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Discussion paper

Explaining the Gender Wage Gap: Estimates from a Dynamic Model of Job Changes and Hours Changes

BY
Kai Liu

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Explaining the Gender Wage Gap: Estimates from a Dynamic Model of Job Changes and Hours Changes

Kai Liu

Norwegian School of Economics *

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Abstract

I address the causes of the gender wage gap with a new dynamic model of wage, hours, and job changes that permits me to decompose the gap into a portion due to gender differences in preferences for part-time work and in constraints. The dynamic model allows the differences in constraints to reflect possible gender differences in job arrival rates, job destruction rates, the mean and variance of the wage offer distribution, and the full-time/part-time wage premium. I find that the differences in preferences explain no more than 5% of the gender gap in hourly wages and 7-20% of the gender gap in weekly wages. The differences in constraints, mainly in the form of differences in the mean offered wages, explain the remaining gender wage gap. Most of the gender differences in employment, hours of work and job turnover can be attributed to the differences in preferences.

JEL: J31, J16, J63

1 Introduction

There is a widely documented gender gap in wages between employed men and women.¹ Isolating how much of this gap is a result of true differences in offered wages faces several challenges. One is that wages differ between full time and part time work, and men and women differ in their hours of work patterns (Blank, 1990). Another is that a different fraction of men and women are employed, which

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¹See Altonji and Blank (1999) for a survey.

leads to a well-known possible selection bias which could differ between men and women. Both of these differences can, however, be a result of offered wage distributions and not just a result of differences in preferences. The goal facing most researchers is how to decompose the observed gender wage gap of employed men and women into differences in preferences and constraints and therefore to isolate the latter from the former. This decomposition is important for policy. If women would have received a higher wage by working full-time but did not choose so due to strong preferences for part-time work, their lower wages reflect outcomes from voluntary choices rather than any malfunctioning of the labor market.

This paper conducts a new decomposition of the gap. The standard static selection model of Heckman (1974) can be used to address the selection-into-employment issue, and a slight modification of that model to allow selection into part-time and full-time work (a three-choice model, along with no-work) can be used to address the selection into part-time and full-time work. However, such a static model does not capture the dynamics of job mobility and movements between part-time and full-time work. Men and women differ not only in cross-sectional fractions in full-time, part-time, and nonemployment but also in their job turnover dynamics: women are more likely to quit jobs for nonemployment and job changes for women are more often involved with changes in hours of work at the same time.² Differences in job turnover behavior can result from differences in preferences, constraints or both.

This paper sets up and estimates a dynamic model of wage, hours, and job changes. The estimated model is used to quantify the relative importance of the preferences for part-time work and various sources of labor market constraints in explaining the gender gap in wages, employment, hours of work and job turnover. The dynamic model allows the differences in constraints to reflect possible gender differences in job arrival rates, job destruction rates, the mean and variance of the wage offer distribution, and the full-time/part-time wage premium. I build and estimate a tractable partial-equilibrium search model with on-the-job search where workers make discrete choices between part-time work and full-time work conditional on firm characteristics, employment, nonemployment and job mobility. Workers are heterogeneous in their preferences for part-time work and are subject to preference shocks. Firms are heterogeneous in their costs of accommodating part-time work (Oi, 1962), which is reflected by a firm-

²See Becker and Lindsay (1994), Altonji and Paxson (1992), Loprest (1992), Sicherman (1996), Keith and McWilliams (1999), Royalty (1998) and Holzer and Lalonde (2000). I provide further evidence in the next section.

specific wage differential between part-time and full-time work. When a worker meets a firm, the worker is informed of two wages: a wage for working full-time and a wage for working part-time for the same job. Therefore, the offered wage distribution consists of two components: the wage distribution for part-time work and the distribution of part-time/full-time wage differential (compensating wage differential), the former of which is allowed to vary by characteristics of the worker. The worker's labor supply decision is similar to the problem studied in the labor supply literature, where the wage depends on the labor supply decision.³ With search frictions, the hours choice becomes worker-firm specific: labor supply decision is determined by the type of the worker, the type of the firm, and the match productivity. As job offers are revealed overtime through off- and on-the-job search, the model predicts a set of transition probabilities governing the dynamics of hours and job changes. The model is estimated by maximum likelihood using the 1996 panel of the Survey of Income and Program Participation (SIPP).

I find that women have a much stronger taste for part-time work. For instance, for workers who are single, high-school educated and without children, the utility cost of full-time work is equivalent to \$17.2 dollars of weekly wages for women and only \$7.7 of weekly wages for men with the same characteristics. The variance of preference shocks is also larger for women. The mean offered wages for part-time work are higher for men than women with the same observed characteristics. Other parameters characterizing the constraints, including the job arrival and destruction rate, the variance of the wage offer distribution and the full-time/part-time wage premium are similar between genders. The mean compensating wage differential is small for both genders, indicating that women are offered lower wages than men regardless of hours of work. I use the model to conduct a counterfactual experiment and find that the differences in preferences explain no more than 5% of the gender gap in hourly wages. The differences in preferences are able to explain 7-20% of the gender gap in weekly wages. Most of the gender gaps in employment, hours of work and job turnover can be attributed to the differences in preferences.

There have been a few papers specifying a behavioral model to explain the gender wage gap. Bowlus (1997) is the first paper which builds a job search model to explain the gender wage gap. She finds that differences in search behavior can explain 20-30% of weekly wage differentials in the US. Recognizing the importance of part-time work among female workers, Bowlus and Grogan (2009) estimated a similar model for each gender and for part-time and full-time workers separately. Their results indicate that the role of search behavior in explaining the gender wage differential varies by hours of work. However, the

³See Moffitt (1984), Lundberg (1985), Altonji and Paxson (1988) and Averett and Hotchkiss (1997).

choice of part-time or full-time work is an endogenous decision which is determined by preference and constraints. Hence, it is important to model workers' selection over jobs and over hours jointly, which is the approach taken in this paper. More recently, Flabbi (2010) estimated the role of taste-based discrimination and Gayle and Golan (2012) consider a model of labor supply, occupational sorting and human capital accumulation with statistical discrimination to explain the declining gender wage gap over time. These papers do not focus on the dynamics of job changes and the effect of preferences for part-time work on the gender gap. Because of the partial-equilibrium framework, one limitation of this paper is that I do not further decompose the differentials in the wage offer distribution into discrimination and productivity differences.

In terms of modeling framework, this paper is close to Dey and Flinn (2005), Bloemen (2008) and Flabbi and Moro (2011). These papers identify workers' preferences for job amenities by estimating models with search frictions. Dey and Flinn (2005) estimates a search model where job offers are characterized by wages and health insurance provision. Bloemen (2008) focuses on the difference between desired hours and offered hours resulting from hours restrictions within jobs. Flabbi and Moro (2011) find that women place a small yet positive value on hours flexibility and the impact of flexibility is substantial on certain labor market outcomes.⁴ These papers ignore the dynamics of job-job transitions and hours changes and do not aim to explain the gender differential. By using a panel data set containing detailed information on jobs, wages and hours changes, this paper identifies the preference for part-time work for both men and women and derive its implications with respect to the gender wage gap.

The rest of the paper proceeds as follows. Section 2 presents descriptive statistics highlighting the gender differential in the dynamics of job mobility and hours changes. Section 3 builds a parsimonious on-the-job search model with endogenous labor supply. Section 4 discusses estimation and identification strategy. Section 5 presents estimation results. Section 6 analyzes the implications to the gender gaps in wages, hours, employment and job turnover. Section 7 concludes.

2 Gender Differences in Job Turnover: Descriptive Statistics

I select a sample of young workers from the 1996 panel of the SIPP. Details of sample selection are left in the Data Appendix. The unit period of analysis is four months (per wave). There are two main

⁴In Flabbi and Moro (2011), due to data limitations, the hours flexibility is equivalent to part-time work in estimation.

advantages of using the SIPP. One is that it has a short recall period, making it an ideal data set to study short-term employment dynamics, which are very common among young workers.⁵ The other advantage is that the SIPP contains a unique job ID for every job an employed worker had through the sample period. It records job specific wages and hours at each interview date (every four months), allowing researchers to obtain the precise wage and hour changes at the time when job transitions take place.

Table 1 presents summary statistics. Women in the sample earn 18% less per hour than men. Close to four-fifth of women are employed and more than 10% of employed women choose to work part-time. In contrast, nearly 95% of men are employed on full-time jobs. In the rest of this section, I present evidence for gender differences in the dynamics of labor market turnover. This paper later concentrates on a model which can explain these differences in job turnover.

1. Women move from employment to nonemployment more often than men. The difference is mainly driven by the higher rate of voluntary exits to nonemployment by women. For both genders, part-time jobs are more likely than full-time jobs to end in nonemployment.

The upper half of Table 2 shows that the transition probability from employment to nonemployment is 0.028 per wave for females, which is over three times than that of men (0.009 per wave). When categorizing the quits by voluntary and involuntary behavior, I find that most of the gender-difference in the probability of quitting to nonemployment can be explained by voluntary behavior.⁶ Female workers voluntarily quit employment at a rate of 0.021 per wave compared with a rate of 0.004 for men. For women, the main reasons for voluntarily exiting to nonemployment are related to family or personal obligations and childcare problems. They account for close to 40% of the total voluntary quits.

The rate of transition to nonemployment is correlated with the type of job the worker has prior to nonemployment: workers of both genders quit to nonemployment much more often from part-time jobs (at the rate of 0.076 per wave for females and 0.034 per wave for males) than from full-time jobs (at 0.02 per wave for females and 0.008 for males).

⁵In the selected sample, if a worker is observed to change jobs in a given calendar year, 19% of them would experience multiple job changes within the same calendar year. This means that job mobility observations at annual frequency understate the extent of job-job transitions by about a fifth. Almost all existing studies on female job mobility use data from the National Longitudinal Survey of Youth, which surveys at annual frequency. The evidence presented in this paper is generally in line with these existing studies. The differences will be highlighted below.

⁶I rely on self-reported reasons for job quits to identify voluntary and involuntary labor market transitions. Involuntary labor market transitions include transitions due to a worker being laid off or fired, slack work and employers going bankrupt or selling the business.

2. *The mean duration of jobs held by male workers is longer than that of female workers. Although the rate of job mobility is similar for both genders, the composition of the job-job transitions is very different. For men, most of the job-job transitions take place between full-time jobs. For women, nearly one quarter of the job-job transitions are between part-time and full-time jobs.*

From the second half of Table 2, we find that the rate of job-job transitions is 0.081 and 0.078 per wave for male and female workers respectively. The difference is very small and is primarily driven by less educated workers. I find that jobs held by men last four months longer on average than jobs held by women.⁷ The difference is significant at the 1% level. Given the fact that women and men make job-job transitions at a similar rate, I conclude that the main reason for the gender difference in job duration lies in the difference in the probability of quitting from employment to nonemployment. Turning to the composition of these transitions, we find that over 85% of the job-job transitions that male workers make are between full-time jobs.⁸ For female workers, transitions between part-time and full-time jobs are quite common: they account for more than one fifth of the total transitions made by women.

