Miss-Allocation: The Value of Workplace Gender Composition and Occupational Segregation

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Abstract

I analyze the value workers ascribe to the gender composition of their workplace and the consequences of these valuations for occupational segregation, tipping, and welfare. To elicit these valuations, I survey 9,000 US adults using a hypothetical job choice experiment. This reveals that women value gender homophily in the workplace and men value gender diversity. Older female workers are more likely to value gender homophily, suggesting that gender norms and discrimination, which have declined over time, may help explain women's desire for homophily. Using these results, I estimate a structural model of occupation choice to assess their consequences for gender sorting and welfare. I find that workers' average composition valuations are not large enough to create tipping points, but they do reduce the female share in male-dominated occupations substantially. Gender composition valuations also create a sorting externality: a welfare-maximizing social planner would reallocate workers to substantially decrease segregation.

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1 Introduction

Although women's labor market outcomes have improved markedly relative to men's in the last several decades, women and men still do very different jobs. In fact, 40% of men perform occupations where less than 20% of workers are female, and 30% of women perform occupations where less than 20% of workers are male, and gender sorting across occupations explains over one third of the mean gender earnings gap.[1] Occupational gender segregation has been studied in both economics and sociology for several decades, but its causes are still an active area of research.[2] In a standard model of occupation choice, the reasons men and women choose different jobs can be divided into a few broad categories: gender differences in skills, gender differences in preferences for tasks or amenities, discrimination, and social norms.[3] Recently, a number of papers have drawn attention to a particular occupational characteristic that men and women may value differently: the gender composition of an occupation itself.

Preferences for gender composition are particularly interesting because they can amplify existing segregation, create tipping points, and create sorting externalities and thus a role for policy intervention. If women value gender homophily, it will be difficult to desegregate a mostly male occupation without central coordination. Pan (2015) and Henry and Sidorov (2020) show that the level and dynamics of occupational gender segregation in the US are consistent with homophilic gender composition valuations in a Schelling (1971)-style model. Yet there is little evidence that causally identifies and quantifies these valuations. Because the gender composition of an occupation is endogenous and tends to move slowly over time, it is difficult to isolate the value of gender composition separately from other occupational characteristics that vary by gender, like tasks, flexibility, and skill requirements. Delfino (2021) and Larson-Koester (2017) provide evidence that women prefer more female occupations, but whether these preferences are large enough to explain aggregate patterns of segregation is unclear.

In this paper, I causally identify how much men and women value the gender composition of their workplace and quantify the importance of these preferences for occupational gender segregation and welfare. Using a novel online survey experiment, I demonstrate that women value majority female workplaces, but the slope of their valuation profile is concave, and men value gender-diverse workplaces. I then build a structural model of occupation choice using

[1] See Tables 4 and 5. Blau and Kahn (2017) and Sloane et al. (2021) estimate similar results.

[2] For a thorough review of the literature, see Cortés and Pan (2018).

[3] Gender differences in skills: see, e.g., Rendall (2018); Yamaguchi (2018); Cortes et al. (2021). Gender differences in preferences: see, e.g., Wiswall and Zafar (2018); Gelblum (2020); Lordan and Pischke (2022). Discrimination: see, e.g., Bertrand and Duflo (2017), Kessler et al. (2019). Social norms: see, e.g., Goldin (2014), Bursztyn and Jensen (2017), Bursztyn et al. (2017), Bertrand et al. (2021).

my survey-estimated composition preferences. Using this model, I show that the average gender composition valuations I estimate are not large enough to produce multiple equilibria and tipping points in gender sorting. However, allowing for preference heterogeneity shows that tipping may be possible for select groups of workers. In addition, these valuations have a large effect on sorting: if workers did not value the gender composition of their job, female shares would be substantially higher in mostly male occupations. Finally, I show that a welfare-maximizing social planner would solve a coordination problem by reallocating workers to reduce segregation substantially. Doing so would increase welfare by the equivalent of a 2% increase in consumption.

The reasons why men and women perform different occupations are often divided into "preferences" and "constraints." In my setting, I hold constraints fixed and measure preferences for gender composition directly. The gender composition of an occupation or workplace is a bundled treatment that may include attributes like expected discrimination or harassment (Folke and Rickne, 2022); gender differences in behavior, e.g., competitiveness (Gneezy et al., 2003; Niederle and Vesterlund, 2007); non-promotable tasks (Babcock et al., 2017); the likelihood of friendship or romantic attachments with coworkers; and differences in information sharing within and across genders (Hampole et al., 2022; Gallen and Wasserman, 2021, 2022). Gender differences in desired occupational and workplace gender composition are not necessarily inherent, biological, or constant over time. I ask, given the current equilibrium differences in workplace behavior between men and women, how much do workers value gender composition?

I begin my analysis by adapting a simple model of occupation choice from Pan (2015) and Henry and Sidorov (2020) which builds on that from Schelling (1971) to build intuition for the key parameters driving the effects of gender composition preferences on gender sorting in equilibrium. In the model, male and female workers choose occupations based solely on the occupational wages and gender compositions. If workers do not value the gender composition of their occupation, only exogenous gender wage gaps create gender sorting across occupations. If workers value the gender composition of their occupation, homophilic gender composition valuations amplify, and heterophilic gender composition valuations dampen, underlying gender sorting. The key parameters that determine the effect of gender sorting preferences are the willingness to pay for a particular level of the female share of an occupation as a fraction of the occupational wage and the wage elasticity of occupational labor supply.

To measure the size and shape of gender composition valuations, I design a hypothetical job choice survey experiment to elicit the willingness to pay for workplace gender composition. In the vein of Wiswall and Zafar (2018), Mas and Pallais (2017), and Maestas et al. (2018), in my survey respondents choose between several pairs of hypothetical job offers at different workplaces that vary randomly in their pay and demographic composition but are within a fixed occupation and firm. For example, in one question respondents choose between two jobs as a sales associate at two different locations of the same retail store chain. I give choices between workplaces within an occupation and firm because this addresses the endogeneity of gender composition by creating random variation and holding fixed other characteristics that might vary with the gender composition of a job, including the occupational tasks, amenities contracted by the firm, and the industry.[4]

I find that both men and women assign non-negligible value to the gender composition of their workplace, but the shape and size of these preferences differ by gender. Women have homophilic composition valuations, but their shape is concave: as the female share of a workplace increases, the marginal benefit of additional women declines. I estimate that women are willing to trade off 4.5% of their wages to avoid a workplace that is all male in favor of a workplace that is evenly gender balanced, but they are not willing to trade off more wages to access a workplace that is more than half female. Men, however, value gender diversity. I estimate that men are willing to trade off 3% of their wages to avoid a workplace that is all male and 2% of their wages to avoid a workplace that is all female in favor of a gender balanced workplace. By causally identifying the willingness-to-pay for workplace gender composition while allowing for non-linearities in its shape over the spectrum of female shares, these estimates enrich prior findings by Delfino (2021) and Larson-Koester (2017) that suggest women are more likely to choose more female-dominated occupations.

The average estimates of gender composition valuation mask substantial heterogeneity across individuals. To detect heterogeneity that is not correlated with observable characteristics, I estimate a latent class logit model (Greene and Hensher, 2003) using the survey data. Among women, I find that around half of respondents choose purely based on the wage and assign zero value to the female share and half of respondents assign a large value to the female share and are willing to trade off over 10% of wages to avoid predominantly male workplaces. Among men, I find that around half of respondents assign zero value to the female share, a quarter of respondents prefer majority male jobs, and a quarter of respondents prefer majority female jobs.

Older men and women are substantially more likely to value gender homophily in the workplace, suggesting that the desire to segregate by gender may have declined as women's

[4] My design is not incentivized, and relies on respondents answering questions in a way that reflects their true preferences. This style of survey experiment has been incentivized by offering customized job postings (Kessler et al., 2019; Bustelo et al., 2022) or information on survey results to respondents (Drake, Marshall et al., 2022). In my setting where workers are highly heterogeneous in employment status, occupation, and location, it was not clear that these incentives would be effective, but I have piloted randomly offering respondents job suggestions that depend on their responses.

labor market outcomes converged towards men's over the twentieth century. For women over 55, the likelihood of valuing a more female workplace increases with age, but for younger women the age profile is flat. Although I cannot directly distinguish whether this is an age or cohort effect, a cohort effect tells an interesting story. These younger workers would have joined the labor force during or after the 1990s, when the increase in women's labor force participation began to slow. This suggests that gendered social norms surrounding work and occupation choice, which have likely lessened over time, may be a driver of homophilic gender composition valuations, as suggested by Akerlof and Kranton (2000), Brock and Durlauf (2001), and Pan (2015).[5]

Additional results from my survey suggest that men value gender-mixed to more female workplaces specifically because of the female coworkers, but women value all aspects of a more female workplace. I find that men have a significantly higher willingness-to-pay for a majority female workplace in occupations that require more interaction with coworkers (such as teaching or working in a retail store) than in occupations that rely more on solo work (such as working as an insurance sales agent in an office). I find no such differences among women. In addition, men are more likely to report they would prefer the coworkers in a mostly female job than a mostly male job, but they are more likely to report they would prefer the work environment, schedule, tasks, and promotion ability in a mostly male job. Women, however, are more likely to report they would prefer a mostly female job than a mostly male job in all of these attributes. This suggests that women not only value having female coworkers, but a more female workforce also serves as a signal of other workplace amenities women value—for instance, family-friendliness (Goldin and Katz, 2016; Mas and Pallais, 2017; Cortés and Pan, 2020; Morchio and Moser, 2020). Since most of these attributes are held constant in my hypothetical choice experiment, my estimates likely provide a lower bound to the total value women assign to a more female work environment.

To understand the aggregate importance of gender composition valuations, I build a structural model that expands on my simple model of occupation choice to quantify the implications of the gender composition valuations I have estimated on gender sorting and welfare in the U.S. In the model, male and female workers choose occupations to maximize their utility from gender-specific wages, amenities, gender composition valuations, and random occupational preference draws while wages adjust to labor supply in equilibrium. I estimate the model using Current Population Survey data on wages and allocations across over 400 occupations in addition to my survey results. A model is necessary to aggregate my reduced form results because understanding the implications of composition preferences

[5] Fernández et al. (2004), Goldin (2014), Bursztyn et al. (2017), Olivetti et al. (2020), Bertrand et al. (2021), and Cortés et al. (2022), among others, also document the importance of social norms for women and men's career choices, particularly as they relate to marriage and children.

across multiple occupations requires solving for a sorting equilibrium.

I use this model to perform three main exercises. First, I measure the aggregate consequences of gender composition valuations by comparing wages and allocations in reality with those that would result if workers assigned no value to workplace gender composition. I find that absent gender composition valuations, the female share in majority male occupations would be up to 5 percentage points higher, and the share of workers in occupations that are less than 20% or more than 80% female would fall by up to 5%. I also find that the part of the gender wage gap that is attributable to occupational gender segregation would fall by 20% if workers did not value gender composition.

Next, I demonstrate that the average gender composition valuations I estiamte are not large enough to create multiple sorting equilibria and tipping points in gender segregation. Average valuations for gender composition would need to be twice as large for women, and four times as large for men, to create pure tipping points in the sense of a sudden shift from a mixed-gender to a gender-segregated equilibrium in an occupation. However, when allowing for preference heterogeneity across individuals, I find that among the groups of women and men that most prefer gender homophily, tipping is possible. Coupled with my results suggesting that the value of gender homophily may have declined over time, this suggests that the tipping points in segregation demonstrated by Pan (2015) could have been caused by homophilic preferences.

Finally, I study a social planner's problem in the model and show that reducing segregation would improve welfare substantially. This occurs because workers' valuations of gender composition create a sorting externality: women (or men) do not take into account the effect their entry into an occupation will have on the utility of men (or women) in that occupation. The social planner, then, allocates more women to male dominated occupations and more men to female dominated occupations so more workers are in occupations that are more gender-mixed, which both genders value.

This paper contributes to the literature in three main areas. First, I estimate credibly and causally women's and men's preferences for workplace gender composition. This provides direct quantitative evidence for the causes of tipping points posited by Schelling (1971); Brock and Durlauf (2001); and Pan (2015) and further understanding of the tendency for women to choose more female jobs shown by Delfino (2021); Larson-Koester (2017); Engel et al. (2022). This also adds to the literature on the importance of non-pecuniary amenities in job choice (Sorkin, 2018; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Bustelo et al., 2022) by showing that the composition of the workplace itself, in addition to amenities provided more directly by the firm, may be an important driver of job choice. This has important implications for our understanding of the causes of inequality across demographic groups. I also show that worker's preferences for gender composition can reduce women's presence in male dominated jobs and that policies to reduce segregation could improve welfare, which contributes more broadly to the literature on the causes of gender segregation across occupations and the consequences of policies to reduce segregation (Hsieh et al., 2018; Kaplan and Schulhofer-Wohl, 2018; Sloane et al., 2021; Gelblum, 2020; Cortés and Pan, 2018; Cortes et al., 2021).

This paper is organized as follows. In Section 2, I outline a basic model of occupation choice with gender composition preferences. I show that composition preferences can act to amplify or dampen existing sorting caused by, for instance, differences in skills or discrimination. In Section 3, I discuss the design and results of the survey I administered to estimate gender composition preferences and their distribution across individuals. Section 4 brings my survey-estimated preferences into a quantitative model of occupation choice, where I measure the aggregate importance of composition preferences and discuss the utility of alternative allocations. Section 5 concludes.

2 Occupation Choice Model

To fix concepts, I present a toy model of occupation choice in which workers value both the wage and gender composition of their occupation, in the spirit of Pan (2015) and Henry and Sidorov (2020). I show that underlying patterns of gender sorting will be amplified by homophilic preferences but dampened by heterophilic preferences. In Section 3, I will measure these preferences directly using a survey experiment.

2.1 Model Environment and Sorting Equilibrium

In my toy model, which is adapted from Henry and Sidorov (2020), male and female workers choose the occupation providing the highest utility from gender composition and wage. If wage differences across occupations cause one occupation to have a higher female share, homophilic composition preferences cause even more women to choose that occupation. Heterophilic preferences have the opposite effect.

In the model environment, there are two genders of workers, $g \in \{f, m\}$, and two occupations, $k \in \{1, 2\}$. Workers of each gender are present in measure 1. Each occupation is characterized by a pair of gender-specific wages $w_{f,k}$ and $w_{m,k}$ and its female share, $f_o = \frac{l_{k,f}}{(l_{k,f}+l_{k,m})}$, where $l_{k,g}$ is the total number of workers of gender g in occupation o. Each gender of worker has some preference profile over the female share of their chosen occupation represented by $h_g(f)$. If preferences are homophilic, $h_g(f)$ is increasing in f for women and decreasing in f for men.

Each individual chooses an occupation to maximize their utility from the occupational wage, the occupational female share, and an idiosyncratic preference draw. The utility function for an individual i of gender g is given by

$$U_i = \max_{k \in \{1,2\}} \log(w_{g,k}) + h_g(f_k) + \varepsilon_{i,k}, \tag{1}$$

where $\varepsilon_{i,k}$ is an idiosyncratic preference shock for individual i in occupation k that is drawn from the CDF G. The idiosyncratic shock is added to the utility function to create dispersion in choices across individuals. I define the function $F_{\varepsilon_2 - \varepsilon_1}(x)$ as the CDF of the difference between the preference shocks in occupation 2 and occupation 1.

An individual i will choose occupation 1 if the utility they obtain in occupation 1 is greater than the utility they obtain in occupation 2:

$$log(w_{1,g}) + h_g(\ell_{1,f}/\ell_1) + \varepsilon_{i,1} > log(w_{2,g}) + h_g(\ell_{2,f}/\ell_2) + \varepsilon_{i,2}. \tag{2}$$

Thus, if wage and gender composition utility is higher in occupation 1, only individuals with a large idiosyncratic preference for occupation 2 will choose this occupation, and vice versa.

Following Henry and Sidorov (2020), I define a sorting equilibrium as an allocation of workers of each gender to occupation such that no small mass of workers could improve their utility by switching occupations. In a sorting equilibrium, the share of workers of each gender in occupation 1 is equal to the probability that utility is higher in occupation 1, or, equivalently, the probability that the relative preference shock in occupation 2 is less than the relative wage and gender composition utility in occupation 1.[6]

$$\ell^*_{1,g} = Pr\left[log(w_{1,g}) + h_g(\ell_{1,f}/\ell_1) + \varepsilon_1 > log(w_{2,g}) + h_g(\ell_{2,f}/\ell_2) + \varepsilon_2\right], \qquad g = \{f, m\}. \tag{3}$$

Multiple equilibria will occur when this system has multiple solutions. Thus, tipping, which I define as a shift from one equlibrium to another, will only be possible if multiple equilibria exist. In the next section, I will use Equation 3 to understand which conditions create the possibility for tipping and characterize the effect of composition preferences on sorting.

2.2 The Partial Equilibrium Effect of Composition Preferences

In this section, I use the model outlined above to determine which parameters will influence the effect of composition preferences on gender sorting when wages are fixed exogenously.

[6] Henry and Sidorov (2020) establish conditions for existence and uniqueness of a sorting equilibrium: essentially, an equilibrium generally exists and will be unique if composition preferences are smooth and of small enough scale.

I find that the effect of composition preferences on sorting and wages will be larger, and tipping more likely, if gender composition preferences are strong relative to wages and if occupation choice is more responsive to changing wages.

We can invert Equation 3 to find the labor supply functions in this model:

$$\log(w_{1g}) - \log(w_{2g}) = \underbrace{F^{-1}_{\varepsilon_2-\varepsilon_1}(\ell_{1g})}_{\text{marginal preference shock}} + \underbrace{\left[h_g\left(\frac{1-\ell_{1f}}{2-\ell_{1f}-\ell_{1m}}\right) - h_g\left(\frac{\ell_{1f}}{\ell_{1f}+\ell_{1m}}\right)\right]}_{\text{difference in composition utility}}.$$

To understand this labor supply function more concretely, I assume that the idiosyncratic preference draw follows a Type I Extreme Value (TIEV) distribution with shape parameter η. The parameter η determines how responsive workers are to changing occupational conditions: if η is large, the variance of the preference shocks is high, which makes occupation choices relatively sticky and workers less responsive to changing occupational conditions. If η is small, the variance of the preference shock is low, which makes occupation choices relatively flexible and workers more responsive to changing occupational conditions.

Under this assumption, we can solve the inverse CDF of the preference shock to write the following labor supply functions:

$$\underbrace{[\log(w_{1g}) - \log(w_{2g})]}_{\text{wage util diff.}} = \underbrace{\eta \cdot \log\left(\frac{\ell_{1g}}{1-\ell_{1g}}\right)}_{\text{pref shock util diff.}} + \underbrace{[h_g(\frac{1-\ell_{1f}}{2-\ell_{1f}-\ell_{1m}}) - h_g(\frac{\ell_{1f}}{\ell_{1f}+\ell_{1m}})]}_{\text{composition utility diff.}}, \quad g = f, m. \tag{4}$$

The first part of Equation 4 is standard: as the relative wage in occupation 1 increases, the relative labor supply to occupation 1 increases; the labor supply is more responsive to wages when the variance of the preference shock is smaller. The second part of this equation illustrates that labor supply will also depend on the relative composition utility of the two occupations: if composition utility is higher in occupation 1, more workers of gender g will choose occupation 1 than they would in the absence of composition preferences.

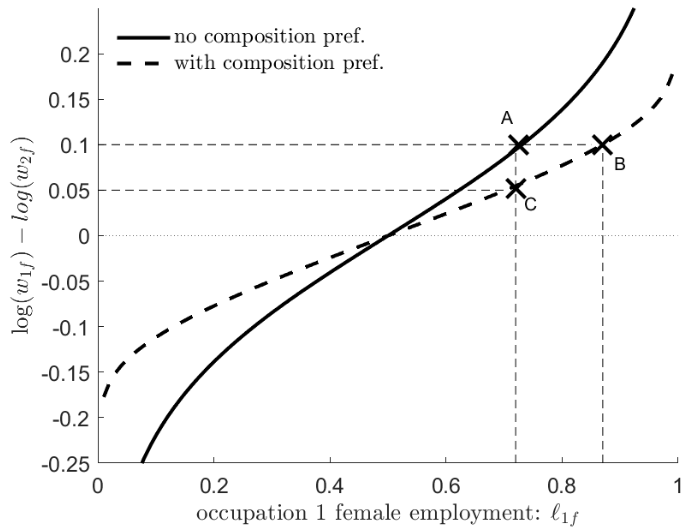


Figure 1: Equilibrium condition with composition preferences

Note: This plot displays the female labor supply function with and without gender composition preference. Here, I set $\eta = 0.1$, $\ell_{1m} = 0.5$, and $h_f(f) = 0.06 \cdot \log(f) - 0.5$.

Homophilic composition preferences will exacerbate gender sorting and reduce female wages in more female jobs. This is illustrated in Figure 3, which plots the female labor supply function with and without composition preferences given a fixed male labor supply to occupation 1. The solid line shows the labor supply function with no gender composition preference, i.e. $h_g(f) = 0 \quad \forall f$. The dashed line shows the labor supply function with homophilic composition preferences. This figure illustrates the two key effects of homophilic composition preferences. First, when female wages are relatively higher in occupation 1, at a fixed wage difference, more women will work in occupation 1 with homophilic composition preferences relative to the number that would work in occupation 1 without composition preferences. This is illustrated by the fact that point B is to the right of point A. Second, if occupation 1 is more than half female, the wage required to attract a fixed number of women to occupation 1 will be lower in the presence of homophilic composition preferences than without composition preferences. This is illustrated by the fact that point C is below point A.

The effect of composition preferences on the sorting equilibrium will be larger when composition preferences are steeper relative to preference shocks and wage differences. As the composition preference function increases in slope, the labor supply function will become flatter. This is illustrated in Figure 2 Panel a. Stronger composition preferences will cause the equilibrium to shift to an even higher level of female employment in occupation 1 than would occur with weaker composition preferences given a fixed wage difference.

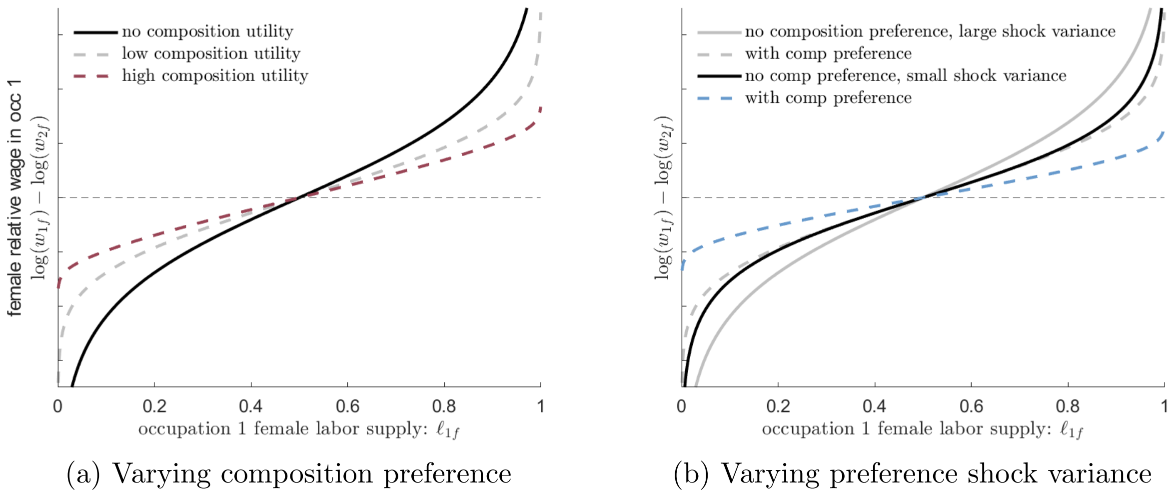


Figure 2: Equilibrium labor supply, varying composition preference, preference shock variance

Note: These plots displays the female labor supply function with and without gender composition preferences of varying scale (panel a) or with varying preference shock variance η (panel b). Here, I set $\eta = 0.1$, $\ell_{1m} = 0.5$, and $h_f(f) = 0.06 \cdot \log(f) - 0.5$ at baseline.

The effect of composition preferences will also be larger when workers are more likely to switch occupations; that is, when the variance of the preference shock is smaller. In Figure 2 Panel b, I plot the labor supply function with and without composition preferences for two values of the TIEV preference shock variance η. When η is relatively larger, workers occupation choices are less responsive to changing wages, so the labor supply function is steeper both with and without composition preferences (grey lines). When η is relatively smaller, workers' occupation choices are more responsive to changing wages, so the labor supply function is flatter. This means that the with the same composition preference function (normalized to wages, i.e., equal willingness-to-pay for different gender compositions), the effect of composition preferences on wages and allocations will be larger when the variance of the preference shock is smaller.

When are tipping points possible in this model? I define a tipping point as a rapid shift between multiple sorting equilibria, either from a gender mixed to a gender segregated equilibrium or vice versa. In order for tipping to occur in this strict sense, either the male or female labor supply function must bend backward at some point. This is illustrated in Figure 3. When the female labor supply function is backward bending, a change in relative wages (possibly caused by a shift in demand) or a change in male labor supply can remove or add a mixed gender equilibrium.

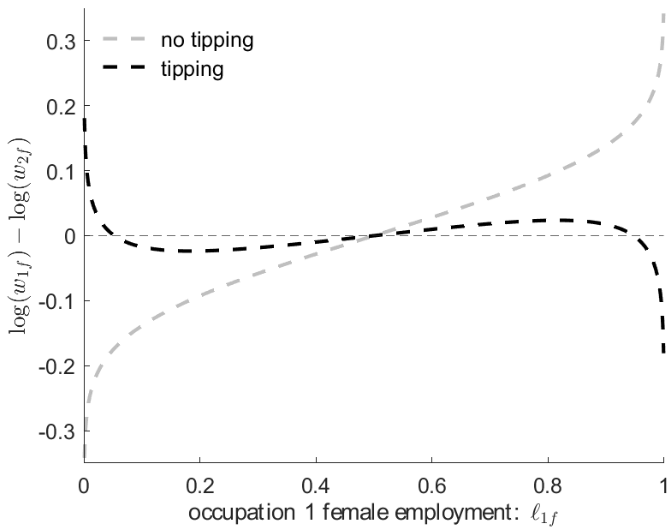


Figure 3: Tipping points in gender composition

Note: This plot displays the female labor supply function with and without gender composition preference. Here, I set $\eta = 0.1$, $\ell_{1m} = 0.5$, and $h_f(f) = 0.06 \cdot \log(f) - 0.5$.

Thus, tipping will be more likely when either gender composition preferences are very strong or occupation choices are very flexible, because both of these conditions will create a flatter labor supply function. Therefore, the key parameters that determine the effect of composition preferences are the slope of the composition valuation function relative to wages and the variance of the occupational preference shocks.

2.3 General Equilibrium Extension

In this section, I evaluate the consequences of gender composition valuations in general equilibrium, where wages can adjust in response to changes in worker allocations across occupations. I find that the effect of composition valuations on sorting will be dampened when wages adjust in response to changing allocations.

To allow for equilibrium wage adjustments, I close the model with a production function that is CES across occupations:

$$Y = \left((A_1 \ell_1)^{\frac{\nu-1}{\nu}} + (A_2 \ell_2)^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}.$$

The two occupations are gross substitutes when $\nu > 1$, and gross complements when $\nu < 1$. A_k is occupation-specific productivity.

To account for gender wage gaps within occupations, I assume that within occupations, the production function is CES across genders, as in Ngai and Petrongolo (2017):

$$\ell_k = \left(q_k(\ell_{k,m})^{\frac{\alpha-1}{\alpha}} + (1-q_k)(\ell_{k,f})^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}},$$

where α is the elasticity of substitution across genders, and q_k represents the relative productivity of men. If $q_k > .5$, men are more productive in the occupation, and if $q_k < .5$, women are more productive. This wedge between male and female productivity can encompass both actual productivity differences (e.g., women are less productive in tasks requiring physical strength or work fewer hours) and pure wage discrimination.

Taking the first order conditions of the profit function gives the following wage equations

$$w_{k,m} = q_k \left(\frac{\ell_k}{\ell_{k,m}}\right)^{1/\alpha} \frac{Y^{\frac{1}{\nu}} A_k^{\frac{\nu-1}{\nu}} p}{\ell_k^{1/\nu}}, \qquad w_{k,f} = (1-q_k) \left(\frac{\ell_k}{\ell_{k,f}}\right)^{1/\alpha} \frac{Y^{\frac{1}{\nu}} A_k^{\frac{\nu-1}{\nu}} p}{\ell_k^{1/\nu}} \quad k = 1, 2,$$

where p is the final good price. The wage for each gender increases in own-gender occupational productivity (q_k for men and $(1-q_k)$ for women), decreases in the own-gender share of labor, and increases in overall occupational productivity A_k.

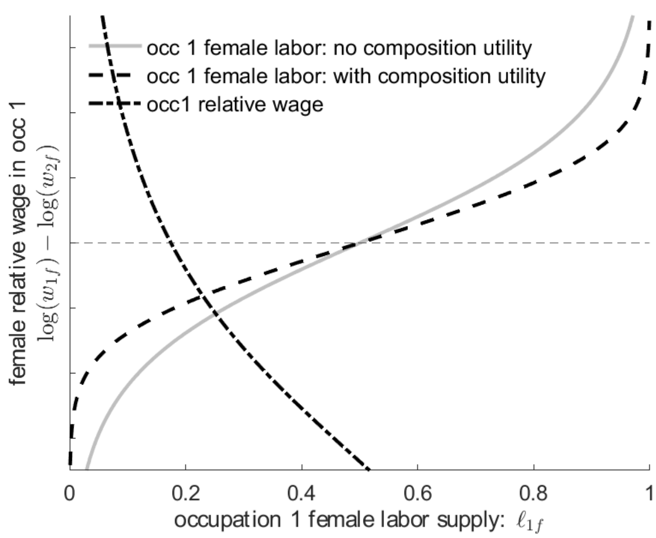


Figure 4: Equilibrium labor supply and demand

Note: This plot displays the occupation 1 female labor supply function with and without gender composition preferences and the occupation 1 equilibrium relative wage function. Here, I set $\nu = 0.1$, $\ell_{1m} = 0.5$, and $h_f(f) = 0.06 \cdot \log(f) - 0.5$ at baseline.

