Occupation Gender Segregation: Empirical Evidence from a Matching Model with Transfers

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Abstract

Women have increased their labor force participation dramatically since 1960, but remain concentrated in certain occupations. I examine whether this concentration reflects workers' preference to work with their own gender as opposed to other worker, or firm, preferences. I build a model of labor supply and demand in which firms maximize profit over the gender and wages of their employees, and workers maximize utility over occupation, wage, and the fraction female in their occupation. Using a Bartik instrumental variables strategy, I find that women strongly prefer to enter into female-dominated occupations, but men show no evidence of gender preference. Given these estimates, equilibrium simulations indicate that equal pay for equal work laws could in fact increase segregation by preventing employers from compensating for a gender preference.

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1 Introduction

As of 2009, approximately 50% of women would need to change occupation in order to have an equal number of men and women in every occupation, and this gap is unlikely to close soon (Blau, Brummund, & Liu, 2013). This segregation is also a major driver of the gender pay gap, with women more concentrated in lower paying occupations (Blau & Kahn, 2017). In this paper I explore one possible driver of segregation and the gender wage gap: workers preferring to work with their own gender (homophily).

I build an empirical model to separately identify homophily from workers' preferences for occupations and firms' preferences for workers. I use my model to quantify the impact of homophily on observed segregation and wage gaps, and to simulate the equilibrium consequences of equal pay for equal work and encouraging entry into occupations in the presence of homophily. Understanding homophily is particularly important for gender equity policy because it could prolong the impact of historical preferences or discrimination, for example if nursing is only female because it was historically female.

To identify homophily I must first separately identify worker and firm preferences using data on shares and wages, which are equilibrium outcomes. To do so I assume that firms are not able to observe the productivity of individual workers beyond their gender. Then, the highest wages paid in an occupation help identify differences in firms' willingness-to-pay by gender, while differences in lowest wages workers are willing to accept help identify gender differences in worker preferences. The second challenge is that there may be unobserved changes to occupations that are correlated with changes to the gender composition. To distinguish these stories, I use the fact that occupations exist in different industries. For example, suppose that accounting in the manufacturing industry is more male-dominated. Then as manufacturing declines, workers may be less likely to view accounting as a male-dominated occupation. I assume that wage and gender composition are the only attributes of occupations that are affected by changes to industries.

I find that women care strongly about the number of women in an occupation, but find no evidence that men care about the number of women, consistent with recent survey evidence (Delfino, 2019). The point estimate in my preferred specification is very high, with an occupation moving from 25% to 75% female being equivalent to an extra $3 million in lifetime income for a woman. Without this preference for higher fraction female, segregation would be much lower, with only 24% as opposed to 41% of workers having to change occupation for all occupations to be 50% female. I also find women are paid on average $275,000 less over the course of their lifetimes because of compensating differentials from the gender preference, with women in highly female-dominated occupations such as nursing losing the most income.

My equilibrium model with estimated gender preference is able to explain multiple stylized facts in the literature. First, I find that women are willing to accept lower wages in an occupation as it becomes more female, and firms only hire men whose preference for that occupation causes them to also accept these lower wages. This is consistent with previous literature which has found that as women enter an occupation, wages go down for both men and women in that field (Levanon, England, & Allison, 2009; Harris, 2018). Second, I find that the gender preference causes more dramatic movement in the fraction female through a feedback loop in response to changes in worker and firm preferences. This is one possible mechanism for "tipping", or rapid movement from male to female, which was found in occupations by Pan (2015).[1]

I use my estimated model to find out if the fraction female in occupations depends on initial conditions. To do so I simulate the decisions of successive cohorts of workers who overlap in the labor market starting from various initial sorting patterns. I find that each occupation tends towards a unique steady state in the fraction female regardless of initial gender composition. For example, my model predicts that nursing would be female-dominated regardless of whether there were norms or barriers that led it to be

[1] "Tipping" has also been found in racial segregation by neighborhoods (Card, Mas, & Rothstein, 2008) and racial composition of schools (Caetano & Maheshri, 2017). Tipping can refer to any rapid change in composition, or only rapid changes caused by moving between multiple equilibria. Here I find unique equilibria in each occupation, so I use tipping to mean any rapid changes.

female-dominated in 1960. This implies that a policy of temporarily pushing more men or women into certain occupations will not lead to convergence to new, and possibly better, sorting patterns, because the steady state sorting pattern is unique.

However, if wages are not allowed to adjust to compensate workers for changes in the fraction female, then in some cases segregation *does* depend on initial conditions. I simulate the consequences of one such policy, equal pay for equal work, in the context of the large estimated preference for women to work with women. The equal pay policy means that women cannot be compensated for working in male-dominated occupations. As a result, firms tend to hire either only men or women, and in many occupations there are multiple steady states at either highly male or female-dominated. Even though men and women are offered more comparable wages within each occupation, the dramatic increase in segregation due to the policy has the unintended consequence of leading to a larger gender wage gap.

Recent literature has identified a number of contributing causes of segregation: preferences over amenities (Olivieri (2014), Wiswall and Zafar (2018))[2], productivity and skill differences (Baker and Cornelson (2018)), and occupational and educational barriers (Hsieh, Hurst, Jones, and Klenow (2016)). I study another possible cause of the persistence of segregation: workers valuing the gender composition of occupations. Previous literature such as Usui (2008); Lordan and Pischke (2015) has looked at whether women prefer to work with women using job satisfaction surveys and employment transitions, but I am the first to quantify the impact of homophily on overall segregation and wage patterns. To do so I build on the methodological insights of Choo and Siow (2006), Salanié (2014a), and Dupuy and Galichon (2017) in empirical transferable utility matching.

Section 2 introduces the model including firm and worker payoffs and equilibrium wages. Section 3 describes the data sources, and Section 4 the estimation and identification. I discuss the parameter estimates in Section 5 and present simulations of segregation dynamics in Section 6, including counterfactuals.

[2]For overview see Bertrand (2011) and Cortes and Pan (2017).

2 Model

2.1 Firm Payoff

In the model, each firm (j) chooses to hire a male or female worker ($g \in \{M, F\}$) to fill a single vacancy. I allow firms to be willing to pay different amounts for male and female workers, but I do not take a stance as to why or how. The firm maximizes log profit π_j^g to maximize its rate of return on its single vacancy. This allows me to abstract away from the number of vacancies at a firm or complementarities between those vacancies. Firm j's payoff is as follows:

$$\pi_{j,t}^g = WTP_{o,t}^g - Wage_{j,t}^g \tag{1}$$

The total payoff to firm j, $\pi_{j,t}^g$, depends on $WTP_{o,t}^g$, the log willingness-to-pay of a firm in occupation o for a worker of gender $g \in \{M, F\}$ in time period t. $WTP_{o,t}^g$ will be estimated for each gender and occupation and time period. The payoff also depends on the log cost of hiring a worker, $Wage_{j,t}^g$, which is observed but varies in equilibrium.

In Appendix 8.1.4, I show that log wages consist of two components in equilibrium:

$$Wage_{j,t}^g = W_{o,t}^g + \xi_{j,t}^g \tag{2}$$

The first term, $W_{o,t}^g$, equates aggregate supply and demand in order to make the matching feasible. This term varies by gender and occupation. Below I refer to $W_{o,t}^g$ as the wage offer component because it is equal to the expected value of the log wage offer in occupation o for gender g, ignoring selection over firms j.

The log dis-amenity value of a particular firm j is denoted $\xi_{j,t}^g$. This dis-amenity heteroeneity value could be, for example, the presence of on-site childcare or other work environment factors, specific to firm j. I take these dis-amenities as fixed and exogenous for the purpose of the model. In equilibrium, wages must exactly compensate workers for the dis-amenity heterogeneity values, making workers indifferent across firms within an occupation. This assumption ensures pairwise stability, meaning that after optimization, no workers or firms could achieve a higher surplus by rematching.

Note that in order for equilibrium wages to be unique I assume a large number of workers of each gender and firms in each occupation (Galichon & Salanié, 2015). I also assume that log firm dis-amenity heterogeneity terms, $\xi^g_{j,t}$, are normally distributed, making wages lognormally distributed. This is a common assumption that matches observed wage distributions.

Assumption 1. *Let the log heterogeneity in firm dis-amenities for each gender, $\xi^g_{j,t}$, be distributed $\mathcal{N}(0, \sigma_{\xi^g_t})$ and independent across j, such that $exp(\xi^g_{j,t})$ is distributed lognormal.*

I also assume that if the equilibrium wage the firm would have to pay to fill its vacancy is greater than its willingness-to-pay, the firm will not fill its job opening and receive a payoff of zero. This will occur for firms that receive large draws of both $\xi^M_{j,t}$ and $\xi^F_{j,t}$, meaning both men and women find the firm very unattractive.

Assumption 2. *A firm will not hire if $\pi^g_{j,t} \leqslant 0$ for both male and female workers.*

Combining Equations 1 and 2 and Assumption 2, the firm solves the following problem in equilibrium:

$$\max \left\{ \max_{g \in \{M,F\}} (\pi^g_{j,t} = WTP^g_{o,t} - W^g_{o,t} - \xi^g_{j,t}), 0 \right\}$$

The firm chooses to hire a male or female worker based on how much they value hiring a man or woman ($WTP^g_{o,t}$), the overall equilibrium cost of hiring a man or women, ($W^g_{o,t}$), and the idiosyncratic cost of hiring men and women at firm j ($\xi^M_{j,t}$ and $\xi^F_{j,t}$). The assumption that firms do not have preferences over individual workers within gender is critical because it allows me to separate the matching problem into two separate discrete choice problems, one for firms and one for workers (Galichon & Salanié, 2015).

