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April 2022(revised Aug 2023) No: 1404

Warwick Economics Research Papers

ISSN 2059-4283 (online)

ISSN 0083-7350 (print)

The Distribution of the Gender Wage Gap: An Equilibrium Model*

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August 6th, 2023

Abstract

We develop an equilibrium model of the labor market to investigate the joint evolution of gender gaps in labor force participation and wages. We do this overall and by task-based occupation and skill, which allows us to study distributional effects. We structurally estimate the model using data from Mexico over a period during which women's participation increased by fifty percent. We provide new evidence that male and female labor are closer substitutes in high-paying analytical task-intensive occupations than in lower-paying manual and routine task-intensive occupations. We find that demand trends favored women, especially college-educated women. Consistent with these results, we see a widening of the gender wage gap at the lower end of the distribution, alongside a narrowing at the top. We derive own and cross-occupation wage elasticities of labor supply varying with skill, gender and time, and our counterfactual estimates demonstrate that ignoring the countervailing effects of equilibrium wage adjustments on labor supplies, as is commonly done in the literature, can be misleading. We find that increased appliance availability was the key driver of increases in the participation of unskilled women, and fertility decline a key driver for skilled women. The growth of appliances acted to widen the gender wage gap and the decline of fertility to narrow it. We also trace equilibrium impacts of growth in college attainment, which was more rapid among women, and of emigration, which was dominated by unskilled men.

JEL classifications: J16, J21, J24, J31, O33
Keywords: Female labor force participation, gender wage gap, technological change, supply-demand framework, task-based approach, wage distribution, wage inequality

*We are grateful to Brian Bell, Chris Bollinger, Carlos Carrillo-Tudela, Costas Cavounidis, Federico Rossi, James Fenske, Simon Quinn, Climent Quintana-Domeque, Marco Manacorda, John Muellbauer, and seminar and workshop participants at Paris School of Economics, University of Oxford, Universidad del Rosario, LACEA, SAEe, and STEG for their comments, and to Atheendar Venkataramani for many helpful discussions and suggestions. Manuel's research time was funded by ESRC grant ES/M010263/1 to the Human Rights Big Data and Technology Project (hrbdt.ac.uk) at the Human Rights Centre, University of Essex. Sonia's research time was funded partially by ERC Advanced Grant No. 885698 (Evidence-VAW) and partially by the University of Warwick and CAGE.

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1 Introduction

A secular increase in the labor force participation of women (FLFP) is one of the most salient features of the labor market over the last century (Killingsworth and Heckman 1987; Costa 2000; Goldin 2006; Fogli and Veldkamp 2011; Fernández 2013; Goldin and Olivetti 2013). Nevertheless, there is limited evidence of how this massive change in the size and composition of the labor force has altered the wage distribution. Economic theory suggests that, as long as men and women are imperfect substitutes in production, increases in women's labor supply will create greater downward pressure on the wages of women than on the wages of men, and hence widen the gender wage gap. The size of this effect will depend upon the elasticity of substitution between male and female labor. We argue that this elasticity is likely to depend on the task content of the occupation. If occupations are ordered across the wage distribution, the impacts of a rise in women's labor supply on the gender wage gap (and on wage inequality within gender) will vary across the wage distribution.

We structurally estimate an equilibrium model that extends the canonical labor demand-supply model discussed in Katz and Autor (1999) (also see Katz and Murphy 1992; Murphy and Welch 1992; Card and Lemieux 2001), allowing male and female labor to be imperfect substitutes, with the degree of substitution varying with occupational task content. Our model provides a unified framework in which four key channels through which FLFP and the gender wage gap are related are studied simultaneously. In addition to imperfect substitutability between types of labor, this includes gender- and skill-biased technical change (that shifts relative demand), trends in marriage, fertility, uptake of home appliances, legislative protection of women's economic rights (non-wage variables that shift relative labor force participation), and skill-upgrading and emigration (changes in demographic composition that shift potential relative labor supplies). In contrast to much of the related literature providing partial equilibrium (PE) estimates, we provide general equilibrium (GE) estimates, allowing labor supplies to respond to changes in the equilibrium wage structure, see Section 2. This appears to be the first attempt to analyze the distribution of gender wage and participation gaps considering demand and supply channels simultaneously in an equilibrium framework.

To capture distributional effects on the gender wage gap, we allow the elasticity of substitution between male and female labor to vary by task-based occupation. We similarly allow the elasticity of substitution between skilled and unskilled labor to vary by occupation. Following Autor, Levy, and Murnane (2003), we categorize occupations as intensive in analytical, routine, or manual tasks. We demonstrate that our synthesis of the traditional labor demand-supply model with the task-based approach is a useful way to analyze distributional effects. This literature has investigated differences in substitution of new technology or capital for labor across task-based occupations. We instead investigate how the arrival of new female labor

substitutes for male labor in different occupations, also allowing for occupational demand shifts that vary by gender and skill.[1]

Our equilibrium approach contrasts with a large literature on women's labor supply that typically takes demand as given, see Keane, Todd, and Wolpin (2011) for a survey. At the other end, most studies of the wage structure assume labor supply is inelastic to wages, an assumption inconsistent with the evidence (Killingsworth and Heckman 1987; Blundell and Macurdy 1999; Keane 2011; Bargain and Peichl 2016), though Johnson and Keane (2013) is one exception in this regard.[2,3] We contribute to the literature on gender gaps in wages and participation by endogenizing labor force participation. We derive own and cross-occupation wage elasticities of labor supply for skilled and unskilled men and women, and study their variation over time. We find that the aggregate elasticity conceals meaningful differences by occupation. Our counterfactual analysis shows that accounting for countervailing labor supply responses to equilibrium wage adjustments (at the gender-occupation-skill level) helps explain the observed distributional patterns.

Our third contribution is that we detail a model-based approach to identification with potentially wide applicability (see Section 5.3) and provide an efficient computational algorithm that encourages re-use and scalability of the framework.[4] Leveraging the tractability of our model we implement Monte Carlo simulations to analyse the performance of the estimator under demand shocks of varying size (Appendix Section C Figures D.6 to D.8). This is relevant to recent debates concerning the validity and robustness of supply and demand model estimates (Ottaviano and Peri 2008; Card 2012; Ottaviano and Peri 2012; Manacorda, Manning, and Wadsworth 2012; Dustmann, Schönberg, and Stuhler 2016; Havranek et al. 2022). We are also able to evaluate the OLS and IV estimators compared to true elasticity parameter values.[5]

We apply this framework to investigate the joint evolution of women's labor

1. Many studies of the allocation of female vs. male labor assume they are perfect substitutes (e.g., Hsieh et al. 2019; Morchio and Moser 2021). Only a small handful of studies has estimated the elasticity of substitution by gender and in none of these studies does it vary by task-based occupation. Among studies with nested-CES systems, Cunha, Heckman, and Schennach (2010) is an example of a study that allows heterogeneity in the elasticity of substitution within the same layer across human capital input types in the formation of non-cognitive and cognitive skills.

2. For instance, see, Katz and Murphy (1992), Katz and Autor (1999), Card and Lemieux (2001), Borjas (2003), Ottaviano and Peri (2012), Manacorda, Manning, and Wadsworth (2012), and Borjas, Grogger, and Hanson (2012).

3. A meta-analysis by Havranek et al. (2022) showed that, of 59 published studies that estimate a skill substitution parameter within the supply and demand framework, 79.7% did regression analysis based on demand-side optimality conditions only, using an OLS or fixed effects estimator. Restricting to studies published in top-5 journals, this share is 87.5%.

4. The solution and estimation code is available for other users on our project website and a comprehensive discussion is in Appendix B.

5. Previous discussions have focused on the robustness of the elasticity estimate to specific modeling choices, like the functional form assumption on relative demand trends (Borjas, Grogger, and Hanson 2012).

force participation and the wage structure in Mexico. Between 1990 and 2014, Mexico experienced one of the largest increases in the FLFP rate in the world (Ñopo 2012; The World Bank 2012) from close to 35% in 1989 to about 58% in 2014, rising from 4.7 to 14.7 million (Figure 1). A motivation for our analysis is that changes in the gender wage gap over this period varied dramatically across the wage distribution (Figure 2). The unconditional gap widened by more than 30 percentage points (pp) at the 5th percentile of the wage distribution, while narrowing by 18 pp at the 95th percentile. This cannot be explained by compositional changes- we conduct a decomposition of the gender wage gap across percentiles of the distribution (Firpo, Fortin, and Lemieux 2009, 2018), which suggests that changes in the gap are primarily wage structure changes (Figure 3).[6]

Our structural estimates are able to explain the distributional patterns in the data. Our first result is that male and female labor are closer substitutes in high-wage analytical task-intensive occupations (elasticity of 2.94) than in lower-wage manual or routine task-intensive occupations (elasticities of 1.09 and 1.28, respectively). This is a new channel through which gender-specific supply and demand shocks within and across occupation and skill groups can impact the male and female wage distributions. It contributes to explaining why the increase in women's LFP exerted greater downward pressure on wages at the lower than at the upper end of the distribution (Figure 6).

We also find that the elasticity of substitution between skilled and unskilled labor is smaller in analytical and routine tasks (1.43) than in manual tasks (elasticity of 3.82). This implies an erosion of the skill premium, although primarily for men because our estimates indicate that changes in relative demand favored women. Indeed, an increase in the relative demand for women has a larger impact on the gender wage gap than any other factor we consider; see the counterfactuals in Figure 10. The increase holds across occupation and skill groups but is skill-biased and thus has significant distributional effects, helping to explain the contraction of the gender wage gap at the top of the wage distribution. Relative demand trends may reflect, inter alia, the impacts of structural change (Goldin 1994; Akbulut 2011; Ngai and Petrongolo 2017; Olivetti and Petrongolo 2016), non-neutral technological change (Galor and Weil 1996; Blau and Kahn 1997; Weinberg 2000; Rendall 2017; Black and Spitz-Oener 2010; Pitt, Rosenzweig, and Hassan 2012; Aguayo-Tellez et al. 2013; Rendall 2013), growing demand for non-cognitive skills, in some of which women may have an advantage (Deming 2017; Cortes, Jaimovich, and Siu 2018), the marketization of home production (Lup Tick and Oaxaca 2010; Akbulut 2011; Olivetti and Petrongolo 2014; Ngai and Petrongolo 2017), or declining discrimination

6. This does not imply that educational upgrading did not play a role. The decompositions are conducted in partial equilibrium, with wages assumed as fixed. However, we shall show that in the equilibrium model, which allows wages to respond to labor supplies, the female-biased increase in college completion rates plays an important role through the wage structure.

against women (Hsieh et al. 2019).

Our finding of skill-biased technical change is in line with findings elsewhere, including in the U.S., where it has been argued to explain rising income inequality (Katz and Autor 1999; Acemoglu and Autor 2011). However, Mexico experienced a compression of wage inequality among men (a decline in the college premium) (Lustig, Lopez-Calva, and Ortiz-Juarez 2013; Messina and Silva 2018), with skill upgrading more than offsetting the increasing demand for skill. Our analysis contributes two new insights. First, that increased participation of skilled women was a driver of the compression of male inequality. Second, that there was no marked decline in the college premium for women despite their (more) rapid skill acquisition.

Turning to the supply side, we confirm earlier results that the aggregate wage elasticity of labor supply is higher among women than men (especially among the unskilled), and that female (but not male) aggregate wage elasticities have decreased over time, in line with women's growing labor market attachment. In fact, forces such as trade and technological change will tend to affect relative wages across task-based occupations. We provide new evidence showing the extent to which this sparks occupational mobility. To take one example, while the aggregate wage elasticity for men is small, male mobility across occupations is significantly influenced by wages in one occupation relative to others. We document considerable heterogeneity in the wage elasticity by occupation, skill and gender (see Figure 9), and demonstrate that accounting for this is relevant to understanding equilibrium outcomes. Overall, we find that the greater flexibility we allow on the demand and the supply side is of substantive relevance in accounting for the distributional patterns in the data.

Our fourth set of findings pertains to non-wage determinants of participation, see Figures 11 and 12. We choose the non-equilibrium series to include most factors discussed in the PE literature. These include fertility (Katz and Goldin 2000; Costa 2000; Cruces and Galiani 2007), marriage (Grossbard-Shechtman and Neuman 1988; Fernández and Wong 2014; Greenwood et al. 2016), improvements in technology and capital used for home production (Costa 2000; Greenwood, Seshadri, and Yorukoglu 2005; Cavalcanti and Tavares 2008; Coen-Pirani, León, and Lugauer 2010) and attitudinal changes towards women's work (Rindfuss, Brewster, and Andrew 1996; Costa 2000; Fernández, Fogli, and Olivetti 2004; Goldin 2006; Fernández 2013), which are often reflected in legislation protective of women's economic rights (Doepke and Zilibotti 2005; Platteau and Wahhaj 2014). We analyze these factors within a single framework, showing how they affect the evolution of the wage and occupational structure, jointly with demand trends and under partial vs general equilibrium constructs.

Our GE estimates indicate that these variables jointly explain about a third of the reduction in the gender participation gap. However, our PE estimates put this figure at 85%. This suggests that previous estimates, which emerge primarily from PE models, are likely to be biased upwards by virtue of ignoring equilibrium wage

adjustments that generate countervailing impacts on labor supplies. The estimates differ markedly by skill, with household appliances being the main driver of participation among unskilled women, and fertility the main driver for skilled women. The counterfactual analysis shows that appliance availability hastened divergence of the gender wage gap at the bottom of the wage distribution, and that fertility decline muted convergence of the gap at the top. The decline of marriage and progressive realization of women's economic rights had smaller though, in cases, notable effects. This is not always analyzed, but we find non-negligible responses of male labor to the supply shifters.

Our final set of findings concerns demographic factors that shifted the size and gender-skill composition of the labor force. These are emigration, which was disproportionately of unskilled men, and skill upgrading, which occurred more rapidly among women. Emigration reduced the gender participation gap and, on account of female labor supply being more wage elastic, and an imperfect substitute for male labor at the unskilled end of the distribution, it led to a widening of the gender wage gap. The increasing share of women with a college degree among potential workers widened the gender participation gap, and narrowed the gender wage gap. In discussing this counterfactual (Section 7.2), we identify the mechanisms by which allowing GE effects magnifies (about threefold) the PE effect on the gender wage gap, and reverses the PE effect on the participation gap. Although skill upgrading and immigration characterize trends in many countries, we provide new evidence that considers not only how these trends feed through labor supplies to the wage structure but, importantly, how this then propogates through an equilibrium process. Our discussions illustrate the importance of allowing imperfect substitution of labor across gender, skill and task-based occupation, and the relevance of similarly disaggregated wage-elasticities of labor supply in propagation of feedback from the equilibrium wage structure.

