_{le}(j), \pi_j\}_{j=1}^{J}$, are estimated jointly along with the other parameters of the model.

B. Data simulation

As discussed in Section II, the optimal decision rules for the dynamic optimization problem can be described using simple static comparisons of one-period utility flows. It is straightforward to simulate data from the model using these optimal decision rules without numerically solving for the value functions that characterize the optimization problem.

The first step when simulating the model is to randomly assign each individual in the data to one of the J discrete types that make up the population distribution of unobserved heterogeneity. Next, a simulated career is formed for each individual in the NLSY97 estimation sample by randomly generating job offers and exogenous job endings, and then assigning simulated choices for each time period based on the res-

25. Eckstein, Ge, and Petrongolo (2009) also take the approach of allowing for heterogeneity in offer arrival and layoff probabilities.

ervation value decision rules. The number of time periods that each simulated person appears in the simulated data is censored to match the corresponding person in the NLSY97 data. Measurement error is added to the simulated accepted wage data based on the assumed measurement error process.

C. Simulated minimum distance estimation

Simulated minimum distance estimation finds the vector of structural parameters that minimizes the weighted difference between vectors of statistics estimated using two different data sets: the NLSY97 data and simulated data from the model. We use the terminology simulated minimum distance to make it clear that during estimation we match moments from the data (as in the simulated method of moments) and the parameters of an auxiliary model (as in indirect inference).[26] In this application, the auxiliary parameters are the parameters of a reduced form wage regression. In the remainder of the paper, for brevity of notation we refer to all of the statistics from the data that are matched during estimation as moments.

Let $\theta = \{\sigma_w, \sigma_\xi, \sigma_\varepsilon\} \cup \{\mu_w(j), b(j), \lambda_u(j), \lambda_l(j), \lambda_e(j), \lambda_{le}(j), \pi_j\}_{j=1}^{J}$ represent the parameter vector that must be estimated.[27] The search model is used to simulate S artificial datasets, where each simulated data set contains a randomly generated employment history for each individual in the sample. The simulated and actual data are each summarized by K moments. The SMD estimate of the structural parameters minimizes the difference between the simulated and sample moments. Let m_k represent the kth moment in the data, and let $m_k^S(\theta)$ represent the kth simulated moment, where the superscript S denotes averaging across the S artificial data sets. The vector of differences between the simulated and actual moments is $g(\theta)' = [m_1 - m_1^S(\theta), \ldots, m_K - m_K^S(\theta)]$, and the simulated minimum distance estimate of θ minimizes the following objective function,

$$(7) \quad \Phi(\theta) = g(\theta)' W g(\theta)$$

where W is a weighting matrix. We use a diagonal weighting matrix during estimation, where each diagonal element is the inverse of the variance of the corresponding moment. We estimate W using a nonparametric bootstrap with 300,000 replications. Bootstrapping the matrix W is convenient because it is not necessary to update the weighting matrix during estimation. Simulated moments are averaged over $S = 25$ simulated data sets.

To provide further intuition behind the estimation algorithm, it is useful to examine the contribution of a single moment condition to the objective function, $\Phi(\theta)$, at the estimated parameter vector, θ. The contribution of the kth moment condition is $[m_k - m_k^S(\theta)]^2/[var(m_k)]$, where $var(m_k)$ is the bootstrapped estimate of the variance of the empirical moment m_k. If the model is correctly specified, deviations between the simulated and empirical moments arise from two sources: sampling variation in m_k,

26. See Stern (1997) for a survey of simulation-based estimation and Smith (1993) for the development of indirect inference.

27. The parameter vector that is estimated does not include the discount factor, δ, because this parameter is set before estimation (Section IV.D).

and simulation error in $m_k^S(\theta)$ because a finite number of random draws is used during estimation.

One important concern is that the SMD objective function shown in Equation 7 is not a continuous function of the parameter vector because simulated choices change discretely as θ changes.[28] As a result, derivative-based optimization routines cannot be used to estimate the model. Instead, we minimize the objective function using simulated annealing, a nonderivative-based global search algorithm that is appropriate for nonsmooth objective functions.[29] In addition, because of the lack of continuity, it is not appropriate to rely on derivative-based, asymptotic approximations to standard errors. Instead, we compute nonparametric bootstrap estimates of the standard errors using 900 draws from the NLSY97 data.

D. Choice of moments and identification

This section discusses the moments targeted during estimation and provides a discussion of how they identify the parameters of the structural model. Throughout this section, we focus on providing examples of the type of variation in the data that identifies each model parameter. Table 6 lists the 65 moments from the NLSY97 that are used to estimate the model. This section begins by describing how the wage offer distribution, nonwage utility offer distribution, and measurement error distribution are identified. Next, it turns to a discussion of how the mean transition parameters (λ's) and the mean unemployment utility flow (*b*) are identified. The section then demonstrates how the distribution of person-specific unobserved heterogeneity is identified. Finally, the section concludes with a discussion of correlation between w and ξ and why, given our data, it cannot be separately identified from transition parameters that differ by person.

1. Identifying the wage and nonwage offer distributions

As is standard in the structural search literature, and described in Section IV.A, we must assume a parametric functional form for the job offer distribution, $F(w,\xi)$.[30] For clarity of exposition, we initially abstract away from person-specific unobserved heterogeneity when discussing identification. In the final portion of this subsection, we explain how the distribution of unobserved heterogeneity is identified.

