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Explaining the gender wage gap: Estimates from a dynamic model of job changes and hours changes

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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.

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JEL classification. D91, J16, J31, J63.

1. Introduction

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

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

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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. This decomposition is important for policy. If women would have received a higher wage by working full-time but did not choose to do 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 can be used 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 work, part-time work, 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 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

[2] See 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.

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

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 (some college attended) individuals, these factors explain 65.8, 33.9, 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. Although these demographic factors explain a sizable share of the gender gap in employment, the impacts on the gender wage gap are 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, particularly when it comes to explaining the gender difference in the present value of a full-time job (taking into account differences in job 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 preexisting 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. Because 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 that 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 United States. 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 that 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) considered 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). Their 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 derives its implications with respect to the gender wage gap. The estimated model also allows for a richer set of observed and unobserved heterogeneity of the worker and the offered wage.

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 4-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 4-month reference period. For every primary and secondary job that a respondent holds, the SIPP assigns a unique job identification and records job-specific monthly earnings.

There are two main advantages of using the SIPP compared to other U.S. panel data sets (such as the National Longitudinal Survey of Youth or the Panel Study of Income Dynamics). 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 job changes within the same calendar year (Liu (2015)). This means that job mobility documented at annual frequency understates the extent

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

of job–job transitions by about one-fifth.[5] The other advantage is that the SIPP contains a unique job identification (ID) for every job an employed worker had through the sample period. It records job-specific wages and hours at each interview date (every 4 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 given 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 and 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 4 months (one wave in the survey).

Table 1 presents summary statistics. Eighty-five 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

Table 1. Summary statistics.

	College				High School			
	Female		Male		Female		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 urban consumer price index (CPI = 1 in 1996:1) and then averaged over a 4-month period (per wave). Standard deviation is abbreviated s.d.

[5]Almost all existing studies on female job mobility use data from the National Longitudinal Survey of Youth, which surveys at an annual frequency. The evidence presented in this paper is generally in line with these existing studies. The differences will be highlighted below.

[6]Job 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.

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 4 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 (PT) jobs are more likely to end in nonemployment than full-time (FT) jobs. For instance, 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

Table 2. Rate of labor market transitions between waves, by gender.

	College		High School	
	Female	Male	Female	Male
From employment to unemployment				
Mean	0.021	0.004	0.032	0.007
From PT jobs	0.064	0.030	0.068	0.014
From FT jobs	0.014	0.003	0.025	0.007
Rate of job–job transition				
Mean	0.054	0.058	0.060	0.058
From PT jobs	0.071	0.177	0.086	0.275
From FT jobs	0.052	0.056	0.055	0.054
Among which:				
From FT to PT (%)	9.41	3.33	14.78	3.05
From PT to FT (%)	9.41	4.44	9.85	6.87
From FT to FT (%)	74.46	91.67	64.04	88.17
From PT to PT (%)	6.72	0.56	11.33	1.91
Job duration				
Mean	10.83	12.24	10.26	12.45
	(0.37)	(0.47)	(0.56)	(0.64)
Part-time job	9.10	6.87	6.05	7.68
	(0.91)	(1.58)	(0.84)	(1.75)
Full-time job	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)

(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 work part time and the 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 4 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.

[7]Hour 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 seem to be frictions in hour adjustment within jobs (Altonji and Paxson (1992), Euwals (2001), Blundell, Brewer, and Francesconi (2008)).

[8]The job durations here are calculated for completed job spells only (in addition to the sample selection criteria outlined in Appendix A).

[9]Between-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 $t-2$.

[10]Her definition of wage growth is based on annual wage growth between years with recorded job changes. Annual wage could be a mixture of wages from the new job and wages from the old job. Annual wage can also be contaminated by the total periods of nonemployment within the year.

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 contrast to part-time jobs 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.

