Gender Segregation in Occupations: Preferences or Homophily?

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Abstract

Women remain concentrated in certain occupations despite the drastic increase in women's labor force participation in the U.S. since 1960. I examine whether occupations remain segregated because workers prefer to enter occupations that already employ more of their own gender. I build a model of labor supply and demand in which firms care about the gender and wages of their employees, and workers get utility from their occupation, wage, and the number of women in their occupation. Using a Bartik instrumental variables strategy, I find that women prefer to enter into female-dominated occupations, but men show no evidence of gender preference. In a world without women's gender preference, occupations would be 50 percent less segregated and the gender wage gap 18 percent smaller. Homophily can mean that a given occupation could be either male or female dominated depending on how many women were in it initially. However, women's preference for working with women would have to be almost twice as strong for the number of women in the past to affect whether an occupation is male or female dominated today.

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Contents

1 Introduction

Women's labor force participation has skyrocketed in the U.S. since 1960, but men and women still go into very different occupations. As of 2009, approximately 50% of women would need change jobs in order to to achieve an equal number of men and women in every occupation, and this gap is unlikely to close soon (Blau, Brummund, & Liu, 2013). Recent literature has identified some contributing causes of segregation: preferences over amenities (Olivieri (2014), Wiswall and Zafar (2018))[1], productivity and skill differences (Baker and Cornelson (2018)), and occupational and educational barriers (Hsieh, Hurst, Jones, and Klenow (2016)). I identify another possible cause of the persistence of segregation: workers valuing the gender composition of occupations.

In particular, this paper examines whether current segregation depends on past segregation because workers care about the gender of their occupation in addition to intrinsic characteristics. This is important because the right policy to address segregation, if any, will depend on what mechanisms are at play. Policymakers have expressed concern about occupational segregation, for example the lack of women in STEM and men in nursing. If these occupations are male or female for historical reasons, then segregation itself may be a barrier to individual careers and the efficiency of the economy as a whole. If, on the other hand, occupations are male or female based on intrinsic characteristics of workers or jobs, then interventions that seek to change the gender composition of occupations alone are likely inappropriate, and policymakers concerned about gender segregation should examine policies to address more specific causes as they deem necessary.

Identifying a preference over occupation fraction female is a difficult empirical problem that involves disentangling many other causes of gender segregation. Workers likely care about intrinsic characteristics of occupations, such as skills and job amenities (see for example DeLeire and Levy (2004) and Reed and Dahlquist (1994)), as much as about the gender of their coworkers (see for example Lordan and Pischke (2015) and

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

Usui (2008)). At the same time, firms may care about which gender is perceived as more productive or valuable, as well as which gender of worker is cheaper to hire. Simply looking at which occupations contain more women will not allow me to distinguish firm and worker preferences, or worker preferences over the fraction female.

The key innovation of this paper, building on the insights of Choo and Siow (2006), Salanié (2014a), and Dupuy and Galichon (2017), is that the distribution of wages can be used to separately identify worker and firm preferences. The intuition is that the right tail of wages tells us more about what firms are willing to pay for workers of a given type, while the left tail tells us more about what workers are willing to accept for a given type of job. Assuming that wage offers are distributed lognormally, and that firms do not care about the productivity of individuals within gender,[2] one can use Maximum Likelihood to estimate firm preferences and the wage offer distribution for male and female workers by occupation. Although the estimation strategy in this paper was developed specifically for segregation in the labor market, it could be used in any context in which a price mechanism clears a two-sided market.

The second identification challenge is to disentangle preferences for the number of women in an occupation from other occupation attributes. If an occupation is becoming more attractive to women, we will observe the fraction female in the occupation going up, and more women entering the occupation, and may incorrectly infer that women are entering the occupation because there are more women, a classic problem of omitted variable bias. To solve this problem I find variation in the fraction female by occupation that is plausibly exogenous to changes in other occupation amenities using Bartik-style instrumental variables. The main identifying assumption is that changes to occupations that workers care about are not correlated across occupations.

For tractability I treat occupation choice as a static choice. Workers choose occupation once at the beginning of their career, based on the contemporary characteristics of the occupations, including fraction female. Therefore, the fraction female in each

[2]Unobserved productivity of individual workers could be included in theory, but would result in very weak identification and likely computational intractability because it would involve joint estimation of the model and integration over multiple sources of unobserved heterogeneity to interpret the wage distribution.

occupation only updates across cohorts of workers.[3] Lifetime wages are set to clear the market in static equilibrium for each cohort of men and women, which requires a large market assumption (continuum of workers and jobs of each type) to guarantee a unique wage equilibrium.

The data moments to identify the model are the shares of male and female workers by gender from the 1960-2000 U.S. Censuses and 2012 3-year ACS, and estimates of lifetime income by occupation, gender, and year constructed using income quantiles from the Census data combined with transition rates from the SIPP 2004 and 2008 panels. I take a two-step estimation approach, first estimating the firm side using maximum likelihood, then the worker side using instrumental variables regression, taking the wage offer distribution estimated on the firm side as data. The structure of the model allows me to simulate transition paths in the fraction female by cohort and determine there is path dependency, all while solving for equilibrium wages and fixing other firm and worker preferences.

I find that women care strongly about the number of women in an occupation, but no evidence that men care about the number of women. The point estimate in my preferred specification is very high, with an occupation change from 25% to 75% female being equivalent to an extra $3 million in lifetime income for a woman. The gender preference leads to more segregated outcomes. With no gender preference, the model predicts no occupations with fraction female greater than 70% or less than 10%, and a Duncan segregation index of 24% in 2012, meaning 24% of male or female workers would have to change occupations to make all occupations 50% female. With the gender preference, the Duncan index is predicted to be almost twice as high at 47%.[4]

Labor supply or demand shocks that affect the fraction female are reinforced by a feedback loop from the gender preference. An illustrative case study is insurance adjustors, which is one of many occupations observed to have moved from male to female by Pan (2015). I find that more women began to become insurance adjusters because

[3]Allowing workers to choose occupation myopically more than once during their lifetime, would lead to faster changes in occupation fraction females, but not otherwise change the dynamics of the model.

[4]The Duncan index in my observed 2012 data is 41%.

firms' demand for women in this occupation rose. Then as more women entered, the occupation became more attractive to women. This in turn made women cheaper to hire, which increased labor demand for female insurance adjusters, providing further reinforcement of the feminization of the occupation. My model predicts that if it were not for women preferring to work with women, insurance adjusters would have become only 50% female, rather than the observed over 70% female (from a starting point of 20% female in 1960). Thus my estimated model provides one possible mechanism that is consistent with the stylized fact that occupations tend to move rapidly from male to female. This phenomenon is referred to as "tipping" by Pan (2015).[5]

Although the gender preference I estimate is very strong, it is largely mitigated by compensating differentials. In a model without endogenous wages, all occupations eventually converge to either 0% or 100% female. Wage adjustment leads to more moderate outcomes. As women enter an occupation, firms can hire the same number of women at lower cost, and lower wages dampen the increase in female labor supply. Likewise as women exit an occupation, firms must pay the remaining women more, which slows the exit of women. I find that these compensating differentials explain 18% of the difference in lifetime income between men and women, with women in highly female dominated occupations suffering the largest loss in earnings. The result that as women enter an occupation, wages go down is consistent with previous literature (Levanon, England, & Allison, 2009; Harris, 2018).

The presence of a gender preference could make it most profitable for occupations to hire only men or majority women. In this case, the segregation today may have been selected due to initial conditions such as historical barriers or norms (Schelling, 1971; Pan, 2015). However the gender preference I estimate would have to be about twice as strong to cause current occupation sorting to depend on past occupation sorting.

There are two important takeaways from this paper for policymakers. First, short run shocks to the fraction female in occupations, such as temporarily pushing more

[5] "Tipping" is also a documented phenomenon in racial segregation by neighborhoods (Card, Mas, & Rothstein, 2008) and racial composition of schools (Caetano & Maheshri, 2017).

men into nursing or women into STEM, will not have long run consequences since there is no historical inertia to overcome. Policymakers seeking to reduce segregation should find specific supply and demand factors that concern them and address them directly, whether it be occupation amenities or discrimination. Second, policymakers should keep in mind that changes to labor supply and demand might have an outsized impact on segregation due to the feedback loop of women wanting to work with women. Making an occupation more attractive to women might have the unintended consequence of making the occupation highly female dominated, and thereby lowering the wages for those women over time through a compensating differential.

Lastly, future research should address the source of the gender preference to determine it is due to gender identity, or workplace environment and amenities. If workplace environment and amenities are the cause, then policymakers who care about reducing segregation and the gender wage gap might consider how to address these to make male-dominated occupations more welcoming to women.

Section 2 introduces the structure of the transferable utility matching model and equilibrium wages. Section 3 describes the empirical specification including recovering the firm side parameters and wage offer distribution, and the decomposition of worker utility into fixed occupation attributes and gender preference. Section 4 describes the data sources. Section 5 presents results, and Section 5 presents simulations of segregation dynamics, including counterfactuals.

2 Model

The identification strategy in this paper builds off empirical applications of matching models to marriage markets (e.g. Choo and Siow (2006) and Chiappori, Salanié, and Weiss (2015)), but differs in that I use data on transfers (wages) to separately identify worker and firm payoffs. In the marriage market, a lack of data on transfers means that only the sum of wage and non-wage utility is identified.[6]. Another key difference from

[6]Fox (2010) is able to estimate payoffs from the interaction of characteristics of both sides of the market but not full payoff functions.

previous literature is that I use the distribution of transfers (wages) for identification.

The first step towards separate identification of firm and worker non-wage parameters is to assume that observed wages are the transfers between job and worker that clear the market. Although some transfers in the labor market may be non-wage, such as enhanced benefits, wages are a natural first-order approximation. Previous literature applying transferable utility to the marriage market has assumed a logit assumption for unobserved transfers because logit is most tractable. I model wages as lognormal in order to match the observed wage distribution, which is greater than zero and has a long right tail.[7] Second, I define an unmatched worker to be a worker who is unemployed or out of the labor force, and an unmatched job to be a posted vacancy that has remained unfilled for a period of time. Since vacancy data is potentially a poor proxy for what it means for a job to be unmatched, I try to limit the importance of the vacancy data in my estimation procedure by choosing a specification that in principle does not require it, by assuming non-negative profit on the job side. Thus identification relies more heavily on the wage distribution.