The mean and standard deviation of the wage offer distribution are identified by moments that describe accepted wages and wage growth from mobility. More specifically, the moments shown in Panel 1 of Table 6 describe the first three job spells

28. Recent examples of papers that use this approach to estimating search models include Dey and Flinn (2008), Eckstein, Ge, and Petrongolo (2009), and Yamaguchi (2010).
29. See Goffe, Ferrier, and Rodgers (1994) for a discussion of the simulated annealing algorithm and FORTRAN source code to implement the algorithm. The primary advantage of this algorithm is that it is a global search algorithm that can escape local optima. The primary drawback is that it typically requires a large number of function evaluations to reach convergence relative to a derivative-based algorithm. However, in our application this is not a binding constraint because simulating data from the model is not computationally expensive.
30. The major difference between our paper and existing work is that we must specify the distribution of ξ in addition to the wage distribution.

within employment cycles using the mean and standard deviation of accepted wages. Recall that employers within a cycle represent a sequence of direct transitions between employers that occur without an intervening spell of unemployment, so mean wages conditional on employer number also provide information about wage growth from job search. As discussed in Barlevy (2008), wage gains from mobility provide useful identifying information about the wage offer distribution.

At first glance, it might appear difficult to distinguish the effects of nonwage utility from measurement error without relying on validation data to identify misreported wages. However, the parameters that determine measurement error in wages (σ_ε), true variation in wage offers (σ_w), and variation in nonwage utility (σ_ξ) actually have very different implications for the moments used during estimation. To understand how σ_ε and σ_ξ are separately identified, it is useful to begin by considering a restricted version of the model which fixes the parameter $\sigma_\xi = 0$. Under this restriction, job-mobility choices are based only on wages so voluntary moves to lower wage jobs must be attributed to measurement error in wages. As a result, this feature of the data identifies σ_ε. In order to match the frequency of wage declines at job transitions shown in Panel 3 of Table 6, σ_ε must be relatively large. However, as σ_ε increases, σ_{w} must decrease, or else the simulated model will generate too much variation in observed wages relative to the data (Panel 1 of Table 6). In other words, when the amount of measurement error in the model is high, the amount of true variation in wage offers must be low in order to match the observed variation in wages in the NLSY97. This property of the model is demonstrated in Columns 1 and 2 of Table 2, which show the parameter estimates for a restricted version of the model that assumes that $\sigma_\xi = 0$ along with the estimates for the unrestricted model. Finally, it is important to note that as σ_w decreases, the model generates lower wage gains from job search. This happens because as σ_w decreases, there is a lower chance that an employed worker will receive a higher outside wage offer.

Next, consider estimating a model that relaxes the restriction $\sigma_\xi = 0$. Using only the job transition moments shown in Panel 3 of Table 6, it is impossible to separately identify σ_ε and σ_ξ, because a voluntary job-to-job move to a lower observed wage could be due to either mis-measurement of the wage or unobserved nonwage utility. The key to identifying the full model with nonwage utility is that during estimation, we simultaneously match moments that capture three features of the data. First, we match the amount of variation in wages (Panel 1 of Table 6). Second, we match the frequency and magnitude of wage declines at job transitions (Panel 3 of Table 6). Third, we match the amount of wage growth as reflected in the mean wages from the first, second and third jobs within job cycles (Panel 1 of Table 6), and the coefficients from a reduced form regression of wages on work experience (Panel 4 of Table 6). For the reasons discussed in the previous paragraph, the model without nonwage utility is unable to simultaneously match these three features of the data. However, the full model is able to match these moments. This is the case because in the model with nonwage utility, as the parameter σ_ξ increases from zero, the amount of measurement error needed to explain the frequency of wage declines at voluntary job transitions falls. As a result, σ_w can be relatively large without causing the model to over predict the amount of wage dispersion in the data. As σ_w increases, the model is able to match the amount of wage growth, the extent of variation in wages, and the frequency of wage declines at job transitions found in the NLSY97 data.

Table 2
Parameter Estimates

Parameter	Notation	Specifications	
		1	2
Standard deviation of wage offers	σ_w	0.3435	0.2691
		(0.0083)	(0.0044)
Standard deviation of nonwage match	σ_ξ	0.3908	0.0000
		(0.0122)	(—)
Standard deviation of measurement error	σ_ε	0.1672	0.2955
		(0.0385)	(0.0153)
Type 1			
Mean wage	$\mu(1)$	1.1774	1.1689
		(0.0252)	(0.0191)
Unemployment utility	$b(1)$	1.7982	1.9879
		(0.0212)	(0.0310)
Reservation utility[a]	$U^*(1)$	1.8163	1.3150
		(0.0205)	(0.0116)
Pr(offer while unemployed)	$\lambda_u(1)$	0.9198	0.3716
		(0.0772)	(0.0391)
Pr(layoff)	$\lambda_l(1)$	0.0905	0.4523
		(0.0671)	(0.0369)
Pr(offer while employed)	$\lambda_e(1)$	0.4214	0.4560
		(0.0663)	(0.0286)
Pr(offer and layoff)	$\lambda_{le}(1)$	0.2545	0.0916
		(0.0463)	(0.0248)
Type 2			
Mean wage	$\mu(2)$	1.7252	1.6776
		(0.0151)	(0.0096)
Unemployment utility	$b(2)$	1.8370	1.7487
		(0.0387)	(0.0233)
Reservation utility[a]	$U^*(2)$	1.8948	1.7508
		(0.0196)	(0.0088)
Pr(offer while unemployed)	$\lambda_u(2)$	0.6299	0.5656
		(0.0523)	(0.0568)
Pr(layoff)	$\lambda_l(2)$	0.0529	0.0533
		(0.0061)	(0.0072)
Pr(offer while employed)	$\lambda_e(2)$	0.5348	0.5349
		(0.0190)	(0.0190)
Pr(offer and layoff)	$\lambda_{le}(2)$	0.0214	0.0256
		(0.0028)	(0.0031)

(*continued*)

Table 2 (*continued*)

Parameter	Notation	Specifications 1	Specifications 2
Type 3			
Mean wage	$\mu(3)$	2.1766	1.8184
		(0.0390)	(0.0093)
Unemployment utility	$b(3)$	1.3484	1.3291
		(0.2462)	(0.0118)
Reservation utility[a]	$U^*(3)$	1.9869	2.1224
		(0.1039)	(0.0111)
Pr(offer while unemployed)	$\lambda_u(3)$	0.1421	0.7747
		(0.0106)	(0.0715)
Pr(layoff)	$\lambda_l(3)$	0.0345	0.0306
		(0.0045)	(0.0055)
Pr(offer while employed)	$\lambda_e(3)$	0.0365	0.2651
		(0.0115)	(0.0428)
Pr(offer and layoff)	$\lambda_{le}(3)$	0.0016	0.0144
		(0.0010)	(0.0045)
Type Probabilities			
Pr(type 1)	π_1	0.1414	0.1182
		(0.0113)	(0.0112)
Pr(type 2)	π_2	0.4989	0.4274
		(0.0368)	(0.0279)
Pr(type 3)	π_3	0.3598	0.4544
		(0.0370)	(0.0244)

Notes: Bootstrapped standard errors in parentheses.
a. The reservation utility levels are computed by solving Equation 8 at the estimated parameters.