3. *Full-time jobs are “better” jobs for both genders: on average, full-time jobs pay a higher hourly wage than part-time jobs and they also last longer than an average part-time job. Job changes from part-time to full-time jobs take place with a large expected wage gain, whereas job changes from full-time to part-time jobs have an expected wage loss.*

Full-time jobs last 50% longer than part-time jobs (last two rows of Table 2). One factor is that part-time jobs are more likely to end in nonemployment (recall from Fact 1). The other factor is that workers quit more often from part-time jobs directly to other jobs. For example, as Table 2 shows, women working part-time switch jobs at a rate of 0.115 per wave compared with 0.072 per wave for full-time female workers. The same relation holds for men.⁹ When examining the wage growth between jobs indexed by their hours of work, we find that the magnitude of wage growth is significantly different for transitions between different jobs (Table 3). The mean wage growth from full-time jobs to part-time jobs is negative (-11.8% for men and -8.9% for women). When moving from part-time jobs to full-time jobs, an average worker would benefit from a sizable wage gain (close to 14.3% for males and 18.5% for females).¹⁰ This evidence suggests that people value part-time work and they desire wage

⁷The job durations here are calculated for completed job spells only (in addition to the sample selection criteria outlined in the Data Appendix).

⁸A full-time job is defined as a job where the worker works for more than 30 hours per week.

⁹See Blank (1998) for similar evidence on the dynamics of part-time jobs from the PSID.

¹⁰Between-job wage growth is defined as changes in log wages between periods t and $t - 1$, conditional on job change

compensations when moving from part-time to full-time jobs.

4. *There is no strong evidence that female and male workers experience differential wage growth within- or between-jobs.*

The middle part of Table 3 shows that within-job wage growth is 1.5% per wave on average, for both men and women. When within-job wage growth is calculated for part-time and full-time jobs separately, again I do not find any significant evidence of gender difference. Although on face value wage changes between jobs seem higher for men, the difference is only significant at the 10% level and becomes insignificant if people aged 35 are excluded from the selected sample.¹¹ When the mean wage growth is calculated between two full-time job, the gender difference remains significant only at the 10% level. In an earlier study, Loprest (1992) provides strong evidence that young women have on average less between-job wage growth than men. However, her definition of wage growth is based on annual wage growth between years with recorded job changes. Annual wage could be a mixture of wages from the new job and wages from the old job. Annual wage can also be contaminated by the total periods of nonemployment within the year. Using the detailed job-specific wage information from the SIPP, I do not find strong evidence for gender differentials in between- and within- wage growth.

5. *Most of the adjustments in hours of work are realized through job changes rather than on-the-job.*

The last two rows in Table 3 show that changes in labor supply are more often associated with job changes. More than one fifth of job changes made by women and more than 10% of job changes made by men end up with changes in hours of work. Hours changes within a job are much less common: they occur at a low probability of less than 5% for both genders. This evidence is consistent with results from other data, which all suggest that there seems to be frictions in hour adjustment within jobs.¹²

3 The Model

I build a simple dynamic model of job search, in which a worker makes labor supply, job mobility and employment decisions jointly. The assumptions of the model are as follows. Both unemployed and employed workers search for job opportunities at no cost. The choice of hours is trichotomous,

taking place in period t . One may question the reliability of the reported hourly wage in the immediate period prior to job change. This result is robust if one defines wage growth as log wage changes between t and $t - 2$.

¹¹Note that, in the selected sample, outliers in wage growth between waves have been dropped. See the Data Appendix for details.

¹²See Altonji and Paxson (1992), Euwals (2001) and Blundell, Brewer, and Francesconi (2008).

ranging from zero hours of work (or unemployment), part-time work to full-time work. There is no separate participation decision. Motivated by the last empirical fact in the previous section, hours of work are assumed worker-firm specific and constant within a job spell. For any given worker, a job offer differs in two dimensions: the value of match and the cost of providing part-time work. Upon receiving an offer, unemployed workers face three choices: work full-time, work part-time, or continue in the unemployment state. Employed workers can exit to nonemployment in two ways, either through layoffs or through voluntary quits following a preference shock. When the employed worker meets another firm, she chooses from full-time work at the new firm, part-time work at the new firm, and working for the current firm under its current working hours arrangement.¹³

An individual i maximizes the expected present value of utility over an infinite horizon. Given a match between firm j and worker i in period t , let us denote the match-specific hours of work by h_{ijt} . Assume that h_{ijt} can take three values, at zero, part-time (h_0) and full-time work (h_1). Let H_{ijt} be an indicator function, where $H_{ijt} = 1$ if the worker works full-time ($h_{ijt} = h_1$) and $H_{ijt} = 0$ if she works part-time ($h_{ijt} = h_0$). h_{ijt} is worker-firm specific and will be determined endogenously by the preference of the worker and the technology of the firm. Period utility during employment, $u(H_{ijt}, y_{ijt}; \alpha_{it})$, is defined over potential labor income from the match y_{ijt} and hour status H_{ijt} . α_{it} is the preference for part-time work that is heterogeneous across workers and evolving stochastically and independently over life. Assume that the marginal utility is increasing in income and decreasing in hours. When the worker is employed, the direct utility function is:

$$u(H_{ijt}, y_{ijt}; \alpha_{it}) = y_{ijt} - \alpha_{it}H_{ijt}, \quad \alpha_{it} > 0 \quad \forall i, t \quad (1)$$

where α can be interpreted as the heterogeneous marginal willingness to pay (MWP) for less working hours. For instance, workers who have a low tolerance for full-time jobs would have a large positive value of α . Throughout the rest of this paper, α_{it} will be referred to as the type of the worker. The utility when the worker is unemployed in period t is given by

$$b(\alpha_{it}) \quad (2)$$

¹³I exclude the possibility that the employer and worker could renegotiate their contract when a worker receives an outside offer (Postel-Vinay and Robin, 2002).

where b is an unspecified function of the worker’s MWP, although one would expect it monotonically increasing in α . The evolution of the MWP in the next period is given by $\alpha_{t+1} \sim B(\alpha'|\alpha_t)$, where $B(\alpha'|\alpha)$ is the conditional probability distribution of next period’s preference given that the current preference is α . Assume that $E(\alpha_{t+1}|\alpha_t) = \alpha_t$, so the worker has rational expectation over the preferences in future periods. Preference shocks, therefore, capture any unobserved permanent deviation in the MWP from the previous period such as a health shock for another member in the household. Allowing for preference shocks rationalizes the voluntary exits to nonemployment which are particularly common among female workers. Given that hours are fixed within jobs, having preference shocks means the contemporaneous hours of work may not be optimal (except for the first period of the job). This would imply additional incentive to change hours of work during job changes.

For the worker i employed by the j th job, her wage rate in period t is given by:

$$\ln(w_{ijt}) = \xi_{ijt}H_{ijt} + a_{ijt} \tag{3}$$

where a_{ijt} is a match-specific wage component and ξ_{ijt} is a match-specific cost of providing part-time work, representing the “price” of part-time job facing the worker. Both a_{ijt} and ξ_{ijt} are assumed constant within a job, hence a_{ijt} is a fixed effect specific to a worker-firm match. We expect the mean of ξ_{ijt} to be positive, reflecting the empirical fact that part-time work typically carries a lower wage rate than full-time work. Fixed costs of hiring and training is one popular explanation for the wage differential (Oi, 1962). While a number of papers in the labor supply literature explore the possibility of an endogenous wage as a function of hours of work¹⁴, the novelty here is that the ξ_{ijt} is heterogeneous across firms. This potentially arises from quasi-fixed labor costs that are different across firms. It is an important parameter of interest, since it is one measure of the constraint facing workers when they choose between part-time and full-time work in the labor market. Therefore, in this framework, each job offer consists of two independent match-specific elements: the cost of providing part-time work (ξ_{ijt}) and the match value (a_{ijt}). I denote the population distribution of ξ and a by $F(\xi)$ and $G(a)$, respectively.¹⁵ Let y_{ijt} be the potential disposable income when the worker is employed with the j th

¹⁴For example, see Moffitt (1984), Fraker and Moffitt (1988) and Averett and Hotchkiss (1997).

¹⁵Hwang, Mortensen, and Reed (1998) show that that it may be optimal for firms to post a higher wage together with job amenity (lower cost for part-time work in our context) since it reduces the expected job turnover in the future. Estimating a search model with hedonic wages when wage posting is allowed is left for future research.

job in period t . Then,¹⁶

$$y_{ijt} = w_{ijt}h_{ijt}, \text{ when } h_{ijt} \in \{h_0, h_1\} \quad (4)$$

Given that wages and hours of work are assumed time-invariant within a worker-firm match, for notational convenience, hereon I drop the time subscript from the notations denoting hours of work and all the parameters in the wage equation. The only place where time subscript is needed is the parameter on the preference for part-time work, where it evolves independently over life.

All individuals begin their lives in the unemployment state. Let $V(\alpha)$ denote the value of nonemployment to a worker of type α .¹⁷ Let $W(H; a, \xi, \alpha)$ be the value of an employment contract between an employee of type α and a type ξ employer with match value a and hour arrangement H . The optimal hour arrangement between the worker-firm match when they meet is determined by

$$\widehat{H}(a, \xi, \alpha) = \arg \max_{H \in \{0,1\}} W(H; a, \xi, \alpha) \quad (5)$$

Given the optimal hour choice \widehat{H} , let us denote the value function of employment between a worker-firm match $\{a, \xi\}$ as $\widehat{W}(a, \xi, \alpha)$. The job offer is acceptable to a worker provided that $\widehat{W}(a, \xi, \alpha)$ is larger than $V(\alpha)$.

The value of nonemployment for the worker is defined as

$$V(\alpha) = b(\alpha) + (1 - \lambda^n)\beta E(V(\alpha')) + \lambda^n \beta E \max[V(\alpha'), \widehat{W}(a', \xi', \alpha')] \quad (6)$$

where λ^n is the probability that an offer arrives in each period, β is the discount factor, and $\widehat{W}(a', \xi', \alpha')$ is the maximized value of employment if a type α' worker is drawn to a job with characteristics (a', ξ') .

When the worker is employed, she receives a new job offer with probability λ^e in every period. She faces a constant and exogenous layoff probability of δ in each period. In the presence of the preference shocks, the worker may also choose to exit employment to nonemployment. The value of employment

¹⁶Given that income and labor supply are linearly additive in the utility function, adding nonlabor income does not affect the choice of hours. Relaxing this assumption to allow for income effects is left for future research.