For clarity of identification, I estimate the two sides of the market, workers and jobs, separately. The job side of the model is a maximum likelihood estimation exploiting the full variation of the observed wage distribution at the individual match level by year. The worker side, by contrast, is an instrumental variables regression at the occupation-year level, where instruments provide clean variation in the fraction female and reservation wage to trace out labor supply.[8]

[7] Unlike the logit case, the variance of the distribution of the maximum of lognormals depends on other model parameters to be estimated, so the variance needs to be jointly estimated unlike in Salanié (2014a) for example.

[8] Combining the two estimation steps using joint GMM is theoretically feasible and would have the advantage that all data moments are used to identify all parameters. However the number of parameters (914 parameters) and the need to pool all years of data (7 million observations) makes joint estimation computationally unattractive.

2.1 Payoff Functions

2.1.1 Firm

Firms are willing to pay different amounts for male and female workers. I do not take a stance as to the cause of the difference. Let WTP_o^g be the most that a job in occupation o would be willing to pay to hire a worker of gender g. The total payoff to job j, π_j^g, also depends on the cost of hiring a worker, $Wage_j^g$, which varies at the job level according to how attractive the job is to workers.

$$\pi_j^g = \frac{WTP_o^g}{Wage_j^g} \tag{1}$$

I specify the payoff function as a ratio for both economic and computational reasons. First, maximizing rate of return is consistent with a firm only filling one vacancy at a time, and allows me to avoid making assumptions about the number of vacancies at a firm or complementarities between those vacancies. Second, the multiplicative specification allows wages to be lognormally distributed, which is common in labor economics to match the observed shape of the wage distribution, while still additive and normal when logged, which is computationally attractive.

The log payoff to the firm j is:

$$\begin{aligned} log(\pi_j^g) =& log(WTP_o^g) - log(Wage_j^g) \\ \equiv& \overline{WTP}_o^g - \overline{Wage}_j^g \end{aligned} \tag{2}$$

2.1.2 Worker

Workers choose an occupation at the beginning of their lives, based on their individual tastes for occupations and the wage offer for their gender in that occupation. The job choice is binding for life.[9] I assume that workers are myopic and do not anticipate future changes in the market that would lead them to want to switch occupations.[10]

The worker's taste for the occupation consists of two components: u_o^g which is common to all workers of gender g matching to jobs in occupation o, and η_o^i which is worker i's specific utility from occupation o. The dis-amenities of job j, which are denoted ξ_j^g, are the same for everyone conditional on gender.

The payoff to worker i from job j is specified as:

$$u_j^i = \frac{u_o^g * Wage_j^g * \eta_o^i}{\xi_j^g} \tag{3}$$

Defining log utility to be $\bar{u}_j^i$ and re-parameterizing in terms of logs we have:

$$\begin{aligned} \bar{u}_j^i \equiv log(u_j^i) &= log(u_o^g) + log(Wage_j^g) + log(\eta_o^i) - log(\xi_j^g) \\ &\equiv \bar{u}_o^g + \overline{Wage}_j^g + \bar{\eta}_o^i - \bar{\xi}_j^g \end{aligned} \tag{4}$$

Furthermore worker utility will be decomposed into a common component and a dependence on the fraction female in the occupation, which is the endogenous amenity of interest.

$$\begin{aligned} \bar{u}_j^i &= \bar{u}_o^g + \overline{Wage}_j^g + \bar{\eta}_o^i - \bar{\xi}_j^g \\ &= \alpha_o^g + \gamma^g F_{o,t-1} + \overline{Wage}_j^g + \bar{\eta}_o^i - \bar{\xi}_j^g \end{aligned}$$

Let $F_{o,t-1}$ be the fraction female among older workers, ages 35-65, in occupation o observed by the younger workers, ages 25-34, at time t as they make their lifetime

[9] Since there is no switching jobs, I assume that education choice is tied to job choice and do not treat education as a separate decision. Lowering switching cost would lead to faster convergence to a fixed point in the fraction female by occupation.

[10] 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.

occupation decisions. The youngest cohort, ages 25-34, observes $F_{o,t-1}$ and makes their occupation choices, producing the number of men and women in each occupation in the time t cohort, $n^F_{o,t}$ and $n^M_{o,t}$. The dynamics of the model result from updating of the fraction female in each occupation with each successive cohort of workers. Since the occupation choice of each worker is fixed for the rest of their working lifetime (assumed to be 40 years), their choice which will influence the fraction female observed by the next three cohorts of workers.

$$F_{o,t-1} = \frac{n^F_{o,t-1} + n^F_{o,t-2} + n^F_{o,t-3}}{(n^F_{o,t-1} + n^M_{o,t-1}) + (n^F_{o,t-2} + n^M_{o,t-2}) + (n^F_{o,t-3} + n^M_{o,t-3})}$$

2.2 Market Clearing Wages

The equilibrium wages I propose, $\overline{Wage}^g_j$, equate supply and demand for workers by gender and jobs by occupation. They do so by compensating the worker for the idiosyncratic dis-amenities of a particular job within occupation, and through a common component W^g_o, which varies by gender and occupation. These equilibrium wages support the pairwise stable matching of workers and jobs through the optimization on both sides of the market. See appendix 9.3 for proof of stability.

$$Wage^g_j = W^g_o * \xi^g_j \tag{5}$$

A firm receives a draw of ξ^M_j and ξ^F_j, which is the amenity value of the job to men and women respectively. The firm then chooses to hire a male or female worker based on the overall productivity of men and women in that occupation (WTP^g_o) and the cost of hiring men and women which varies in order to compensate exactly for the utility or disutility experienced by the worker due to ξ^M_j and ξ^F_j. This is a compensating differential at the job level.

Compensating differentials also emerge at the occupation level through the common component of wages, W^g_o, which will vary according to the utility that workers receive from occupations, as well as the value that jobs have for male and female workers, in order to equate supply and demand. This component of wages can be thought of as the result of a market-wide open-ended ascending price auction where jobs make wage bids for workers, but each job can only "win" one worker.[11]

Plugging in equilibrium wages we have the following equilibrium utility for workers:

$$
\begin{aligned}
\bar{u}_o^i &= \bar{u}_o^g + \overline{Wage}_j^g + \bar{\eta}_o^i - \bar{\xi}_j^g \\
&= \bar{u}_o^g + \bar{W}_o^g + \bar{\xi}_j^g + \bar{\eta}_o^i - \bar{\xi}_j^g \\
&= \bar{u}_o^g + \bar{W}_o^g + \bar{\eta}_o^i \\
&= \alpha_o^g + \gamma^g F_{o,t-1} + \bar{W}_o^g + \bar{\eta}_o^i
\end{aligned}
\tag{6}
$$

Workers are exactly compensated for the job dis-amenities, ξ_j^g, in equilibrium, leaving the taste for occupation, $\bar{\eta}_o^i$, as the heterogeneity at the individual worker level.

The equilibrium payoff to a firm is

$$
\begin{aligned}
\bar{\pi}_j^g =& \overline{WTP}_o^g - \overline{Wage}_j^g \\
=& \overline{WTP}_o^g - \bar{W}_o^g - \bar{\xi}_j^g
\end{aligned}
\tag{7}
$$

Firms care only about the value proposition of hiring a man or woman ($\overline{WTP}_o^g - \bar{W}_o^g$), and the idiosyncratic appeal of their job to men and women, $\bar{\xi}_j^g$. This means that, as on the worker side, there is only one source of heterogeneity in the equilibrium payoff. This is a critical assumption because it allows me to separate the matching problem into two separate discrete choice problems, one for each side of the market (Galichon & Salanié, 2013b). The cost of this assumption is that there is no individual worker productivity heterogeneity. Selection on productivity is orthogonal to my research question, but it may lead me to underestimate the value of amenities of small

[11] In order for equilibrium wages to not depend on sample size I must assume a large number of workers of each gender and jobs of each occupation (Galichon & Salanié, 2013a).

occupations and overestimate the appeal of large occupations.

3 Empirical Strategy

Estimation follows from distributional assumptions on the unobserved heterogeneity on each side of the market.

3.1 Firm Estimation

Assumption 1. *Let the heterogeneity in job amenities for each gender, ξ_j^g, be distributed lognormal and independent across j, such that $\bar{\xi}_j^g = ln(\xi_j^g)$ is distributed $\mathcal{N}(0, \sigma_\xi^g)$.*

I also assume that if a job is unattractive enough, it will not be filled. This allows me to identify the model without use of vacancy data on the firm side. In practice I use vacancy data in estimation for stability of the estimator and to avoid relying too much on extreme data points for identification.

Assumption 2. *A firm will not hire a worker if the wage for men is higher than the willingness-to-pay for men (WTP_o^M) and the wage for women is higher than the firm's willingness-to-pay for women (WTP_o^F).*

$$\bar{\pi}_j^g = \overline{WTP}_o^g - \overline{Wage}_j^g < 0 \quad \text{for} \quad g \in \{M, F\} \qquad \Longrightarrow \qquad j \text{ unfilled}$$

We observe log wages ($\overline{Wage}_j^g$), but the only wages that are observed are the wages that maximize the job's choice over male, female, or not hiring any worker, so the observed data are the result of both selection and truncation. The selection and truncation depends on the $\bar{W}_o^g$, which is an unknown equilibrium object to be estimated, as well as the scale of the unobserved job heterogeneity, σ_ξ^g, which is unknown.[12] To

[12]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 et al. (2015), who uses many markets to identify these parameters, I use the observed wage distribution as suggested in Salanié (2014a).

back out the unobserved wage offer distribution from the observed wages I use Tobit Type 5 maximum likelihood estimation. This allows me to estimate WTP_o^g, W_o^g and σ_ξ^g while accounting for selection and truncation. See Appendix 9.6 for the likelihood function in the notation of Amemiya (1985) and my notation.