2. *Mean transition parameters and unemployment utility flow*

Before considering identification of the mean and covariance matrix of the distribution of person-specific unobserved heterogeneity, we first discuss how the across-type means of the parameters $\{b(j),\lambda_u(j),\lambda_l(j),\lambda_e(j),\lambda_{le}(j)\}_{j=1}^{J}$ are identified.

The layoff rate, λ_l, is identified by the empirical transition rate from employment into unemployment (moment 11 in Table 6). The job offer arrival rate, λ_e, is identified by moments that describe job-to-job transitions.[31] Within the model, the probability of a job-to-job transition for a worker employed in a job with utility U is $\lambda_e Pr(U' > U)$. Taking the parametric distribution $H(U)$ as given, λ_e is identified by moments that

31. We follow the search literature in assuming that job-to-job mobility is restricted by randomness in offer arrivals, but there is no direct monetary or non-monetary job switching cost.

describe the frequency of job-to-job transitions, such as the empirical job-to-job transition rate (moment 12).[32]

An important distinction between this paper and the existing literature is that we allow for three possible explanations for observed wage declines at direct job-to-job transitions. The possible explanations are measurement error in wages, involuntary job endings that occur at the same time as outside job offers, and nonwage utility. To the best of our knowledge, this is the first paper to build a model that incorporates all of these explanations, and estimates the model to quantify the importance of each.[33] The most straightforward of these three possible explanations from the perspective of identification is involuntary job endings that occur at the same time as outside job offers. The probability that this event occurs is represented in the model by the parameter λ_{le}. As discussed in Section III, we use data from the NLSY97 on the reason that jobs end to distinguish between voluntary and involuntary direct transitions between employers. If an individual reports that a job ends involuntarily, and he moves to a new job without experiencing an intervening spell of unemployment, then a simultaneous exogenous job ending and accepted outside offer has occurred. The probability that this type of transition occurs is $\lambda_{le}Pr(U' > U^*)$. Taking $H(U)$ and U^* as given, the fraction of direct job-to-job transitions in the data that are involuntary (moment 33) identifies λ_{le}.

To see the importance of accounting for involuntary transitions between employers during estimation, note that within the structure of the model, a voluntary transition to a lower wage job can only be explained by measurement error or nonwage utility. In contrast, if a job exogenously ends and a new offer is received, a worker could move to a job that offers lower utility than his previous job because it is preferable to unemployment. More concretely, suppose that a job-paying wage w exogenously ends, and the worker simultaneously receives a new outside job offer (w',ξ'), where $w' < w$. The worker will accept a wage decrease equal to $(w' - w)$ instead of becoming unemployed if $U(w',\xi') > U^*$. If the presence of involuntary transitions in the data was ignored during estimation, it would force the model to account for all negative wage changes at job transitions in the data with either measurement error in wages or nonwage utility.

It remains to discuss identification of the utility flow from unemployment, b, and the arrival rate of job offers for the unemployed, λ_u. The reservation utility (as derived in Appendix 1) for the unemployed is defined by the following equation,

$$(8)\quad U^* = b + \delta[\lambda_u - (\lambda_e + \lambda_{le})]\int_{U^*}^{\infty} \frac{1 - H(U')}{(1-\delta) + \delta\{\lambda_e[1 - H(U')] + \lambda_l + \lambda_{le}\}}dU',$$

and the transition rate out of unemployment is $\lambda_u Pr(U' > U^*)$. Note that U^* is not a primitive of the model—it is determined by optimal job search behavior. During estimation, we fix the monthly discount rate to $\delta = 0.998$. It is clear from Equation 8 that both λ_u and b will impact the unemployment durations generated by the model.

32. As discussed in French and Taber (2011), non-parametric identification of λ_e requires exclusion restrictions in the form of observable variables that affect λ_e but do not affect $\Pr(U' > U)$. In our model and with these data, there are no obvious candidates for exclusion restrictions. Unfortunately, information on rejected job offers, which would provide direct information about λ_e, is not available in the NLSY97.

33. Flinn (2002) allows for measurement error in wages, Wolpin (1992) allows for both measurement error in wages and simultaneous exogenous job endings and outside job offers, and Bonhomme and Jolivet (2009) allow for simultaneous job endings and job offers in a search model where specific nonwage job characteristics enter the utility function.

To see how these parameters are separately identified, it is useful to consider a simple thought experiment. Suppose that unemployment durations in the data are very long. There are two possible explanations for this within the context of the model. In the first explanation, both b and λ_u are very high, so workers remain unemployed because they receive a lot of job offers but choose to reject many offers because they place a high value on leisure. In the second explanation, both b and λ_u are very low, so workers remain unemployed because job offers are rare. The key to distinguishing between these two explanations is that they have different implications for job mobility. In the first explanation, only very good job offers are accepted by the unemployed, so initial jobs will tend to last for a long time. In the second explanation, the value of initial jobs will be lower, so workers will more frequently move to better jobs. Based on this intuition, in addition to matching features of the unemployment duration distribution during estimation (Moments 10, 18–20), we also match the mean employment duration of the first job in an employment cycle (Panel 1 of Table 6).

