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Estimates from a Dynamic Model of Job Changes
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ABSTRACT

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

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 hours of 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 wage cost of part-time work. The model is estimated using the 1996 panel of the Survey of Income and Program Participation. I find that the preference for part-time work increases with marriage and number of children among women but not among men. These demographic factors explain a sizable fraction of the gender gap in employment, but they explain no more than 6 percent of the gender wage gap. Differences in constraints, mainly in the form of the mean offered wages and rates of job arrival and destruction, explain most of the gender wage gap. Policy simulation results suggest that, relative to reducing the wage cost of part-time work, providing additional employment protection to part-time jobs is more effective in reducing the gender wage gap.

JEL Classification: D91, J31, J16, J63

Keywords: gender gap, job mobility, part-time work

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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 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. In a dynamic model with labor market frictions, the conditional wage differential between full-time and part-time work is no longer a result of preferences differences (Hwang, Mortensen, and Reed, 1998).

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

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

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.

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. Workers are heterogeneous in their work preferences and are subject to preference shocks due to fertility. Firms are heterogeneous in the costs of offering part-time work, reflected as differences in the offered wages for full-time and part-time work (Oi, 1962). In addition, the baseline wage (full-time wage) depends on individual characteristics and worker-firm match quality. In a frictional labor market, there is a distribution of firms offering the same worker different match values. The worker's labor supply decision is similar to the problem studied in the labor supply literature, where the wage itself depends on the labor supply decision.³ An additional feature of the model is that job offer arrival rates and destruction rates differ between full-time work and part-time work. Therefore, besides any direct utility-augmenting effects, hours of work at the intensive margin may also be a productive factor in sustaining a worker-firm match.

The model is estimated by simulated maximum likelihood using the 1996 panel of the Survey of Income and Program Participation (SIPP). I use the estimated model to evaluate the relative importance of various factors in explaining the gender gap in hourly wages. In order of importance, the key factors explaining the gender wage gap are the mean offered wage (conditional on individuals' characteristics), job search parameters, wage cost of part-time work provision and demographic factors affecting the part-time work preferences. For instance, among high-education (college) individuals, they explain 65.8, 33.9, and 9.8 and 5.5 percent of the gender wage gap, respectively. I find that marriage and children strongly increase the preference for part-time work among women relative to men. While these demographic factors explain a sizable share of the gender gap in employment, the impacts on the gender wage gap is rather limited. In fact, reducing the impacts of demographics on women's part-time work preference tends to *reduce* both full-time wage and (especially) part-time wage, because of the changes in the reservation wages which decrease the average match quality in steady state. Driven by the increase of women working full-time, the overall wage (unconditional on hours) *increases* slightly. Overall, the evidence points to the importance of labor market constraints in generating the gender wage gap. Difference in the job search parameters is also important, particular when it comes to explaining the gender difference in the present value of a full-time job (taking into account of differences in job

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

durations).

I use the model to conduct two counterfactual experiments. In an Equal Pay policy, where the offered hourly wage is invariant to hours of work, the gender gap in employment is reduced by 11.3 percent among the high-educated and 23.6 percent among the low-educated. Its impact on the pre-existing gender wage gap is rather limited. It reduces the overall gender wage gap by 1.3 percent among high-education individuals and 4.8 percent among low-education individuals. Since the policy provides incentive for part-time work, overall wage decreases. An alternative Equal Protection policy is more effective in reducing the gender wage gap. The model estimates suggest that the rate of job destruction from part-time jobs is a few times greater than from full-time jobs. When the job destruction probability is equalized between full-time and part-time work (to the lower level of full-time jobs), the overall gender wage gap can be reduced by 6.1 percent and 10 percent, among high- and low-education individuals, respectively.

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 percent 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 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 (2012). 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 (2012) 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 With the exception of Dey and Flinn (2005), these papers do not study the dynamics of job-job transitions and hours changes. 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 model also allows for a richer set of observed and unobserved heterogeneity of the worker and the firm.

The rest of the paper proceeds as follows. Section 2 presents the data and descriptive statistics highlighting the gender differential in job turnover. Section 3 builds a dynamic model of job mobility and labor supply, followed by estimation and identification strategy discussed in Section 4. Section 5 presents the estimation results. Section 6 conducts counterfactual analysis to decompose the gender gap and counterfactual policy evaluations. Section 7 concludes.

2 Data and Descriptive Statistics

2.1 The Data

The data set I use is the 1996 panel of the 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 and income for each member of the household over the four-month reference period. For every primary and secondary job that a respondent holds, the SIPP assigns a unique job ID and records job-specific monthly earnings.

There are two main advantages of using the SIPP compared to other US panel data sets (such as the NLSY or the PSID). First, it has a short recall period, making it an ideal data set to study short-term employment dynamics. For instance, job mobility is very common especially among young workers. If a young worker changed jobs in a given calendar year, about one-fifth of them had multiple

⁴In Flabbi and Moro (2012), due to data limitations, the hours flexibility is equivalent to part-time work in estimation.

job changes within the same calendar year (Liu, 2013). This means that job mobility documented at annual frequency understates the extent of job-job transitions by about a fifth.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), which makes it possible to obtain more precisely measured changes in job-specific wages and hours when job transitions take place.

Details of sample selection are left in Appendix A. For each gender group, I construct two separate panels, one consisting of low-education individuals (those with high school education) and the other including high-education individuals (those with college education). Each panel contains individuals aged between 23 to 35.⁶ The final samples consists of 1032 women and 782 men in the high-education sample and 613 women and 564 men in the low-education sample. The unit period of analysis is four months (one wave in the survey).

Table 1 presents summary statistics. 85 percent of college-educated women and 74 percent of high school educated women are employed. Among those employed women, around 85 percent work full-time. In contrast, nearly all men are employed and 98 percent of them are employed by full-time jobs. Among high-education individuals, the mean hourly wage of men working full-time is 13.71 dollars, whereas the mean hourly wage of full-time working women is 10 percent lower at 12.25 dollars. Gender wage gap is more pronounced among low-education individuals. The mean hourly full-time wage of men is 11.24 dollars, which is almost 2 dollars more than the full-time wage earned by women.

2.2 Descriptive Statistics: Gender Differences in Job Turnover

Table 2 presents descriptive evidence on gender differences in job turnover. Among high-education individuals, the rate of transition from employment to nonemployment (every four months) is 2.1 percent for women, which is over five times than the rate of men (0.4 percent). Interestingly, for both men and women, part-time jobs are more likely to end in nonemployment than full-time jobs. For instance,

⁵Almost 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.

⁶Job mobility is most frequent and is the most important way for wage growth in early careers (Topel and Ward, 1992). Fertility shocks are also common during these ages. Both events provide important identifications to the decomposition of the gender gap (discussed later). Focusing on the mobility and fertility decisions in this period creates the foundation for the persistent gender differentials to observe over the whole labor market career.

Table 1: Summary Statistics

	College-female		College-male		HS-female		HS-male	
	mean	s.d	mean	s.d	mean	s.d	mean	s.d
Age	29.75	3.24	29.89	3.09	29.74	3.27	29.62	3.27
Has children	0.59	0.49	0.46	0.50	0.75	0.43	0.53	0.50
Married	0.70	0.46	0.63	0.48	0.66	0.47	0.61	0.49
White	0.77	0.42	0.80	0.40	0.71	0.45	0.73	0.45
Metropolitan residence	0.84	0.37	0.83	0.37	0.75	0.43	0.75	0.43
Hours of work per week	32.99	16.13	44.66	9.71	27.88	17.92	42.00	10.08
Employed	0.85	0.36	0.99	0.09	0.74	0.44	0.98	0.15
FT work among employed	0.87	0.33	0.98	0.13	0.84	0.37	0.98	0.14
Hourly wage: full time	12.25	4.89	13.71	5.23	9.27	3.40	11.24	3.88
Hourly wage: part time	11.60	5.74	10.23	4.48	8.04	3.25	9.04	3.80
Number of individuals	1032		782		613		564	
Number of observations	8828		6719		5154		4827	

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

among high-education women, the transition probability from a part-time job to unemployment is 6.4 percent, whereas the probability of moving from full-time job to unemployment is only 1.4 percent. The rate of direct job to job transitions is quite similar between men and women (5.4 and 5.8 percent, respectively). However, composition of the job-job transitions is very different across genders. For women, about 20 percent of the transitions involve changes in the hours of work (either from part-time and full-time or vice versa). Among men, close to 90 percent of job-job transitions are between full-time jobs. Fewer men work part-time and among those who do, part-time work appeared transitory: the transition probability from part-time to full-time jobs is a few times higher than the rate of transition between part-time jobs. For women, transitions between part-time jobs are common and account for 6.7 percent of total job-job transitions among the high-educated and 11.3 percent among the low-educated.⁷

The differences in job turnover lead to differences in the mean duration of jobs. The average job duration among high-education women is 43 months (10.8×4), which is about 5 months shorter than the average job duration held by men.⁸ Part of this is because more women working part-time and the

⁷Hour changes are much more common between jobs than within jobs. For instance, among high-education women, the fraction of hour changes within job spell per period is 3.6 percent (1.8 percent from full-time to part-time and 1.7 percent from part-time to full-time). Among low-education women, the fraction of hour changes within job spell is 3.9 percent (1.9 percent from full-time to part-time and 2.0 percent from part-time to full-time). These findings are also consistent with a small literature suggesting that there seems to be frictions in hour adjustment within jobs (Altonji and Paxson, 1992; Euwals, 2001; Blundell, Brewer, and Francesconi, 2008).

⁸The job durations here are calculated for completed job spells only (in addition to the sample selection criteria outlined

mean duration of part-time jobs is shorter than the mean duration of full-time jobs. Among full-time workers, the job duration of women remains about 5 months (1.2×4) shorter relative to men. Given that the rates of job mobility from full-time jobs are similar between genders, the main reason for job duration differences appears to be that female workers are more likely to quit to unemployment than male workers.

The last three rows of Table 2 show wage growth between jobs and within jobs. There is no significant evidence that men and women experience differential wage growth within jobs. Among high-education men and high-education women, within-job wage growth (every four months) is 1.2 percent and 1.6 percent, respectively. When within-job wage growth is calculated for full-time jobs, again I do not find any significant evidence of gender difference. Turning to wage growth between job-job transitions, I find some notable gender differences. The between-job wage growth is 6.4 percent for men and 2.9 percent for women.⁹ The standard errors of between-job wage changes are large, possibly reflecting measurement errors. The evidence is in line with Loprest (1992), who provides strong evidence that young women on average have smaller between-job wage growth than men.¹⁰ This empirical observation underlies the importance of modeling job-job transitions in explaining the gender wage gap.