As both elasticity of substitution parameters and labor supply elasticities play an important role in many strands of the literature, our equilibrium approach to analysis (and decomposition) of the wage distribution can be used for other purposes, including the study of immigration or declining labor force participation (Krueger 2017; Abraham and Kearney 2020). For example, Dustmann, Schönberg, and Stuhler (2016), discussing the range of estimates on the effects of immigration on wages, argue that the assumption that the labor supply elasticity is homogenous across different groups of natives can be problematic as it ignores differential employment responses. Our framework can be applied to carry out those types of analyses.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the model structure to profile the main forces at work. Section 3 discusses the data and stylized facts. Section 4 presents a decomposition of changes over time in the gender wage gap across the wage distribution, showing that these are driven by wage structure changes. In Section 5, we formulate an equilibrium model

of the labor market and describe the estimation strategy. We discuss model fit, estimates of demand- and supply-side parameters, and wage elasticities in Section 6. In Section 7, through counterfactual exercises, we investigate the relative contribution of non-wage determinants of labor supply, demographics, and gender- and skill-biased technological changes to the evolution of gender wage and participation gaps under both PE and GE assumptions. Robustness exercises using alternative specifications of the model and different measures of labor supply are in Section 8. Section 9 concludes. A comprehensive discussion of identification and estimation is in Appendix Section B. Monte Carlo simulations assessing the performance of the equilibrium estimator alongside that of OLS and IV is in Appendix Section C.

2 Framework

We discuss a simplified version of the full model from Section 5 to fix ideas. We highlight the role of gender substitutability in demand, the relevance of endogenizing occupational participation in supply, and how demographic changes, net migration, and labor supply shifters enter the model.

At time t, given a CES production function that aggregates labor across males and females ($gen \in \{k, f\}$) of some skill level within three task-based occupation sub-nests ($o \in \{o_1, o_2, o_3\}$), demand optimality in a competitive equilibrium requires that:

$$\log\left(\frac{W_{o,k,t}}{W_{o,f,t}}\right) = \log\left(\frac{\alpha_{o,t}}{1-\alpha_{o,t}}\right) - \frac{1}{\sigma_{\rho_o}}\log\left(\frac{L_{o,k,t}}{L_{o,f,t}}\right), \tag{2.1}$$

where $L_{o,k,t}$ and $L_{o,f,t}$ are labor inputs from male and female workers respectively, $W_{o,k,t}$ and $W_{o,f,t}$ are the wages of male and female workers respectively, $\alpha_{o,t}$ is the 'share' parameter that varies over time due to gender-biased demand changes, and $\rho_o \in (-\infty, 1]$ is a function of the elasticity of substitution (σ_{ρ_o}) between male and female labor: $\sigma_{\rho_o} \equiv \frac{1}{1-\rho_o}$. In a departure from most previous related work, all values are specific to the three task-based occupations. In the full model, we also allow for skill- and occupation-biased technological change, and for heterogeneity in substitutability between skilled and unskilled labor by occupation groups.

On the supply-side, male and female workers choose among three market occupations and home production. In a setting with random utility, the labor supply functions are:

$$L^s_{o,gen,t} = L^{pop}_{gen,t} \times F_o\left(\left\{\psi W_{\hat{o},gen,t} + \boldsymbol{\pi}'_{\hat{o}}\boldsymbol{B}_{gen,t}\right\}_{\hat{o}=1}^{3}\right), \tag{2.2}$$

where supply $L^s_{o,gen,t}$ is occupation- and gender-specific. $L^{pop}_{gen,t}$ is the gender-specific number of potential workers at time t. $\boldsymbol{B}_{gen,t}$ is a vector of observed variables that shifts the relative utility of occupations for each gender and across occupations. While many studies focus on a single determinant, in the full model, we consider all

of the main factors discussed in the literature. Specifically, we incorporate time-series of fertility, marital status, women's economic rights, and appliance availability as shifters of LFP and occupation-skill-specific labor supplies. We additionally analyze gender-skill upgrading and net migration as drivers of demographic change, which affect the number of potential workers $L^{pop}_{gen,t}$.

What we wish to communicate with this brief sketch of the model is that this simple structure is general enough to contain four key channels through which FLFP and the gender wage gap are related: imperfect substitutability of female for male labor (σ_ρ), non-neutral (gender-biased) technological changes (α_t), shifters of occupational (and overall LFP) participation rates ($\boldsymbol{\pi}$), and demographic compositional changes ($L^{pop}_{gen,t}$). In contrast to large sections of the related literature, we will model these channels as operating in a context in which labor supply is allowed to respond to changes in the wage structure via ψ.

As discussed in the previous section, much of the literature on women's labor supply takes demand as given. Among those papers that apply the supply-demand framework, most estimate some variation of Equation (2.1) under the assumption of predetermined inelastic short-run labor supply. This often implies a fixed probability for $F_o(\cdot)$, which shuts down $\boldsymbol{\pi}$ and ψ. In our setting, non-zero $\boldsymbol{\pi}$ allows supply shifters to affect participation and occupation decisions, for both genders. Non-zero ψ, on the other hand, allows LFP and occupation participation rates to respond to changes in the wage structure, arising from either supply-side ($\boldsymbol{B}_{gen,t}$, $L^{pop}_{gen,t}$) or demand-side (α_t) forces. Finally, the magnitude of equilibrium effects and their propagation across occupations depend on occupation-specific gender substitutability and the substitutability of task-based occupations themselves.

Consider the elasticity of substitution between male and female labor in Equation (2.1). If male and female labor are not very substitutable in occupation o, that is, if σ_{ρ_o} is small, a large increase in female labor supply will impose downward pressure on female wages in occupation o and, to a much lesser extent, on male wages, leading to an increase in the gender wage gap. Now, when ψ is positive, the greater downward wage pressure on female wages depresses female labor supply, attenuating the impact of FLFP on the gender wage gap. Furthermore, changes specific to one occupation are amplified, through equilibrium, to all occupations and worker groups, and they can have distributional effects. By endogenizing labor supply, our framework allows us to study these general equilibrium effects.

Our framework for equilibrium labor force participation and wage analysis introduces parameters on the demand- and supply-side that have to be pinned down by time-series variation in observed equilibrium labor quantities (L) and wages (W) across gender, occupation, and skill groups. The data series needs to have sufficient variation to distinguish the separate effects on L and W of i) supply- vs. demand-side parameters, and ii) demand trends and elasticities of substitution by gender, skill, and occupation. Building on standard assumptions on the demand-side (polynomial

restriction on trends) and supply-side (multinomial discrete choice), we characterize the equilibrium solution, discuss identification challenges as the time-series of available quantities and prices expands, and provide a scalable and efficient empirical equilibrium estimation routine, see Section 5.3. The modeling and estimation are potentially of value in formulating and addressing questions beyond the question at hand in this paper.

3 Data and Descriptive Statistics

We use thirteen rounds of the nationally representative Mexican Household Income and Expenditure Survey (ENIGH) from 1989 to 2014. We restrict attention to individuals aged 25-55 (prime-age workers). Wages correspond to real hourly labor earnings for full-time workers. Using the 18 groups in the Mexican occupation classification, we construct three groups defined by whether the activities performed on the job are predominantly manual, routine, or analytical (Autor, Levy, and Murnane 2003), see Appendix A.3. The occupational groups each represent about a third of the workforce, and are also aligned across the wage distribution, see Table 1. The Table shows substantial occupational sorting by gender. Appendix A explains sample construction and provides data sources and definitions for all variables used in the analysis.

Labor force participation. In 1989, the labor force participation rate[7] of the entire prime-age population in Mexico was 64.2%, the female participation rate (FLFP rate) was 35%, and women accounted for 29% of the workforce. By 2014 this picture had changed dramatically: overall participation was 76%, the FLFP rate was 58%, and women represented 41% of the workforce (see Panels (a) and (c) Figure 1). This increase in FLFP in 25 years was one of the largest in the Latin American region (Ñopo 2012), and among the largest in the world (The World Bank 2012). The preceding statistics are from the ENIGH survey. Using decadal census data allows us to go further back in time, to 1960, and it corroborates these trends (Panels (b) and (d) of Figure 1). Bhalotra and Fernández (2023) provide a descriptive analysis of the longer time series.

Three stylized facts characterize the evolution of labor force participation during this period (Table 2). First, the absolute increase was larger among low-skilled women (defined as women with at most secondary education), their LFP rate rising from 35.7 to 55.4% between C.1992 and C.2012. LFP among high-skilled women (defined as college educated) rose from 71.7 to 77.4%. While the volume of the increase in FLFP came from low-skilled women, the proportional change in

7. We define the labor force participation rate as the proportion of prime-age individuals (25-55 years old) who either worked or sought employment in the previous month relative to the total number of individuals within this age bracket. Our definition of work includes all sectors, occupations, and the informal economy, irrespective of the nature of the activities or if the work complies with the country's formal labor laws and protections (*i.e.* if the job is formal or informal).

participation of high-skilled women was large because the initial share of the female workforce with a college-education was only 14.5% in C.1992, rising to 24.0% in C.2012 (Table D.1). Second, there was a substantial increase in participation across all age groups within the 25-55 range. Third, the LFP rate of prime-age men was stable at about 94% across the period.

Potential workers. The number of workers of any gender and skill emerging on the labor market depends not only on the labor force participation rate, but also on population growth and changes in the gender and skill composition of the population. Between 1989 and 2014, the Mexican prime age population—individuals born in and remaining in Mexico—increased by 90%, from 25.2 million to 48.0 million. There were two significant trends that altered the gender-skill composition.

One was gender-biased **educational (skill) upgrading**. The share of skilled women among potential female workers increased from 6.4% to 19.7%, corresponding to an addition of 4.2 million women (Panel (a), Figure D.3). This led to convergence with the share of skilled men among potential male workers, which increased from 15.9% to 21.3%, an increase of 3.0 million. The share of women within the prime age population was stable at around 53% between 1989 and 2014.

The other was the trend in **emigration**. During 1989–2014, the Mexican-born prime age population increased by 101%, from 27.3 to 54.9 million. The share that emigrated increased from 8% to 13%, with most of the increase representing unskilled males (Panel (c), Figure D.3). The share of emigrants increased for all groups other than skilled women Brücker, Capuano, and Marfouk (2013). We analyze these trends by implementing counterfactuals that shut down their growth over time.

Wage structure. At the same time that women were increasingly joining the workforce, the wage structure changed substantially. Figure 2 (Panel a) shows a striking pattern whereby the wages of men evolved more favorably than the wages of women at the lower end of the wage distribution, while the reverse was the case at the upper end. This is a motivating fact for the analysis in this paper.

The following stylized facts underpin it. First, there was an overall tendency for real wages to decline on account of the 'Tequila Crisis' of 1994 and the Great Recession of the late 2000s. Second, the male wage distribution contracted sharply over the period, driven by male wage growth in the lower-tail of the distribution being higher than in the upper-tail, a pan Latin America phenomenon (López-Calva and Lustig 2010; Levy and Schady 2013; Lustig et al. 2016; Acosta et al. 2019; Fernández and Messina 2018). Third, we do not see a similar compression of the female wage distribution. Wage growth for women was ever so slightly u-shaped, with wages at the bottom and the top performing better than in the middle.

Figure 2 (Panel b) shows how the unconditional gender wage gap evolved

across the wage distribution.[8] The gender gap increased by 10 to 32% among workers with below median wages, and declined by 5 to 20% among workers above the 80th percentile. These pattern are replicated using the 1990 and 2010 Mexican Census (Panel b).

Determinants of women's participation. We now consider how the four observable non-wage determinants of FLFP that we analyze evolved over the sample frame. The trends are in Figure D.2. Fertility, defined as the percentage of women with at least one under-5 child, declined sharply, by about 20 pp, and more sharply among skilled (relative to unskilled) women. The share of women who were married or partnered fell 3 to 10 pp and, again, the decline was sharper among skilled women. The share of women who had a home appliance (refrigerator or washing machine) rose by more than 30 pp for the unskilled to reach close to 90% availability by the end of the period, whereas availability among skilled was more or less constant at about 95%. The Women in Business and Law (WBL) index, which measures women's economic rights as captured by legislation facilitating women's work participation, increased by close to 20 pp.[9] In contrast to the first three variables for which we have data by gender and skill group, WBL naturally only varies in the aggregate time series. Overall, there was substantial variation in predictors of FLFP over the period studied, consistent with the large increase in FLFP.

4 Unconditional Quantile Decomposition of the Gender Wage Gap

Changes in the gender wage gap following increases in FLFP could reflect changes in the skill composition of women vs men, or changes in returns to the skills of women vs men (i.e., wage structure changes). In this section, we use the pooled decomposition method of Oaxaca and Ranson (1994), extended to quantiles by Firpo, Fortin, and Lemieux (2009, 2018) to illuminate this question. Figure 2 (Panel b) shows how much the change in the gender wage gap varied across the wage distribution, underlining the importance of conducting the decomposition at different percentiles.

The lower Panel of Appendix Table D.1 documents changes in the education and age composition of the workforce. It shows, as discussed in the preceding section, that college attainment rose more rapidly among women than men, and this could in principle explain convergence of the gender pay gap at the top of the distribution. We also observe that the average worker is becoming older, and more so among women (because of the increase in married women's FLFP). If the gender wage gap increases with age (Barth, Kerr, and Olivetti 2017; Adda, Dustmann, and Stevens

8. The series in Panel (b) of Figure 2 is calculated by subtracting the values of the male and female series, shown in Panel (a).

9. It rose from 61.3 in 1989 to 80.6 in 2014. As a point of reference, the average score in high-income OECD countries is 94.7 points, while the countries with the lowest WBL are found in the Middle East and North Africa (MENA) region, where the average score is 49.6 points (Hyland, Djankov, and Goldberg 2020).

2017), this could be a factor behind the widening of the mean gender gap.