Allowing for equilibrium wage adjustments will dampen the effect of composition valuations on sorting and make tipping less likely. This is illustrated in Figure 4, which adds an equilibrium relative occupational demand curve to the previous labor supply plots. As more women enter an occupation, their relative wage in that occupation will fall, dampening the effect of composition preferences. It is notable, however, that accounting for equilibrium wage adjustments does not erase the effects of gender composition preferences, because the wage does not fully internalize the effect of a worker's entry into an occupation on the utility of the other gender.

3 Measuring the Value of Workplace Gender Composition

To measure the amenity value of workplace gender composition, I design and administer a survey with an embedded hypothetical job choice conjoint experiment to causally identify the amount respondents are willing to pay, as a fraction of their wages, to be in a job with their preferred female share. This is meant to simulate an ideal experiment in which occupational gender compositions are changed at random. I find that women on average value jobs with a higher female share, but their valuations are concave in the female share. Women are willing to trade off 4.5% of their wages to avoid an all-male workplace favor of a gender-balanced workplace, but they are not willing to trade off additional wages be in a majority female workplace rather than a gender-balanced workplace. I find that men on average value gender diversity. Men are willing to trade off 2-3% of their wages to avoid both all-female and all-male workplaces in favor of a gender balanced job. In section 4, I use these estimates in a quantitative model to determine their consequences for gender sorting in the aggregate.

3.1 Survey Design

The main section of my survey is a hypothetical job choice conjoint experiment in which respondents choose between several pairs of job offers which vary randomly in pay and workplace demographic composition. Through this design, I can causally identify the respondents' willingness-to-pay for the female share of a job.

3.1.1 Hypothetical Job Choice Survey Experiment

My survey instrument is designed to elicit the willingness-to-pay for the gender composition of a particular workplace within a fixed occupation and firm. I focus on a choice between workplaces, rather than occupations, for three main reasons. First, the estimand of interest is the effect of gender composition on utility within an occupation, which requires holding the occupation itself fixed. Second, a choice between workplaces is easier to simulate in an online survey setting, which more closely resembles a choice between online job advertisements than a lifetime human capital decision. Finally, a choice between workplaces holds fixed other amenities that may vary with the gender composition of an occupation.

The hypothetical job choice conjoint instructs respondents to choose between pairs of workplaces within a fixed occupation that vary in their wages and demographic composition. An example of a question respondents see in this section is included in Appendix B Figure B.1. For each pair of jobs, respondents are instructed that in each job they will be performing the same occupation at different locations of the same firm, which are a similar distance from their home. For each individual job, respondents are given the pay (hourly and annual equivalent), hours (for this section, all are full-time), and three characteristics of the demographic composition of the job: gender (share female or share male); age (share under 40); and parental status (share with children). Respondents are asked to select the job they would be more likely to choose if offered both within each pair. Respondents see nine to eleven of these choices, within five occupations: high school teacher, insurance sales agent, retail sales associate, nurse, and software developer.[7]

One reason the survey presents a choice between workplaces, rather than occupations, is that the choice over a specific job rather than an entire occupation is easier to simulate in an online survey setting. Conjoint designs for hypothetical job choices are used frequently in the labor literature, and choices in these surveys have been shown to be correlated with realized job choices (see e.g. Wiswall and Zafar (2018); Mas and Pallais (2017); Maestas et al. (2018); Folke and Rickne (2022)).[8] Relative to a choice between occupations, a choice between job offers is easier to simulate in an online survey, which more closely resembles choices applicants make in real life when they, for instance, apply for different jobs on a website. Occupation choice, however, involves long-term human capital investments, which are harder to simulate in an online survey.

Another reason I design the choice as one between workplaces within a specific occupation and firm is that it holds fixed many amenities of a job that might vary with the female share. These may include formally contracted amenities, like schedule flexibility or paid parental leave, and job tasks. In the ideal experiment, in which the gender composition of an occupation changes randomly and rapidly, these characteristics will not change in the short run. On the whole, the workplace choice presents a cleaner exercise that better isolates

[7]The first three occupations are chosen because they are gender-balanced in reality, and thus realistically could vary widely in workplace gender composition. The last two occupations are chosen to test for heterogeneity based on actual occupational gender composition because they are very segregated in reality.

[8]Gender composition differs from other amenities whose values are elicited in conjoint surveys because it is unlikely to be communicated directly to applicants. This is similar to the prevalence of workplace sexual harassment, which Folke and Rickne (2022) elicit valuations for in a conjoint design that includes vignettes about an employee experiences of sexual harassment. In both cases, although the job characteristic is unlikely to be directly advertised by the firm, it may be conveyed to the applicant through informal channels such as conversations with current or past employees.

the amenity value of gender composition itself rather than associated attributes.

To incorporate the results from the survey of workplace choices into a model of occupation choice, we must understand how the gender composition of an occupation is related to the gender composition of a workplace. At the extreme end, if there is no gender sorting at the firm level within an occupation, workplace composition preferences won't matter at all for occupation choice because workers can choose the firm with their preferred gender composition within any occupation. However, this is unlikely to be the case. Hellerstein et al. (2008) estimate that as of 2000, 61 percent of gender segregation across firms was explained by gender segregation across occupations, suggesting adjusting for the difference between occupations and firms would undo on average 40% of the workplace-level valuations. In addition, I consider a static model of occupation choice, and when initial human capital investments are made, it is much more likely that individuals know the approximate gender composition of an occupation than the distribution of firm gender compositions within occupations. Finally, even within a firm, one's closest coworkers are most likely those that perform the same occupation, so differences in segregation across firms do not necessarily undo segregation across occupations.

3.1.2 Variations in Job Choice Experiment

I include several variations on the hypothetical job choice conjoint across iterations of the survey to assess the robustness of my results and the reasons respondents value workplace gender composition.

In the first variation of the survey, respondents only see the pay and demographic composition of each job and no other information. This design eliminates possible effects of prior perceptions of specific occupations, which may affect the fixed-occupation workplace choice described above. It also allows for social norm effect on these job choices: without listing a specific occupation, respondents' perception of the societal view of the job may depend on the reported gender composition. However, with such a simple design it is also possible that respondents infer characteristics of the job that I do not intend to evaluate, such as job tasks and contracted amenities.

In the second variation, respondents again do not see a specific occupation but also see additional amenities of each job. This design allows me to analyze the mechanisms for the measured gender composition valuations by holding fixed other amenities that might vary with occupational gender composition. I separately control for two additional amenities: the probability of promotion or firing, and the job hours and schedule flexibility.

In the final variation, respondents choose between two specific occupations and I randomly vary whether they see the true gender composition of the occupation. In this setting, I can evaluate whether respondents still value gender composition when they are choosing between two different occupations, which more closely matches the model exercise in Section 4. This survey exercise is slightly more complex to analyze because the effect of information on the female share of an occupation will depend on the respondent's prior perception of the female share. Thus, in this section I do not include wage information, and instead I use this as a qualitative robustness check on the more standard conjoint designs.

3.1.3 Remaining Survey Structure

The survey is structured as follows. First, respondents answer a standard set of demographic questions regarding their age, gender, education, marital status, and family structure. I then ask respondents about the occupation, industry, hours, and wages of their current or most recent job. The hypothetical job choice conjoint experiment follows. After the conjoint experiment, I ask respondents to report their expectations about how their experience in a mostly female and mostly male occupations might differ. The purpose of this section is to disentangle the possible reasons for gender composition preferences. Finally, I ask respondents for their opinions on three gender attitudes using questions adapted from the General Social Survey and Pew American Trends Panel. The full survey is available upon request.

3.2 Survey Data

I fielded my survey online to a sample of 8,850 US adults in multiple waves from October 2021 to October 2022. I designed the survey in Qualtrics and recruited participants using Lucid Theorem, a service that connects survey participants with academic researchers.[9]

An online survey is useful because it provides a controlled setting in which to run randomized experiments at a low cost, but there are several potential drawbacks. The main possible problems with an online survey are non-representative samples, inattentive respondents, and lack of external relevance. In this section, I discuss the first two issues and address their relevance in my setting. I address external relevance in Section 3.4.5. Reassuringly, I find that my sample is overall demographically similarly to the U.S. population and mostly quite attentive.

[9]Lucid, like many other online survey panel providers used by academic researchers, sources participants from multiple companies that recruit individuals to take online surveys. In contrast with a service like MTurk, I do directly solicit participants; rather, I send an order for participants to Lucid, which funnels my order to a third-party survey respondent recruiter. Respondents may have been recruited through emails, push notifications, in-app pop-ups, or through sites offering multiple survey opportunities. (See `https://lucidtheorem.com/faq`.) Coppock and McClellan (2019) compare results from several survey experiments conducted through Lucid, MTurk, and probability samples. For all but one of five experiments, they find experimental effects that matched the sign and significance of the original estimates on the probability sample.

Table 1: Survey Demographics vs. March CPS

		CPS Share	Survey Share	Difference	t-stat
age	<18	0.000	0.003	0.003	
	18-24	0.112	0.123	0.011	3.281
	25-34	0.170	0.195	0.025	5.835
	35-44	0.138	0.197	0.059	13.928
	45-54	0.158	0.166	0.008	2.000
	55-64	0.182	0.151	-0.031	-8.246
	65-74	0.139	0.127	-0.012	-3.427
	75-84	0.072	0.034	-0.037	-19.349
	85+	0.029	0.004	-0.025	-35.484
edu	less than high school	0.096	0.036	-0.060	-29.968
	bachelor's degree or greater	0.329	0.319	-0.010	-2.077
	high school diploma	0.292	0.279	-0.013	-2.817
	some college	0.283	0.363	0.080	15.670
race	other race	0.000	0.008	0.008	
	Asian or Pacific Islander	0.049	0.049	0.000	0.110
	Black or African American	0.094	0.124	0.030	8.465
	Hispanic or Latino	0.108	0.081	-0.027	-9.444
	Multiracial or Biracial	0.010	0.018	0.008	5.726
	Native American or Alaskan Native	0.006	0.014	0.008	6.389
	White or Caucasian	0.733	0.706	-0.027	-5.505
sex	female	0.521	0.520	-0.001	-0.221
	male	0.479	0.476	-0.003	-0.588
	other	0.000	0.004	0.004	

This table compares the distribution of demographic characteristics of the sample for my survey conducted via Lucid in October 2021 and the March CPS samples from 2014 through 2019. Lucid targets the distributions of these characteristics, although not necessarily at the level of detail shown here.

My survey sample is broadly similar to the population-representative March CPS pooled from 2014-2019 limited to individuals aged 18 and up, as shown in Table 1[10]. My survey respondents are relatively younger and more educated than the US population, but there is sufficient presence of the under-represented groups to enable re-weighting.[11] In Appendix B, I compare my survey respondents to the CPS ASEC respondents on other characteristics that one might expect to vary with gender composition preferences, including income, realized occupational gender composition, and attitudes toward gender and work. I find that my sample is similar to the CPS on these characteristics.

[10]CPS ASEC data accessed via Flood et al. (2018).

[11]Among my survey respondents, Black people are slightly over-represented and Hispanic under-represented relative to the CPS. However, this may be due the fact that Hispanic ethnicity is a separate question in the CPS, whereas I ask for race and ethnicity in one question.

To ensure my data is of high quality, I also include several attention checks within my survey and limit my analysis to the subset of respondents who pass these attention checks. Overall, 78% of respondents pass all attention checks.[12] Most importantly, I include an attention check within the hypothetical job choice conjoint, where respondents see a choice between two jobs that differ only in their wages. As we see in Figure B.15, 85% of respondents choose the higher wage job. This is a similar rate of inattention to that found by Mas and Pallais (2017), who found that 14.5% of individuals chose the lower-paying job given a choice between two otherwise identical jobs to apply for. It is reassuring that the rates of inattention are similar, given Mas and Pallais (2017) had an incentivized choice between actual jobs and my survey is purely hypothetical and not incentivized. Results of my survey are similar whether or not I include respondents that failed one or more attention check.

Finally, I check that respondents' answers are consistent across questions within the hypothetical job choice module and find that in the vast majority of cases they are. First, I check that if respondents see the exact same pair of jobs twice, they make the same choice in both scenarios. As shown in Appendix B Table B.1, in 87% of such instances respondents choose the same job in both cases. Because it is fairly rare for respondents to see the exact same choice twice (it only happens 60 times), I also check that if respondents see the same pair of female shares with possibly differing wages, they either choose the same female share in both cases or make choices that represent internally consistent bounds on their willingness-to-pay for a particular female share. As detailed in Appendix B Table B.2, I find that respondents make internally consistent choices in 98% of these cases.

3.3 Estimation Strategy

Given the randomized design of the hypothetical job choice experiment, I can use a simple conditional logit model to estimate the willingness-to-pay for the female share of a job. I also estimate a latent class logit model to determine the degree of preference heterogeneity, which allows me to determine for which share of the population gender composition preferences will be an important determinant of job choice.

3.3.1 Average Preferences by Gender

To estimate the average willingness-to-pay (WTP) for the gender composition of an occupation, I use a standard multinomial logit model. From equation 1,

$$U_i = \max_{j \in J} \log(w_{g,j}) + h_g(f_j) + \varepsilon_{i,j}.$$

[12] In Appendix B, I provide further details on the attention checks and compare the demographics of attention check passers to all survey respondents.

To estimate the function $h_g(f_j)$, which I will now assume is the average gender composition preference within each gender, I run a logit regression on the survey choice data of the form

$$P(\text{choose job j}|j,k) = g\left(\hat{\beta_w}\log(w_j) + \sum_f \hat{\beta_f}\mathbb{1}(f_j = f) + \kappa X_j) + \varepsilon_{i,j}\right). \tag{5}$$

The probability of choosing job j given a choice between jobs j and k is a function of the wages in each job w_j and w_k, the female shares of each job f_j and f_k, the other listed characteristics of the jobs in vectors X_j and X_k, and idiosyncratic preference draws for each job $\varepsilon_{i,j}$ and $\varepsilon_{i,k}$.

Importantly, the "pure" wage elasticity β_w and gender composition elasticities β_f, that is, the responsiveness to wages and gender composition holding the preference draw fixed, are not identified separately from the variance of the preference draw η. The parameters I identify are $\hat{\beta_w} = \frac{\beta_w}{\eta}$ and $\hat{\beta_f} = \frac{\beta_f}{\eta}$. For my willingness-to-pay estimates this is not important because the variance of the preference draw is differenced out when I calculate the elasticity to gender composition relative to the wage elasticity. However, in the quantitative model in Section 4, I will normalize the pure wage elasticity to 1 and thus set the variance of the preference draw η to $\frac{1}{\hat{\beta_w}}$.

Given this estimation, I can calculate the willingness-to-pay for a given gender composition relative to a baseline gender composition by taking the exponential of the ratio of the gender composition coefficient to the wage coefficient:[13]

$$WTP_f = 1 - \exp\left(\frac{-\beta_f}{\beta_w}\right). \tag{6}$$

The WTP is positive for a good amenity and negative for a bad amenity: if an amenity is good, the worker will be willing to accept a lower wage in exchange for access to the amenity, and if an amenity is bad, the worker will need a higher wage in exchange for accepting the amenity.

3.3.2 Heterogeneous Preferences

The logit model described above allows me to estimate the average demographic valuations within each gender. However, these estimates may mask substantial heterogeneity. Understanding heterogeneity can both improve our understanding of what underlying attributes contribute to gender composition valuations and inform firm- and economy-wide policies to

[13]Details on the steps to this willingness-to-pay formula are described in Appendix A.

reduce segregation.

I estimate heterogenous composition valuations using a latent class logit model that allows me to detect heterogeneity that may not correlate with observable characteristics, following Greene and Hensher (2003). In this model, rather than assuming that all individuals of a given gender have the same preference parameters, I assume there are Q preference types indexed by q. Then, the probability that an individual of class q makes some choice j in situation t is

$$Prob[\text{choice j by individual i in choice situation t}|\text{ class q}] = \frac{\exp(x'_{it,j}\beta_q)}{\sum_{j=1}^{J_t}\exp(x'_{it,j}\beta_q)} = P_{it|q}, \quad (7)$$

where $x_{it,j}$ are the characteristics of choice j in situation t and β_q is a vector of class-specific preference parameters. This means that the probability that an individual of type q makes some choice is fixed within class q but varies across classes. I provide further details on the maximum likelihood estimation procedure in Appendix C.2.

I use a latent class model with a discrete number of types rather than estimating preferences at the individual level for two reasons. First, estimating preferences across the entire spectrum of gender compositions would require observing a large number of choices per person.[14] In the context of an online survey, respondent fatigue and inattention are relevant concerns, so asking respondents to make twenty or more choices of the same format is not desirable. Second, inputting preferences into a numerical model requires a discrete number of preference types, so discretization is required regardless. Thus, although I assess individual-level preference estimates to check validity and robustness, I rely on a discrete number of classes for most heterogeneity analysis.

3.4 Survey Results

I find that, on average, women are willing to trade off 4.5% of their wages to avoid an all-male workplace, but they do not value additional women once a job is at least 50% female. Men are willing to trade off 3% of their wages to avoid an all-female workplace and 5% of their wages to avoid an all-male workplace. However, these average estimates belie substantial heterogeneity.

[14] Drake, Marshall et al. (2022) develop a procedure to elicit individual-level WTPs using a Bayesian Adaptive Choice Experiment in which the questions that respondents see depend on their prior answers in such a way to maximize the information in each answer. I did not implement this method due to computational limitations, but this provides a promising avenue for further study.

3.4.1 Average Preference Results

Women, on average, prefer mostly female workplaces, while men prefer gender diversity. Figure 5 shows the estimated WTPs for each possible female share separately for men and women, in which we see that both women and men most value workplaces that are 40-70% female, but women have a stronger distaste for male-dominated workplaces. I use a 50% female workplace as the baseline so the WTP for a 50% female job is always zero, and other WTPs are relative to a 50% female job. In Table 2, I show the estimated willingness to pay (WTP) for each gender, age, and education share by gender, age, and education groups.[15]

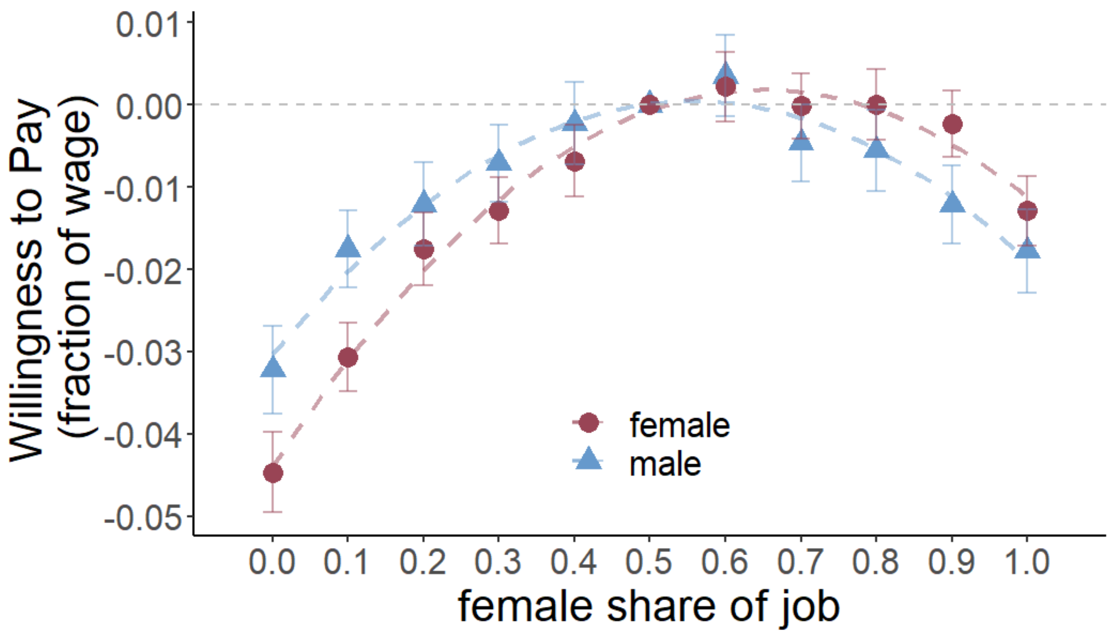


Figure 5: Average Willingness to Pay for gender composition

Note: This figure shows the willingness-to-pay, as a fraction of the wage, for each possible female share estimated on data from the conjoint job choice in my survey using equation 5. Bars show 95% confidence intervals estimated using the delta method.

Women, on average, prefer majority female workplaces and dislike majority male workplaces, but they do not desire complete gender segregation, as shown in red in Figure 5. Women's composition valuations can be split into three regions. For workplaces that are less than half female, women have a negative willingness-to-pay, meaning they dislike mostly male workplaces. Women are willing to pay 4.5% of wages to avoid an all-male workplace. For workplaces between 50 and 90 percent female, women's willingness-to-pay is approximately zero, meaning that there is no additional utility for having more women once a job is at

[15] I show all coefficient estimates for equation 5 in Appendix Table C.3. Notably, the coefficient on the log wages for men and women is nearly identical.

least gender balanced. Finally, for workplaces above 90 percent female, women have a small negative willingness-to-pay, suggesting that complete segregation is not desirable. Overall, women dislike being a gender minority, but do not want complete gender segregation.

Men have a strikingly similar composition valuation profile to women: they dislike majority male and majority female workplaces and prefer gender-mixed to majority female workplaces. For both workplaces that are less than 30 percent male and more than 90 percent female, men have a negative willingness-to-pay, meaning they dislike both predominantly female and predominantly male workplaces. Among workplaces between 40 and 80 percent female, men appear largely indifferent. On the whole, men dislike gender segregated workplaces with either gender in a large majority and prefer gender-mixed workplaces.

My WTP estimates enrich prior research suggesting women are more likely to choose more female jobs or workplaces by pinpointing their particularly strong distaste for predominantly male workplaces. They also complement prior estimates suggesting that men do not value gender composition by clarifying that men prefer gender diversity. In particular, Wiswall and Zafar (2018) estimate that women have a small positive WTP for more female workplaces for jobs in the range of 26-72% female, and Delfino (2021) finds that women are more likely to apply for a social work job when the advertisement contains a female rather than a male picture. [16] Larson-Koester (2017) also estimates that women value more female occupations and men do not value gender composition using observational data on occupation choice.[17] Folke and Rickne (2022) find a 10% WTP to avoid a job with a reported incident of sexual harassment, and an increasing likelihood of sexual harassment for workers who do not match the gender majority of their firm, corroborating my results for women.

Relative to estimates of valuations for other job characteristics in the literature, the 4.5% WTP I find among women to avoid an all-male workplace is about half as large as Mas and Pallais (2017)'s estimate of the WTP for the ability to work from home (7-10%)[18] and much smaller than their estimate of the WTP to avoid employer discretion in scheduling

[16] Wiswall and Zafar (2018), using a similar survey, estimate an average WTP of -.08% among men and -.04% among women for the percent of men at a job, but the estimates are not significantly different from zero. If we multiply their female WTP by fifty for a move from a 70 to 20% male job, the resulting 2 percent is actually quite similar to my estimate of 3 percent for women's WTP for a similar move. For men, their estimate would translate into a 4 percent WTP for the same move compared to about 2 percent in my sample. Notably, the male shares in their survey range from only 26 to 72%, so we cannot extrapolate these estimates to the entire range I measure. Delfino (2021) finds that showing applicants a picture of a male worker for a social work recruitment advertisement has no effect on men's likelihood of applying but decreases women's likelihood of applying, which fits with women's desire to avoid mostly male workplaces and men's relatively symmetric preferences.

[17] Larson-Koester (2017) estimates a discrete choice model of occupation choice using data from the SIPP, ACS, and CPS and finds that women have increasing but concave utility in the female share of an occupation and men have no significant preference over the female share of an occupation.

[18] Notably, this experiment was run before the COVID-19 pandemic.

(around 25-30%). Relative to the WTPs for other demographic characteristics I measure, the WTPs for gender composition are similar or larger. I find, as shown in Table 2, that respondents with a bachelor's degree have a 4% WTP for a job where 60% of workers have a bachelor's degree relative to a job where only 10% of workers have a BA, which is similar to the WTP among women for the jobs that are the most female. I also find preferences for age homophily in the same range.[19]

Overall, my results suggest that both men and women care about the gender composition of their job, but their valuations are not symmetric. Women value more female jobs, but this preference is concave, indicating that women primarily have a distaste for the most male jobs. Men, on the other hand, most prefer gender-mixed jobs and dislike jobs that are gender segregated in either direction. Men's WTP for their most preferred gender composition is about half that of women. Even without formally aggregating these preferences using the structural model, these estimates tell us that women's average composition preferences may help explain gender segregation, because women have mostly homophilic valuations, but men's average composition valuations will not help explain segregation, because men prefer gender-mixed jobs.

3.4.2 Heterogeneous Valuation Results

I estimate a latent class logit model to detect underlying heterogeneity in gender composition valuations and find that the average preference estimates among women are a mix of one type of respondent that has large valuations for more female jobs and one type that does not value the female share of a job at all. The average preference for diversity among men is a mix of men who do not value the gender composition of a job, men who prefer more female jobs, and men who prefer more male jobs.

I select the number of classes in the latent class logit model using cross-validation.[20] Through these exercises, I chose $Q = 2$ classes for women and $Q = 3$ classes for men.

I find that among women, there is a class that only values higher wages and a class that prefers more female workplaces, as illustrated in Figure 6. The wage-preferring class, shown in dark blue, has a large coefficient on the wage but a close to zero coefficient on all

[19]In Appendix B Table C.9, I show the estimated WTPs for all characteristics including respondents who fail one or more attention check, which are slightly larger than the WTPs for the attentive sample but overall similar. I also include estimates that are re-weighted by observable demographics to match the demographic distribution of the CPS.

[20]See Appendix C for details. I run a 10-fold cross validation exercise on the log-likelihood for models with 1 to 10 classes. I also evaluate the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for each number of classes. The details of these exercises are in Appendix B, Figures C.16 and C.17. I also assess the estimated preference classes for 1 to 5 classes, and among those ranked highly by the cross-validation and AIC/BIC, select a number of classes where the WTPs across classes are clearly distinguishable. Appendix B Figures C.18 and C.19 show the estimated WTPs for models with 1 to 5 classes.