2.1.1 Worker

For the purposes of the model, I divide workers into four ten-year cohorts by age: ages 25-34, 35-44, 45-54, and 55-64. Every 10 years a young cohort of workers (ages 25-34) makes an occupation choice. The young cohort observes the fraction female in the occupation among the previous three cohorts of workers (ages 35-65), which I denote $F_{o,t-1}$. I assume that the job choice is binding for life,[3] which implies that the choice of the young cohort of workers will then influence the fraction female observed by the next three cohorts of workers. Lowering switching costs would lead to faster convergence to a fixed point in the fraction female by occupation, but not change the substantive dynamics of the model. I also assume that workers are myopic and do not anticipate future changes in the market that would lead them to want to switch occupations.[4]

In the model, a worker i of gender g in time t chooses a firm j in occupation o to maximize log utility as follows:

$$\max_j u^i_{j,t} = \alpha^g_o + \beta^g_t + \gamma^g F_{o,t-1} + Wage^g_{j,t} + \eta^i_{o,t} - \xi^g_{j,t} \tag{3}$$

The main parameter of interest is γ^g, which reflects utility that gender g receives from the observed fraction female in the occupation, $F_{o,t-1}$. The model assumes that workers care about the fraction female at the occupation level, which could reflect social norms regarding the gender of the occupation, or an expectation of working

[3]To assess the impact of this assumption, I examine the extent to which workers switch occupations during their working lifetime in the PSID. I find that the average worker who spends most years working spends 80% of working years in the same broad occupation category.

[4]Relaxing myopia would mean that the endogenous attribute of interest, the fraction female, would depend on expectations over other workers' occupation choices, which in turn are affected by the fraction female. This would pose a challenge to tractability.

with colleagues within the same occupation. Recall that $F_{o,t-1}$ is subscripted $t-1$ to indicate that it reflects the decisions of the previous three cohorts of workers. The preference that all workers of gender g have for occupation o is given by α_o^g. This could reflect any sort of gender specific taste for type of work that does not vary over time. Variation over time in the attractiveness of employment vs. non-employment by gender is captured by β_t^g. Workers also care about the wage they are offered by firm j, ($Wage_{j,t}^g$), and the dis-amenities at firm j, denoted $\xi_{j,t}^g$, which are the same for everyone conditional on gender. Worker i's specific taste for occupation o is $\eta_{o,t}^i$.

Recall that in equilibrium the wage is given by $Wage_{j,t}^g = W_{o,t}^g + \xi_{j,t}^g$. Therefore the log utility maximization problem of the worker in equilibrium can be simplified to:

$$\max_{o \in O} u_o^i = \alpha_o^g + \beta_t^g + \gamma^g F_{o,t-1} + W_{o,t}^g + \eta_{o,t}^i \tag{4}$$

Workers are exactly compensated for the firm dis-amenities, $\xi_{j,t}^g$, in equilibrium. This means that the taste for occupation, $\eta_{o,t}^i$, is the only heterogeneity at the individual worker level. The implication is that workers do not have preferences over individual firms within an occupation. As on the firm side, this allows me to separate the sides of the market into two discrete choice problems.

I make the following two assumptions, which are standard in the discrete choice literature (Berry, 1994): a logit assumption on taste heterogeneity and a normalization of the value of the outside option.

Assumption 3. *Let the worker taste heterogeneity for occupations, $\eta_{o,t}^i$, be independently distributed extreme value type 1, with scale parameters scale parameters σ_η^M and σ_η^F to be estimated.*

Assumption 4. *Let the log utility from non-employment be normalized to zero ($u_N^g = 0$).*

Since no wages are received in non-employment, this leaves only the idiosyncratic taste for non-employment η_N^i. I then leverage well-known properties of extreme value distributions to obtain relative occupation choice probabilities in terms of utility parameters. I denote the share of workers of gender g who match to occupation o in time t as $s^g_{o,t}$, and the share who choose non-employment as $s^g_{N,t}$.

$$ln(s^g_{o,t}) - ln(s^g_{N,t}) = \frac{\alpha^g_o + \beta^g_t + \gamma^g F_{o,t-1} + W^g_{o,t}}{\sigma^g_\eta} \tag{5}$$

We now have worker utility parameters written in terms of observed shares $s^g_{o,t}$ and $s^g_{N,t}$. Below I discuss the data used to identify the model, and then the estimation strategy for both the firm and worker sides of the model.

3 Data

The data elements needed to estimate the model described above are: expectations of lifetime labor income by occupation, gender, and cohort ($Wage^g_{j,t}$), shares of workers by gender and age cohort choosing each occupation and non-employment ($s^g_{o,t}$ and $s^g_{N,t}$), and a measure of unfilled jobs by occupation (jobs for which $\pi^g_{j,t} \leqslant 0$).

While the Census and ACS provide cross sectional wage and occupation, the Survey of Income and Program Participation (SIPP) is needed to provide a panel for the construction of lifetime labor income estimates.[5] Using pooled data from the 2004 and 2008 SIPP panels, which are four and five years long respectively, I construct transition rates through five quantiles of earnings and occupations by worker age and gender.[6] This transition matrix is then used to simulate worker career paths from the starting point of workers aged 25-35 in the Census and ACS. Their assigned choice of occupation is taken as the occupation they start out in at ages 25-35 as observed in the Census, which means that the occupation choice can be interpreted as including

[5] Public use Census 1960, 1970, 1980, 1990, 2000, and 2012 three-year ACS data obtained from IPUMS (Ruggles, Genadek, Goeken, Grover, & Sobek, 2015). SIPP data from the 2004 and 2008 panels are constructed using the NBER files (U.S. Census Bureau, 2017). Occupation codes are constructed by aggregation of the IPUMS harmonized codes (occ1990) to achieve sufficient sample size. See Table 1 for the full list of occupation codes.

[6] I assume that transition rates depend only on the current state not the past history, but this assumption could be relaxed with the addition of more data.

the expectation of all future transitions.

The Job openings and Labor Turnover Survey (U.S. Bureau of Labor Statistics, 2017) is used to construct a measure of unfilled jobs by occupation. Since JOLTS does not directly contain occupation, only NAICS industry codes, industries are projected into occupations using contemporaneous occupation industry shares estimated in CPS (Flood, King, Ruggles, & Robert, 2015). The estimated openings by occupation is then divided by the total number of people employed in the occupation to get the ratio of openings to employed.

4 Empirical Strategy

I estimate the firm side and the worker side of the model separately in two stages. In the first stage, I estimate the firm parameters ($WTP^g_{o,t}$, $\sigma_{\xi^g_t}$) and equilibrium wage offers ($W^g_{o,t}$) using maximum likelihood estimation for each cross section of Census or ACS data.

In the second stage, I estimate the worker side using an instrumental variables regression at the occupation-year level. The common equilibrium wage offers ($W^g_{o,t}$), estimated in the first stage, are treated as data in the second stage regression. Instruments, discussed below, provide clean variation in the fraction female and reservation wage to trace out labor supply parameters (α^g_o, γ^g, σ^g_η).

4.1 Step 1: Firm Estimation and Identification

4.1.1 Firm Estimation

We observe only those log wages ($Wage^g_{j,t}$) that maximize the firm's choice over male, female, or not hiring any worker. Therefore the observed data are the result of both selection and truncation. The selection and truncation depends on what firms are willing to pay for workers ($WTP^g_{o,t}$), the equilibrium wage offers ($W^g_{o,t}$) needed to clear the market, and the scale of the unobserved firm dis-amenity heterogeneity, $\sigma_{\xi_t^g}$.[7] All of these elements are unknown and to be estimated. To estimate $WTP^g_{o,t}$, $W^g_{o,t}$ and $\sigma_{\xi_t^g}$ jointly while accounting for selection and truncation, I use Tobit Type 5 maximum likelihood estimation. I estimate the likelihood separately on individual level data for each of six cohorts of workers between 1960 and 2012 ($t \in \{1960, 1970, 1980, 1990, 2000, 2012\}$).

Let $\mathcal{I}($ j unfilled) be equal to one if firm j's job is unfilled. Then the likelihood contribution of firm j is given by:

$$LL_j = \prod_j (Pr(j \text{ hire g}|Wage^g_{j,t}) * Pr(Wage^g_{j,t}) * (1 - Pr(j \text{ unfilled})))^{(1-\mathcal{I}(j \text{ unfilled}))}$$
$$* (Pr(j \text{ unfilled}))^{\mathcal{I}(j \text{ unfilled})}$$

Recall that Assumption 1 states that log wages are normally distributed. Therefore we can rewrite the log likelihood in terms of normal distributions. Let $\Phi_{0,\sigma_{\xi_t^g}}$ and $\phi_{0,\sigma_{\xi_t^g}}$ be the normal cdf and pdf respectively, with location zero and scale $\sigma_{\xi_t^g}$. Then the components of the log likelihood can be written as follows:

$$Pr(j \text{ hire g}|Wage^g_{j,t}) = \Phi_{0,\sigma_{\xi_t^{g\prime}}}(WTP^g_{o,t} - Wage^g_{j,t}) - (WTP^{g\prime}_{o,t} - W^{g\prime}_{o,t})),$$
$$Pr(Wage^g_{j,t}) = \phi_{0,\sigma_{\xi_t^g}}(Wage^g_{o,t} - W^g_{o,t}), \text{ and}$$
$$Pr(j \text{ unfilled}) = \Phi_{0,\sigma_{\xi_t^g}}(-(WTP^g_{o,t} - W^g_{o,t}) * \Phi_{0,\sigma_{\xi_t^{g\prime}}}(-(WTP^{g\prime}_{o,t} - W^{g\prime}_{o,t})).$$

Thus we have parameters $WTP^g_{o,t}$ and $\sigma_{\xi_t^g}$ and equilibrium wage offers $W^g_{o,t}$ as

[7] Estimating scale is important because is governs the elasticity of labor supply to changes in wages or other non-wage amenities such as the gender ratio in the counterfactual, as well as the demand response to changes in equilibrium wage. Unlike Chiappori, Salanié, and Weiss (2015), who uses many markets to identify these parameters, I use the observed wage distribution as suggested in Salanié (2014a) and Dupuy and Galichon (2017).

a function of data. $Pr(j \text{ unfilled})$ is the probability that we do not observe a match, which I impute from the JOLTS vacancy data.[8] Predicted shares, or $Pr(j \text{ hire g}|Wage^g_{j,t})$, are observed in the Census/ACS, and wages, or $Wage^g_{j,t}$, are imputed using the Census and SIPP as described in Section 3 above. This concludes the first stage of estimation.