We first estimate separate regressions per gender-period of the re-centered influence function (RIF) of $q_{\tau,gen,t}$—the τ'th quantile of the corresponding wage distributions—on a vector $X_{gen,t}$ of socio-demographic characteristics.[10] Denoting $\hat{\gamma}_{gen,t}$ as the estimated parameter vector, differences over time between the initial (t = C.1992) and final (t = C.2012) period of the estimated wage quantile can be expressed as:

$$\Delta_t \hat{q}_{\tau,gen} = \underbrace{\left(\overline{X'}_{gen,\text{C.2012}} - \overline{X'}_{gen,\text{C.1992}}\right) \hat{\gamma}_{gen,P}}_{\Delta_t \hat{q}_{X,\tau,gen}} + \underbrace{\overline{X'}_{gen,P} \left(\hat{\gamma}_{gen,\text{C.2012}} - \hat{\gamma}_{gen,\text{C.1992}}\right)}_{\Delta_t \hat{q}_{S,\tau,gen}}, \tag{4.1}$$

where overbars represent averages, and $\hat{\gamma}_{gen,P}$ and $\overline{X}_{gen,P}$ correspond to the estimated vectors of parameters and the explanatory variables from a regression that pools observations across the two periods. Here, $\Delta_t \hat{q}_{X,\tau,gen}$ corresponds to the composition effect and $\Delta_t \hat{q}_{S,\tau,gen}$ is the wage structure effect.

Since we are interested in the effects of composition and price changes on the gender wage gap, we estimate the difference between males ($gen = k$) and females ($gen = f$) of each component at 19 different percentiles:

$$\underbrace{\Delta_t \hat{q}_{\tau,k} - \Delta_t \hat{q}_{\tau,f}}_{\text{Overall}} = \underbrace{\left(\Delta_t \hat{q}_{X,\tau,k} - \Delta_t \hat{q}_{X,\tau,f}\right)}_{\text{Composition}} + \underbrace{\left(\Delta_t \hat{q}_{S,\tau,k} - \Delta_t \hat{q}_{S,\tau,f}\right)}_{\text{Wage Structure}}. \tag{4.2}$$

The decomposition results are shown graphically in Figure 3, which plots the estimates at all 19 percentiles. At all percentiles, wage structure effects are quantitatively more important than compositional effects. They contribute 63% of the observed rise in the gender wage gap at the 5th percentile, and close to 90% at the 25th. They over-predict the fall in the gap at the 95th percentile (-22.5 log points observed vs. -34.7 log points attributed to the wage structure). Moreover, wage structure effects line up remarkably well with observed relative wages across the distribution.

The Figure also shows that if the wage structure had remained constant at its average level over the two periods, compositional effects would have led to a larger gender wage gap. Thus changes in the skill and age of the workforce contributed to a widening of the gap at the lower tail, and have impeded further convergence at the top of the distribution.[11]

10. The vector includes dummies for seven education categories, six age categories in five-year intervals, and all possible interactions of education and age levels

11. As women's participation increases, selection implies that the average wage of women will fall, other things equal. If unobservables driving selection into the labor force scale with observables then our finding here that observables (gender, education, and ages) do not account for much of the change in the wage structure suggests that unobservables are unlikely to drive the distributional changes that we document.

The results from this section motivate our equilibrium analysis, which illuminates the factors driving wage structure changes. Our equilibrium model endogenously generates the wage structure.[12] Although education as a worker characteristic does not play an important role in the decomposition exercise which takes wages as given, we show that once we allow wages to respond to labor supplies, the female-biased increase in college completion rates play an important role through the wage structure.

5 Theoretical Model

5.1 Demand Side

Aggregate production in the economy is a function of labor, we abstract from capital.[13] Labor is divided into four types according to gender and skill (college). The technology is described by a three-level nested constant elasticity of substitution (CES) function, with nests corresponding to occupation, skill, and gender.[14] At the top level, output is produced by a CES combination of labor in the three types of market occupations by task-content:

$$Y_t = Z_t \left[\alpha_{1,t} L_{a,t}^{\rho_1} + (1-\alpha_{1,t}) \Big(\alpha_{2,t} L_{r,t}^{\rho_2} + (1-\alpha_{2,t}) L_{m,t}^{\rho_2} \Big)^{\rho_1/\rho_2} \right]^{1/\rho_1}, \tag{5.1}$$

where Y_t is total output at time t; Z_t is a scale parameter that is allowed to vary over time to capture neutral productivity changes;[15] $L_{a,t}$, $L_{r,t}$, and $L_{m,t}$ are the total demand of labor in analytical, routine, and manual task-intensive occupations, respectively; $\rho_1 \in (-\infty, 1]$ is a function of the elasticity of substitution (σ_{ρ_1}) between labor in non-analytical (routine and manual) vs. analytical task-intensive occupations ($\sigma_{\rho_1} \equiv \frac{1}{1-\rho_1}$); $\rho_2 \in (-\infty, 1]$ is a function of the elasticity of substitution (σ_{ρ_2}) between labor in routine vs. manual task-intensive occupations ($\sigma_{\rho_2} \equiv \frac{1}{1-\rho_2}$); and the α's are time-varying 'share' parameters that we discuss below.

In the second level of the production technology, labor in each occupation is

12. This is influenced by skill upgrading, emigration, and shifters of labor supply and relative demand by gender, skill, and occupation.

13. In the nested CES production function with constant returns to scale, and assuming capital is not fixed and can fully adjust, changes to the capital stock can be equivalently represented by changes in the share parameters. Since we are not primarily interested in capital-skill or capital-gender complementarities, we simplify the model by omitting capital altogether. For a discussion on the role of fixed capital in nested CES production functions, see Ottaviano and Peri (2008), Card (2012), Ottaviano and Peri (2012), and Manacorda, Manning, and Wadsworth (2012).

14. We test how sensitive the results are to the ordering of the levels in the production technology, we discuss results using alternative model specifications in the robustness checks.

15. Z_t captures changes in neutral (aggregate) productivity as well as all non-labor inputs, including capital, residually. In CES demand systems where aggregate labor is combined with non-labor inputs, the relative demand optimality among labor inputs in gender, skill and occupation subgroups is not a function of the prices and productivity parameters of non-labor inputs contained residually in the Z_t term.

divided into two groups, skilled (s) and unskilled (u), using a CES combination:

$$L_{occ,t} = \left[\alpha_{3,occ,t} L_{s,occ,t}^{\rho_{3,occ}} + (1-\alpha_{3,occ,t}) L_{u,occ,t}^{\rho_{3,occ}}\right]^{1/\rho_{3,occ}} \quad \text{for} \quad occ = a, r, m, \tag{5.2}$$

while at the third level labor is disaggregated in each occupation-skill group between female workers, indexed by f, and male workers, indexed by k:

$$L_{edu,occ,t} = \left[\alpha_{4,skl,occ,t} L_{k,skl,occ,t}^{\rho_{4,occ}} + (1-\alpha_{4,skl,occ,t}) L_{f,skl,occ,t}^{\rho_{4,occ}}\right]^{1/\rho_{4,occ}} \quad \text{for} \quad edu = s, u, \quad \text{and} \quad occ = a, r, m. \tag{5.3}$$

The parameters in the second and third levels have an analogous interpretation to those in Equation (5.1). An innovative feature of our model is that the elasticities of substitution between male and female labor, and between skill groups, are allowed to vary based on the task-content of occupations.

Our set-up is related to Johnson and Keane (2013), who also model labor demand based on nested-CES aggregation, allowing differences by gender, skill, and occupation. They consider ten 1-digit occupations directly rather than task-based occupation groups. Importantly, within occupations, they assume that the elasticities of substitution across gender and education groups are homogeneous—meaning that $\rho_{3,occ} = \rho_3$ and $\rho_{4,occ} = \rho_4$ for all occ groups. By allowing the elasticities to vary within each occupation, we introduce a new transmission mechanism of gender-specific demand and supply shocks within and across occupation and skill groups. Our results show this is empirically relevant in explaining the evolution of the gender wage gap (see Section 6.2).

The share parameter (α) for each CES sub-nest can be interpreted as indexing the share of work activities allocated between different types of labor within each CES combination (Katz and Autor 1999). They are allowed to vary over time to capture non-neutral technical change and other factors that shift relative labor demand. As discussed in Section 1, we depart from previous studies in allowing demand shifts to be gender and skill-biased and to vary by occupational category. We allow for demand shifts between occupations ($\alpha_{1,t}$ and $\alpha_{2,t}$), capturing forces like technical change that differentially affect jobs depending on their task-content;[16] between skilled and unskilled labor within occupations ($\alpha_{3,occ,t}$), capturing skill-biased technical change that can be general or occupation-specific;[17] and between men and women within occupation-skill groups ($\alpha_{4,skl,occ,t}$), capturing gender-biased

16. See Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2008), Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014), and Burstein, Morales, and Vogel (2019) and automation Acemoglu and Restrepo (2018, 2019, 2021).

17. As in Katz and Murphy (1992), Machin, Reenen, and Van Reenen (1998), Berman, Bound, and Machin (1998), and Katz and Autor (1999).

demand changes.[18] It may also capture changes to the aggregate capital stock and to relative labor demand due to changes in Beckerian taste discrimination over time (Hsieh et al. 2019).[19]

The demand-side of the model has two types of parameters that we need to estimate: 8 parameters that are functions of the elasticities of substitution (ρ_1, ρ_2, $\rho_{3,a}$, $\rho_{3,r}$, $\rho_{3,m}$, $\rho_{4,a}$, $\rho_{4,r}$, and $\rho_{4,m}$); and a group of time varying demand shift parameters that vary by gender, skill, and occupation (Z_t, $\alpha_{1,t}$, $\alpha_{2,t}$, $\alpha_{3,a,t}$, $\alpha_{3,r,t}$, $\alpha_{3,m,t}$, $\alpha_{4,s,a,t}$, $\alpha_{4,s,r,t}$, $\alpha_{4,s,m,t}$, $\alpha_{4,u,a,t}$, $\alpha_{4,u,r,t}$, and $\alpha_{4,u,m,t}$). As argued by Johnson and Keane (2013) and as we discuss in Appendix Section B.2, it is possible to fit the trends in relative wages perfectly if we do not impose any restrictions on the evolution of the relative demand parameters, but this would mean that we would not be able to identify the parameters capturing the elasticities of substitution. We impose a 3rd order polynomial restriction on the trends for the share parameters. For example, the parameter $\alpha_{1,t}$ is allowed to change according to

$$\log \alpha_{1,t} = a_{1,0} + a_{1,1}t + a_{1,2}t^2 + a_{1,3}t^3. \tag{5.4}$$

Additionally, to flexibly account for neutral technological changes, we allow for t-specific Z_t values without parametric restrictions.

As is clear from Equation (2.1), any changes in relative wages that are not explained by movements in relative supplies are absorbed by the relative demand parameters. In total, there are 65 elasticity and share parameters on demand-side that we need to estimate.[20] Identification and estimation are discussed below.

5.2 Participation and Occupational Choice on the Supply Side

Male and female workers of different skill (education) levels sort into different market occupations based on time-invariant preferences and wages. The model allows gender-specific comparative advantage associated with differences in physical, sensory, motor, and spatial aptitudes.[21] Comparative advantage will reflect in marginal productivity, and hence influence occupational sorting through wages.

18. See Acemoglu, Autor, and Lyle (2004), Black and Spitz-Oener (2010), Pitt, Rosenzweig, and Hassan (2012), and Burstein, Morales, and Vogel (2019).

19. In a Beckerian taste discrimination framework, the marginal utility of an employer from hiring a female worker can be lower due to utility loss associated with discriminatory tastes (Hsieh et al. 2019; Morchio and Moser 2021). Given labor participation and wage data, we trace out differential gender labor demands. We cannot distinguish demand differences due to discrimination from real productivity differences. Thus the $\alpha_{4,skl,occ,t}$ share parameter we estimate could be capturing changes in discrimination over time or changes in real productivity. Empirically, real productivity and discrimination are also entangled: recent research literature has found that gender-based discrimination (harassment) has real productivity impacts (Folke and Rickne 2020; Cici et al. 2021).

20. This include $(3+3+2) = 8$ elasticities of substitution, $(6+3+2) \times 4 = 44$ coefficients associated with the third order polynomials of α shares, and 13 t-specific Z_t parameters.

21. See for instance, Galor and Weil (1996), Black and Juhn (2000), Rendall (2017, 2013), Baker and Cornelson (2018), and Ngai and Petrongolo (2017).

We model occupational choice using a random utility framework. The utility a worker receives from choosing to enter the workforce in one of the three market occupations at time t is

$$U(occ \mid gen, skl, t) = \psi_{gen,skl,occ} + \psi_1 \log\left(W_{gen,skl,occ,t}\right) + \epsilon_{gen,skl,occ,t}, \tag{5.5}$$

where $\psi_{gen,skl,occ}$ is a time-invariant parameter capturing non-pecuniary rewards (such as occupational job flexibility, or the mission-orientation of a job) from choosing occupation *occ*; and ψ_1 measures the weight in utility terms that a worker gives to wages ($W_{gen,skl,occ,t}$) in log units.[22] $\epsilon_{gen,skl,occ,t}$ is an idiosyncratic taste shock assumed to be independent and identically distributed extreme value. The assumption about the distribution of the taste shock generates a tractable multinomial logit form for the choice probabilities.[23]

The utility from staying in home production is modeled symmetrically for men and women. The literature has linked movements of women into the labor market to changes in contraceptive technology and fertility, marriage markets, social norms and attitudes towards women's work, and improvements in technology and capital (e.g., appliances) used for home production. The utility from choosing home production, denoted by h, takes the form:

$$\begin{aligned} U(h \mid gen, skl, t) = & \pi_{1,gen} + \pi_{2,gen,skl} Pr(\text{child} = 1 \mid gen, skl, t) \\ & + \pi_{3,gen,skl} Pr(\text{married} = 1 \mid gen, skl, t) \\ & + \pi_{4,gen,skl} Pr(\text{appliance} = 1 \mid gen, skl, t) \\ & + \pi_{5,gen,skl} \text{WBL}_t + \epsilon_{gen,skl,h,t}. \end{aligned} \tag{5.6}$$

$\pi_{1,gen}$ are gender-specific intercepts.[24] $Pr(B = 1 \mid gen, skl, t)$ are time- and group-specific proportions of individuals with young children, a proxy for fertility (child), in stable partnerships (we label this married), and who own household appliances (appliance). WBL_t is the score on a work-related legislation index, and $\epsilon_{gen,skl,h,t}$ is a idiosyncratic taste shock assumed to be independent and identically distributed extreme value.

22. The log wage assumption allows the relative odds of choosing to work over leisure to approach zero as the wage tends toward zero. We model two skill levels, but the framework can be extended to a finer classifications of labor skills. In settings where labor demand is specific to gender and occupation but not skill, wages are sometimes more restrictively assumed to be log-additive given some base efficiency wage unit (Böhm et al. 2019).

23. Given this assumption on the error distribution, occupational selection is driven by individual- and occupation-specific random factors that do not impact productivity. Alternatively, one might assume that the error terms come from individual- and occupation-specific productivity draws that generate heterogeneous earnings given occupation-specific skill-prices (Burstein et al. 2020). Preference and productivity draws might both drive occupational selection, but are difficult to empirically disentangle. We model only preference shocks given the perceived importance of idiosyncratic non-wage factors in determining women's labor participation decisions.