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, the 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 ($h^p_{ijt}=0$, $h^f_{ijt}=1$), part-time work ($h^p_{ijt}=1$, $h^f_{ijt}=0$), or continue in the unemployment state ($h^p_{ijt}=h^f_{ijt}=0$). The employment indicator is denoted by $h_{it}\equiv h^p_{ijt}+h^f_{ijt}$. 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

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

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.[11] She faces direct utilities of part-time work (α^p_h) and unemployment $(\alpha_h+\alpha^p_h)$.[12] These parameters should in general be positive, reflecting the value

[11] The quadratic parameter ϕ_0 also has a qualitative effect similar to the interaction between income and leisure. For instance, suppose ϕ_0 is negative. Then, relative to part-time work, the additional utility gain at full-time employment from a given increase in total income is lower. This effect is qualitatively the same as having a positive interaction between income and leisure.

[12] These preference parameters are normalized with respect to full-time work.

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 over time due to the arrival of children. An additional child arrives exogenously because of fertility shocks. I model births as a stochastic process that follows

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

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

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

where $\mathbf{x}_{ni}$ is a vector of predetermined 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

$$y_{ijt} = w_{ijt} \times H_{ijt}. \tag{3}$$

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

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

$$ln(w_{ijt}) = \mathbf{x}_{wi}\boldsymbol{\beta}_w - \xi_{ijt}h^p_{ijt} + a_{ijt}, \tag{4}$$

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 are independently distributed. Thus, both are fixed effects specific to a worker–firm match.[13] The mean of ξ_{ijt} is expected to be positive, reflecting the

[13] In the absence of firm data one cannot distinguish between a pure firm effect and a pure match effect. Component a_{ijt} can be thought of 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 spell is observed for the individual.

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, given that it is one measure of the constraint facing workers when they choose between part-time and full-time 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 σ^2_{a0}. The wage cost of part-time work follows a distribution F, which is assumed independent of G.[14]

Intertemporal optimization problem. All individuals begin their lives in the unemployment state. Let $\boldsymbol{\alpha}_{it}$ denote the set of state variables summarizing the individual's characteristics, where $\boldsymbol{\alpha}_{it} \equiv \{n_{it}, x_{hi}, x_{wi}, \textit{type}\}$. 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 $V(\boldsymbol{\alpha}_{it})$ denote the value of nonemployment. The value of nonemployment for the worker is defined as

$$\begin{aligned} V(\boldsymbol{\alpha}_{it}) &= u_{it}\big(h^p = 0, h^f = 0\big) + \big(1 - \lambda^n\big)\beta E\big(V(\boldsymbol{\alpha}_{i,t+1})\big) \\ &\quad + \lambda^n \beta E \max\big[V(\boldsymbol{\alpha}_{i,t+1}), W(\mathbf{S}_{ij,t+1}, \boldsymbol{\alpha}_{i,t+1})\big], \end{aligned} \tag{5}$$

where λ^n is the probability that an offer arrives in each period and β is the discount factor and $W(\mathbf{S}_{ij,t+1}, \boldsymbol{\alpha}_{i,t+1})$ 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 $W(\mathbf{S}_{ij,t+1}, \boldsymbol{\alpha}_{i,t+1})$ is larger than $V(\boldsymbol{\alpha}_{i,t+1})$. The value function of employment with firm j is given by[15]

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

where

$$\begin{aligned} &J_k(\mathbf{S}_{ijt}, \boldsymbol{\alpha}_{it}) \\ &\quad = u_{ijkt} + \lambda^e_k(1 - \delta_k)\beta E \max\big[W(\mathbf{S}_{ij,t+1}, \boldsymbol{\alpha}_{i,t+1}), W(\mathbf{S}_{ij',t+1}, \boldsymbol{\alpha}_{i,t+1}), V(\boldsymbol{\alpha}_{i,t+1})\big] \\ &\qquad + \big(1 - \lambda^e_k\big)(1 - \delta_k)\beta E \max\big[W(\mathbf{S}_{ij,t+1}, \boldsymbol{\alpha}_{i,t+1}), V(\boldsymbol{\alpha}_{i,t+1})\big] \\ &\qquad + \delta_k \beta E\big(V(\boldsymbol{\alpha}_{i,t+1})\big), \end{aligned} \tag{7}$$

[14]The distribution of wage offers conditional on worker and firm type is determined by the distribution of match-specific productivity, which is exogenously given. This setup can be interpreted as workers having no bargaining power and receiving a take-it-or-leave-it offer from firms. Although it is potentially very interesting to provide foundations to the offered wage equation in a 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.