3.2 Worker Estimation

Assumption 3. *Let the worker taste heterogeneity for occupations, η_o^i, be independently distributed extreme value type 1.*[13]

The location parameter of η_o^i is normalized to zero, and the scale parameter is estimated separately for each gender, resulting in two scale parameters σ_η^M and σ_η^F for men and women respectively. I leverage well known properties of extreme value distributions to obtain occupation choice probabilities in terms of utility parameters. Recall that $log(u_g^i) = log(u_o^g) + log(W_o^g) + \eta_o^i \equiv \bar{u}_o^g + \bar{W}_o^g + \eta_o^i$.

$$Pr(i \in g \text{ chooses } \forall j \in o) = \frac{exp(\frac{\bar{u}_o^g + \bar{W}_o^g}{\sigma_\eta^g})}{\sum_{k \in O} exp(\frac{\bar{u}_k^g + \bar{W}_k^g}{\sigma_\eta^g})}$$

Assumption 4. *I normalize the log utility from non-employment to be zero ($\bar{u}_N^g = 0$).*

Since no wages are received in non-employment, this leaves only the idiosyncratic taste for non-employment η_N^i. We can then define the probability of choosing occupation o relative to the probability of choosing non-employment in terms of the share of workers of gender g who match to occupation o (s_o^g), and the share that choose non-employment (s_N^g), which are observed. Recall that the non-wage utility ($\bar{u}_o^g$) can then be decomposed into utility from the occupation (α_o^g) and utility from the fraction female ($\gamma^g F_{o,t-1}$).

[13] Also known as gumbel for maxima or logit.

$$\begin{aligned} ln\left(\frac{Pr(i \in g \text{ chooses } \forall j \in o)}{Pr(i \in g \text{ chooses } N)}\right) &= ln(s_o^g) - ln(s_N^g) \\ &= \frac{\bar{u}_o^g + \bar{W}_o^g}{\sigma_\eta^g} = \frac{\alpha_o^g + \gamma^g F_{o,t-1} + \bar{W}_o^g}{\sigma_\eta^g} \end{aligned} \tag{8}$$

This equation 8 cannot be estimated in the cross section because there are only as many moments as occupations, and I must estimate γ^g and σ_η^g in addition to an α_o^g for each occupation. Therefore I pool all six cross sections of data (1960-2012), allowing me to estimate the occupation-specific intercepts, α_o^g and use time variation in fraction female and reservation wages to identify coefficients $\frac{\gamma^g}{\sigma_\eta^g}$ and $\frac{1}{\sigma_\eta^g}$. In order to better match time variation in shares, a time effect β_t^g is added. In addition, in the spirit of Berry (1994), $\epsilon_{o,t}^g$ represents changes over time in the utility of workers due to changes in unobserved occupation attributes, so changes not due to movement in the fraction female or the reservation wages.

$$ln(s_{o,t}^g) - ln(s_{N,t}^g) = \frac{\beta_t^g + \alpha_o^g + \gamma^g F_o + \bar{W}_{o,t}^g + \epsilon_{o,t}^g}{\sigma_\eta^g}$$

Unfortunately using time variation means that estimates of $\frac{\gamma^g}{\sigma_\eta^g}$ and $\frac{1}{\sigma_\eta^g}$ 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 $\epsilon_{o,t}^g$.

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_o^g.

In the worker identification section below I introduce Bartik-style instruments that exploit variation in the industry composition of occupations to isolate changes over time in the fraction female and wage by occupation that are caused by labor demand shifts, allowing me to get clean identification of the labor supply parameters of the worker.

3.3 Identification

I first discuss the identification in the first stage maximum likelihood estimation of the firm parameters ($\overline{WTP}_o^g$ and σ_ξ^g) and centers of the equilibrium wage offer distributions (W_o^g). Then I discuss identification in the second stage instrumental variables regression of the worker parameters (α_o^g, γ^g, and σ_η^g).

3.3.1 Firm Identification

I observe the share of jobs that are filled by men and women in each occupation, and the $Wage_o^F$ and $Wage_o^M$ for those matches that do occur. From these moments I need to identify how much the firm is willing to pay for men and women in each occupation (WTP_o^F and WTP_o^M) and the center of the wage offer distributions for men and women by occupation (W_o^F and W_o^M). The willingness-to-pay will be primarily pinned down by the shares and the right tail of the wage distribution (the most firms are willing to offer for workers of a gender in an occupation), while the wage offers will be primarily pinned down by the left tail of the wage distribution (the least workers are willing to accept for a job in an occupation).

Figures 1 and 2 illustrate identification by comparing the observed wage distribution in two very different occupations. In both occupations, women are paid less than men, but in Sales Representatives, Finance, and Business Services, this is due to firms being willing to pay women less, while in Health Service Occupations, this is the result of women being willing to work for less.

The willingness of firms to pay more for men in Sales Representatives, Finance, and Business Services manifests itself in the wage distribution through a long right tail male wages, well beyond the support of the female wage distribution. By contrast, in Health

Service Occupations, the estimated willingness-to-pay gap is very small because the support of the right tails of the male and female wage distributions broadly overlaps.

Without the use of vacancy data the willingness-to-pay of the firm would in fact be identified from the maximum wage observed for each gender. Because this relies heavily on a single data point that could be an outlier or sampling error, I prefer to use a specification with vacancy data to help pin down how many jobs remain unfilled in the far right tail.

For women in Health Services Occupations, the left tail of the observed wage distribution has a lot of density close to zero, implying that female workers are willing to work for very little in Health Service Occupations, so we would expect wage offers for women to be low in this occupation. The observed wage distribution for women in Sales Representatives, Finance, and Business Services is centered much further to the right, implying women need to be compensated more highly to work in this occupation, so we would expect the center of the wage offer distribution to be higher. Therefore the shape of the observed wage distributions and the shares together identify the locations of the wage offer distributions (W_o^F and W_o^M) for each gender and occupation. Wage offers are be needed to back out worker utility parameters.

3.3.2 Worker Identification

Recall that the worker's occupation choice depends on a fixed value for the occupation, as well as wages and the fraction female, which may change across cohorts of workers. Since the occupation fixed effects (α_o^g) capture the fixed value of the occupations to men and women, the identification concern is that we would expect changes in the fraction female and the wage offer to be correlated with changes in the value of the occupation not captured in the α_o^g. I therefore need instruments to get clean variation in W_o^g and $F_{o,t-1}$ to identify the worker utility parameters.

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 industry level changes to predict wage offers and fraction female by occupation, under the assumption that industry level changes are driven by labor demand and not confounded by labor supply changes. For example, if wages in manufacturing are going up over time because the production technology in manufacturing has become more efficient, then we would expect this to have an impact on the wages of workers in occupations employed in manufacturing that is due to labor demand and independent of occupation amenities. Identification will be threatened if worker preferences for industry vary over time, or if worker preferences for occupations are changing over time in a way that is correlated across occupations. This type of instrument is commonly called a Bartik instrument.

Let p_{Io} be the fraction of occupation o in industry I, and $\hat{F}_{Io}$ the fraction female in industry I excluding workers in occupation o. I exclude the occupation that is being instrumented for so that changes in occupation amenities will not be included in estimates of changes in industry wages and fraction female. The industry composition p_{Io} is be fixed in 1950, prior to the sample data. Then the predicted fraction female in occupation o in time t is as follows:

$$\hat{F}_{o,t} = \sum_{I} p_{Io} * \hat{F}_{Io,t}$$

The predicted wage is similarly the sum over industry of the industry wage by the industry composition. For the instrument to work it is necessary that each industry contain multiple occupations. At the level of aggregation I use, 14 major industries,[14] every industry has employment in almost all occupations.

I also use a more standard Bartik instrument, which predicts changes in occupation wage offers and fraction female due to changes in the relative size of industries. For example, if manufacturing is declining, the number of administrative assistants who

[14]Industries used are aggregates of the harmonized IPUMS codes of ind1990. Industries are 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.

work in manufacturing will decrease, and we can use this to predict changes in the wage offer and fraction female of administrative assistants. The key identifying assumption is that changes in the prominence of certain industries due to production technology or demand side factors, not labor supply changes.

Let the occupation*industry composition, $p_{Io,initial}$, and the fraction female, $F_{Io,initial}$ be fixed at the initial period (1950). Let $size_{Io,t}$ be the total employment level in industry I excluding occupation o in year t. I exclude the instrumented occupation in the estimation of industry size. The predicted occupation fraction female is then:

$$\hat{F}_{o,t} = \sum_{I} p_{Io,initial} * F_{Io,initial} * \frac{size_{Io,t}}{size_{Io,initial}}$$

The last Bartik-style instrument predicts changes in the fraction female of occupations over time by interacting changes in the overall labor force participation rate of relative to women with the initial fraction female by occupation. The idea is that as the relative value of home and work changes, women may be more likely to enter occupations that historically have had more women due to higher fixed values of those occupations (α_g^o).[15]

The instrument is constructed as follows. Let $F_{o,initial}$ be the fraction female in the occupation in the initial period, 1950. 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

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

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

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

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

The instrument will be invalid if the changes in labor force attachment are driven by changes in occupation amenities, and these changes are correlated with initial amenities. For example, if high fraction female occupations in the initial period are becoming relatively more attractive to women over time, and this change is driving the increase in female labor force participation, the instrument will be invalid.

Lastly, I include the willingness-to-pay estimates WTP_o^g from the firm side of the model as instruments. The WTP_o^g are a measure of how much firms value workers should be uncorrelated with unobserved amenities, assuming amenities are fixed, and therefore are a good proxy for labor demand side factors that will shift the reservation wage and the relative number of men or women through firm preference for hiring men vs. women, whether this be consumer demand driven, productivity differences, or discrimination.