3. *Identifying the distribution of unobserved heterogeneity*

The final group of moments shown in Panel 5 of Table 6 identifies the distribution of person-specific heterogeneity in the model. In many cases, the intuition behind identification of these parameters closely parallels simpler panel data models of wages and employment durations. For example, the within-person covariance in wages (Moment 46) helps identify the person-specific component of wages, just as it would in a simpler panel data model of wages. When there is no heterogeneity in μ_w across people, the model generates a within-person covariance of zero between wages on employers that are separated by unemployment spells.

We have already discussed identification of the mean of the unobserved heterogeneity terms $\{\mu_w(j), b(j), \lambda_u(j), \lambda_l(j), \lambda_e(j), \lambda_{le}(j)\}_{j=1}^{J}$. It remains to discuss identification of the variance-covariance matrix of this distribution. Throughout this discussion, we take as given that the discrete distribution of unobserved heterogeneity has three points of support. As a result of this assumption, all variance-covariance terms (and means) are functions of the type-specific parameters and type probabilities. For example, the covariance between the mean wage offer and the layoff rate is $cov(\mu_w, \lambda_l) = \sum_{j=1}^{3} \pi_j \mu_w(j) \lambda_l(j) - [\sum_{j=1}^{3} \pi_j \mu_w(j)][\sum_{j=1}^{3} \pi_j \lambda_l(j)]$.

In general, the variance-covariance terms are identified by moments that summarize across-person variation in observable variables, and covariances between these variables. More specifically, each entry in Table 7, which is located in Appendix 2, lists the moments that identify each term in the covariance matrix, where the moment numbers refer to Table 6. Diagonal elements refer to variances, and off-diagonal elements refer to covariances. For example, entry (6,6) of this table indicates that $var(\lambda_l)$ is identified by across-person standard deviation in the fraction of the career spent unemployed (Moment 39), the standard deviation of the number of firms per employment cycle (Moment 42), and the across-person standard deviation of the total number of transitions into unemployment (moment 45). The intuition behind how these moments identify $var(\lambda_l)$ is fairly straightforward. If there is a large amount of variation in layoff rates (λ_l) across types, then this will be reflected in moments that summarize across-person variation in time spent unemployed (Moment 39), number of firms worked for over the career (Moment 42), and transitions into unemployment (Moment 45).

As an example of how the covariance terms are identified, consider entry (3,1) of Table 7. This entry indicates that $cov(\lambda_u,\mu_w)$ is identified by the covariance between the unemployment duration and the wage on the first job after unemployment (Moment 47), and the covariance between a person's average wage over the career and the fraction of his career spent unemployed (Moment 49). Similarly, entry (5,4) of this table shows that $cov(\lambda_{le},\lambda_e)$ is identified by the covariance between the number of voluntary and involuntary job-to-job transitions that workers make over their career. The intuition is that if this empirical moment is positive, it indicates that workers who make a large number of voluntary job transitions also tend to make a large number of involuntary transitions. Within the model, these types of mobility will be positively correlated if $cov(\lambda_{le},\lambda_e)$ is positive.

In the interest of brevity, we omit further discussion of identification of the covariance matrix because the intuition behind identification of the remaining parameters closely follows the three preceding examples.

4. Heterogeneous transition parameters vs. correlation between w *and* ξ

Our model assumes that the wage and nonwage components of job offers are uncorrelated, however, arguments can be made in favor of either positive (health insurance) or negative (risk of injury or death) correlation between w and ξ. Moments that might identify this correlation include ones that capture the relationship between wages, and voluntary job-to-job moves and job/employment durations. For example, if wage and nonwage utility offers are positively correlated then the relationship between current wages and the frequency of voluntary job-to-job moves is steeper than when they are negatively correlated. With positive correlation, a person in a high-wage job in all likelihood also has a high ξ and is less likely to move to another job voluntarily. By the converse argument, a person in a low-wage job likely also has a low ξ and job offers are likely to dominate their current job so that the worker is more likely to move to another job voluntarily.

However, because differences across individuals in expected wage offers, the value of nonemployment, and transition parameters affect these moments similarly, it is difficult to separately identify a correlation between wage and nonwage utility offers from across-person variation in $\{\mu_w(j),b(j),\lambda_u(j),\lambda_l(j),\lambda_e(j),\lambda_{le}(j)\}_{j=1}^{J}$. Indeed, we were unable to estimate a model with both heterogeneity in transition parameters and correlation between w and ξ.

In order to understand this feature of the model, consider a simple example where there are two types of workers who differ in both mean wage offers and job offer arrival rates while employed.[34] Suppose that type 1 workers have a low mean wage offer, $\mu_w(1)$, and a high job offer rate $\lambda_e(1)$. In contrast, type 2 workers have a high $\mu_w(2)$, and a low $\lambda_e(2)$. In this example, high-wage workers will tend to make fewer job-to-job transitions than low-wage workers, so wages and job-to-job mobility will be negatively correlated, just as they would be in a world where offers of w and ξ were

34. Although this example focuses on across person differences in λ_e and μ_w, it is important to keep in mind that similar examples could be constructed with the parameters b, λ_l and λ_{le}, because they also affect job-to-job moves and job and employment durations.

positively correlated.[35] This example provides just one illustration of how across-person variation in $\{\mu_w(j), b(j), \lambda_u(j), \lambda_l(j), \lambda_e(j), \lambda_{le}(j)\}_{j=1}^{J}$ can be observationally equivalent to correlation between w and ξ. Because there is no obvious reason to prefer one specification over the other, we maintain the assumption of independence between w and ξ job offers throughout the paper.[36]

V. Empirical Results

This section discusses the estimated structural model. It begins with a discussion of the estimated parameters and their impact on labor market outcomes. Next, we discuss the ability of the estimated model to fit the data. Finally, we consider implications of our model for the estimation of compensating wage differentials.