¹⁷Throughout the rest of this section, I also drop the worker, the firm and the time subscripts. x' is used to denote the state variable in the next period.

at a job (a, ξ) working H hours is given by

$$\begin{aligned}
W(H; a, \xi, \alpha) &= u(H, y; \alpha) + \lambda^e(1 - \delta)\beta E \max[W(H; a, \xi, \alpha'), \widehat{W}(a', \xi', \alpha'), V(\alpha')] \\
&+ (1 - \lambda^e)(1 - \delta)\beta E \max[W(H; a, \xi, \alpha'), V(\alpha')] + \delta\beta E(V(\alpha'))
\end{aligned} \tag{7}$$

The model implies a set of interesting results concerning the decision rules of job mobility and labor supply decisions. The first result is that, given a worker-employer match, the choice of match-specific hours is made simply by comparing the period utility from part-time and from full-time work. That is,

$$\widehat{H}(a, \xi, \alpha) = \arg \max_{H=\{0,1\}} u(H, y; \alpha) \tag{8}$$

This result builds on two assumptions. First, the evolution of α is exogenous and independent from other state variables in the model. Second, people have rational expectations over the future α 's. Since wages are stationary within a job, workers also have rational expectations over the future value of the job at the time they decide whether to accept the job offer (i.e. current utility from the job is a perfect predictor for expected utility from the job in the future). Therefore, conditioning on the current job offer and preference, the labor supply decision can be rephrased into a static model. Dynamic changes in hours of work may occur when the worker receives an outside job offer or a permanent shock to his preference.

The second result is that the employment decision (or the choice of zero hour) can be characterized by a unique reservation utility level $\bar{u}(\alpha)$ given by

$$\bar{u}(\alpha) = b(\alpha) + \mu(\lambda^n, \lambda^e, \delta, \alpha, B, G, F) \tag{9}$$

where the function μ is the gain from unemployment search. Job offers with a period utility level above $\bar{u}(\alpha)$ are accepted, and jobs offering period utility less than $\bar{u}(\alpha)$ are rejected. This result is a generalization from the reservation wage implied by a standard on-the-job search model with income-maximizing agents.¹⁸

¹⁸See Bloemen (2008) for derivations of an analytical expression of the reservation utility in a similar context but without on-the-job search. The approach here is to estimate the μ function nonparametrically (see Section 4.1 for details).

Given a specific worker-firm match, utility maximization leads to the following labor-supply function:

$$\widehat{h} = 0, \text{ if } \bar{u}(\alpha) > u(1, y; \alpha) \text{ and } \bar{u}(\alpha) > u(0, y; \alpha) \quad (10)$$

$$\widehat{h} = h_0, \text{ if } u(0, y; \alpha) > \bar{u}(\alpha) \text{ and } u(0, y; \alpha) > u(1, y; \alpha) \quad (11)$$

$$\widehat{h} = h_1, \text{ if } u(1, y; \alpha) > \bar{u}(\alpha) \text{ and } u(1, y; \alpha) > u(0, y; \alpha) \quad (12)$$

where \widehat{h} denotes optimal hour choice on a given match. The labor supply function depends on the location of $\bar{u}(\alpha)$, relative to the utility from part-time and from full-time work. Figure 1 draws the cutoff values under two cases of $\bar{u}(\alpha)$, holding everything fixed except for the value of the match. For a type α worker matched to a type ξ firm, if the value of nonemployment is low, then worker would not work if match is less than a_B , work part-time if match value is between a_B and a_A , and work full-time if match value is higher than a_A . However, if the value of nonemployment is high enough, part-time work may never be optimal. In this case, she works full-time as long as the match is above a_C and works at zero hours as long as the match is below a_C . Given that the utility function is monotonically increasing in the value of match, the decision to work can be characterized by a critical match \bar{a}_H that is dependent of the type of firm the individual meets out of nonemployment. Then, given worker's and firm's types and under some mild condition¹⁹, there exists a set of critical values $\{a^*(\xi), \bar{a}_0, \bar{a}_1(\xi)\}$ that spreads out workers into different work hour arrangement:

$$\widehat{h} = 0, \text{ if } a < \min\{\bar{a}_0, \bar{a}_1(\xi)\} \quad (13)$$

$$\widehat{h} = h_0, \text{ if } \bar{a}_0 < a < a^*(\xi) \quad (14)$$

$$\widehat{h} = h_1, \text{ if } a > \max\{a^*(\xi), \bar{a}_1(\xi)\} \quad (15)$$

$$a^*(\xi) = \ln \alpha - \ln(e^\xi h_1 - h_0) \quad (16)$$

$$\bar{a}_0 = \ln(\bar{u}(\alpha)) - \ln h_0 \quad (17)$$

$$\bar{a}_1(\xi) = \ln(\bar{u}(\alpha) + \alpha) - \ln h_1 - \xi \quad (18)$$

Employment Dynamics The labor supply equations are sufficient to analyze employment dynamics. This includes transitions from nonemployment to part-time and to full-time work, and from

¹⁹The condition is $\bar{u}(\alpha) > 0$, which guarantees the existence of critical match value for employment. Otherwise, an unemployed worker would accept any draws of matches from the labor market.

part-time and full-time work to nonemployment. To derive the transition probabilities, I derive the conditions such that part-time work is a feasible choice, conditional on the type of the worker. Conditional on α , part-time work is in the worker's choice set as long as $\bar{a}_0 < \bar{a}_1(\xi)$. This implies that the cost of providing part-time work is not too large:

$$\bar{a}_0 < \bar{a}_1(\xi) \text{ iff } \xi < k_0, \text{ where } k_0 = \ln \frac{h_0}{h_1} + \ln(\bar{u}(\alpha) + \alpha) - \ln(\bar{u}(\alpha)) > \ln \frac{h_0}{h_1} \quad (19)$$

Whenever a firm's cost of providing part-time work exceeds k_0 , a utility maximizing worker of type α would never choose to work part-time, regardless of the match value offered by the firm. The larger the worker's preference for hour is, the higher k_0 is and there would be a larger range of firms at which she would accept part-time work. For a type α worker, the transition probability from nonemployment to part-time work is $\lambda^n \int_{\xi < k_0} [G(a^*(\xi)) - G(\bar{a}_0)] dF(\xi)$. The probability of moving from nonemployment to full-time work is $\lambda^n (\int_{\xi < k_0} \tilde{G}(a^*(\xi)) dF(\xi) + \int_{\xi > k_0} \tilde{G}(\bar{a}_1(\xi)) dF(\xi))$, where $\tilde{G}(x) = 1 - G(x)$. To derive the transition probabilities into nonemployment, I consider only new arrivals of α , holding a and ζ fixed. Provided that there is no external offer, the probability of quitting from part-time work to nonemployment is $p\tilde{B}(\bar{a}^{-1}(a, h_0)|\alpha)$, where $\bar{a}(\bar{a}^{-1}(a, h), h) = a$. Quitting from current full-time work to nonemployment happens with probability $p\tilde{B}(\bar{a}^{-1}(a, h_0)|\alpha)$ if $\xi < k_0$. If $\xi > k_0$, the probability of leaving the current full-time job to nonemployment is $p\tilde{B}(\bar{a}^{-1}(a, h_1)|\alpha)$.

Job Mobility Dynamics The final set of results describes the dynamics of job-job transition. When an employed worker of type α receives an outside job offer (denoted by (a', ξ')), she compares the value of continuing employment with the current firm with the optimal value of working for the alternative employer $(\widehat{W}(a', \xi', \alpha))$. Assuming there is no cost of switching jobs, it is easy to show that this comparison is equivalent to comparing the period utilities between the two firms.²⁰ For a given worker of type α , let $v(a, \xi, \alpha)$ be the indirect utility function after the optimal hour is chosen. I use $u(\widehat{H}(a, \xi, \alpha^0), y; \alpha)$ to denote the period utility from the current employer, where α^0 is the MWP when the current job started and $\widehat{H}(a, \xi, \alpha^0)$ is the optimal hour choice back then (which may no longer be

²⁰The intuition of this result is as follows. For a given worker, any match draw $\{a, \xi\}$ from $G(a)$ and $F(\xi)$ maps to a unique indirect utility, v . There will be a unique distribution of v , $D(v)$, facing the worker in the labor market. We then can transform the state variables a and ξ to v , and the problem becomes a standard partial-equilibrium on-the-job search model where workers search for jobs offering better utilities v (instead of wages alone).

optimal under the present MWP). The job mobility decision becomes:

$$\begin{aligned}
M &= 1 \text{ if } M^* > 0; \quad M = 0 \text{ otherwise} \\
M^* &= v(a', \xi', \alpha) - u(\widehat{H}(a, \xi, \alpha^0), y; \alpha)
\end{aligned} \tag{20}$$

Compared with a standard on-the-job search model (Burdett, 1978), the difference here is that the decision rule for job mobility is generally not just a function of the match values. In addition to the match values, it depends on the type of firm the worker meets, the worker's preference, as well as the worker's predictable component of wages that are common across employers. Provided that the current job is acceptable (i.e., $\hat{h} > 0$), the reservation match values for job mobility to happen are given by

$$a^{\hat{h}, \hat{h}'} = \begin{cases} a + \xi - \xi', & \text{if } \hat{h} = h_1 \text{ and } \hat{h}' = h_1 \\ \ln(e^{a+\xi}h_1 - \alpha) - \ln h_0, & \text{if } \hat{h} = h_1 \text{ and } \hat{h}' = h_0 \\ \ln(e^a h_0 + \alpha) - \ln h_1 - \xi', & \text{if } \hat{h} = h_0 \text{ and } \hat{h}' = h_1 \\ a, & \text{if } \hat{h} = h_0 \text{ and } \hat{h}' = h_0 \end{cases}$$

where job mobility takes place whenever there is an offer such that $a' > a^{\hat{h}, \hat{h}'}$.²¹ Conditional on the type of the worker, when there is a new arrival of a and ξ , the probability that the worker chooses to exit the current job to work full-time on the new job is $\int \tilde{G}(\max\{a^{\hat{h}, h_1}, a^*(\xi')\})dF(\xi')$. The probability of leaving the current job to work part-time on the new job is $\int_{\xi' < a^{*-1}(a^{\hat{h}, h_0})} [G(a^*(\xi')) - G(a^{\hat{h}, h_0})]dF(\xi')$, where $a^{*-1}(a^{\hat{h}, h_0})$ is the cutoff value for the type of the outside firm ξ' such that $a^*(a^{*-1}(a^{\hat{h}, h_0})) = a^{\hat{h}, h_0}$. Intuitively, when a worker meets a firm that makes part-time work very costly relative to her current employer ($\xi' > a^{*-1}(a^{\hat{h}, h_0})$), she would never choose to quit the current job and work part-time on the new job.

²¹Note that if $a' > a^{\hat{h}, \hat{h}'}$, it follows that the indirect utility from the new job must be larger than than her current job, for any type of firm ξ' . Since worker is employed on the current job, this implies that the new job must be above the reservation utility (i.e. $\hat{h}' > 0$).