4 Data

The primary data elements needed to estimate the model described above are: expectations of lifetime labor income by occupation and gender, shares of workers by gender and age cohort choosing each occupation and non-employment, and a measure of unfilled jobs by occupation.

While the Census and ACS provide cross sectional wage and occupation, the SIPP is needed to provide a panel for the construction of lifetime labor income estimates.[16] 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. Because of limited sample size, I assume that transition rates depend only on the current state not the past history. This transition matrix is then used to simulate worker career paths from the starting point of workers

[16] 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 appendix 9.5 for the full list of occupation codes.

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 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.

To assess the impact of my assumption that workers make lifetime occupation choices, I examine the extent to which workers switch occupations during their working lifetime. In the PSID, the average worker who spends most years working spends 80% of working years in the same occupation[17] Furthermore, for 85% of workers in the PSID the modal occupation for ages 25-35 is also the modal occupation for ages 25-55. My simulated lifetime income sample overestimates occupation transitions relative to the PSID, likely because occupation choice is more history dependent in reality. Either way, occupation choice appears to be fairly stable for a lot of people, and to the extent that people do transition, this is included in the expected value of the initial occupation choice.

[17] I include observations that appear in the PSID for at least 25 years between 1968 and 2011, beginning before age 30 and ending after age 55, and are not missing occupation data. This results in a sample of 764 workers.

5 Model Estimates

5.1 Model Parameters and Fit

Figures 3 and 4 compare the observed wage distributions and the model predicted wage distributions for a few example occupations. The model predicted wages look very similar to observed wages.[18] The fraction female observed in the Census data matches the model predicted fraction female in the cross section, and mostly follows with the model predicted fraction female over time, though not exactly since workers do not necessarily stay in their starting occupation for their lifetime, and the endogenous updating of the fraction female is not a moment targeted in the model.

Table 1 shows the model estimates from the first stage of estimation by occupation, averaged across years. The first column is the 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 female wage offer to male wage offer ($\frac{\bar{W}_o^F}{\bar{W}_o^M}$, 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 ($\frac{\overline{WTP}_o^F}{\overline{WTP}_o^M}$), which varies from .37 to 1.14.

In general women have lower reservation wages than men ($\frac{\bar{W}_o^F}{\bar{W}_o^M} < 1$) and are less valued by jobs ($\frac{\overline{WTP}_o^F}{\overline{WTP}_o^M} < 1$). 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, women like, and are valued most at, highly female dominated occupations such as Administrative Support, Financial Records Processing Occupations, and Health Service Occupations, and women dislike and are valued least 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

[18]The full set of job side model parameter values and histograms of the model fit of the lifetime income distributions and shares can be found in the online appendix.

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 $\bar{W}_o^g$ control for the fact that in observed wages, we see only the most attractive jobs filled 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 selection effects, which would downward bias any estimated correlation. I do not find a statistically significant correlation between my estimates of lifetime income and average fraction female in an occupation, but I do 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).

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. I find a strong preference on the part of women against entering in to male-dominated occupations, which is around twice the preference for log wages, meaning that if the log wage offers in an occupation went up by 10%, this would have an equivalent effect on log utility ($\bar{u}_o^F$) as a 5 % increase to the fraction female. I do not find evidence that men's utility depends on the fraction female. 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.[19]

Tables 2 and 3 show the results of the fixed effect regression, and the fixed effect regression with instruments for fraction female and wage offers described above. The first stage has a Kleibergen-Papp F statistic of around 10 for women and 8.6 for men. 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.[20] I report only the linear specification for men and the cubic specification for women because these seem to fully capture the functional form and obtain the highest first stage F statistics in the IV specification.

In the un-instrumented regression in the first column, both men and women have a negative wage coefficient. The wage coefficient then becomes positive in the instrumented regression in the second column. This implies that there may be time-varying omitted variables, not controlled for by the fixed effects, such as changes in occupation amenities, or skill requirements. The instrumented specifications should avoid this endogeneity by identifying off of labor demand shocks.

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, but the standard errors are high, so I cannot rule out moderate effects in either direction. The lack of precision could be due to a lack of variation over time in men's labor market outcomes, which is corroborated by the much higher total sum of squares in the female regression.

For women the estimated preference is 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. So if an occupation moved from

[19]Results from a beta distribution specification follow a similar pattern.

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

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

The first question I can answer with this model is whether occupation segregation is stable over time. Since I find that women have a preference over the fraction female, we might expect the fraction female to evolve endogenously causing some occupations to become more male or female over time, even if every other aspect of labor supply and demand is fixed. In these simulations the only changes to worker utility are due to changes in the fraction female $F_{o,t-1}$, and changes to the equilibrium wage.[21] All other inputs are fixed at the 2012 values, the last year of data.

Given my parameter estimates, the model predicts that only a few occupations will see substantial evolution in the fraction female in the future. Figure 6 shows four occupations predicted to become more female, and two occupations predicted to become less female. Health diagnosing occupations is predicted to move from 38% to 60% female, engineers, architects and surveyors from 17% to 30%, math computer and natural science from 32% to 43%, and precision production occupations 25% to 38%. Meanwhile machine operators, fabricators, assemblers, testers moves from 20% to 5% female, and metal, wood, plastic, print, textile from 30% to 10%.

[21] I solve for the new $\bar{W}_o^{*g}$ the equates the supply and demand for workers and jobs, given the changes to worker utility due to the evolution of fraction female.

Although the male preference for working with men is close to zero and not statistically significant, these predicted future patterns hold broadly even if men are given a coefficient on fraction female at the lower bound of the confidence interval. So even if men had a relatively strong preference against working with women, most occupations would see little change in segregation based on endogenous evolution of the fraction female alone.

It appears that most occupations are in a steady state in the fraction female, meaning that roughly the same number of women are entering each year as are retiring. The next question is whether these steady states are stable, or whether, for example, a shock to the number of women in an occupation in a given cohort could create a feedback loop causing "tipping" to a new steady state.

6.1 Steady States by Occupation

My model is uniquely positioned to answer the question of whether occupations might have more than one stable segregation pattern, where stable means that the relative number of women entering the occupation is the same as the relative number of women retiring from the occupation. With a strong preference over the fraction female, as I have estimated, it possible that a given occupation could have either a high or low stable fraction female, and the equilibrium that is selected would depend on historical sorting patterns.

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 this occupation to be majority female based on preferences for fixed attributes of occupations and workers. However the occupation was historically female, and the preference for women to work with women means that firms can hire women for cheaper than men in this occupation, which cause the occupation to maintain majority female status based purely on inertia. On the other hand, I estimate that firms value men and women in Administrative Support roughly equally and women appear to like the occupation much more than men . So it seems unlikely that this occupation is 89% female for purely for historical reasons.

This question of which, if any, occupations are segregated for historical reasons can be answered by using the estimated model to search systematically for steady states in the fraction female by occupation. To do so I 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 fixed points, where the fraction female this period is the same as the fraction female in next period, by observing intersections with the 45 degree line.

I find that every occupation has one unique equilibrium in the fraction female. The equilibria are close to the observed 2012 values of fraction female, and where there is deviation from the observed fraction female they are close to the long run steady state. The transition graphs for some selected occupations are shown in Figures 7 through 8. This means that given my estimated parameter values, the model predicts current segregation patterns to emerge regardless of historical gender segregation patterns.

6.2 Wage Adjustment Process

Wage adjustment in equilibrium is the main reason that we observe unique steady states in every occupation. To take a closer look at how wages adjust to compensate for the preference over fraction female, I plot the response of wage to a change in the fraction female in two case studies. Specifically I set a female dominated occupation to be 0% female, and separately, a male dominated occupation to be 100% female, and observe how wage adjustment facilitates convergence back to the unique stable equilibria, which occurs after about eight cohorts of workers.

In the first simulation I set nursing ("Health Technologists and Technicians") to be 0% female in 1960. In reality nursing was close to 100% female in 1960. If wages were fixed, 0% female would be a steady state in the fraction female for nursing. With equilibrium wages the female wage offer must be set high to equate supply and demand, while compensating women for the disutility of the low fraction female.

Women with particularly high utility from nursing are enticed to enter the occupation by the high wages, which in turn makes nursing more attractive for the next cohort. This in turn lowers the equilibrium wage offers for the next cohort of women, which also makes women cheaper for firms to hire. This process continues until nursing is female-dominated and simulated wage offers have dropped to the levels estimated in the data.

In the second simulation, I set "Mechanics and Repairers" to be a 100% female in 1960 when in reality it was close to 0% female. If wages were fixed, the occupation would converge to a majority female stable equilibrium at around 80% female. However, with wage adjustment, which can be seen in Figure 10, female wages quickly 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 stable equilibrium at around 0% female.

6.3 Conditions for Multiple Steady States

Although the estimated parameter values produce only one steady state in the fraction female for each occupation, the model does allow for multiple equilibria to emerge. Below I explore two scenarios that could lead to multiple equilibria in the fraction female. First, doubling the magnitude of the preference for women to work with women, and second, fixing equilibrium wages so they are not allowed to adjust and form compensating differentials.

I find that doubling the preference over the fraction female produces multiple equilibria in some occupations, such as Postsecondary Teachers, and Engineers Architects and Surveyors. These occupations have one equilibrium at close to 0% female and another at majority female. Intuitively, a very strong gender preference makes it cheapest for an occupation to hire either all men or majority women. The initial fraction female would determine to which equilibrium the occupation converges.

Next I fix the wage so that the gender composition reflects only labor supply, and the wage will no longer be able to adjust to clear the market as the fraction female changes. When wages are fixed most occupations (27 out of 34) have two stable equilibria, one that is near zero percent female and one that is majority female. Clearly it is important to have a model with equilibrium wages, like my model, to accurately assess the impact of the gender preference. In the next section I drill down deeper into how wage adjustment leads to less segregated outcomes.