4.1.2 Firm Identification

Figures 1 and 2 illustrate the separate identification of firms' willingness-to-pay ($WTP^F_{o,t}$ and $WTP^M_{o,t}$) and center of the wage offer distributions for men and women by occupation ($W^F_{o,t}$ and $W^M_{o,t}$) by simulating observed wage distributions under different parameter values.

The top panels of Figure 1 and 2 show the wage distributions of men and women when they have identical preferences over occupations, and firms have no preference over male and female workers (implying $WTP^F_{o,t} = WTP^M_{o,t}$ and $W^F_{o,t} = W^M_{o,t}$). In this baseline case it can be seen that the wage distributions of men and women are identical.

The lower panel of Figure 1 illustrates the impact of worker preferences on the observed wage distribution. In this simulation I assume that men prefer to work in the occupation more than women. The male preference for the occupation implies that the wage offers required to clear the market for men are lower than those of women ($W^F_{o,t} > W^M_{o,t}$). The lower equilibrium wage offers for men mean than firms tend to hire more men into the occupation because they are cheaper to hire, and also that the male wage distribution has more mass closer to zero. Note also that in the bottom half of Figure 1 the right tails of the male and female distributions still overlap substantially. The right tail of the wage distribution represents firms who are compensating workers for bad firm amenity draws, that is high $\xi^g_{j,t}$. Because, in this simulation, firms' willingness-to-pay for both men and women is the same ($WTP^F_{o,t} = WTP^M_{o,t}$), both men and women can match with the firms with the worst amenities and therefore appear in the right tail of the wage distribution.

The lower panel of Figure 2 shows the impact of firm preferences on the observed

[8] Results do not appear sensitive to imputation method.

wage distribution. In the bottom panel, as opposed to the top panel, firms prefer to hire men, holding all else equal. As in Figure 1, this means that more men are hired into the occupation, but the implication for the observed wage distribution is very different. Examining the bottom panel of Figure 2 we see that in the case of firms preferring to hire men, the bulk of the male wage distribution is shifted to the right, in fact well past the right tail of the female wage distribution. This is because firms are willing to pay more for men and therefore even with a worse dis-amenity draw for men $\xi_{j,t}^{M} > \xi_{j,t}^{F}$, will choose to pay more to hire the man. The only women who are hired into this occupation are those that match to firms with very good amenity draws for women, and are therefore cheap to hire.[9]

Figures 3 and 4 further illustrate identification by comparing the actual (not simulated) observed wage distribution in two occupations with very different estimated parameter values: "Sales Representatives, Finance, and Business Services," and "Health Service Occupations."

In "Health Services Occupations" in Figure 3, we see that the observed wage distribution for women is centered to the left of the male wage distribution. At the same time, the right tails of the male and female wage distributions broadly overlap. This is a pattern similar to the simulated data in Figure 1. The model rationalizes this pattern by estimating that the wage offer distribution for women is lower than for men in this occupation ($W_{o,t}^{F} < W_{o,t}^{M}$) while the willingness-to-pay on the part of firms is roughly similar ($WTP_{o,t}^{F} = WTP_{o,t}^{M}$).

In "Sales Representatives, Finance, and Business Services" in Figure 4 we see that the observed wage distribution mirrors more closely the simulated patterns in Figure 2. We see that the bulk of the density of male wages are centered to the right of the bulk of the density of female wages, and that the long right tail of male wages extends well

[9]Identification could be confounded if workers select into occupations based on individual productivity (as in a Roy model). Such selection would lead my model to overestimate gaps in wage offers between men and women in segregated occupations. For example, relatively high wages for men in nursing may reflect wage premia for individual talent, not just dislike of the occupation. The more segregated the occupation, the greater the bias. Unfortunately incorporating Roy-style heterogeneity into the model would make the estimation routine described in the next section intractable.

beyond the support of the female wage distribution. The model rationalizes this pattern by estimating similar wage offer distributions for men and women ($W^F_{o,t} = W^M_{o,t}$), but a higher willingness-to-pay on the part of firms for men ($WTP^F_{o,t} < WTP^M_{o,t}$). The intuition from these examples generalizes to other occupations where both the wage offer distributions and the willingness-to-pay parameters may differ by gender at the same time.

4.2 Step 2: Worker Estimation and Identification

In the second stage of estimation, I take the centers of the wage offer distributions estimated in the previous step, ($W^g_{o,t}$), and treat them as data in occupation level regressions. I pool all six cross sections of Census/ACS data (1960-2012) into a single regression for each gender. This allows me to estimate the occupation-specific intercepts, α^g_o and use time variation in fraction female and reservation wages to identify their coefficients in the worker utility function, $\frac{\gamma^g}{\sigma^g_\eta}$ and $\frac{1}{\sigma^g_\eta}$. Following Berry (1994), I add an error term $\epsilon^g_{o,t}$ to represent changes over time in the utility of workers due to changes in unobserved occupation attributes. Any changes not due to movement in the fraction female or the wage offers will be captured by $\epsilon^g_{o,t}$. Let $s^g_{o,t}$ be the share of workers of gender g choosing occupation o in time t, and $s^g_{N,t}$ the share of non-employed workers. Then the final estimating equation is as follows.

$$ln(s^g_{o,t}) - ln(s^g_{N,t}) = \frac{\alpha^g_o + \beta^g_t + \gamma^g F_o + W^g_{o,t} + \epsilon^g_{o,t}}{\sigma^g_\eta}$$

Unfortunately using time variation means that estimates of $\frac{\gamma^g}{\sigma^g_\eta}$ and $\frac{1}{\sigma^g_\eta}$ likely suffer from omitted variable bias. Changes over time in both the gender ratio and the reservation wage are likely correlated with changes in unobserved occupation attributes $\epsilon^g_{o,t}$. For example if an occupation is becoming more family friendly over time, and this causes more women to enter the occupation, the coefficient on fraction female will be biased upward for women. Similarly if occupation amenities deteriorate over time, this may be correlated with increases in wages, causing a downward bias on the coefficient on the reservation wage $W^g_{o,t}$. I therefore need instruments to get clean variation in $W^g_{o,t}$ and fraction female $F_{o,t-1}$ to identify the worker utility parameters.

4.2.1 Worker Identification

In this section I introduce Bartik-style instruments to identify the labor supply parameters of the worker. Occupations exist in a variety of different industries, and these industries have different wage offers and fraction females, and also experience different changes in wage offers and fraction female. The idea behind my first two instruments is to use the exposure that occupations have to changes in industries to predict changes in wage offers and fraction female by occupation. The key assumption is that wage and gender composition are the only attributes of occupations that are affected by changes to industries.

For example, suppose that wages in manufacturing occupations, other than the occupation being instrumented for, are going up over time. This could be due to changes to the output market or production technology. Then workers might expect to see an increase in the wages of administrative assistants working in the manufacturing industry. The more administrative assistants work in manufacturing, the more we would expect wages to go up in the occupation. Identification will be threatened if wages are going up because the job amenities are getting worse for all occupations in manufacturing. Likewise if manufacturing is becoming more female over time, a worker might view administrative assistance as a more female occupation since they are more likely to work with women. Again the more administrative assistants work in manufacturing the greater the impact. Identification is threatened if all jobs in manufacturing are becoming more welcoming to women at the same time.

For the instrument to work it is also necessary that each industry contain multiple occupations. At the level of aggregation I use, 14 major industries,[10] every industry

[10]Industries used are aggregates of the harmonized IPUMS codes of ind1990. Industries are as follows:

has employment in almost all occupations. The predicted fraction female and wage in occupation o in time t are the weighted sum across industries of industry level fraction female and wage as follows:

$$\hat{F}_{o,t} = \sum_I p_{Io,1950} * \hat{F}_{Io,t}$$
$$\hat{W}_{o,t} = \sum_I p_{Io,1950} * \hat{W}_{Io,t}$$

Where $p_{Io,1950}$ is the fraction of occupation o in industry I fixed in 1950, prior to the sample data, and $\hat{F}_{Io,t}$ and $\hat{W}_{Io,t}$ are the fraction female and wage, respectively, in industry I in year t, excluding workers in occupation o. I exclude the occupation that is being instrumented for so that changes to that occupation will not contaminate estimates of changes in industry wages and fraction female.