A. Parameter estimates

This section presents the estimation results based on the theoretical model discussed in Section II and the econometric methodology described in Section IV. The estimated parameters for two specifications of the model are given in Table 2. In both specifications, we allow for unobserved worker heterogeneity. The first and preferred Specification 1 allows for utility from nonwage job characteristics. In the second Specification 2, workers are wage maximizers so that nonwage job characteristics are unimportant to workers' job choice and mobility decisions. There are two key results that are worth highlighting.

First, the estimate of the standard deviation of measurement error in wages for our preferred Specification 1 seems reasonable, in that it falls within the range of estimates found in validation studies. In particular, the estimated standard deviation of measurement error is 0.1672 and for wage offers is 0.3435. Along with the variation in mean wages due to unobserved heterogeneity, these coefficients imply that about 11 percent of the variation in wage offers is due to the presence of measurement error. This fraction is reassuringly within the ranges reported in the validation studies surveyed by Bound, Brown, and Mathiowetz (2001). On the other hand, when the model is estimated under the restriction that $\sigma_\xi = 0$ (Table 2, Specification 2), the estimated standard deviation of measurement error nearly doubles, so measurement error accounts for fully one-third of the variation in wage offers. More importantly, as alluded to in our discussion of identification (Section IV.D), without modeling utility from nonwage job characteristics, the higher relative importance of measurement error depresses the estimated standard deviation in wage offers from 0.3435 to 0.2691. Taken together, these two specifications of the model clearly demonstrate that empirical search models that ignore nonwage utility will provide an upward-biased estimate of the extent of measurement error in wages, and will also provide a downward biased estimate of the amount of variation in the wage offer distribution.

35. Our parameter estimates are consistent with this hypothetical example: Table 2 shows that the type with the highest mean wage offer has the lowest job offer arrival rate while employed

36. Although beyond the scope of this paper, matched worker-firm data could provide additional information that would allow for the separate identification of a correlation term.

Table 3
Steady State Cross Section of Simulated Wages and Utility by Employer

		Specification	
		1	2
Employer 1	Mean wage	2.13	2.10
	Mean utility	2.42	2.10
Employer 2	Mean wage	2.17	2.16
	Mean percent change in wage	10.0%	8.7%
	Mean utility	2.59	2.16
	Mean percent change in utility	17.0%	8.7%
	mean($\Delta\xi$)/mean(Δutility)	0.56	0.00
Employer 3	Mean wage	2.17	2.18
	Mean percent change in wage	8.5%	7.7%
	Mean utility	2.67	2.18
	Mean percent change in utility	13.5%	7.7%
	mean($\Delta\xi$)/mean(Δutility)	0.57	0.00
All employers	Mean wage	2.14	2.13
	Mean percent change in wage	9.4%	8.3%
	Mean utility	2.50	2.13
	Mean percent change in utility	15.6%	8.3%
	mean($\Delta\xi$)/mean(Δutility)	0.56	0.00

Notes: Specifications 1 and 2 refer to the estimates in Table 2.

The implications of adding nonwage utility to the standard on-the-job search model are made even more apparent by comparing simulated data from Specifications 1 and 2 of the model. Table 3 presents mean wages and utility, and percent changes in wages and utility, by employer number within a job cycle. These simulated data are obtained by simulating careers for five million artificial agents over a 3,000 month time horizon. A comparison of the mean wage changes between Columns 1 and 2 of Table 3 demonstrates that the compressed wage offer distribution in the model that ignores nonwage utility generates lower wage growth from job mobility. Notice that between employers 1 and 2, between employers 2 and 3, and over all voluntary transitions, the mean percentage increases in wages are 10.0, 8.5, and 9.4 for our preferred Specification 1. But for Specification 2, where the estimated wage offer distribution has been compressed by the assumption that $\sigma_\xi = 0$, the mean percentage increases are only 8.7, 7.7, and 8.3. That is, the compressed wage offer distribution results in lower wage growth due to mobility.

Second, and perhaps more importantly from our perspective, utility from nonwage job characteristics is a very important factor as workers evaluate job offers. In particular, Table 2 shows that the variation in the utility from the nonwage match is slightly larger than the variation in the wage offer distribution (0.3908 vs. 0.3435). As a result, the standard deviation of the total utility of a job offer is 0.5203. This is nearly twice the standard deviation of total utility (the log-wage) of 0.2691 when nonwage utility is omitted from the model. These results imply that the standard on-the-job search model underestimates the gains from mobility in two ways. First, as pointed out in the prior paragraph, in the absence of nonwage utility, estimated measurement error must rise and consequently, the estimated variation in wage offers must fall. As a result, wage growth from job-to-job transitions will also be depressed. Second, ignoring nonwage utility misses an important component of job-to-job utility increases. The first column of Table 3 shows that, on average, the mean percentage increases in total utility between employers 1 and 2, 2 and 3, and over all voluntary transitions are 17.0, 13.5, and 15.6. Quantitatively, mobility to higher nonwage matches is an important component of the total gains to workers from job mobility: increases in ξ account for 56 percent of the total gains in utility (mean($\Delta\xi$)/mean(ΔU)) at the first transition between employers, 57 percent of the total gains at the second transition, and 56 percent of the total gains across all transitions. In aggregate, the benefits to workers from job mobility are considerably understated by models that ignore nonwage utility.

As discussed in the previous paragraph, differences in the simulated data between Specifications 1 and 2 arise from two sources. First, a direct effect from eliminating nonwage utility, and second, an indirect effect from changes in other estimated parameters (such as the wage offer distribution) caused by estimating the model under the restriction that $\sigma_\xi = 0$. To isolate the direct effect of nonwage utility on workers, we simulate a counterfactual data set that uses the parameter estimates from Specification 1, but imposes the condition that workers do not search over nonwage job characteristics by setting $\sigma_\xi = 0$. Summary statistics for this counterfactual experiment are shown in Table 4.