Table 2: Willingness to Pay for Demographic Composition

coefs	all	female	male	< 40	> 40	no kids	has kids
0% female	-0.039	-0.045	-0.032	-0.031	-0.044	-0.042	-0.033
	(-0.043,-0.036)	(-0.049,-0.04)	(-0.038,-0.027)	(-0.037,-0.026)	(-0.049,-0.04)	(-0.047,-0.038)	(-0.039,-0.027)
10% female	-0.025	-0.031	-0.018	-0.021	-0.027	-0.027	-0.02
	(-0.028,-0.022)	(-0.035,-0.027)	(-0.022,-0.013)	(-0.026,-0.016)	(-0.031,-0.023)	(-0.031,-0.023)	(-0.025,-0.014)
20% female	-0.015	-0.018	-0.012	-0.015	-0.015	-0.016	-0.013
	(-0.019,-0.012)	(-0.022,-0.013)	(-0.017,-0.007)	(-0.021,-0.01)	(-0.019,-0.011)	(-0.021,-0.012)	(-0.019,-0.007)
30% female	-0.01	-0.013	-0.007	-0.011	-0.01	-0.011	-0.01
	(-0.014,-0.007)	(-0.017,-0.009)	(-0.012,-0.002)	(-0.016,-0.007)	(-0.014,-0.006)	(-0.015,-0.007)	(-0.015,-0.004)
40% female	-0.005	-0.007	-0.002	-0.006	-0.004	-0.005	-0.004
	(-0.008,-0.001)	(-0.011,-0.002)	(-0.007,0.003)	(-0.011,-0.001)	(-0.008,0)	(-0.009,-0.001)	(-0.01,0.001)
50% female							
60% female	0.003	0.002	0.004	-0.001	0.005	0.004	0.001
	(0,0.006)	(-0.002,0.006)	(-0.001,0.008)	(-0.006,0.004)	(0.001,0.009)	(0,0.008)	(-0.005,0.006)
70% female	-0.002	0	-0.005	-0.002	-0.002	-0.002	-0.002
	(-0.005,0.001)	(-0.004,0.004)	(-0.009,0)	(-0.007,0.003)	(-0.006,0.002)	(-0.006,0.002)	(-0.007,0.003)
80% female	-0.002	0	-0.006	0	-0.004	-0.002	-0.002
	(-0.006,0.001)	(-0.004,0.004)	(-0.01,-0.001)	(-0.005,0.006)	(-0.008,0)	(-0.006,0.001)	(-0.008,0.004)
90% female	-0.007	-0.002	-0.012	-0.004	-0.009	-0.008	-0.005
	(-0.01,-0.004)	(-0.006,0.002)	(-0.017,-0.007)	(-0.008,0.001)	(-0.013,-0.005)	(-0.012,-0.004)	(-0.01,0.001)
100% female	-0.015	-0.013	-0.018	-0.008	-0.019	-0.018	-0.009
	(-0.018,-0.012)	(-0.017,-0.009)	(-0.023,-0.013)	(-0.013,-0.003)	(-0.024,-0.015)	(-0.022,-0.014)	(-0.015,-0.004)
30% kids	0.001	0	0.002	0.001	0.001	0.004	-0.005
	(-0.001,0.004)	(-0.003,0.004)	(-0.001,0.006)	(-0.003,0.005)	(-0.002,0.004)	(0.001,0.007)	(-0.009,-0.001)
50% kids							
70% kids	0.002	0.005	-0.002	0.002	0.001	0	0.006
	(-0.001,0.004)	(0.002,0.008)	(-0.005,0.002)	(-0.002,0.006)	(-0.002,0.005)	(-0.003,0.003)	(0.002,0.01)
30% <40	0.003	0.003	0.004	0.002	0.004	0.004	0.002
	(0.001,0.006)	(0,0.006)	(0,0.008)	(-0.001,0.006)	(0.001,0.007)	(0.001,0.007)	(-0.002,0.006)
50% <40							
70% <40	-0.006	-0.007	-0.006	0.001	-0.011	-0.008	-0.003
	(-0.009,-0.004)	(-0.01,-0.004)	(-0.009,-0.002)	(-0.003,0.004)	(-0.014,-0.007)	(-0.011,-0.005)	(-0.007,0.001)
lefthand job	0.005	0.005	0.006	0.005	0.005	0.005	0.007
	(0.004,0.006)	(0.004,0.006)	(0.004,0.007)	(0.004,0.007)	(0.004,0.007)	(0.003,0.006)	(0.005,0.009)
num. obs.	29972	16495	13334	11215	18757	20355	9617
num. indiv.	2772	1525	1234	1037	1735	1889	883

Note: this table shows the willingness-to-pay for each share of each demographic group estimated using data from the conjoint job choice in my survey. The logit coefficients that underlie these estimates are shown in Appendix Table C.3, which also includes the number of observations and individuals in each regression.

demographic characteristics. The female-preferring class, shown in light blue, also tends to choose higher wage jobs but has a large willingness-to-pay to avoid the most male jobs.[21]

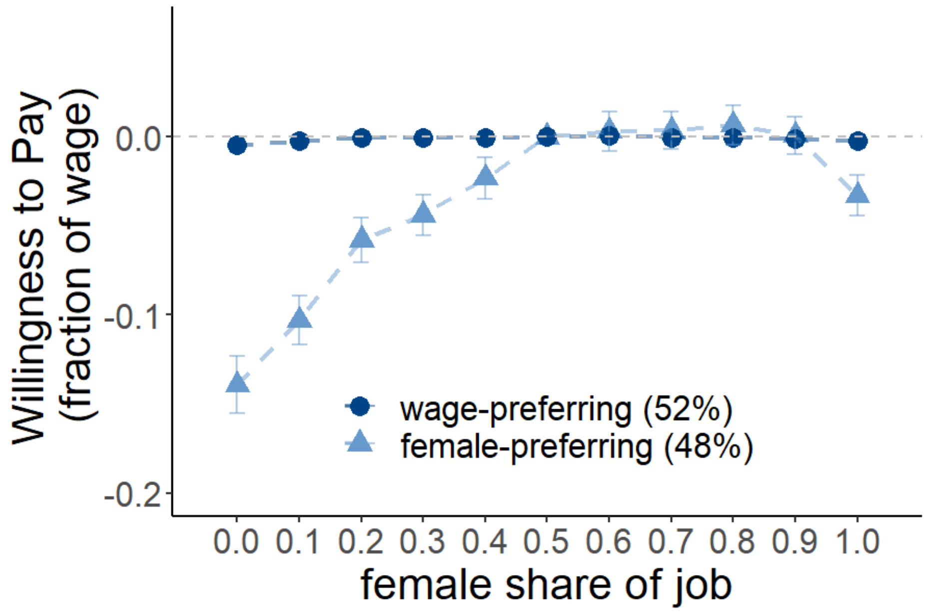


Figure 6: WTP for gender composition by Class, Female

Note: This figure shows the willingness-to-pay, as a fraction of the wage, for the two classes among women estimated using the latent class logit model described in Section 3.3.2. Bars show 95% confidence intervals estimated using the delta method.

Around half of my female sample values higher wages but assigns little to no value to demographic composition. The wage-preferring class constitutes 52% of women in my sample. This class has an extremely large coefficient (181) on the log wage, implying a member of this class would have over a 99.9% probability of choosing a job where the wage is 10% higher, all else equal. This class also has marginally negative, but small, WTPs for jobs less than 20% female. The WTPs for other demographic characteristics in this class are small and not significantly different from zero. All of this suggests that the wage-preferring class is motivated mostly by higher wages.

The other half of my female sample has high valuations for mostly female workplaces. I estimate that the remaining 48% of the female sample comes from this female-preferring class.[22] This class has large, negative WTPs for all female shares below 50%. This class also has a slight preference for younger workplaces where more coworkers have children. Members

[21] Estimates of all coefficients and WTPs are included in Appendix C Tables C.5 and C.6.

[22] This class has a relatively large coefficient on the wage (15), which implies that given a choice between two jobs, one of which has a 10% lower wage, a woman from the female-preferring class will choose the higher wage job with a probability of 81%.

of this class prefer higher wage jobs, but are willing to trade off a significant fraction of their wages for jobs that have more women.

Overall, the WTP estimates in Figure 6 and Table C.6 suggest that the latent class logit picks up on important heterogeneity in gender composition preferences among female respondents. The negative average WTP for mostly male workplaces among women shown in Figure 5 is in fact an amalgam of the WTPs of two groups of women: one that highly values more female jobs and one that does not value more female jobs.[23]

I find that among men, there is a class that only values higher wages, a class that prefers more female workplaces, and a class that prefers more male workplaces, as illustrated in Figure 7. As among women, the wage-preferring class, shown in dark blue, has a large coefficient on the wage but a close to zero coefficient on all demographic characteristics. The female-preferring class, shown in light blue, dislikes mostly male workplaces but is mostly indifferent between workplaces over 50% female. Finally, the male-preferring class, shown in yellow, dislikes mostly female workplaces but is mostly indifferent between workplaces under 50% female.

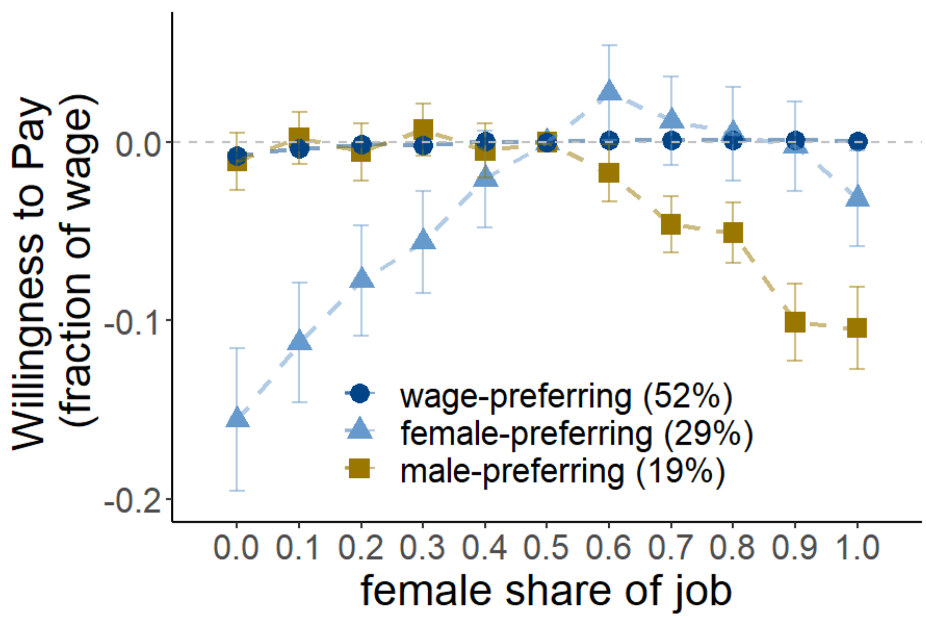


Figure 7: WTP for gender composition, Male, Q=3 Latent Classes

Note: This figure shows the willingness-to-pay, as a fraction of the wage, for the three classes among men estimated using the latent class logit model described in Section 3.3.2. Bars show 95% confidence intervals estimated using the delta method. The inattentive class is omitted.

Similarly to the female sample, I estimate that 52% of the male sample comes from a

[23] See Table C.8 and C.7 for all WTP and coefficient estimates by class.

wage-preferring class. The male wage-preferring class again has a large coefficient (181) on the log wage, which is almost identical to the log wage coefficient for the female wage-preferring class. Thus, as in the corresponding female class, a member of this class would have over a 99.9% probability of choosing a job with a 10% higher wage, all else equal. This class also has a small negative WTP for 0-10% female workplaces, but the WTPs for all other demographic characteristics are small and not significantly different from zero. As in the female sample, this class seems to be motivated mostly if not entirely by higher wages.

In contrast to the female sample, in the male sample, the group with significant preferences for demographic composition comes from two distinct classes. I denote these as the female-preferring class, which makes up 29% of the male sample, and the male-preferring class, which makes up 19% of the male sample.

The female-preferring class among men assigns the most value to workplaces that are 50-90% female. For this class, the willingess-to-pay to avoid an all-male workplace is around 15% of wages. Members of this class still prefer higher wage jobs, but are willing to trade off a significant fraction of their wages for jobs that have more women.

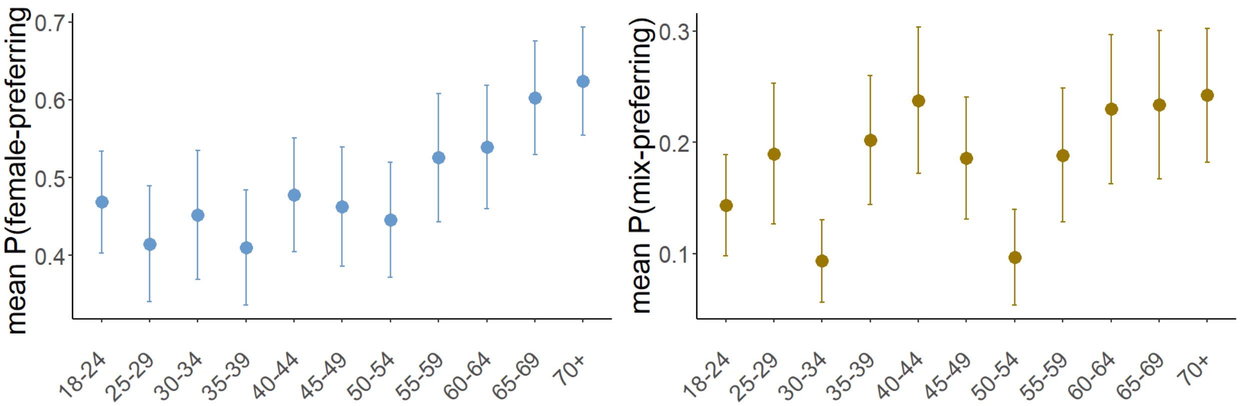
Finally, the male-preferring class most prefers gender-mixed to male-dominated workplaces, and dislikes majority female workplaces. This class has a willingness-to-pay of around 10% to avoid an all female workplace. As shown in Table C.7, the coefficient on the log wage for this class is only 9.295, implying a member of this class would choose a job with a 10% higher wage with a 71% probability. This causes the estimated WTPs to be noisier, and suggests this class may be slightly less attentive.

As a whole, the latent class logit also picks up on important gender composition preference heterogeneity among men. The average hump-shaped preference profile for men, which suggested an average preference for gender mixed jobs, is in fact an amalgam of wage-preferring, male-preferring, and female-preferring classes. Rather than preferring gender diversity, then, the latent class estimates suggest that men also prefer gender sorting to some extent but they do not all prefer to sort with their own gender.

3.4.3 Covariates of Valuation Heterogeneity

I find that older men and women are more likely to value gender homophily, suggesting that the value of gender sorting may have declined over time as women's participation and labor market options have increased. However, most heterogeneity in composition valuations is not explained by observable characteristics, suggesting that individual heterogeneity is important.

Older women are significantly more likely to belong to the female-preferring class, while older men are somewhat more likely to belong to the male-preferring class. Figure 8 plots the posterior probability of belonging to the class that prefers own-gender workplaces separately for women and men. Women over 55 are more likely than women under 55 to belong to the female-preferring class, and this probability continues to rise for older ages. Older men are also somewhat more likely to belong to the class that prefers more male workplaces, although the pattern is less clear than that for women.



(a) Female

(b) Male

Figure 8: Age and Probability of Belonging to Female-Preferring Class

Note: This figure plots the average posterior probability of belonging to the own-gender-preferring preference class by age bin.

If we assume that these age patterns are at least in part due to cohort effects, the age profiles suggest that composition valuations of men and women may be converging over time, matching a broader trend of gender convergence in the labor market. Notably, the age profile of women's composition values mirrors the time trend of women's labor force participation, which rose through the 20th century before flattening out in the mid 1990s. Women under 55 were likely to enter the labor market during or after the mid-1990s, when women's labor force participation began to flatten. One reason that older women are more likely to prefer gender homophily may be that these women were more likely to experience gender discrimination in the labor market. Similarly, older men may be more likely to subscribe to more traditional gender norms. However, in this cross-sectional data it is not possible to distinguish cohort from age effects, so some caution is required in interpreting these results.

I also find that younger, unmarried men are more likely to belong to the class that prefers more female workplaces. This suggests that marriage market matching could be a motivation for men who prefer more female workplaces, as they might be more likely to meet potential romantic partners at a workplace with more women. This could also be evidence that men with more progressive gender attitudes prefer to work around more women. The demographic covariates of the valuation classes are summarized in Figures C.20 and C.21.

3.4.4 Channels for Composition Valuation

Evidence from additional survey questions and robustness checks suggests that men value mixed to more female workplaces primarily for the coworker interactions, while women value all aspects of more female workplaces.

Men are more likely to choose more female workplaces when an occupation involves more direct interaction with coworkers, suggesting coworker interactions are an important driver of men's composition valuations. I can detect this heterogeneity by estimating WTPs separately for the specific occupations used in the hypothetical workplace choice. Figures C.30 and C.31 illustrate this difference. Men value female workplaces more when the occupation in question is a retail store worker, a teacher, or a nurse, occupations that typically involve frequent face-to-face interaction with coworkers. In contrast, men's valuations of mostly female workplaces are lower when the occupation in question is a software developer or insurance sales agent, office-based occupations which may involve less face time with coworkers. Women's valuations display much less heterogeneity across occupations.

Additionally, in an alternative design in which respondents choose between jobs without a specific occupation listed, women's composition valuations are similar to the fixed-occupation workplace choice, but men value mostly male jobs more, suggesting that men's desire for mixed to more female jobs is specifically about the workplace. As shown in Figure C.32, men are willing to pay less to avoid mostly male and more to avoid mostly female jobs when the occupation is unknown. This suggests that if men infer the specific occupation being performed from the gender composition, they are somewhat more likely to choose mostly male occupations, and therefore they may prefer the tasks or amenities in mostly male occupations. Then, their stronger preference for more female workplaces in the fixed-occupation workplace choice is more likely about coworkers rather than other inferred job characteristics.

Finally, in a section of the survey in which respondents report how satisfied they expect to be with various attributes of a mostly female and a mostly male job, women expect to be more satisfied with most aspects of a female job, while men expect to be more satisfied with the coworkers in a female job but all other attributes in a male job. This is illustrated in Figure 9, which shows the share of respondents who report they would be more satisfied with the listed attribute in a mostly female job minus the share who report they would be more satisfied in a mostly male job. Women are more likely to report they would be more satisfied with the coworkers, schedule, work environment, tasks, and promotion probability in a mostly female job, even though they expect to earn less in a mostly female job. Men, on the other hand, are only more likely to report that they would prefer the coworkers in a mostly female job, and appear indifferent or prefer a mostly male job on all other listed attributes.

Overall, it seems that women prefer many attributes of majority female jobs, but men particularly like the coworkers in majority female jobs. However, this does not necessarily imply that for women the female share is only a signal of other job qualities. In particular, the fact that older women are more likely to value more female workplaces, women with kids are no more likely to value female workplaces, and estimated valuations change little when additional amenities are included in the conjoint design suggest that women also value female coworkers in addition to other characteristics of more female jobs.

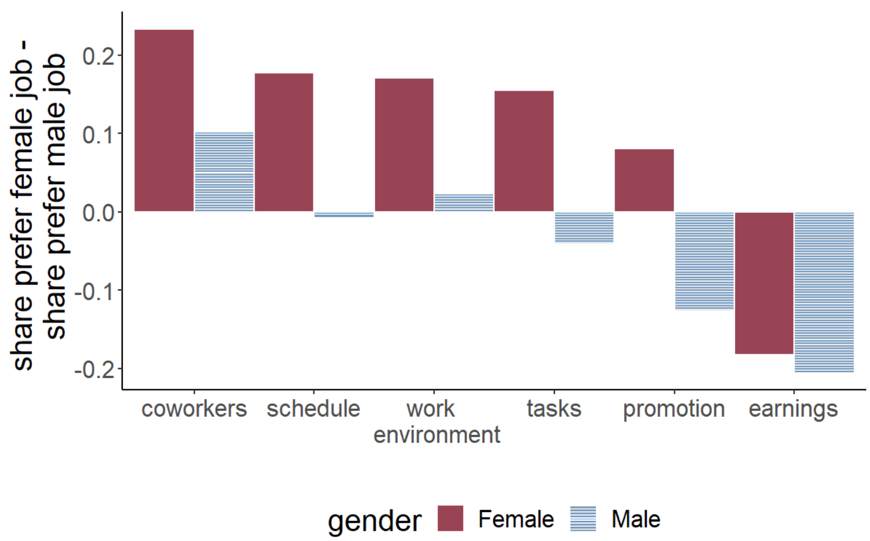


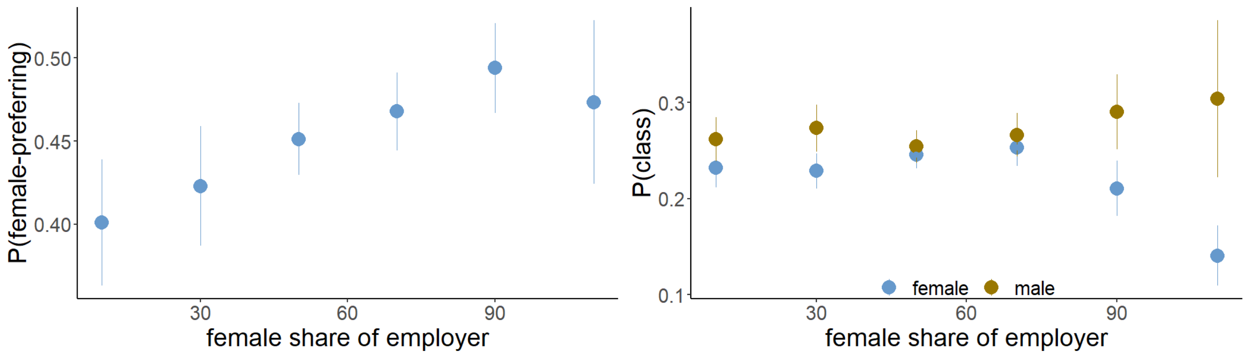
Figure 9: Share Preferring Female Job minus Share Preferring Male Job on Each Attribute

Note: This figure plots the share of respondents who report that they would be more satisfied with a female job minus the share who report they would be more satisfied with a male job on the listed attribute, separately for men and women.

3.4.5 Validation and External Relevance

The survey results shown thus far illustrate that women and men do value the gender composition of their workplaces. The model of occupation choice in Section 2 shows that workers who value more female workplaces will choose more female occupations, all else equal. In this section, I evaluate the external relevance of the survey-estimated valuations by measuring whether they correspond to real-life occupation choices.

The survey includes multiple measures of the true gender composition of a respondent's occupation, job, and employer. First, early in the survey, respondents report their occupation from a drop-down list of 26 Census occupation groups. I then calculate the female share of the reported occupation using the March CPS sample from 2014-2019. I also ask respondents to report the gender composition of their employer and their coworkers who perform the same job as they do. Finally, I ask respondents to report whether they think their job is viewed by others as more likely to be done by a man or a woman.



(a) Female

(b) Male

Figure 10: Most Likely Preference Class and Female Share of Employer

Note: This figure plots probability of belonging to each composition valuation class (omitting the wage-preferring class) against bins of the reported female share of the respondent's employer..

Women who report working for employers with a higher female share are more likely to belong to the female-preferring class, but men who report working for employers with a higher female share are somewhat more likely to belong to the male-preferring class. This is illustrated in Figure 10, which shows a binned scatter plot of the probability of belonging to each preference class against the reported female share of the respondent's employer, separately for men and women.

It is possible that women's preference class correlates more with their job choice for several reasons: women's valuations are more precisely estimated, women's valuations may better correspond to stable and well-formed preferences, and other job characteristics might cause men to choose jobs that do not align with their gender composition valuation. First, for the female-preferring group among men, the estimated WTPs are large but imprecisely estimated, so it is possible that in reality the WTPs are much smaller for this group. Second, it is possible that survey estimated composition valuations are simply more relevant to job choice for women than they are for men. I find that the male valuation results are noisier overall, and are less stable across variations and survey waves, suggesting gender composition valuations are perhaps less stable or less well-formed among men.

Finally, men might choose jobs that do not align with their valuations for gender composition because these jobs are preferable for other reasons. As demonstrated in the previous section, women seem to prefer many attributes of more female workplaces, while men only prefer female coworkers. Thus, although men in the female-preferring class report valuing workplaces with more female coworkers, other attributes of these jobs may be unappealing to men. This demonstrates the importance of holding "all else equal" in my survey design—in reality, these jobs are not otherwise identical, so the fact that men's valuations do not seem to correlate with their actual job choices does not mean they wouldn't choose jobs more aligned with their composition valuations given the chance to do so "all else equal." In addition, for both men and women, employer-side frictions like discrimination may prevent them from choosing a job that aligns with their gender composition valuation.

4 Quantifying the Aggregate Effects of Gender Composition Preferences

Now that I have estimated the size and shape of gender composition valuations for men and women, I input these valuation estimates into a more detailed version of the occupation choice model described in Section 2 to quantify their effects on gender gaps in the labor market. I find that if workers assigned no value to gender composition, female shares in mostly male occupations would be up to five percentage points higher. I also find that reallocating workers across occupations to address the sorting externality created by composition values would improve welfare by as much as a 2 percent increase in consumption.

4.1 Quantitative Model Environment

To perform quantitative exercises using the survey-estimated preferences, I expand the toy model from Section 2 to include multiple occupations, unobserved amenities, and a nested occupation choice structure.

The utility function in the quantitative model is as follows:

$$U_i = \max_{s,k\in s}\left\{Z_s + \log(w_{k,g}) + a_{k,g} + h_g\left(\frac{\ell_{kf}}{\ell_k}\right) + \varepsilon_{i,k,s}\right\}. \tag{8}$$

As in Section 2, $w_{k,g}$ is an occupation- and gender-specific wage, and $h_g\left(\frac{\ell_{kf}}{\ell_k}\right)$ is the gender-specific gender composition utility function. In addition, $a_{k,g}$ is an occupation- and gender-specific amenity, $Z_{s,g}$ is a nest- and gender-specific amenity, and $\varepsilon_{i,k,s}$ is an individual-specific occupation-level preference shock that follows a generalized extreme value distribution with correlation $1-\lambda_s$ within nests and no correlation across nests.

There are three additions to the quantitative model relative to the toy model. First, there are now K occupations indexed by k rather than only two occupations. Non-participation is considered its own occupation. Second, I add a gender- and occupation-specific residual amenity $a_{k,g}$. Mathematically, this term allows me to match observed occupation shares, which in reality are based on characteristics in addition to gender composition and wages. Practically, this term will include both positive and negative amenities, like flexibility and danger, as well as barriers to entry, like education. Third, the structure of the individual preference shocks is now nested. I apply a nested logit structure to the model so that preference shocks are more correlated within an occupation nest than across nests.

A nested occupation choice accounts for the fact that some occupations are more closely related than others. Formally, the nested logit model breaks the *independence of irrelevant alternatives* that is inherent to the standard multinomial logit model: it is no longer the case that a utility change in a single occupation will have equal effects on all other occupations. With the nested logit structure on preference shocks, the share in occupation k within nest s is

$$\frac{\ell_{k,g}}{\sum_{j\in s}\ell_{j,g}} = \frac{\exp(V_{k,g}/\lambda_s)}{\sum_{j\in B_s}\exp(V_{j,g}/\lambda_s)}, \tag{9}$$

where $V_{k,g} = \log(w_{k,g}) + a_{k,g} + h_g\left(\frac{\ell_{kf}}{\ell_k}\right)$. The shares of each nest in overall employment are given by

$$P_{B_s} = \frac{\exp(Z_s'\alpha + \lambda_s IV_s)}{\sum_l \exp(Z_l'\alpha + \lambda_l IV_l)}$$

where

$$IV_s = \log\sum_{j\in B_s}\exp(V_j/\lambda_s).$$

This structure ensures that in counterfactual exercises where utilities shift across occupations, workers will be more likely to switch to an occupation that is more closely related to their initial occupation.

As in the simple model, production is CES across occupations, and production is CES across genders within an occupation.

$$\begin{aligned} Y &= \left(\sum_j (A_j\ell_j)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \\ \ell_j &= \left(q_j(\ell_{j,m})^{\frac{\alpha-1}{\alpha}} + (1-q_j)(\ell_{j,f})^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\alpha}{\alpha-1}}. \end{aligned}$$

4.2 Estimation

I estimate the model using data from the March CPS and my survey. I calibrate the substitution elasticities of the aggregate and occupational production functions externally. My data on allocations ($\ell_{g,k}$) and wages ($w_{g,k}$) across occupations by gender come from the March CPS. I use data on workers aged 18 and up from 2014 to 2019. I divide workers into 434 occupations using 2010 Census occupation codes. For occupation- and gender-specific wages, I take the average annual earnings from the prior year for each occupation, residualized on education, age, age squared, usual weekly hours, and year fixed effects. I calculate the allocations across occupations as the share of workers of each gender with a given occupation listed as their main occupation in the previous year. I define non-participation or unemployment as its own occupation. I provide additional details on the sample construction in Appendix A.

To apply my survey-estimated composition valuations in the model, I fit quadratic functions to the average composition value separately for men and women. These functions are plotted with the composition value estimates in Figure 5. This approximation allows me to estimate gender composition utility for compositions I do not directly elicit values for in the survey. I also derive the value of the variance of the Type I EV preference shock, ν from my survey. This parameter is the inverse of the wage elasticity estimated in the survey.

Next, I calibrate two parameters of the production functions externally. I set the elasticity of substitution across occupations η in the aggregate production function equal to 1.5, based on estimates of the elasticity of substitution across skilled and unskilled occupations. This implies that occupations are gross substitutes. I set the elasticity of substitution across genders α equal to 2.5, following estimates in Ngai and Petrongolo (2017). This implies that within occupation, genders are also gross substitutes, but genders are more substitutable within occupations than occupations are. A non-infinite value for the elasticity of substitution across genders can be due to differences in production stemming from, for example, differences in hours or differences in the specific tasks performed within an occupation.

Table 3 summarizes the values and sources of parameters that enter the model estimation.

Table 3: Model Parameter Sources

Parameter	**Meaning**	Value	Source
	Occupation Characteristics		
$w_{g,k}$	Occupation-Gender wage		March CPS
$\ell_{g,k}$	Occupation-Gender allocation		March CPS
	Worker Utility Parameters		
$h_g(\ell_{f,k}/\ell_k)$	Gender composition valuation function		Survey
ν_g	Type I EV preference shock variance		Survey
	Externally Calibrated Parameters		
η	Sub. Elasticity Across Occupations	1.5	Labor Literature
α	Sub. Elasticity Across Genders	2.5	Ngai and Petrongolo (2017)

This table shows the sources of parameters that are determined outside the model.

Finally, the nested logit model requires occupations be divided into nests before estimation. To do this, I follow Nimczik (2022) and Schubert et al. (2021) by defining a network of occupations based on observed worker flows. Intuitively, I combine occupations that workers frequently flow between into the same nest. The full details of the nest estimation process, and the estimated nests, are described in Appendix A.

For non-participation, I normalize the values of the amenity, wage, and composition utility to zero. This pins down the overall level of the amenities $a_{j,g}$ for each gender. Given wages and composition preferences, the amenity $a_{j,g}$ across occupations is the residual utility needed to rationalize allocations across occupations.

The overall occupational productivities A_j and relative gender productivities q_j are determined by gender-specific wages and occupational allocations. Taking the first order conditions of the profit function gives the wage for each gender as a function of labor supply, A_j, and q_j, so given wages and allocations, I can back out A_j and q_j for each occupation. Intuitively, A_j depends on the level of wages relative to total labor, and q_j depends on the gender wage gap. I normalize the level of output so that wages sum to total output.

4.3 Tipping and Labor Supply to a Single Occupation

In this section, I derive the labor supply function for a single occupation from my model and use my survey-estimated preferences to analyze the possibility of tipping and the effect of composition valuations on labor supply to a single occupation. I find that female gender composition valuations would need to be twice as large, and male valuations three times as large, as those estimated to create tipping. However, the estimated valuations can still have large effects on the labor supply to a single occupation.

Recall from Section 2 that the degree to which composition valuations affect sorting, and whether tipping points are possible, are determined by both the variance of the type I EV preference shock and the magnitude of composition preferences. A low variance of preference shocks and a high valuation of gender composition will both make the effect on sorting larger and tipping more likely.