24. We normalize $\psi_{gen,s,m} = 0$ in Equation (5.5). Since $\pi_{1,gen}$ in Equation (5.6) vary by gender but not by skill, all the constants are uniquely pinned down.

Given the assumed distribution of the taste shocks, the probability that a worker chooses one of the market occupations or home production is

$$Pr(d_O = 1 \mid gen, skl, t) = \frac{\exp(\widehat{U}(O \mid gen, skl, t))}{\sum_{occ=a,r,m,h} \exp(\widehat{U}(occ \mid gen, skl, t))} \quad \text{for} \quad O = a, r, m, h\,, \tag{5.7}$$

where $\widehat{U}$ is equal to U without the idiosyncratic shocks. We use these probabilities to find the total labor supply of each type in each occupation. For example, the total supply of female workers with college education in analytical task-intensive occupations is

$$L^s_{f,s,a,t} = L^{pop}_{f,s,t} \times Pr(d_a = 1 \mid f, s, t)\,, \tag{5.8}$$

where $L^{pop}_{f,s,t}$ is the number of in-Mexico prime-age potential female workers with college education at time t. More generally, $L^{pop}_{gen,skl,t}$ changes over t due to increases in population, gender-specific skill upgrading, and gender- and skill-specific patterns of net migration. We refer to $Pr(d_O = 1 \mid gen, skl, t)$ as the gender- and skill-specific occupation participation rate. Thus the gender- and skill-specific labor force participation rate is $LFP_{gen,skl,t} = \sum_{occ \in \{a,r,m\}} Pr(d_{occ} = 1 \mid gen, skl, t)$.

A key feature of our counterfactual analysis is that we consider the potentially countervailing effects on FLFP from equilibrium wage adjustments due to shifts in the supply curves associated with demographic composition ($L^{pop}_{gen,skl,t}$), or changes in the supply shifters $Pr(d_O = 1 \mid gen, skl, t)$,[25] see Equation 5.8. The importance of these countervailing effects will depend on the wage elasticity of labor supply, which is heterogeneous across gender-skill groups and can vary over time.

Beyond wages and time-invariant preferences, participation in the labor market depends on a linear combination of supply shifters that we take as exogenous. Moreover, the skill-gender composition of employment, which determines the number of potential workers, is also taken as given. A long-standing structural literature on female labor supply studies dynamic responses of education, fertility, marriage, and labor market choices to changes in the costs and returns of human capital accumulation and the paths of earnings, taxes, and transfers using partial equilibrium (PE) models that do not allow for endogenous adjustments of skill prices.[26] PE models can handle greater choice complexity and dynamics because only an "inner-loop" for the dynamic life-cycle problem needs to be solved, and there is no need to worry

25. Additionally, we refer to $Pr(d_O = 1 \mid gen, t) = \sum_{skl \in \{s,u\}} \left(L^{pop}_{gen,skl,t} / L^{pop}_{gen,t} \right) \times Pr(d_O = 1 \mid gen, skl, t)$ as the gender-specific occupation participation rate, and the gender-specific labor force participation rate is $LFP_{gen,t} = \sum_{skl \in \{s,u\}} \left(L^{pop}_{gen,skl,t} / L^{pop}_{gen,t} \right) \times LFP_{gen,skl,t}$.

26. See reviews in Blundell and Macurdy (1999), Keane (2011), Keane, Todd, and Wolpin (2011), and Blundell (2017).

about a potential multi-dimensional "outer-loop" of market clearing conditions.[27]

Recently, Hsieh et al. (2019), Burstein et al. (2020), and Morchio and Moser (2021) have explored equilibrium wage responses in papers that do not focus on FLFP changes over time, but that allow for gender-specific labor supplies. However, in these papers, occupational selection in gender and education cells is based on unobserved shocks. Possibly most closely related to our framework, Johnson and Keane (2013) build an equilibrium model of male and female labor supply with endogenous education and occupation choices. However, since FLFP is not a focus of their paper, they do not consider changes in supply shifters, instead they account for changes in LFP over time with indirect utility time trends.

By linking occupational choices to a rich array of observables, we allow for direct counterfactual comparisons among the different predictors identified in the literature. Since our focus is on the distributional impacts of FLFP, and how demand and supply elasticities shape the propagation mechanisms within an equilibrium framework, we abstain from endogenizing supply-side observables and educational choices. With this simplification, we can differentiate labor types flexibly while maintaining the model computationally feasible and with a tractable equilibrium.

Importantly, in the setting of Mexico, we observe strong secular trends in the time series of education[28] and our supply shifters (see Figures D.2 and D.3), so allowing these choices to depend upon future wages may not be as relevant. For example, the college premium declined, and mean real wages fluctuated strongly during the analysis period (Lustig, Lopez-Calva, and Ortiz-Juarez 2013; Messina and Silva 2018). If the wage premium for going to college were the main driver of college attendance, we would expect a decline instead of an increase.

5.3 Equilibrium and Estimation

The equilibrium model generates a prediction of wages and labor supply for the four worker types in the three market occupations in every time period. With 13 years of data, there are $(12 + 12) \times 13 = 312$ predictions in total that are a function of the 94 parameters of the model, including 29 on the supply-side and 65 on the demand-side.

27. In PE and reduced-form models with treated and untreated local labor markets, sometimes GE of policy treatments on local wages can be estimated (Attanasio, Meghir, and Santiago 2012; Breza and Kinnan 2021). However, a GE model is required to predict equilibrium effects of changes beyond the domain of policy treatment variations. As an exception to this literature, Lee and Wolpin (2006) build a GE model with occupational selection among blue, white and pink collar jobs, and allow for endogenous education and experience accumulation. However, Lee and Wolpin (2006) take the fertility process as given, do not consider marital status, and, more importantly, they do not consider gender.

28. The percentage of potential workers with a college education increased among women from 6.4 to 19.7, and among men from 15.9 to 21.5 between 1989 and 2015. A linear regression of the share of women with a college education on calendar year produces a linear coefficient of 0.0053 (0.53 percentage points increase per year), with an R^2 of 0.986, almost a perfect fit. For men, the linear coefficient is 0.0025, with an R^2 of 0.898.

Appendix Section B.1 defines and characterizes the equilibrium as a system of equations for male and female wages; Appendix Section B.2 clarifies variations in the data that pin down share and elasticity parameters across nests, and discusses the potential benefits of equilibrium estimation; and Appendix Section B.3 delineates an estimation strategy that pins down reasonable estimator starting values for the large-dimensional parameter space. The analysis we provide in Appendix Section B.2 can be used to evaluate whether existing papers use the appropriate polynomial order and, accordingly, whether they are appropriately identified.

We describe the broad approach here. To provide analytical clarity to the equilibrium problem, we consider the overall nested-CES problem in separate nest groups. We discuss the de-nesting in Appendix Section B.1.1. Within one period and for one skill group, the equilibrium wage for women in an occupation is a function of the equilibrium wages of men across the different occupations (analytical, routine, and manual). The equilibrium wage relationships across genders generate a system of nonlinear equations for female wages that characterizes the equilibrium, see Appendix Sections B.1.2 and B.1.3. In Appendix Section B.1.4, we solve for the equilibrium explicitly via nested root search as well as via a faster but less stable contraction algorithm.

While the nested-CES demand system is commonly estimated in the labor economics literature, it is less common to estimate both demand and supply parameters in an equilibrium context. We develop an estimation framework that allows us to do this. Given the large number of parameters involved in estimating the model, we discuss the key identification challenges and solutions that arise. In Appendix Section B.2.1, we discuss the identification of parameters across nests using relative wages within and across nests. The lowest nest directly faces observed wages and labor quantities, higher nest layers generate aggregate wages and quantities based on lower level parameters and observables. In Appendix Section B.2.2, we discuss the necessary data requirements for jointly identifying ρ and α (the elasticity and share parameters on the demand-side) via equilibrium supply-shifters. In Appendix Section B.2.3, we discuss the data requirements for possibly identifying variations in the α parameter over time under polynomial restrictions. We show that identification is based on the concept of time-invariance in demand parameters after differencing. In our equilibrium setting where labor supply is elastic to wages, we show in Appendix Sections B.2.4 and B.2.5 that estimation relying only on supply-side participation equations suffers from the potential endogeneity of wages, and estimation relying only on demand-side optimality equations can suffer from bias due to mismeasurement and shocks to relative demand trends. Finally, in Appendix Sections B.2.6 and C, we discuss the benefits and examine the performance of our equilibrium estimator.

Estimation proceeds by searching for the set of demand- and supply-side parameters that generates the best fit between equilibrium predictions and the cor-

responding observed values in the data. However, it is computationally challenging to directly search for minimizing parameters in a 94-dimensional parameter space globally. We estimate the model by first performing a preliminary round of linear and nonlinear least squares estimation of different components of the model to generate reasonable starting values to initialize equilibrium estimation. We generate different starting values as we explore alternative values of the eight ρ (elasticity) parameters. We discuss details of the estimation parameter space in Appendix Section B.3.1. We discuss how parameter values are initialized conditional on ρ in Appendix Section B.3.2. We discuss the error structure and weight matrix from the score of the log-likelihood function in Appendix Section B.3.3.

6 Model Fit and Estimates

6.1 Model Fit to the Data

In general, the model predictions consistently track long-term trends and short-term variations in the data. Figure 4 shows the skill-weighted relative (i.e., male to female) wage and relative supply series by occupation group, and aggregate LFP by gender. Figure 5 Panel (a) shows relative wages by occupation and skill. It shows the overall decline in male relative to female wages for skilled workers and the flat or rising gender wage gap for unskilled workers. Panel (b) shows declining shares of men relative to women in analytical (skilled and unskilled), unskilled manual, and unskilled routine occupations. Appendix Table D.2 shows observed and predicted mean wages and occupation shares for all groups at the start and end of the period, showing a good fit across all cells.

6.2 Demand Side Elasticity of Substitution

By Occupation and Gender. The elasticities of substitution between male and female labor are estimated to be around 1.1 and 1.3 in manual and routine task-intensive occupations, respectively, and 2.9 in analytical task-intensive occupations (Table 3). Thus, consistent with our starting premise, male and female labor are closer substitutes in occupations that rely more on analytical skills, and which tend to lie towards the upper end of the wage distribution (Table 1).

Using these estimates we performed back-of-the-envelope calculations using Equation (2.1). Taking the actual occupation-specific increase in the supply of female relative to male labor, the estimated substitution elasticities imply a widening of the gender wage gap across occupations, but most in manual and least in analytical task-intensive occupations. The actual widening of the gender wage gap in all occupations (and most of all analytic) was smaller than predicted by the estimated elasticity. This is consistent with another result we report below which is that demand trends favored women (especially in analytic occupations).

The key channel through which gender labor substitutability impacts equilibrium outcomes is through its effects on the wage elasticity of demand for female and male workers.[29] Holding all else constant, consider a rise in the female wage. If female and male labor are closer substitutes, this will induce more substitution of female by male labor than if they were not. Thus, the higher the elasticity of substitution between male and female labor, the larger (more negative) is the elasticity of female labor demand with respect to the female wage. By virtue of allowing gender-substitutability to vary by occupation, we allow the wage elasticity of demand for female (and male) workers to vary across occupations. Holding all else constant, in occupations with higher gender-substitutability, female wages will fall more slowly when female labor force participation increases. Figure 6 traces out the female wage elasticity of demand for female labor by varying female wages in one skill and occupation group at a time, holding all else constant. Using the estimated elasticities of substitution, the left panel column shows that the wage elasticity of demand in analytical occupations is substantially larger than in manual and routine occupations. In the right column, we find nearly identical wage elasticities of demand acorss occupations after setting $\rho_{4,a}$ and $\rho_{4,m}$ equal to the estimate for $\rho_{4,r}$.

By Occupation and Skill. We provide among the first estimates of elasticities of substitution between skilled and unskilled labor by task-based occupation. Our estimates are 1.4 in analytical, 1.4 in routine and 3.8 in manual task-intensive occupations (Table 3). Consistent with intuition, the unskilled are closer substitutes for skilled workers in manual occupations. Our estimates are not out of line with existing estimates of substitutability of skilled and unskilled labor that average over occupations: 1.25 to 3 in Latin America (Fernández and Messina 2018; Manacorda, Sánchez-Paramo, and Schady 2010) and 1.5 in the U.S. (Katz and Murphy 1992; Ciccone and Peri 2005; Johnson and Keane 2013).

6.3 Demand Trends by Occupation, Gender and Skill

Figure 7 shows model predictions for the evolution of the log relative share parameters, $\log\left(\frac{\alpha}{1-\alpha}\right)$, see Equation (5.4). We show the evolution of demand by nest and the estimated aggregate output to productivity trends related to the neutral aggregate productivity Z_t term. We find evidence of both gender-biased and skill-biased

29. The elasticity of occupation- and skill-specific female labor demand, $L_{f,skl,occ,t}$, with respect to occupation- and skill-specific female wage, $W_{f,skl,occ,t}$, is:

$$\frac{dL_{f,skl,occ,t}}{dW_{f,skl,occ,t}} = \left(\frac{-1}{1-\rho_{4,occ}}\right) \cdot \left(\frac{1}{1+\left(\frac{1-\alpha_{4,skl,occ,t}}{\alpha_{4,skl,occ,t}}\right) \cdot \left(\frac{W_{k,skl,occ,t}}{W_{f,skl,occ,t}} \cdot \frac{1-\alpha_{4,skl,occ,t}}{\alpha_{4,skl,occ,t}}\right)^{\frac{\rho_{4,occ}}{1-\rho_{4,occ}}}}\right).$$

The demand-wage elasticity asymptotes toward $\left(\frac{-1}{1-\rho_{4,occ}}\right)$ as $W_{f,skl,occ,t}$ increases.

technical change.[30]

Relative demand for female labor. The most striking pattern is that demand evolved to favor female relative to male labor in every skill-occupation group (Panels a and b), with the largest increase among college-educated (skilled) women (Panel b). Analytical task-intensive work did not exhibit the largest increase in relative female demand due to a high starting value but it maintained the highest level throughout, approaching parity by 2014. The effect size is large: for skilled workers in analytical occupations, the model predicts that demand trends alone would have led the gender wage gap to narrow by 39 log points.