My second instrument uses changes in the relative size of industries to predict changes in occupation wages offers and fraction female. For example, if manufacturing is declining, then administrative assistants will be less impacted by the prevailing fraction female and wage level in manufacturing. Workers considering the occupation will see that more jobs are now in the service sector, not manufacturing, and update their expectations of wages and fraction female accordingly. The key identifying assumption is that occupations are the same regardless of what industry they are in, except for expected wage and fraction female. The predicted fraction female or wage in occupation o and time t respectively can be written as a weighted sum over industry, of initial industry fraction female or wage, times the growth rate by industry as follows:

Agriculture, Forestry and Fisheries; Mining; Construction; Manufacturing; Transportation, Communications, and other public utilities; Wholesale Trade; Retail Trade; Finance, Insurance, and Real Estate; Business and Repair Service; Personal Services; Entertainment and Recreation Services; Professional and Related Services; Public Administration.

$$\hat{F}_{o,t} = \sum_I p_{Io,1950} * F_{Io,1950} * \frac{size_{Io,t}}{size_{Io,1950}}$$
$$\hat{W}_{o,t} = \sum_I p_{Io,1950} * W_{Io,1950} * \frac{size_{Io,t}}{size_{Io,1950}}$$

I fix both the occupation*industry composition ($p_{Io,1950}$) and the industry fraction female and wage ($F_{Io,1950}$ and $W_{Io,1950}$ at 1950. $\frac{size_{Io,t}}{size_{Io,1950}}$ is the growth in industry I excluding occupation o relative to 1950.

The last Bartik-style instrument predicts changes in the fraction female of occupations over time based on the initial fraction female in occupations in 1950, and the relative growth rates of male and female labor force participation. The idea is that as women enter the labor force they are more likely to enter occupations that historically have had more women.[11] The instrument is constructed as follows. Let the number of men and women employed in all occupations except o in time period t be $\#M_t$ and $\#W_t$. I define the relative growth in female vs. male employment r_t as

$$r_t = \frac{\frac{\#F_t}{\#M_t}}{\frac{\#F_{1950}}{\#M_{1950}}}$$

Let $F_{o,1950}$ be the fraction female in the occupation in 1950. Then the fraction female in occupation o predicted by the instrument in time t, $\hat{F}_{o,t}$ is as follows:

$$\hat{F}_{o,t} = F_{o,initial} * r_t$$

The instrument will be invalid if, for example, occupations that had high fraction female in 1950 are becoming relatively more attractive to women over time, and this change is driving the increase in female labor force participation. It is more likely that the relative increase in female labor force participation was the result of a broader change in norms and the value of home work than driven by changes to

[11] This is similar to instrumenting for immigration patterns based on overall flows of immigrants and initial shares (Altonji & Card, 1991).

female-dominated occupations.

Lastly, I include the willingness-to-pay estimates $WTP^g_{o,t}$ from the firm side of the model as instruments. The $WTP^g_{o,t}$ are a measure of how much firms value male vs. female workers, and therefore should be uncorrelated with changes in unobserved occupation amenities.

5 Model Estimates

5.1 Model Parameters and Fit

The fraction female by occupation observed in the Census/ACS data matches the model predicted fraction female for the young cohort, since shares of workers by gender and occupation are moments targeted in estimation. There is some discrepancy when I allow the model to endogenously update the overall fraction female over time. This is because workers do not necessarily stay in their starting occupation for their lifetime, as assumed in the simulations. Histograms comparing the model predicted and actual lifetime income distributions can be found in the online appendix, and generally show a good fit, since wage distributions by occupation and gender are also targeted in estimation.

Table 1 shows the results of the first stage of estimation. Parameters $WTP^g_{o,t}$ and $W^g_{o,t}$ were estimated separately for each of the six cohorts of workers, but the results in the table are the averages within occupation across these six cohorts ($\overline{WTP^g_o}$ and $\overline{W^g_o}$) for ease of interpretation. The first column is the observed fraction female, varying from .02 to .89, and all 34 occupations are ordered from highest fraction female (administrative support) to the lowest fraction female (construction and extraction). In the second column we see the ratio of the average female wage offer to male wage offer ($\frac{\overline{W^F_o}}{\overline{W^M_o}}$, which varies from .36 to 2.66, and in the third column we see the ratio of the firms' wilingness-to-pay for women vs. men ($\frac{\overline{WTP^F_o}}{\overline{WTP^M_o}}$), which varies from .37 to 1.14.

In general, women have lower wage offers than men ($\frac{\overline{W_o^F}}{\overline{W_o^M}} < 1$) and are less valued by firms ($\frac{\overline{WTP_o^F}}{\overline{WTP_o^M}} < 1$). In general, the higher the fraction female, the lower the wage offers for women are in the occupation, relative to men. On the other hand, firms tend to be willing to pay more for women relative to men in high fraction female occupations. Intuitively these results are consistent with the idea that women like, and are most valued at, highly female-dominated occupations such as Administrative Support, Financial Records Processing Occupations, and Health Service Occupations. Similarly, women dislike, and are least valued at, highly male occupations such as Engineers, Architects, and Surveyors, Mechanics and Repairers, and Construction and Extraction.

It has been noted that both men and women have lower wages the higher the female share in an occupation (see eg. Macpherson and Hirsch (1995); Levanon et al. (2009); Addison, Wang, and Ozturk (2017); Harris (2018)). Unlike the mean wage by occupation, the centers of the wage offer distributions W_o^g control for the fact that in observed wages, we see only the most attractive firms filling their vacancies in each occupation, and by the workers that satisfy the firm's payoff maximization. Thus, using the model allows me to look at the correlation between wage offers and fraction female unconditional on firm selection effects, which would downward bias any estimated correlation. I find that female wage offers are negatively correlated with the fraction female (correlation coefficient -0.77), while male wage offers are positively correlated with the fraction female (correlation coefficient 0.6), despite no statistically significant correlation between my raw estimates of lifetime income and fraction female.

Lower wage offers for women in female-dominated occupations could be consistent with a female preference for working with women producing a compensating differential, but could also be the result of a strong preference for certain occupations. Similarly, the high wage offers for men in female occupations could be consistent with a male preference against working with women or strong tastes for occupations. In the next section, I present the results of the instrumental variables regression of worker utility, and discuss whether the fraction female has a causal impact on worker utility.

5.2 Worker Preference Results

As discussed above, I estimate worker utility parameters by regressing worker utility on occupation fixed effects, model predicted wage offers, and the fraction female, using Bartik-style instruments for the fraction female and wage offers. Tables 2 and 3 show the results both instrumented and un-instrumented fixed effects regressions by gender described above. The first stage has a Kleibergen-Papp F statistic of around 10 for women and 8.6 for men.[12] Estimation is done using limited information maximum likelihood for robustness to weak instruments, but two stage GMM results are similar, and standard errors clustered at the occupation level.[13]

In the un-instrumented regression in the first column, both men and women have a negative wage coefficient. This implies that there may be time-varying omitted variables, such as changes in occupation amenities or skill requirements, not controlled for by the fixed effects. The instrumented specifications should avoid this endogeneity by identifying off of industry level wage changes (excluding the instrumented occupation). Indeed, the wage coefficient becomes positive in the instrumented regression in the second column. By contrast, the signs of the fraction female coefficients do not change with the addition of instruments. In both specifications men have no preference over the fraction female and women have a strong preference over the fraction female. However, the standard errors for men are high, so I cannot rule out moderate effects for men in either direction.

Figure 5 shows the relationship between log utility and the fraction female for men and women. Women have increasing utility in the fraction female, and the increase is steeper the fewer women there are in the occupation. By contrast for men, utility is relatively flat in the fraction female and not statistically different from zero. The magnitude of the female preference is around twice the preference for log wages, mean-

[12] I report only the linear specification for men and the cubic specification for women because these have the highest first stage F statistics in the IV specification, but results for other functional forms including a beta distribution are qualitatively similar.

[13] I expect errors correlated within occupation due to occupation fixed effects and possible differences in model fit across occupations.

ing that if the log wage offers in an occupation went up by 10%, this would have an equivalent effect on log utility (u_o^F) as a 5% increase to the fraction female. For women the estimated preference for fraction female is also economically significant in terms of the impact on occupation choice. The average marginal effect of moving the fraction female in a single occupation from 20% ($F = .2$) to 80% ($F = .8$) would be to entice 124% more women to enter that occupation in equilibrium, that is allowing wages to adjust to clear the market. So if an occupation moved from relatively male-dominated to relatively female-dominated that would just over double the number of women who would enter that occupation in equilibrium.

The non-wage utility that workers get from each of the occupations (α_o^g) are reported in Table 4, measured in log millions of dollars. These are the fixed effects from the regressions in Tables 2 and 3 with the excluded category being "Teachers, Postsecondary". Generally we see that women have higher utility than men for female occupations and vice versa. The only male-dominated occupations ($F < .2$) in which women have higher non-wage utility than men are Protective Service and Health Diagnosing Occupations, and there are no female-dominated occupations ($F > .8$) in which men have higher non-wage utility.

6 Counterfactuals

There are two policy implications from the result that women prefer to enter more female occupations. First, the gender composition of occupations might be path-dependent, allowing past preferences to affect current sorting. For example, Food Preparation and Service Occupations is majority female at 74%, but employers are willing to pay more for men (See Table 1 $\frac{\overline{WTP}_o^F}{\overline{WTP}_o^M} = .74$), and men value the occupation more than women (See Table 4, fixed effect of 1.66 vs. 1.35), so we might not expect ex ante for this occupation to be majority female. However the occupation was historically female, and the preference for women to work with women means that firms can hire women for cheaper. It is an empirical question as to whether this occupation could become majority male if enough men chose it and drove up wages for women. I use my model to test empirically whether temporarily nudging more men or women into any given occupation might lead to convergence to a new (and possibly more efficient) gender composition.

Second, the estimated gender preference has implications for policies that target gender equity through wage equity. Because employers compensate women through a combination of wage and non-wage amenities, including the fraction female, allowing employers to pay women less in female-dominated fields and more in male-dominated fields moderates segregation. Therefore policies to enforce equal pay for men and women will have two countervailing impacts on the gender wage gap: equalizing wages within occupation and increasing segregation across occupation.