Thus, to measure the effect of composition preferences on sorting and tipping for a single occupation, I adjust the labor supply function from Section 2 to fit the quantitative model. With multiple occupations, I can write the labor supply function for a single occupation k within nest S as

$$\log(w_{k,g}) - \log(w_{j,g}) = \\ \lambda_s \left[\log(\ell_{k,g}) - \log(\ell_{j,g})\right] + \left[a_{j,g} - a_{k,g}\right] + \left[h_g\left(\frac{\ell_{j,f}}{\ell_{j,f} + \ell_{j,m}}\right) - h_g\left(\frac{\ell_{k,f}}{\ell_{k,f} + \ell_{k,m}}\right)\right], \tag{10}$$

where j is a generic occupation within nest s. If the number of occupations in the nest is large enough, the labor supply to occupation k will not effect labor supply or composition utility in occupation j, so these terms can be held constant in the labor supply function.[24]

I conclude that tipping points in gender composition are unlikely with the average survey-estimated gender composition valuations, but accounting for the value of gender composition can create significant changes in sorting across occupations. Figure 11 plots the labor supply functions with and without survey-estimated composition valuations separately for women (panel a) and men (panel b).

[24]Need a better explanation here. Do we hold the other occupation fixed, or is it some amalgam of utility in the other occupations? I really want it to be an outside option, essentially, so I think it's fine how it is but it needs to be explained better.

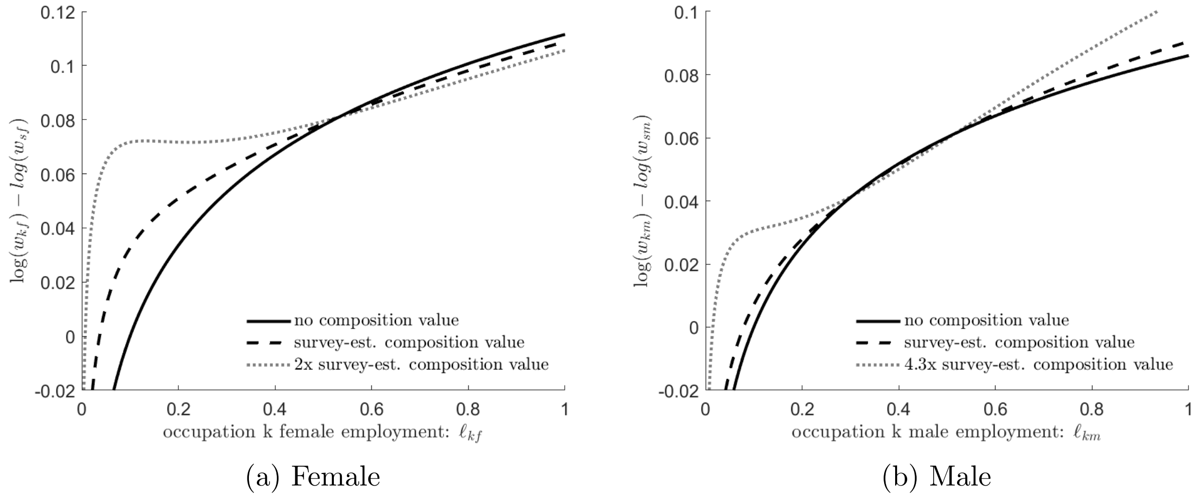


Figure 11: Labor supply plots with survey-estimated composition valuations

Note: This figure shows labor supply plots using survey-estimated composition preferences. The labor supply function is Equation 4.3. For normalization, I assume that the outside option occupation s is 50% female, and that opposite gender employment in the focal occupation k is equal to .5, so that when $\ell_{k,g} > .5$ occupation k is majority same-gender.

For women, gender composition valuations will lead to slight increases in female employment in majority-female jobs and larger decreases in female employment in majority-male jobs. This is illustrated in the figure by the fact that the dashed line (with composition valuation) is to the right of the solid line when $\ell_{k,f} > 0.5$ and to the left of the solid line when $\ell_{k,f} < 0.5$.

For men, gender composition valuations lead to slight decreases in male employment in both majority female jobs and majority male jobs relative to gender-mixed jobs. This is illustrated in Figure 11 by the fact that the dashed line (labor supply with composition valuation) is to the left of the solid line (labor supply without composition valuations) when $\ell_{k,m} > 0.5$ and when $\ell_{k,m} < 0.5$.

Figure 11 also shows that gender composition valuations would need to be larger for both men and women to generate tipping. The dotted line in both figures shows labor supply with composition valuations that are increased in magnitude just enough to generate tipping, i.e., a backward-bending labor supply curve. For women, valuations would need to be twice as large as those I estimate in the survey. For men, valuations would need to be three times as large as those I estimate in the survey.

We can also use this simple labor supply function to calculate the maximum possible effect of valuing gender composition on employment in a single occupation. Given the labor supply function in Equation 4.3, the maximum change in the log difference in employment in two occupations caused by composition valuations is $\lambda_s \cdot [\min_f h_g(f) - \max_f h_g(f)]$, holding wages and amenities fixed. For the estimated preferences, this value is $\exp\left(\lambda_{s,f} \cdot [h_f(0) - h_f(1)]\right) = \exp(-1.6) \approx 0.20$. This means that if female workers are choosing between the most least female occupation and the most female occupation, employment will be 80% *lower* in the least female occupation than it would be if workers assigned zero value to gender composition. For men, this value is $\exp\left(\lambda_{s,f} \cdot [h_m(0) - h_m(0.5)]\right) = \exp(-.84) = 0.4315$. This means that if male workers are choosing between the most male occupation and a perfectly gender-mixed occupation, employment will be 57% lower in the most male occupation than it would be if male workers assigned zero value to gender composition. These effects are quite large, but I note that in the aggregate model workers choose between more than two occupations so the average employment effects will be smaller.

On the whole, we can conclude that the survey estimates of the value of gender composition can create large changes in employment by gender in particular occupations. However, these valuations would still need to be 2-3 times larger to create tipping. The next section assesses how these valuations effect the overall degree of sorting in the labor market.

4.4 Aggregate Importance of Composition Valuations

Next, I use the estimated occupation choice model to calculate the effect of gender composition valuations on overall occupational gender segregation and gender wage gaps. To do this, I remove gender composition valuations from the model and calculate counterfactual allocations and wages.

Formally, to remove gender composition valuations, I take the existing model estimates of occupational productivity and preference parameters and set the composition value $h_g(\ell_{g,k}/\ell_k)$ to zero. I then solve for the counterfactual wages $w'_{j,g}$ and allocations $\ell'_{j,g}$ that would occur in the absence of gender composition valuations:

$$\frac{\ell'_{j,g}}{\ell_g} = \frac{\exp[\log(w_{j,g}) + a_{j,g}]}{\sum_k \exp\left[log(w_{k,g}) + a_{k,g}\right]} \quad j = 1, ..., J.$$

I estimate the new allocations (and wages) in both partial and general equilibrium. In partial equilibrium, I keep wages fixed to their true values at the occupation-gender level. In general equilibrium, I allow wages to adjust in response to changes in worker allocations across occupations by gender. I also estimate this counterfactual separately considering the average gender composition valuations by gender and the heterogeneous valuations estimated using the latent class logit model.[25]

[25]For the heterogeneous preference model, results will depend on how the different gender composition preference types are initially allocated across occupations. In the results that follow, I assume that there is no

Figure 12 illustrates that absent composition valuations, mostly male occupations would be relatively more female and mostly female occupations would be relatively more male. I estimate that if workers did not value gender composition, the female shares of occupations that are between 10 and 30 percent female in reality would be, on average, five percentage points higher. Conversely, I estimate that if workers did not value gender composition, the female shares of occupations between 75 and 90 percent female would be about 1.5 percentage points lower. These differences are mostly due to women, who are less likely to choose mostly male jobs relative to mostly female jobs given their somewhat homophilic composition valuations. Thus, it does appear that workers' valuations of gender composition contribute to gender segregation across occupations.

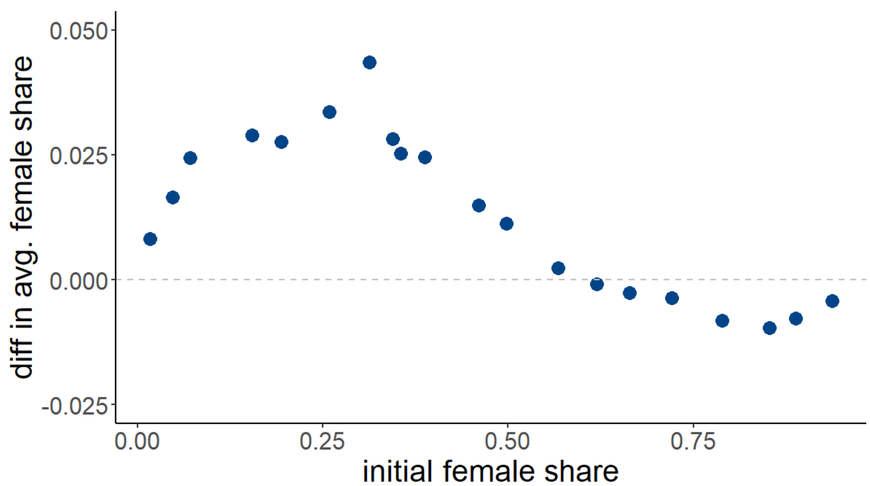


Figure 12: Changes in Occupational Female Shares with No Composition Valuation

Note: This figure shows results from a counterfactual exercise where I eliminate composition valuations and re-calculate allocations and wages across occupation and gender. Here, I use average valuations by gender and do not allow wages to adjust in general equilibrium. This figure displays a binscatter of the difference in the female share of an occupation (counterfactual - true) against the true female share of the occupation. Bins are weighted by employment.

Removing composition valuations also reduces the share of workers in very gender-segregated occupations. In reality, 38.9% of workers are in occupations that are either less than 20% female or more than 80% female. Without composition valuations, this share falls to 35.5%. The overall effects of composition valuations on segregation are summarized in Table 4.

Finally, gender composition valuations, and in particular women's higher valuation of

sorting across occupations by preference type: that is, within gender, the distribution of workers across occupations is equal for each preference type. However, I am currently estimating this counterfactual separately with different assumptions about how types sort across occupations in order to bound the estimates.

Table 4: Changes in Allocations: No Gender Composition Preference

		true	no comp. value	PE no female comp. value	no male comp. value	GE no comp. value
share switching occupations	female		0.041	0.041	0.006	0.004
	male		0.056	0.009	0.056	0.006
avg. female share	female	0.630	0.626	0.620	0.639	0.629
	male	0.308	0.310	0.316	0.299	0.308
share in occs under 20 pct. Female	female	0.046	0.036	0.038	0.042	0.046
	male	0.396	0.360	0.331	0.436	0.396
	total	0.237	0.213	0.198	0.258	0.237
share in occs over 80 pct. Female	female	0.296	0.299	0.303	0.294	0.296
	male	0.032	0.033	0.031	0.034	0.032
	total	0.152	0.154	0.154	0.152	0.152
duncan-duncan		0.490	0.482	0.469	0.506	0.489

Note: This table shows results from a counterfactual exercise where I eliminate composition preferences and re-calculate allocations and wages across occupation and gender. I use the WTPs for gender composition estimated in Section 3.4.1. In the PE columns, I do not allow wages to adjust in response to changing allocations.

more female workplaces, increase the gender wage gap. I find that absent gender composition valuations, the gender wage gap due to gender sorting across occupations would fall from 8 percent to 7.6 percent, a 5 percent reduction. This occurs because the more female occupations that women are drawn to due to their homophilic composition valuations tend to pay less on average. These results are summarized in Table 5.

Overall, this exercise suggests that gender composition valuations are large enough to have a substantial effect on gender sorting across occupations. I estimate that if workers did not value gender composition, mostly male occupations would be significantly more female, and the gender wage gap would be modestly reduced

4.5 Social Planner's Solution

In this section, I investigate how a welfare-maximizing social planner would allocate workers by gender across occupations. A social planner's solution may improve welfare in this context because composition valuations create a sorting externality: individuals do not take into account the effects of their entry into an occupation on the utility of others in that occupation. I find that a social planner would choose an allocation that would vastly reduce segregation, which would improve welfare by the equivalent of a 2% increase in consumption.

Table 5: Changes in Gender Wage Gaps: No Gender Composition Preference

		true	PE no comp. value	no female comp. value	no male comp. value	GE no comp. value
Avg.	Female	1483	1488	1488	1483	1485
Wage	Male	1914	1917	1914	1917	1912
Avg. Male Wage	Female	1760	1768	1768	1760	1764
Avg. Female Wage	Male	1557	1560	1557	1560	1545
Wage Gap	actual	-0.225	-0.224	-0.222	-0.226	-0.223
(Female-Male)	(Male Wage)	-0.080	-0.078	-0.076	-0.082	-0.077
	(Female Wage)	-0.047	-0.046	-0.044	-0.049	-0.039

Note: The wage gap is measured as the mean male minus female wage divided by the male wage, $\frac{w_m - w_f}{w_m}$. This table shows results from a counterfactual exercise where I eliminate composition preferences and re-calculate allocations and wages across occupation and gender. The "Average Preference" columns use the WTPs for gender composition estimated in Section 3.4.1, and the "Heterogeneous Preference" columns use the WTPs estimated in the latent class logit model in Section 3.4.2. In the PE columns, I do not allow wages to adjust in response to changing allocations. In the "male wage" row, I set $w_{f,j} = w_{m,j}$ and calculate overall wage gaps given true allocations, and vice versa in the "female wage" row.

Consider the following social planner's problem:

$$\begin{aligned}
\max_{\varphi,c} \sum_i u_{i,g(i)} &\left(\frac{\ell_{k(i,\varphi)f}}{\ell_{k(i,\varphi)}}, a_{k(i,\varphi)g(i)}, c_{i,\varphi}\right) \\
\text{s.t. } \sum_i c_{i,\varphi} &\leq \left(\sum_k (A_k \ell_{k(\varphi)})^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}, \\
\ell_k &= \left(q_k(\ell_{k,m})^{\frac{\alpha-1}{\alpha}} + (1-q_k)(\ell_{k,f})^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\alpha}{\alpha-1}}, \\
u_{i,g(i)}\left(\frac{\ell_{k(i,\varphi)f}}{\ell_{k(i,\varphi)}}, a_{k(i,\varphi)g(i)}, c_{i,\varphi}\right) &= log(c_{i,\varphi}) + h_{g(i)}\left(\frac{\ell_{k(i,\varphi)f}}{\ell_{k(i,\varphi)}}\right) + a_{k(i,\varphi)g(i)}, \\
\sum_k \ell_{k,g} &\leq \ell_g, \quad g = f, m.
\end{aligned} \tag{11}$$

The social planner chooses the allocation of workers to occupations φ that maximizes the sum of the individual utilities, subject to the constraint that total consumption is less than or equal to total output and total labor in each occupation is less than or equal to the number of total workers. For closed form analysis of the social planner's problem, I omit the type I extreme value preference draws.[26]

[26]As noted by Brock and Durlauf (2001) and Davis and Gregory (2021), the sum of extreme value draws is not extreme value distributed and does not have a convenient closed form. In addition, as noted by Davis and Gregory (2021), the preference draws are not observed and differing assumptions about their distribution (even within the extreme value family) will lead to different conclusions about welfare-maximizing policies. Thus, for the moment I ignore these preference draws, but in the quantitative model I will consider the

The planner will equalize the social marginal benefit of labor across occupations for men and women, as shown in Equation 15.

$$
\begin{aligned}
&a_{k,g} + h_g\left(\frac{\ell_{k,f}}{\ell_k}\right) + (\ell_{k,f})\left(\frac{\partial}{\partial \ell_{k,g}} h_f\left(\frac{\ell_{k,f}}{\ell_k}\right)\right) + (\ell_{k,m})\left(\frac{\partial}{\partial \ell_{k,g}} h_m\left(\frac{\ell_{k,f}}{\ell_k}\right)\right) + \frac{\ell}{Y}\left(\frac{\partial Y}{\partial \ell_{k,g}}\right) \\
&= a_{j,g} + h_g\left(\frac{\ell_{j,f}}{\ell_j}\right) + (\ell_{j,f})\left(\frac{\partial}{\partial \ell_{j,g}} h_f\left(\frac{\ell_{j,f}}{\ell_j}\right)\right) + (\ell_{j,m})\left(\frac{\partial}{\partial \ell_{j,g}} h_m\left(\frac{\ell_{j,f}}{\ell_j}\right)\right) + \frac{\ell}{Y}\left(\frac{\partial Y}{\partial \ell_{j,g}}\right), \\
&\qquad \forall j,k \qquad g = f, m.
\end{aligned}
\tag{12}
$$

The marginal benefit of labor in an occupation for gender g is equal to the composition utility in that occupation for gender g, plus the female labor in the occupation times the marginal derivative of the female composition utility with respect to gender g labor, plus the male labor in the occupation times the marginal derivative of the male composition utility with respect to gender g labor, plus the marginal product of that occupation weighted by the marginal utility of consumption.[27]

In the decentralized sorting equilibrium without random preference shocks, individual utility must be equated across occupations at an interior solution. In general equilibrium, the wage will equal the marginal product of labor in each occupation, so we will have

$$
\log\left(\frac{\partial Y}{\partial \ell_{k,g}}\right) + h_g\left(\frac{\ell_{k,f}}{\ell_k}\right) + a_{k,g} = \log\left(\frac{\partial Y}{\partial \ell_{j,g}}\right) + h_g\left(\frac{\ell_{j,f}}{\ell_j}\right) + a_{j,g}, \quad \forall j,k, \qquad g = f, m.
\tag{13}
$$

How does this differ from the social planner's solution? The social planner will not only want to equalize own-gender utility across occupations but also account for the effect each individual has on the utility of people of their own gender and the other gender in their occupation. In addition, the social planner will weight individual contributions to output by their marginal utility. The fact that the wage does not account for all effects of an individual's occupation choice in general equilibrium means that sorting preferences create externalities and thus a potential for policy to improve welfare.

The social planner will reallocate workers across occupations to reduce segregation by making male-dominated occupations more female and female-dominated occupations more male. Figure C.36 shows the change in female shares across occupations under the social planner's solution. Overall, the social planner will decrease the share of workers that are in very segregated occupations (less than 20% female or more than 80% female) by half, from 40% to 20%.

importance of idiosyncratic preferences.

[27] I provide the detailed steps of the social planner's solution in Appendix A.

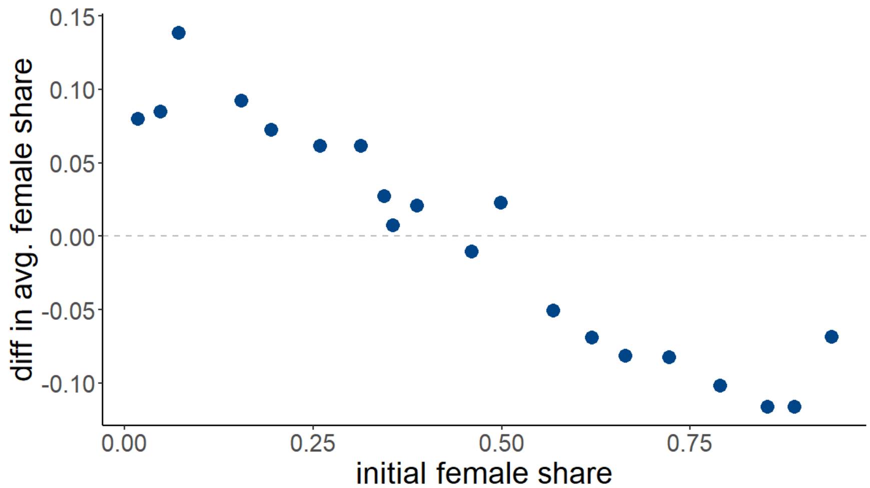


Figure 13: Changes in Occupational Female Shares in Social Planner's Solution

Note: This figure shows results the social planner's solution to maximize welfare by reallocating workers across occupations. Here, I use average valuations by gender. This figure displays a binscatter of the difference in the female share of an occupation (social planner - true) against the true female share of the occupation. Bins are weighted by employment.

The social planner will move towards desegregation because both genders are the happiest in jobs that are between 40 and 80 percent female. Given that both men and women, on average, dislike majority male workplaces, the social marginal utility of increasing female employment, and reducing male employment, in mostly male occupations is large. Men and women also dislike extremely female dominated workplaces, but less than they dislike male dominated workplaces, so the social planner will decrease female shares in these occupations by less than they change the female shares in the mostly male occupations.[28] This change in allocations improves total welfare as much as a 2% increase in consumption for all individuals.[29]

The social planner reduces segregation by overcoming the problem of the marginal gender minority worker. Although both genders will be better off as an occupation becomes more gender mixed, a single woman (or man) will be reluctant to enter a majority male (or female) occupation because she cannot guarantee that others will follow. If individuals could collude to create a large shift in the gender share of an occupation, desegregating would be easier, but in a decentralized equilibrium individuals will be more likely to choose occupations that

[28]Notably, the female shares change slightly less in the most segregated occupations, because in these occupations the gender difference in the residual amenity $a_{k,g}$ is so large that even with female share significantly closer to 50%, this occupation still offers low utility for the gender minority.

[29]To compute this consumption-equivalent welfare increase, I set individual consumption equal in both the decentralized equilibrium and social planner's solution, and increase consumption in the decentralized equilibrium until the total utility is equal in both cases. This nets out the change in welfare from the social planner's reallocation of consumption across individuals.

already fit their preferred gender composition valuation.

The solution to the planner's problem suggests that desegregation is a desirable policy goal because both men and women would potentially be better off if occupations, particularly those with very high or very low female shares, were less segregated. Although reducing segregation to the degree that the social planner would is unlikely to be feasible, this exercise demonstrates that policies that reduce the cost of entry into an occupation for the gender minority could be fruitful. For instance, policies that improve amenities that women value highly or subsidize education in particular fields for a certain gender could help reduce segregation and benefit workers of all genders.

5 Conclusion

In this paper, I study whether workers value the gender composition of their workplace and how this affects occupational gender segregation and the worker welfare. Using a novel online survey, I estimate that both men and women are willing to trade off a nontrivial portion of their wages for a job that has their preferred gender composition. I find that women prefer jobs that are at least 50% female, and men prefer gender-mixed jobs and dislike gender-segregated jobs. Importantly, these preferences are heterogeneous across individuals. I estimate that most women and men do not care about the gender composition of their jobs, but around half of women and men are willing to trade off a nontrivial portion of their wages for a job with their preferred gender composition. Importantly, older workers are more likely to value workplace gender homophily, suggesting that homophily has become less valuable as men and women's labor market outcomes converged over the twentieth century.

I use these estimated valuations in a structural model of occupation choice to assess their implications for occupational gender segregation in the aggregate. I find that if workers did not value the gender composition of their occupation, the female shares of majority male occupations would be up to 5 percentage points higher, and 5 percent fewer workers would work in occupations that are less than 20% or more than 80% female. Additionally, because mostly female occupations tend to have lower wages, removing gender composition preferences would reduce the portion of the gender wage gap due to occupational sorting by nearly 10% in partial equilibrium. Finally, I show that a welfare-maximizing social planner would significantly reduce gender segregation, which would improve welfare as much as a 2% increase in consumption.

In all, this paper shows that the gender composition of a workplace is an important amenity that can have large consequences for occupation choice and worker welfare. This complements our understanding of the importance of non-wage amenities for job choice by showing that who performs a job may be as important as the benefits a workplace provides.

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A Appendix: Two-Occupation Model Details

A.1 Social Planner's Problem

A particularly interesting consequence of composition valuations is a sorting externality: individuals do not take into account the effects of their entry into an occupation on the utility of others in that occupation. I consider the effect of this externality using a social planner's problem.

Consider the following social planner's problem:

$$\begin{aligned}
&\max_{\varphi,w} \sum_i u_i \left(\frac{\ell_{k(i,\varphi)g(i)}}{\ell_{k(i,\varphi)}}, c_i \right) \\
\text{s.t.} \ &\sum_i c_{i,\varphi} \leq \left((A_1 \ell_1)^{\frac{\nu-1}{\nu}} + (A_2 \ell_2)^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}, \\
&\ell_k = \left(q_k (\ell_{k,m})^{\frac{\alpha-1}{\alpha}} + (1-q_k)(\ell_{k,f})^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}}, \\
&\sum_k \ell_{k,g} \leq \ell_g, \quad g = f, m. \qquad (14)
\end{aligned}$$

The social planner chooses the allocation of workers to occupations φ that maximizes the sum of the individual utilities, subject to the constraint that total consumption is less than or equal to total output. For closed form analysis of the social planner's problem, I omit the type I extreme value preference draws.[30]

Ultimately, the planner will equalize the social marginal benefit of labor in the two occupations for men and women. The marginal benefit of labor in an occupation is equal to the composition utility in that occupation, plus the total labor in the sector times the marginal derivative of the composition utility with respect to female (male) labor, plus the marginal product of that occupation weighted by the marginal utility of consumption, as

[30] As noted by Brock and Durlauf (2001) and Davis and Gregory (2021), the sum of extreme value draws is not extreme value distributed and does not have a convenient closed form. In addition, as noted by Davis and Gregory (2021), the preference draws are not observed and differing assumptions about their distribution (even within the extreme value family) will lead to different conclusions about welfare-maximizing policies. Thus, for the moment I ignore these preference draws, but in the quantitative model I will consider the importance of idiosyncratic preferences.

shown in Equation 15.[31]

$$h_g\left(\frac{\ell_{1,f}}{\ell_1}\right)+(\ell_{1,f}+\ell_{1,m})\left(\frac{\partial}{\partial \ell_{1,g}}h_g\left(\frac{\ell_{1,f}}{\ell_1}\right)\right)+\frac{\ell}{Y}\left(\frac{\partial Y}{\partial \ell_{1,g}}\right)=$$
$$h_g\left(\frac{\ell_{2,f}}{\ell_2}\right)-(\ell_{2,f}+\ell_{2,m})\left(\frac{\partial}{\partial \ell_{1,g}}h_g\left(\frac{\ell_{2,f}}{\ell_2}\right)\right)+\frac{\ell}{Y}\left(\frac{\partial Y}{\partial 1-\ell_{1,g}}\right),\quad g=f,m. \tag{15}$$

In the decentralized sorting equilibrium without random preference shocks, individual utility must be equated across occupations at an interior solution. In general equilibrium, the wage will equal the marginal product of labor in each occupation, so we will have

$$\log\left(\frac{\partial Y}{\partial \ell_{1,g}}\right)+h_g\left(\frac{\ell_{1,f}}{\ell_1}\right)=\log\left(\frac{\partial Y}{\partial 1-\ell_{1,g}}\right)+h_g\left(\frac{\ell_{2,f}}{\ell_2}\right),\quad g=f,m. \tag{16}$$

How does this differ from the social planner's solution? The social planner will not only want to equalize own-gender utility across occupations but also account for the effect each individual has on the utility of people of their own gender and the other gender in their occupation. In addition, the social planner will weight individual contributions to output by their marginal utility. The fact that the wage does not account for all effects of an individual's occupation choice in general equilibrium means that sorting preferences create externalities and thus a potential for policy to improve welfare.

A.2 Solution to Social Planner's Problem

With two occupations and two genders, we can write the Lagrangian for the social planner's problem as follows:

$$\sum_g \ell_{1,g}\left(log(w_{1,g})+h_g\left(\frac{\ell_{1,f}}{\ell_{1,f}+\ell_{1,m}}\right)\right)+$$
$$\sum_g(\ell_g-\ell_{1,g})\left(log(w_{2,g})+h_g\left(\frac{\ell_f-\ell_{1,f}}{(\ell_f-\ell_{1,f})+(\ell_m-\ell_{1,m})}\right)\right)+$$
$$\lambda\Bigg[\left((A_1(\ell_1))^{\frac{\eta-1}{\eta}}+(A_2(\ell_2))^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}-$$
$$(\ell_{1,f}w_{1,f}+\ell_{1,m}w_{1,m}+(\ell_f-\ell_{1,f})w_{2,f}+(\ell_m-\ell_{2,m})w_{2,m})\Bigg]$$

Taking the FOC with respect to occupation 1 employment for each gender and wages for each gender and occupation gives us

[31] I provide the detailed steps of the social planner's solution in Appendix A.

$$\begin{aligned}
\ell_{1,f}: \quad & (log(w_{1,f}) + h_f\left(\frac{\ell_{1,f}}{\ell_{1,f}+\ell_{1,m}}\right) + \varepsilon_{1,f}) + \\
& (\ell_{1,f}+\ell_{1,m})\left(\frac{\partial}{\partial \ell_{1,f}} h_g\left(\frac{\ell_{1,f}}{\ell_{1,f}+\ell_{1,m}}\right)\right) + \\
& -\left(log(w_{2,f}) + h_f\left(\frac{\ell_f-\ell_{1,f}}{(\ell_f-\ell_{1,f})+(\ell_m-\ell_{1,m})}\right) + \varepsilon_{1j}\right) + \\
& (\ell_f-\ell_{1,f}+\ell_m-\ell_{1,m})\left(\frac{\partial}{\partial \ell_{1,f}} h_g\left(\frac{\ell_f-\ell_{1,f}}{(\ell_f-\ell_{1,f})+(\ell_m-\ell_{1,m})}\right)\right) + \\
& \lambda\left[\left(\frac{\partial Y}{\partial \ell_{1,f}} - w_{1,f}\right) - \left(\frac{\partial Y}{\partial 1-\ell_{1,f}} - w_{2,f}\right)\right] = 0 \\
\ell_{1,m}: \quad & (log(w_{1,m}) + h_g\left(\frac{\ell_{1,f}}{\ell_{1,f}+\ell_{1,m}}\right) + \varepsilon_{1,f}) + \\
& (\ell_{1,m}+\ell_{1,f})\left(\frac{\partial}{\partial \ell_{1,m}} h_m\left(\frac{\ell_{1,f}}{\ell_{1,f}+\ell_{1,m}}\right)\right) + \\
& -\left(log(w_{2,m}) + h_m\left(\frac{\ell_f-\ell_{1,f}}{(\ell_f-\ell_{1,f})+(\ell_m-\ell_{1,m})}\right) + \varepsilon_{1m}\right) + \\
& (\ell_m-\ell_{1,m}+\ell_f-\ell_{1,f})\left(\frac{\partial}{\partial \ell_{1,m}} h_m\left(\frac{\ell_f-\ell_{1,f}}{(\ell_f-\ell_{1,f})+(\ell_m-\ell_{1,m})}\right)\right) + \\
& \lambda\left[\left(\frac{\partial Y}{\partial \ell_{1,m}} - w_{1,m}\right) - \left(\frac{\partial Y}{\partial 1-\ell_{1,m}} - w_{2,m}\right)\right] = 0 \\
w_{j,g}: \quad & \sum_{j(i)=j} \frac{1}{w_{j,g}} - \lambda \ell_{j,g} = 0
\end{aligned}$$

And, for the complementary slackness condition, we have

$$\lambda\Bigg[\left((A_1(\ell_{1,f}+\ell_{1,m}))^{\frac{\eta-1}{\eta}} + (A_2(\ell_f-\ell_{1,f}+\ell_m-\ell_{1,m}))^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} - \tag{17}$$

$$(\ell_{1,f}w_{1,f} + \ell_{1,m}w_{1,m} + (\ell_f-\ell_{1,f})w_{2,f} + (\ell_m-\ell_{2,m})w_{2,m})\Bigg] = 0 \tag{18}$$

Solving through on the first order condition for wages, we see

$$\ell_{j,g}/w_{j,g} = \lambda \ell_{j,g} \text{ for all } j, g$$

so

$$\lambda = \frac{1}{w}, \text{ where } w = w_{j,g} \text{ for all } j, g.$$

That is, the social planner will want to equalize wages across genders and occupations.