[15]Because 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 (i) part-time work ($h^p = 1$, $h^f = 0$) and (ii) full-time work ($h^p = 0$, $h^f = 1$) and 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, the 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.[16] Additionally, it allows current labor supply decisions to have dynamic effects on future wages, because wage growth in this type of models is driven by job turnovers determined by these parameters. For instance, if full-time work has a low layoff probability, full-time work would become a productive factor in sustaining the worker–firm match. This would imply higher future wages on average. Also, when the job offer arrival probability is higher if the individual works part time (relative to full-time work) as the estimated parameters later suggest, the model allows for part-time work to be a stepping stone to full-time work. Part-time work may be attractive even when the offered wage is low, because the individual takes into account that, by working part time, she can sample new offers and climb up the job ladder at a faster rate in the future.

3.1 *Analysis of the model*

Labor supply decisions. Given the worker and firm types, there exists a set of critical values $\{a^*(\xi), \bar{a}(\xi)\}$ that spreads out workers into different work hour arrangements,[17]

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

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

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

where $\bar{a}(\xi)$ is the reservation match for an unemployed individual to work for a job type ξ. It is defined as the solution that equalizes 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 $\bar{a}(\xi)$. The term $a^*(\xi)$ is the cutoff value for choosing full-time work, which solves the equation $J_1(a, \xi) = J_2(a, \xi)$. The individual works full time if the job is acceptable and the match value is greater than $a^*(\xi)$.[18]

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

[17] In the remainder of this section, I drop the worker, firm, and time subscripts given that they do not 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 ($\boldsymbol{\alpha}_{it}$).

[18] If 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, given that 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.

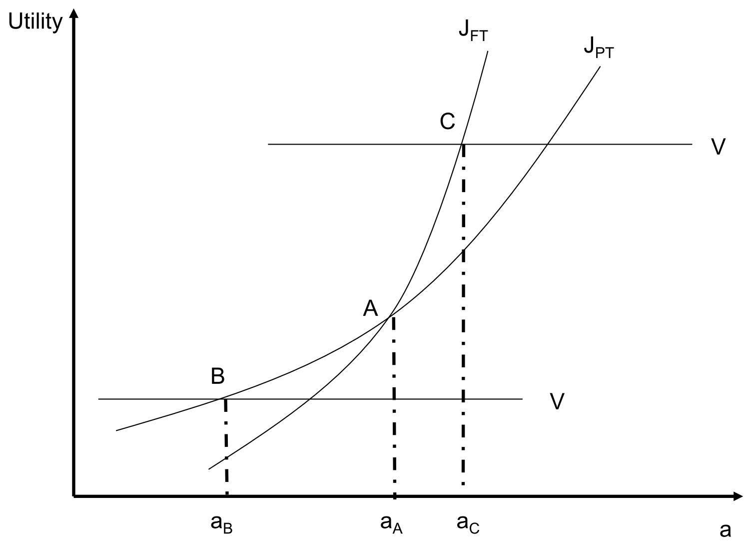

FIGURE 1. Critical match quality of hours of work.

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, would choose part-time work if the match value is between a_B and a_A, and would choose full-time work if the 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 on the type of firm the individual meets out of nonemployment.

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 $\boldsymbol{\alpha}$ worker, the transition probability from nonemployment to part-time work is

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

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

$$\lambda^n\left(\int_{\xi<k_0} \widetilde{G}\big(a^*(\xi)\big)\,dF(\xi) + \int_{\xi>k_0} \widetilde{G}\big(\bar{a}(\xi)\big)\,dF(\xi)\right), \tag{12}$$

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

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:

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

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 $a' > a_r(\xi', a, \xi)$.[19]

Job mobility dynamics is richer in the current model because 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

$$\lambda_k^e \int \widetilde{G}\big(\max\big\{a_r\big(\xi', a, \xi\big), a^*\big(\xi'\big)\big\}\big)\,dF\big(\xi'\big). \tag{14}$$