The counterfactual experiment demonstrates that even with our preferred estimate of the wage offer distribution from Specification 1, eliminating nonwage utility affects workers' optimal search strategies. In particular, if workers do not search over nonwage job characteristics, they have less flexibility in the choice over job offers and as a result, are optimally more selective (U^* increases). Also, in the baseline model workers are willing to accept low-wage job offers that offer high nonwage utility, but in the counterfactual model they are not able to make this tradeoff. Both of these effects increase the counterfactual mean steady-state log-wage relative to the baseline specification (2.31 vs. 2.14).

Despite the fact that the mean log-wage rises by nearly 8 percent when there is no variation in nonwage utility, the average discounted sum of log-wages over the career only rises by 2.4 percent in the counterfactual model. This happens because without the consideration of nonwage job characteristics, workers do not take poorly paid jobs, so the rate of employment actually falls from 0.68 to 0.65. That is, the presence of nonwage job characteristics provides workers with greater flexibility in the selection of jobs, resulting in less time spent unemployed.

Table 4 also shows the discounted expected value of lifetime utility in the baseline and counterfactual simulated labor markets. The average discounted expected value of lifetime utility is an estimate of the value function, and can be used to quantify the welfare impact of search over nonwage utility. On average, the mean discounted sum of lifetime utility when workers can search over nonwage job characteristics is 289.9

Table 4
Career and Steady State Outcomes: Baseline vs. Counterfactual ($\sigma_\xi = 0$) Simulations

	Notation	Model Specification: Baseline	Model Specification: Counterfactual	Percent change
Mean discounted sums over career				
Log-wages	$\Sigma_{t=0}^{T}\delta^t w_t/N$	189.9	194.4	+2.4%
Employment utility	$\Sigma_{t=0}^{T}\delta^t (w_t+\xi_t)/N$	221.2	194.4	−12.1%
Lifetime utility	$\Sigma_{t=0}^{T}\delta^t (U_t)/N$	289.9	273.9	−5.5%
Steady state summary statistics				
Mean wage		2.14	2.31	
Employment utility		2.50	2.31	
Employment rate		0.68	0.65	

Notes: Baseline simulation uses the estimates from Specification 1. Counterfactual simulation uses the estimates from Specification 1, but imposes $\sigma_\xi = 0$.

whereas when workers only search over wages, mean lifetime utility is 273.9. This difference of 16.0 “utils” implies that an average worker living in our counterfactual world could be made just as well off as an average worker from Specification 1 with an additional weekly payment of $41.30 (assuming a 40-hour work week). With a mean steady-state wage of about $8.50 or weekly earnings of about $340, $41.30 amounts to 12 percent of a typical worker’s weekly earnings. In other words, the average worker is willing to sacrifice 12 percent of his earnings to retain the option value of searching over nonwage job characteristics.

Unobserved worker heterogeneity is also an important consideration in estimating our model. However, its primary importance for our purposes is as a control so that we obtain unbiased estimates of the parameters of primary interest. Nevertheless, it is worth discussing the parameter estimates that capture unobserved worker heterogeneity because the estimates provide evidence of substantial unobserved differences across workers. Since it is sometimes difficult to see how differences in these primitive parameters across types translate into labor market outcomes, Table 5 summarizes outcomes in the simulated data conditional on type. This table also shows the discounted expected value of lifetime utility for each type. Although we do not directly compute the value function during estimation, it is straightforward to approximate the value function using the average discounted lifetime utility realized in a large number of simulated careers generated by the model.[37]

Unobserved heterogeneity across workers has a large effect on labor market outcomes. Type 1 workers have the shortest average employment duration, the second longest average unemployment duration, and by far the lowest average log-wage.

37. The value function estimates are based on 5,000,000 simulated individuals over 3,000 months.

Table 5
Mean Outcomes by Type in Simulated Data

	Type 1	Type 2	Type 3	All Types
Employment duration	3.16	15.06	28.56	19.60
Unemployment duration	9.91	4.27	10.94	8.28
Log-Wage	1.57	2.05	2.35	2.14
Utility (while employed)	2.08	2.48	2.58	2.50
Discounted expected value of lifetime utility	242.13	303.15	290.26	289.89
Proportion	0.14	0.50	0.36	1.00

Notes: Durations in months.

Type 3s have by far the longest average employment duration of nearly 29 months, but also experience the longest mean unemployment duration because they have the lowest unemployed job offer probability. Type 3s on average receive a log-wage that is about 50 percent larger that of Type 1s, and is about 15 percent larger than that of a Type 2 worker. The differences in parameter values across types translate into moderate differences in the expected discounted value of lifetime utility. The discounted expected value of lifetime utilities for Type 2 and 3 workers are fairly similar and are 20–25 percent higher than the discounted expected value of lifetime utility for the frequently unemployed, low-wage, Type 1 workers.

B. Model fit

It is also interesting to note that the model does a good job fitting the data. Table 6 shows the moments from the NLSY97 data used to estimate the model along with the simulated moments generated by the parameter estimates shown in Table 2 for Specification 1 of the model. Overall, the fit of the model to these moments is very good. Because there are a large number of moments in the table, this section will discuss only a small subset of moments that seem particularly relevant. In particular, Panel 1 shows that the model captures the upward trend in average wages and employment durations as individuals move between employers within employment cycles. The model matches the standard deviation of wages for the first job in a cycle quite closely, although the model tends to under predict wage dispersion at subsequent jobs.

The model also does a good job matching the transition and duration moments shown in Panels 2 and 3 of Table 6. In particular, the model closely tracks patterns in mean wage changes in the NLSY97 data. Importantly, given the focus of the paper, the model predicts that 39.8 percent of job-to-job transitions will involve a wage decrease while 36.4 percent of job-to-job transitions in the NLSY97 data have this feature. Panel 4 of Table 6 shows that the model slightly under-predicts the reduced form wage-experience profile, which is perhaps not surprising because the search model does not allow for wage growth due to human capital. Finally, the model is in general successful in fitting the within person covariance moments which are generated by unobserved heterogeneity, and in fitting the across-person moments shown in Panel 5 of Table 6.