The empirical facts documented above are qualitatively similar among low-education individuals. However, there are also some notable differences. Transition rates from employment to unemployment are higher for the low-educated, and job mobility involving part-time work is more common. Among low-education women, 11.3 percent of job-job transitions are between part-time jobs, which is larger than the share of part-time to full-time transitions (at 9.85 percent). This stands in contrary to part-time job held by high-education women, where transition to a full-time job is more likely than transition to another part-time job. The overall rate of transition from full-time jobs to part-time jobs is also higher among low-education women than high-education women.

in Appendix A).

⁹Between-job wage growth is defined as changes in log wages between periods t and $t - 1$, conditional on job change 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 $t - 2$.

¹⁰Her 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.

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

	College		High school	
	Female	Male	Female	Male
From employment to unemployment				
<i>Mean</i>	0.021	0.004	0.032	0.007
<i>From PT jobs</i>	0.064	0.030	0.068	0.014
<i>From FT jobs</i>	0.014	0.003	0.025	0.007
Rate of job-job transition				
<i>Mean</i>	0.054	0.058	0.060	0.058
<i>From PT jobs</i>	0.071	0.177	0.086	0.275
<i>From FT jobs</i>	0.052	0.056	0.055	0.054
Among which: <i>From FT to PT (%)</i>	9.41	3.33	14.78	3.05
<i>From PT to FT (%)</i>	9.41	4.44	9.85	6.87
<i>From FT to FT (%)</i>	74.46	91.67	64.04	88.17
<i>From PT to PT (%)</i>	6.72	0.56	11.33	1.91
Job duration				
<i>Mean</i>	10.83	12.24	10.26	12.45
	(0.37)	(0.47)	(0.56)	(0.64)
<i>Part-time job</i>	9.10	6.87	6.05	7.68
	(0.91)	(1.58)	(0.84)	(1.75)
<i>Full-time job</i>	11.27	12.49	11.67	12.81
	(0.41)	(0.49)	(0.68)	(0.63)
Between-job wage growth	0.029	0.064	-0.010	0.062
	(0.020)	(0.021)	(0.021)	(0.023)
Within-job wage growth	0.016	0.012	0.014	0.011
	(0.003)	(0.003)	(0.003)	(0.003)
Within-job wage growth: FT job	0.015	0.012	0.012	0.011
	(0.003)	(0.003)	(0.003)	(0.003)

3 The Model

I build a 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. An individual i maximizes the expected present value of utility over an infinite horizon. In each decision period (t), both unemployed and employed workers search for job opportunities at no cost. For any given worker, a job offer j differs in two dimensions: the value of match and the wage cost of part-time work. As a result, labor supply decision is worker-firm specific and will be determined endogenously by the preference of the worker and the technology of the firm. Upon receiving an offer, unemployed workers face three choices: full-time work ($h_{ijt}^p = 0, h_{ijt}^f = 1$), part-time work ($h_{ijt}^p = 1, h_{ijt}^f = 0$), or continue in the unemployment state

($h_{ijt}^p = h_{ijt}^f = 0$). The employment indicator is denoted by $h_{it} \equiv h_{ijt}^p + h_{ijt}^f$. For an employed worker receiving a job offer, she can either remain in the current job or switch to the new employer and choose the optimal hours of work. Employed workers can exit to nonemployment in two ways, either through exogenous layoffs or through voluntary quits following a fertility shock.

Utility function. The baseline utility function is specified as the following:

$$\begin{aligned}
u_{ijt} = & y_{ijt} + \phi_0 y_{ijt}^2 + \alpha_h^p(1 - h_{ijt}^f) + \alpha_h(1 - h_{ijt}) \\
& + \alpha_{hn} n_{it}(1 - h_{ijt}^f) + \mathbf{x}_{hi} \boldsymbol{\beta}_h(1 - h_{ijt}^f) \\
& + \sum_{k=2}^K \mathbf{1}\{type = k\} (\mu_{hk}(1 - h_{ijt}^f))
\end{aligned} \tag{1}$$

The individual's utility depends on her income (y_{it}), which is determined by a budget constraint that is discussed in detail below. There is an income effect that is generated by the parameter ϕ_0 . She faces direct utilities of part-time work (α_h^p) and unemployment ($\alpha_h + \alpha_h^p$).¹¹ These parameters should in general be positive, reflecting the value of additional leisure relative to full-time work. The model allows the utilities to differ by certain state variables. In particular, parameter α_{hn} captures differential utilities of unemployment and part-time work when there is an additional child. The vector of covariates \mathbf{x}_{hi} is assumed to affect the utility of unemployment and part-time work via parameter vector $\boldsymbol{\beta}_h$. The model can allow for K unobserved "types" of individuals, and the type-specific utilities of unemployment and part-time work (type-1 being normalized to zero) are denoted by μ_{hk} . Therefore, individual unobserved heterogeneity enters into the model via these permanent components in preference which take a discrete factor representation (e.g., Heckman and Singer (1984)).

The work preference may change overtime due to the arrival of children. Additional child arrives exogenously because of fertility shocks. I model births as a stochastic process that follows:

$$n_{it+1} = \begin{cases} n_{it} + 1, & \text{with probability } \rho_i \\ n_{it}, & \text{with probability } 1 - \rho_i \end{cases}$$

¹¹These preference parameters are normalized with respect to full-time work.

The probability of a fertility shock, ρ_i , follows a logistic function

$$\rho_i = \frac{\exp(\mathbf{x}_{ni}\boldsymbol{\beta}_f)}{1 + \exp(\mathbf{x}_{ni}\boldsymbol{\beta}_f)} \quad (2)$$

where \mathbf{x}_{ni} is a vector of pre-determined observed characteristics of the individual (including a constant). To reduce computational burden, the individual can have up to two children.

Budget Constraint and Wage Function. The individual consumes all her income each period. When the worker meets employer j in period t , the potential disposable income in each alternative is given by

$$y_{ijt} = w_{ijt} \times H_{ijt} \quad (3)$$

Gross earnings is the product of the wage rate (w_{ijt}) and work hours (H_{ijt}). H_{ijt} may take three weekly work hours: 0, 30, 40 corresponding to $h_{ijt} = 0$, $h_{ijt}^p = 1$, and $h_{ijt}^f = 1$, respectively.

The log *offered* wage rate by employer j to worker i in period t is given by:

$$\ln(w_{ijt}) = \mathbf{x}_{wi}\boldsymbol{\beta}_w - \xi_{ijt}h_{ijt}^p + a_{ijt} \quad (4)$$

where \mathbf{x}_{wi} is a vector of observed individual characteristics (including a constant), a_{ijt} is a match-specific wage component and ξ_{ijt} is a match-specific cost of part-time work, representing the “price” of part-time job facing the worker. a_{ijt} and ξ_{ijt} are constant within a job spell and independently distributed. Thus, both are fixed effects specific to a worker-firm match.¹² The mean of ξ_{ijt} is expected to be positive, reflecting the empirical fact that part-time work typically carries a lower *accepted* wage rate than full-time work. Fixed costs of hiring and training is one potential explanation for the wage differential (Oi, 1962). The novelty here is that the ξ_{ijt} is heterogeneous across firms, which could arise 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

¹²In the absence of firm data one cannot distinguish between a pure firm effect and a pure match effect. a_{ijt} can be thought as capturing the part of the matching rent that accrues to the worker. I take the bargaining process that produces this sharing outcome as given. Note that individual heterogeneity in the form of “ability” types in the offered wage equation may be attempted (which may be correlated with unobserved preference types), when more than one job spells are observed for the individual.

work in the labor market. In this framework, each job offer consists of two independent match-specific elements: the wage cost of part-time work (ξ_{ijt}) and the match value (a_{ijt}). Following the empirical job search literature (since Flinn and Heckman (1982)), the distribution of offered match values follows a normal distribution G with zero mean and variance of σ_{a0}^2 . The wage cost of part-time work follows a distribution F , which is assumed independent of G .¹³

Intertemporal Optimization Problem. All individuals begin their lives in the unemployment state. Let α_{it} denote the set of state variables summarizing the individual's characteristics, where $\alpha_{it} \equiv \{n_{it}, x_{hi}, x_{wi}, type\}$. The set of state variables summarizing the firm's characteristics and match quality is denoted by $\mathbf{S}_{ijt} \equiv \{a_{ijt}, \xi_{ijt}\}$. Let $V(\alpha_{it})$ denote the value of nonemployment. The value of nonemployment for the worker is defined as

$$V(\alpha_{it}) = u_{it}(h^p = 0, h^f = 0) + (1 - \lambda^n)\beta E(V(\alpha_{i,t+1}) + \lambda^n \beta E \max[V(\alpha_{i,t+1}), W(\mathbf{S}_{ij,t+1}, \alpha_{i,t+1})]) \quad (5)$$

where λ^n is the probability that an offer arrives in each period and β is the discount factor. $W(\mathbf{S}_{ij,t+1}, \alpha_{i,t+1})$ is the value of employment if the worker is offered a job with characteristics $\mathbf{S}_{ij,t+1}$. The job offer is acceptable to a worker provided that $W(\mathbf{S}_{ij,t+1}, \alpha_{i,t+1})$ is larger than $V(\alpha_{i,t+1})$. The value function of employment with the firm j is given by¹⁴

$$W(\mathbf{S}_{ijt}, \alpha_{it}) = \max_{k \in \mathcal{H}_{ijt}} J_k(\mathbf{S}_{ijt}, \alpha_{it}) \quad (6)$$

where

$$J_k(\mathbf{S}_{ijt}, \alpha_{it}) = u_{ijkt} + \lambda_k^e(1 - \delta_k)\beta E \max[W(\mathbf{S}_{ij,t+1}, \alpha_{i,t+1}), W(\mathbf{S}_{ij',t+1}, \alpha_{i,t+1}), V(\alpha_{i,t+1})] \\ + (1 - \lambda_k^e)(1 - \delta_k)\beta E \max[W(\mathbf{S}_{ij,t+1}, \alpha_{i,t+1}), V(\alpha_{i,t+1})] + \delta_k \beta E(V(\alpha_{i,t+1})) \quad (7)$$

¹³The wage offers distribution conditional on the worker and the firm's type is determined by the distribution of match-specific productivity, which is exogenously given. This set up can be interpreted as the workers have no bargaining power, and receive a take-it-or-leave-it offer from firms. While it is potentially very interesting to provide foundations to the offered wage equation in general equilibrium framework, for computational reasons and given the nature of the data available, the estimation of a general equilibrium model is beyond the scope of this paper.