6.1 Homophily and Path-Dependence

The homophily I have estimated means that segregation could depend on initial conditions. If segregation is path dependent, then temporarily increasing the number of workers of one gender could have long run consequences through moving an occupation from one steady state fraction female to another.[14]

Using my model it is possible to search systematically for steady states in the fraction female. To do so, I allow wage offers ($W^g_{o,t}$) to clear the market for each cohort of workers, and the fraction female to update endogenously across cohorts. I then graph the mapping between fraction female in the current period and the next period, by occupation, at ten equidistant starting points between 0% female and 100% female using 2012 parameter values, and show a fitted line through these points. By examining these graphs it is easy to find steady states where the fraction female this period is the same as the fraction female in next period, by observing intersections with the 45 degree line. If the fraction female crosses the 45 degree line multiple times, this implies multiple steady states in the fraction female.

I find that every occupation has one unique steady state in the fraction female.

[14] For an illustrative model of multiple steady states in the fraction female, see appendix of Pan (2015).

This means that given my estimated parameter values, the model predicts current segregation patterns to emerge regardless of historical segregation patterns. The top left panels of Figures 8 and 9 show the unique steady states for Health Technologists and Technicians and Engineers, Architects, and Surveyors. Like all occupations, the unique steady states in these occupations are stable, meaning that any arbitrary perturbation to the fraction female will eventually converge back to the unique steady state.

If the gender preference were approximately doubled, many occupations would have multiple steady states in the fraction female. The bottom left panel of Figures 8 and 9 shows these same occupations, but with homophily twice as large. In this case Health Technologists and Technicians still has a unique steady state, but Engineers, Architects, and Surveyors now has three steady states, two of which are stable. Note that a doubling of the gender preference seems unlikely since the estimated preference is already economically large.

Since every occupation has a unique steady state fraction female, policies that only temporarily alter number of men or women in an occupation will not have long run consequences. I run simulations to illustrate the mechanisms that render temporary policies ineffective in the long run and find that compensating differentials play a key role in making segregation stable in equilibrium.

My first simulation mimics a policy that temporarily encourages men to enter nursing to overcome gender barriers. In Figure 6, I set nursing ("Health Technologists and Technicians") to be 0% female in 1960, when in reality nursing was close to 100% female in 1960. The equilibrium wage offer for women in nursing that clears the market increases dramatically when nursing is a male occupation, to compensate women for their strong estimated preference against being in a highly male occupation. These high wage offers mean that some women in the next cohort (with high taste for nursing) are enticed to enter nursing. This entry of women then makes nursing more attractive for the following cohort of women, which in turn makes women cheaper for firms to hire, increasing demand for female nurses. This feedback loop continues until nursing is female-dominated and simulated wage offers have dropped to the levels estimated in the data.

In the second simulation, shown in Figure 7, I set "Mechanics and Repairers" to be a 100% female in 1960 when in reality it was close to 0% female. Men with the highest taste for the occupation still choose it. Female wages then skyrocket as more and more men start to become Mechanics and Repairers. After about eight cohorts, women are no longer affordable to hire and the occupation has converged to its unique steady state at around 0% female.

If it were not for compensating wage differentials both of these occupations would be path dependent in the fraction female. The top right panel of Figure 8 illustrates the steady states in nursing if wages are not allowed to clear the market. Nursing would remain 0% female if it ever dropped below around 35% female. Similarly, mechanics and repairers would converge to a majority female steady state at around 80% female if it ever reached 80% or more female. With wage offers free to adjust, however, policies would need to change underlying job amenities, or labor demand through quotas or wage subsidies, in order to have long-run impact.

6.2 Homophily and Equal Pay for Equal Work

One policy to intended to increase equity in the labor market is equal pay for equal work. In this last set of simulations, I fix the ratio of female to male wage offers $\left(\frac{W^F_{o,t}}{W^M_{o,t}}\right)$ to be equal to the ratio of female to male labor force participation, as measured in hours over the lifetime by gender and occupation. This fixed ratio means that on average men and women must be offered the same per hour worked within an occupation.[15] Factors that would normally affect $\left(\frac{W^F_{o,t}}{W^M_{o,t}}\right)$, such as willingness-to-pay by occupation or differential taste for occupation (including based on the fraction female), can no longer directly influence wage offers.

In this simulation 13 out of 34 occupations have multiple steady states in the fraction female. Of the remaining 21 occupations that have only one steady state, 16

[15] Note that individual firms can still offer men and women differently based on firm-specific amenities and this can still result in wage gaps if, for instance, only the most female-friendly firms hire women.

are only stable at 0% female, and 5 at close to 100% female. The bottom right panels of Figures 8 and 9 illustrate the steady states for nursing and engineering under equal pay for equal work. In both cases the stable steady states are more segregated then when wages are free to adjust.

Overall, equal pay for equal work results in even higher segregation, and a larger gender pay gap, than the status quo. Table 5 shows a comparison of segregation and gender wage gaps under various counterfactual regimes. In the second column of Table 5 we see that if there were no preference on the part of women against working in male-dominated occupations, women would earn 85% of what men earn, and only 24% of workers would have to change occupation to reach 50% female.[16] Requiring that men and women be paid equally per hour of work in a given occupation wildly increases segregation. Under equal pay for equal work 80% of workers would have to change occupations for each occupation to have 50% women, compared to 41% in the status quo. As a result of this increase in segregation, equal pay actually widens the pay gap slightly from the status quo, putting the wages of women at 65% those of men instead of 71% in the status quo.

The mechanism for the increased segregation under equal pay for equal work is that women cannot be offered higher wages than men in male-dominated occupations. Similarly, men cannot be offered higher wages than women in occupations they dislike, such as nursing. Therefore under equal pay, women exit male occupations such as engineering, and men exit female occupations such as nursing, resulting in more segregated occupations. Female-dominated occupations have the lowest wages, in part to negatively compensate for the increase in the fraction female, so this increased segregation results in an increase in the gender wage gap. The overall wage levels for both men and women also fall resulting in an increase in non-employment. Note that this result depends heavily on the strong gender preference I estimate on the part of women. My model simulations show that equal pay would reduce segregation and the gender wage gap in the absence of the estimated homophily preference.

[16] This is the Duncan Segregation Index (Otis Dudley Duncan & Beverly Duncan, 1955).

7 Conclusion

Nursing was historically female due to explicit gender barriers, and has continued to be female-dominated to this day. In this paper, I study whether occupations such as nursing continue to be segregated today because workers prefer to work in occupations with the same gender (homophily), as opposed to persistent gender barriers or preferences for occupations. I distinguish homophily using a structural model of the labor market. I impose a specific payoff structure within transferable utility matching that allows me to leverage the wage distribution to separately identify firm and worker preferences, and I use industry-level demand shocks to trace out worker taste for fraction female and wages.

I find that women prefer not to work in male-dominated occupations, and this increases segregation (from around 24% to 41%) and the gender wage gap (from around 85% to 71%). I find that, for the estimated parameters, each occupation has a single unique steady state in the fraction female. This means, for example, that pushing more women into STEM or men in nursing will not lead more to follow, rather the occupation will tend back to its original sorting pattern. Equity policies need to target the underlying causes of segregation.

My model is well positioned to study gendered policies with equilibrium consequences, such as equal pay for equal work laws. Given my estimated parameters, equal pay actually leads to drastically more segregation, which ultimately increases the gender wage gap despite narrower gaps within occupation. The mechanism for this result, and the unique steady state result, is compensating wage differentials. To equate supply and demand, women must be paid more to work in male-dominated occupations.

The mechanism of segregation explored in this paper, homophily preference over the fraction female, merits future research. In particular, understanding the cause of women preferring not to work in male-dominated occupations could be policy relevant. Reducing this preference could be an important policy target if it is the result of male sexism, and this could be explored using regional variation in sexism as in Charles, Guryan, and Pan (2018). Future work could also embed a Roy-style model within the matching model to account for unobserved productivity heterogeneity. Lastly, although this paper focused only on the fraction female in occupations, future work could extend this model to look at race, age, or any other group preference or endogenous amenity, and the mitigating effects of compensating differentials on segregation.