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

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

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 4 months, corresponding to the interview frequency in the SIPP. The data are divided into four groups by gender and education of the in-

[19]Note 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. Because the worker is employed on the current job, this implies that the new job must be above the reservation utility for employment (i.e., $h > 0$).

dividual: 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 to be 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 ($\boldsymbol{\beta}_h, \alpha_h^p, \alpha_h, \alpha_{hn}, \phi_0$), wage equation parameters ($\boldsymbol{\beta}_w, \sigma_{a0}^2$), labor market friction parameters ($\lambda^n, \lambda_k^e, \delta_k$) ($k = \{1, 2\}$), fertility shock parameters $\boldsymbol{\beta}_f$, and type-specific parameters ($\mu_{h2}, \pi_{h2}, \xi^1, \xi^2, \pi_{\xi 2}$), where both worker and firm types are discretized into two points of support. The discount factor is not estimated and is fixed at 0.9.[20] The offered wage equation is estimated jointly with choice probabilities predicted by the structural 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 the 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 a different proportion of the population working part time, full time, or 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) sorting into different hours of work. Combined with the observed conditional wage distribution and the distributional assumption (log normal) 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.[21] 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.

[20]The 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.

[21]As 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.

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 an additional restriction to identify the work preferences. Because 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 panel data set contains a unique job ID that 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 a small part-time wage penalty is high. If the wage on the new job is high, it would suggest the latter, given that the individual may accept low wages if she values part-time work highly. In general, because unobserved heterogeneity in the model takes the form of discrete types and wage offers are independent and identically distributed (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.[23]

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, whereas 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).

[22]I rank all the regional unemployment rates. The regional unemployment rate is constructed such that it is equal to 1 if the regional unemployment rate is above the median and is equal to 0 elsewhere.

[23]See, for example, 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.

4.2 *Estimation strategy*

To ease computational burden, the fertility shock parameters $\boldsymbol{\beta}_f$ are estimated outside the structural model. I estimate the parameters $\boldsymbol{\beta}_f$ (see equation (2)) by estimating a logit regression.[24] 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, Dey and Flinn (1992, 2005)). Because job offers are i.i.d., for a given worker, each cycle is independent of each other.[25] 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

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

where d is the duration of the unemployment spell. Consistent with notations in the previous section, T_j corresponds to the duration of employment with the jth employer (job tenure) within the cycle, and $\widetilde{w}_j$ and $\widetilde{H}_j$ correspond to the observed wage and hour status ($h > 0$) with the jth employer. Information regarding wage and hour dynamics within a given job is ignored, so $\widetilde{w}_j$ and $\widetilde{H}_j$ correspond to the wage and hour observed at the beginning of the jth job spell.[26]

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

$$\widetilde{w}_j = w_j e^{v_j}, \tag{17}$$

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

$$P(\widetilde{H}_j = 40) = \frac{\exp\bigl(\bigl(a_j - a_j^*(\xi)\bigr)/c\bigr)}{1 + \exp\bigl(\bigl(a_j - a_j^*(\xi)\bigr)/c\bigr)}, \tag{18}$$

where c is the smoothing parameter. As c goes to zero, $P(\widetilde{H}_j = 40)$ goes to 1 if the match value is above the reservation value for full-time work and to zero otherwise.[27]

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

[25] For 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 $T = 0$.

[26] Hour 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 (2015)). 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)).

[27] In estimation, c is fixed at 0.01.

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.[28]

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.[29] Conditional on T_0, the complete likelihood function consists of products over workers and cycles,

$$\begin{aligned} L = &\prod_{i \in Y_1} L^{(1)}(d, T_1, \widetilde{w}_1, \widetilde{H}_1, \widetilde{w}_2, \widetilde{H}_2 | T_0) \prod_{i \in Y_2} L^{(2)}(d, T_1, \widetilde{w}_1, \widetilde{H}_1 | T_0) \\ &\times \prod_{i \in Y_3} L^{(3)}(d, T_1, \widetilde{w}_1, \widetilde{H}_1 | T_0) \prod_{i \in Y_4} L^{(4)}(d | T_0), \end{aligned} \tag{19}$$

where $i \in Y_m$ denotes the set of workers who belong to the mth 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 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 cases, 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 unemployment duration, and the wage and labor supply of the first job. In the last case, the observation period ends while the individual is still in an ongoing unemployment spell. Therefore, only the unemployment duration contributes to the likelihood. The construction of the likelihood function is discussed in detail in Appendix B.[30]

[28]Measurement errors are also necessary to satisfy the support condition of the maximum likelihood estimator.