Our results line up with a literature showing that structural change has favored female labor. As discussed in the Introduction, some studies emphasize labor reallocation from goods to service industries (Lup Tick and Oaxaca 2010; Akbulut 2011; Ngai and Petrongolo 2017), others the changing skill requirements of the economy with the role of brawn declining and cognitive and social skills rising (Galor and Weil 1996; Blau and Kahn 1997; Weinberg 2000; Rendall 2017; Black and Spitz-Oener 2010; Aguayo-Tellez et al. 2013; Rendall 2013; Juhn, Ujhelyi, and Villegas-Sanchez 2014; Deming 2017; Cortes, Jaimovich, and Siu 2018). The estimated increase in the relative demand for female labor is also consistent with a decline in employer discrimination reflected through wages. A fall in discrimination will additionally be captured by the estimated impacts of growth in the WBL index of legislative protection of women's economic rights on female labor supply.

Relative demand by skill and occupation. Abstracting from gender, relative demand trends evolved to favor skilled relative to unskilled labor, see Panel (c) of Figure 7. Potential drivers of skill-biased demand shifts in Mexico are trade and investment liberalization (Feenstra and Hanson 1997; Hanson 2003; Sánchez-Páramo and Schady 2003; Behrman, Birdsall, and Szekely 2007; Caselli 2014) and the growth of foreign direct investment (Feenstra and Hanson 1997) in this period. In Panel (d) of Figure 7, we see no change in relative demand in analytical task-intensive occupations (which had higher female shares at baseline), but a slight increase in the first decade in routine relative to manual task intensive work.

The results confirm that Mexico experienced skill-biased technical change, a phenomenon argued to explain rising income inequality in developed economies. However, Mexico experienced a decline in wage inequality among men, largely driven by a fall in the college premium (Lustig, Lopez-Calva, and Ortiz-Juarez 2013; Messina and Silva 2018). Our counterfactual analysis demonstrates that this is because educational upgrading, compounded by increased labor force participation among skilled women, more than offset the increased demand for skill. We believe we are the first to uncover this specific channel in the literature studying the fall

30. Since we do not explicitly model capital, the variation in the aggregate capital stock might be reflected in the evolution of these shares.

in earnings inequality in Latin America during the 2000s (López-Calva and Lustig 2010; Levy and Schady 2013; Lustig et al. 2016; Acosta et al. 2019; Fernández and Messina 2018).

Total labor requirement scaled by productivity. Panels (e) and (f) of Figure 7 show that the aggregate output to productivity ratio $\frac{Y_t}{Z_t}$ approximately doubles from 1989 to 2014, which matches closely with a doubling of real GDP per capita in Mexico in this time span. This implies a relatively flat, but slightly downward trending pattern in Z_t, which captures changes in neutral aggregate productivity.[31]

6.4 Supply Side Wage Elasticities

While there is one wage parameter ψ_1 across gender and skill groups, the effects of wages on occupational choices, including the participation margin, can be heterogeneous and evolve over time. These wage elasticities of labor supply are key to understanding the countervailing effects on FLFP from equilibrium wage adjustments. We conduct the analysis at three levels. We first analyze the effects of increasing wages in all occupations on aggregate labor supply. We then deviate from most existing work in estimating impacts of increasing the occupation-specific wage on aggregate labor supply; and then on labor supply to that and the other occupations. The occupation-specific own- and cross-wage elasticities are important ingredients for the counterfactual analysis. The top panel of Table 4 presents the average marginal effects (AME) of wages on aggregate labor supply by gender and skill, in percentage point (pp) units, while the bottom panel presents the respective wage elasticities.[32]

Aggregate gender- and skill-specific labor supply responses to an increase in wages across occupations. Consider a simultaneous increase in wages in all occupations (column 1). In line with previous work (Killingsworth and Heckman 1987; Blundell and Macurdy 1999), we find that female LFP is more sensitive to wages than male LFP, particularly among the unskilled. We estimate an elasticity of 0.529 and 0.341 for unskilled and skilled female workers, respectively, the corresponding estimates being 0.060 and 0.062 for men. These numbers are close to the averages reported in meta-analyses (Evers, Mooij, and Vuuren 2008; Keane 2011; Bargain and Peichl 2016). Figure 8 shows that female (but not male) aggregate wage elasticities have decreased over time, consistent with women's increasing engagement and attachment to the labor market. A similar tendency has been shown

31. In Appendix Section B.1.1, we show that the optimal labor demand in constant-returns CES problems is a function of the $\frac{Y_t}{Z_t}$ ratio. In Appendix Section B.2.1, we discuss that Z_t cannot be separately identified from $\frac{Y_t}{Z_t}$. $\frac{Y_t}{Z_t}$ captures a total (labor) factor productivity re-scaled output term that captures the total labor/output requirement from aggregating across skill-, occupation- and gender-specific labor units.

32. For AME, we evaluate the total derivative of aggregate LFP with respect to wages in the direction of equidistance increases for all wages. For elasticity, we divide the percentage increase in labor supply by a percent increase in wages that is common across occupation-specific wages.

for America Heim (2007) and Blau and Kahn (2007). Our counterfactual analysis will discuss potential drivers of this.

Aggregate gender- and skill-specific labor supply responses to an increase in occupation-specific wages. Changes in LFP can be better understood by considering the sum of occupation-specific supply responses to their respective wage changes. Columns 2-4 of Table 4 decompose the results in column 1, where all wages are changing, by the separate effects of wages in manual, routine, and analytical occupations. Trade or technological change may move the wage in one occupational class and not in the others.[33] The aggregate of unskilled women and men is most responsive to the manual-task wage and least to the wage in analytical occupations. Conversely, participation of skilled workers is most responsive to the analytical task-wage.

Occupation-, gender- and skill-specific labor supply responses to an increase in occupation-specific wages. We now decompose the net effects just discussed to consider how changes in occupation-specific wages influence own- and cross-occupation labor supply. See Figure 9 and Appendix Tables D.4 and D.5. All own-wage elasticities are positive, and cross-wage elasticities negative. Elasticities specific to gender-skill-occupation-year are in the Figures. Here we summarize the main patterns. Changes in analytical task wages produce labor supply responses that are actually similar between men and women, but differentiated by skill, being larger among skilled workers. When manual wages change, unskilled men are the most responsive group, and skilled women the least. When routine wages change, the patterns are broadly similar except that now skilled women are more responsive and the own- vs cross-wage elasticity indicate that they will move between analytical and routine task jobs as a function of the relative wage. Notably, while aggregate male labor supply is not very elastic to occupation-specific wages (Table 4), male mobility across occupations is influenced by the wage in one occupation vs another.

Overall, our finding of large (and time-varying) occupation-skill-gender specific labor supply responses to the equilibrium wage structure underlines the relevance of accounting for these responses in a general equilibrium model. These results are important beyond the context of this study. Within the supply and demand framework, the most common strategy to estimate an equation like (2.1) is to assume that labor supply is inelastic, include a low-order polynomial for the relative demand trend, and use an OLS or fixed effects estimator. If labor supplies are elastic, the results from this type of exercises can be misleading (see Appendix Section C).

Moreover, the finding that elasticities are heterogeneous and time-varying is also important. In a survey of the literature on the impact of immigration on native

33. For AME, values in columns 2-4 are partial derivatives that sum up to the total derivative value in column 1.

wages, Dustmann, Schönberg, and Stuhler (2016) argue that the range of estimates found in the literature can be partly accounted for by the assumption that the labor supply elasticity is homogeneous across different groups of natives. The reason is that by making this assumption researchers are bypassing employment responses.

6.5 Supply Side Non-Wage Determinants of Labor Force Participation

We now discuss estimates of average marginal effects (AME) of the four supply-side shifters on gender-skill-occupation specific labor supply, see Table 5 and Appendix Table D.6).[34] In contrast to many existing studies, we provide estimates by skill and for men and women. We summarize the results here but consider them again in the counterfactual analysis, where we provide an accounting of the importance of these factors for the evolution of gender gaps in LFP and wages. **Fertility.** The percentage of skilled women with young children (fertility) declined by 20 pp over the sample period. We estimate that a 10 pp decrease in fertility increases participation of skilled women by 6 pp. Fertility decline *decreases* LFP of unskilled women and men (0.63 pp and 1.3 pp), consistent with parenthood increasing the higher earnings target. Skilled male labor supply is almost perfectly inelastic to fertility, consistent with the strong labor market attachment of this group. **Stable partnerships.** The decline in cohabitation rates has insignificant effects on women's participation but raises male LFP, with larger impacts on unskilled men. **Household appliance availability.** Reducing appliance availability in 1989 by 10 pp for unskilled (from 63.0%) and skilled (from 95.6%) women respectively, FLFP would decrease by 5 and 18pp, respectively. However, as the skilled group had close to complete uptake at baseline, the growth in appliance uptake was among unskilled women (see Figure D.2.). Appliances also increase LFP of skilled men, but reduce LFP of unskilled men. **Women's economic rights.** Improvements in gender and work related laws and regulations, captured by the WBL index, have a small positive effect on FLFP, twice as large for skilled as for unskilled women. A 10 pp increase in the WBL from 1989 is estimated to lead to an increase in FLFP of 2.5 pp for skilled and 1.3 pp for unskilled women. The marginal effects of an increase in the WBL on male LFP are close to zero.

7 Counterfactuals

Using the estimated parameters of the equilibrium model, in this section we evaluate and compare, in one internally-consistent framework, various factors considered by

34. AME is calculated by taking the numerical derivative of the probability of choosing home production with respect to the given variable. The margins are interpreted as the percentage point (pp) changes in the probability of leisure conditional on skill and gender given a one pp increase in the respective supply-side variable (and, thus, the signs are reversed for occupation-specific labor supply).

different strands of the literature as important for changes in gender wage and participation gaps. We evaluate non-wage predictors of LFP, changes in the gender-skill composition of the potential workforce, and skill and gender-biased technological change by occupation.

We compute general equilibrium (GE) wage responses given counterfactual changes in demand and supply over time. Where relevant, we compute supply-side partial equilibrium (PE) results given observed wages in each year. Comparisons of GE with PE estimates illuminate the role of endogenous wage responses. We demonstrate that PE tends to over-state the contribution of supply shifters by virtue of ignoring equilibrium wage adjustments that generate countervailing impacts on labor supplies. This is important because research that estimates structural models of female labor supply has typically taken wages (and labor demand) as given and provided PE counterfactuals (Keane, Todd, and Wolpin 2011; Böhm et al. 2019). In the case of changes in demographic composition, we document a case of GE reversing the sign of the PE effect.

Our main findings are as follows. The baseline model predicts an overall narrowing of the aggregate gender participation gap of 19.9 pp, driven solely by the increase in FLFP. A narrowing is evident across all occupation and skill groups. Our counterfactual analysis indicates that increasing appliance availability, which increased unskilled FLFP, was the largest contributor, accounting for 28% of the overall narrowing of the LFP gap. Fertility decline was the main driver of FLFP growth among skilled women, but it had a smaller effect on the overall gap because of higher baseline participation rates and relative group size. Interestingly, we find that the increasing share of skilled women in the population acted to widen the participation gap. This is explained by the countervailing effect of wages on participation and how the compositional change impacts wages and occupational sorting across all groups.[35]

Alongside a narrowing of the gender participation gap, there was a narrowing of the overall gender wage gap by 6.3 log points. But underlying this number are substantial distributional changes: the gender wage gap declined by 10.4 log points among skilled workers and increased by 9.6 points among the unskilled. The narrowing of the skilled gender wage gap reflects favorable demand trends that dominated the increased labor supply in this group. The latter results from increasing college completion rates and higher participation due to declining fertility. The increase in the unskilled gender wage gap reflects the opposite: relative labor supply of unskilled women, driven by appliance availability and the emigration of unskilled men, dominated the rising demand for women in this group.

35. The rising share of skilled women dampened wage growth for skilled women, which, in turn, cramped further rises in their participation. It also crowded out some of the potential increase in the share of unskilled women joining the labor force, essentially because growth in the relative demand for women's labor was skill-biased.

Overall, across skilled and unskilled women, the single largest influence on the aggregate gender wage gap in this period was the growing demand for female labor. This outward shift in the demand for female labor explains why the participation gap and the wage gap move in the same direction. We estimate that, if there were no increase in the relative demand for women then, rather than decreasing, the overall gender wage gap would have grown by 17.6 log points.

Our estimates are potentially sensitive to the fact that we do not endogenize college completion. The extent to which this would modify our estimates here depends on the elasticity of college choices to expected wages. As discussed in Section 5.2, Mexico exhibits a secular increase in college completion in the analysis period. That this occurred even though the college premium decreased, and mean real wages exhibited substantial fluctuations in this period suggests that endogenous responses of college attendance to wages may be small. Moreover, any impact on our estimates from counterfactuals that vary non-wage determinants of LFP and relative demand trends will be muted by offsetting effects on wages and quantities.

We now elaborate on each result. In each counterfactual exercise, we fix the variable or parameter of interest to its value in 1989, and keep it constant across the years. We then compare the predicted equilibrium wages and labor supplies under the counterfactual scenario with the baseline model predictions. In Tables 6 and 7, each cell reports changes over time in the gender differences in labor supply and wages by skill and by occupation-skill groups. The first column shows the prediction of the baseline model, successive columns present results from counterfactuals that shut down the mechanism indicated in the column header. Thus if a mechanism in column 5 (for example) has a large impact on the outcome, this is reflected in a large *difference* between the estimate in column 5 and the estimate in the first column. For ease of exposition, the counterfactual results are also visualized in Figures 10, 11, and 12.

7.1 Non-Wage Determinants of LFP

The gender participation gap. The estimates are in the first block of Table 6. The headline result is that the rapid rise in household appliances among unskilled women was the main driver of their LFP, while fertility decline was the main driver of the LFP of skilled women. Male labor supply is not substantially impacted by either. See Figure 11.

Under PE, in the absence of any increase in appliances, FLFP of unskilled women in routine task-intensive occupations would have increased from 10% to 12%, whereas in fact this rate increased to 16%. In the absence of fertility decline, FLFP of skilled women in routine occupations would have increased from 8.5% to 14.5%, but in fact this rate increased to 18%. In contrast, the counterfactual and the actual participation paths largely overlap for unskilled women under the

fertility counterfactual, and for skilled women under the appliance counterfactual given more muted changes in the shifters, see Figure D.2. This pattern of results holds by occupation too. Visualizations are provided in Panels (b-d) of Figure 11. The GE estimates additionally account for the fact that, as more women are driven into work, women's wages fall, and this inhibits further increases in women's labor supply. The PE-GE difference is large, for example, it halves the positive impact of appliance availability on the FLFP of unskilled women. Since a larger number of unskilled women participate, equilibrium wage effects are larger in this group.