7.1 Figures and Tables

Figure 1: Simulated Impact of Worker Preferences on Observed Wage Distribution

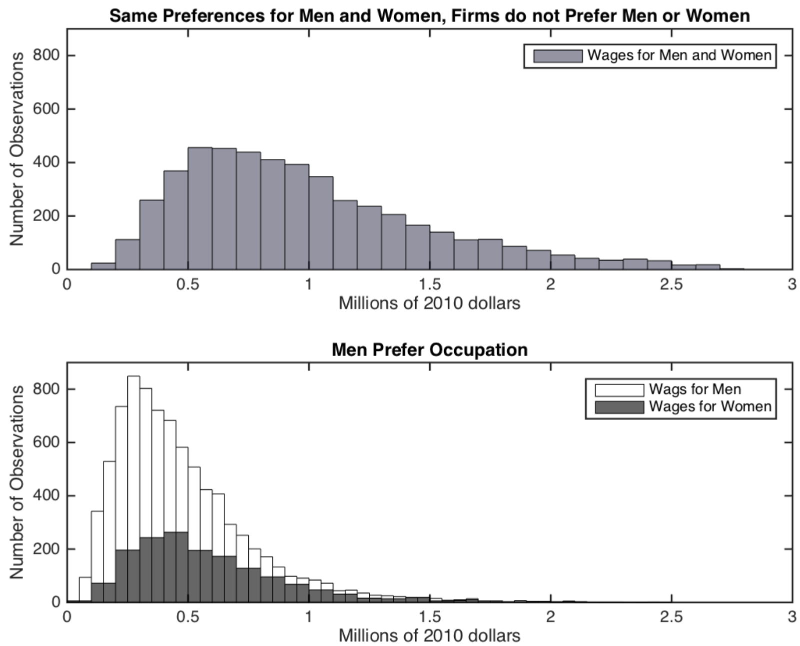

Figure 2: Simulated Impact of Firm Preferences on Observed Wage Distribution

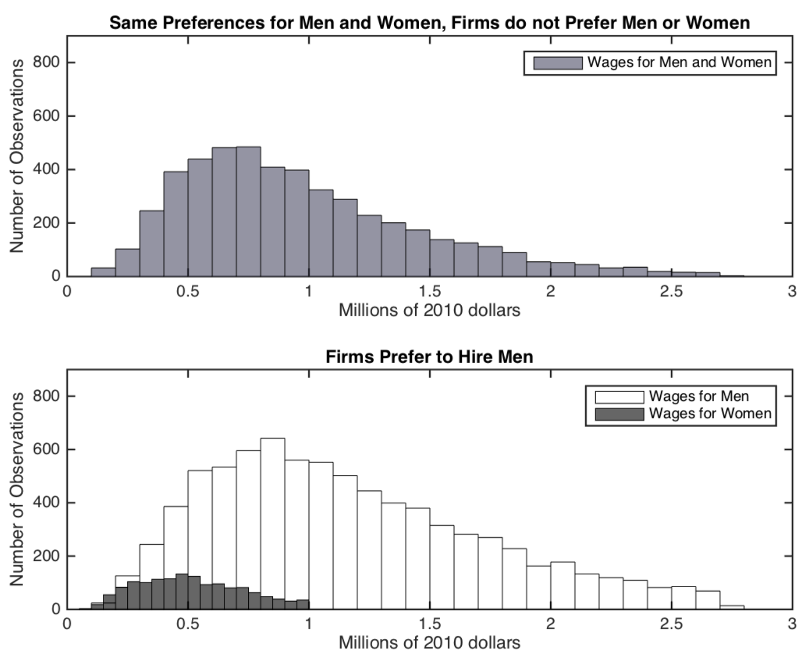

Figure 3: Lifetime Wages in Health Service Occupations

Figure 4: Lifetime Wages in Sales Representatives, Finance, and Business Services

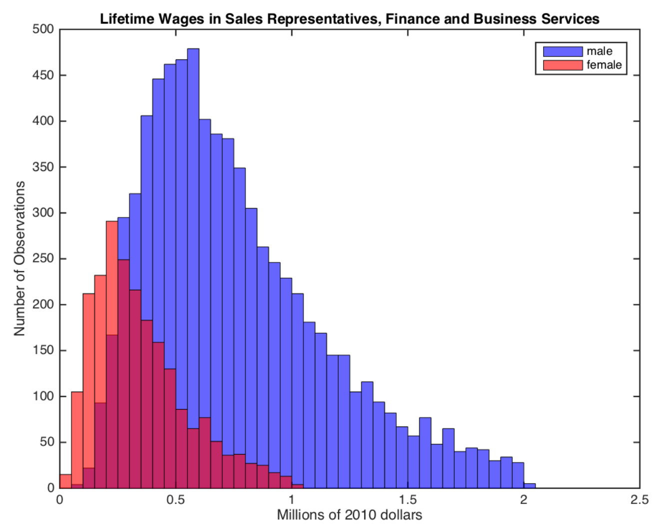

Figure 5: Male and Female Log Utility by Fraction Female in Occupation

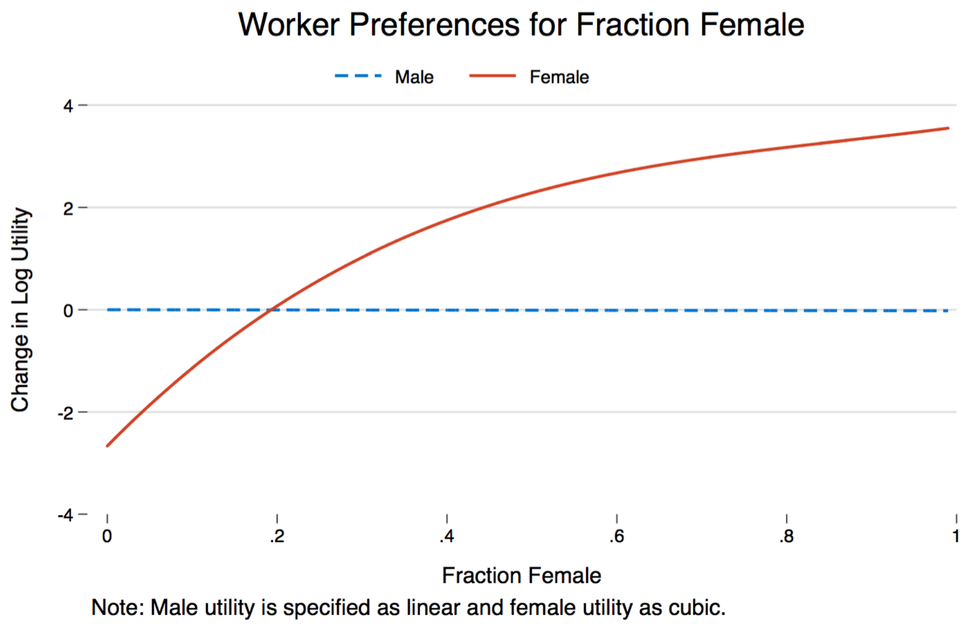

Figure 6: Setting Health Technologists and Technicians to 0% Female in 1960, Changes in Wage Offers

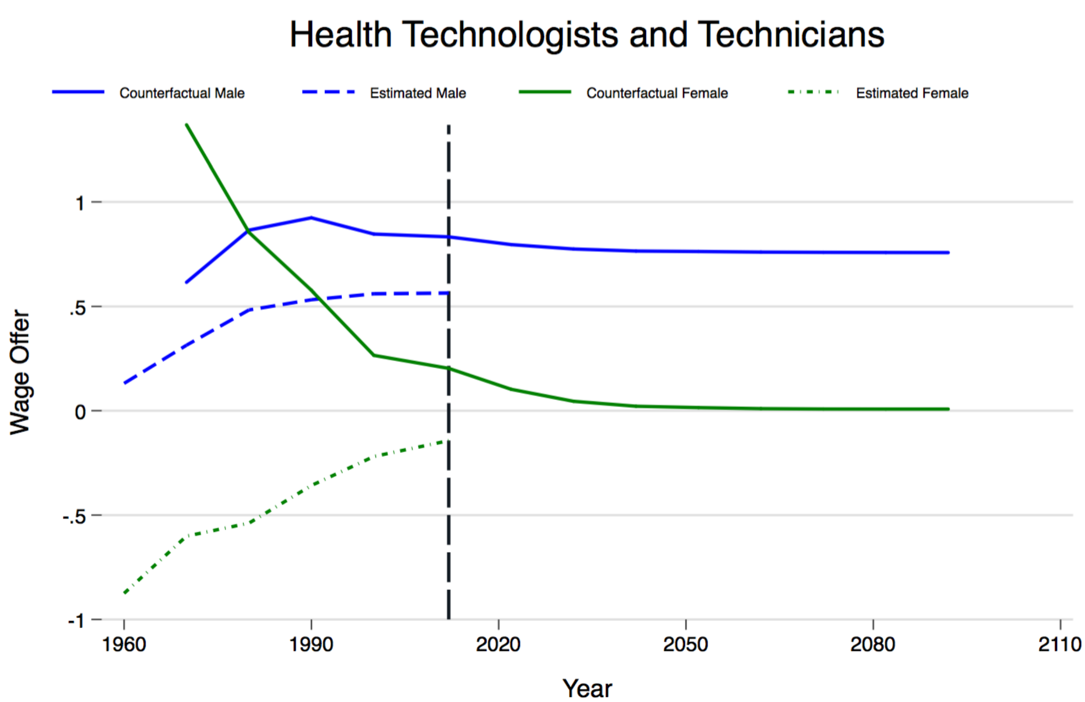

Figure 7: Setting Mechanics and Repairers to 100% Female in 1960, Changes in Wage Offers