In the last set of simulations, I allow wages to adjust up and down, but I fix the ratio of male to female wages. I fix wage ratio at the ratio of male to female labor force participation, as measured in hours over the lifetime by gender and occupation. This roughly approximates an equal pay for equal work law that would prohibit wage variation based on productivity or labor supply factors (differential taste for job amenities for example). In the case of a fixed male-to-female wage ratio, 13 out of 34 occupations have multiple steady states in the fraction female. Of the remaining 21 occupations that have only one equilibrium, 16 are only stable at 0% female, and 5 at close to 100% female. As a result, equal pay for equal work produces even more segregation in the counterfactual than fixing the wages at their 2012 values (which may reflect compensating differentials by gender or productivity differences in addition to hours differences).

Figures 7 and 8 show examples of transitions in the fraction female in two example occupations. Health Technologists and Technicians has a single female dominated steady state, but with fixed wages it also has a steady state at 0% female. Under equal pay for equal work, both of these steady states become more female. Engineers, Architects, and Surveyors has a single male dominated steady state. With fixed wages it has two steady states, one close to 0% female and one close to 100% female, and under equal pay for equal work only the 0% female steady state remains.

Table 5 shows the gender wage gap and a measure of segregation under various counterfactual regimes, as compared with the status quo. In the status quo model as estimated, the ratio of female to male lifetime wages, or gender wage gap, is 0.71, and

41% of worker would have to change occupations to achieve parity.[22] If there were no preference on the part of women against working in male-dominated occupations, the gender wage gap would be reduced to 0.85, and the segregation index would be only 24%. Not allowing wage adjustment to compensate for changes in the fraction female would result in a similar wage gap as in the status quo, 0.70, and a higher segregation index of 54%. Requiring that men and women be paid equally per hour of work in a given occupation widens the pay gap slightly, putting women at earning 0.65 times that of men, but wildly increases segregation, producing an index of 80%.

The equal pay requirement tends to increase women's pay by pinning it to that of men, but at the same time, the inability to adjust pay according to how men and women value occupations differently, and how firms value men and women differently, creates steady states that are close to 0% or 100% female, which drastically increases segregation. The increased segregation in turn lowers wages for women since concentration in certain occupations means low wage offers through the compensating differential of a high fraction female. Thus overall equal pay laws actually result in lower wages for women.

7 Conclusion

"We've got half the population that is way underrepresented in those fields [math, science, and engineering] and that means that we've got a whole bunch of talent...not being encouraged the way they need to." (President Obama 2013)[23]

It is an open policy question as to what sort of encouragement would lead more women to enter male occupations and vice versa. Ideally we might see that a few men or women entering a field might lead to a flood of followers. I find women do prefer to go into occupations that already have more women. However, womens' preference is not strong enough that simply putting more women in a field will lead more women to enter in the long run. I also find no evidence that men prefer to enter occupations

[22]This measure is called the Duncan Segregation Index.

[23]`https://obamawhitehouse.archives.gov/administration/eop/ostp/women`

that already have more men.

The reason that putting more men or women in an occupation has no long-run effect on segregation is that wages are free to adjust. As the fraction female goes up, wages for women go down, which slows the entry of women into the occupation. The level of gender preference would have to be two times as large as I estimate in order to overcome the tendency to converge back to the original sorting pattern through wage adjustment.

The preference on the part of women to work with women increases gender segregation by creating a feedback loop that amplifies the impact of gender differences in labor supply and demand. According to my simulations, the"tipping" patterns documented by Pan (2015) might be the result of changes in the perceived productivity of men and women, compounded by a feedback loop from the preference of women to work with women. This feedback loop mechanism also exacerbates the gender wage gap by lowering wages in female dominated occupations through compensating differentials.

The estimates of this model are likely imperfectly predictive of the future of occupation gender segregation, but the model does prove useful for learning about the role of wages in two-sided matching with an endogenous amenity. This paper focused on the fraction female in occupations, but future work could use this model to look at race, age, or any other group preference or endogenous amenity, and the moderating effect of price adjustment.

In addition, although I do not find evidence of tipping between multiple equilibria given my estimated parameter values, it is clear that this could occur under different circumstances, such as a stronger gender preference or stickier wages (for example equal pay for equal work laws). Future work is needed to fully understand occupation gender segregation, and could benefit from considering how tipping is mitigated by compensating differentials.

8 Appendix

8.1 Figures

Figure 1: Lifetime Wages in Sales Representatives, Finance, and Business Services