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

[30]Because 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 utilize 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 who are

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 that determine 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 and 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, including heterogeneity in the wage offer and parameters that characterize the distribution of the costs of part-time jobs and measurement errors.[31]

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 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 a 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.[32] The preference for work (α_2) is larger for high-education women than high-education men. The difference is insignificant among low-education 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.

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.

[31] The parameters of fertility shocks are shown in Appendix Table A.1.

[32] The 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.

Table 3. Estimated parameters.

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

Note: Standard errors are given in parentheses.

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

TABLE 4. Estimated offered wage parameters.

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

Note: Standard errors are given in parentheses.

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 conforms 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 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 an 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

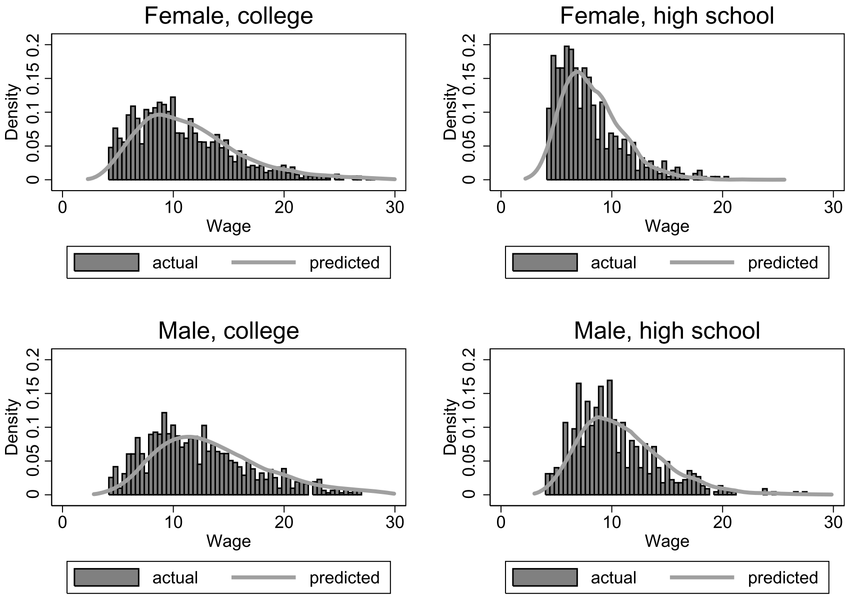

FIGURE 2. Actual and predicted wage distributions for workers.

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.[33]

Figure 2 plots the actual and predicted wage distributions of workers. Actual wages are based on the observed wage in the first job spell ($\widetilde{w}_1$ 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 conditional on the individual's observed characteristics and initial condition when $\widetilde{w}_1$ is observed.[34] The model is able to predict the essential features of the wage distribution (such as the wage where density peaks) for each subsample. 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

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

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

[34] For 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.

TABLE 6. Wage elasticities of labor supply.

	Baseline	Wage Incr. By 10%	Elasticity	Baseline	Wage Incr. By 10%	Elasticity
	High-education women			High-education men		
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
	Low-education women			Low-education men		
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

workers when $\widetilde{w}_1$ 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 cutoff 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.

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.[35]

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 pre-

[35] Individual 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	% of Gender Gap No Work
				High-education women				
Baseline	0.30	0.08	0.63	11.14	9.43	11.36		
High-education men	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 probability	0.09	0.14	0.78	11.43	9.77	11.72	15.6%	75.6%
Layoff probability	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%
				Low-education women				
Baseline	0.25	0.14	0.61	8.19	7.49	8.35		
Low-education men	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 probability	0.12	0.23	0.65	8.36	7.70	8.58	6.9%	64.0%
Layoff probability	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. The final two columns show the percentage of the baseline gender gap explained by each factor.

dicted 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; 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.