In aggregate, the model predicts a narrowing of the gender gap in LFP in favor of women by 19.9 pp. Without the observed increase in household appliances, the gap would have narrowed by 14.3 pp (28% of 19.9 pp) under GE, and 7.5 pp (62% of 19.9 pp) under PE. Without fertility decline, it would have narrowed by 17.9 pp (10% of 19.9 pp) under GE and 16.5 pp (17% of 19.9 pp) under PE. The relatively small share of skilled women in the population reduces the aggregate effects of the fertility counterfactual. Increasing WBL contributed to reducing LFP gaps in all skill and occupation groups, and the decreasing share of stable partnerships slightly widened the LFP gap among the unskilled. The time-series of aggregate LFP gap changes is shown in Panel (a) of Figure 11 and changes between end-points are visualized along the x-axis of Appendix Figure D.4.

The gender wage gap. Under both GE and PE, increasing appliance availability increases the gender wage gap, while decreasing fertility reduces it. Marriage and women's rights have relatively small impacts. See Panel (a) of Figure 10, and Panel (a) of Appendix Figure D.4.

The baseline prediction is a narrowing of the aggregate gender wage gap of 6.3 log points. The PE counterfactual shows that, absent the rise in appliance availability, the wage gap would have narrowed by 10.6 (68.2% more than the baseline), which establishes that rising appliance availability has tended to increase the wage gap. The PE effect works by changing the skill composition of the workforce—appliances increase the relative supply of unskilled women who earn lower wages. The GE estimate is a narrowing of the wage gap by 12.2 log points (93.6% more than in baseline). GE additionally allows that, as the supply of unskilled female labor increases, their relative wage falls and this leads to further divergence of women's wages relative to those of men.

The PE counterfactual shows that, absent fertility reduction, the gender wage gap would have narrowed by 3.3 points. The corresponding GE estimate is 5.6 log points. Both numbers are smaller than the baseline of 6.3 points, indicating that fertility reduction decreased the wage gap. The PE effect is again compositional, but now lower fertility increases the participation of skilled women who earn higher wages, with little effect on unskilled women. The additional channel in the GE effect is that increased participation of skilled women generates downward pressure

on skilled female wages, leading to a smaller reduction of the wage gap compared to PE.

The extent to which changes in labor supply affect the gender wage gap is determined by $\rho_{4,occ}$, or the elasticity of substitution between male and female labor. Our finding that this elasticity is small in lower-paying manual and routine task-intensive occupations, which employ a disproportionate share of unskilled workers, acts to sharpen the relative wage effects of the appliance counterfactual. The greater ease with which women can substitute men in analytical tasks, which are more likely to be occupied by skilled workers, blunts the relative wage effects of the fertility counterfactual. In particular, downward wage pressure from higher skilled female participation is transmitted to male wages, moderating the downward pressure on the gender wage gap. Previous studies analyzing the role of, for example, appliances, and fertility, have not studied their important distributional effects.

The skill premium. Our baseline model predicts a log (skilled/unskilled) wage ratio among women that is fairly stable (-1.4 log points decline). Beneath the surface though, are some large movements that happen to offset one another. In the absence of fertility decline, the female skill premium would have increased by 7.5 pp, while in the absence of increased appliance ownership, it would have decreased by 6.4 pp. These counterfactuals demonstrate that evolution of the skill premium depends on labor supply responses ofskilled and unskilled workers.

Changes in women's participation can also impact the skill premium for males, a phenomenon largely ignored in the literature on wage inequality, whether in the U.S. or in Mexico. The size of this impact will depend on the elasticity of substitution between male and female labor. The baseline model shows that the male skill premium declined over the period by 21.5 log points. The counterfactuals show that, if not for appliance growth, it would have declined by 20.5 points and, if not for fertility decline, it would have declined 18.3 points. Fertility decline had a larger impact on the male skill premium because of the higher substitutability of men and women in skill-intensive occupations, which transmits more readily the downward pressure on skilled female wages to skilled male wages. However, the magnitude of the fertility effect is limited by the relatively small number of skilled women.

7.2 Demographic Changes

Relative skill upgrading. College completion rates rose more rapidly among women than men over the analysis period. We construct a counterfactual in which we fix the gender composition of the skilled population at its 1989 level. We do this by allowing the number of skilled males and the gender-specific population to increase as observed, maintaining the female share among the skilled at 31.2%, its initial level. By 2014, under this counterfactual, there are 2.2 million skilled women rather than the actual 5.0 million, and the difference is added to the number of

unskilled women.

As the share of skilled female workers increases, since they earn higher wages and have higher LFP rates (see Panel (b) of Figure D.3), under PE, the compositional impact is to reduce the gender gap in participation and wages. Thus under the counterfactual that shuts down the actual increase in skilled women among potential workers, the gender wage gap increases by 5.3 log points in contrast to the baseline decline of -6.3 log points, see the second block of Table 7. The gender participation gap declines by 17.8 pp instead of the baseline of 19.9 pp, see Table 7 (first block).

Under GE, there is feedback from equilibrium wages to labor supplies. This counterfactual illustrates nicely the role that the substitutability of male and female labor, the substitutability of skilled and unskilled labor, and the wage elasticity of supply play in the propagation of this feedback. This highlights the relevance of allowing variation in these elasticities by occupation.

We now elaborate the mechanisms at play. An increase in skilled female labor supply pushes down skilled female wages. Given high substitutability of male and female labor in analytical task-intensive occupations ($\rho_{4,a}$), where skill is concentrated, skilled labor demand moves in favor of women and the demand for skilled men contracts, driving down skilled male wages. At this stage, the high degree of substitutability of skilled vs unskilled labor in manual task-intensive occupation ($\rho_{3,m}$) plays a role: as skilled wages are lower, there is a contraction in demand for male and female unskilled workers. This contraction is stark due to the sharp growth in the relative productivity of skilled female workers (decreasing $\alpha_{4,skl,occ,t}$ and increasing $\alpha_{3,occ,t}$). Overall, there is a reduction in wages across gender and skill groups.[36]

Now consider the GE effect of skill upgrading on the gender LFP gap, which is to widen it (by -24.2 pp, which exceeds the baseline of -19.9 pp), see Panel (a) of Figure 12. This is the reverse of the PE effect. The reason is essentially that the overall fall in wages has a larger impact on female than on male LFP, given that the aggregate wage elasticity is larger for females (see Panel (b) of Figure 12).

While accounting for GE effects reverses (widens) the direction of changes in the gender LFP gap implied by PE (a narrowing), GE magnifies the narrowing of the gender wage gap that was established under PE—the counterfactual coefficients are +9.6 (GE) and +5.3 (PE) log points instead of the baseline -6.3 log points—see the third block of Table 7. This holds for skilled and unskilled workers but the relative wage effects on unskilled workers dominate because they are a much larger share of the population.

The GE feedback effects from wages also have implications for the skill premium. Consider the fourth Panel of Table 7, which shows the impact of holding

36. The demand-driven fall in unskilled male wages is unambiguous. However, the demand contraction for unskilled female workers is counteracted by the concurrent contraction in female unskilled labor supply. It turns out that, on balance, unskilled female wages fall as well.

fixed the gender composition of skilled workers on the gender-specific skill premium. On its own, the increased share of skilled women significantly decreased the female skill premium by 42.2 log points (from +40.8 under the counterfactual to -1.4 at baseline).

Emigration. There was an increase in emigration rates over the analysis period, led by unskilled men. Emigration affects the occupational and wage structure by changing the number of potential workers in each skill-gender group (e.g., changing $L^{pop}_{f,s,t}$ in Equation (5.8)). We explain the mechanism in detail in Appendix Section A.2.1. We conduct a counterfactual in which we fix the share of emigrants in the Mexican-born population by gender and skill at its 1989 level. Rising emigration created upward pressure on wages, especially among the unskilled, increasing their participation rates. Unskilled women reacted more than unskilled men given their larger aggregate wage-elasticity, and this led to a narrowing of the overall gender participation gap.[37] Since the labor supply of men adjusts less than that of women, male wages absorb most of the impact, and there is an increase in the unskilled and the overall gender wage gap. The magnitude of this effect is similar to that of the appliances counterfactual.

7.3 Demand Side Share Parameters

To quantify the impact of relative demand trends, we run two counterfactuals in which we fix either the gender-skill-occupation shares ($\alpha_{4,skl,occ,t}$) or the skill-occupation shares ($\alpha_{3,occ,t}$) to their 1989 values. We find that increasing female-demand-share ($1-\alpha_{4,skl,occ,t}$) had the largest impact on the narrowing of the gender wage gap of all the mechanisms that we analyze counterfactuals for (see the second block of Table 7). As shown in Section 6.3, relative demand trends strongly favored women across occupation and skill groups. Absent this, the gender wage gap would have increased by 17.6 log points instead of declining by 6.3 points as predicted in the baseline. In fact, the growing demand for women's labor counteracted the downward pressure on female wages arising from rapid increases in FLFP.

Even when we shut down $\alpha_{4,skl,occ,t}$, the labor supply of women increases substantially, closing the participation gap with men, albeit at a slower pace relative to the baseline (see the overall row in the first block of Table 7 and Panels (c) and (d) of Figure 12). But with the growth in relative female demand shut down, the relative female wage adjusts downward (see the overall row in the second block of Table 7).

Fixing the gender-skill-occupation shares ($\alpha_{4,skl,occ,t}$) also has significant distributional effects. The gender wage gap increases in both skill groups, but more among the skilled, reversing the observed pattern. This demonstrates that the actual contraction of the gender wage gap at the top of the wage distribution was primarily

37. The counterfactual, phrased in the inverse, is -16.7 pp compared with the baseline -19.9 pp.

driven by stronger labor demand for skilled women (see Figure 7). The latter also translates into an increase in the skill premium for women, and a decrease for men.

In our final counterfactual, we fix the skill-occupation shares ($\alpha_{3,occ,t}$) at their initial value. What is strongly affected now is the skill premium. The counterfactual shows a decline relative to baseline predictions (see the last block of Table 7). This confirms that skill-biased technical change raised the skill premium.

8 Robustness Checks

The baseline estimates defined earnings for full-time workers, see Appendix A. We re-estimated the model including earnings of part-time workers. Including part-time worker income reduces the elasticity of substitution between male and female labor in manual and routine task-intensive occupations to 0.80 and 0.97, respectively. Replacing the head count measure of labor supply with total hours leaves the estimates unchanged. We restricted the $\boldsymbol{\alpha}$ share parameters to follow a cubic trend in their natural logarithm. The cubic trends provided the best fit. We confirmed that quadratic polynomials did not allow sufficient flexibility, while the coefficients associated with the quartic polynomials were not statistically significant in most cases. Importantly, the estimates are not sensitive to functional form. We checked robustness to switching the order of the second and third nests of the production technology, and to varying which of the two occupational groups has the common elasticity. The rank order of the values of the elasticities of substitution between male and female labor is maintained in all cases: the manual and routine task-intensive occupations elasticities lie between 0.7 and 1.2, while the analytical task elasticity lies between 1.9 and 2.6. The corresponding estimates of the parameters from the supply-side of the model remain essentially unchanged. These additional results are available on request.

9 Conclusions

We develop a model that allows that demand and supply forces to interact in equilibrium and jointly explain the observed paths of wages by gender, skill, and task-based occupation. Our approach marks a departure from most previous work on women's labor supply, which takes labor demand as fixed. It also marks a departure from the standard labor supply-demand model often used, for instance, to analyze immigration, by virtue of endogenizing labor supply. Our estimates suggest that, even in settings where total labor supply is fixed, it is relevant to consider the sorting of labor across occupations, in response to equilibrium wages. We quantify the relative importance of demand, supply, and demographic factors and their distributional consequences, within and between genders and across the wage distribution.

While our empirical results speak specifically to the experience of Mexico as it

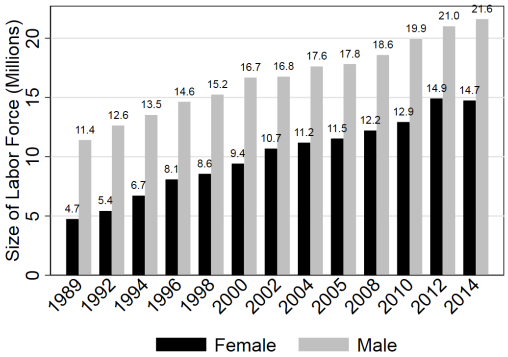
entered the twenty-first century, the demand, supply, and demographic mechanisms are of general interest in contemporary richer and poorer countries. Our equilibrium framework and associated solution, identification, and estimation results are applicable in other gender settings and in non-gender settings where a nested-CES production function is appropriate for describing input aggregation, and multinomial discrete choice assumptions can sufficiently capture the relative tradeoffs for participating in alternative occupations.

Tables and Figures

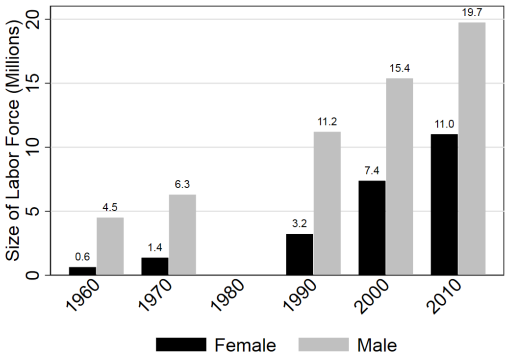
Figure 1: Labor Force Participation by Gender

Absolute Numbers

(a) Survey Data

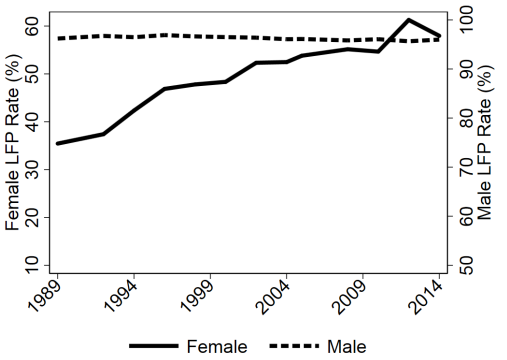


(b) Census Data

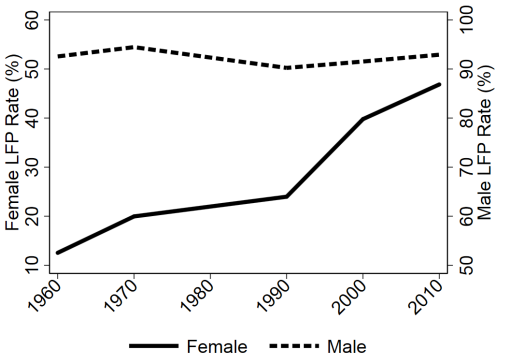


Gender-specific Participation Rates

(c) Survey Data



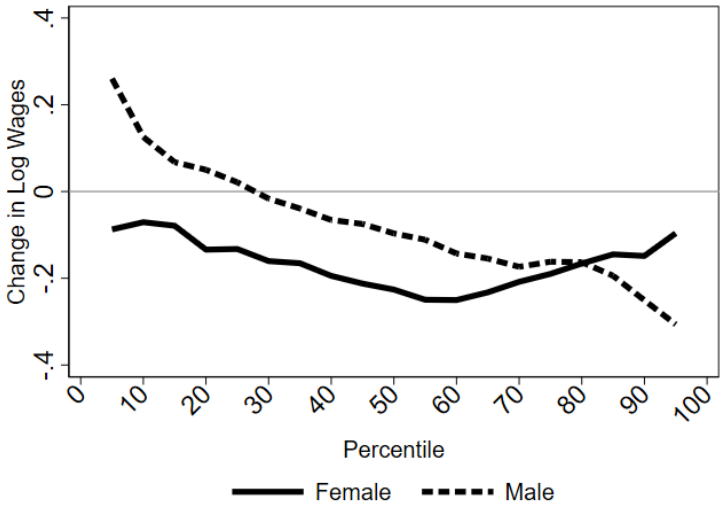
(d) Census Data



Notes: The labor force participation rate is defined as the proportion of prime-age individuals (25-55 years old) who either worked or sought employment in the previous month relative to the total number of individuals within this age bracket. Our definition of work includes all sectors, occupations, and the informal economy, irrespective of the nature of the activities or if the work complies with the country's formal labor laws and protections (*i.e.* if the job is formal or informal). Sample weights are used in all calculations. See Appendix Section A.1 for details on the construction of the series.