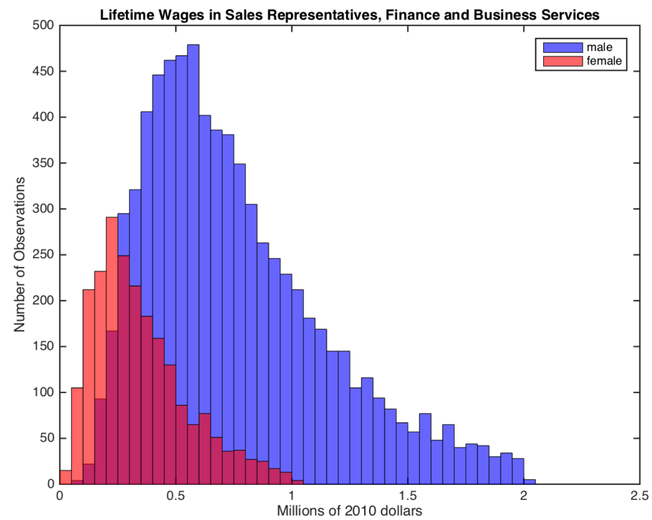


Figure 2: Lifetime Wages in Health Service occupations

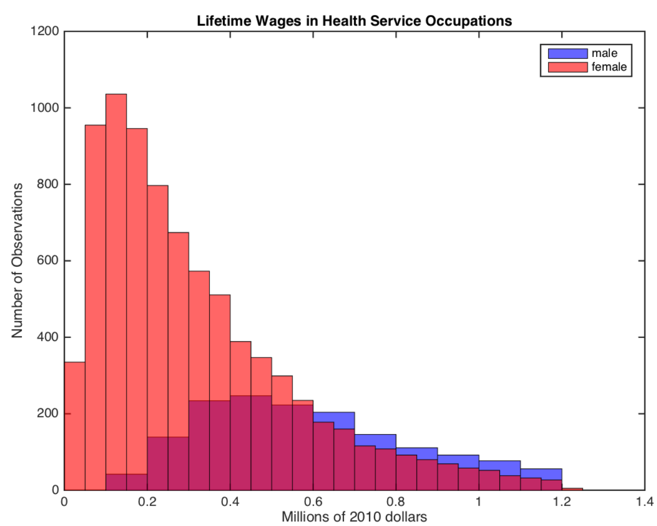


Figure 3: Model Fit

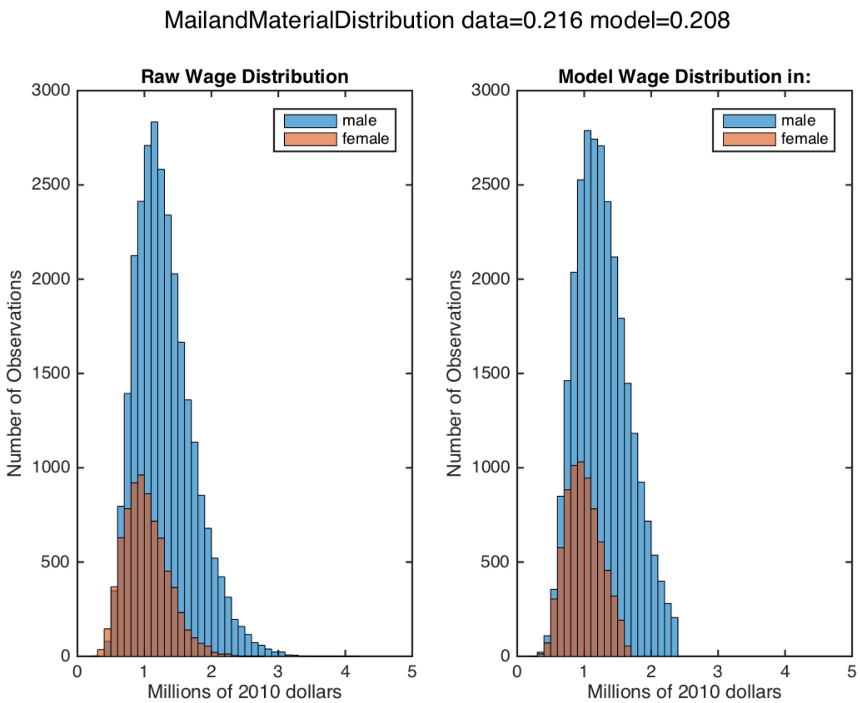


Figure 4: Model Fit

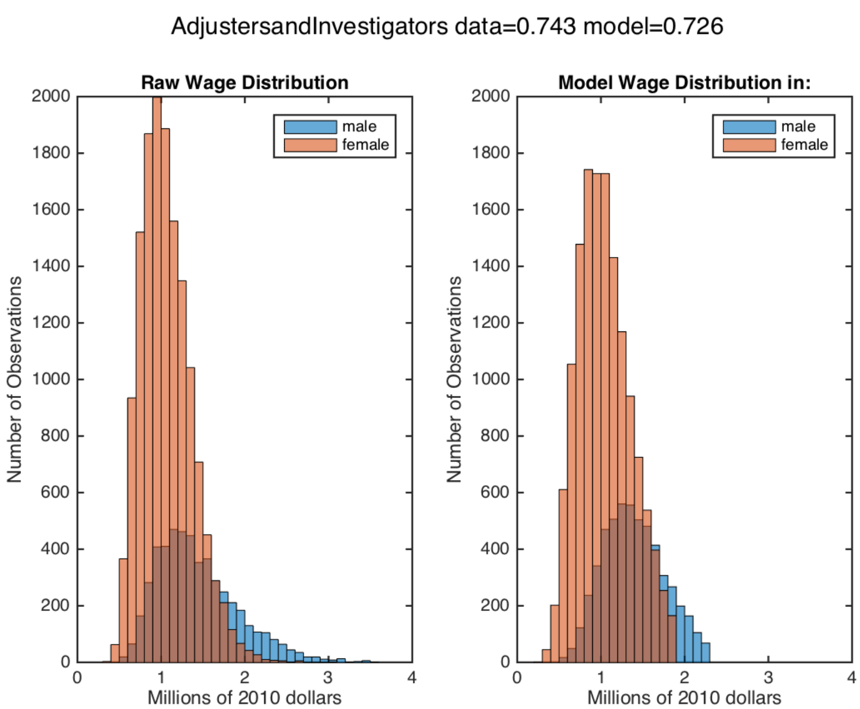


Figure 5: Male and Female Log Utility by Fraction Female in Occupation

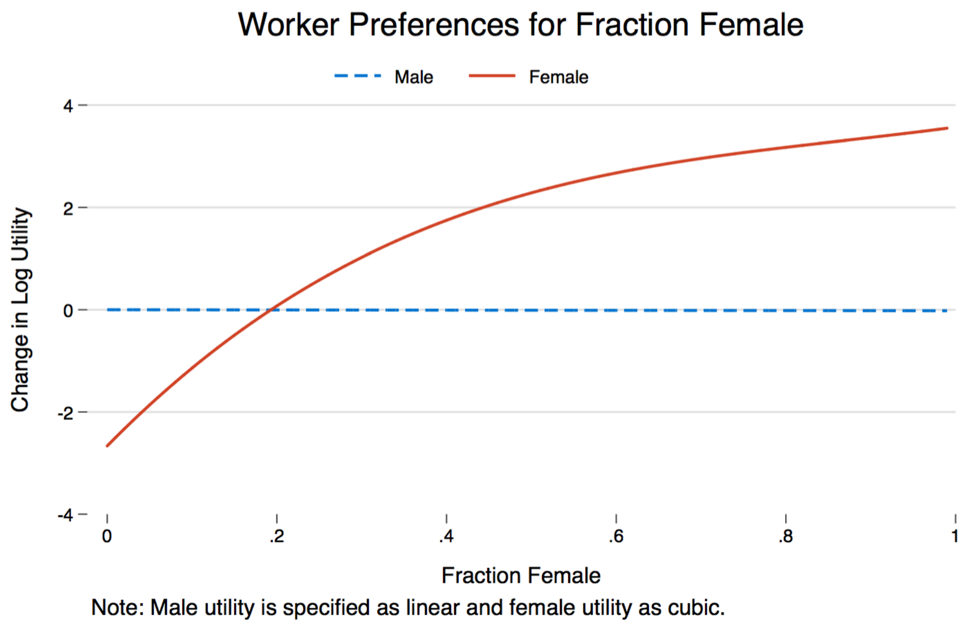


Figure 6: Status Quo: Simulated Occupation Segregation Patterns

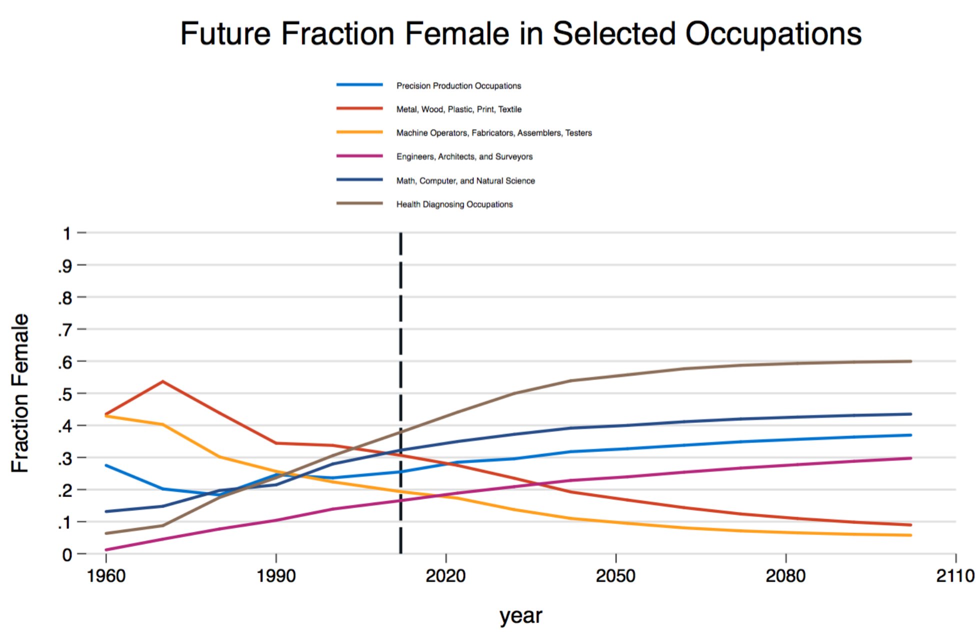


Figure 7: Transitions in Fraction Female Across Periods

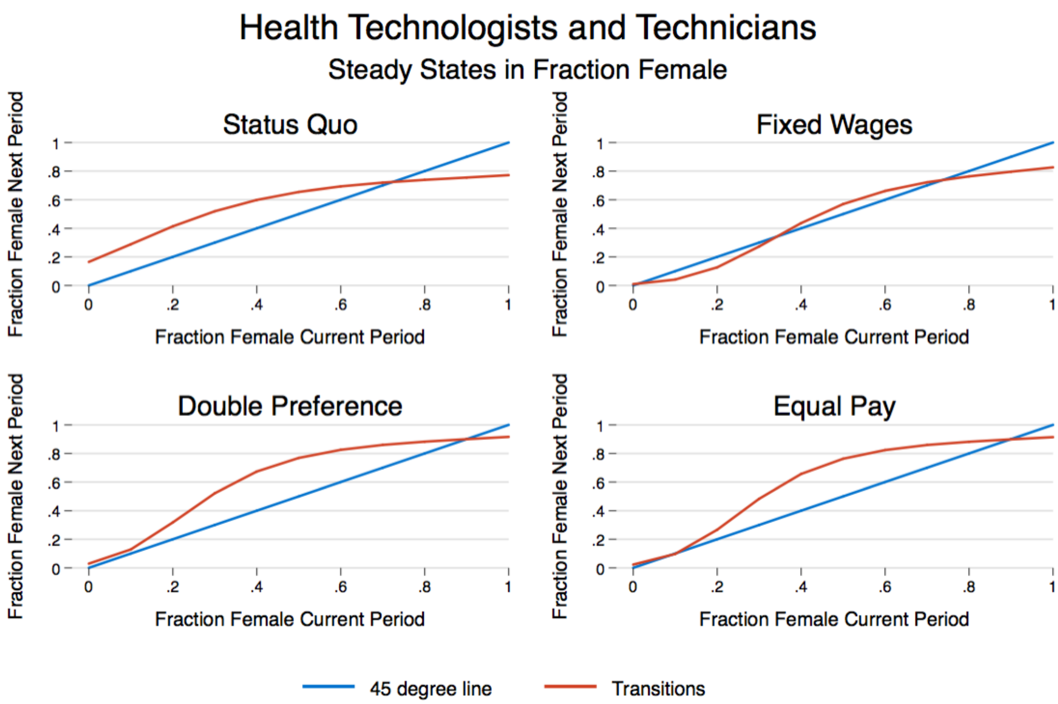


Figure 8: Transitions in Fraction Female Across Periods

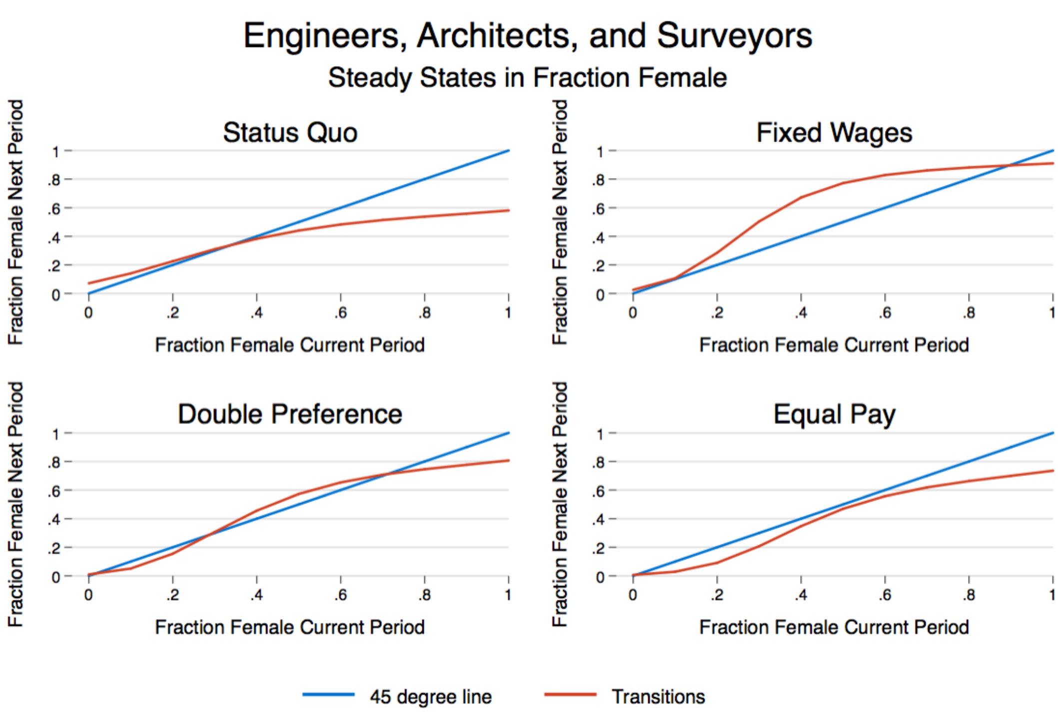


Figure 9: Status Quo: Simulated Occupation Segregation Patterns

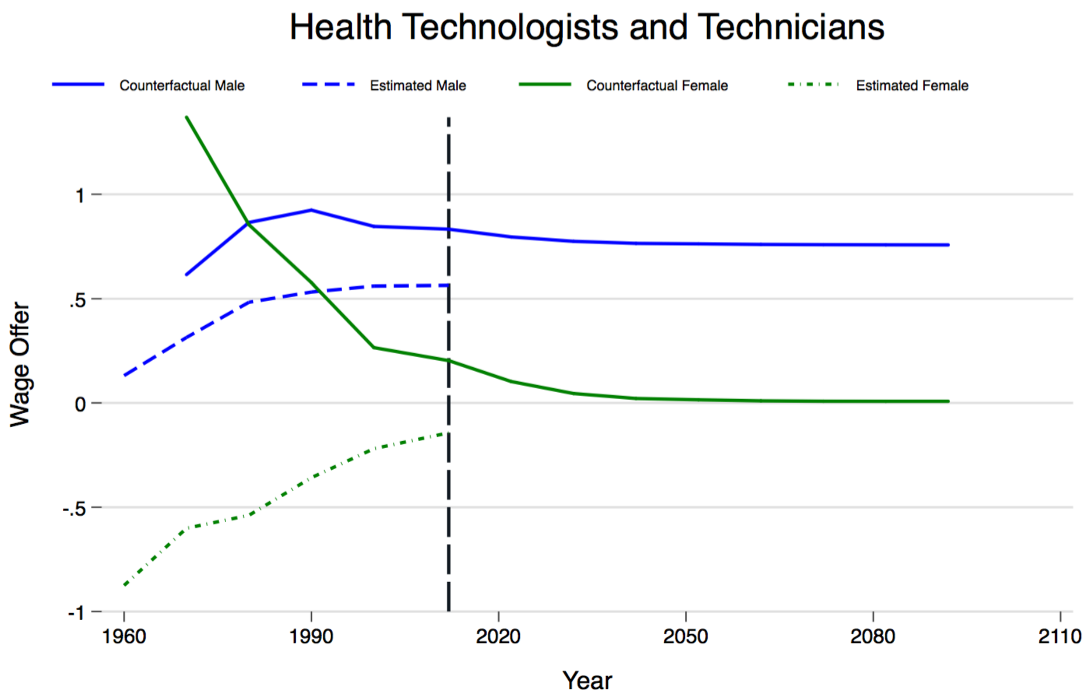
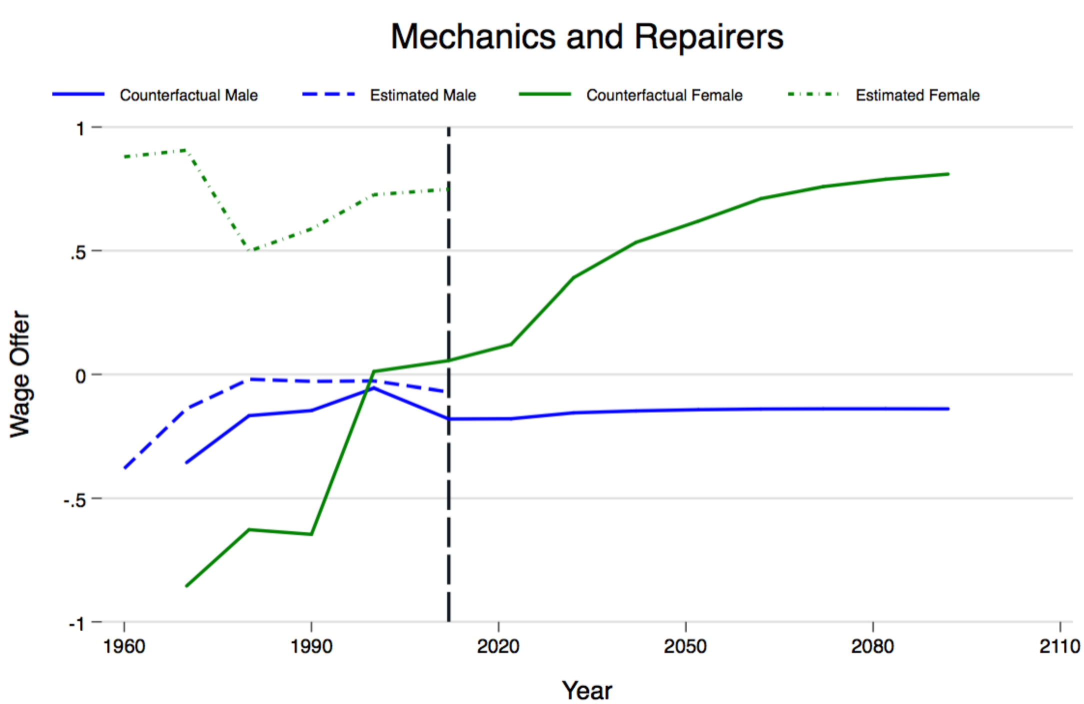


Figure 10: Status Quo: Simulated Occupation Segregation Patterns



8.2 Tables

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
Total	0.45	0.95	0.67

Gaps are the ratio of female to male values. Reservation wages and willingness to pay are estimated from the transferable utility matching model using Census and ACS data matched to simulated lifetime income data from the SIPP. Values are the average across data years (1960, 1970, 1980, 1990, 2000, 2012) within occupation.

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%

Table 6: Ratio of Female to Male Lifetime Income in Millions

	Parameter		
Cell	GenderPref	NoGenderPref	Difference
Teachers, Postsecondary	0.61	0.69	-0.08
Teachers, Except Postsecondary	0.72	0.91	-0.19
Social Scientists, Lawyers, Judg	0.82	0.96	-0.13
Social, Recreation, and Religiou	0.62	0.77	-0.15
Writers, Artists, Entertainers,	0.74	0.81	-0.06
Health Technologists and Technic	0.61	0.78	-0.17
Technicians except health	0.59	0.60	-0.01
Sales Representatives, Finance a	0.73	0.75	-0.02
Sales Workers, Retail and Person	0.64	0.73	-0.09
Administrative Support	0.61	0.83	-0.22
Records Processing Occupations,	0.71	0.92	-0.21
Financial Records Processing Occ	0.58	0.78	-0.20
Mail and Material Distribution	0.70	0.71	-0.01
Adjusters and Investigators	0.63	0.78	-0.15
Miscellaneous Administrative Sup	0.65	0.84	-0.19
Protective Service	0.65	0.61	0.04
Food Preparation and Service Occ	0.67	0.77	-0.10
Health Service Occupations	0.73	0.99	-0.26
Cleaning and Building Service Oc	0.59	0.60	-0.01
Private Household and Personal S	0.65	0.86	-0.21
Agriculture, Forestry and Fishin	0.71	0.61	0.10
Mechanics and Repairers	0.70	0.56	0.15
Construction and Extraction	0.64	0.50	0.14
Precision Production Occupations	0.74	0.73	0.01
Metal, Wood, Plastic, Print, Tex	0.65	0.67	-0.01
Machine Operators, Fabricators,	0.80	0.75	0.06
Road, Rail and Water Transportat	0.70	0.57	0.13
Material Moving, Laborers	0.68	0.59	0.10
Executive, Administrative, and M	0.68	0.74	-0.05
Management Related Occupations	0.67	0.76	-0.09
Engineers, Architects, and Surve	0.75	0.68	0.07
Math, Computer, and Natural Scie	0.65	0.67	-0.02
Health Diagnosing Occupations	0.61	0.66	-0.05