4 Identification and Estimation

4.1 The Empirical Model

The decision period in the model is four months, corresponding to the interview frequency in the SIPP. Assume that the distribution of firms' costs ($F(\xi)$) is discrete. It takes two values, ξ^1 and ξ^2 , with $0 < \xi^1 < \xi^2$. The probability that the firm is a high-cost type ($P(\xi_{ij} = \xi^2)$) is π . Both workers' preferences and the match-specific wage in every external job offer vary with socioeconomic characteristics. That is,

$$\ln \alpha_{it} = Z_i \theta + \epsilon_{it} \quad (21)$$

$$\epsilon_{it} = \epsilon_{it-1} + \phi_{it} \quad (22)$$

$$a_{ij} = X_i \beta + \eta_{ij} \quad (23)$$

where

$$E(\phi_{it}) = E(\eta_{ij}) = E(\epsilon_{i0}) = 0 \quad (24)$$

and

$$E(\epsilon_{i0}^2) = \sigma_{\epsilon_0}^2, E(\phi_{it}^2) = \sigma_{\phi}^2, E(\eta_{ij}^2) = \sigma_{\eta}^2 \quad (25)$$

$$E(\epsilon_{i0} \eta_{ij}) = E(\phi_{it} \eta_{ij}) = E(\epsilon_{i0} \phi_{it}) = 0 \quad \forall t, E(\phi_{it} \phi_{it-s}) = 0 \quad \forall s < t \quad (26)$$

The unobserved preference of the worker follows a random walk process subject to permanent shock ϕ_{it} in every period. I maintain the standard assumption that the match value of any job offer is independent from the unobserved heterogeneity of the worker ($\sigma_{\phi\eta} = 0$). The marginal distributions of all error terms are assumed normally distributed. The population distribution of worker's type at the beginning of life then follows a log normal distribution $LN(Z_i \theta, \sigma_{\epsilon_0}^2)$. The model is very flexible in that it permits selection from choices of hours, employment and job mobility. Estimating the wage equation alone or estimating the wage equation with any strict subset of the choice equations will be biased. As first noted in Bjorklund and Moffitt (1987) and Heckman and Robb (1985), the heterogeneity in ξ

generates additional selection bias because ξ directly enters both the hour selection equation and the wage equation.

In the dynamic model of search behavior, the decisions of job mobility and hours of work on a given job are essentially static. The only decision that is dependent on expected values in the future is the employment decision, where the reservation utility for employment, $\bar{u}(\alpha)$, is a sum of the period utility from unemployment and the expected gain from unemployment search. From equation (9), I choose to approximate \bar{u} in a reduced form given by

$$\bar{u}(\alpha_t) = b_u + b_w(X_i\beta) + b_\alpha\alpha_t \quad (27)$$

where b_u is a constant, and b_w and b_α estimate the effect of the worker's permanent wage and her preference for leisure respectively on the reservation utility. The coefficients of the covariates are unspecified functions of the structural parameters of the model. In estimation, \bar{u} is estimated in a flexible way without imposing any restriction from the model. $b_\alpha\alpha_t$ captures the person-specific random effects in employment choices that are correlated with the random effects (α_t) in the job mobility and match-specific hour choice equations. If $b_\alpha > 0$, then an increase to the preferences for part-time work leads to an increase in the reservation utility for employment, which raises the quality of employed workers.

The full empirical model consists of the following:

Wage equations :

$$\ln w_{ij} = \xi_{ij} + a_{ij}, \text{ if } h_{ij} = h_1 \quad (28)$$

$$\ln w_{ij} = a_{ij}, \text{ if } h_{ij} = h_0 \quad (29)$$

$$a_{ij} = X_i\beta + \eta_{ij} \quad (30)$$

Ordered probit of match-specific hours:

$$h_{ij} = 0, \text{ if } a_{ij} < \min\{\bar{a}_0, \bar{a}_1(\xi_{ij})\}$$

$$h_{ij} = h_0, \text{ if } \bar{a}_0 < a_{ij} < a^*(\xi_{ij})$$

$$h_{ij} = h_1, \text{ if } a_{ij} > \max\{a^*(\xi_{ij}), \bar{a}_1(\xi_{ij})\}$$

$$a^*(\xi_{ij}) = \ln \alpha_{it} - \ln(e^{\xi_{ij}} h_1 - h_0) \quad (31)$$

$$\bar{a}_0 = \ln(\bar{u}_{it}) - \ln h_0 \quad (32)$$

$$\bar{a}_1(\xi_{ij}) = \ln(\bar{u}_{it} + \alpha_{it}) - \ln h_1 - \xi_{ij} \quad (33)$$

$$\bar{u}_{it} = b_u + b_w(X_i\beta) + b_\alpha\alpha_{it} \quad (34)$$

$$\ln \alpha_{it} = Z_i\theta + \epsilon_{it} \quad (35)$$

$$\epsilon_{it} = \epsilon_{it-1} + \phi_{it} \quad (36)$$

The nonemployment mobility equations:

$$D_{it} = 1, \text{ if } D_{it}^* > 0; D_{it} = 0, \text{ if } D_{it}^* \leq 0$$

$$D_{it}^* = v(a_{ij}, \xi_{ij}, \alpha_{it}) - \bar{u}_{it} = y_{ij} - (b_\alpha + \hat{H}_{ij})\alpha_{it} - b_w(X_i\beta) - b_u \quad (37)$$

where $D_{it} = 1$ when a worker chooses to switch from nonemployment to employment, and $D_{it} = 0$ when the worker voluntarily switches from employment to nonemployment. \hat{H}_{ij} is the match-specific optimal hour choice given by the ordered probit model.

The job mobility equations for an employed worker:

$$M_{it}^{\hat{h}_{ij}, \hat{h}_{ij}} = 1, \text{ if } M_{it}^* \geq 0; M_{it}^{\hat{h}_{ij}, \hat{h}_{ij}} = 0, \text{ if } M_{it}^* < 0$$

$$M_{it}^* = a_{ij'} - a_{it}^{\hat{h}_{ij}, \hat{h}_{ij}} \quad (38)$$

$$a_{it}^{\hat{h}_{ij}, \hat{h}_{ij}} = \begin{cases} a_{ij} + \xi_{ij} - \xi_{ij'}, & \text{if } \hat{h}_{ij} = h_1, \hat{h}_{ij'} = h_1 \\ \ln(e^{a_{ij} + \xi_{ij}} h_1 - e^{Z_i\theta + \epsilon_{it}}) - \ln h_0, & \text{if } \hat{h}_{ij} = h_1, \hat{h}_{ij'} = h_0 \\ \ln(e^{a_{ij}} h_0 + e^{Z_i\theta + \epsilon_{it}}) - \ln h_1 - (\xi_{ij'}), & \text{if } \hat{h}_{ij} = h_0, \hat{h}_{ij'} = h_1 \\ a_{ij}, & \text{if } \hat{h}_{ij} = h_0, \hat{h}_{ij'} = h_0 \end{cases}$$

The empirical model is estimated on the male and female sample separately. Therefore, all parameters in the model are assumed gender specific. Labor market constraints are characterized by the job arrival and destruction rate, the distribution of the offered wage distribution and the distribution of full-time/part-time wage differential. Parameters describing the preference for part-time work include the mean and variance of α_0 and the variance of preference shocks.

4.2 Identification

The panel data set contains detailed information on job-specific hours of work and wages in every period. The unique job ID allows us to trace the job mobility and employment decisions over the entire sample period. To identify the model, apart from nonlinearities and distributional assumptions, we need at least one variable that shifts the worker’s preference Z_i but is not included in X_i in the wage equation. This is the usual exclusion restriction in any selection model. The excluded variables include number of children and marital status, which are assumed exogenous and uncorrelated to the error term in the wage equation.²² Since the wage itself is in the equations of employment and hour choices, we also need one additional variable in the wage equation that is not included in Z_i . I use regional unemployment rate as an additional exclusion restriction.²³

The reservation utility is estimated without imposing any restriction from the model. Each job offer carries an indirect utility, v , after hour choices. Suppose the distribution of indirect utilities for a given worker is $K(v)$. $K(v)$ depends on the distribution of matches and the distribution of types of firms in the labor market. The probability of exiting the nonemployment state is $\lambda_n(1 - K(\bar{u}))$. If we choose to nonparametrically approximate \bar{u} , λ_n is not identified in general. I fix the offer arrival rate per period at 0.7 and estimate \bar{u} . The identification of the initial heterogeneity in the worker’s MWP (ϵ_{i0}) relies on observations from the first period of work life, which is usually not observed in a short panel like the SIPP. The approach is to simulate the model from the beginning of the work life up to the first period of observations, thereby integrating out all the left-censored labor market histories. The following section discusses this approach in detail.

²²In the context of female labor force participation, Hyslop (1999) provides evidence that these variables are exogenous.

²³I rank all the regional unemployment rates. The regional unemployment rate is constructed such that it is equal to one if the regional unemployment rate is above the median and is equal to zero elsewhere.

4.3 Estimation Strategy

The unit of analysis is an “employment cycle”. Following the empirical job search literature, a complete employment cycle begins with an unemployment spell and ends with another unemployment spell (if any) or a right-censored employment spell (Wolpin, 1992; Dey and Flinn, 2005). Because job offers are i.i.d., for a given worker, each cycle is independent of each other.²⁴ The complete likelihood function is then the product of the likelihood of each employment cycle. Each employment spell consists of one or more job spells, in between which the worker makes a direct job-job transition. Formally, an employment cycle c is

$$c = (d, T_1, \tilde{w}_1, \tilde{H}_1, \dots, T_J, \tilde{w}_J, \tilde{H}_J) \quad (39)$$

where d is the duration of unemployment spell. Consistent with notations in the previous section, T_j corresponds to the duration of employment with the j th employer (maximum job tenure) within the cycle, and \tilde{w}_j and \tilde{H}_j correspond to the observed wage and hour status ($h > 0$) with the j th employer. Information regarding wage and hour dynamics within a given job is ignored, so \tilde{w}_j and \tilde{H}_j correspond to the wage and hour observed at the beginning of the j th job spell.²⁵ Assume that the observed wages and hour status are measured with error. The mapping between true wage w_j and observed wage \tilde{w}_j is given by

$$\tilde{w}_j = w_j e^{v_j} \quad (40)$$

where v_j , the measurement error, is assumed i.i.d over j . The reported hour status, \tilde{H}_j , is measured correctly with probability γ . Therefore, $\gamma = P(\tilde{H}_j = 1 | H_j = 1) = P(\tilde{H}_j = 0 | H_j = 0)$. Nonemployment is measured without error.