¹⁴Since the decision period is discrete, additional restrictions are placed on the timing of the events. In particular, it is assumed that the individual is only able to receive a job offer conditional on the current job not being displaced. When the individual is displaced, she has to remain unemployed for at least one period.

where \mathcal{H}_{ijt} denotes the index representation of the choice set, including (1) part-time work ($h^p = 1, h^f = 0$) and (2) full-time work ($h^p = 0, h^f = 1$). u_{ijkt} denotes the utility of alternative k , where k is an index representation of the choices. Given the hours choice k , λ_k^e is the job offer arrival rate when the worker is employed and δ_k is the exogenous layoff probability in each period. Therefore, besides the direct impact on the offered wage (through parameter ξ_{ijt}) and utility, part-time/full-time work decision also influences the on-the-job offer arrival probability and job destruction rate. This captures essential patterns of job turnovers in the data.¹⁵ Additionally, it allows current labor supply decisions to have dynamic effects on future wages, since wage growth in this type of models is driven by job turnover which is determined by these parameters. For instance, if full-time work implies a low layoff probability and a high probability of attracting external offers, individuals choosing full-time work will experience faster wage growth through a high probability of sampling an acceptable offer and a low probability of resetting to unemployment. In this case, full-time work becomes a productive factor in sustaining the worker-firm match.

3.1 Analysis of the Model

Labor Supply Decisions. Given the worker and firm's type, there exists a set of critical values $\{a^*(\xi), \bar{a}(\xi)\}$ that spreads out workers into different work hour arrangement:¹⁶

$$h^p = 0, h^f = 0 \text{ if } a < \bar{a}(\xi) \tag{8}$$

$$h^p = 1, h^f = 0 \text{ if } \bar{a}(\xi) < a < a^*(\xi) \tag{9}$$

$$h^p = 0, h^f = 1 \text{ if } a > \max\{a^*(\xi), \bar{a}(\xi)\} \tag{10}$$

$\bar{a}(\xi)$ is the reservation match for an unemployed individual to work for a job type ξ . It is defined as the solution which equalize the value of unemployment and employment ($V = W(a, \xi)$). The individual accepts a job offer from type ξ firm if the match value is above $\bar{a}(\xi)$. $a^*(\xi)$ is the cutoff value for choosing full-time work, which solves the following equation: $J_1(a, \xi) = J_2(a, \xi)$. The individual works full-time

¹⁵For instance, Table 2 shows that the probability of exiting from employment to unemployment is unanimously higher for part-time jobs than full-time jobs.

¹⁶In the remainder of this section, I drop the worker, firm and time subscript given that they don't add much to the discussion. Although the individual's type is not made explicit, the analysis in this section is conditional on the type of the worker (α_{it}).

if the job is acceptable and the match value is greater than $a^*(\xi)$.¹⁷

The labor supply function for a worker-firm match depends on the values of unemployment, part-time work and full-time work. Figure 1 draws the cutoff values under two values of unemployment, 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 the worker would not work if the offered match is less than a_B , choose part-time work if match value is between a_B and a_A , and full-time work if match value is higher than a_A . However, if the value of nonemployment is sufficiently high, 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 $\bar{a}(\xi)$ that is dependent of the type of firm the individual meets out of nonemployment.

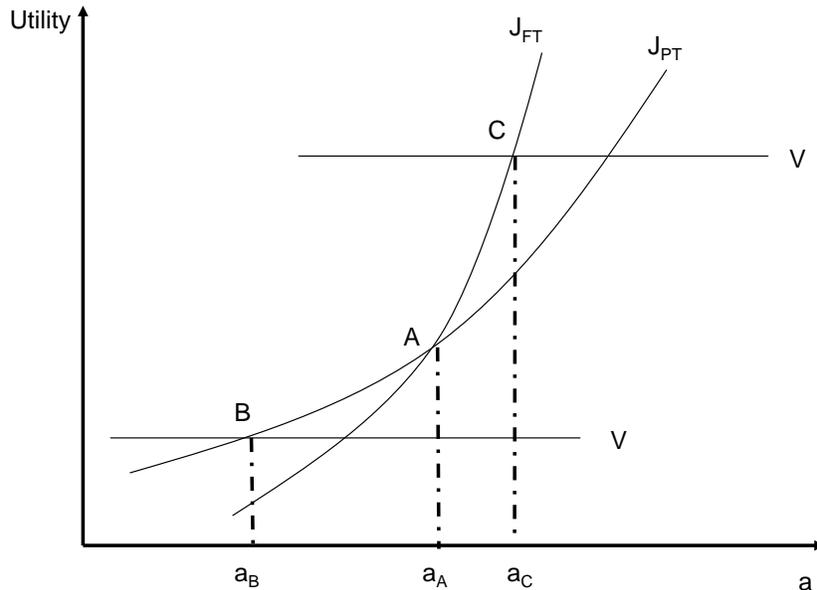


Figure 1: Critical match quality of hours of work

¹⁷If the probabilities of offer arrival and layoff do not vary by the hours of work, the choice of match-specific hours is made simply by comparing the contemporaneous utility between part-time and full-time work. In the current model, since the choice of hours on the current job also affects the continuation value in the future, the reservation wage for part-time/full-time work is also different from the implications of a static model.

Employment Dynamics Conditional on α , part-time work is in the worker's choice set as long as $\bar{a}(\xi) < a^*(\xi)$. This implies that the cost of providing part-time work is less than some cutoff value k_0 . 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

$$\lambda^n \int_{\xi < k_0} [G(a^*(\xi)) - G(\bar{a}(\xi))] dF(\xi) \quad (11)$$

The probability of moving from nonemployment to full-time work is

$$\lambda^n \left(\int_{\xi < k_0} \tilde{G}(a^*(\xi)) dF(\xi) + \int_{\xi > k_0} \tilde{G}(\bar{a}(\xi)) dF(\xi) \right) \quad (12)$$

where $\tilde{G}(x) = 1 - G(x)$.

Job Mobility Dynamics When an employed worker 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:

$$\begin{aligned} M &= 1 \text{ if } M^* > 0; \quad M = 0 \text{ elsewhere} \\ M^* &= W(a', \xi') - W(a, \xi) \end{aligned} \quad (13)$$

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 and observed and unobserved characteristics of the worker. Formally, the reservation match for job mobility is defined as $a_r(\xi', a, \xi)$ where $W(a_r(\xi', a, \xi), \xi') = W(a, \xi)$. Job mobility takes place provided that there is an offer whose offered match value satisfies $a' > a_r(\xi', a, \xi)$.¹⁸

¹⁸Note that if a new job is acceptable, it follows that the value of the new job must be larger than that of her current job. Since the worker is employed on the current job, this implies that the new job must be above the reservation utility for employment (i.e. $h > 0$).

Job mobility dynamics is richer in the current model since the worker can combine changes in hours of work with job mobility. Conditional on the type of the worker and the current job, the probability that the worker chooses to exit the current job to work full-time on the new job is

$$\lambda_k^e \int \tilde{G}(\max\{a_r(\xi', a, \xi), a^*(\xi')\}) dF(\xi') \quad (14)$$

The probability of leaving the current job to work part-time on the new job is

$$\lambda_k^e \int_{\xi' < k_1} [G(a^*(\xi')) - G(a_r(\xi', a, \xi))] dF(\xi') \quad (15)$$

where k_1 is the cutoff value for the type of the outside firm ξ' such that $a^*(k_1) = a_r(k_1, a, \xi)$ and λ_k^e is the probability of offer arrival conditional on the current choice of work hours k . When a worker meets a firm that makes part-time work very costly relative to her current employer ($\xi' > k_1$), she would never choose to quit the current job and work part-time on the new job.

4 Identification and Estimation

The decision period in the model is four months, corresponding to the interview frequency in the SIPP. The data is divided into four groups by gender and education of the individual: male-high school, male-college, female-high school and female-college. The empirical model is estimated separately on each subsample. Therefore, all parameters in the model are assumed gender and education specific. The assumption follows under the notion that jobs are segregated by gender and education groups (Bowlus, 1997).

For each subgroup, the parameter set consists of utility function parameters $(\beta_h, \alpha_h^p, \alpha_h, \alpha_{hn}, \phi_0)$, wage equation parameters $(\beta_w, \sigma_{a_0}^2)$, labor market friction parameters $(\lambda^n, \lambda_k^e, \delta_k)$ ($k = \{1, 2\}$), fertility shock parameters β_f , and type-specific parameters $(\mu_{h2}, \pi_{h2}, \xi^1, \xi^2, \pi_{\xi^2})$ where both the worker and firm types are discretized into two points of support. The discount factor is not estimated and fixed at 0.9.¹⁹ The offered wage equation is estimated jointly with choice probabilities predicted by the structural

¹⁹The annualized discount factor is 0.73 (0.9^3). Rust (1994) shows that the discount factor is nonparametrically unidentified in infinite-horizon discrete choice models such as the one considered in this paper. In Keane and Wolpin (1997), the estimated discount factor (from a finite-horizon dynamic discrete choice model of career choice among young men) is 0.78. I find that the slope of the estimated likelihood function is small around changes to the discount factor, so the estimation results are similar if the discount factor is set at a higher rate.

model.

4.1 Identification

The key empirical challenge is to separately identify the distribution of preferences for hours of work, the skill distribution (which takes the form of match-specific productivity) and the distribution of cost of providing part-time work. Given the implied selection rule spreading workers into different hours of work, these parameters can be identified even with cross-sectional data on hours of work and earnings. For instance, by changing labor supply preferences, the reservation wages change which leads to different proportion of the population work part-time, full-time, or work at all (as implied by equations 8-10). At the same time, the average match quality conditional on hours of work shifts due to individuals (responding to changes in the reservation match quality) sort into different hours of work. Combined with the observed conditional wage distribution and the distributional assumption on the unobserved match quality, preferences for hours of work and the skill distribution are separately identified. By similar arguments, the wage cost of part-time work affects the wage equation directly through the part-time/full-time wage differential and indirectly through changes in the composition of match qualities (conditional on hours of work) resulting from self-selection on wage gains.²⁰ The indirect effects are predicted by the structure of the model and the distributional assumptions on the match quality, as in a similar class of models. The dispersion of wage residuals conditional on full-time and part-time work (heteroskedasticity) identifies the heterogeneity of the wage cost of part-time work, as in the class of random coefficients models.