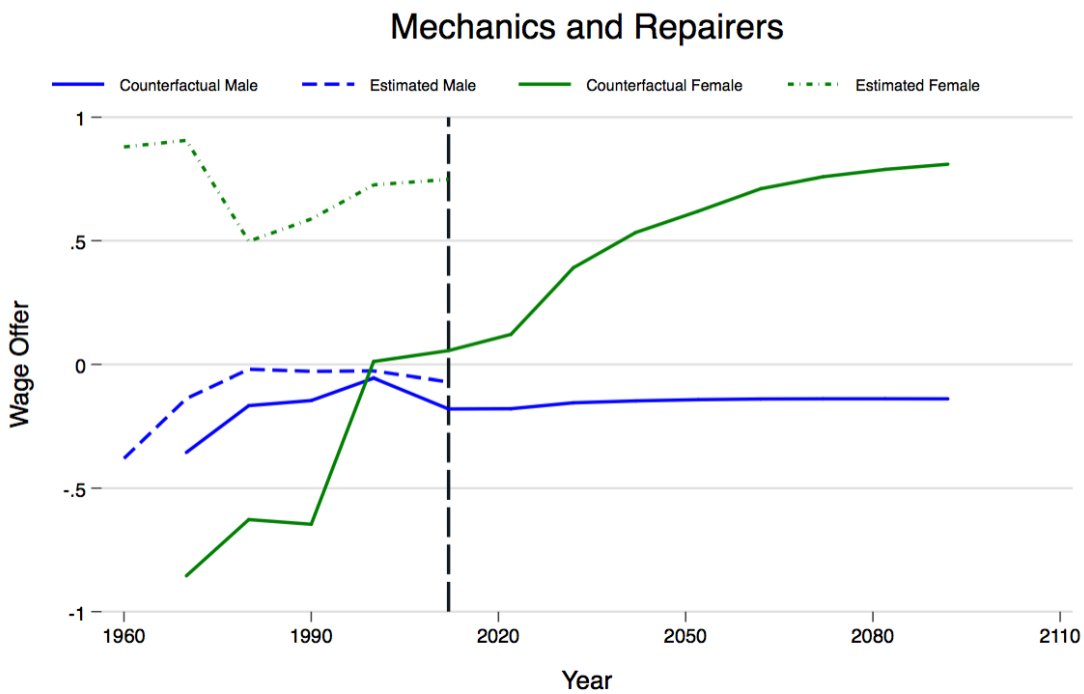

Figure 8: Transitions in Fraction Female Across Periods

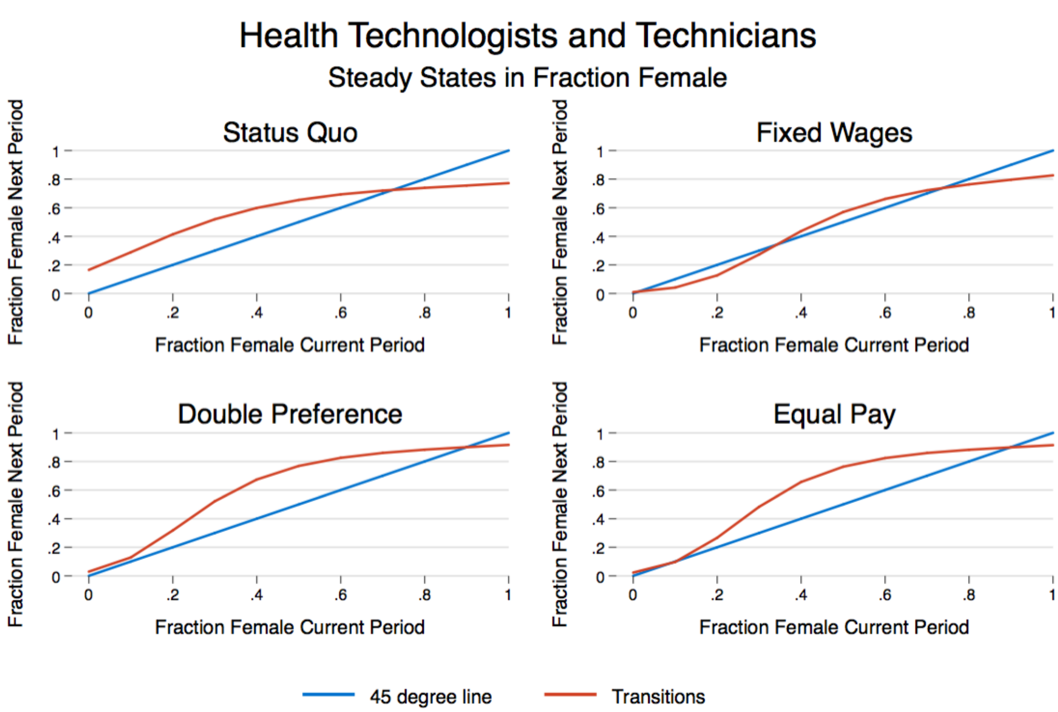

Figure 9: Transitions in Fraction Female Across Periods

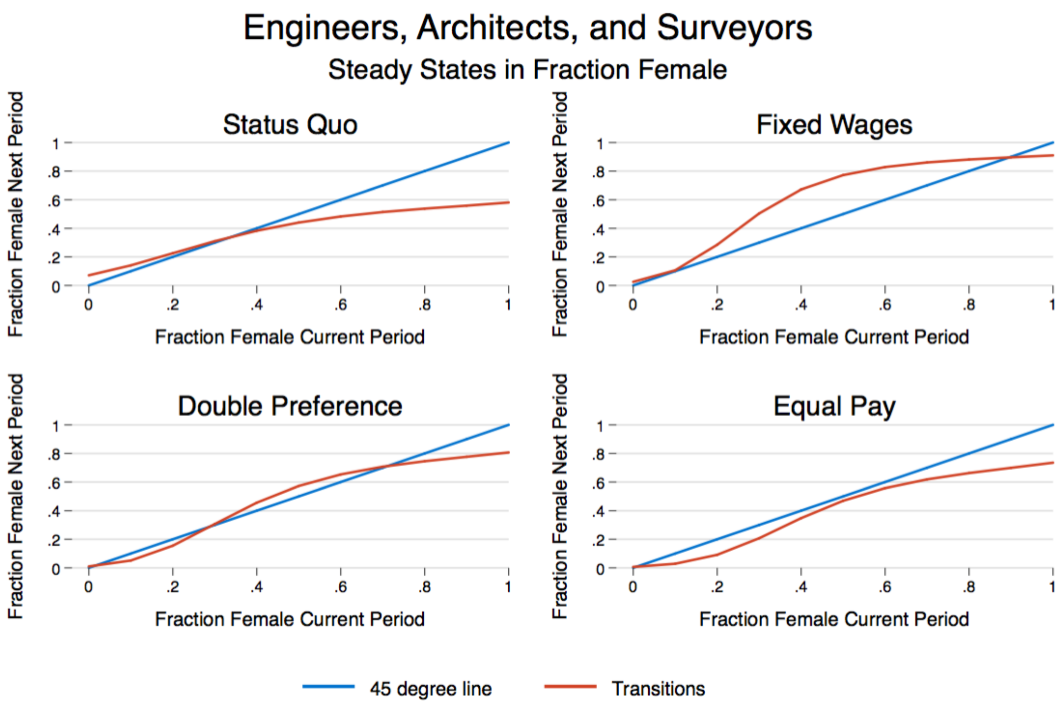

Table 1: **Average Model Estimates by Occupation**

Occupations	F	$\frac{\bar{W}_o^F}{\bar{W}_o^M}$	$\frac{\overline{WTP}_o^F}{\overline{WTP}_o^M}$
Administrative Support	0.89	0.36	0.97
Financial Records Processing Occupations	0.89	0.36	0.88
Health Service Occupations	0.89	0.37	1.05
Health Assessment and Treating and Thera	0.88	0.42	1.14
Health Technologists and Technicians	0.85	0.41	0.81
Private Household and Personal Service	0.83	0.39	0.89
Miscellaneous Administrative Support Occ	0.81	0.45	0.85
Teachers, Except Postsecondary	0.77	0.51	0.88
Records Processing Occupations, Except F	0.77	0.50	0.94
Food Preparation and Service Occupations	0.74	0.60	0.74
Adjusters and Investigators	0.57	0.55	0.76
Sales Workers, Retail and Personal Servi	0.56	0.61	0.63
Metal, Wood, Plastic, Print, Textile	0.51	0.81	0.54
Social, Recreation, and Religious Worker	0.47	0.60	0.72
Writers, Artists, Entertainers, and Athl	0.44	0.85	0.66
Social Scientists, Lawyers, Judges, Urba	0.42	0.91	0.82
Management Related Occupations	0.41	0.79	0.66
Machine Operators, Fabricators, Assemble	0.41	1.09	0.58
Teachers, Postsecondary	0.39	0.76	0.62
Sales Representatives, Finance and Busin	0.34	0.94	0.60
Mail and Material Distribution	0.32	0.98	0.60
Executive, Administrative, and Manageria	0.31	0.95	0.61
Cleaning and Building Service Occupation	0.27	0.86	0.52
Technicians except health	0.24	0.99	0.54
Math, Computer, and Natural Science	0.24	1.13	0.62
Precision Production Occupations	0.22	1.09	0.53
Health Diagnosing Occupations	0.19	1.09	0.59
Agriculture, Forestry and Fishing	0.19	1.47	0.48
Material Moving, Laborers	0.17	1.46	0.47
Protective Service	0.13	1.30	0.49
Road, Rail and Water Transportation	0.09	1.75	0.42
Engineers, Architects, and Surveyors	0.05	1.92	0.53
Mechanics and Repairers	0.04	2.38	0.41
Construction and Extraction	0.02	2.66	0.37

Table 2: Decomposition of Utility for Male Workers: Panel Evidence

	FE	IV
Fraction Female ($\frac{\gamma^M}{\sigma^M\_\eta}$)	0.666	-0.0197
	(0.644)	(1.049)
Latent Wage Offer	-0.916	1.704
	(0.564)	(1.705)
Constant	-2.615***	
	(0.294)	
Year dummies	Yes	Yes
Observations	204	204
KP rk F=		8.508

Standard errors in parentheses are clustered at the occupation level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.0001$

Table 3: Decomposition of Utility for Female Workers: Panel Evidence

	FE	IV
Fraction Female ($\frac{\gamma^F}{\sigma^F - \eta}$)	2.870***	4.570**
	(0.577)	(1.540)
Squared distance from parity	-4.384***	-7.329
	(0.915)	(3.772)
Cubed distance from parity	-4.506	6.662
	(2.605)	(9.716)
Latent Wage Offer	-0.151	1.932
	(0.299)	(1.039)
Constant	-5.165***	
	(0.224)	
Year dummies	Yes	Yes
Observations	204	204
KP rk F=		10.02

Standard errors in parentheses are clustered at the occupation level.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.0001$