Workers are heterogeneous with respect to their preferences for hours and for work. Let Ω_t define a worker’s type in period t of the employment cycle, i.e., $\Omega_t = \{Z, X, \epsilon_t\}$. Z and X are observed, and ϵ_t is the unobserved preference of the worker. For a given worker, entry into unemployment essentially resets

²⁴For any unemployed worker, the reservation utility for a job offer is independent from the previous jobs she had. In this sense, entry into the unemployment state essentially restarts the job search process. Note that all workers begin the search process from the unemployment state at the beginning of life.

²⁵Liu (2011) shows that wage variations within jobs (apart from deterministic growth component) contain persistent match-specific shocks. Wages at the beginning of a job spell do not absorb match-specific shocks.

the search process, meaning that previous employment cycles are independent from the job offers once one becomes unemployed. Let Ω contains the entire history of the worker's type over the employment cycle: $\Omega = \{\Omega_t\}_{t=1}^\tau$ where τ denotes the length of the observed employment cycle. Due to the i.i.d assumption on the offer draws, the duration of unemployment spell within a cycle is independent from job spells in the cycle, leading to

$$P(c; \Omega) = P(d; \Omega)P(T_1, \tilde{w}_1, \tilde{H}_1, \dots, T_J, \tilde{w}_J, \tilde{H}_J; \Omega) \quad (41)$$

$P(c; \Omega)$ forms the basis of the likelihood function. Since the wage one is willing to accept depends on the wage and the type of firm of the previous job, job spells within cycles are not independent. I use simulation methods to construct likelihood contributions involving completed or censored job spells. The complete likelihood function consists of products over workers and cycles.

An unemployed worker, with probability λ^n , receives i.i.d draws of a and ξ from $F(\xi)$ and $G(a)$ respectively. Conditional on the worker's type, the probability of becoming employed in every period is given by

$$p(D = 1; \Omega_t) = \pi p(D = 1; \Omega_t, \xi_1 = \xi^2) + (1 - \pi) p(D = 1; \Omega_t, \xi_1 = \xi^1) \quad (42)$$

where

$$p(D = 1; \Omega_t, \xi_1 = \xi) = \begin{cases} \lambda_n \tilde{G}(\bar{a}_0), & \text{if } \xi < k_0 \\ \lambda_n \tilde{G}(\bar{a}_1(\xi)), & \text{if } \xi > k_0 \end{cases} \quad (43)$$

If there is only unemployment spell in the sample, the conditional likelihood function is simply given by

$$L^{(4)}(d | \Omega) = \prod_{t=1}^d (1 - p(D = 1; \Omega_t)) \quad (44)$$

There are two estimation issues. First, to integrate out the unobserved heterogeneity in preferences and calculate the unconditional likelihood, it is necessary to know the distribution of worker's type at the beginning of the employment cycle. This distribution is different from the population distribution

$B(\alpha)$ due to selection: because of the preference shocks, exit to nonemployment itself is endogenous so the distribution of worker's type conditional on being unemployed is different from $B(\alpha)$. Second, since the SIPP is a short panel, it is common that only a part of the employment cycle is observed. A large proportion of workers are employed continuously throughout the sampling period. Dropping these workers incurs large information loss, and since quit to nonemployment is non-random, these workers should be fundamentally different from workers who experience unemployment spells in the data. Including these employed workers means that one needs to predict the distribution of accepted match values and firm types on the first observation date, which is different from the exogenous population distribution of firm types $F(\xi)$ and matches $G(a)$.

To resolve either of these missing-data issues, for every worker in the sample, I simulate R sample paths starting from the beginning of life until the first observation date. If the worker is unemployed on the first observation date, then the state variables contain $\{D_{c(1)}, X_{c(1)}, Z_{c(1)}, \alpha_{c(1)}\}$, where $c(t)$ is a mapping from the observation date t (number of periods in the cycle) to the life-cycle age. $D_{c(1)}$ signifies whether the worker is unemployed at the beginning of the cycle. Since all workers start off their lives unemployed, all the state variables at the beginning of life are exogenous. I simulate draws $\{\alpha_t, \xi_t, a_t\}_{t=1}^{c(1)}$, from the start of life up to period $c(1)$. This set of draws completely determines the evolution of employment status up to period $c(1)$. The simulated α 's at age $c(1)$ conditional on $D_{c(1)} = 0$ form a consistent estimator of the distribution $B(\alpha_{c(1)} | D_{c(1)} = 0)$, which is the distribution we need to evaluate the unconditional likelihood function. If the unemployed worker becomes employed within the same cycle, I simulate the match component of the first job (a_1) by first drawing ζ_1 from a uniform distribution defined on $[0, 1]$. Then, the inverse of the c.d.f function G at $\tilde{\zeta}_1$ produces the simulated (a_1), which is a random draw from a truncated normal distribution $G(a)$ with a lower truncation point \bar{a}_0 if $\xi_1 < k_0$ and $\bar{a}(h_1, \xi_1)$ if $\xi_1 > k_0$.²⁶ Given ξ_1 and a_1 and worker's type in period $d + 1$ (Ω_{d+1}), we can determine the hour status and wage at the beginning of the first job. I use H_1^1 and w_1^1 to refer to the wage and optimal hour arrangement respectively when the first job is a low-cost type. Analogously, let us use H_1^2 and w_1^2 to define the wage and hour arrangement if the job is a high-cost type.

If the worker is employed on the first observation date, the state variables include

$\{D_{c(1)}, X_{c(1)}, Z_{c(1)}, a_{c(1)}, \xi_{c(1)}, \alpha_{c(1)}\}$, where $D_{c(1)} = 1$.²⁷ Similar to the treatment applied to the unem-

²⁶ $\tilde{\zeta}_1 = G(c) + (G(d) - G(c) * \zeta_1)$, where c and d are the desired lower and upper truncation points of G respectively.

²⁷Since we know the starting date of worker's job, I impute the employment cycle to include the elapsed (left-censored)

ployed worker, I simulate the complete employment histories starting from the beginning of life. The distribution of the simulated $(a_{c(1)}, \xi_{c(1)}, \alpha_{c(1)})$'s conditional on $D_{c(1)} = 1$ is a consistent estimator of the joint distribution of $(a_{c(1)}, \xi_{c(1)}, \alpha_{c(1)}) | D_{c(1)} = 1$.

Given the draws from the first job and type of the worker, I now derive the conditional choice probabilities. There are three ways to exit the first job spell. First, she may quit to unemployment involuntarily, which happens with a constant probability δ . Second, she may quit to another employer, either to work full-time or to work part-time. Third, she may quit to unemployment voluntarily. Let P denote the likelihood of quitting from a full-time job. Then, the probability that she exits the current job $\{\xi_1, a_1\}$ at tenure level t_1 is

$$P(a_1, \xi_1, \Omega_{d+t_1}) = P(M_{12} = 1; a_1, \xi_1, \Omega_{d+t_1}) + \delta + P(D = 0; a_1, \xi_1, \Omega_{d+t_1}) \quad (45)$$

which is simply the sum of the probabilities associated with a layoff, job mobility and a voluntary quit to unemployment.

The probability of job mobility from the current job can be expressed as:

$$\begin{aligned} P(M_{12} = 1; a_1, \xi_1, \Omega_{d+t_1}) &= \pi P(M_{12} = 1; a_1, \xi_1, \xi_2 = \xi^2, \Omega_{d+t_1}) \\ &+ (1 - \pi) P(M_{12} = 1; a_1, \xi_1, \xi_2 = \xi^1, \Omega_{d+t_1}) \end{aligned} \quad (46)$$

$\{\xi_1, a_1\}$ and Ω_{d+t_1} determine the hour status H_1 at tenure t_1 with the first job. Since the decision rule for job mobility is contingent on the hour arrangement with the second firm, the probability that a job-job transition takes place from the current job to a type ξ_2 firm can be expressed as

$$P(M_{12} = 1; a_1, \xi_1, \xi_2, \Omega_{d+t_1}) = \sum_{m=0}^1 P(M_{12} = 1, H_2 = m; a_1, \xi_1, \xi_2, \Omega_{d+t_1}) \quad (47)$$

where $P(M_{12} = 1, H_2 = m; a_1, \xi_1, \xi_2, \Omega_{d+t_1})$, $m = \{0, 1\}$ is the joint probability of quitting the current job to work m hours on the second job, conditional on the type of the second job. These probabilities

job spells. So in this case, the first observation date refers to the date when the worker started her current job.

are given by

$$\begin{aligned}
& P(M_{12} = 1, H_2 = 1; a_1, \xi_1, \xi_2, \Omega_{d+t_1}) = \\
& \begin{cases} \lambda^e(1 - \delta)\tilde{G}(\max\{a^{1,1}(a_1, \xi_1, \xi_2), a^*(\xi_2)\}), & \text{if } H_1 = 1 \\ \lambda^e(1 - \delta)\tilde{G}(\max\{a^{0,1}(a_1, \xi_1, \xi_2), a^*(\xi_2)\}), & \text{if } H_1 = 0 \end{cases} \quad (48)
\end{aligned}$$

$$\begin{aligned}
& P(M_{12} = 1, H_2 = 0; a_1, \xi_1, \xi_2, \Omega_{d+t_1}) = \\
& \begin{cases} \lambda^e(1 - \delta)[G(a^*(\xi_2)) - G(a^{1,0}(a_1, \xi_1))], & \text{if } H_1 = 1 \text{ and } \xi_2 \leq a^{*-1}(a^{1,0}) \\ \lambda^e(1 - \delta)[G(a^*(\xi_2)) - G(a^{0,0}(a_1))], & \text{if } H_1 = 0 \text{ and } \xi_2 \leq a^{*-1}(a^{0,0}) \end{cases} \quad (49)
\end{aligned}$$

where $\tilde{G}(x) = 1 - G(x)$ and $a^*(\xi)$ is the critical value between choosing part-time and full-time work, conditional on the type of the second firm. Note that if $\xi_2 > a^{*-1}(a^{H_1,0})$, then $a^*(\xi_2)$ is smaller than $\hat{a}^{H_1,0}$. In this case, the likelihood of transiting to a part-time job is zero.