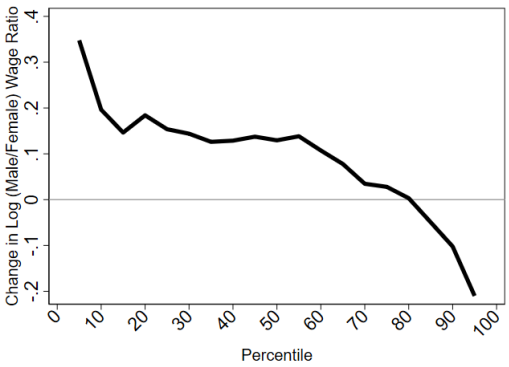
Figure 2: Distribution of Changes in Log Hourly Wages by Gender between C.1992 and C.2012

(a) Males and Females by Percentile

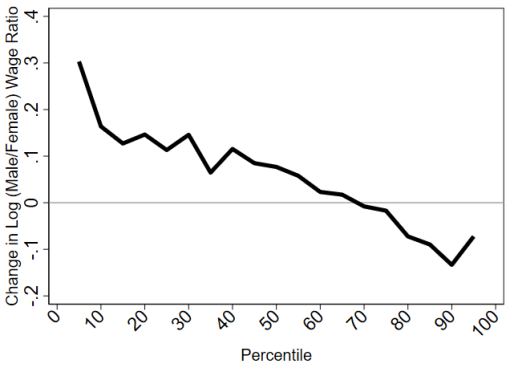


(Log) Gender Wage Gap by Percentile

(b) ENIGH

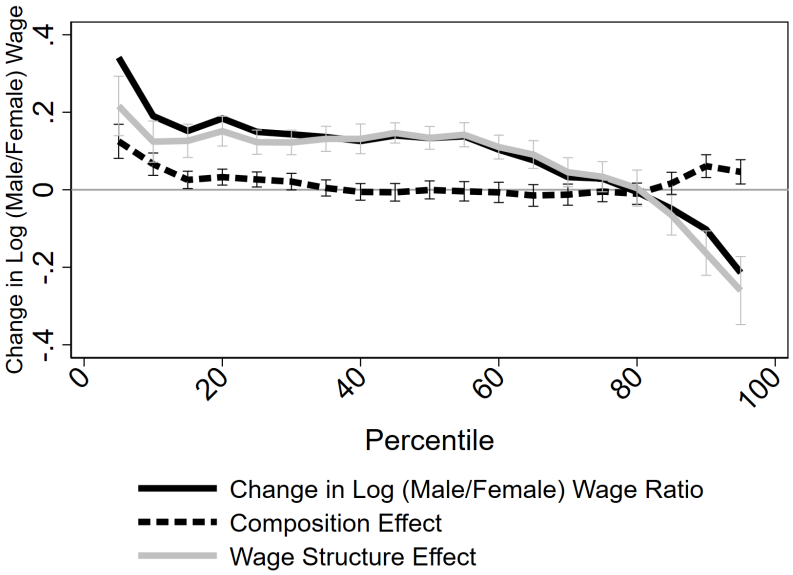


(c) Census



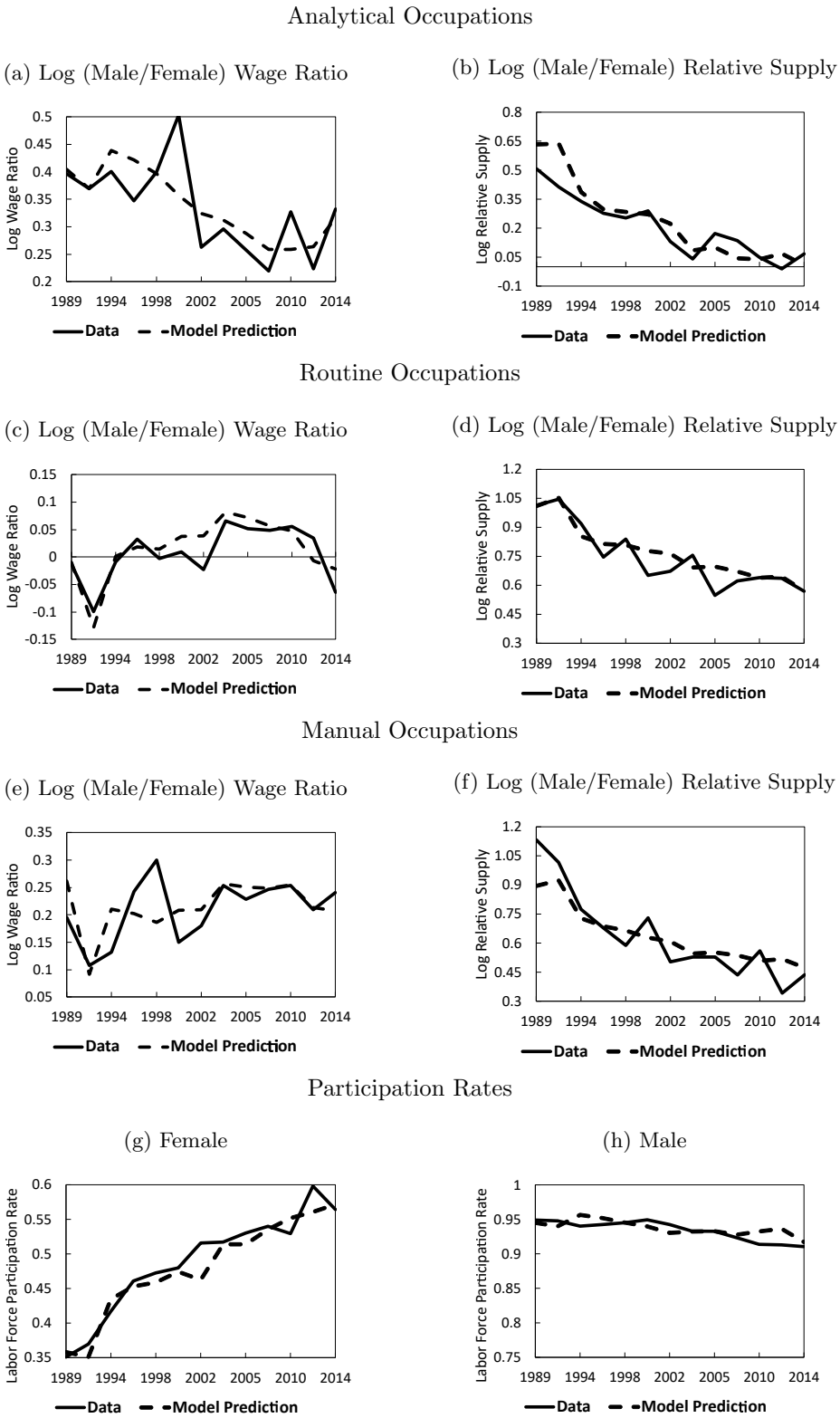
Notes: The series in Panel (a) are constructed by computing the change in real log hourly wages between C.1992 and C.2012 at each percentile of the male and female distribution, respectively. Panel (b) shows the change in log (male/female) hourly wages by percentile between C.1992 and C.2012, calculated using the survey data from ENIGH. Panel (c) replicates the exercise using information on monthly labor earnings and hours worked from the 1990 and 2010 Mexican CENSUS. The sample was restricted to the prime-age population working more than 35 hours a week. To increase the sample size in ENIGH, we joined surveys from 1989, 1992, and 1994 (C.1992), and from 2010, 2012, and 2014 (C.2012).

Figure 3: Decomposition of the Gender Wage Gap by Percentile of the Distribution



Notes: The Figure shows results of the Oaxaca-Blinder decomposition of the unconditional change in the log (male/fermale) wage ratio between C.1992 and C.2012 by percentile. The estimation is done separately for 19 percentiles. Confidence intervals are estimated via bootstrap with 500 replications. Sample weights used in all calculations. The wage structure effect dominates, tracking the data. The composition effect is fairly constant across the distribution and close to zero. See discussions in Section 4.

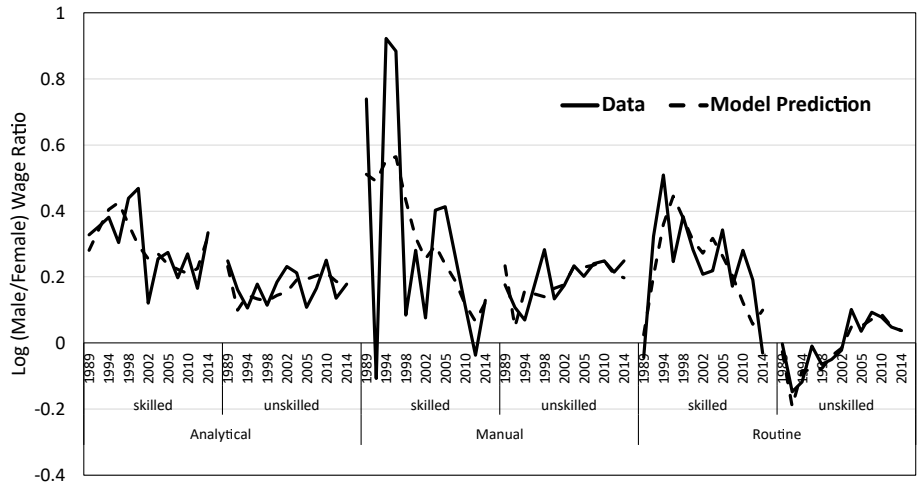
Figure 4: Model Fit
Data and Model Predictions for Relative Wages, Relative Supplies and Participation Rates



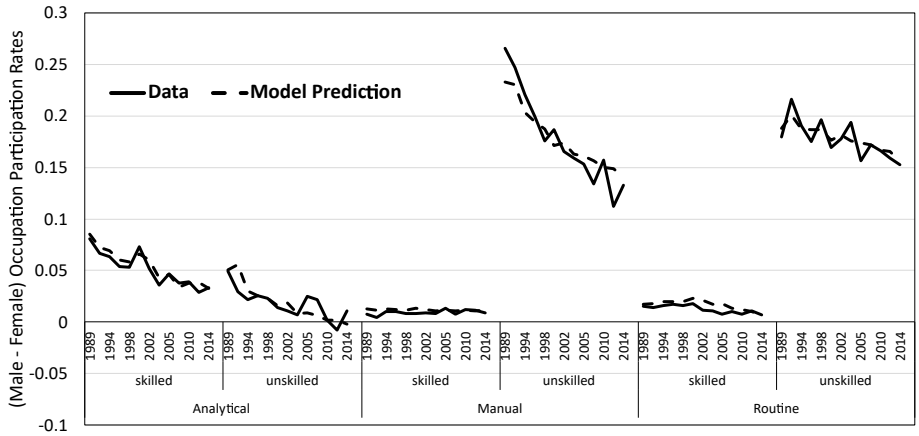
Notes: The different panels depict the series of log (male/female) relative wages, log (male/female) relative labor supplies (= demands), and LFP rates from both the raw data and as predicted from the model, showing a close fit. See discussions in Section 6.1.

Figure 5: Model Fit
Data and Model Predictions for Male to Female Relative Wages and Male and Female Occupation Participation Rates Differences

(a) Log (Male/Female) Wage Ratio

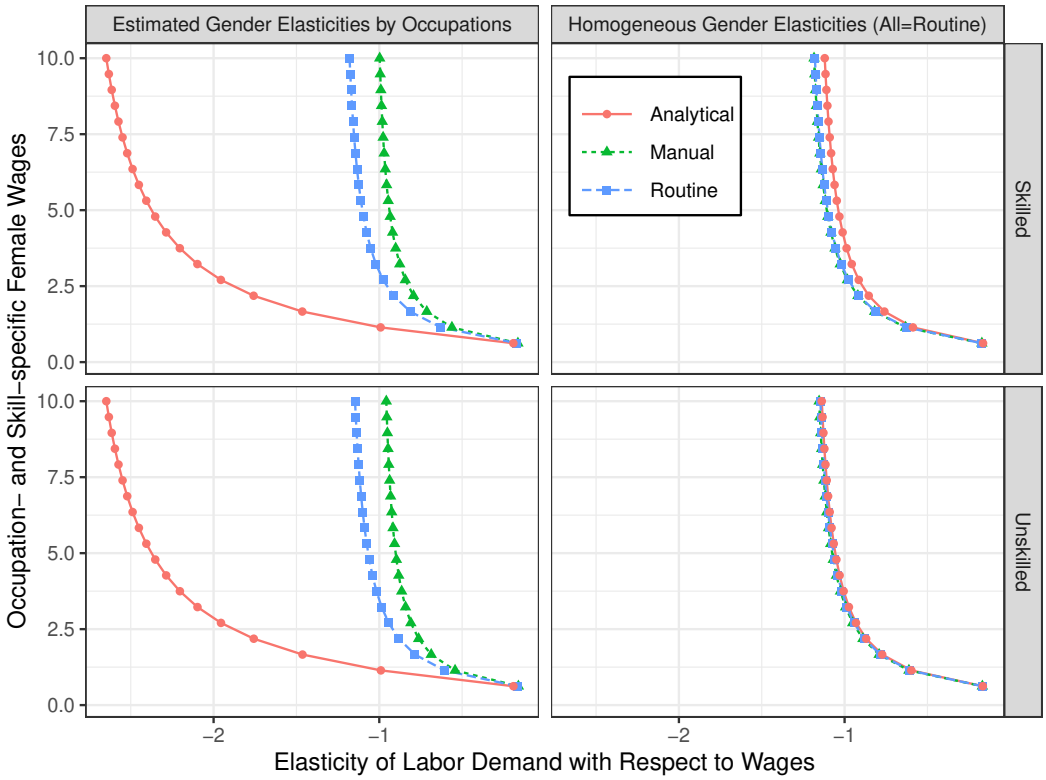


(b) (Male - Female) Occupation Participation Rates



Notes: The panels depict log (male/female) relative wages and (male - female) occupation participation rates differences (See Footnote 25 for definition). The skill- and occupation-specific results from the first block of the model columns of Tables 6 and 7 show the differences between the averages of the first three years and the final three years based on the Model Prediction lines in the present Figure. See discussions in Section 6.1.