The panel data set contains a unique job ID which is used to trace job mobility, employment and associated wage dynamics in the event of a job change. The employment and job mobility dynamics, combined with job-specific wages, provide additional information for identification. For instance, conditional on the wage and hours of the current job, if the rate of transition to part-time jobs is high, it could indicate that either individuals tend to have a high preference for part-time work or the proportion of jobs with small part-time wage penalty is high. If the wage on the new job is high, it would suggest the latter since the individual may accept low wages if she values part-time work highly. In general, since

²⁰As first discussed in the heterogeneous treatment effects literature (Bjorklund and Moffitt (1987) and Heckman and Robb (1985)), heterogeneity in the offered part-time and full-time wage differential ξ generates additional selection bias because ξ directly enters both the labor supply equation and the wage equation.

unobserved heterogeneity in the model takes the form of discrete types and wage offers are i.i.d., the panel structure of the data (containing repeated observations of a given worker and a given worker-job match) is sufficient to identify the parameters of unobserved heterogeneity.²¹

Apart from nonlinearities and distributional assumptions, exclusion restrictions are included as additional sources of identification. We need at least one variable that shifts the worker's preference \mathbf{x}_{hi} but is not included in \mathbf{x}_{wi} in the wage equation. This is the usual exclusion restriction in any selection model where wage is unobserved for nonworkers. The excluded variables include number of children and marital status, which are assumed exogenous and uncorrelated to the error term in the wage equation. Note that the number of children evolves over time subject to unexpected fertility shocks, which provide additional restriction to identify the work preferences. Since the wage itself is in the equations of employment and hour choices, we also need one additional variable in \mathbf{x}_{wi} that is not included in \mathbf{x}_{hi} . I use regional unemployment rate and metropolitan residence as wage instruments (e.g., Keane and Moffitt (1998)).²²

The labor market friction parameters can be identified using information from the observed wage distribution (Flinn and Heckman, 1982). Intuitively, if the rate of employment is low, a relatively untruncated distribution of observed wages would imply a low job offer arrival probability, while a heavily truncated distribution would imply a high taste for unemployment (i.e., high work reservation wage). The same argument can be extended to the distribution of observed wages conditional on hours of work, from which the job offer arrival probability is identified separately for part-time jobs and full-time jobs. The offered wage distribution can be recovered from the truncated distribution of observed wages due to the log-normal distributional assumption (which satisfies the identification condition in Flinn and Heckman).

²¹See, e.g., Chan (2013). This is in contrast with Flabbi and Moro (2012), where identification of worker's type and the cost of work flexibility is based on cross-sectional data on accepted wages, unemployment durations and an indicator of flexibility. In their context, the identification of worker's type relies on discontinuity in the accepted wage distribution.

²²I 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.

4.2 Estimation Strategy

To ease computational burden, the fertility shock parameters β_f are estimated outside the structural model. I estimate the parameters β_f (see equation (2)) by estimating a Logit regression.²³ The rest of the parameters are estimated by maximum likelihood.

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

$$c = (d, T_1, \tilde{w}_1, \tilde{H}_1, \dots, T_J, \tilde{w}_J, \tilde{H}_J) \quad (16)$$

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 (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

The observed wages are measured with error. The mapping between true wage w_j and observed wage \tilde{w}_j is given by

$$\tilde{w}_j = w_j e^{v_j} \quad (17)$$

²³Recall that fertility shocks are exogenous and depend on a set of pre-determined individual characteristics. The sampling errors associated with these estimates are ignored. Therefore, the calculated standard errors of the structural estimates may be underestimated.

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 $T = 0$.

²⁵Hour changes are much more common between jobs than within jobs. For instance, among high-education women, the fraction of hour changes within job spell per period is 3.6 percent, whereas the fraction of hour changes between jobs is close to 20 percent (Table 2). Recent papers have emphasized the importance of modeling within-job wage change and job mobility decisions jointly (see, e.g., Bagger, Fontaine, Postel-Vinay, and Robin (2014) and Liu (2013)). Nevertheless, among young workers, wage growth between jobs is more important in driving overall wage growth than wage growth within jobs (Topel and Ward, 1992).

where v_j , the measurement error, is assumed i.i.d over j . Reported work hours are measured without error, but the likelihood function of work hours is smoothed by

$$P(\tilde{H}_j = 40) = \frac{\exp((a_j - a_j^*(\xi))/c)}{1 + \exp((a_j - a_j^*(\xi))/c)} \quad (18)$$

where c is the smoothing parameter. As c goes to zero, $P(\tilde{H}_j = 40)$ goes to 1 if the match value is above the research value for full-time work and to zero otherwise.²⁶

Measurement errors and the smoothing procedure play three roles in the estimation. First, they capture the measurement and reporting errors in survey data. Second, they serve to smooth over inconsistency between the model and the qualitative features of the data. For example, under certain specifications, the model could imply that moving from a part-time job to a full-time job after fertility shock to women is a zero probability event. If there are such transitions observed in the data, then the model will predict zero likelihood for these transitions at all points in the parameter space. The smoothing procedure means the probability of these events is positive in the parameter space. Third, they serve as a smoother of the likelihood so that gradient-based numerical optimization algorithms can be applied to maximize the objective function. For example, because of the classical measurement error assumptions, the simulated job-specific wages have a simple mapping to the observed wages.²⁷

Let T_0 be the initial condition at the beginning of the sample. If the individual was unemployed at the first interview, this is the number of unemployment periods prior to the first interview date. If the individual was employed at the first interview, this refers to the elapsed duration of the current job.²⁸ Conditional on T_0 , the complete likelihood function consists of products over workers and cycles:

$$L = \prod_{i \in Y_1} L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 \mid T_0) \prod_{i \in Y_2} L^{(2)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid T_0) \prod_{i \in Y_3} L^{(3)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid T_0) \prod_{i \in Y_4} L^{(4)}(d \mid T_0) \quad (19)$$

where $i \in Y_m$ denotes the set of workers who belong to the m th case of the likelihood function. In the first case, the individual has two consecutive job spells following the completion of an unemployment spell (if observed in the sampling period). In this case, the likelihood contribution is defined with respect

²⁶In estimation, c is fixed at 0.01.

²⁷Measurement errors are also necessary to satisfy the support condition of the maximum likelihood estimator.

²⁸The SIPP contains retrospective questions on previous employment history. See Appendix A on how these variables are constructed from the data.

to the duration of the unemployment spell, the duration of the first job spell, and the wages and labor supply statuses associated with the first two jobs (fixed at their onset). In the second and third case, the individual has one job spell in the employment cycle, either due to transition into unemployment at the conclusion of the first job spell (third case) or due to the fact that the first job spell is right-censored (second case). The likelihood contribution is defined with the duration of the unemployment duration, the wage and labor supply of the first job. In the last case, the observation period ends while the individual is still in an on-going unemployment spell. Therefore, only the unemployment duration contributes to the likelihood. The construction of the likelihood function is discussed in details in Appendix B.²⁹

In each iteration in the parameter space, computation of the likelihood for a given individual consists of nested loops. In the inner loop, the likelihood is computed conditional on the expected value functions. The likelihood is computed as the weighted average of the type-specific likelihoods, where the weights are the type probabilities. In the outer loop, the expected value functions in the dynamic programming problem are computed by fixed-point iteration. Reservation wages determining the choice of hours, employment and job mobility are computed. The presence of worker and firm (observed and unobserved) heterogeneity increases the state space and the value function is solved at every combination of worker and firm types. The standard errors are computed using the Berndt, Hall, Hall, and Hausman (1974) (BHHH) algorithm.

5 Estimation Results

Tables 3-4 present the simulated maximum likelihood estimates for the model. Each column corresponds to estimates from one gender and education group. For ease of exposition, I distinguish three sets of parameters: (i) parameters that define the worker’s preference for hours of work and employment, including observed and unobserved preference heterogeneity; (ii) job search parameters, including the job offer arrival rates and the probability of layoff; (iii) parameters that characterize the offered wage,

²⁹Since the SIPP is a short panel, it is quite common that the employment cycle is left-observed. For instance, a large proportion of workers are employed continuously throughout the sampling period. To avoid the initial condition problem, Dey and Flinn (2005) primarily utilizes job spell and wage information observed immediately after an unemployment spell (where transition to unemployment is completely exogenous in their model). Here, all individuals are used in the likelihood function, including those already employed at the first interview date. The initial condition problem is addressed by exploiting information available on the first interview date (T_0). See Appendix B for details.

Table 3: Estimated Parameters

	College		High school	
	Female	Male	Female	Male
<i>Preference parameters</i>				
Type 1 Intercept (α_h^p)	25.04 (2.274)	45.50 (9.231)	24.20 (3.620)	45.89 (4.466)
Type 2-type 1 (μ_{h2})	71.75 (1.596)	78.93 (20.42)	61.52 (1.107)	77.38 (24.15)
Fraction of type 2 individuals (π_{h2})	0.65 (0.050)	0.38 (0.086)	0.41 (0.052)	0.29 (0.056)
White (β_{h1})	10.93 (2.906)	18.23 (6.589)	12.17 (2.869)	8.50 (8.460)
Married (β_{h2})	11.89 (2.402)	-1.60 (1.069)	8.37 (2.899)	-1.72 (5.405)
Number of children (α_{hn})	21.51 (1.723)	4.18 (1.132)	14.23 (2.003)	0.52 (1.591)
α_h	221.88 (2.131)	180.23 (8.288)	168.78 (3.042)	172.52 (0.035)
$\phi_0 \times 10^4$	-1.58 (0.310)	-5.21 (1.157)	-1.84 (0.588)	-5.01 (1.565)
<i>Job search parameters</i>				
Offer arrival: unemployed (λ^n)	0.06 (0.007)	0.25 (0.057)	0.12 (0.011)	0.36 (0.067)
Offer arrival: FT work (λ_{FT}^e)	0.20 (0.011)	0.24 (0.020)	0.19 (0.016)	0.30 (0.028)
Offer arrival: PT work (λ_{PT}^e)	0.26 (0.015)	0.64 (0.054)	0.37 (0.031)	0.78 (0.095)
Layoff: FT work (δ_{FT})	0.01 (0.001)	0.00 (0.000)	0.02 (0.002)	0.00 (0.001)
Layoff: PT work (δ_{PT})	0.04 (0.005)	0.03 (0.010)	0.06 (0.007)	0.08 (0.013)
$\ln L$	-3322.48	-2107.69	-2096.72	-1514.90

Note: Standard errors are in parentheses.

including heterogeneity in the wage offer and parameters that characterize the distribution of the costs of part-time jobs and measurement errors.³⁰

There are large differences between men and women in the impact of demographics on the preference for part-time work (α^p). For both high- and low-education women, marriage and having children raise the preference for part-time work. For instance, each additional child increases the preference

³⁰The parameters of fertility shocks are shown in Appendix Table A1.