The probability of a voluntary quit to unemployment from the current job is given by

$$\begin{aligned}
& P(D = 0; a_1, \xi_1, \Omega_{d+t_1}) = \\
& \begin{cases} (1 - \delta - P(M_{12} = 1; a_1, \xi_1, \Omega_{d+t_1}))p\tilde{B}(\bar{a}^{-1}(a_1, h_0); \Omega_{d+t_1}), & \text{if } H_1 = 1 \text{ and } \xi_1 < k_0 \\ (1 - \delta - P(M_{12} = 1; a_1, \xi_1, \Omega_{d+t_1}))p\tilde{B}(\bar{a}^{-1}(a_1, h_1, \xi_1); \Omega_{d+t_1}), & \text{if } H_1 = 1 \text{ and } \xi_1 > k_0 \\ (1 - \delta - P(M_{12} = 1; a_1, \xi_1, \Omega_{d+t_1}))p\tilde{B}(\bar{a}^{-1}(a_1, h_0); \Omega_{d+t_1}), & \text{if } H_1 = 0 \end{cases} \quad (50)
\end{aligned}$$

Given the wage and hour decisions at the first job, I show how to obtain the wage and hour arrangement associated with the second job spell. First, ζ_2 is drawn from a uniform distribution defined on $[0, 1]$. Suppose the worker finds a job with a high cost firm, that is, $\xi_2 = \xi^2$. If the worker decides to switch to this job and work full-time, then $a_2^{H_1,1}(\xi^2)$ is a random draw from a truncated normal distribution with the lower truncation point given by the maximum of $a^{H_1,1}$ and $a^*(\xi^2)$. If the worker chooses to switch to the high cost firm and work part-time, then we draw $a_2^{H_1,0}(\xi^2)$ from a truncated normal distribution with $a^{H_1,0}$ being the lower point of truncation and $a^*(\xi^2)$ being the upper point of truncation. The case when the worker locates a low cost firm can be defined analogously. Given the wage and hour status on the second job, we could identify the critical value to leave the second job. Repeating the preceding process, we determine the likelihood of quitting from the second job and the

draws of match quality and firm type on the third job. In principle, we can iterate the process until the end of the employment cycle.

To minimize computational burden, I only use the information of up to the first two job spells in every employment cycle in the likelihood function. This includes: $\{d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2, \}$. Given that SIPP is a short panel, the information loss is little since few workers in the data change jobs more than twice in a single employment cycle. Given a worker whose first job is of type ξ_1 , the likelihood associated with a particular simulated sample path of one employment cycle is given by

$$\begin{aligned}
& L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 \mid \xi_1, \zeta_1, \zeta_2, \Omega) \\
&= \prod_{t=1}^d (1 - p(D = 1; \Omega_t)) p(D = 1; \Omega_{d+1}, \xi_1) \times h(\tilde{w}_1 | w_1) \times p(\tilde{H}_1 | H_1) \prod_{\tau=1}^{T_1} (1 - P(a_1, \xi_1, \Omega_\tau)) \\
&\times \{ \pi [P(M_{12} = 1, H_2 = 0; a_1, \xi_1, \xi_2 = \xi^2, \Omega_{d+T_1+1}) h(\tilde{w}_2 | w_2^{H_1,0}(\xi_2 = \xi^2)) p(\tilde{H}_2 | H_2 = 0) \\
&+ P(M_{12} = 1, H_2 = 1; a_1, \xi_1, \xi_2 = \xi^2, \Omega_{d+T_1+1}) h(\tilde{w}_2 | w_2^{H_1,1}(\xi_2 = \xi^2)) p(\tilde{H}_2 | H_2 = 1)] \\
&+ (1 - \pi) [P(M_{12} = 1, H_2 = 0; a_1, \xi_1, \xi_2 = \xi^1, \Omega_{d+T_1+1}) h(\tilde{w}_2 | w_2^{H_1,0}(\xi_2 = \xi^1)) p(\tilde{H}_2 | H_2 = 0) \\
&+ P(M_{12} = 1, H_2 = 1; a_1, \xi_1, \xi_2 = \xi^1, \Omega_{d+T_1+1}) h(\tilde{w}_2 | w_2^{H_1,1}(\xi_2 = \xi^1)) p(\tilde{H}_2 | H_2 = 1)] \} \quad (51)
\end{aligned}$$

where density functions h and p are generated from the measurement error assumption. Averaging over simulation paths and individual types, we form the likelihood contribution for this worker:

$$\begin{aligned}
& L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2) \\
&= \frac{1}{R} \sum_{r=1}^R \{ \tilde{\pi} L(d, t_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 \mid \xi_1 = \xi^2, \zeta_1(r), \zeta_2(r), \Omega(r)) \\
&+ (1 - \tilde{\pi}) L(d, t_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 \mid \xi_1 = \xi^1, \zeta_1(r), \zeta_2(r), \Omega(r)) \} \quad (52)
\end{aligned}$$

where $\tilde{\pi} = \pi$ if the worker is unemployed on the first observation date (i.e. $d > 0$). Otherwise, when $d = 0$, $\tilde{\pi}$ is estimated from the simulated distribution of F on the first observation date. $\Omega(r)$ contains the r th draw of a sequence of the worker's type $\{\epsilon_{it}(r)\}_{t=1}^{d+T_1+1}$. Under the assumptions of the model, each $\epsilon_{it}(r)$ is a random draw from distribution B , with the upper truncation point \bar{a}^{-1} imposed during periods of employment to ensure that the worker does not quit to nonemployment during the job tenure.

If there is only one job spell in the employment cycle, then the likelihood contribution is simpler.

Suppose the first job spell is right-censored, the conditional likelihood function is

$$\begin{aligned}
& L^{(2)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid \xi_1, \zeta_1, \Omega) \\
&= \prod_{t=1}^d (1 - p(D = 1; \Omega_t)) p(D = 1; \Omega_{d+1}, \xi_1) \times h(\tilde{w}_1 \mid w_1) \times p(\tilde{H}_1 \mid H_1) \prod_{\tau=1}^{T_1} (1 - P(a_1, \xi_1, \Omega_\tau)) \quad (53)
\end{aligned}$$

and if the first job spell ends with an unemployment spell, we have

$$\begin{aligned}
& L^{(3)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid \xi_1, \zeta_1, \Omega) \\
&= \prod_{t=1}^d (1 - p(D = 1; \Omega_t)) p(D = 1; \Omega_{d+1}, \xi_1) \times h(\tilde{w}_1 \mid w_1) \times p(\tilde{H}_1 \mid H_1) \\
&\quad \times (\delta + P(D = 0; a_1, \xi_1, \Omega_{d+T_1+1})) \times \prod_{\tau=1}^{T_1} (1 - P(a_1, \xi_1, \Omega_\tau)) \quad (54)
\end{aligned}$$

In either case, the unconditional likelihood contribution from this worker is:

$$\begin{aligned}
L^{(m)}(d, T_1, \tilde{w}_1, \tilde{H}_1) &= \frac{1}{R} \sum_{r=1}^R \{ \tilde{\pi} L(d, t_1, \tilde{w}_1, \tilde{H}_1 \mid \xi_1 = \xi^2, \zeta_1(r), \Omega(r)) \\
&\quad + (1 - \tilde{\pi}) L(d, t_1, \tilde{w}_1, \tilde{H}_1 \mid \xi_1 = \xi^1, \zeta_1(r), \Omega(r)) \}, \quad m = \{2, 3\} \quad (55)
\end{aligned}$$

Averaging over a large number of simulation paths and over all possible individual types, we obtain the unconditional likelihood contribution for this worker. The sample likelihood is given by

$$L = \prod_{i \in Y_1} L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2) \prod_{i \in Y_2} L^{(2)}(d, T_1, \tilde{w}_1, \tilde{H}_1) \prod_{i \in Y_3} L^{(3)}(d, T_1, \tilde{w}_1, \tilde{H}_1) \prod_{i \in Y_4} L^{(4)}(d) \quad (56)$$

where $i \in Y_m$ denotes the set of workers who belong to the m th case of the likelihood function.

5 Estimation Results

Table 4 presents the simulated maximum likelihood estimates for the model. For ease of exposition, I distinguish five sets of parameters: (i) parameters that define labor market opportunities, including heterogeneity in the wage offer, the job offer arrival rate, the probability of layoff, and parameters that characterize the distribution of the costs of part-time jobs; (ii) parameters that characterize the mean

wage offered from all firms; (iii) parameters that define the worker's preference to hours, including observed and unobserved preference heterogeneity and preference shocks; (iv) parameters that define the reservation utility for employment and (v) measurement error parameters.

I begin the discussion with the first set of parameters. In general, men and women face similar labor market opportunities in terms of the heterogeneity in match offers, the offer arrival probability and the probability of layoff. For both genders, there is strong evidence for the heterogeneity in the costs of part-time job provisions. More than 10% of the firms in the labor market are high-cost firms. For female workers, the full-time wages offered by high-cost firms are 3.6% higher than the part-time wages they would offer to the same worker. The wage penalty for part-time work appears higher for male workers: the full-time wages offered by high-cost firms are 5.9% higher than the part-time wages. Most firms find it less costly to accommodate part-time work: the full-time and part-time wage differential is merely 6 cents for women and 4 cents for men, for workers earning an hourly wage rate of \$10. Therefore, I conclude that the true wage differential between full-time and part-time jobs is small.

From the estimated log wage equation, we find that young workers with some college education are offered an average hourly wage that is around 27% more than high school graduates. The offered hourly wages are 1.6% less if male workers belong to areas of high unemployment rate and 1.2% higher for female workers in areas of high unemployment rate. There is a large gap in the mean wages offered to females and males with identical observed characteristics. For example, between women and men who are high school graduates and who live in the region with low unemployment rate, the difference in the mean offered wage is \$1.37 per hour. Note that the log wage equation is exogenous in the model and it reflects pay policy of the firms. Therefore, the identified male-female difference in the log wage equation can be interpreted as gender differences in productivity and/or discrimination.

Next, we turn to estimated parameters on preferences. There are striking differences in the preference for part-time work between men and women. Women have a much stronger taste for hours: for workers who are single, high-school educated and who do not have any children, the utility cost of full-time work is \$17.2 of weekly wages for women and only \$7.7 of weekly wages for men with the same characteristics. Among women, the preference for part-time work is much stronger for those who are married and have children (over \$36 in terms of weekly wages). The effects of marriage and children on men's preferences for part-time work are very different: married men have less preference for part-time work and children

have much a smaller positive effect. These findings are consistent with the story of sexual division of labor developed in Becker (1985). For both genders, college educated people have smaller preferences for part-time work. The effects of preference on hours of work and employment outcomes will be shown in the next section. Besides the permanent difference in preferences between genders, there is also a significant difference in the magnitude of preference shocks. The variance of the preference shocks of women is more than three times larger than that of men (0.121 vs. 0.036). A large preference shock is essential to generate the high frequency of voluntary transitions to nonemployment.

Finally, let us turn to the parameters defining the reservation utility for employment and the measurement errors. Not surprisingly, women on average have a higher reservation utility than men. Consistent with theoretical predictions, the reservation utility is lower for workers whose potential wages are higher. The preference for part-time work is positively correlated with the random effects in the reservation utility for work. Therefore, workers with strong tastes for part-time work also have high reservation utilities for employment. The estimated measurement errors are similar to those in other studies.²⁸ The estimated misclassification error in hours is 0.14 for females and 0.06 for males. To some extent, it is a reflection that it is more difficult to fit the model to the data on females than to the data on males.