C. Implications for compensating wage differentials

The empirical literature on compensating wage differentials often yields mixed results. For example, Brown (1980) showed that even controlling for individual characteristics, hedonic estimates are "often wrong signed or insignificant." In this section, we provide a brief discussion of this topic to illustrate the implications of incorporating nonwage job characteristics into a search model to standard, static hedonic estimates of compensating wage differentials. In Sullivan and To (2012), we discuss in detail how and why a variety of labor market frictions can yield biased compensating wage differential estimates when nonwage job characteristics are an important factor in job choice.

Broadly speaking, a bias arises because optimal search behavior by workers implies that all accepted job offers are truncated from below. Since total utility for employed workers is typically greater than their reservation utility level, observed job choices do not directly reveal the willingness to pay for nonwage job characteristics.[38] Given our additively separable utility function, $U = w + \xi$, the known tradeoff between log-wages and nonwage utility is one-to-one so that in a frictionless labor market, the marginal-willingness-to-pay is -1. Although our simulated data set reveals a tradeoff between wages and nonwage job characteristics, the fact that most jobs offer total utility strictly above the reservation level biases willingness-to-pay estimates toward zero. Indeed, estimating a traditional hedonic regression of simulated log-wages on ξ yields a slope coefficient of only -0.49. Search frictions result in a severely attenuated compensating wage differential estimate.

In general, when search frictions are an important feature of the labor market, compensating wage differential estimates will be biased. This is similar to the findings of Bonhomme and Jolivet (2009), who estimate a model with several nonwage job characteristics. They find strong preferences for amenities but little evidence of compensating differentials in their simulated data. Our aggregate approach with choice over just two dimensions clearly illustrates the primary reason that search frictions result in biased compensating wage differential estimates. In our model, biased compensating wage differential estimates arise because search frictions imply that acceptable jobs typically provide utility greater than the reservation level. This explanation differs from that of Hwang, Mortensen, and Reed (1998), who show that compensating wage differential estimates are biased because in equilibrium, total job valuation is correlated with the amenity level.

VI. Concluding Remarks

This paper develops and estimates an on-the-job search model that allows workers to search across jobs based on both wages and job-specific nonwage utility flows. Estimating the model provides a direct test of the widespread assumption that workers act as pure income maximizers. We estimate the structural model by simulated minimum distance using the NLSY97. The importance of nonwage utility is revealed through voluntary job-to-job moves, wage changes at transitions, and job

38. Indeed, with a continuous wage offer distribution, it must be the case that acceptable job offers almost always yield utility greater than the reservation level.

durations. Measurement error in wages is separately identified from nonwage utility because incorrectly attributing events not explained by observed wages to measurement error compresses the estimated wage offer distribution and as a result, causes the model to generate too little wage growth relative to the data.

The empirical results show that workers place a substantial value on nonwage job characteristics. When searching for a job, workers face slightly more dispersion in nonwage utility matches than in wage offers. Furthermore, utility from nonwage job characteristics accounts for more than half of the total gains to workers from job mobility. Standard income maximizing models of on-the-job search, which are frequently used to quantify the gains to mobility, are missing a sizable fraction of the gains from search.

Our model also provides a framework for understanding the difficulty that economists have had in estimating compensating wage differentials. In a frictionless competitive labor market, equally able workers must receive the same total compensation and the estimated wage differential for a job attribute will equal the workers' willingness-to-pay for that attribute. In contrast, in a labor market with search frictions, total utility will in general exceed a worker's reservation utility and different, equally able workers will receive different compensation packages, biasing estimates of compensating wage differentials.

Appendix 1

Derivation of Reservation Utility

The reservation utility level for unemployed agents, U^*, solves $V^e(U) = V^u$. To derive U^*, we must first rearrange Equations 3 and 2 so that common terms can be collected when evaluated at $U = U^*$. Subtracting $\delta V^e(U)$ from both sides of Equation 3:

$$(1-\delta)\, V^e(U) = U + \delta[\lambda_e E\max\{0, V^e(U') - V^e(U)\} + \lambda_l(V^u - V^e(U)) + \lambda_{le} E\max\{V^u - V^e(U), V^e(U') - V^e(U)\}.$$

Evaluating this at $U = U^*$:

$$(9)\quad (1-\delta)V^e(U^*) = U^* + \delta(\lambda_e + \lambda_{le})\int_{U^*}^{\infty}[V^e(U') - V^u]dH(U')$$

Similarly, subtracting δV^u from both sides of Equation 2,

$$(10)\quad (1-\delta)V^u = b + \delta\lambda_u \int_{U^*}^{\infty}[V^e(U') - V^u]dH(U').$$

Evaluating at $U = U^*$, we can equate Equations 9 and 10, integrate by parts and solve to get:

$$U^* = b + \delta[\lambda_u - (\lambda_e + \lambda_{le})]\int_{U^*}^{\infty}\frac{1 - H(U')}{(1-\delta) + \delta\{\lambda_e[1 - H(U')] + \lambda_l + \lambda_{le}\}}dU'.$$

When $\lambda_u > \lambda_e + \lambda_{le}$ (the probability of receiving an offer while unemployed is greater than that when employed), an unemployed worker's reservation wage exceeds the one-period utility flow from unemployment.