Although 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 to the baseline, even as the share of full-time work increases relative to part-time work. 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 a 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 reduce the reservation wage for full-time employment, which leads to a 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.[36]

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. Because 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 model. Higher job offer probabilities and lower layoff probabilities (relative to the current values of women) help women 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

[36] In a general equilibrium model (e.g., Mortensen (1990), Bowlus (1997)), firms also have incentives to lower the average offered full-time wage in response to the reduction in the preference (because 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.

in Bowlus (1997), despite the differences in model specifications, estimation, and data. Although 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.[37]

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 explain only a small fraction of the predicted 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 taking into account 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.[38] 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.[39] 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 Tables 7 and 8 combined indicates that the gender gap is even more pronounced due to men having longer full-time job spells in addition to higher

[37] See Chan (2013) for similar evidence.

[38] Note 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.

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

Table 8. Sources of gender differences in job turnover.

	Job Duration			FT Job Spell	
	PT	FT	No Work	PV	% Gender Gap
			High-education women		
Baseline	13.2	23.8	28.1	270.2	
High-education men	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 probability	11.3	26.2	5.3	306.9	28.6%
Layoff probability	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%
			Low-education women		
Baseline	9.9	20.4	13.7	170.4	
Low-education men	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 probability	9.0	18.3	4.6	157.0	−11.1%
Layoff probability	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. The final column shows the percentage of the baseline gender gap explained by each factor.

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

6.2 *Evaluating counterfactual policies*

Table 9 and 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).

TABLE 9. Effects of counterfactual policies: high-education individuals.

	Baseline	Equal Pay	Equal Protection
		High-education women	
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
		High-education men	
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
% change in gender gap			
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.

TABLE 10. Effects of counterfactual policies: low-education individuals.

	Baseline	Equal Pay	Equal Protection
		Low-education women	
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
		Low-education men	
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
% change in gender gap			
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.

These policies aim to promote equality between part-time and full-time workers, which have been in place in many countries in Europe.[40]

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. Although the part-time wage does increase among women, it increases even more among men. Full-time wage also increases, because the equalization of offered part-time and full-time wage means that individuals must require a higher wage so as to work full time. Equal pay leads to a large increase in the fraction of part-time work and a large decrease in 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.[41]

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). Given that the policy reduces the destruction rate of part-time jobs, part-time wage tends to increase relative to the baseline (because 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 a 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 the gender gap in both 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

[40] In 1997, the European Union (EU) introduced a directive that provides protection to part-time workers in terms of both pay and benefits. Following the EU directive, in 2000, the United Kingdom adopted the Part-Time Workers (Prevention of Less Favorable Treatment) Regulations. This legislation mandated the same hourly rates of pay and benefits for 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.

[41] Interestingly, 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 nonmarket work for high-education women relative to high-education men (see Table 3).

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).[42]

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 importance, the remaining key factors explaining the gender wage gap are the job search parameters, the 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. Although 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 have promoted 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 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

[42]Throughout 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.

unit in the analysis of this paper is 4 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 U.S. 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 4 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.[43] 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.[44] I drop full-time students, the self-employed, the disabled, those who appeared less than 3 years (out of 4 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 percent 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 1 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 Section 4.2 for details).

Appendix 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 by[45]

$$p(D=1|\mu_{hk}) = \sum_j \pi_{\xi j} p\big(D=1|\xi=\xi^j,\mu_{hk}\big) = \sum_j \lambda_n \pi_{\xi j} \widetilde{G}\big(\bar{a}\big(\xi^j\big)\big), \tag{B.1}$$

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

[44]Because the SIPP is a short panel and the expected college completion age is 23, this selection criterion ensures that the highest completed education level is obtained for each individual.