Based on the estimated parameters, I compute the uncompensated labor supply elasticity at the extensive margin and at the intensive margin conditioning on employment. Since the wage is a function of hours of work, I consider a small parametric shift in the wage rate at $H = 0$ by increasing the constant term in the log wage equation. The elasticities measure the average percentage change in hours of work (at the intensive margin) and probability of employment (at the extensive margin) for workers with less than 15 years of potential experience in the labor market. For male workers, the wage elasticity is close to zero at both intensive and extensive margins. I find that female workers have a larger wage elasticity than male workers, at both margins. Women's wage elasticity ranges from 0.08 to 0.14 at the extensive margin and from 0.02 to 0.04 at the intensive margin. Workers who have stronger tastes for part-time work (e.g. married women and women who have children) tend to have greater wage elasticities. The incorporation of wage differential between part-time and full-time work implies that labor supply is less sensitive to small changes in the wage (Moffitt, 1984; Averett and Hotchkiss, 1997). In addition, the model assumes hour restrictions within jobs that prevent workers from adjusting their hours within the

²⁸For example, Dey and Flinn (2005).

same employer. This is another factor responsible for the small elasticities implied from the model.

6 Explaining the Gender Gap: The Role of Preferences for Part-time Work

Given the estimates from the model, I conduct counterfactual experiments to assess the effect of preferences for part-time work on gender gaps. I create a counterfactual group of males who are given the preference parameters of the females.²⁹ By comparing men, women and the counterfactual group, I estimate the contribution from the preferences for hours of work to the gender gap in wages, employment, full-time work and job turnover.

6.1 Gender Differences in Wages, Employment, and Hours of Work

Table 5 shows the estimated labor market outcomes for various groups of workers with different personal and family characteristics. Panels A and B show that the differences in preferences account for more than 80% of the gender gap in employment and more than 70% of the gender gap in the fraction of full-time work. However, even though preferences have large impacts on the distribution of hours of work and that part-time jobs pay lower wages than full-time jobs do, preferences alone explain no more than 5% of the gender gap in hourly wages (Panel C). There are two reasons. First, larger preferences for part-time work also raise the reservation utility for employment (the estimated b_α is positive and significant). Therefore, the average match quality for employed workers goes up as workers require a job offer with better match quality. The threshold match value where the worker is indifferent between working full-time and part-time also goes up, which implies higher accepted wages conditional on hours of work. Second, the estimated compensating wage differentials (ξ 's) are small for both genders and the gender gap in the mean offered part-time wages is large, meaning that women's counterfactual wage for working full-time remains smaller than men. As a result, shifts in the hours of work have little impact on the mean unconditional wages since women are offered lower wages than men regardless of hours of work.

²⁹The preference parameters include the mean and the variance of initial preferences and the variance of preference shocks. The counterfactual sample contains a panel of 10,000 young workers starting from the beginning of life for 45 periods (15 years). I evaluate the mean predictions from the model over the 45 periods without any measurement error assumptions on the wages and the hours.

Panel D shows the results using weekly wages. The effects on the weekly-wage gap are much larger: preference for part-time work can explain between 7%-20% of the weekly-wage difference between genders. More of the gender wage gap among married workers with children can be explained by preferences. Given that the preferences have little impact on hourly wages, the impact on the weekly wages is largely transmitted through changes in chosen hours of work.

6.2 Gender Differences in Job Turnover

Table 6 presents the predicted moments characterizing job turnover including transitions between jobs and between employment and nonemployment. I conclude that majority of the differences in job turnover between genders can be explained by differential preferences (Column (4)). When given the preference parameters of female workers, the counterfactual group of men would behave more like women in the labor market: they quit more often from employment to nonemployment and switch jobs more often with hours changes. The estimated probability of switching from a part-time job to another job is lower, whereas the estimated probability of leaving a full-time job is higher. Since the counterfactual men value part-time work more, full-time jobs tend to be chosen when the match qualities are higher, which implies lower turnover and higher wages for full-time jobs. Therefore, the labor market exhibits positive sorting, where workers who have stronger preferences for part-time work are eventually matched with part-time jobs and they tend to stay on part-time jobs for a longer period. The predicted turnover behaviors are consistent with the descriptive evidence of job turnover for young workers (see Section 2).³⁰

The estimated labor market dynamics illustrate some other interesting features of the model regarding the difference between part-time and full-time jobs. Note that for a given worker, the rate of job-job transitions from part-time jobs is higher than that from full-time jobs. Also, we observe that part-time jobs are more likely to end in voluntary nonemployment (the rate of involuntary nonemployment is independent of job types by assumption). Therefore, the model captures the fact that full-time jobs last longer than part-time jobs on average. The estimated part-time wage gap is much larger than the small mean compensating wage differentials offered by firms. For example, for men, the predicted mean

³⁰Note, however, that even conditional on observed characteristics, the simulated sample and the actual data are not directly comparable because of both left- and right-censoring of the SIPP. In the simulated sample, every person is observed for the entire first 15 years. In the SIPP, individuals are observed for a maximum of 4 years in the first 15 years of life.

part-time and full-time wage differentials is between \$0.6 and \$1.5 per hour, which are much larger than the full-time wage premium offered by firms. This indicates that the selection mechanism, characterized by workers who value part-time work choosing to work in part-time jobs with low match productivity (as opposed to the compensating wage differentials offered by the firm), is a major factor driving the part-time wage gap.

7 Conclusion

I propose a simple dynamic search model where workers choose between employment, nonemployment and different jobs distinguished by match productivity and costs of providing part-time work. In particular, the model is based on the premise that workers have heterogeneous and nonstationary preferences for part-time work, which could lead to job separations into nonemployment or into other jobs with possibly different hours of labor supply. I derive three choice equations implied from the model (choices of job-specific hours of work, employment and job mobility) and estimate them jointly with the offered wage equation for young women and young men separately. The estimates demonstrate that women have stronger tastes for part-time work and are subject to greater variations in preference shocks. Except for differences in the mean offered wages, men and women face similar labor market opportunities in terms of the heterogeneity in the match productivity, the offer arrival probability and the probability of a layoff.

I use the estimated model to conduct counterfactual experiments to assess the contribution of constraints and preferences to the gender wage gap. A large portion of the observed gender difference in hourly wages is due to differences in the mean offered wages. Differential preferences for part-time work explain no more than 5% of the gender gap in hourly wages. The effect on weekly wages is much larger, ranging from 7%-20% of the weekly wage difference. Preferences explain most of the gender differences in chosen hours of work, employment and job turnover. In terms of the true hourly wage gap before selection, close to 90% of firms pay part-time work only about 0.5% less than full-time work, whereas the rest reward full-time work by paying 3-6% higher. I conclude that most of the empirical part-time wage gap can be explained by endogenous selection based on preferences, where workers who value part-time work more are willing to accept a lower value of match.

The model can be extended to accommodate gender-specific preferences for other nonpecuniary

aspects of a job, such as flexibility of work schedule, for which women arguably have stronger preference. The difficulty is that information on the flexibility of work schedule is not available in most surveys. Given that the mean offered wage distribution explains the majority of gender wage gap, an important avenue for future research is to understand the sources of this difference.³¹

³¹See recent papers by Flabbi (2010) and Gayle and Golan (2012) on the role of taste-based discrimination and statistical discrimination.

A Data Appendix

The data set I use is the 1996 panel of Survey of Income and Program Participation (SIPP). The 1996 SIPP is a four-year panel comprising 12 interviews (waves). Each wave collects comprehensive information on demographics, labor market activities, types and amounts of income, and participation in welfare programs for each member of the household over the four-month reference period. For every primary and secondary job that a respondent holds, SIPP assigns a unique job ID and records job-specific monthly earnings.

I focus on the primary job, which is defined as the job generating the most earnings in a wave. Although SIPP has monthly information on job change and earnings, the time unit in the analysis of this paper is four months (a wave). This avoids the seam bias if we were using monthly variables. Real monthly earnings and wages are derived by deflating the reported monthly earnings and wages by monthly US urban CPI. Reported hourly wage rates are used whenever the worker is paid by the hour. For these workers, their real wages per wave are the mean of monthly real wages over four months. For workers who are not paid hourly, their real wages are obtained by dividing real earnings per wave by reported hours of labor supply per wave.³² Job change is identified from a change in job ID between waves. No job ID would be assigned to individuals who were unemployed through the wave.

The original SIPP 1996 panel has 3,897,177 person-month observations. I keep individuals aged between 20 and 35.³³ I drop full-time students, the self-employed, the disabled, those who completed less than half of the interviews and those who were recalled by their previous employer after a separation. I select workers who have at least high school education. I trim the population of those whose real wage is in the top or bottom 1% of the real wage distribution by wave. Since wage change is an important parameter in this paper, I also drop those with outliers in changes in wages.³⁴ In the first wave of SIPP, respondents are asked the starting date of the present job. I use this information to construct the correct job tenure for workers with elapsed job duration when they are first sampled. Subsequently, the tenure of the present job in the next wave is just the recoded job tenure plus one unless a job change is observed in the sample. In this way, information regarding job tenure is available through the sample period. The unit of analysis is an employment cycle. A complete employment cycle begins with an unemployment spell and ends with workers quitting from employment to nonemployment. Given our estimation strategy, I keep observations from the beginning of the sample period (regardless of the worker's employment status) up to the end of the first employment cycle (if observed in the sample) or to the end of the sample period, whenever the cycle is right-censored. To reduce the cost of simulating the likelihood function, two more selection criteria are imposed. First, when there are more than two job spells observed in the same employment cycle within the sample, only the first two jobs are kept.

³²For each month, respondents report their hours of work per week and how many weeks worked. Monthly labor supply is calculated as $\text{hours per week} \times (\text{weeks worked} / \text{weeks in month}) \times 4.33$

³³I also tried selecting individuals aged between 23 and 32. None of the five stylized facts is sensitive to the particular age restriction. The gender-difference in between-job wage growth becomes insignificant if we exclude people aged 35, confirming the weak evidence for the gender difference in between-job wage growth (see stylized fact 4).

³⁴An outlier is defined as one whose hourly wage falls by more than 75% or grows by more than 250%. This is not influenced by periods of unemployment.

Second, I truncate the maximum length of job spells at 30 periods (10 years).³⁵ The final sample consists of 3,082 men and 3,548 women.

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³⁵About 8% of the observations are dropped.