Appendix 2

Moments and Identification of Covariance Matrix of Unobserved Heterogeneity

Table 6
Moments of the NLSY97 Data and Simulated Data

Moment Number	Description	Data	Simulated
	Cycle Moments (Panel 1)		
1	Mean log-wage (employer 1)	1.979	1.958
2	Standard deviation of log-wage (employer 1)	0.425	0.421
3	Mean employment spell duration (employer 1)	8.939	8.730
4	Mean log-wage (employer 2)	2.038	2.041
5	Standard deviation of log-wage (employer 2)	0.458	0.384
6	Mean employment spell duration (employer 2)	9.271	9.444
7	Mean log-wage (employer 3)	2.061	2.071
8	Standard deviation of log-wage (employer 3)	0.457	0.346
9	Mean employment spell duration (employer 3)	9.738	9.910

(*continued*)

Table 6 (*continued*)

Moment Number	Description	Data	Simulated
	Transition and Duration Moments (Panel 2)		
10	Mean unemployment spell duration	5.909	5.514
11	Pr(transition into unemployment)	0.047	0.055
12	Pr(job-to-job transition)	0.036	0.039
13	Mean total number of voluntary job-to-job transitions	1.451	1.400
14	Mean total number of involuntary job-to-job transitions	0.257	0.262
15	Mean total number of transitions into unemployment	1.879	1.654
16	Mean number of firms per cycle	1.698	1.708
17	Mean total number of employers over entire career	4.376	4.297
18	Pr(unemployment duration = 1)	0.238	0.320
19	Pr(unemployment duration = 2)	0.170	0.125
20	Pr(unemployment duration = 3)	0.109	0.096
21	Pr(employment duration = 1)	0.142	0.163
22	Pr(employment duration = 2)	0.141	0.136
23	Pr(employment duration = 3)	0.121	0.113
24	Across-person mean fraction of quarters unemployed	0.275	0.290
	Wage Change Moments (Panel 3)		
25	Mean Δw at job-to-job switch	0.081	0.099
26	Mean Δw at job-to-job switch $\vert \Delta w > 0$	0.359	0.393
27	Mean Δw at job-to-job switch $\vert \Delta w < 0$	–0.327	–0.337

28	Pr(wage decrease at job-to-job transition)	0.364	0.398
29	Pr(wage decrease at involuntary job-to-job transition)	0.460	0.518
30	Mean Δw at involuntary job-to-job switch	–0.017	–0.048
31	Mean Δw at involuntary job-to-job switch $\|\Delta w > 0$	0.322	0.340
32	Mean Δw at involuntary job-to-job switch $\|\Delta w < 0$	–0.345	–0.401
33	Fraction of job-to-job transitions that are involuntary	0.151	0.157
	Wage Regression (Panel 4)		
34	Constant	1.931	1.952
35	Experience	0.006	0.003
36	Experience^2/100	–0.002	–0.002
	Variance and Covariance Moments (Panel 5)		
37	Across-person standard deviation of wages	0.313	0.296
38	Across-person standard deviation of unemployment duration	5.900	4.114
39	Across-person standard deviation of fraction of quarters unemployed	0.259	0.250
40	Across-person standard deviation of total number of firms	2.944	2.793
41	Standard deviation of unemployment duration	7.732	6.564
42	Standard deviation of number of firms per cycle	1.151	1.034
43	By person: standard deviation of total number of voluntary job-to-job transitions	1.709	1.658
44	By person: standard deviation of total number of involuntary job-to-job transitions	0.625	0.582
45	By person: standard deviation of total number of transitions into unemployment	1.793	1.647
46	Within-person covariance in wages	0.045	0.059
47	cov(1st wage, 1st unemployment duration)	–0.144	–0.066

(*continued*)

Table 6 (*continued*)

Moment Number	Description	Data	Simulated
48	cov(1st unemployment duration, 1st employment duration)	–1.405	–1.920
49	Within-person cov(average wage, fraction of quarters unemployed)	–0.033	–0.040
50	cov(wage, transition into unemployment)	–0.056	–0.003
51	cov(wage, involuntary job-to-job transition)	0.002	–0.003
52	cov(wage, voluntary job-to-job transition)	–0.014	–0.012
53	cov(wage, employment duration)	0.914	1.165
54	cov(employment duration, voluntary job-to-job transition)	–0.342	–0.529
55	cov(employment duration, involuntary job-to-job transition)	–0.115	–0.084
56	cov(unemployment duration, involuntary job-to-job transition)	–0.108	–0.034
57	cov(unemployment duration, voluntary job-to-job transition)	–0.117	–0.238
58	cov(Δw, Δ employment duration) at voluntary job-to-job switch	0.749	0.203
59	cov(first unemployment duration, dummy for 2nd unemployment spell)	–0.126	–0.072
60	By person: cov(number involuntary job-to-job transitions, number voluntary job-to-job transitions)	0.239	0.234
61	By person: cov(number voluntary transitions, number transitions into unemployment)	0.558	0.480
62	By person: cov(number involuntary transitions, number transitions into unemployment)	0.258	0.219
63	By person: cov(average unemployment duration, number involuntary transitions)	–0.415	–0.307
64	By person: cov(average unemployment duration, number voluntary transitions)	–2.235	–2.533
65	By person: cov(average unemployment duration, number transitions into unemployment)	0.116	–0.054

Notes: Simulated data is generated using the estimated model.

Table 7
Identification of Variance-Covariance Matrix of the Distribution of Unobserved Heterogeneity

		μ_w 1	b 2	λ_u 3	λ_e 4	λ_{le} 5	λ_l 6
1	μ_w	2, 5, 8, 37,46	.	.	.	.	.
2	b	47, 48, 49, 57	37, 38, 39, 40, 41, 42, 43	.	.	.	.
3	λ_u	47, 49	38, 39, 41, 47, 49	41, 38, 39	.	.	.
4	λ_e	52, 53	48, 52, 53, 57, 59, 64	48, 57, 59, 64	40, 42, 43	.	.
5	λ_{le}	50, 51, 53	50, 51, 53, 56, 63	56, 63	60	40, 42, 44, 45	.
6	λ_l	49, 50, 53	48, 49, 50, 53, 65	48, 65	54, 61	55, 62	39, 42, 45

Notes: Entries refer to the moments listed in Table 6 that identify the corresponding variance-covariance terms. For example, entry (3,1) of this table (where 3 refers to the row number and 1 refers to the column number) indicates that cov(λ_u, μ_w) is identified by Moments 47 and 49.

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