Health Assessment and Treating a	0.78	1.07	-0.29

Note: GenderPref is ratio of female to male predicted lifetime incomes in the main specification, and NoGenderPref is the same but with the coefficients on fraction female set to zero. The Difference column is GenderPref minus NoGenderPref. Positive differences mean that women earn relatively more due to the preference over the fraction female, and negative differences means that women earn relatively less due to the preference over fraction female.

8.3 General Model Structure

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 $j \in o \in O = \{1, 2, ..., 34\}$.[24] Under additive separability we have that the total surplus from a match between worker i and job j, S_j^i, can be decomposed:

$$S_j^i = S_o^g + \eta_o^i + \xi_j^g \tag{9}$$

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

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

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, 2013b).

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.

9 Equilibrium Wages and Stability

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.

9.1 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

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

9.2 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 $\bar{u}^i_{j(i)} + \bar{\pi}^{i(j)}_j \geqslant \bar{u}^i_j + \bar{\pi}^i_j, \quad \forall i, j$. In addition, each worker and job must attain higher surplus than their outside option, or $\bar{u}^i_{j(i)} \geqslant \bar{u}^i_N$ and $\bar{\pi}^{i(j)}_j \geqslant \bar{\pi}^N_j$, where N represents not working for the worker, and not hiring for the firm.*

Note that on the left hand side $\bar{u}^i_{j(i)} + \bar{\pi}^{i(j)}_j$ includes the wage paid out to the worker and by the job in their respective matches. On the right hand side $\bar{u}^i_j + \bar{\pi}^i_j$ 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).

9.3 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

$$j^* \in o^* = \arg\max_o (\bar{u}_o^g + \bar{W}_o^g + \eta_o^i)$$
$$i^* \in g^* = \arg\max_g (\overline{WTP}_o^g - \bar{W}_o^g - \bar{\xi}_j^g)$$

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 $\bar{u}_j^i = \bar{u}_{-j}^i$, and likewise for job j, $\bar{\pi}_j^i = \bar{\pi}_j^{-i}$, therefore the pairwise stability inequality holds trivially for observationally equivalent (same g and o) candidate matches:

$$\bar{u}_{j(i)}^i + \bar{\pi}_j^{i(j)} = \bar{u}_j^i + \bar{\pi}_j^i \quad \forall i, i(j) \in g \quad \forall j, j(i) \in o$$

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

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

and for job j

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

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, $\bar{u}^i_N = \bar{\eta}^i_N$. The value to the firm of not hiring a worker is simply zero, $\bar{\pi}^j_N = 0$.

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. The empirical implications of market clearing will be discussed in the empirical section below.