Table 4: Fixed effects by occupation

Occupation	F	Male	Female
Administrative Support	.89	.36	2.04
Health Service Occupations	.89	-.54	1.28
Financial Records Processing Occupations	.89	-.84	.75
Health Assessment and Treating and Therapists	.88	-.7	.82
Health Technologists and Technicians	.85	-.71	.2
Private Household and Personal Service	.83	.33	1.66
Miscellaneous Administrative Support Occupations	.81	.34	1.14
Records Processing Occupations, Except Financial	.77	-1.07	-.32
Teachers, Except Postsecondary	.77	1.02	1.48
Food Preparation and Service Occupations	.74	1.66	1.35
Adjusters and Investigators	.57	.38	1.17
Sales Workers, Retail and Personal Services	.56	2.06	1.85
Metal, Wood, Plastic, Print, Textile	.51	1.52	.42
Social, Recreation, and Religious Workers	.47	-.07	.54
Writers, Artists, Entertainers, and Athletes	.44	.96	.31
Social Scientists, Lawyers, Judges, Urban Planners, Librarians	.42	.17	-.15
Machine Operators, Fabricators, Assemblers, Testers	.41	2.67	1.1
Management Related Occupations	.41	1.33	1.29
Teachers, Postsecondary	.39	0	0
Sales Representatives, Finance and Business Services	.34	1.66	1.25
Mail and Material Distribution	.32	1.82	1.39
Executive, Administrative, and Managerial Occupations	.31	2.5	2.35
Cleaning and Building Service Occupations, Except Household	.27	1.22	1.34
Technicians except health	.24	1.59	1.6
Math, Computer, and Natural Science	.24	1.02	.89
Precision Production Occupations	.22	2.06	1.84
Agriculture, Forestry and Fishing	.19	2.22	1.2
Health Diagnosing Occupations	.19	-.22	.33
Material Moving, Laborers	.17	2.79	1.96
Protective Service	.13	1.66	1.73
Road, Rail and Water Transportation	.09	2.64	1.89
Engineers, Architects, and Surveyors	.05	1.38	1.17
Mechanics and Repairers	.04	2.73	1.35
Construction and Extraction	.02	2.93	1.1

Table 5: Counterfactual Gender Wage Gap and Segregation

Statistic:	**Status Quo**	**No Pref**	**Fixed Wages**	**Equal Pay**
Gender Wage Gap	0.71	0.85	0.70	0.65
Segregation Index	41%	24%	54%	80%

8 Appendix

8.1 Transferable Utility Matching

When a worker and a job match, total surplus is created from the match. In the worker's case the value of a match reflects the amenities of the job. A job might have a particularly collegial environment, or free child care for example. Amenities may be valued differently by gender. On the job side the payoff is the willingness-to-pay for a worker, which could reflect productivity, and differ by gender due to gender differences in turnover, differences in search cost by gender, differences in productivity, or devaluation, for example. The wage determines the split of the total surplus between the worker and the firm.

The most general payoff structure in a matching model would allow each possible match between a worker i and a job j to have its own unobserved match quality. To make the problem empirically tractable, I assume that no portion of the payoff depends on unobservable characteristics of both firm and worker, which is a standard assumption in empirical matching. So although the surplus may depend on i or j, it may not depend on i and j.

Assumption 5. *Additive Separability: No component of surplus depends on unobserved characteristics of both workers and firms.*

Formally, let g denote gender, which is observed as either male (M) or female (F) in this model. Let o denote occupation. We therefore have workers $i \in g \in G = \{M, F\}$ and jobs $j \in o \in O = \{1, 2, ..., 34\}$.[17] Under additive separability we have that the total surplus from a match between worker i and job j, S^i_j, can be decomposed:

$$S^i_j = S^g_o + \eta^i_o + \xi^g_j \tag{6}$$

Note that there are components that vary at the occupation*gender level (S^g_o), the

[17]Thirty-four occupations are chosen according to data constraints discussed below.

occupation*worker level (η_o^i), and the gender*job level (ξ_j^g), but never the worker*job level. In other words, additive separability implies that there is no ξ_j^i or η_j^i. This assumption is important because it allows me to separate the matching problem into two separate discrete choice problems, one for each side of the market (Galichon & Salanié, 2015).

The components of total surplus that depend on unobservables of either the worker (η_o^i) or the job (ξ_j^g) can theoretically come from the worker's utility function, the job payoff function, or both. In order to gain identifying power from the observed wage distribution, and because my research question is focused the the role of worker utility in occupation choice, I assume all unobserved components of surplus originate from the worker's utility. This means that only workers have preferences over unobservables, and jobs care only about whether they chose to hire a male or female worker.

Assumption 6. *η_o^i and ξ_j^g are primitives in the worker's utility function.*

In other words, each worker has an individual taste for each occupation (η_o^i) and each job differs in how attractive it is to men and women (ξ_j^g). The job amenity heterogeneity can be thought of as any component of the attractiveness of a job that is orthogonal to the overall attractiveness of the occupation, which is included in S_o^g. For example child care offerings at a particular employer might differ relative to the average child care offerings in that occupation.

8.1.1 Equilibrium Wages

In the following section I outline conditions for a matching to be feasible and stable. I then introduce the equilibrium wage vector and show that it supports feasibility and stability.

8.1.2 Feasibility

A matching is feasible if every worker is matched to at most one job and every job matched to at most one worker. Formally, following Galichon and Salanié (2015), let

μ_j^i be equal to either 0 or 1 where 1 indicates a match between worker i and job j. Then for every i and j a feasible matching has

$$\sum_{k \in \mathcal{J}} \mu_k^i \leqslant 1 \text{ and } \sum_{k \in \mathcal{I}} \mu_j^k \leqslant 1$$

Similarly following Galichon and Salanié (2015), the matching must be feasible given the number of men and women and jobs in each occupation available in the market, or

$$\sum_{j \in \mathcal{J}} \mu_j^g \leqslant n_g, \ \forall g \text{ and } \sum_{i \in \mathcal{I}} \mu_o^i \leqslant n_o, \ \forall o$$

8.1.3 Stability

Intuitively, pairwise stability implies that no worker and job that are not currently matched with each other, would prefer to match with each other. Let i and j be a so called "blocking pair", and let i be currently matched to $j(i)$ and j to $i(j)$. Then pairwise stability states that the sum of the individual surpluses from the existing matches (i with $j(i)$ and j with $i(j)$) must be greater than the surplus of the blocking pair (i and j). Therefore even with any possible transfer, i and j will not both prefer to match with each other, because the total possible surplus is lower.

Definition 1. *Pairwise Stability: In a matching where i is paired with $j(i)$ and j is paired with $i(j)$, it must be the case that $u_{j(i)}^i + \pi_j^{i(j)} \geqslant u_j^i + \pi_j^i, \quad \forall i, j$. In addition, each worker and job must attain higher surplus than their outside option, or $u_{j(i)}^i \geqslant u_N^i$ and $\pi_j^{i(j)} \geqslant \pi_j^N$, where N represents not working for the worker, and not hiring for the firm.*

Note that on the left hand side $u_{j(i)}^i + \pi_j^{i(j)}$ includes the wage paid out to the worker and by the job in their respective matches. On the right hand side $u_j^i + \pi_j^i$ the wage will cancel within the match leaving the underlying total surplus.

Following Shapley and Shubik (1972), the pairwise stable matching will be unique and the competitive equilibrium will coincide with the pairwise stable matching, but the competitive equilibrium wage vector may not be unique. I assume the observed wages are the equilibrium wages described in Galichon and Salanié (2015) and Salanié (2014b). These are the wages that make workers indifferent over jobs within each occupation, and jobs indifferent over workers within each gender. As the sample size of men and women goes to infinity, the equilibrium wages will be unique (Galichon & Salanié, 2015).

8.1.4 Proof of Pairwise Stability

Workers choose an occupation to maximize utility, and firms choose a worker to maximize rate of return, so the chosen job j^* and worker i^* respectively must satisfy

$$j^* \in o^* = \arg\max_o (u_o^g + W_o^g + \eta_o^i)$$
$$i^* \in g^* = \arg\max_g (WTP_o^g - W_o^g - \xi_j^g)$$

From this it is clear than within an occupation, workers are indifferent to which job they are matched to, and likewise within gender, jobs are indifferent to which worker they are matched to.

This implies that if worker i were to match with a different job within the same occupation, we would have $u_j^i = u_{-j}^i$, and likewise for job j, $\pi_j^i = \pi_j^{-i}$, therefore the pairwise stability inequality holds trivially for observationally equivalent (same g and o) candidate matches:

$$u_{j(i)}^i + \pi_j^{i(j)} = u_j^i + \pi_j^i \quad \forall i, i(j) \in g \quad \forall j, j(i) \in o$$

Now consider matching worker i to a job in a different occupation. Both workers and jobs choose the occupation or gender that produces the highest payoff for them, given the wage vector. Let the optimal occupation be o^* and optimal gender g^*. Therefore we know that for worker i

$$u^i_{j(i)} > u^i_j \quad \forall j(i) \in o^* \text{ and } \forall j \in o \neq o^*$$

and for job j

$$\pi^{i(j)}_j > \pi^i_j \quad \forall i(j) \in g^* \text{ and } \forall i \in g \neq g^*$$

Therefore pairwise stability holds with strict inequality for all candidate matches that are not observationally equivalent (different g or o) to the competitive equilibrium.

The second part of pairwise stability is the requirement that the choice payoffs be greater than the outside option payoffs. Recall that the outside option for the worker is remaining unemployed is equal to the idiosyncratic taste for non-employment, $u^i_N = \eta^i_N$. The value to the firm of not hiring a worker is simply zero, $\pi^j_N = 0$.

Another key aspect of the equilibrium wage vector is that it must be feasible, which in the case of this labor market is equivalent to equating supply and demand at the level of male and female workers and occupations. Crawford and Knoer (1981) and Roth and Sotomayor (1990) prove the existence of such an equilibrium in a model with transfers. Intuitively, as long as the common component of wage, or W^g_o, is free to adjust, supply and demand can adjust until the market clears.

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