Table 4: Estimated Offered Wage Parameters

	College		High school	
	Female	Male	Female	Male
<i>Offered wage parameters</i>				
Intercept	2.08 (0.010)	2.05 (0.024)	1.77 (0.000)	1.92 (0.000)
High unemployment rate	-0.01 (0.003)	-0.01 (0.018)	-0.01 (0.016)	-0.01 (0.005)
White	0.05 (0.009)	0.17 (0.022)	0.08 (0.012)	0.13 (0.020)
Metro area residence	0.07 (0.006)	0.12 (0.022)	0.11 (0.010)	0.10 (0.020)
Match heterogeneity ($\sigma_{a_0}^2$)	0.04 (0.003)	0.04 (0.006)	0.03 (0.003)	0.03 (0.005)
Low cost firm (ξ^1)	0.06 (0.013)	0.21 (0.041)	0.00 (0.002)	0.18 (0.018)
High cost firm (ξ^2)	0.30 (0.010)	0.86 (0.236)	0.36 (0.021)	0.59 (0.306)
Fraction of high-cost firm ($\pi_{\xi 2}$)	0.70 (0.035)	0.95 (0.014)	0.68 (0.040)	0.88 (0.026)
<i>Measurement errors</i>				
σ_v^2	0.14 (0.006)	0.13 (0.006)	0.08 (0.005)	0.10 (0.005)

Note: Standard errors are in parentheses.

for part-time work by 21.5 dollars (of weekly wages) for high-education women and 14.2 dollars for low-education women. The impact of marriage is roughly one half of the impact of an additional child. Marriage and fertility have asymmetric effects on the work preferences by gender. For men, the estimated effects are small and mostly insignificant. There is also high degree of heterogeneity in the part-time work preferences across all subsamples. The differences between the preferences of type-2 and type-1 individuals range from 61 to 71 dollars. Conditional on education, type-2 individuals form a larger group among women than among men, even though men of each type place a greater value for part-time work than women of the same type. Overall, only after accounting for the impacts of demographic factors, women show stronger tastes for part-time work than men.³¹ The preference for work (α_2) is larger for high-education women than high-education men. The difference is insignificant among low-education

³¹The average baseline preferences in the population (without any demographic impacts) are quite similar between high-education women and men (54.9 and 57.8 dollars). Among the low-educated, the average baseline preferences are 39.6 dollars for women and 54.9 dollars for men.

individuals. The estimated quadratic term of income (ϕ_0) is negative and significant, implying that the utility change from an income change is smaller relative to the case of linear utility.

Turning to the estimated job search parameters, there are sizable differences between genders in the offer arrival rate and the probability of layoff. For high-education women, the probability of receiving a job offer in each period is 0.06 if they are unemployed, 0.20 if they are employed on a full-time job, and 0.26 if they work part-time. In comparison, for high-educated men, the offer arrival probability is higher in each state of labor supply. The estimated layoff probability is also higher for women than for men. The difference is especially pronounced conditional on full-time work. For instance, the probability of full-time job destruction per period is 1.2 percent for high-education women and only 0.1 percent for high-education men. Another important finding is that the probabilities of job offer arrival and layoff vary greatly by current hours of work across all subsamples. Offer arrival probability is higher when the individual is working part-time than full-time, partly due to the high rate of turnover of part-time jobs. It may also indicate that part-time workers search harder for better job opportunities, perhaps due to the lower opportunity costs of conducting on-the-job search. The probability of job destruction is much higher among part-time workers than full-time workers, which broadly conform to descriptive evidence from the data that part-time job spells are shorter than full-time job spells. As evidenced in the counterfactual analysis below, the differences in job search parameters between full-time and part-time of work is another important margin affecting labor supply decisions.

Table 4 shows the estimated offered wage parameters. For each education-gender group, the coefficient on local unemployment rate is negative. Holding all else equal, for workers living in states with high unemployment rate, the offered hourly wages are about 1 percent less than workers living in areas of low unemployment rate. Workers who are white and/or residing in metropolitan areas receive higher wage offers on average. Compared with men of the same characteristics, white women have a smaller offered wage premium than white men. Firms are heterogeneous in the cost of accommodating part-time work (expressed as a wage penalty for part-time work). Among high-educated women, about 30 percent of jobs are offered by low-cost firms, whose offered part-time wage is reduced by 6 percent. The remaining majority of jobs are provided by high-cost firms, where the offered part-time wage is about 70 percent lower than full-time wage (holding everything else constant). Interestingly, relative to women, men tend to face even greater wage cost for working part-time. For both high- and low-educated

men, close to 90 percent of jobs belong to the high-cost group. These high-cost firms pay the same man 59 percent (low-education) and 86 percent (high-education) less, if he chooses to work part-time over full-time.³²

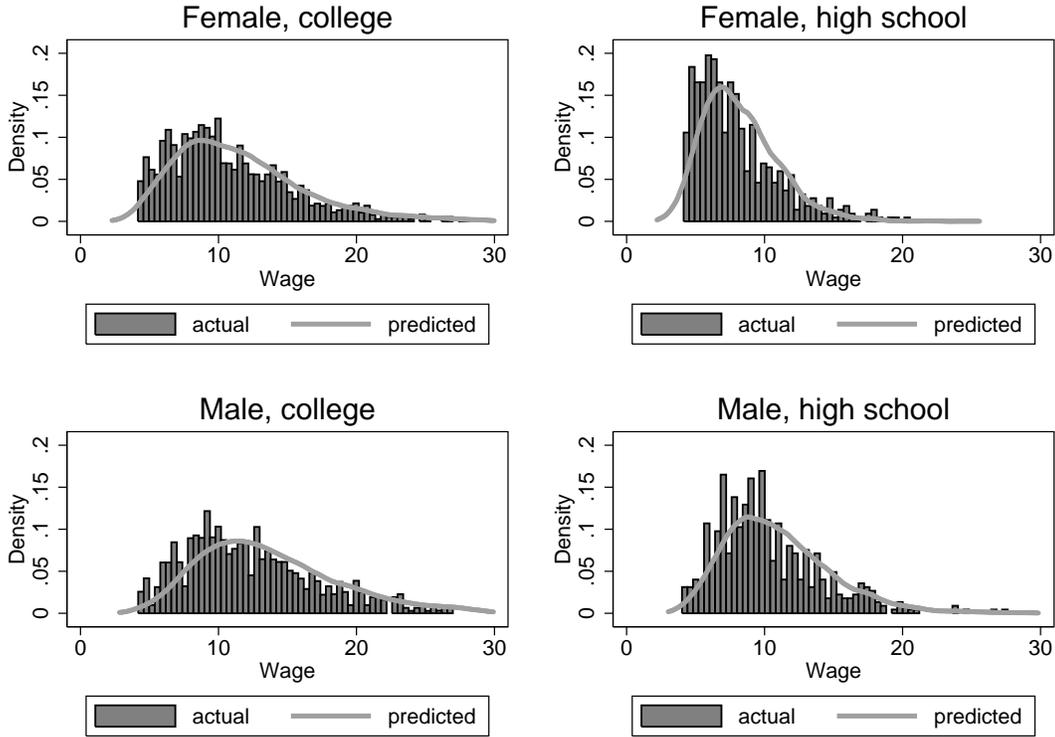


Figure 2: Actual and predicted wage distributions for workers

Table 5: Predicted and actual full-time choices

	FT-data (%)	FT-predicted (%)
High-education women	83.3	85.0
Low-education women	79.0	75.0
High-education men	97.2	96.7
Low-education men	96.3	94.7

Figure 2 plots the actual and predicted wage distributions of workers. Actual wages are based on the observed wage in the first job spell (\tilde{w}_1 in the likelihood function). Predicted wages are calculated by simulating 20 paths into steady state for each individual. Each simulated wage in steady state is drawn

³²I have tried to increase the number of firm types to three. For the samples of men, the additional type is not precisely estimated.

conditional on the individual’s observed characteristics and initial condition when \tilde{w}_1 is observed.³³ The model is able to predict the essential features of the wage distribution (such as the wage where density peaks), for each sub-sample. However, the model tends to underpredict the fraction of workers with low wages. Table 5 reports the predicted and actual fraction of full-time work among workers when \tilde{w}_1 is observed. Overall, the model predicts the fraction of full-time workers fairly accurately.

Based on the estimated parameters, I compute the uncompensated labor supply elasticity. I consider a 10 percent increase in the mean offered wage rate at the baseline. The elasticities measure the average percentage change in the fraction of part-time, full-time and total employment in steady state. Table 6 shows that the wage elasticity of employment is small and close to zero for men (0.06 among high-educated and 0.26 among low-educated). Women have a higher wage elasticity of employment (0.93 among high-educated and 0.70 among low-educated). The same pattern of gender difference is also seen at the margin of part-time and full-time work. For instance, the wage elasticity of full-time work for high-education women is 1.29, whereas it is only 0.09 for high-education men. Note that the discrete set of hours of work means that the value of the elasticity depends on the distribution of heterogeneity around the cut off points (reservation wages). It is also determined by the shape of the budget constraint (especially the kink generated by the wage cost of part-time work). These estimates will be different if the baseline budget constraint is different.

Table 6: Wage Elasticities of Labor Supply

	Baseline	Wage incr. by 10%	Elasticity	Baseline	Wage incr. by 10%	elasticity
	<i>High education women</i>			<i>High education men</i>		
Work	0.70	0.77	0.93	0.98	0.99	0.06
PT	0.08	0.06	-1.91	0.03	0.02	-0.74
FT	0.63	0.71	1.29	0.96	0.96	0.09
	<i>Low education women</i>			<i>Low education men</i>		
Work	0.75	0.80	0.70	0.95	0.98	0.26
PT	0.14	0.12	-1.59	0.03	0.01	-5.30
FT	0.61	0.68	1.22	0.93	0.96	0.42

³³For workers, it contains the elapsed duration of the current job (if the current spell is left-censored) or the preceding duration of unemployment spell in the same employment cycle (if the current job spell is not left-censored). Both durations are identified using the retrospective questions on employment histories (see Appendix A for details). Conditioning on these duration spells is necessary given that the distribution of these durations may differ between the steady state and the data due to many young workers in the data.