Combining this with the complementary slackness condition, assuming the constraint binds so $\lambda = 0$, we see

$$\left[\left((A_1(\ell_{1,f} + \ell_{1,m}))^{\frac{\eta-1}{\eta}} + (A_2(\ell_f - \ell_{1,f} + \ell_m - \ell_{1,m}))^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} = w(\ell_f + \ell_m) \right]$$

Or, put more simply

$$w = \frac{Y}{\ell}. \tag{19}$$

B Appendix: Data

B.1 Survey Design

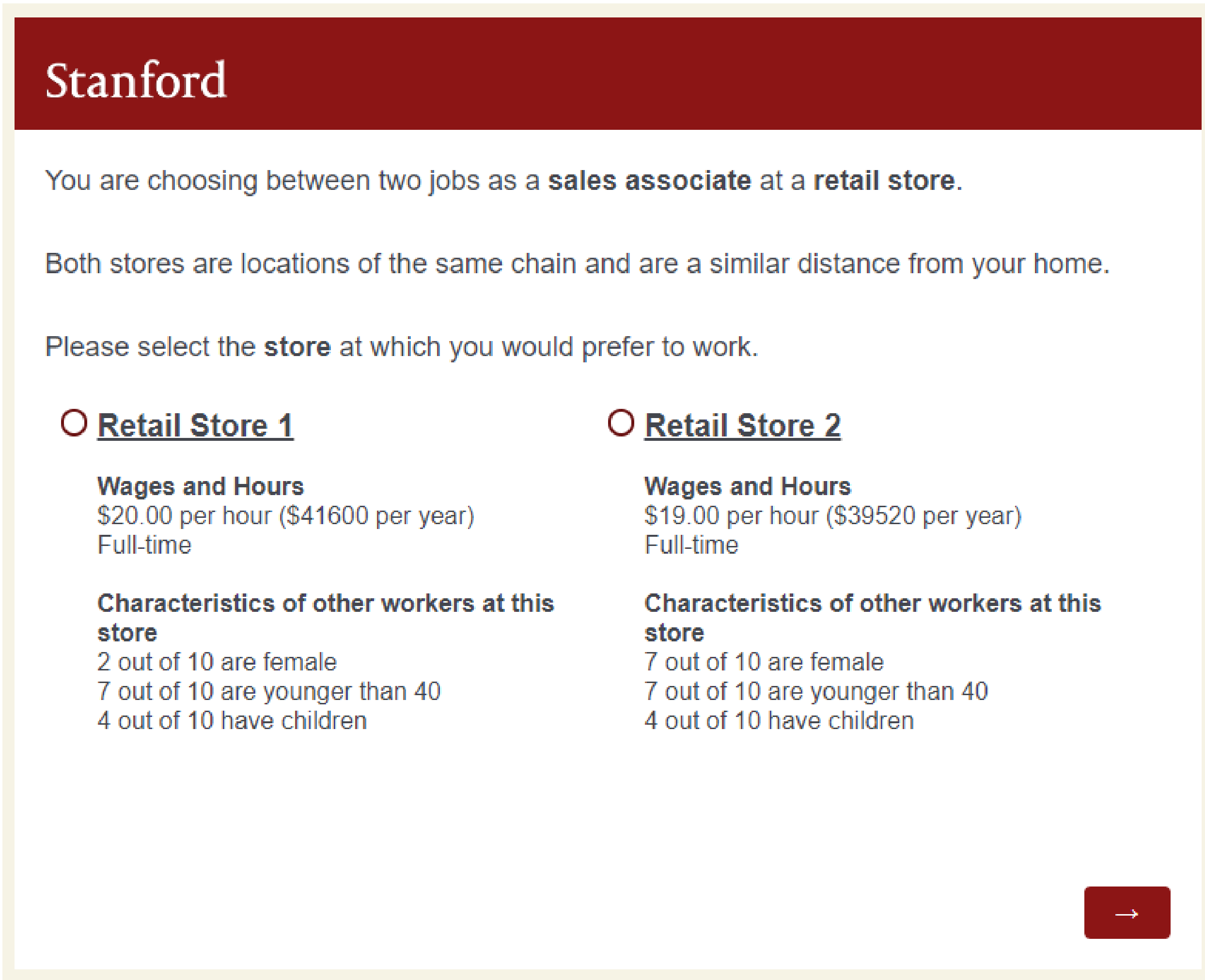


Figure B.1: Example Hypothetical Job Choice

B.2 Survey Descriptive Statistics

A primary concern with online survey samples is representativeness. The respondents are a convenience sample of participants who have opted in to an online survey panel or website. This sample is inherently non-random. The primary concern with such a sample is whether survey results can be generalized to a broader population, i.e., working adults in the United States. Reassuringly, several papers in political science have conducted survey experiments using both online convenience samples from Lucid and similar providers and traditional random samples and found similar results.[32]

Whether survey results can be generalized to a larger population relies on both the presence of different types of people in the survey sample and the heterogeneity of the treatment effect of interest, here, gender composition preferences. If there is no population-level heterogeneity in gender composition preferences, the survey sample does not need to be demographically representative to make inferences about the general population. Either way, the average preference estimates for the survey and the population will be the same. If, on the other had, gender composition preferences are highly variable in the population, we must understand which individual characteristics co-vary with these preferences to re-weight and estimate population-level statistics. In this case, it is again not necessary that the survey sample exactly matches the population distribution of relevant traits, only that there is sufficient presence of each group in the sample to re-weight to match the population.

To assess whether my survey has sufficient representation across demographic groups, I compare my survey sample to the CPS Annual Social and Economic Supplement (CPS ASEC, commonly referred to as the March CPS) pooled from 2014-2019. I first compare my sample to the CPS ASEC by sex, age, race, and education in Table 1. My conjoint experiment measures preferences for sex, age, and educational composition of an occupation, so these characteristics are likely to be important covariates of composition preferences. These characteristics, in addition to race, are targeted by Lucid Theorem.

[32] Coppock and McClellan (2019) compare results from several survey experiments conducted through Lucid, MTurk, and probability samples. For all but one of five experiments, they find experimental effects that matched the sign and significance of the original estimates on the probability sample. Boas et al. (2020) compare Qualtrics, which recruits survey participants in a similar manner to Lucid, with probability samples and samples recruited through Facebook and MTurk and found that the Qualtrics sample was the most demographically and politically representative. They also find that treatment effects and in particular treatment effect heterogeneity by partisanship are similar in the benchmark probability samples (from the General Social Survey and YouGov Polimetrix) and the Qualtrics sample.

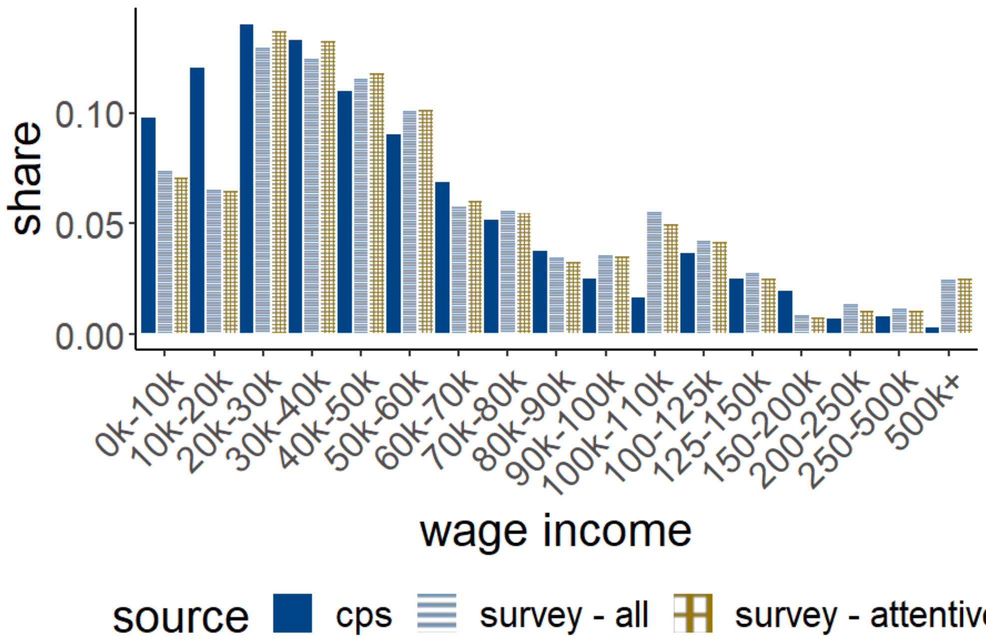


Figure B.2: Income Distribution: Survey vs. March CPS

This plot shows the distribution of individual annual wage income in the CPS ASEC from 2014 through 2019 and my survey. The distribution of incomes is overall similar, although my survey sample has less mass at the lowest incomes and more mass at the highest incomes.

Figure B.9 compares the distribution of reported annual income in my survey to that in the CPS ASEC. Relative to the CPS, respondents to my survey reported incomes that were higher on average; in particular, the lowest income groups were somewhat under-represented. On the whole, however, the distributions are relatively similar, which is reassuring given that one might expect income to be mis-reported in surveys. One might expect income to co-vary with gender composition preferences because female-dominated occupations have lower income on average. Thus, workers with a strong preference for those jobs might tend to have lower incomes.

Next, I compare the distribution of occupational female shares among survey respondents to that in the CPS. Naturally, I expect people who prefer more female occupations to work in more female occupations and vice versa. Figure B.3 compares the distribution of employment by occupational female shares in my survey and the CPS. Here, I calculated the survey respondents' occupational female shares by linking their reported occupation to that occupation in the CPS and calculating the occupation's female share in the CPS.[33] The distribution of female shares in survey-reported occupations is overall relatively similar to

[33]Specifically, I use the groups of the IPUMS CPS variable occ10ly, which are approximately equivalent to 2-digit SOC codes.

that in the CPS with representation across the spectrum of female shares. In appendix B figure B.5, I compare the CPS occupational female share distribution to survey respondents' reported female shares of their employers and coworkers and the reported gender perception of their jobs and find similar results.

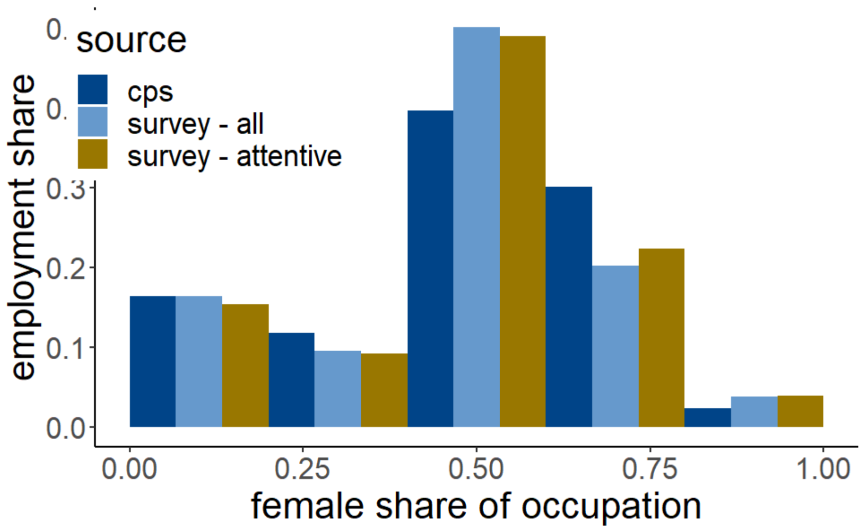


Figure B.3: Female shares: Survey vs. CPS

This plot shows the distribution of occupational female shares in the CPS ASEC from 2014 through 2019 and my survey. I calculate the female share of a respondent's occupation by linking their reported occupation to that occupation in the CPS. I group occupations at the level of the group headings of the IPUMS CPS variable *occ10ly*.

Finally, I compared the distribution of attitudes towards gender and work in my survey to surveys with population-representative random samples. Gender composition preferences may be related to an individual's view on gender roles and whether men and women should perform different tasks on the job and at home. Thus, I asked my survey respondents two questions from the General Social Survey (GSS) on gender roles and work and gender-based affirmative action and one question from the Pew American Trends Panel about gender attitudes.

In the first question from the GSS, shown in Figure B.4 Panel a, I asked survey respondents whether they agree or disagree with the following statement:

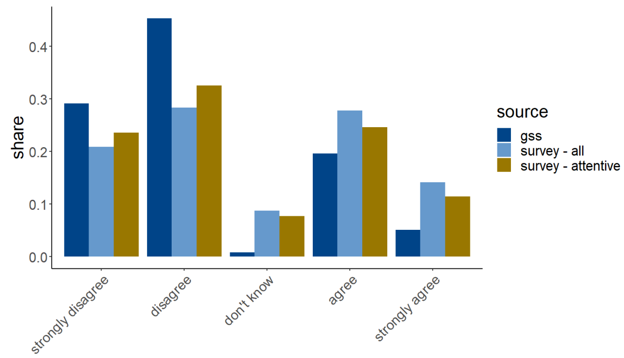
> *"It is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family."*

Relative to the GSS respondents, my survey respondents were more likely to agree or strongly agree with this statement, potentially indicating more conservative attitudes towards gender roles and work.

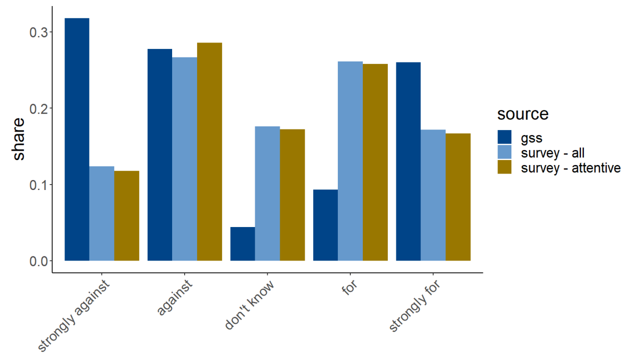
In the second question from the GSS, shown in Figure B.4 Panel b, I asked respondents the following question about gender-based affirmative action:

> *"Some people say that because of past discrimination, women should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of women is wrong because it discriminates against men. What about your opinion - are you for or against preferential hiring and promotion of women?"*

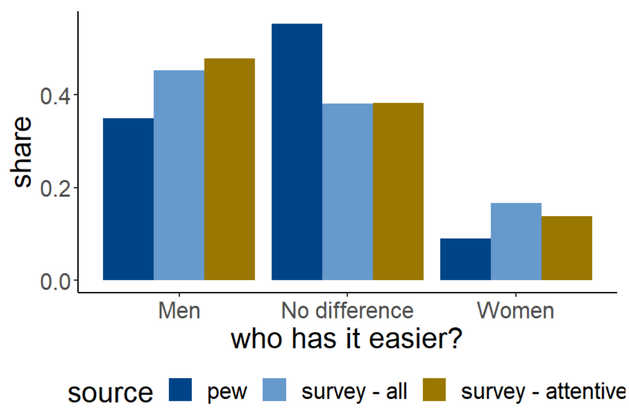
Here, respondents to my survey were more likely to select the less-extreme options relative to GSS respondents, suggesting weaker preferences in either direction regarding gender-based affirmative action.



(a) GSS: Man Should Work, Woman Stay at Home



(b) GSS: Affirmative action for women in jobs



(c) Pew: Which Gender has it Easier?

Figure B.4: Gender Attitudes vs. Representative Surveys

These plots show the distribution of answers to three questions about gender attitudes in population representative surveys in green and my survey in coral. The first two questions come from the General Social Survey and the third from the Pew American Trends Panel. Descriptions of each question are detailed in the text.

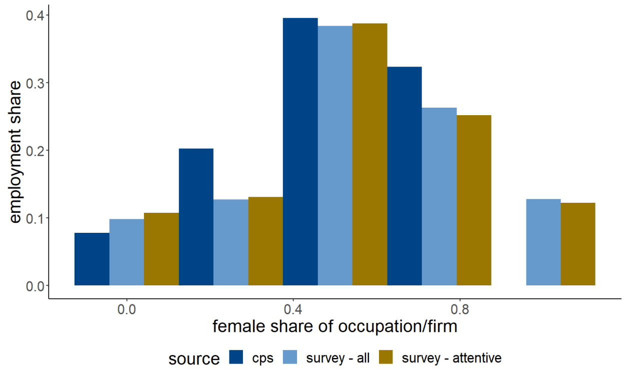
In the last question about gender attitudes, from the Pew American Trends Panel, shown in Figure B.4 Panel c, I asked survey respondents the following question:

"All things considered, who do you think has it easier in our country these days?"

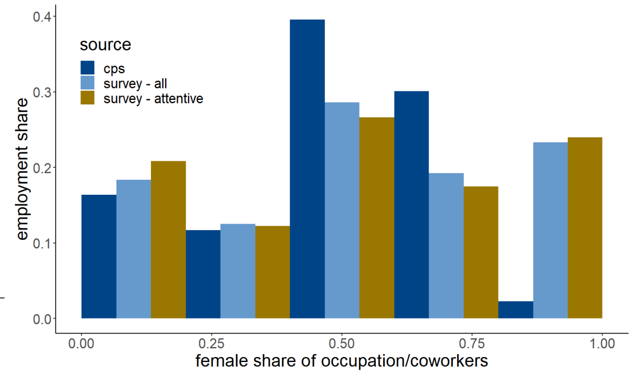
My survey respondents were slightly more likely to answer that women or men have it easier and less likely to answer no difference.

The answers to these questions suggest that the attitudes toward gender and work in my survey sample might differ from the general population, but not in straightforward ways. Respondents report more conservative attitudes toward gender roles, but more neutral stances toward affirmative action, than GSS respondents. Relative to the Pew survey, my respondents have more extreme attitudes toward gender-based privilege. Nonetheless, it is reassuring that there is representation across the spectrum of gender attitudes among my survey respondents.

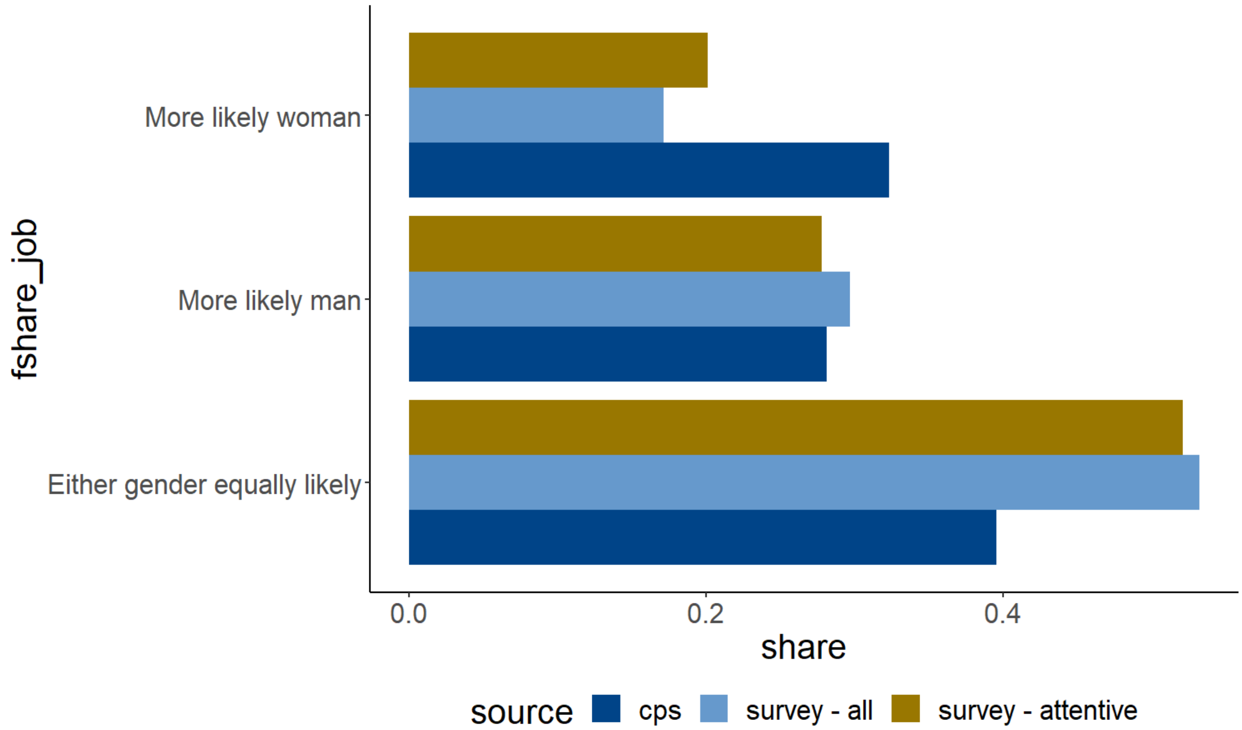
Overall, comparing the composition of my survey sample to surveys with population-representative random samples indicates that the survey sample is representative enough of the general population. My survey sample has similar distributions of age, education, race, sex, income, and occupational female shares to the general population. Attitudes toward gender and work in my sample seem to differ somewhat from the population, but there is large variation in reported gender attitudes, which makes re-weighting possible. I am currently working on providing estimates of gender composition preferences that are re-weighted by demographic characteristics.



(a) Female Share of Employer



(b) Female Share of Coworkers with Same Job



(c) Reported Gender Norm of Job

Figure B.5: Reported Female shares: Survey vs. CPS

B.2.1 Additional Demographics

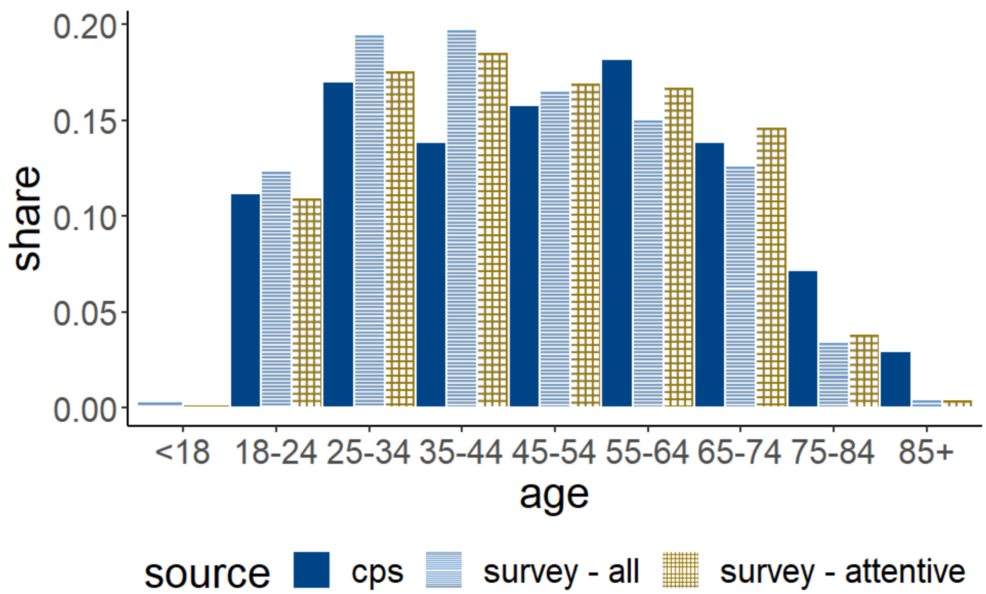


Figure B.6: Age Distribution: Survey vs. March CPS

This plot shows the distribution of ages in the CPS ASEC from 2014 through 2019 and my survey.

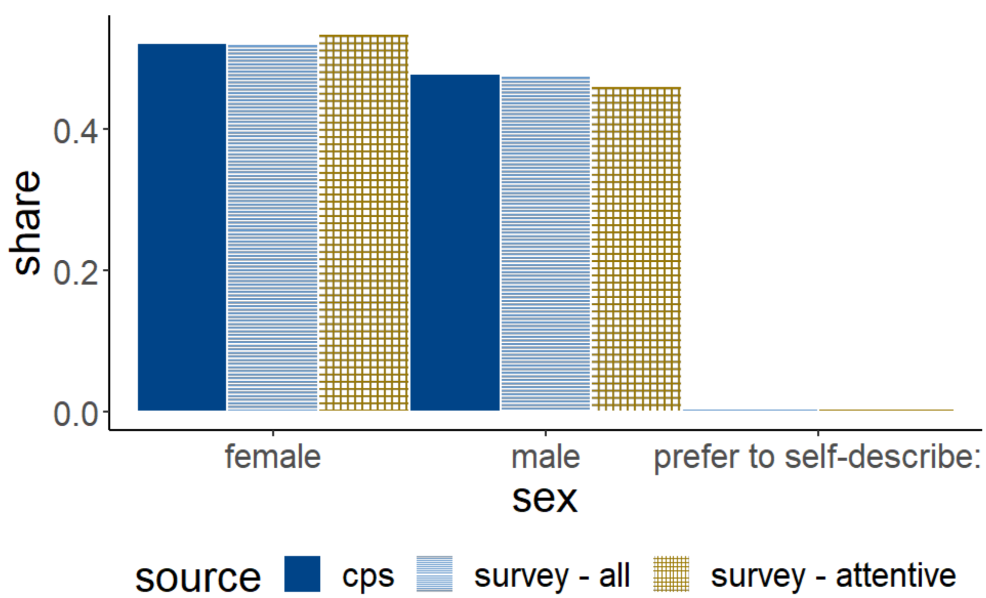


Figure B.7: Sex Distribution: Survey vs. March CPS

This plot shows the distribution of sex in the CPS ASEC from 2014 through 2019 and my survey.

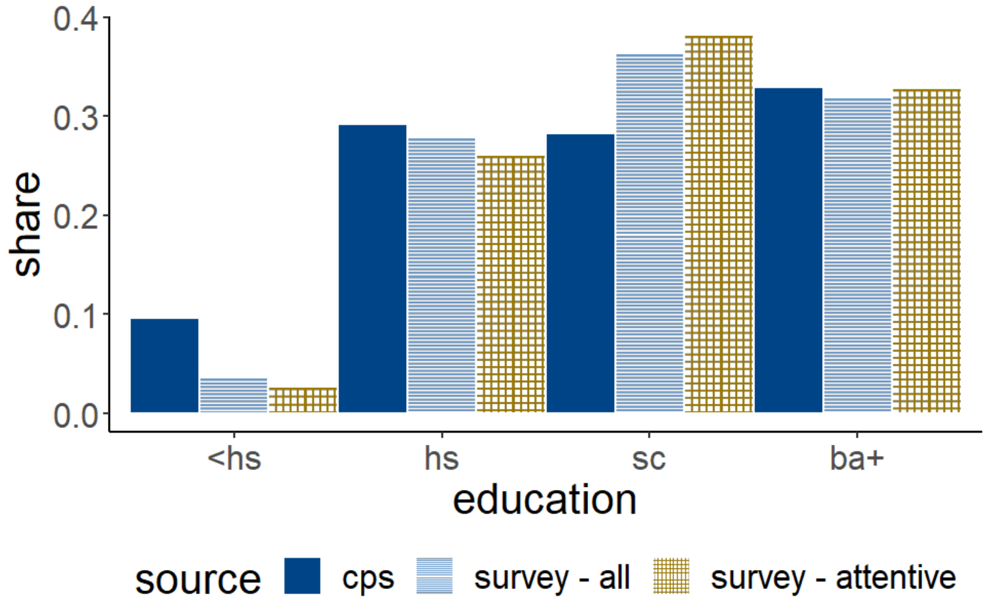


Figure B.8: Education Distribution: Survey vs. March CPS

This plot shows the distribution of education in the CPS ASEC from 2014 through 2019 and my survey.