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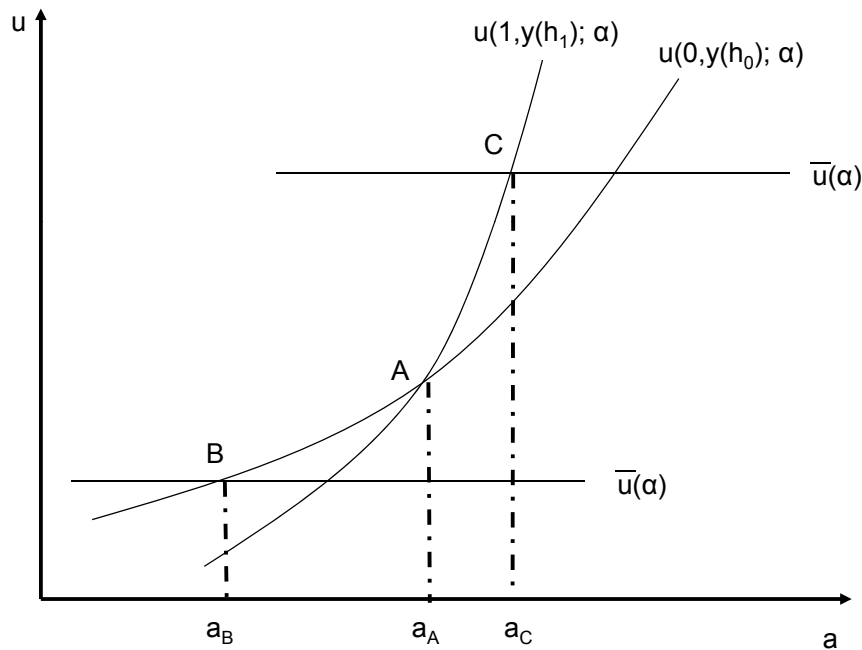


Figure 1: Critical Match Values of Work Hours

Table 1: Summary Statistics

	Female		Male	
	mean	s.d	mean	s.d
Age	29.02	4.13	28.77	4.23
At least some college	0.65	0.47	0.61	0.49
Married	0.62	0.49	0.55	0.50
Has children	0.51	0.50	0.39	0.49
White	0.73	0.44	0.75	0.43
Hours of work per week	30.86	17.09	42.46	11.35
Unemployed	0.19	0.40	0.03	0.17
Employed and work full-time	0.69	0.46	0.94	0.24
Employed and work part-time	0.12	0.33	0.04	0.19
Hourly wage	10.74	5.13	12.69	5.98
Hourly wage: full-time	11.02	5.03	12.83	5.97
Hourly wage: part-time	9.17	5.37	9.07	5.22
Number of individuals	3548		3082	
Number of observations	23976		20601	

Note: Wages are deflated using the monthly CPI-Urban (CPI=1 in 1996:1) and then averaged over a four-month period (per wave).

Table 2: Rate of Labor Market Transitions Between Waves, By Gender

	Female	Male
From employment to unemployment		
<i>Mean</i>	0.028	0.009
	(0.001)	(0.001)
<i>From PT jobs</i>	0.076	0.034
	(0.005)	(0.007)
<i>From FT jobs</i>	0.020	0.008
	(0.001)	(0.001)
<i>Percentages of voluntary separations (%)</i>	0.75	0.46
<i>Among voluntary quits:</i>		
<i>Family or personal obligations (%)</i>	31.2	6.5
<i>Childcare problems (%)</i>	15.6	3.2
Rate of job-job transition		
<i>Mean</i>	0.078	0.081
	(0.002)	(0.002)
<i>From PT jobs</i>	0.115	0.231
	(0.007)	(0.018)
<i>From FT jobs</i>	0.072	0.076
	(0.002)	(0.002)
<i>Among which: From FT to PT (%)</i>	11.4	5.7
<i>From PT to FT (%)</i>	11.3	6.8
<i>From FT to FT (%)</i>	68.3	84.8
<i>From PT to PT (%)</i>	9.1	2.8
Job duration		
<i>Mean</i>	8.63	9.74
	(0.18)	(0.20)
<i>Part-time job</i>	6.47	6.30
	(0.33)	(0.50)
<i>Full-time job</i>	9.36	10.10
	(0.21)	(0.21)

Table 3: Between- and Within-job Wage and Hour Changes, By Gender

	Female	Male
Between-job wage growth		
<i>Mean</i>	0.015 (0.011)	0.041 (0.011)
<i>From FT to PT</i>	-0.089 (0.034)	-0.118 (0.056)
<i>From PT to FT</i>	0.185 (0.028)	0.143 (0.041)
<i>From FT to FT</i>	0.010 (0.014)	0.044 (0.011)
<i>From PT to PT</i>	-0.036 (0.029)	0.022 (0.064)
Within-job wage growth		
<i>Mean</i>	0.015 (0.002)	0.015 (0.002)
<i>FT job</i>	0.014 (0.002)	0.015 (0.002)
<i>PT job</i>	0.022 (0.004)	0.015 (0.010)
Changes in hours between jobs	0.227 (0.011)	0.125 (0.009)
Changes in hours within jobs	0.048 (0.002)	0.021 (0.001)

Table 4: Estimated Parameters

	Female	Male
<i>Labor market opportunities</i>		
Match heterogeneity ($\sigma_{a_0}^2$)	0.075 (0.001)	0.070 (0.001)
Offer arrival probability (λ^e)	0.176 (0.003)	0.177 (0.002)
Layoff probability (δ)	0.011 (0.000)	0.011 (0.000)
Low cost firm (ξ^1)	0.006 (0.000)	0.004 (0.000)
High cost firm (ξ^2)	0.036 (0.001)	0.059 (0.001)
Fraction of high-cost firm (π)	0.111 (0.000)	0.113 (0.000)
<i>Offered wage parameters</i>		
Constant	1.710 (0.003)	1.932 (0.006)
College	0.278 (0.002)	0.265 (0.002)
High unemployment rate	0.012 (0.000)	-0.016 (0.000)
<i>Preference parameters</i>		
Preference heterogeneity ($\sigma_{e_0}^2$)	0.624 (0.002)	0.777 (0.002)
Preference shock (σ_ϕ^2)	0.121 (0.004)	0.036 (0.001)
Constant (θ_0)	2.845 (0.010)	2.043 (0.021)
College	-0.051 (0.000)	-0.104 (0.001)
Married	0.288 (0.002)	-0.074 (0.001)
Child	0.470 (0.004)	0.060 (0.001)
<i>Reservation utility parameters</i>		
b_α	0.872 (0.001)	0.906 (0.001)
b_u	5.834 (0.156)	4.859 (0.054)
b_w	-0.042 (0.000)	-0.050 (0.001)
<i>Measurement errors</i>		
σ_v^2	0.144 (0.003)	0.144 (0.004)
γ	0.859 (0.002)	0.944 (0.002)
$\ln L$	-14585.4	-11436.5

Table 5: The Simulated Gender Gap in Wages, Employment and Full-time Work

A. Employment				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Low skilled, single, no children	0.91	0.97	0.92	82.1%
Low skilled, married, have children	0.84	0.97	0.86	84.9%
High skilled, single, no children	0.92	0.97	0.93	83.0%
High skilled, married, have children	0.87	0.97	0.89	85.9%

B. Full-time Work Conditional on Employment				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Low skilled, single, no children	0.90	0.99	0.92	72.0%
Low skilled, married, have children	0.79	0.99	0.83	79.5%
High skilled, single, no children	0.93	0.99	0.95	76.6%
High skilled, married, have children	0.84	0.99	0.88	77.6%

C. Hourly Wages				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Low skilled, single, no children	7.30	9.06	9.05	0.3%
Low skilled, married, have children	7.31	9.07	9.03	2.3%
High skilled, single, no children	9.65	11.83	11.79	2.0%
High skilled, married, have children	9.63	11.83	11.77	2.9%

D. Weekly Wages				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Low skilled, single, no children	285.1	361.1	355.6	7.2%
Low skilled, married, have children	277.9	361.7	346.8	17.8%
High skilled, single, no children	379.9	472.6	465.7	7.5%
High skilled, married, have children	371.2	472.6	457.3	15.1%

Note: This table presents the mean simulated outcomes for 10,000 young workers in their young careers (45 periods/15 years), based on the parameter estimates from Table 4. The moments are predictions from the model without any measurement error assumption. High-skilled workers refer to those with at least some college education. Low-skilled workers refer to high-school graduates. Column (3) show the mean simulated wages for male workers assuming the preference parameters of the female counterparts. Column (4) = $\frac{(2)-(3)}{(2)-(1)}$.

Table 6: Gender Differences in Job Turnover

A. Low skilled, Married, with Children				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Rate of employment to nonemployment transitions				
<i>All</i>	0.029	0.012	0.026	85.4%
<i>From PT jobs</i>	0.077	0.045	0.079	105.5%
<i>From FT jobs</i>	0.016	0.011	0.016	91.3%
<i>Percentages of voluntary separations</i>	0.619	0.068	0.583	93.5%
Rate of job-job transitions				
<i>All</i>	0.050	0.045	0.050	100.0%
<i>From PT jobs</i>	0.056	0.079	0.061	80.9%
<i>From FT jobs</i>	0.048	0.045	0.048	88.2%
Percentages of job-job transitions that are:				
<i>From PT to FT</i>	0.146	0.008	0.120	81.1%
<i>From FT to FT</i>	0.631	0.970	0.686	83.6%
<i>From FT to PT</i>	0.102	0.012	0.099	97.1%
<i>From PT to PT</i>	0.121	0.010	0.095	75.9%
B. High skilled, Married, without Children				
	Females	Males	Males w/ Female's Pref's	Gap Explained by Pref's
	(1)	(2)	(3)	(4)
Rate of employment to nonemployment transitions				
<i>All</i>	0.025	0.011	0.023	87.5%
<i>From PT jobs</i>	0.076	0.039	0.080	111.2%
<i>From FT jobs</i>	0.015	0.011	0.015	95.3%
<i>Percentages of voluntary separations</i>	0.556	0.018	0.524	93.9%
Rate of job-job transitions				
<i>All</i>	0.049	0.045	0.049	82.5%
<i>From PT jobs</i>	0.063	0.081	0.068	70.3%
<i>From FT jobs</i>	0.047	0.045	0.046	43.8%
Percentages of job-job transitions that are:				
<i>From PT to FT</i>	0.110	0.004	0.087	78.9%
<i>From FT to FT</i>	0.702	0.985	0.750	82.9%
<i>From FT to PT</i>	0.096	0.007	0.089	92.2%
<i>From PT to PT</i>	0.093	0.005	0.074	78.3%

Note: This table presents simulated moments for 10,000 young low-skilled workers starting from the beginning of life for 45 periods (15 years), based on the parameter estimates from Table 4. The moments are predictions from the model without any measurement error assumption. High-skilled workers refer to those with at least some college education. Low-skilled workers refer to those with only a high school education. Column (3) show the mean simulated wages for male workers assuming the preference parameters of the female counterparts. Column (4) = $\frac{(2)-(3)}{(2)-(1)}$.

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NHH

**Norges
Handelshøyskole**

Norwegian School of Economics

NHH
Helleveien 30
NO-5045 Bergen
Norway

Tlf/Tel: +47 55 95 90 00
Faks/Fax: +47 55 95 91 00
nhh.postmottak@nhh.no
www.nhh.no