6 Counterfactual Analysis

6.1 Evaluating Sources of the Gender Gap

Using the estimates from the model, I conduct counterfactual analysis to assess the effect of various factors on gender gaps. The counterfactual analysis is carried out by simulating 20 paths in steady state for every individual in the sample.³⁴

The top panel of Table 7 reports contributions of various factors in explaining the gender gap in wage and employment, among high-education individuals. I report predicted outcomes under different counterfactual scenarios. The gender gap is defined as the difference between the baseline scenario and the “high-education men” scenario (second row) where the predicted outcomes are based on the estimated parameters of high-education men. The contribution of a factor, expressed as a fraction of the gender gap, is defined as the difference in the predicted outcome between the baseline scenario and the counterfactual scenario where the factor is kept fixed at men’s value. I consider the following factors: work preferences including the preference for not working and the preference for part-time work, job search parameters including the job offer arrival probabilities and layoff probabilities, and the offered wage consisting of the wage cost of part-time provision, mean offered wage (conditional on individuals’ characteristics) and match heterogeneity. In order of importance, the key factors explaining the gender wage gap are mean offered wage, job search parameters, wage cost of part-time work provision and demographics in the part-time work preferences. They explain 65.8, 33.9, 9.8 and 5.5 percent of the gender wage gap, respectively. The key factors explaining the gender employment gap are job search parameters, preference for work, demographics in the part-time work preferences and mean offered wage. They explain 133, 28.8, 23 and 22.6 percent of the gender gap in employment, respectively.

While work preferences can explain a large part of the gender gap in employment, they explain only a small fraction of the gender gap in hourly wages. For instance, if the preference for not working among high-education women is reduced to the value of high-education men, employment would increase by 8 percent as more individuals are attracted into employment. At the same time, the reservation wage for employment is lower, which, in this case, reduces the average wage of part-time work from over 9.43 to 8.85 dollars. As a result, the overall wage (unconditional on hours of work) decreases slightly relative

³⁴Individual covariates are fixed at the first interview date. The unobserved type of each individual is drawn from the type probability distribution at the beginning of each path. All individuals are unemployed at the beginning of each simulation path and steady state outcomes are evaluated after simulating the model for 80 periods.

Table 7: Sources of Gender Gap in Wage and Unemployment

	No work	PT	FT	Wage	PT wage	FT wage	% of gender gap	
							Wage	No work
<i>High-education women</i>								
<i>Baseline</i>	0.30	0.08	0.63	11.14	9.43	11.36		
<i>High-education men</i>	0.02	0.03	0.96	12.96	9.95	13.04	100.0%	100.0%
Pref for work	0.22	0.09	0.69	11.07	8.85	11.36	-4.2%	28.8%
Pref for PT work–demographics	0.23	0.03	0.74	11.24	8.50	11.34	5.5%	23.0%
Pref for PT work–types	0.31	0.09	0.60	11.10	9.43	11.36	-2.2%	-5.6%
Offer arrival prob.	0.09	0.14	0.78	11.43	9.77	11.72	15.6%	75.6%
Layoff prob.	0.13	0.08	0.79	11.48	9.69	11.65	18.3%	58.1%
PT wage penalty	0.29	0.00	0.71	11.32	7.80	11.33	9.8%	1.2%
Mean offered FT wage	0.23	0.06	0.71	12.34	9.71	12.56	65.8%	22.6%
Match heterogeneity	0.29	0.07	0.63	11.20	9.47	11.40	3.0%	0.9%
<i>Low-education women</i>								
<i>Baseline</i>	0.25	0.14	0.61	8.19	7.49	8.35		
<i>Low-education men</i>	0.05	0.03	0.93	10.60	7.95	10.68	100.0%	100.0%
Pref for work	0.27	0.14	0.59	8.20	7.49	8.37	0.7%	-9.2%
Pref for PT work–demographics	0.19	0.07	0.74	8.23	7.41	8.30	1.7%	31.1%
Pref for PT work–types	0.29	0.19	0.52	8.17	7.39	8.45	-0.9%	-19.3%
Offer arrival prob.	0.12	0.23	0.65	8.36	7.70	8.58	6.9%	64.0%
Layoff prob.	0.16	0.09	0.76	8.50	7.48	8.62	13.1%	47.0%
PT wage penalty	0.25	0.02	0.73	8.27	6.36	8.31	3.3%	-0.3%
Mean offered FT wage	0.17	0.10	0.73	9.78	8.63	9.94	66.0%	42.3%
Match heterogeneity	0.25	0.13	0.62	8.36	7.58	8.53	7.1%	1.6%

Note: The predictions from the model are without any measurement error assumption. High-education workers refer to those with at least some college education. Low-education workers refer to those with only a high school education. Final two columns show the percentage of the baseline gender gap explained by each factor.

to the baseline, even as the share of full-time work increases relative to part-time. Similar arguments apply to changes in part-time work preference. For instance, when the impacts of demographics on part-time work preference are reduced to the value of high-education men, average wage among women only shows small increase from 11.14 to 11.24 dollars. As part-time work preference is reduced, full-time work is more attractive than part-time work and unemployment, resulting in a rise in full-time work among women (from 0.63 to 0.74) and a drop in the percentage of unemployment and part-time work. Smaller preferences for part-time work reduces the reservation wage for full-time employment, which leads to small reduction in the average full-time wage. Part-time wage in steady state also decreases from 9.43 to 8.5 dollars, as part-time workers of high match-specific wage now switched to full-time work. Overall, the rise in the average wage from a reduction in the part-time work preference (due to

asymmetric demographic effects) is completely driven by an increase in the share of full-time work.³⁵

The fact that the offered wage explains the largest fraction of the gender wage gap indicates the importance of labor market constraints in generating the gender wage gap. Among high-education individuals, the mean offered wage is the main channel driving the positive gender wage gap. This is the wage component that is not match-specific and may be interpreted as differences in return to general human capital. In fact, the estimated match heterogeneity is quite similar between genders and hence has negligible impact on the gender wage gap. When high-education women face the part-time wage penalty of high-education men (which is much larger), they choose more full-time work as expected which reduces the overall gender wage gap. Average wages conditional on hours of work are lower, however. Since the reservation wage for full-time work also decreases, the full-time wage is *reduced* from 11.36 to 11.33 dollars. Job search behaviors characterized by job offer probabilities and layoff probabilities can also explain a sizable share of the gender wage gap. These parameters govern the speed of wage progression in this type of models. Higher job offer probabilities and lower layoff probabilities (relative to the current values of women) help women to climb up the job ladder by sampling high wage offers faster and reducing the risk of going down the ladder which “resets” the wage progression process. The total contribution of job search behavior in explaining the gender wage gap (around 30 percent) is quite similar to the evidence presented in Bowlus (1997), despite the differences in model specifications, estimation and data. While the contribution of offered wage exceeds that of job search behavior in explaining the gender wage gap, their relative importance is reversed when it comes to the gender gap in employment. This is mainly due to the small wage elasticity of labor supply implied by the model, relative to the job offer probability elasticity.³⁶

The bottom panel of Table 7 reports the contributions of various factors in explaining the gender gap in wage and employment, among low-education individuals. In general, the order of importance of various factors in explaining the gender gaps is comparable to the high-education women. Mean offered wage accounts for the majority of the gender wage gap and job search behavior is the most significant contribution to the gender gap in employment. There are some notable differences. For instance, demographics in part-time work preferences explains only a small fraction of the predicted

³⁵In a general equilibrium model (e.g. Mortensen (1990), Bowlus (1997)), firms also have incentive to lower the average offered full-time wage in response to the reduction in the preference (since more workers now want to work full-time, firms can lower wages and still attract workers). The reduction in the offered wage will increase the gender wage gap further, meaning that the contribution from part-time work preference in this paper is likely to be an upper bound.

³⁶See Chan (2013) for similar evidence.

wage gap. They still can reduce the gender gap in employment by 31 percent. In the meantime, they also reduce both part-time wage and full-time wage due to changes in the reservation wage. The average wage, after taken into account of compositional changes in labor supply, is only slightly higher than the baseline wage (from 8.19 to 8.23 dollars). Interestingly, the quantitative role of job offer and destruction probabilities is smaller for the gender wage gap among low-education individuals. Together they explain 20 percent of the gender wage gap. Match heterogeneity plays a slightly more important role for the low-educated than for the high-educated.

Table 8 presents the predicted job and unemployment spells in steady state under the baseline and each counterfactual scenario.³⁷ Among both high- and low-education individuals, women on average have shorter full-time job spells and longer unemployment spells relative to men. Naturally, much of the gender gap in job and unemployment durations is driven by different job offer arrival and destruction probabilities between genders.³⁸ The counterfactual simulations suggest that changes in reservation wage also play an important role. For instance, when high-education women are able to receive job offers at the same frequency as high-education men (higher arrival probability per period), the full-time job duration *increases* from 23.7 to 25.4 periods. This is due to an increase in the average match quality in steady state (evidenced also in the predicted wages in Table 7) which increases the reservation wage for job mobility. Reducing women's work preferences shortens unemployment spells. Reducing the women's preference for part-time work (for example through a reduction in the demographic impacts) shortens both part-time and full-time job spells. As full-time jobs become more valuable relative to part-time work and unemployment, the effect on the latter is mainly driven by a lower predicted average match quality among full-time jobs.

The evidence from Table 7 and Table 8 combined indicates that the gender gap is even more pronounced due to men having longer full-time job spells in addition to higher wages than women. The final two columns in Table 8 calculate the present value of an average full-time job by multiplying the predicted full-time wage with predicted full-time job duration. Among high-education individuals, the present value of an average full-time job for men is 398.3 dollars, which is 47 percent higher than that for women. Job search parameters become the most important in explaining this definition of gender gap than the mean offered baseline wage. This is because increasing women's offer arrival probabilities and

³⁷Note that individuals in the data are observed for a maximum of 4 years during ages 23-35. Therefore, the simulated spells in steady state are not directly comparable to the spells observed in the data.

³⁸Recall from Table 3 that men tend to have higher rate of job arrival and lower rate of job destruction than women.

lowering layoff probabilities reinforces two factors: it increases both the hourly wage and job durations for full-time work.

Table 8: Sources of Gender Differences in Job Turnover

	Job duration			FT job spell	
	PT	FT	No work	PV	% gender gap
<i>High-education women</i>					
<i>Baseline</i>	13.2	23.8	28.1	270.2	
<i>High-education men</i>	21.3	30.6	9.3	398.3	100.0%
Pref for work	11.8	23.8	17.8	270.9	0.6%
Pref for PT work–demographics	8.8	22.9	24.4	259.1	-8.6%
Pref for PT work–types	13.6	22.9	28.6	260.5	-7.5%
Offer arrival prob.	11.3	26.2	5.3	306.9	28.6%
Layoff prob.	16.0	30.6	37.9	356.6	67.5%
PT wage penalty	12.6	22.8	38.6	258.6	-9.1%
Mean offered FT wage	13.7	23.7	23.2	297.4	21.3%
Match heterogeneity	13.2	23.9	28.5	272.6	1.9%
<i>Low-education women</i>					
<i>Baseline</i>	9.9	20.4	13.7	170.4	
<i>Low-education men</i>	9.9	27.3	12.0	291.3	100.0%
Pref for work	11.0	20.4	15.0	170.7	0.2%
Pref for PT work–demographics	9.3	20.3	10.0	168.3	-1.7%
Pref for PT work–types	10.4	22.4	15.8	189.6	15.9%
Offer arrival prob.	9.0	18.3	4.6	157.0	-11.1%
Layoff prob.	9.1	29.7	16.6	256.3	71.1%
PT wage penalty	10.6	21.1	23.6	175.5	4.3%
Mean offered FT wage	9.7	21.0	7.5	209.1	32.0%
Match heterogeneity	10.3	20.7	13.7	176.5	5.0%

Note: The predictions from the model are without any measurement error assumption. High-education workers refer to those with at least some college education. Low-education workers refer to those with only a high school education. Final column show the percentage of the baseline gender gap explained by each factor.