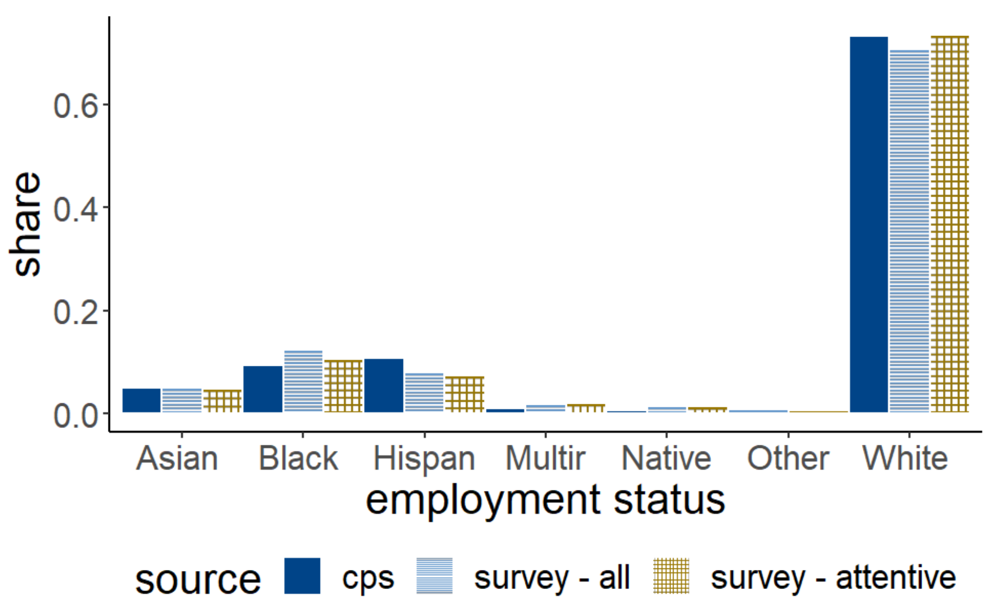


Figure B.9: Race Distribution: Survey vs. March CPS

This plot shows the distribution of race in the CPS ASEC from 2014 through 2019 and my survey.

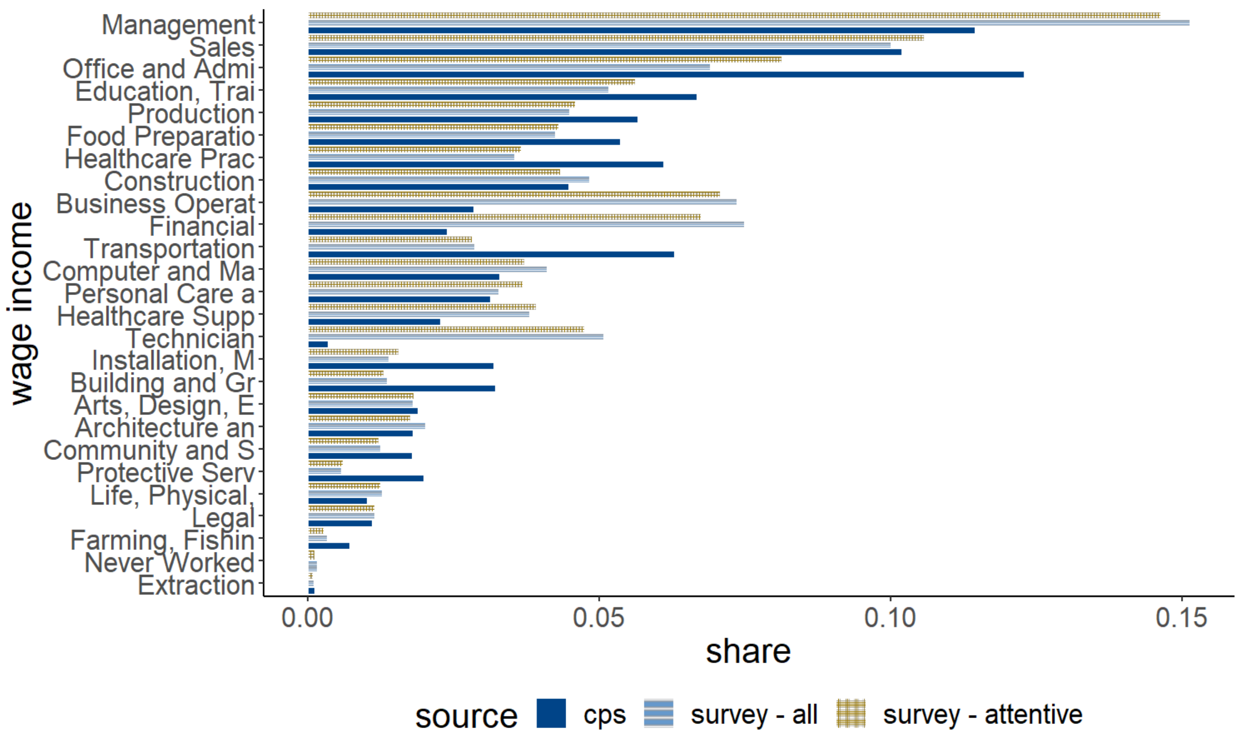


Figure B.10: Occupation Distribution: Survey vs. March CPS

This plot shows the distribution of occupations among employed respondents in the CPS ASEC from 2014 through 2019 and my survey.

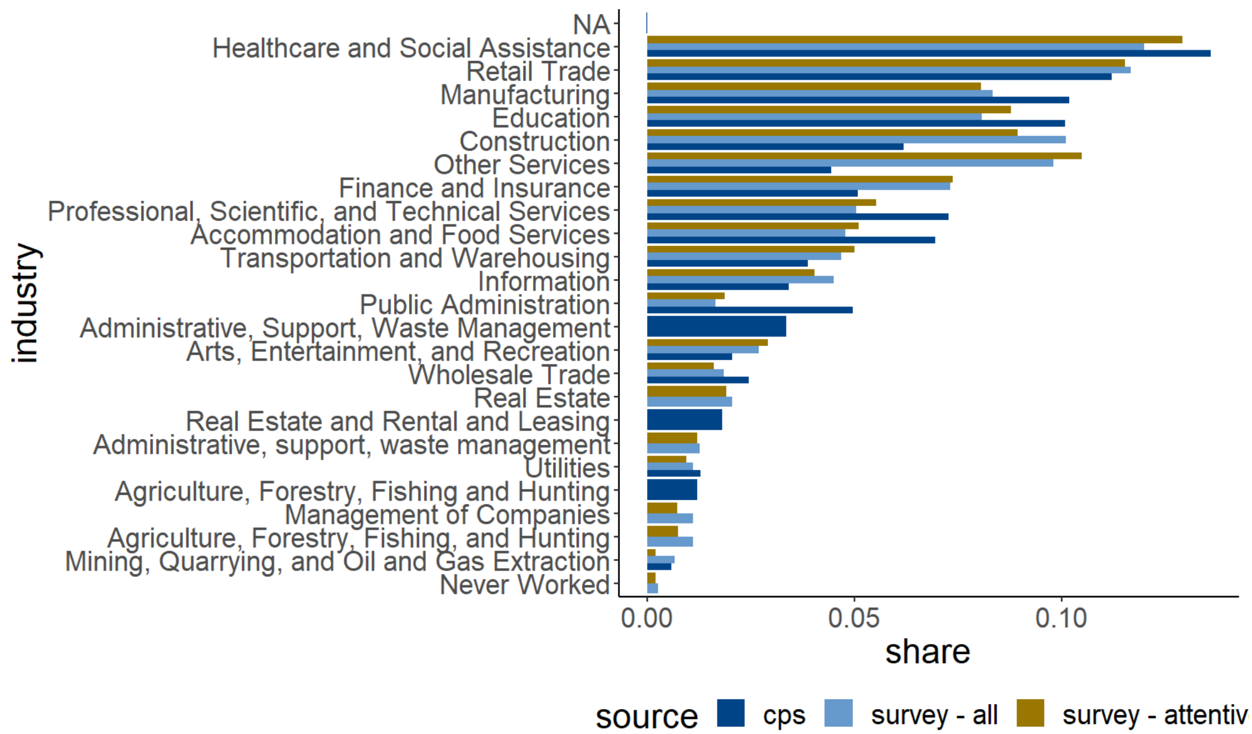


Figure B.11: Industry Distribution: Survey vs. March CPS

This plot shows the distribution of industries among employed respondents in the CPS ASEC from 2014 through 2019 and my survey.

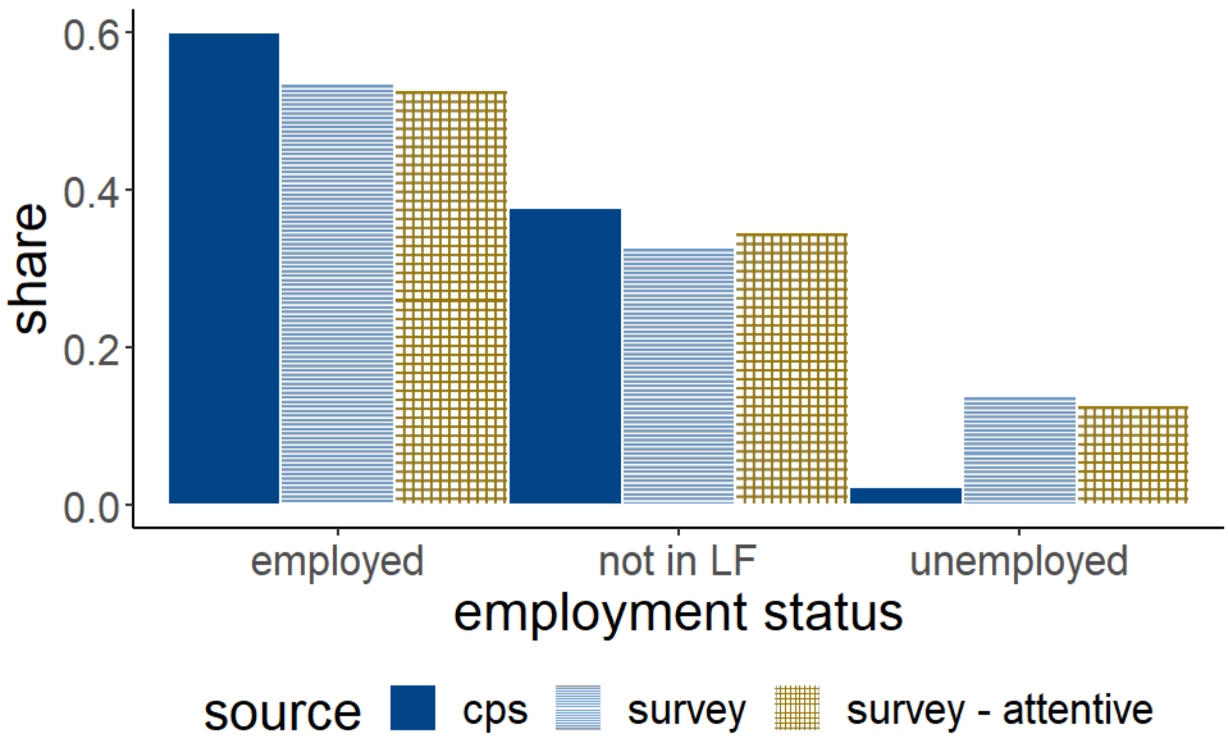


Figure B.12: Employment Status Distribution: Survey vs. March CPS

This plot shows the distribution of employment status among respondents in the monthly CPS averaged over 2022.

B.3 Data Quality

A primary concern with online surveys is that respondents may be inattentive and not provide answers based on true preferences. I include several attention checks within my survey and find that the majority of respondents are attentive, and rates of attention are similar to incentivized job choice experiments found in the literature.

The simplest check for inattentive respondents is to look for people who complete the survey too quickly. Figure B.13 shows the distribution of the time taken to complete the survey in minutes. The average respondent completed the survey in 10.6 minutes, and the median respondent completed the survey in 7.6 minutes. There is a long right tail in the distribution of response times, but this is not concerning, as respondents may stop the survey midway and return to it later.

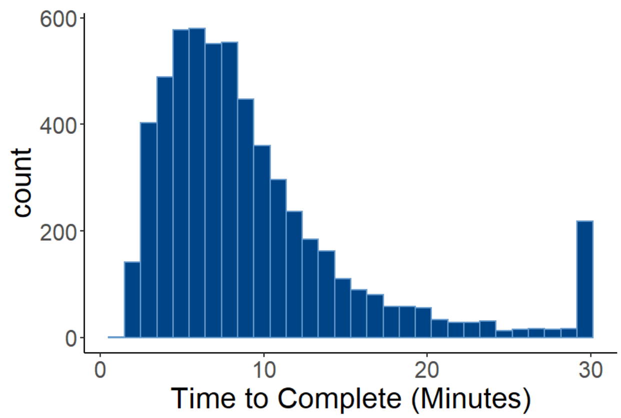


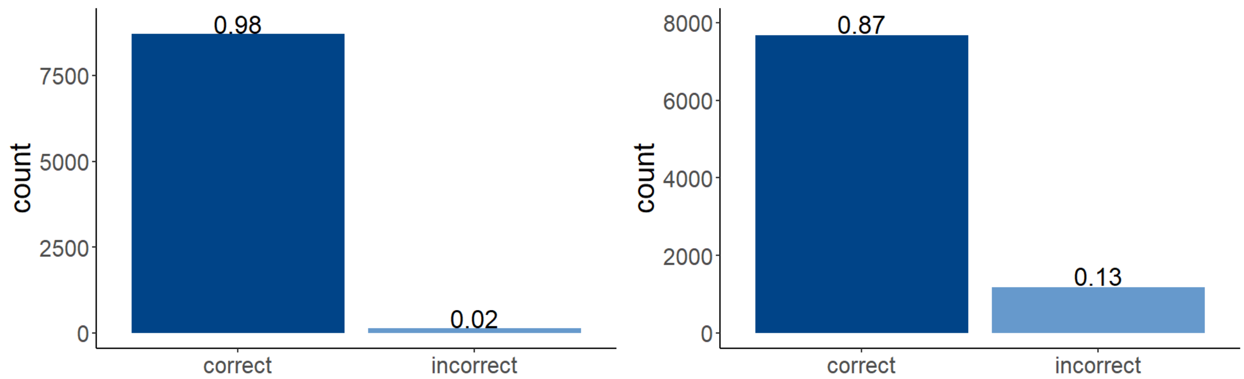
Figure B.13: Distribution of Survey Completion Time

This plot shows the distribution of time taken to complete my survey in minutes. Completion times are truncated at 30 minutes. The average completion time is 10.6 minutes, and the median is 7.6 minutes.

My survey included three attention checks, which were placed at the beginning, middle, and end of the survey instrument. Attention checks are a common method in survey design to distinguish low-effort respondents, whose responses may be discarded or down-weighted in the ultimate analysis.[34]

At the beginning and end of the survey, I had two basic attention checks. During the demographic information section, I included a question that simply asks respondents to write the number "13" in a text box. Responses to this question are shown in Figure B.14 Panel a. At the end of the survey, among the questions about gender attitudes, I included a multiple choice question with an agreement scale, where the question asks respondents to select "disagree." Responses to this question are shown in Figure B.14 Panel b. For both questions, the vast majority of respondents passed the attention check. As is expected given respondent fatigue, the rate of correct responses was lower for the attention check at the end of the survey.

[34] Alvarez et al. (2019) found that respondents who failed attention checks completed surveys faster, had a higher incidence of "don't know" responses, and provided lower-intensity responses regarding attitudes and behavior.



(a) Text Entry (Beginning)

(b) Multiple Choice (End)

Figure B.14: Attention Checks

These plots show the share of survey respondents answering the attention check questions correctly and incorrectly. In the text entry question, shown in Panel a, respondents are given a text entry box and instructed *"As a data quality check, please type the number 13 in the box."*. In the multiple choice question, shown in Panel b, respondents are given a multiple choice scale from strongly agree to strongly disagree and instructed *"Please select 'disagree' for data quality control."*

I also included an attention check within the hypothetical job choice conjoint, where respondents saw a choice between two jobs that differed only in their wages. As we see in Figure B.15, 85% of respondents choose the higher wage job. This is a similar rate of inattention to that found by Mas and Pallais (2017), who found that 14.5% of individuals chose the lower-paying job given a choice between two otherwise identical jobs to apply for. It is reassuring that the rates of inattention are similar, given Mas and Pallais (2017) had an incentivized choice between actual jobs and my survey is purely hypothetical and not incentivized. Results of my survey are similar whether or not I include respondents that failed one or more attention check.

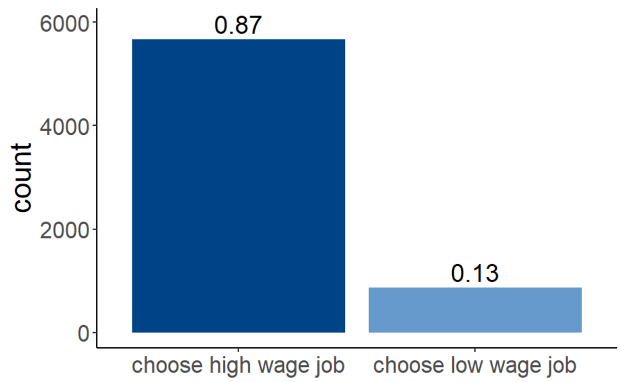


Figure B.15: Hypothetical Job Choice Attention Check

This plots show the share of survey respondents who choose the higher and lower wage job in a choice where the two jobs are identical except for the wage. This attention check occurs amid the other job choice questions at a randomized position.

I further assessed respondent attentiveness by evaluating the internal consistency of choices in the hypothetical job choice conjoint. First, I compared the choices of individual respondents who saw the same question twice. Because the job attributes and wages are randomized for five of the six questions that respondents saw, a small fraction of respondents saw the same question twice. If respondents were paying attention and answering according to a well-behaved utility function, they should have chosen the same alternative when faced with the same choice multiple times. In Table B.1, we see that 53 respondents saw the exact same choice more than once, and of those, 41 respondents (77%) made the same choice both times, while 12 respondents (23%) made a different choice.

Table B.1: Repeated Choice Consistency

	Count	Share
different choice	8	0.13
same choice	52	0.87
Total	60	1.00

This table shows the number and shares of respondents who made the same choice when they saw an identical pair of options in the job choice conjoint multiple times.

To include more data points, I also check for consistency across questions where individuals chose between jobs with the same attributes twice, but possibly with different wages. I present a brief example below to show how to check for consistency when wage pairs differ.

Suppose an individual is choosing between the jobs below, and denote by WTP_a the willingness to pay for attribute a. If $WTP_a > 0$, a job with attribute a is preferred, and if

$WTP_a < 0$, a job without attribute a is preferred.

	job 1	job 2
attribute a	1	0
wage	w1	w2

Below, I enumerate what each possible choice and wage difference implies about WTP_a:

job chosen	wage difference	implication
1	$w1 < w2$	$WTP_a \geq w2 - w1 > 0$
1	$w2 < w1$	$WTP_a \geq w2 - w1 < 0$
2	$w1 < w2$	$WTP_a \leq w2 - w1 > 0$
2	$w2 < w1$	$WTP_a \leq w2 - w1 < 0$

We see that each choice implies an upper or lower bound for WTP_a. If the observed choices reveal multiple lower or multiple upper bounds, they are consistent (this means the respondent chose the job with the same attribute both times). If the observed choices reveal a lower and an upper bound, we can test for consistency by checking whether the lower bound is less than or equal to the upper bound.

For instance, if we found that an individual chose job 1 when $w_1 = 1$ and $w_2 = 2$, we would conclude that $WTP_a \geq 1$. If that individual later chose job 2 when $w_1 = 2$ and $w_2 = 1.5$, we would conclude $WTP_a \leq .5$. These choices would be inconsistent, then, as they would imply that $WTP_a \geq 1$ and $WTP_a \leq .5$.

Table B.2 shows the results of this consistency check. Of the 581 respondents who saw two pairs of jobs with the same choice between female shares, but possibly different wages, 360 chose the same female share both times, giving either two lower or two upper bounds for their WTP for that female share. Of the 221 respondents who chose different alternatives and thus produced a lower and upper bound on the WTP, 85% had choices that produced non-overlapping bounds.

Table B.2: Consistency Test for Job Choice Conjoint

Choice	Bounds	Count	Share	Share of Different Job Choosers
chose same job		697	0.74	
chose different jobs	bounds not consistent	21	0.02	0.09
chose different jobs	bounds consistent	219	0.23	0.91

This table enumerates all choices made by respondents who saw the same pair of jobs multiple times possibly with different wages. Choosing the same job both times is consistent. When choosing a different job in each case, a lower and upper bound for the WTP for that pair of attributes is produced. These bounds are consistent if the lower bound is less than the upper bound.

Overall, the survey respondents appear to be relatively attentive. The majority of respondents took a reasonable amount of time to complete the survey and passed most attention checks. In most cases, respondents provided internally consistent answers within the job choice conjoint experiment. The results in the next section include respondents who failed attention checks, but results are nearly identical when they are excluded from the sample. In addition, through the latent preference type model, I will be able to distinguish inattentive respondents that these attention checks might not pick up.

C Estimation

C.1 Calculating the Willingness-to-Pay

Below, I discuss how to convert the regression coefficients into willingness-to-pay estimates. Consider this example: a worker is choosing between jobs 1 and 2, with wages w_1 and w_2, respectively. Job 2 has some attribute X that job 1 does not have. The worker's utility function is

$$U_i = \beta_w \ln(w_j) + \beta X_j + \varepsilon_{ij}, \tag{20}$$

where ε_{ij} follows a type I extreme value distribution.

Then, the probability of choosing job 1 is

$$P(\text{choose job 1}|\text{job 1, job 2}) = \frac{1}{1 + \exp(X\beta + ln(w_2/w_1)\beta_w)}. \tag{21}$$

The worker is then indifferent between the two jobs when this probability is .5, and the difference between the wages exactly cancels out the utility from the amenity

$$.5 = \frac{1}{1 + \exp(X\beta + ln(w_2^*/w_1^*)\beta_w)}. \tag{22}$$

When we rearrange, we get

$$exp(-\beta/\beta_w) = w_2^*/w_1^*. \tag{23}$$

This means that when the ratio between the wages in job 2 and job 1 is exactly equal to $exp(-\beta/\beta_w)$, the worker will be indifferent between the job with the amenity and the job without the amenity. To express this as a percent of the wage in job 1, I take $1 - w_2^*/w_1^*$, so

$$WTP_f = 1 - \exp\left(\frac{-\beta_f}{\beta_w}\right). \tag{24}$$

C.2 Maximum Likelihood Estimation of Latent Class Logit Model

Let H_{iq} denote the prior probability of class q for individual i. Then the likelihood for individual i is

$$P_i = \sum_{q=1}^{Q} H_{iq} P_{i|q}, \tag{25}$$

and the log-likelihood for the sample is

$$\ln L = \sum_{i=1}^{N} \ln P_i = \sum_{i=1}^{N} \ln \left[\sum_{q=1}^{Q} H_{iq} \left(\prod_{t=1}^{T_i} P_{it|q} \right) \right]. \tag{26}$$

I can estimate the parameters either using an EM-type algorithm, where the class probabilities H_{iq} and the parameters β are estimated iteratively, or estimate them jointly in a one-step maximum likelihood. Here, I estimate all parameters jointly in one step. I select the number of classes Q by evaluating the Aikake Information Criterion (AIC) and Bayesian Information Criterion (BIC) and running a 10-fold cross validation on the log-likelihood.

C.3 Demographic Conjoint Results

Table C.3: Conjoint Coefficients

	All	Female	Male
log wage	27.56*	28.54*	26.77*
	[26.78; 28.35]	[27.45; 29.64]	[25.62; 27.91]
0% female	−1.06*	−1.25*	−0.85*
	[−1.15; −0.97]	[−1.37; −1.12]	[−0.98; −0.71]
10% female	−0.68*	−0.86*	−0.47*
	[−0.76; −0.59]	[−0.98; −0.75]	[−0.59; −0.34]
20% female	−0.42*	−0.50*	−0.32*
	[−0.51; −0.33]	[−0.62; −0.38]	[−0.46; −0.19]
30% female	−0.29*	−0.36*	−0.19*
	[−0.37; −0.20]	[−0.48; −0.25]	[−0.31; −0.06]
40% female	−0.13*	−0.19*	−0.06
	[−0.22; −0.04]	[−0.32; −0.07]	[−0.19; 0.07]
60% female	0.08	0.06	0.09
	[−0.01; 0.17]	[−0.06; 0.19]	[−0.04; 0.23]
70% female	−0.06	−0.00	−0.12
	[−0.14; 0.03]	[−0.12; 0.11]	[−0.25; 0.00]
80% female	−0.06	0.00	−0.15*
	[−0.15; 0.02]	[−0.12; 0.12]	[−0.28; −0.02]
90% female	−0.19*	−0.06	−0.32*
	[−0.27; −0.10]	[−0.18; 0.05]	[−0.45; −0.20]
100% female	−0.41*	−0.37*	−0.47*
	[−0.50; −0.32]	[−0.49; −0.25]	[−0.60; −0.34]
30% have kids	0.03	0.01	0.07
	[−0.03; 0.10]	[−0.08; 0.10]	[−0.03; 0.16]
70% have kids	0.05	0.13*	−0.04
	[−0.02; 0.12]	[0.04; 0.23]	[−0.15; 0.06]
30% under 40	0.09*	0.08	0.10*
	[0.02; 0.16]	[−0.01; 0.17]	[0.00; 0.20]
70% under 40	−0.17*	−0.20*	−0.15*
	[−0.24; −0.10]	[−0.29; −0.11]	[−0.25; −0.05]
lefthand job	0.15*	0.14*	0.16*
	[0.12; 0.17]	[0.10; 0.18]	[0.12; 0.20]
Num. obs.	29972	16495	13334
Num. indiv.	2772	1525	1234

* Null hypothesis value outside 95% credible interval.
Omitted baseline categories are 50% female, 50% have kids, and 50% under 40.
Each individual sees 7-10 choices. Thirteen individuals chose to self-describe gender.

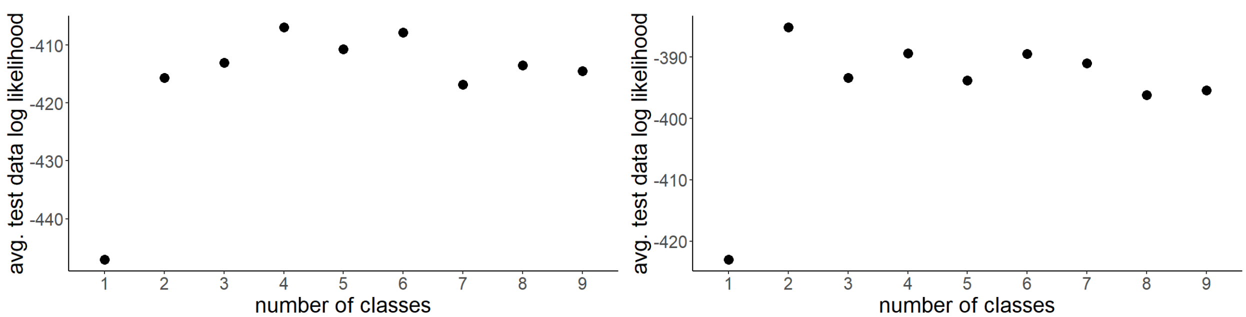
coefs	all	female	male	noba	ba	young	old	nok
10% female	-0.025	-0.033	-0.017	-0.024	-0.026	-0.021	-0.027	-0.02
	(-0.029,-0.021)	(-0.039,-0.027)	(-0.022,-0.011)	(-0.029,-0.019)	(-0.033,-0.019)	(-0.028,-0.013)	(-0.032,-0.022)	(-0.032,-
30% female	-0.007	-0.013	-0.001	-0.006	-0.01	-0.005	-0.008	-0.00
	(-0.011,-0.003)	(-0.018,-0.007)	(-0.007,0.004)	(-0.01,-0.001)	(-0.017,-0.004)	(-0.012,0.002)	(-0.013,-0.004)	(-0.014,-
50% female								
70% female	-0.002	0.003	-0.007	-0.001	-0.004	0.005	-0.005	-0.00
	(-0.006,0.002)	(-0.002,0.009)	(-0.013,-0.002)	(-0.006,0.004)	(-0.011,0.003)	(-0.002,0.012)	(-0.01,0)	(-0.00
90% female	-0.004	0.006	-0.015	-0.002	-0.008	0.003	-0.008	-0.00
	(-0.008,0)	(0,0.011)	(-0.021,-0.01)	(-0.007,0.003)	(-0.014,-0.001)	(-0.004,0.01)	(-0.013,-0.003)	(-0.011,-
10% BA	-0.001	-0.003	0.001	0.007	-0.016	0.002	-0.003	-0.00
	(-0.006,0.004)	(-0.009,0.004)	(-0.007,0.008)	(0.001,0.014)	(-0.025,-0.008)	(-0.007,0.01)	(-0.009,0.003)	(-0.008,0
30% BA								
60% BA	-0.005	-0.008	-0.002	-0.014	0.015	-0.006	-0.005	-0.00
	(-0.01,0)	(-0.015,-0.001)	(-0.009,0.005)	(-0.02,-0.008)	(0.006,0.023)	(-0.015,0.003)	(-0.011,0.001)	(-0.009,0
30% kids	0.003	0.005	-0.001	0.003	0.006	0	0.004	0.00
	(-0.009,0.014)	(-0.011,0.021)	(-0.018,0.016)	(-0.012,0.018)	(-0.012,0.024)	(-0.021,0.02)	(-0.01,0.018)	(-0.006,0
50% kids								
70% kids	0.004	0.004	0.003	-0.002	0.013	0.012	-0.001	0.00
	(-0.008,0.015)	(-0.011,0.019)	(-0.014,0.02)	(-0.016,0.013)	(-0.005,0.031)	(-0.007,0.032)	(-0.016,0.013)	(-0.006,0
30% <40	0.003	0.005	0	0.003	0.001	-0.009	0.009	0.00
	(-0.002,0.007)	(-0.002,0.011)	(-0.006,0.007)	(-0.002,0.009)	(-0.006,0.008)	(-0.017,-0.001)	(0.004,0.015)	(-0.002,0
50% <40								
70% <40	-0.01	-0.01	-0.011	-0.01	-0.01	0.003	-0.018	-0.01
	(-0.015,-0.006)	(-0.016,-0.003)	(-0.018,-0.004)	(-0.016,-0.004)	(-0.018,-0.002)	(-0.005,0.011)	(-0.024,-0.013)	(-0.02,-0
lefthand job	0.003	0.001	0.004	0.002	0.004	0.004	0.002	0.00
	(0.001,0.004)	(-0.001,0.003)	(0.002,0.006)	(0,0.004)	(0.001,0.006)	(0.001,0.007)	(0,0.004)	(0,0.0
num. obs.	11630	6125	5465	6276	3030	4483	7147	163
num. indiv.	1990	935	1048	1046	505	767	1223	310

Table C.4: Estimated WTPs, Limited to Respondents Who Pass All Attention Checks

C.4 Heterogeneous Preferences

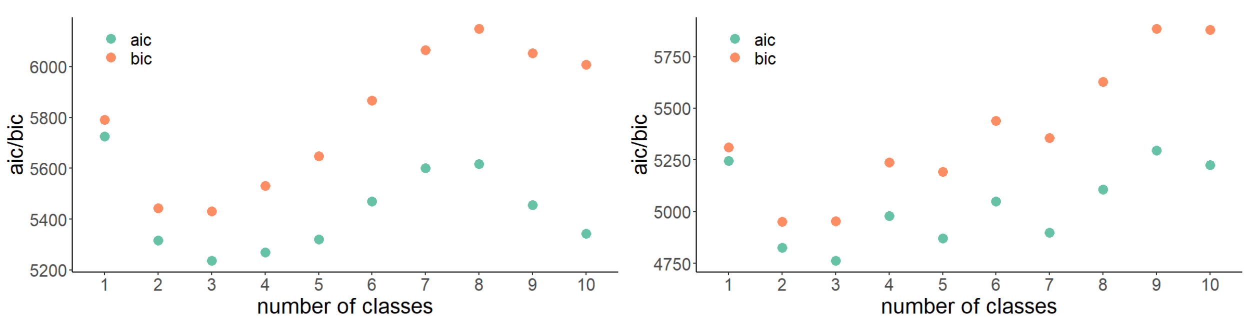
For both genders, I find that a portion of the sample comes from what I term an inattentive class. The inattentive class is distinguished by very small (1.75 for women and -2.45 for men) coefficients on the wage and noisy coefficients on the demographic characteristics. These wage coefficients imply that given a choice between two jobs with one job having a 10% lower wage, a woman from the inattentive class will choose the higher wage job with a probability of 54%, and a man from the inattentive class will choose the higher wage job with a probability of 44%.