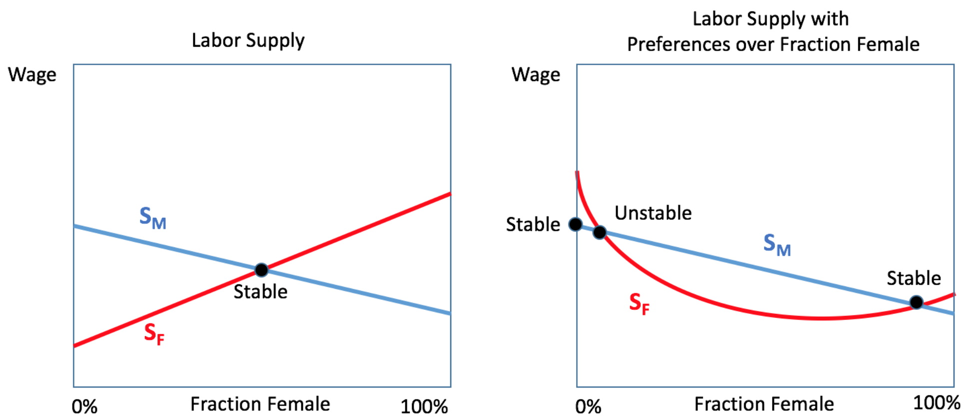
9.4 Pan 2010 Tipping Model

To illustrate the concept of "tipping" I refer to the model of Pan (2015), illustrated below in Figure 11. In this stylized model, an occupation can hire either male or female workers to fill a fixed number of positions. As more women are hired, fewer men are hired, and the fraction female goes up. Assuming upward sloping supply curves for men and women, wages must go up as more workers of either gender are hired. Therefore, assuming equal productivity, firms continue to hire men or women until wages are equalized, which depends on the shape of the supply curves. Tipping points emerge if one or more of the supply curves are not always upward sloping. In the righthand side of Figure 11, we see the case where the female labor supply curve becomes downward sloping at very low fractions female, illustrating a scenario where women are so strongly averse to entering male dominated occupations that hiring more women actually allows the occupation to pay lower wages to women.

In this stylized model, the location of stable and unstable sorting equilibria depends only on the male and female labor supply curves in the occupation, which could depend on how non-wage amenities, wages, and fraction female are valued by men and women.[25] Another key factor affecting the gender mix in the occupation is that firms may not have the same willingness to pay for male and female workers. Firms may values workers of one gender less due to productivity or skill differences, or taste-based or statistical discrimination, or devaluation. Such a gap willingness-to-pay on the firm side will drive a wedge between male and female wages and push the mixed-gender equilibrium in an occupation up or down. Thus both supply and demand factors impact the fraction female in an occupation, and also the tipping point or stability of that fraction female, if there are preferences over occupation gender in the labor supply curves.

[25] In Pan (2015) the locations of the unstable equilibria, and therefore the tipping points, are fixed to be the same across occupations within blue collar or white collar categories.

Figure 11: Stylized Model of Tipping from Pan 2010



9.5 List of occupation Codes

Note that not all component occupations exist in all years of data.

Adjusters and Investigators

Administrative Support

Agriculture, Forestry and Fishing

Cleaning and Building Service

Construction and Extraction

Engineers, Architects, and Surveyors

Executive, Administrative, and Managerial

Financial Records Processing

Food Preparation and Service

Health Assessment and Treating and Therapists

Health Diagnosing

Health Service

Health Technologists and Technicians

Machine operators, Fabricators, Assemblers, Testers

Mail and Material Distribution

Management Related

Material Moving, Laborers

Math, Computer, and Natural Science

Mechanics and Repairers

Metal, Wood, Plastic, Print, Textile

Miscellaneous Administrative Support

Precision Production

Private Household and Personal Services

Protective Service

Records Processing

Road, Rail and Water Transportation

Sales Representatives, Finance and Business Services

Sales Workers, Retail and Personal Services

Social Scientists, Lawyers, Judges

Social, Recreation, and Religious Workers

Teachers, Except Postsecondary

Teachers, Postsecondary

Technicians except health

Writers, Artists, Entertainers, and Athletes

9.6 Joint Likelihood Tobit Type 5

$$
\begin{aligned}
y_{1j}^* &= \overline{WTP}_o^F - \bar{W}_o^F - \xi_j^F - (\overline{WTP}_o^M - \bar{W}_o^M - \xi_j^M) \\
y_{2j}^* &= \bar{W}_o^F + \bar{\xi}_j^F \\
y_{3j}^* &= \bar{W}_o^M + \bar{\xi}_j^M \\
y_{2j} &= y_{2j}^* && \text{if } y_{1j}^* > 0 \\
y_{2j} &= 0 && \text{if } y_{1j}^* \leqslant 0 \\
y_{3j} &= y_{3j}^* && \text{if } y_{1j}^* \leqslant 0 \\
y_{3j} &= 0 && \text{if } y_{1j}^* > 0
\end{aligned}
$$

Let $f_{1,3}$ be the joint density of y_{1j}^* and y_{3j}^*, and likewise $f_{1,2}$.

$$
\begin{aligned}
L &= \prod_F \int_{-\infty}^{0} f_{1,3}(y_{1j}^*, y_{3j}) dy_{1j}^* \prod_M \int_0^{\infty} f_{1,2}(y_{1j}^*, y_{2j}) dy_{1j}^* \\
&= \prod_j Pr(y_{1j}^* \leqslant 0, y_{3j})^{\mathcal{I}(y_{3j})} * Pr(y_{1j}^* > 0, y_{2j})^{\mathcal{I}(y_{2j})} \\
&= \prod_j (Pr(y_{1j}^* \leqslant 0 | y_{3j}) * Pr(y_{3j}))^{\mathcal{I}(y_{3j})} * (Pr(y_{1j}^* > 0 | y_{2j}) * Pr(y_{2j}))^{\mathcal{I}(y_{2j})} \\
&= \prod_j (F_1(0|y_{3j}) * f_3(y_{3j}))^{\mathcal{I}(y_{3j})} * (F_{-1}(0|y_{2j}) * f_2(y_{2j}))^{\mathcal{I}(y_{2j})}
\end{aligned}
$$

Where F_1 is the cdf of y_{1j}^*, F_{-1} the cdf of $-y_{1j}^*$, f_3 is the pdf of y_{3j}^*, and f_2 the pdf of y_{2j}^*.

$$
\begin{aligned}
y_{2j} = y_{3j} = 0 \qquad & \text{if} \quad \overline{WTP}_o^M - \bar{W}_o^M - \bar{\xi}_j^M < 0 \\
& \text{and} \quad \overline{WTP}_o^F - \bar{W}_o^F - \bar{\xi}_j^F < 0
\end{aligned}
$$

Translating into my notation, if the job is filled, its contribution to the likelihood function takes the form

$$\begin{aligned} LL_{j_{\text{filled}}} &= \prod_{j_{\text{filled}}} Pr(j \text{ hire g}, Wage_j^g) * Pr(j \text{ filled}) \\ &= \prod_{j_{\text{filled}}} Pr(j \text{ hire g}|Wage_j^g) * Pr(Wage_j^g) * Pr(j \text{ filled}) \end{aligned}$$

If the job is unfilled, its contribution is

$$LL_{j_{\text{unfilled}}} = \prod_{j_{\text{unfilled}}} Pr(j \text{ unfilled})$$

$\mathcal{I}($ j unfilled$)$ be the indicator function equal to one if the job j is unfilled, and similarly for $\mathcal{I}(j \text{ filled})$. Then the total likelihood is given by

$$LL_j = \prod_j (Pr(j \text{ hire g}|Wage_j^g) * Pr(Wage_j^g) * Pr(j \text{ filled}))^{\mathcal{I}(j \text{ filled})} * (Pr(j \text{ unfilled}))^{\mathcal{I}(j \text{ unfilled})}$$

$Pr(j$ unfilled$)$ is the probability that we do not observe a match, which I impute from the JOLTS vacancy data.[26] This occurs when hiring neither women nor men produces willingness-to-pay higher than cost.

$$\overline{WTP}_o^M - \bar{W}_o^M - \bar{\xi}_j^M < 0 \quad \text{and} \quad \overline{WTP}_o^F - \bar{W}_o^F - \bar{\xi}_j^F < 0$$

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

The $Pr(j \text{ filled}) = 1 - Pr(j \text{ unfilled})$ is then

$$\begin{aligned} &1 - Pr(\xi_j^F < -(\overline{WTP}_o^F - \bar{W}_o^F), \quad \xi_j^M < -(\overline{WTP}_o^M - \bar{W}_o^M)) \\ &= 1 - \Phi_{0,\sigma_\xi^F}(-(\overline{WTP}_o^F - \bar{W}_o^F) * \Phi_{0,\sigma_\xi^M}(-(\overline{WTP}_o^M - \bar{W}_o^M)) \end{aligned}$$

Let Φ_{0,σ_ξ^g} and ϕ_{0,σ_ξ^g} are the cdf and pdf of the normal distribution with location zero and scale σ_ξ^g. Recall that

$$\overline{Wage}_j^g = \bar{W}_o^g + \bar{\xi}_j^g$$

Then other terms in the likelihood are as follows:

$$\begin{aligned} Pr(j \text{ hire M}|\overline{Wage}_j^M) &= \Phi_{0,\sigma_\xi^F}(\overline{WTP}_o^M - \overline{Wage}_j^M) - (\overline{WTP}_o^F - \bar{W}_o^F)) \\ Pr(\overline{Wage}_j^M) &= \phi_{0,\sigma_\xi^M}(\overline{Wage}_o^M - \bar{W}_o^M) \\ Pr(j \text{ hire F}|\overline{Wage}_j^F) &= \Phi_{0,\sigma_\xi^M}(\overline{WTP}_o^F - \overline{Wage}_j^F) - (\overline{WTP}_o^M - \bar{W}_o^M)) \\ Pr(\overline{Wage}_j^F) &= \phi_{0,\sigma_\xi^F}(\overline{Wage}_j^F - \bar{W}_o^F) \end{aligned}$$

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