6.2 Evaluating Counterfactual Policies

Table 9-10 present the effects of counterfactual policies on hours of work and wages in steady state, for low- and high-education individuals, respectively. Two counterfactual policies are considered: Equal Pay where the wage cost of part-time work provision is reduced to zero and Equal Protection where the job destruction probabilities between full-time and part-time work are equalized (at the lower layoff rate from full-time work). These policies aim to promote equality between part-time and full-time workers,

Table 9: Effects of Counterfactual Policies: High-education Individuals

	Baseline	Equal pay	Equal protection
<i>High-education women</i>			
No work	0.30	0.30	0.23
PT	0.08	0.28	0.18
FT	0.63	0.42	0.58
Wage	11.14	11.10	11.09
PT wage	9.43	10.39	10.00
FT wage	11.36	11.58	11.43
Utility	398.23	403.88	403.97
<i>High-education men</i>			
No work	0.02	0.05	0.01
PT	0.03	0.34	0.08
FT	0.96	0.61	0.91
Wage	12.96	12.89	12.79
PT wage	9.95	12.46	10.10
FT wage	13.04	13.12	13.04
Utility	376.30	396.06	378.62
<i>% change in gender gap</i>			
Wage		-1.3%	-6.1%
No work		-11.3%	-19.4%

Note: The predictions from the model are without any measurement error assumption. High-education workers refer to those with at least some college education. Low-education workers refer to those with only a high school education.

which have been in place in many countries in Europe.³⁹

For both men and women, Equal Pay reduces the gender gap in employment by 11.3 percent among the high-educated and 23.6 percent among the low-educated (second columns). It also reduces the overall gender wage gap by 1.3 percent among high-education individuals and 4.8 percent among low-education individuals. Interestingly, this reduction in the overall gender wage gap is not driven by the level of part-time wages where the elimination of the wage penalty should have large positive effects. While the part-time wage does increase among women, it increases even more among men. Full-time wage also increases, since the equalization of offered part-time and full-time wage means that individuals must require a higher wage in order to work full-time. Equal Pay leads to a large increase in the fraction

³⁹In 1997, the European Union introduced a directive which provides protection to part-time workers in terms of both pay and benefits. Following the EU directive, in 2000, the UK adopted the The Part-time Workers (Prevention of Less Favorable Treatment) Regulations. This legislation mandated the same hourly rates of pay and benefits between part-time and full-time workers. It also specifies that any dismissal due to the nature of working hours shall be regarded as unfairly dismissed.

Table 10: Effects of Counterfactual Policies: Low-education Individuals

	Baseline	Equal pay	Equal protection
<i>Low-education women</i>			
No work	0.25	0.21	0.17
PT	0.14	0.31	0.28
FT	0.61	0.48	0.55
Wage	8.19	8.15	8.20
PT wage	7.49	7.75	7.88
FT wage	8.35	8.41	8.36
Utility	304.42	309.68	311.27
<i>Low-education men</i>			
No work	0.05	0.06	0.02
PT	0.03	0.24	0.13
FT	0.93	0.70	0.84
Wage	10.60	10.45	10.37
PT wage	7.95	9.84	8.54
FT wage	10.68	10.67	10.66
Utility	332.45	341.66	334.99
<i>% change in gender gap</i>			
Wage		-4.8%	-10.0%
No work		-23.6%	-25.9%

Note: The predictions from the model are without any measurement error assumption. High-education workers refer to those with at least some college education. Low-education workers refer to those with only a high school education.

of part-time work and a large decrease the fraction of full-time work. The absolute increase in part-time work is more pronounced among men than women. As a result, overall wage decreases due to the compositional changes in part-time/full-time work and the drop is more pronounced among men. The policy increases welfare among both men and women, expressed in terms of average period-utility in the steady state (including the utility flows from unemployment). In terms of relative welfare gains (as a fraction of baseline utility), men benefit more from the policy than women do.⁴⁰

Similar to Equal Pay, Equal Protection also reduces the gender gap in unemployment, especially among low-education women. For instance, among low-education individuals, the fraction of women not working drops from 0.25 to 0.17, whereas the fraction of unemployed men decreases from 0.05 to 0.02 (third columns). Since the policy reduces the destruction rate of part-time jobs, part-time wage

⁴⁰Interestingly, among high-education individuals, the average period-utility is larger among women relative to men. This is largely driven by the large estimated value of non-market work for high-education women relative to high-education men (see Table 3).

tends to increase relative to the baseline (since the average match quality of part-time jobs improves in steady state). The impact on full-time wage is more complex. On the one hand, Equal Protection reduces unemployment and the reservation wage to work, which should have negative impact on the average match quality. On the other hand, conditional on work preferences, it increases the reservation wage for full-time work due to the rise in the value of part-time work. The positive effect appears to be dominating among high-education women (whose full-time wage increases from 11.36 to 11.43 dollars), whereas the negative effect dominates among low-education men (whose full-time wage decreases from 10.68 to 10.66 dollars). Among low-education individuals, the overall gender wage gap is reduced by 10 percent. Among high-education individuals, Equal Protection has smaller effects on both the gender gap in wage and unemployment. The gender gaps in wage and unemployment are reduced by 6.1 and 19.4 percent, respectively. The relative welfare gains from the Equal Protection are larger among women than among men. For instance, among low-education individuals, women's welfare increases by about 2 percent (from 304.42 to 311.27), whereas men's welfare only increases by less than 1 percent (from 332.45 to 334.99).⁴¹

7 Conclusion

In this paper, I used a dynamic structural model to analyze sources of the gender wage gap. In the model, individuals make discrete choices of hours of work and job mobility where each job is characterized by the match quality and the wage cost of part-time work. Labor supply decisions at the intensive margin directly affect the utilities, the offered hourly wages and the stability of a worker-firm match (through affecting the job arrival and destruction rates). The structural model was estimated using the 1996 panel of the SIPP.

I used the estimated model 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, including job arrival rates, job destruction rates, the mean and variance of the wage offer distribution, and the wage cost of part-time work. Among both high- and low-education individuals, about 65 percent of the observed gender difference in hourly wages is due to differences in the mean offered wages. In order of

⁴¹Throughout this paper, the unit of a decision maker is an individual. Policy changes may affect the allocation of market and home production within a household, which are not captured by the model. This important extension is left for future research.

importance, the remaining key factors explaining the gender wage gap are the job search parameters, wage cost of part-time work and demographic factors affecting the part-time work preferences. Differences in the job search parameters account for 30 percent of the gender wage gap among high-education individuals. They play a more prominent role when it comes to explaining the gender gap in the present value of full-time jobs, which is amplified by the gender differences in job duration. While marriage and children can explain a sizable fraction of the gender gap in employment, they explain no more than 6 percent of the gender wage gap. The findings suggest that most of the observed gender wage gap of employed men and women attributes to labor market constraints.

The findings have important policy implications. In recent years, many countries promote equal opportunities between working part-time and working full-time. Two main pillars of the reform are Equal Pay and Equal Protection. The former corresponds to the case in the model where the wage cost of part-time work provision is reduced to zero. The latter can be modeled as that the job destruction probability is equalized between full-time and part-time work. The estimated model allows us to broadly investigate the implications of these policies by conducting counterfactual policy evaluations. For instance, relative to the Equal Pay, Equal Protection is more effective in reducing the gender wage gap (especially among low-educated individuals).

APPENDIX

A Construction of the Samples

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.⁴² 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.

From the original SIPP 1996 panel, I keep individuals aged between 23 and 35.⁴³ I drop full-time students, the self-employed, the disabled, those who appeared less than three years (out of four years) of the interviews and those who were recalled by their previous employer after a separation. I select individuals 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. 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 interviewed. 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. For individuals who were unemployed at the first survey, year and month when the individual last worked are recorded in the SIPP Topical Module (surveyed in the first wave). I use this information to compute unemployment durations that were left-censored for these individuals. After these corrections, job tenure and unemployment spells are non-left-censored 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. To create a sample used for estimation, I keep observations from the beginning of the sample period (including both employed and unemployed individuals at that time) 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. When there are more than two job spells observed in the same employment cycle within the sample, only the first two jobs are kept (see the Estimation Section for details).

⁴²For each month, respondents report their hours of work per week and how many weeks worked. Monthly labor supply is calculated as $\text{hours per week} \times (\text{weeks worked} / \text{weeks in month}) \times 4.33$

⁴³Since the SIPP is a short panel and the expected college completion age is 23, this selection criteria ensures that the highest completed education level is obtained for each individual.

B The Likelihood Function

Unemployment Spell Only. 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 unobserved type μ_{hk} , the probability of becoming employed in every period is given by⁴⁴

$$p(D = 1 | \mu_{hk}) = \sum_j \pi_{\xi^j} p(D = 1 | \xi = \xi^j, \mu_{hk}) = \sum_j \lambda_n \pi_{\xi^j} \tilde{G}(\bar{a}(\xi^j)) \quad (1)$$

where $\tilde{G}(\bar{a}(\xi^j)) = 1 - G(\bar{a}(\xi^j))$ and ξ^j is the potential type of the new job.⁴⁵ If there is only one unemployment spell in the sample, then the conditional likelihood function is simply given by

$$L^{(4)}(d | T_0, \mu_{hk}) = \prod_{t=1}^d (1 - p(D = 1 | \mu_{hk})) \quad (2)$$

μ_h is the unobserved type of the individual which needs to be integrated out. The unconditional likelihood function is then

$$L^{(4)}(d | T_0) = \sum_k L^{(4)}(d | T_0, \mu_h = \mu_{hk}) \times P(\mu_{hk} | T_0) \quad (3)$$

Note that $P(\mu_{hk} | T_0) \neq \pi_{hk}$ because of possible selection into unemployment after preference shocks. Using Baye's rule, I evaluate the conditional probability that the individual is of type k as

$$P(\mu_{hk} | T_0) = \frac{P(T_0 | \mu_{hk}) \pi_{hk}}{\sum_i P(T_0 | \mu_{hi}) \pi_{hi}} \quad (4)$$

where π_{hk} is the fraction of type- k worker in the population and the conditional probability $P(T_0 | \mu_{hk})$ can be estimated directly from the structural model. This yields the “best” summary of the individual's unobserved type given the data available.