These estimates suggest that the respondents classified as inattentive are essentially answering the hypothetical job choice questions at random: we would expect that even if respondents do not care about the demographic composition of the job, they should choose higher wage jobs on average, while this group does not. I estimate that 28.5% of women and 16.8% of men belong to the inattentive class. The estimated logit coefficients for every class, including the inattentive class, are shown in Appendix B Tables C.5 and C.7. In the remainder of this analysis, I omit the inattentive group for both genders.



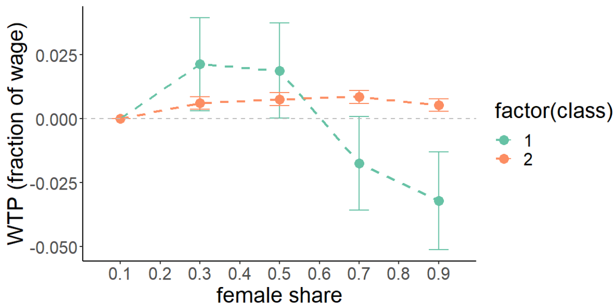
(a) Female (b) Male

Figure C.16: Avg. Test Log Likelihood in 10-fold Cross-Validation

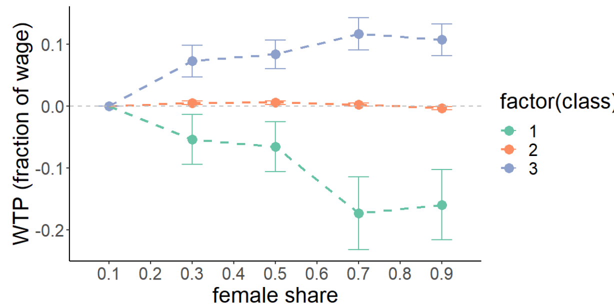


Female Male

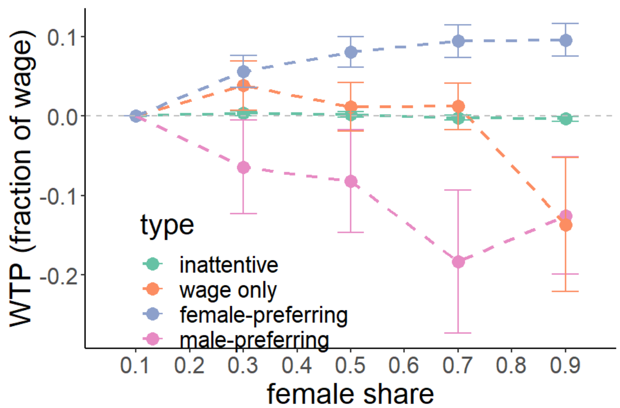
Figure C.17: Akaike Information Criterion and Bayesian Information Criterion



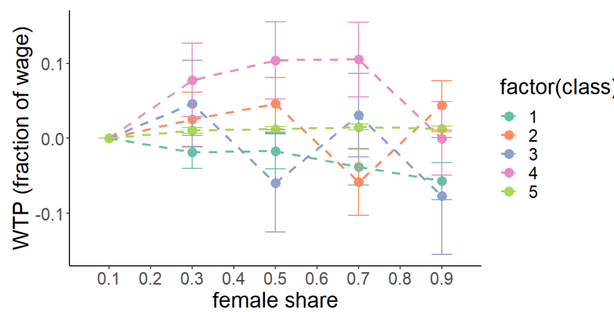
2 Types



3 Types (Drop Inattentive)

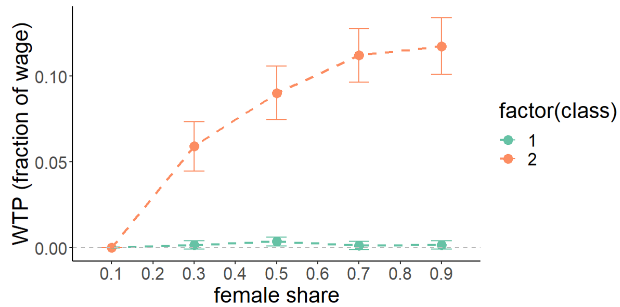


4 Types

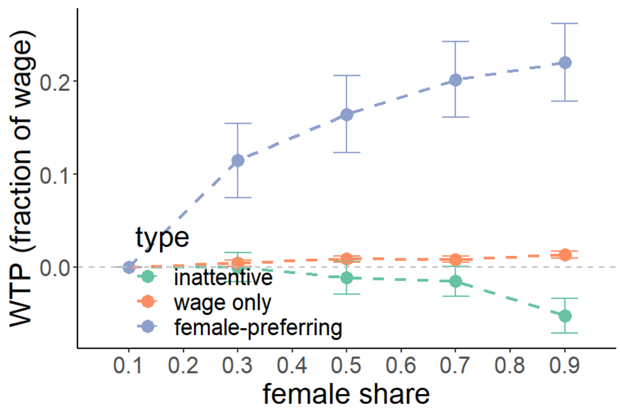


5 Types

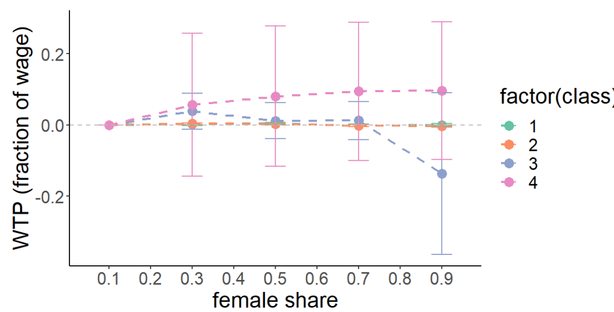
Figure C.18: Heterogeneous WTPs for Men, 2 to 5 Classes



2 types



3 types



4 types

Figure C.19: Heterogeneous WTPs for Women, 2 to 4 Classes

	wage-preferring	female-preferring
log(w)	181.255	15.283
	(168.747,193.763)	(14.229,16.338)
0% female	-0.842	-1.993
	(-1.126,-0.558)	(-2.171,-1.815)
10% f	-0.423	-1.498
	(-0.681,-0.165)	(-1.665,-1.331)
20% f	-0.09	-0.861
	(-0.384,0.205)	(-1.032,-0.69)
30% f	-0.129	-0.656
	(-0.389,0.132)	(-0.819,-0.492)
40% f	-0.082	-0.352
	(-0.377,0.213)	(-0.525,-0.178)
60% f	0.106	0.048
	(-0.18,0.392)	(-0.121,0.217)
70% f	-0.065	0.051
	(-0.329,0.199)	(-0.109,0.211)
80% f	-0.137	0.1
	(-0.433,0.16)	(-0.067,0.267)
90% f	-0.202	0.012
	(-0.458,0.054)	(-0.148,0.171)
100% f	-0.463	-0.495
	(-0.754,-0.173)	(-0.662,-0.329)
30% have kids	-0.062	0.078
	(-0.267,0.144)	(-0.049,0.205)
60% have kids	-0.043	0.25
	(-0.253,0.167)	(0.122,0.378)
30% <40	-0.079	0.194
	(-0.282,0.124)	(0.068,0.319)
70% <40	-0.123	-0.295
	(-0.326,0.08)	(-0.42,-0.17)
class share	0.52	0.48

Table C.5: Female Latent Class Logit Coefficients

Table C.6: Willingness-to-Pay by Class, Female Latent Class Logit

coefs	wage-preferring	female-preferring
0% female	-0.005	-0.139
	(-0.006,-0.003)	(-0.155,-0.123)
10% female	-0.002	-0.103
	(-0.004,-0.001)	(-0.117,-0.089)
20% female	0	-0.058
	(-0.002,0.001)	(-0.07,-0.046)
30% female	-0.001	-0.044
	(-0.002,0.001)	(-0.055,-0.032)
40% female	0	-0.023
	(-0.002,0.001)	(-0.035,-0.012)
50% female		
60% female	0.001	0.003
	(-0.001,0.002)	(-0.008,0.014)
70% female	0	0.003
	(-0.002,0.001)	(-0.007,0.014)
80% female	-0.001	0.006
	(-0.002,0.001)	(-0.004,0.017)
90% female	-0.001	0.001
	(-0.003,0)	(-0.01,0.011)
100% female	-0.003	-0.033
	(-0.004,-0.001)	(-0.044,-0.022)
30% kids	0	0.005
	(-0.001,0.001)	(-0.003,0.013)
50% kids		
70% kids	0	0.016
	(-0.001,0.001)	(0.008,0.025)
30% <40	0	0.013
	(-0.002,0.001)	(0.004,0.021)
50% <40		
70% <40	-0.001	-0.019
	(-0.002,0)	(-0.028,-0.011)

Note: This table shows the willingness-to-pay, as a fraction of the wage, for each attribute for the two preference classes among women estimated using the latent class logit model described in Section 3.3.2. 95% confidence intervals are in parentheses. The logit model coefficients are shown in Appendix Table C.5.

	wage-preferring	female-preferring	male-preferring
log(w)	181.212	26.159	9.295
	(165.782,196.642)	(23.016,29.302)	(7.898,10.692)
0% female	-1.336	-0.28	-1.344
	(-1.659,-1.014)	(-0.69,0.13)	(-1.604,-1.084)
10% f	-0.59	0.062	-0.99
	(-0.884,-0.297)	(-0.315,0.439)	(-1.231,-0.75)
20% f	-0.223	-0.144	-0.694
	(-0.55,0.104)	(-0.559,0.271)	(-0.941,-0.447)
30% f	-0.287	0.183	-0.505
	(-0.591,0.018)	(-0.195,0.561)	(-0.749,-0.262)
40% f	0.081	-0.124	-0.19
	(-0.254,0.416)	(-0.522,0.275)	(-0.434,0.054)
60% f	0.245	-0.451	0.26
	(-0.079,0.569)	(-0.866,-0.036)	(0.01,0.511)
70% f	0.184	-1.178	0.112
	(-0.122,0.491)	(-1.569,-0.787)	(-0.12,0.344)
80% f	0.186	-1.296	0.045
	(-0.126,0.497)	(-1.72,-0.872)	(-0.199,0.288)
90% f	0.207	-2.514	-0.021
	(-0.1,0.513)	(-3.01,-2.018)	(-0.253,0.212)
100% f	0.093	-2.593	-0.289
	(-0.218,0.405)	(-3.132,-2.055)	(-0.527,-0.051)
50% have kids	-0.064	0.147	-0.206
	(-0.301,0.173)	(-0.17,0.464)	(-0.396,-0.015)
60% have kids	0.017	0.087	-0.392
	(-0.228,0.262)	(-0.204,0.378)	(-0.577,-0.206)
50% <40	-0.192	-0.115	-0.087
	(-0.427,0.044)	(-0.427,0.197)	(-0.274,0.099)
70% <40	-0.226	-0.301	-0.374
	(-0.451,-0.001)	(-0.596,-0.006)	(-0.562,-0.185)
class share	0.518	0.29	0.192

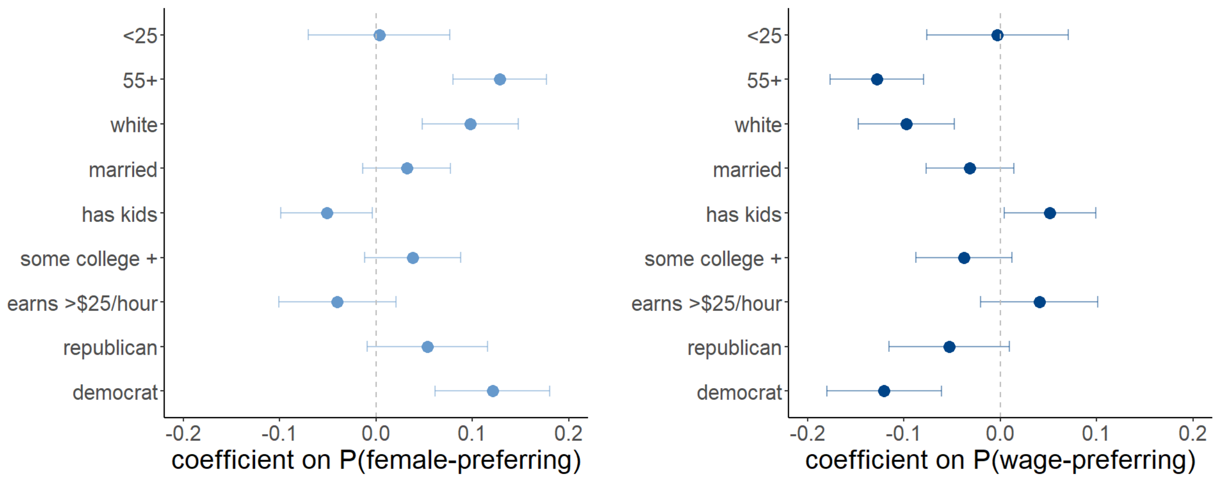
Table C.7: Male Latent Class Logit Coefficients

Table C.8: Willingness-to-Pay by Class, Male Latent Class Logit

coefs	wage-preferring	female-preferring	male-preferring
0% female	-0.007	-0.156	-0.011
	(-0.009,-0.006)	(-0.196,-0.115)	(-0.027,0.005)
10% female	-0.003	-0.112	0.002
	(-0.005,-0.002)	(-0.146,-0.079)	(-0.012,0.017)
20% female	-0.001	-0.078	-0.006
	(-0.003,0.001)	(-0.109,-0.047)	(-0.021,0.01)
30% female	-0.002	-0.056	0.007
	(-0.003,0)	(-0.085,-0.027)	(-0.007,0.021)
40% female	0	-0.021	-0.005
	(-0.001,0.002)	(-0.048,0.006)	(-0.02,0.011)
50% female			
60% female	0.001	0.028	-0.017
	(0,0.003)	(0.001,0.054)	(-0.033,-0.001)
70% female	0.001	0.012	-0.046
	(-0.001,0.003)	(-0.013,0.037)	(-0.062,-0.03)
80% female	0.001	0.005	-0.051
	(-0.001,0.003)	(-0.021,0.031)	(-0.068,-0.034)
90% female	0.001	-0.002	-0.101
	(-0.001,0.003)	(-0.027,0.023)	(-0.122,-0.079)
100% female	0.001	-0.032	-0.104
	(-0.001,0.002)	(-0.058,-0.005)	(-0.127,-0.081)
30% kids			
50% kids	0	-0.022	0.006
	(-0.002,0.001)	(-0.044,-0.001)	(-0.006,0.018)
70% kids	0	-0.043	0.003
	(-0.001,0.001)	(-0.065,-0.021)	(-0.008,0.014)
30% <40			
50% <40	-0.001	-0.009	-0.004
	(-0.002,0)	(-0.03,0.011)	(-0.016,0.008)
70% <40	-0.001	-0.041	-0.012
	(-0.002,0)	(-0.063,-0.019)	(-0.023,0)

Note: This table shows the willingness-to-pay, as a fraction of the wage, for each attribute for the two preference classes among men estimated using the latent class logit model described in Section 3.3.2. 95% confidence intervals are in parentheses. The logit model coefficients are shown in Appendix Table C.7.

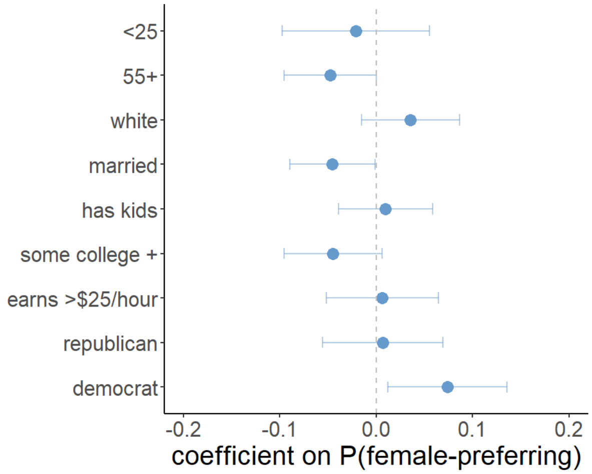
C.5 Observable Heterogeneity



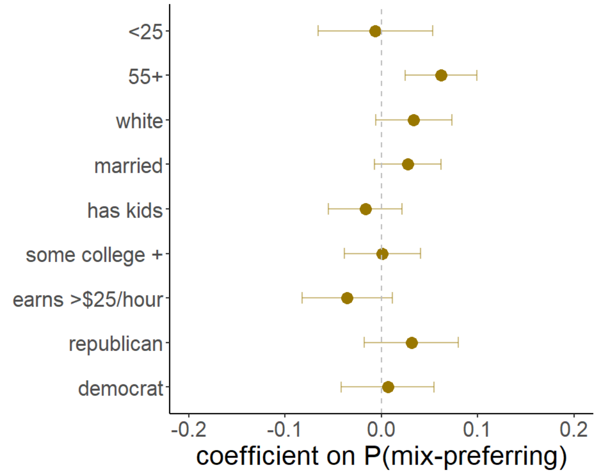
(a) Female-Preferring Class

(b) Wage-Preferring Class

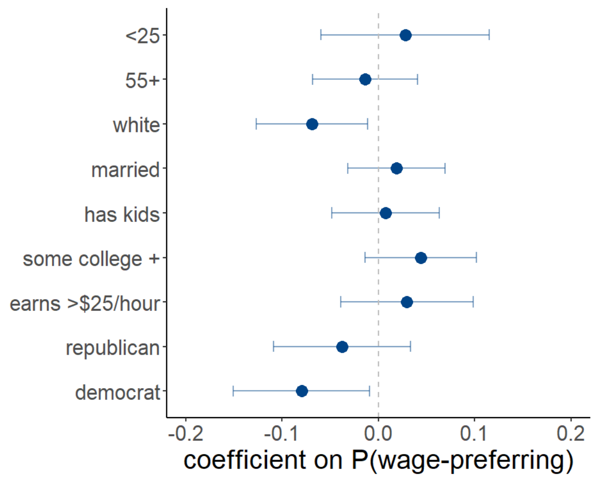
Figure C.20: Correlates of Preference Class: Women



(a) Female-Preferring Class

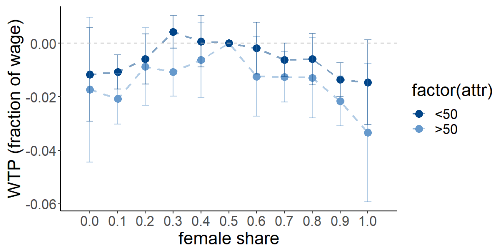


(b) Male-Preferring Class

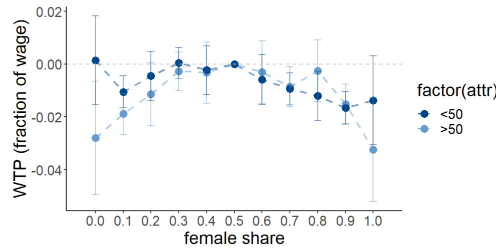


(c) Wage-Preferring Class

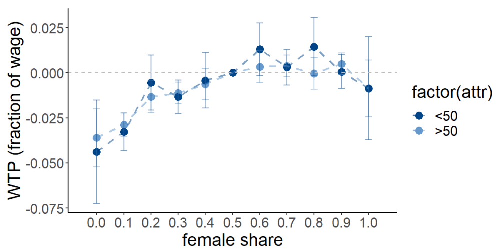
Figure C.21: Correlates of Preference Class: Men