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

where $\widetilde{G}(\bar{a}(\xi^j)) = 1 - G(\bar{a}(\xi^j))$ and ξ^j is the potential type of the new job.[46] If there is only one unemployment spell in the sample, then the conditional likelihood function is simply given by

$$L^{(4)}(d|T_0, \mu_{hk}) = \prod_{t=1}^{d} \bigl(1 - p(D=1|\mu_{hk})\bigr), \tag{B.2}$$

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

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

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

$$P(\mu_{hk}|T_0) = \frac{P(T_0|\mu_{hk})\pi_{hk}}{\sum_i P(T_0|\mu_{hi})\pi_{hi}}, \tag{B.4}$$

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

$$P(c) = P(d)P(T_1, \widetilde{w}_1, \widetilde{H}_1, \dots, T_J, \widetilde{w}_J, \widetilde{H}_J). \tag{B.5}$$

The term $P(c)$ forms the basis of the likelihood function. Because 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 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 so as to minimize computational burden. This includes $\{d, T_1, \widetilde{w}_1, \widetilde{H}_1, \widetilde{w}_2, \widetilde{H}_2, \}$.[47]

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

[46] Note 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)).

[47] Given that SIPP is a short panel, the information loss is little because few workers in the data change jobs more than twice in a single employment cycle.

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

$$m(a_1, \xi_1, \mu_{hk}) = p(D=0|a_1, \xi_1, \mu_{hk}) + p(M=1|a_1, \xi_1, \mu_{hk}) + \delta, \tag{B.6}$$

where $p(D=0|a_1, \xi_1, \mu_{hk})$ is the likelihood of voluntary quit to unemployment.[48] The probability that a job–job transition takes place can be written as

$$p(M=1|a_1, \xi_1, \mu_{hk}) = \lambda_e(1-\delta)\sum_j \pi_{\xi j}\widetilde{G}\big(a_r\big(\xi_2^j, a_1, \xi_1\big)\big), \tag{B.7}$$

where it is summed over the potential types of new jobs (ξ_2^j denotes the new job of type j and $\pi_{\xi j}$ 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

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

where density functions h and p are generated from the measurement error assumption. Note that to evaluate $h(\widetilde{w_2}|w_2(\xi^j))$ and $p(\widetilde{H_2}|H_2)$, I rely on a simulation method to draw $f(a_2|\xi_2, \xi_1, a_1, \mu_{hk})$. 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 and 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 heterogeneity, firm heterogeneity, and match heterogeneity of the first job (a_1). Because a_1 is the match value of an *accepted* offer, it no longer follows the exogenous population distribution of matches $G(a)$. I use a simulation method to draw a_1 from $G(a_1|\xi_1, \mu_{hk})$, which follows a truncated normal distribution with a lower trun-

[48]The probability of voluntary quit is given by $(1-p(M=1|a_1, \xi_1, \mu_{hk})-\delta) \times \frac{\exp((\bar{a}(\xi_1)-a_1)/c)}{1+\exp((\bar{a}(\xi_1)-a_1)/c)}$. 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.

Table A.1. Fertility shock parameters.

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

cation point given by the reservation value for employment (at $\bar{a}(\xi_1)$).[49] 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

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

I use 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:

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

Interview 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).[50] The T_0 reveals additional information that can be used to 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

[49] I draw ζ_1 from a uniform distribution defined on the interval $[0, 1]$. Then the inverse of the cumulative distribution 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.

[50] When 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 (B.4).

observing T_0 at the first interview. The unconditional likelihood function can be written as

$$\begin{aligned} & L^{(1)}(d, T_1, \widetilde{w}_1, \widetilde{H}_1, \widetilde{w}_2, \widetilde{H}_2 | T_0) \\ & \quad = \frac{1}{S} \sum_k \sum_p \sum_s L^{(1)}\big(d, T_1, \widetilde{w}_1, \widetilde{H}_1, \widetilde{w}_2, \widetilde{H}_2 | \mu_{hk}, \xi_1^p, a_1^s, T_0\big) \\ & \qquad \times \pi_{hk} \pi_{\xi p} \omega\big(\mu_{hk}, \xi_1^p, a_1^s\big), \end{aligned} \tag{B.11}$$

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

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

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

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

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

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

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