One or Two Job Spells. For a given worker, entry into unemployment essentially resets the search process, meaning that previous employment cycles are independent from the job offers once one becomes unemployed. 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

$$P(c) = P(d) P(T_1, \tilde{w}_1, \tilde{H}_1, \dots, T_J, \tilde{w}_J, \tilde{H}_J) \quad (5)$$

$P(c)$ 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. Below I use

⁴⁴Note that the likelihood function is defined on each individual, which is always conditional on her observed characteristics $\alpha^- \equiv \{n, x_h, x_w\}$.

⁴⁵Note that, when the probability of exiting unemployment is constant given the individual's type, it is irrelevant whether the beginning of the unemployment spell is observed (see also Dey and Flinn (2005)).

simulation methods to construct likelihood contributions involving completed or censored job spells.

For all likelihood contributions involving job spells, I only use information of up to the first two job spells in every employment cycle in the likelihood function in order to minimize computational burden. This includes: $\{d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2, \}$.⁴⁶

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 move to another employer, either to work full-time or to work part-time. Third, she may quit to unemployment voluntarily due to a fertility shock. Let P denote the likelihood of quitting from a full-time job. Then, the probability that she exits the current job $\{\xi_1, a_1\}$ is

$$m(a_1, \xi_1, \mu_{hk}) = p(D = 0 \mid a_1, \xi_1, \mu_{hk}) + p(M = 1 \mid a_1, \xi_1, \mu_{hk}) + \delta \quad (6)$$

$p(D = 0 \mid a_1, \xi_1, \mu_{hk})$ is the likelihood of voluntary quit to unemployment.⁴⁷ $p(M = 1 \mid a_1, \xi_1, \mu_{hk})$, the probability that a job-job transition takes place, can be written as

$$p(M = 1 \mid a_1, \xi_1, \mu_{hk}) = \lambda_e(1 - \delta) \sum_j \pi_{\xi_j} \tilde{G}(a_r(\xi_2^j, a_1, \xi_1)) \quad (7)$$

where it is summed over the potential types of new jobs (ξ_2^j denotes the new job of type j and π_{ξ_j} is the fraction of type- j firms in the population).

Conditional on the first job of type ξ_1 and match value a_1 and the unobserved type of the individual, the likelihood of one employment cycle is given by

$$\begin{aligned} L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 \mid \mu_{hk}, \xi_1, a_1, T_0) \\ = \lambda_n \tilde{G}(\bar{a}(\xi_1)) \prod_{t=1}^d (1 - p(D = 1 \mid \mu_{hk})) \times h(\tilde{w}_1 \mid w_1) \times p(\tilde{H}_1 \mid H_1) \prod_{\tau=T_0+1}^{T_1} (1 - m(a_1, \xi_1, \mu_{hk})) \\ \times \{ \lambda_e(1 - \delta) \sum_j \pi_{\xi_j} \tilde{G}(a_r(\xi_2^j, a_1, \xi_1)) h(\tilde{w}_2 \mid w_2(\xi^j)) p(\tilde{H}_2 \mid H_2) \} \end{aligned} \quad (8)$$

where density functions h and p are generated from the measurement error assumption. Note that in order to evaluate $h(\tilde{w}_2 \mid w_2(\xi^j))$ and $p(\tilde{H}_2 \mid H_2)$, I rely on simulation method to draw $f(a_2 \mid \xi_2, \xi_1, a_1, \mu_{hk})$. First, ζ_2 is drawn from a uniform distribution defined on the interval $[0, 1]$. Then a_2 is a random draw from a truncated normal distribution with the lower truncation point given by the reservation wage for switching to the second job, $a_r(\xi_2, a_1, \xi_1)$. Given a_2, ξ_2 , wage and hour status on the second job can be predicted.

To form the likelihood contribution for the individual, we need to average over unobserved individual

⁴⁶Given 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.

⁴⁷The probability of voluntary quit is given by $(1 - p(M = 1 \mid a_1, \xi_1, \mu_{hk}) - \delta) \times \frac{\exp((\bar{a}(\xi_1) - a_1)/c)}{1 + \exp((\bar{a}(\xi_1) - a_1)/c)}$. Note that, given the setup of the model, quit to unemployment is conditional on not being displaced from the current job and not receiving a superior offer from a different employer. The logistic function is used to smooth over inconsistency between the model and the data, where as previously, c is a smoothing parameter fixed at 0.01.

heterogeneity, firm heterogeneity, and match heterogeneity of the first job (a_1). Since a_1 is the match value of an *accepted* offer, it no longer follows the exogenous population distribution of matches $G(a)$. I use simulation method to draw a_1 from $G(a_1 | \xi_1, \mu_{hk})$, which follows a truncated normal distribution with a lower truncation point given by the reservation value for employment (at $\bar{a}(\xi_1)$).⁴⁸ Given that the reservation match value depends on the type of the job and the type of the worker, each simulated draw of a_1 (denoted as a_1^s) is conditional on the type of the job and the type of the worker. The unconditional likelihood function becomes:

$$\begin{aligned} L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 | T_0) \\ = \frac{1}{S} \sum_k \sum_p \sum_s L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 | \mu_{hk}, \xi_1^p, a_1^s, T_0) P(\mu_{hk}, \xi_1^p, a_1^s | T_0) \end{aligned} \quad (9)$$

I use the Bayes' rule to evaluate the posterior distribution of the firm and individual's unobserved types and the (simulated) match draws, conditional on the information observed at the first interview T_0 :

$$P(\mu_{hk}, \xi_1^p, a_1^s | T_0) = \frac{P(T_0 | \mu_{hk}, \xi_1^p, a_1^s) \pi_{hk} \pi_{\xi p}}{\frac{1}{S} \sum_k \sum_p \sum_s P(T_0 | \mu_{hk}, \xi_1^p, a_1^s) \pi_{hk} \pi_{\xi p}} \quad (10)$$

where T_0 is the elapsed duration of the current job at the first interview date (if the individual was employed then) or periods of unemployment that are left-censored (if the individual was unemployed then).⁴⁹ T_0 reveals additional information which can be used identify the initial joint distribution of match quality, unobserved types of the firm and the worker. The conditional probability, $P(T_0 | \mu_{hk}, \xi_1^p, a_1^s)$, is the likelihood of observing T_0 at the first interview. The unconditional likelihood function can be written as:

$$\begin{aligned} L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2; T_0) \\ = \frac{1}{S} \sum_k \sum_p \sum_s L^{(1)}(d, T_1, \tilde{w}_1, \tilde{H}_1, \tilde{w}_2, \tilde{H}_2 | \mu_{hk}, \xi_1^p, a_1^s, T_0) \pi_{hk} \pi_{\xi p} \omega(\mu_{hk}, \xi_1^p, a_1^s) \end{aligned} \quad (11)$$

where $\omega(\mu_{hk}, \xi_1^p, a_1^s) \equiv \frac{P(T_0 | \mu_{hk}, \xi_1^p, a_1^s)}{\frac{1}{S} \sum_k \sum_p \sum_s P(T_0 | \mu_{hk}, \xi_1^p, a_1^s) \pi_{hk} \pi_{\xi p}}$. For each tuple $\{\mu_{hk}, \xi_1^p, a_1^s\}$, the likelihood contribution is multiplied by a weight that is proportional to the likelihood of observing initial condition T_0 .

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

⁴⁸I draw ζ_1 from a uniform distribution defined on the interval $[0, 1]$. Then, the inverse of the c.d.f function G at $\tilde{\zeta}_1$ (where $\tilde{\zeta}_1 = G(\bar{a}(\xi_1)) + (1 - G(\bar{a}(\xi_1)) \times \zeta_1)$) produces the simulated (a_1). For each combination of the individual and firm types, I simulate 10 draws.

⁴⁹When T_0 is the elapsed unemployment durations, $P(\mu_{hk}, \xi_1^p, a_1^s | T_0) = P(\mu_{hk} | T_0) \times P(\xi_1^p, a_1^s | \mu_{hk})$. Then, $P(\mu_{hk} | T_0)$ can be evaluated using equation (4).

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

$$\begin{aligned}
& L^{(2)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid \mu_{hk}, \xi_1, a_1, T_0) \\
&= p(D = 1 \mid \xi_1, \mu_{hk}) \prod_{t=1}^d (1 - p(D = 1 \mid \mu_{hk})) \times h(\tilde{w}_1 \mid w_1) \times p(\tilde{H}_1 \mid H_1) \prod_{\tau=T_0+1}^{T_1} (1 - m(a_1, \xi_1, \mu_{hk}))
\end{aligned} \tag{12}$$

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

$$\begin{aligned}
& L^{(3)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid \mu_{hk}, \xi_1, a_1, T_0) \\
&= p(D = 1 \mid \xi_1, \mu_{hk}) \prod_{t=1}^d (1 - p(D = 1 \mid \mu_{hk})) \times h(\tilde{w}_1 \mid w_1) \times p(\tilde{H}_1 \mid H_1) \\
&\quad \times (\delta + p(D = 0 \mid a_1, \xi_1, \mu_{hk})) \times \prod_{\tau=T_0+1}^{T_1} (1 - m(a_1, \xi_1, \mu_{hk}))
\end{aligned} \tag{13}$$

In either case, the unconditional likelihood contribution is obtained by averaging over a large number of simulation paths and over all possible individual types:

$$\begin{aligned}
& L^{(m)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid T_0) \\
&= \frac{1}{S} \sum_k \sum_p \sum_s L^{(m)}(d, T_1, \tilde{w}_1, \tilde{H}_1 \mid \mu_{hk}, \xi_1^p, a_1^s, T_0) \pi_{hk} \pi_{\xi p} \omega(\mu_{hk}, \xi_1^p, a_1^s), \quad m = \{2, 3\}
\end{aligned}$$

Table A1: Fertility Shock Parameters

	College		High school	
	Female	Male	Female	Male
Married	0.964*** (0.215)	2.012*** (0.314)	0.156 (0.290)	1.148*** (0.318)
Regional unemployment	0.092 (0.157)	-0.144 (0.172)	0.203 (0.275)	-0.207 (0.246)
White	-0.045 (0.189)	0.088 (0.230)	-0.032 (0.303)	0.282 (0.306)
Metro residence	0.117 (0.219)	-0.053 (0.225)	0.258 (0.340)	0.247 (0.286)
Constant	-4.984*** (0.323)	-5.643*** (0.413)	-5.081*** (0.455)	-5.598*** (0.462)

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