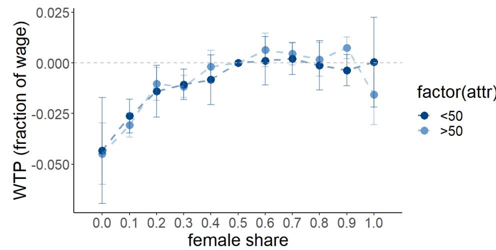
Men: CPS Occupation F Share



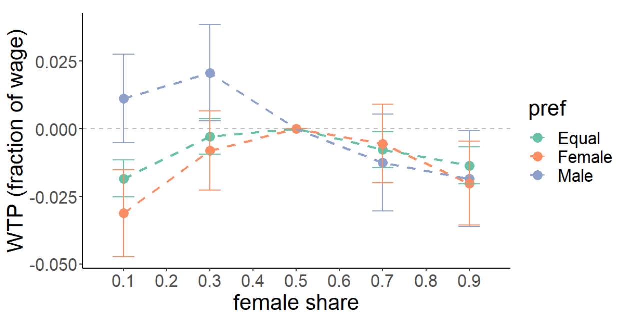
Men: Reported Employer F Share



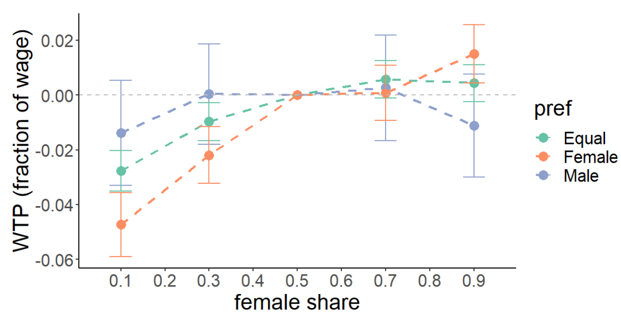
Women: CPS Occupation F Share



Women: Reported Employer F Share

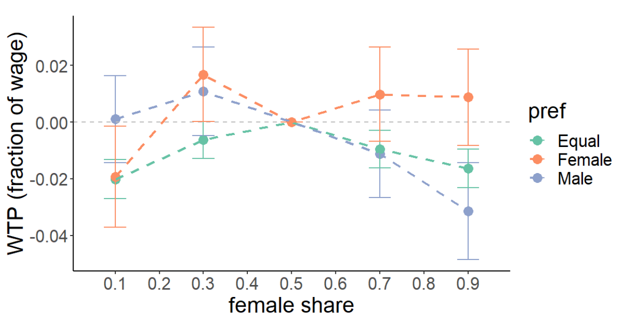


(a) Men

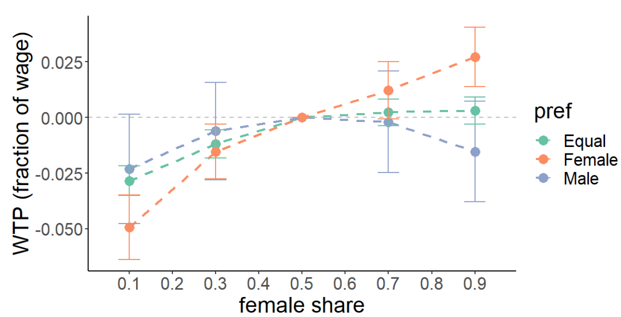


(b) Women

Figure C.23: More Satisfied with Coworkers: Male or Female

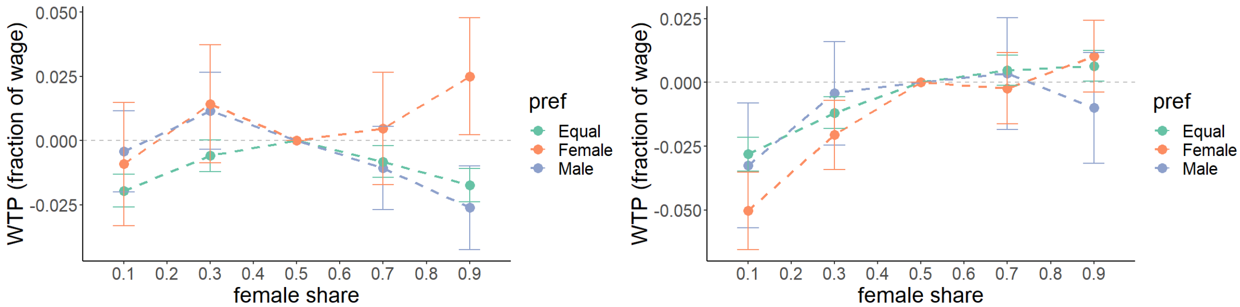


(a) Men



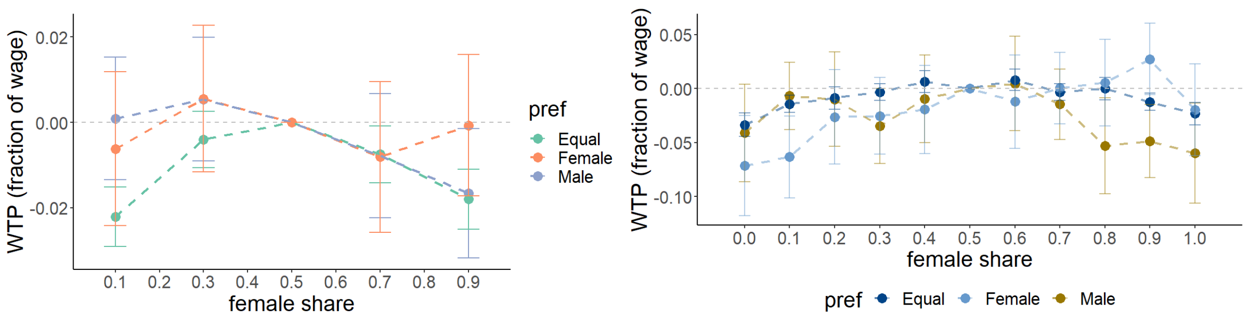
(b) Women

Figure C.24: More Satisfied with Work Environment: Male or Female



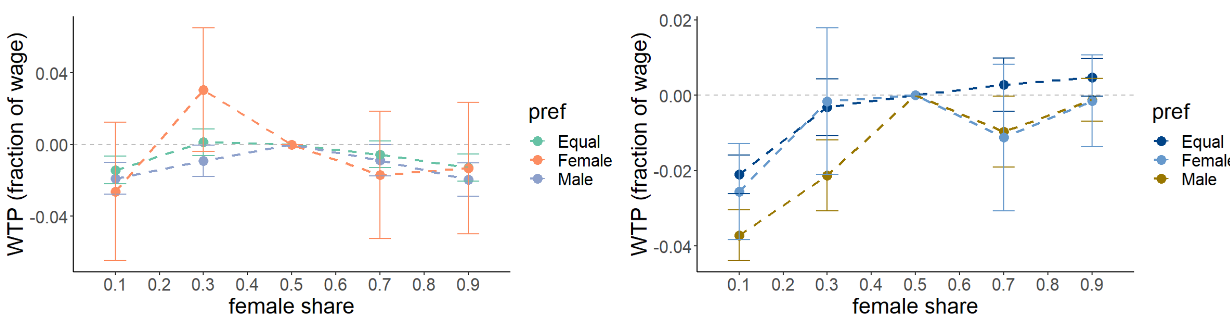
(a) Men (b) Women

Figure C.25: More Satisfied with Tasks: Male or Female



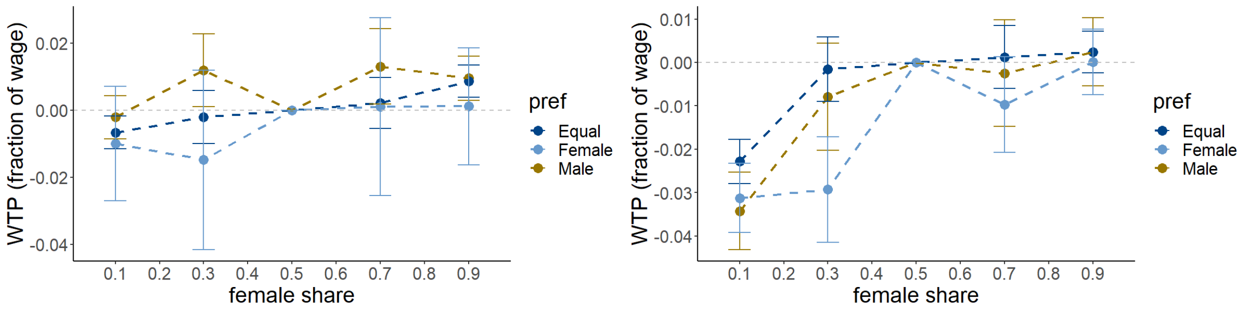
(a) Men (b) Women

Figure C.26: More Satisfied with Schedule: Male or Female



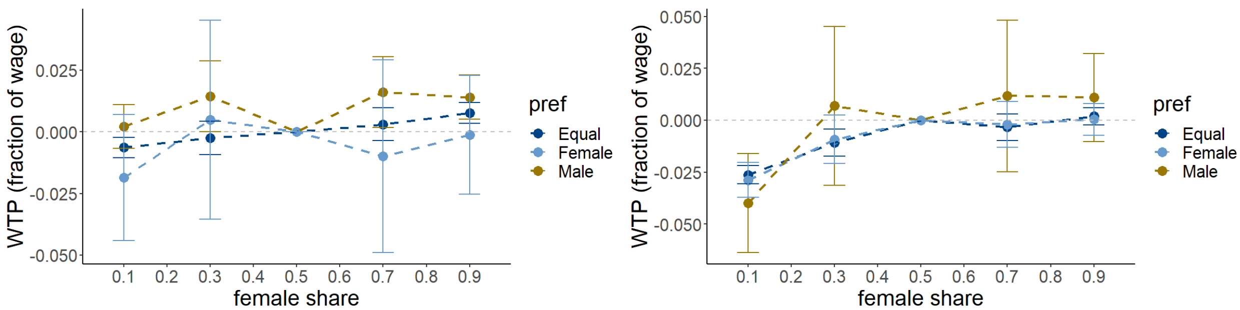
(a) Men (b) Women

Figure C.27: Earn More: Male or Female



(a) Men (b) Women

Figure C.28: More Likely to be Promoted: Male or Female



(a) Men (b) Women

Figure C.29: Family Would Prefer: Male or Female

Table C.9: Willingness-to-Pay, Limited to Attention Check Passers

coefs	all	female	male	noba	ba	young	old	noki
10% female	-0.025	-0.033	-0.017	-0.024	-0.026	-0.021	-0.027	-0.02
	(-0.029,-0.021)	(-0.039,-0.027)	(-0.022,-0.011)	(-0.029,-0.019)	(-0.033,-0.019)	(-0.028,-0.013)	(-0.032,-0.022)	(-0.032,-
30% female	-0.007	-0.013	-0.001	-0.006	-0.01	-0.005	-0.008	-0.00
	(-0.011,-0.003)	(-0.018,-0.007)	(-0.007,0.004)	(-0.01,-0.001)	(-0.017,-0.004)	(-0.012,0.002)	(-0.013,-0.004)	(-0.014,-
50% female								
70% female	-0.002	0.003	-0.007	-0.001	-0.004	0.005	-0.005	-0.00
	(-0.006,0.002)	(-0.002,0.009)	(-0.013,-0.002)	(-0.006,0.004)	(-0.011,0.003)	(-0.002,0.012)	(-0.01,0)	(-0.00
90% female	-0.004	0.006	-0.015	-0.002	-0.008	0.003	-0.008	-0.00
	(-0.008,0)	(0,0.011)	(-0.021,-0.01)	(-0.007,0.003)	(-0.014,-0.001)	(-0.004,0.01)	(-0.013,-0.003)	(-0.011,-
10% BA	-0.001	-0.003	0.001	0.007	-0.016	0.002	-0.003	-0.00
	(-0.006,0.004)	(-0.009,0.004)	(-0.007,0.008)	(0.001,0.014)	(-0.025,-0.008)	(-0.007,0.01)	(-0.009,0.003)	(-0.008,0
30% BA								
60% BA	-0.005	-0.008	-0.002	-0.014	0.015	-0.006	-0.005	-0.00
	(-0.01,0)	(-0.015,-0.001)	(-0.009,0.005)	(-0.02,-0.008)	(0.006,0.023)	(-0.015,0.003)	(-0.011,0.001)	(-0.009,0
30% kids	0.003	0.005	-0.001	0.003	0.006	0	0.004	0.00
	(-0.009,0.014)	(-0.011,0.021)	(-0.018,0.016)	(-0.012,0.018)	(-0.012,0.024)	(-0.021,0.02)	(-0.01,0.018)	(-0.006,0
50% kids								
70% kids	0.004	0.004	0.003	-0.002	0.013	0.012	-0.001	0.00
	(-0.008,0.015)	(-0.011,0.019)	(-0.014,0.02)	(-0.016,0.013)	(-0.005,0.031)	(-0.007,0.032)	(-0.016,0.013)	(-0.006,0
30% <40	0.003	0.005	0	0.003	0.001	-0.009	0.009	0.00
	(-0.002,0.007)	(-0.002,0.011)	(-0.006,0.007)	(-0.002,0.009)	(-0.006,0.008)	(-0.017,-0.001)	(0.004,0.015)	(-0.002,0
50% <40								
70% <40	-0.01	-0.01	-0.011	-0.01	-0.01	0.003	-0.018	-0.01
	(-0.015,-0.006)	(-0.016,-0.003)	(-0.018,-0.004)	(-0.016,-0.004)	(-0.018,-0.002)	(-0.005,0.011)	(-0.024,-0.013)	(-0.02,-0
lefthand job	0.003	0.001	0.004	0.002	0.004	0.004	0.002	0.00
	(0.001,0.004)	(-0.001,0.003)	(0.002,0.006)	(0,0.004)	(0.001,0.006)	(0.001,0.007)	(0,0.004)	(0,0.0
num. obs.	11630	6125	5465	6276	3030	4483	7147	163
num. indiv.	1990	935	1048	1046	505	767	1223	310

C.6 Channels and Robustness

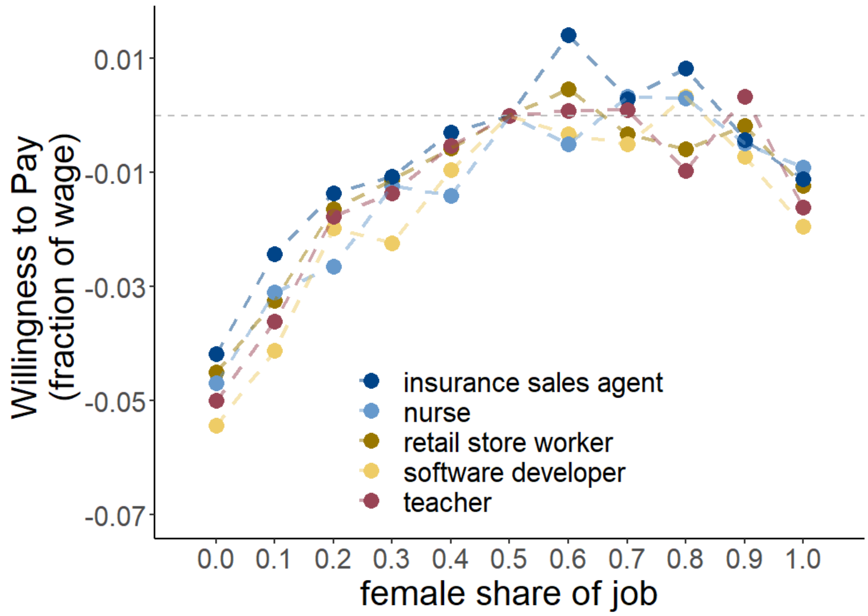


Figure C.30: WTP for Female Share by Occupation in Workplace Choice, Female

Note: This figure plots the willingness-to-pay for each possible female share for women, split by the occupation listed in the hypothetical workplace choice.

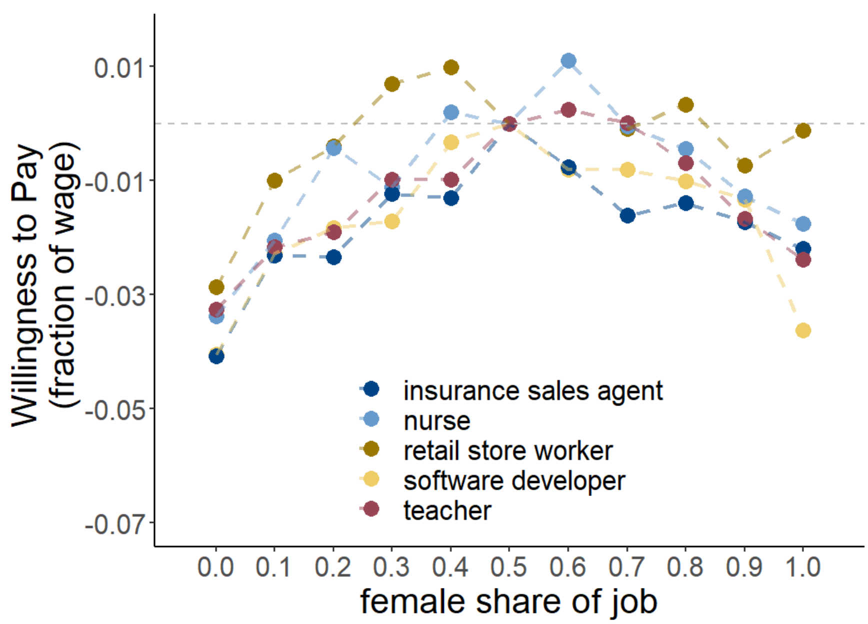


Figure C.31: WTP for Female Share by Occupation in Workplace Choice, Male

Note: This figure plots the willingness-to-pay for each possible female share for men, split by the occupation listed in the hypothetical workplace choice.

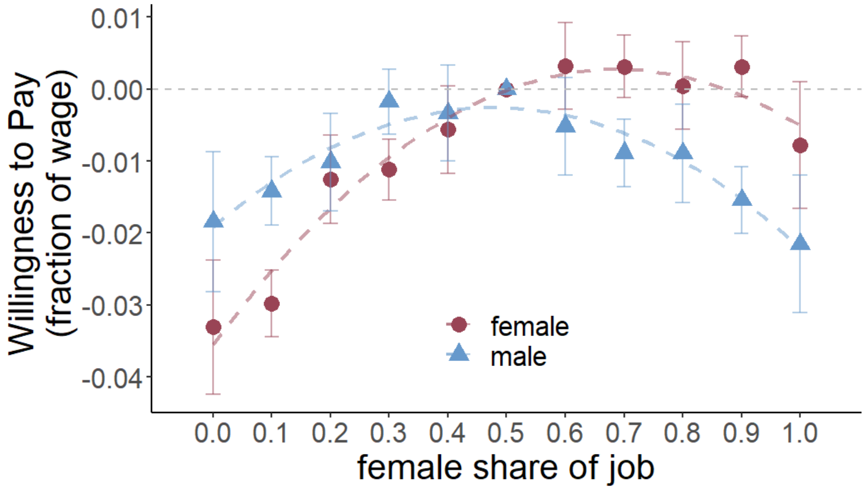


Figure C.32: WTP for Female Share, No Occupation Listed in Choice

Note: This figure plots the willingness-to-pay for each possible female share for men and women in the hypothetical choice with no occupation listed.

C.7 The Partial Equilibrium Effect of Composition Preferences

In this section, I will use the model outlined above to determine which parameters will influence the effect of composition preferences on gender sorting when wages are fixed exogenously. I find that the effect of composition preferences will be large if gender composition preferences are large relative to other determinants of occupation choice. This can occur under two conditions: either workers are very responsive to changing occupation characteristics and switch occupations easily (i.e. low variance in the idiosyncratic preference shock) or the willingness-to-pay for preferred gender composition is large.

As noted above, the model will be in a sorting equilibrium when the following system of equations holds:

$$\ell^*_{1,g} = Pr\left[log(w_{1,g}) + h_g(\ell_{1,f}/\ell_1) + \varepsilon_1 > log(w_{2,g}) + h_g(\ell_{2,f}/\ell_2) + \varepsilon_2\right], \qquad g = \{f, m\}$$

To understand this condition more concretely, assume that the idiosyncratic preference draw follows a Type I Extreme Value (TIEV) distribution with shape parameter η. The parameter η determines how responsive workers are to changing occupational conditions: if η is large, the variance of the preference shocks is high, which makes occupation choices relatively sticky and workers less responsive to changing occupational conditions. If η is small, the variance of the preference shock is low, which makes occupation choices relatively flexible and workers more responsive to changing occupational conditions. Under this assumption, the following equations characterize the sorting equilibrium:

$$\underbrace{\eta \cdot \log\left(\frac{\ell_{1g}}{1-\ell_{1g}}\right)}_{\text{pref shock util diff.}} - \underbrace{[\log(w_{1g}) - \log(w_{2g})]}_{\text{wage util diff.}} = \underbrace{[h_g(\frac{\ell_{1f}}{\ell_{1f}+\ell_{1m}}) - h_g(\frac{1-\ell_{1f}}{2-\ell_{1f}-\ell_{1m}})]}_{\text{comp. utility diff.}}, \quad g = f, m.$$

This implies that at a sorting equilibrium, the difference between the two preference shocks $\varepsilon_2 - \varepsilon_1$ for the marginal worker (who is indifferent between the two occupations) is $\eta \cdot \log\left(\frac{\ell_{1g}}{1-\ell_{1g}}\right)$.

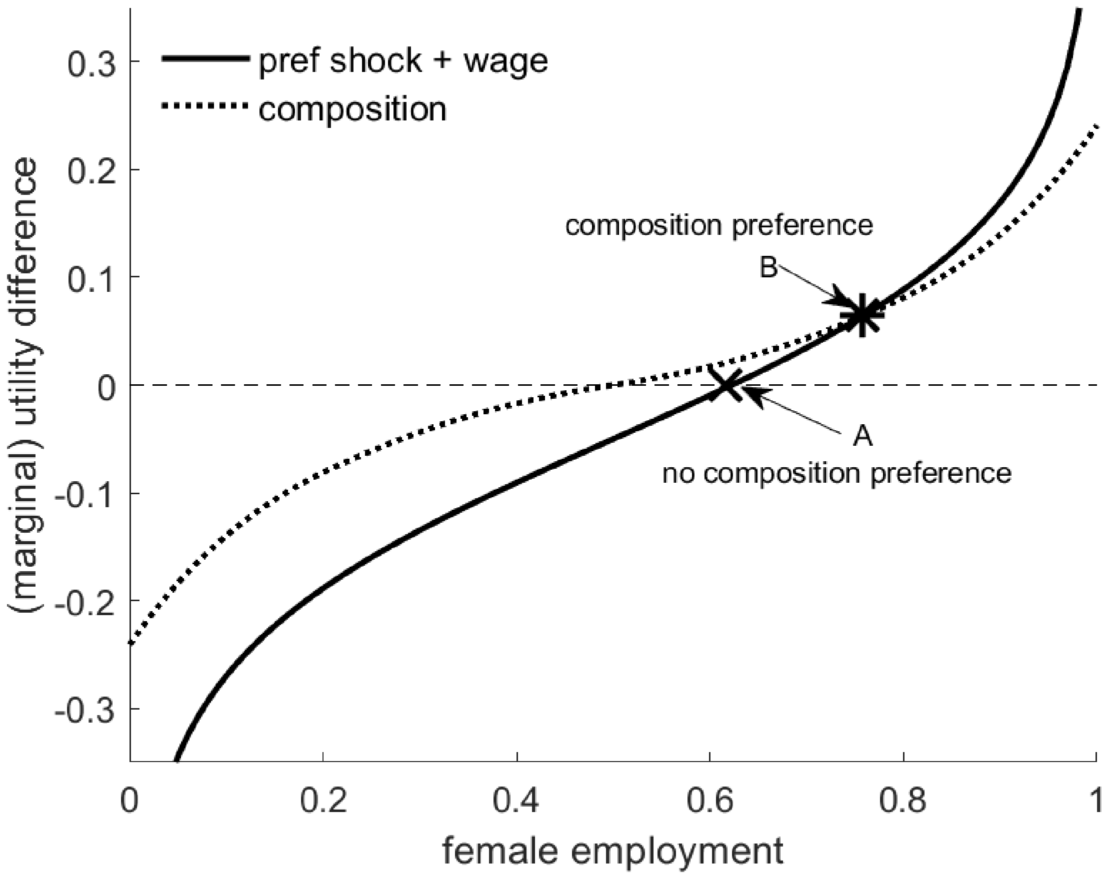


Figure C.33: Equilibrium condition with composition preferences

Note: This plot shows the preference shock utility difference for the marginal worker (solid line) and the composition utility difference (dotted line) against female employment in occupation 1.

Figure C.33 illustrates this equilibrium condition graphically. The solid line in this figure shows the preference shock difference for the marginal worker as a function of female employment in occupation 1 plus the wage utility difference, $\varepsilon_2 - \varepsilon_1 = \eta \cdot \log\left(\frac{\ell_{1g}}{1-\ell_{1g}}\right) + [\log(w_{2f}) - \log(w_{1f})]$. This line illustrates that, for instance, if 40% of women work in occupation 1 ($\ell_{1f} = 0.4$), the marginal female worker, who is indifferent between the two occupations, will have a preference utility difference of $\varepsilon_2 - \varepsilon_1 = -0.1$.

Visualizing this sorting equilibrium condition for one gender illustrates that the slope of the preference shock difference relative to the slope of the composition and wage utility difference will determine the size of the effect of composition preference and whether multiple equilibria, and thus tipping points, are possible. In Figure C.33, I plot the female marginal preference shock utility difference plus wage difference (solid line) and difference in composition utility (dashed line) against female employment in occupation 1, with the wage difference ($w_{1f} - w_{2f}$) fixed at 5% and male employment in occupation 1 fixed at 0.5. Because the wage difference is fixed, it does not affect the slope of either line, but determines the level of the preference shock and wage utility line.

With composition preferences, a sorting equilibrium occurs where the marginal preference shock utility difference is equal to the composition utility difference. In this example, this occurs at point B, where $\ell_{1,f} = 0.8$: at this point, the difference in preference shocks and log wages for the marginal worker is equal to the difference in composition utility between the two occupations. Without composition preferences, a sorting equilibrium occurs where the preference and wage difference intersects the x-axis. In this example, this would occur at point A, where $\ell_{1,f} = 0.6$: at this point, the difference in preference shocks for the marginal worker is equal to the log wage difference.

The effect of composition preferences on the sorting equilibrium will be larger when composition preferences are steeper relative to preference shocks and wage differences. As the composition preference function increases in slope, so too will the slope of the difference in composition utility between the two occupations. This is is illustrated in Figure C.34. With relatively weaker composition preferences (dotted line), the sorting equilibrium occurs at point B as in Figure C.33 with 75% of women working in occupation 1, relative to 60% at point A without composition preferences. With relatively stronger composition preferences (star line), the sorting equilibrium occurs at point C with over 90% of women working in occupation 1.

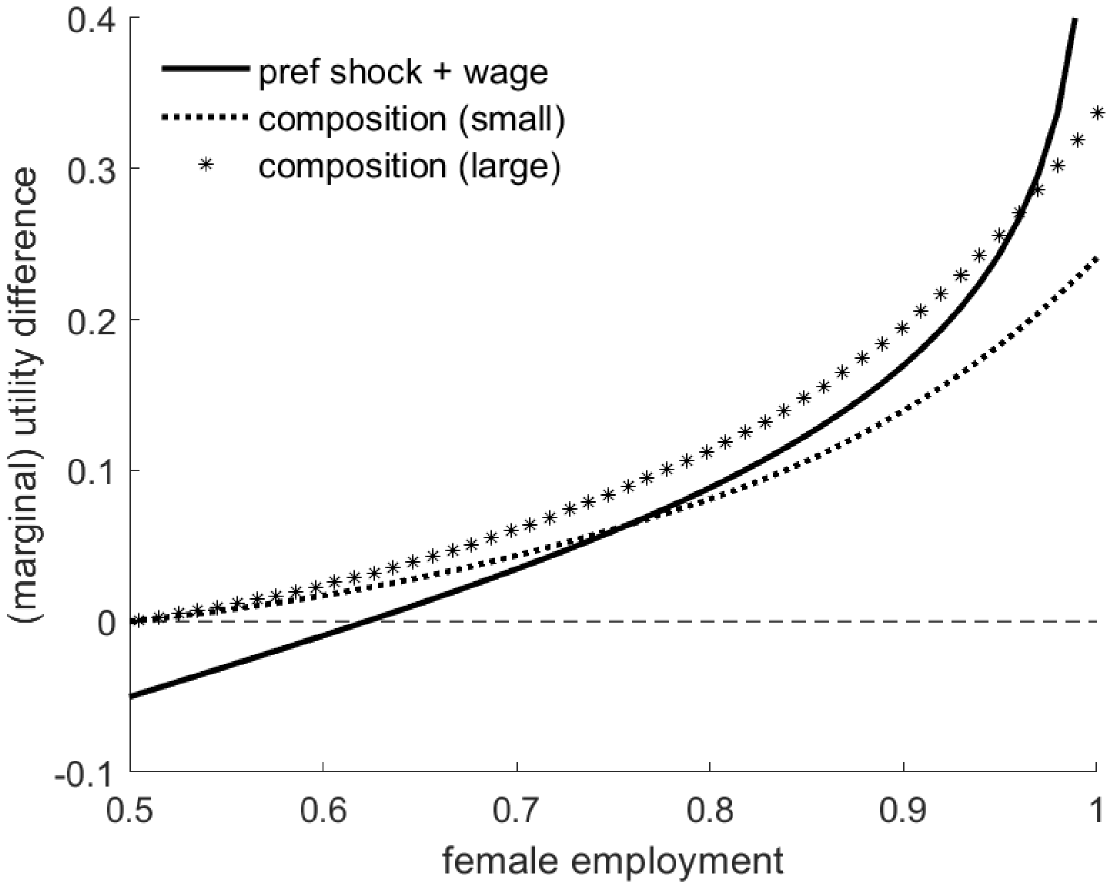


Figure C.34: Equilibrium condition with composition preferences of varying slope

Note: This plot shows the preference shock utility difference for the marginal worker (solid line) and the composition utility difference (dotted line) against female employment in occupation 1.

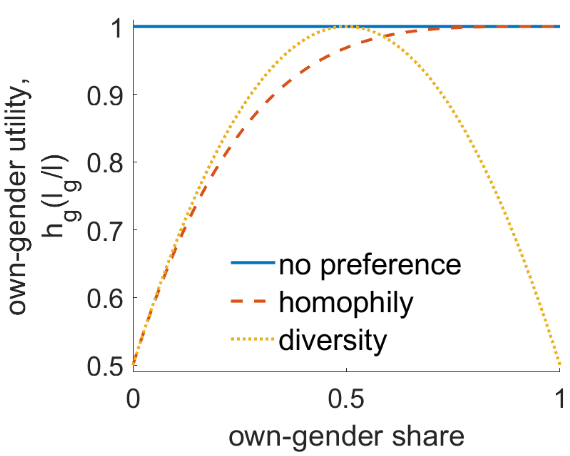
For multiple equilibria to occur, these lines must intersect multiple times.

To assess how gender composition preferences can affect occupational segregation, I set wages exogenously and solve for gender sorting in equilibrium with and without gender composition preferences. I find that the effect of gender composition preferences on sorting will depend on both gender sorting due to exogenous wage differences and the shape and size of the gender composition preference function.

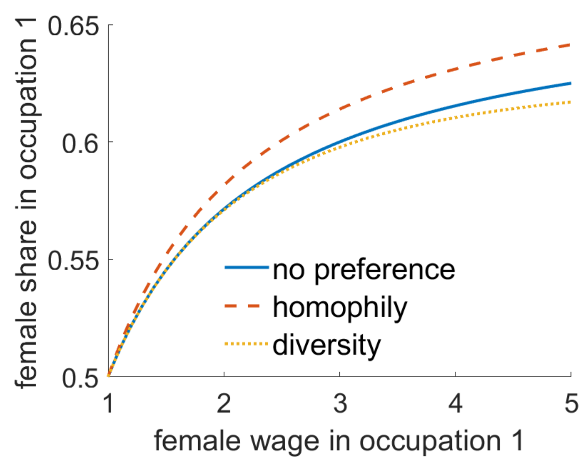
In this exercise, I exogenously vary the underlying level of gender sorting by fixing the male and female wages in occupation 2 and the male wage in occupation 1 and varying the relative female wage in occupation 1. I assume that preference shocks are *i.i.d.* type I extreme value for both genders and occupations. This gives the following functional form for the share of gender g workers in occupation o:

$$\frac{l_{o,g}}{l_g} = \frac{exp(log(w_{o,g}) + h_g(f_o))}{\sum_{o=1,2} exp(log(w_o, g) + h_g(f_o))}. \tag{27}$$

I illustrate the importance of the shape of gender composition preferences by plotting the female share in occupation 1 under three possible functional forms for gender composition preferences. These preferences are plotted in Figure C.35 Panel A. I first consider no preferences, represented by the solid blue line. With no gender composition preference, a worker's utility is unaffected by the gender composition of their occupation. I next consider homophilic preferences, represented by the red dashed line. With homophilic preferences, workers prefer occupations that have a higher share of their own gender. Finally, I consider preferences for diversity, represented by the yellow dotted line. With preferences for diversity, workers most prefer occupations that are half male and half female, and dislike occupations that are segregated in favor of either gender. In this exercise, I assume that both men and women have identically shaped composition preferences but prefer their own gender in the homophilic case.



(a) Example Gender Composition Preferences



(b) Simulated Female Share in Occupation 1

Figure C.35: Modeled Female Shares with Varying Wages and Preferences

Note: These plots illustrate a numerical exercise showing the effect of gender composition preferences in partial equilibrium. In Panel (a), I plot three possible shapes for the female share preference function $h_g(f)$. In Panel (b), I plot the female share in occupation 1 for the three different preference shapes as I vary the female wage in occupation 1 from 1 to 5, holding the female wage in occupation 2 and the male wage in occupations 1 and 2 fixed at 1. The red dashed line shows that homophilic preferences amplify sorting, and the yellow dotted line shows that diversity-preferring preferences dampen sorting.

Figure C.35 Panel B illustrates that homophilic preferences will increase gender sorting due to exogenous wage differences while preferences for diversity will decrease gender sorting due to exogenous wage differences. This figure plots the female share in occupation 1 for each of the preference forms described above as the female wage in occupation 1 varies from 1 to 5. Since wages in occupation 1 for men and occupation 2 for men and women are fixed to 1, at each wage in this plot the female share in occupation 1 will be above 50%. Without gender composition preferences (blue line), the direct wage effect causes more women to join occupation 1 as its relative wage rises from 1 to 5. With homophilic composition preferences, this sorting is amplified: the female share in occupation 1 is higher than it would be without composition preferences, and the difference will increase as the wage gap increases. With diversity-loving preferences, this sorting is dampened: the female share in occupation 1 is lower than it would be without composition preferences.

Gender composition preferences will have more of an effect on sorting when they are larger in scale. In Figure C.35, we see that when the wages in occupation 1 and 2 are relatively close for women, diversity-loving preferences have almost no effect on sorting. This is because the scale of this preference is very small at female shares near 50%. Similarly, as the female wage in occupation 1 grows, the effect of both non-zero gender composition preferences grows, as the utility effect of the preferences increases at more extreme levels of gender sorting.

There are three main takeaways from the baseline model of composition preferences and occupation choice. First, composition preferences will interact with pre-existing gender differences to amplify or dampen sorting. That is, there must be some outside gender difference for composition preferences to matter. This could come from productivity differences, gender discrimination, or task preferences, for example. Next, the shape of composition preferences is important, and determines how much composition preferences change sorting relative to a world without composition preferences. Finally, the scale of composition preferences is also important, with stronger preferences implying a larger effect on sorting.

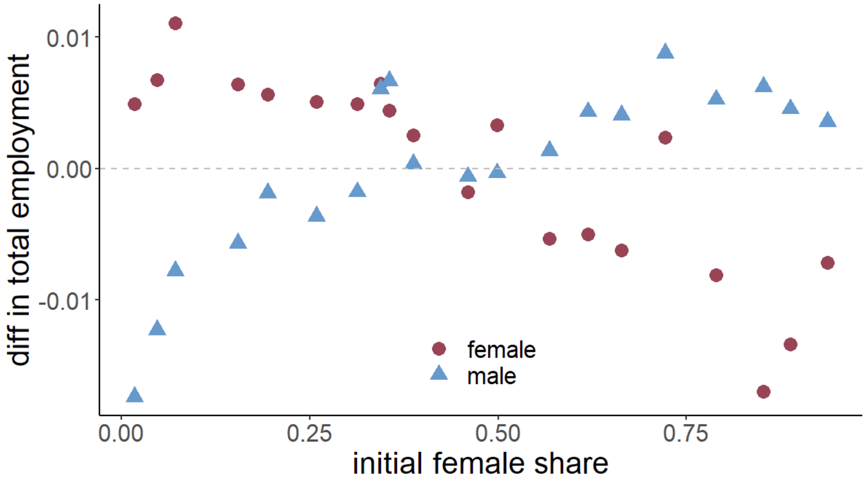


Figure C.36: Changes in Occupational Employment in Social Planner's Solution

Note: This figure shows results the social planner's solution to maximize welfare by reallocating workers across occupations. Here, I use average valuations by gender. This figure displays a binscatter of the difference in employment by sex in an occupation (social planner - true) against the true female share of the occupation. Bins are weighted by employment.