Figure 6: The Elasticity of Demand for Female Workers to Female Wages by Occupations and Skills.

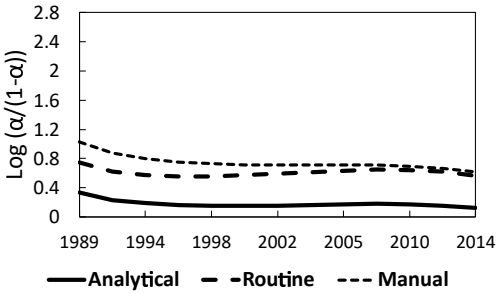


Notes: In this figure, we show the wage elasticity of demand. For each skill- and occupation-specific female wage, we hold all else constant, and vary only the female wage in one skill and occupation group to derive the skill- and occupation-specific demand curves. We then compute the skill- and occupation-specific wage elasticities of demand. In the two subfigures on the left, we use wages and estimated parameter values from 2002. Elasticity curves across occupations differ due to heterogeneous occupation-specific gender elasticity of substitution. In the two subfigures on the right, we set the manual and analytical gender elasticities to the estimated value for routine task-intensive occupations (which is in between the estimated manual and analytical elasticities). The figure demonstrates that the assumption of homogeneous gender elasticity of substitution across occupations in effect imposes the restriction that the wage elasticity of demand is similar across occupations. Given that the gender elasticities of substitution do not vary over time, results are similar across years. See discussions in Section 6.2.

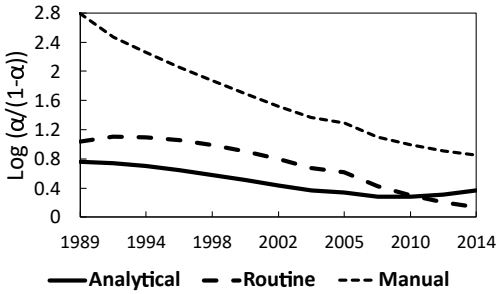
Figure 7: Estimates of the Relative Demand Indexes and Total Factor Productivity

Production Technology: α Share Parameter

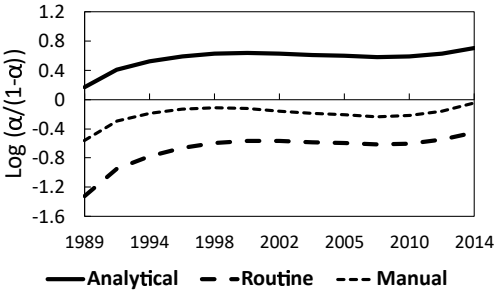
(a) Level III, Unskilled
Male Share $\alpha_{4,u,occ,t}$ (vs. Female)



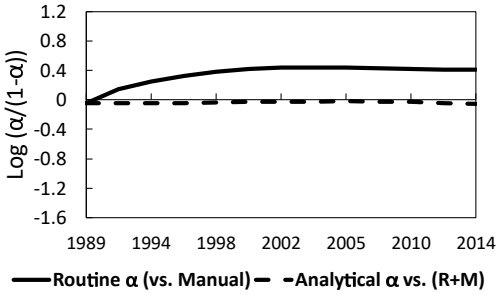
(b) Level III, Skilled
Male Share $\alpha_{4,s,occ,t}$ (vs. Female)



(c) Level II
Skilled Share $\alpha_{3,occ,t}$ (vs. Unskilled)

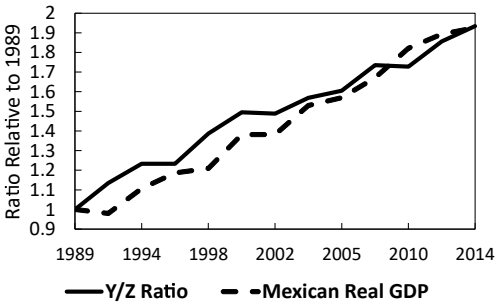


(d) Level I, Routine Share $\alpha_{2,t}$ (vs. Manual),
Analytical Share $\alpha_{1,t}$ (vs. Rou. + Man.)

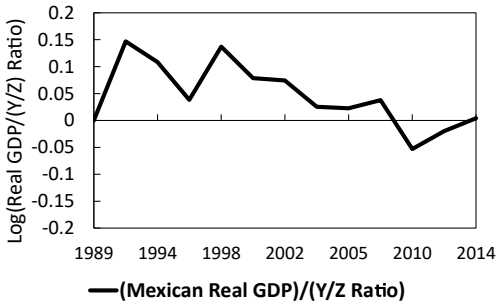


Production Technology: $\frac{Y}{Z}$ Output Productivity Ratio

(e) $\frac{Y}{Z}$ and Real GDP Per Capita

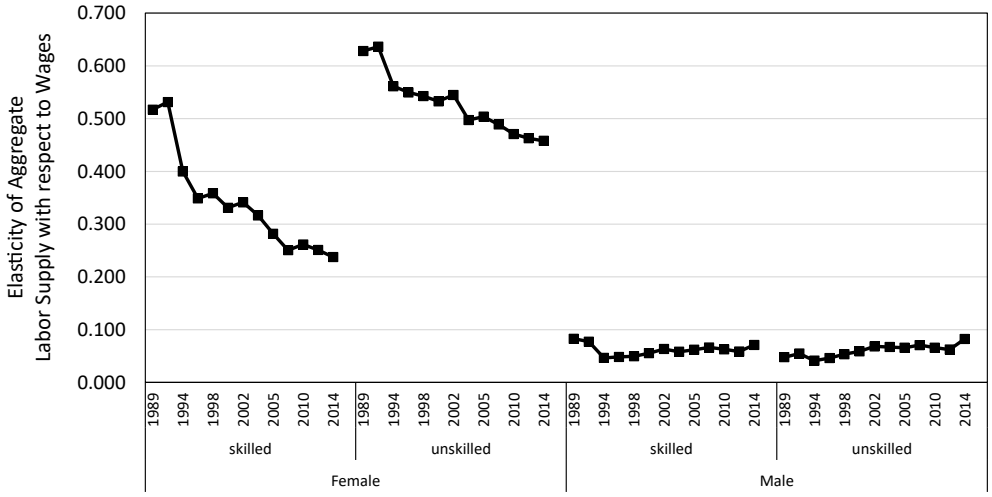


(f) Total Factor Productivity (Z)



Notes: Panels (a)-(d) show the estimated relative demand indexes captured by the natural logarithm of the ratio of α and $1-\alpha$. Panel (e) shows the estimated output to productivity ratio $\frac{Y}{Z}$, plotted along real GDP per capita relative to 1989 using FRED data. Panel (f) is the natural logarithm of the ratio of real GDP per capita by the $\frac{Y}{Z}$ ratio. See discussions in Sections 6.3 and 7.3.

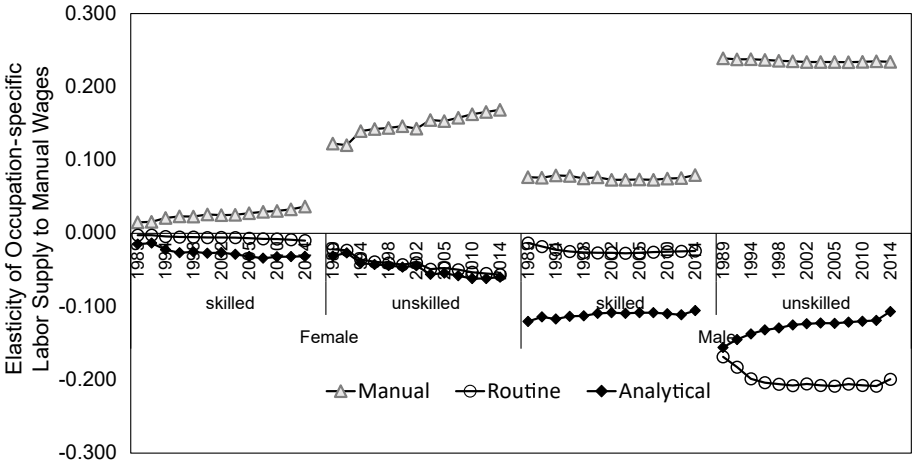
Figure 8: Estimates of Aggregate Wage Elasticity
The Elasticity of Gender- and Skill-specific Aggregate Labor Supply with Respect to Wages



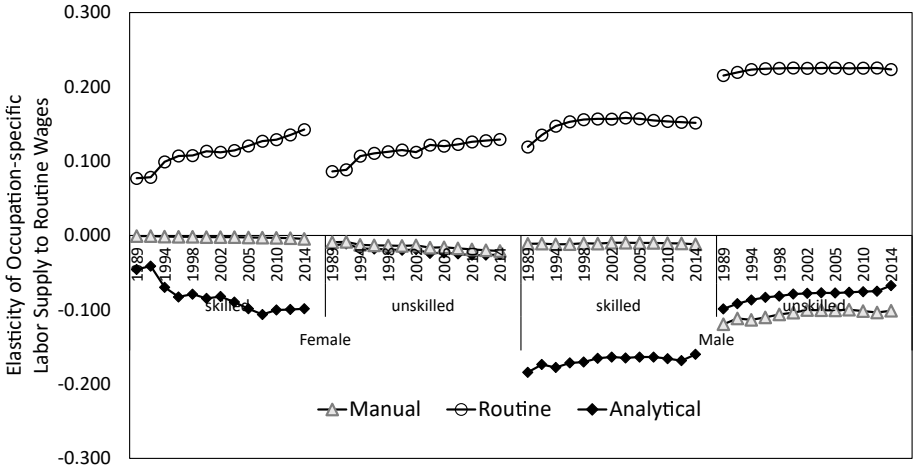
Notes: The panel depicts elasticities. It shows the ratio of a percentage change in the aggregate labor supply—for each gender and skill group—over a percentage increase in wages. The same percentage increase in wages is applied to all occupation-specific wages concurrently. Year-specific elasticities are computed. The first column in the bottom panel of Table 4 shows the averages of the elasticities over time. See Figure 9 for the own- and cross-elasticities of occupation-specific labor supplies with respect to occupation-specific wages. See discussions in Section 6.4.

Figure 9: Estimates of Own and Cross Wage Elasticity
The Elasticity of Occupation-specific Labor Supply to Occupation-specific Wage

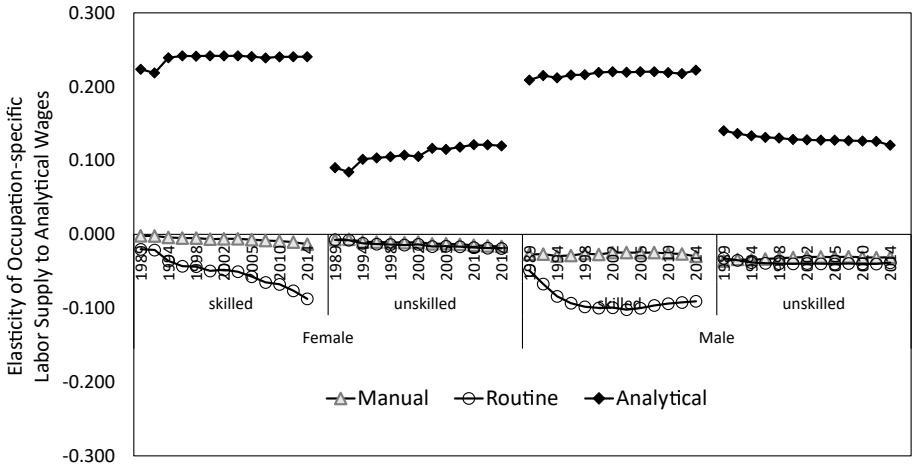
(a) Own and Cross-Elasticities of **Manual** Wages



(b) Own and Cross-Elasticities of **Routine** Wages



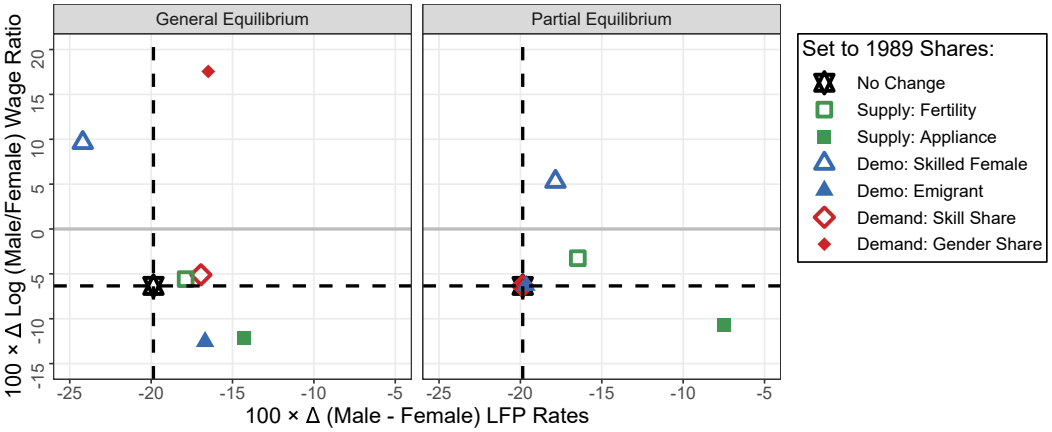
(c) Own and Cross-Elasticities of **Analytical** Wages



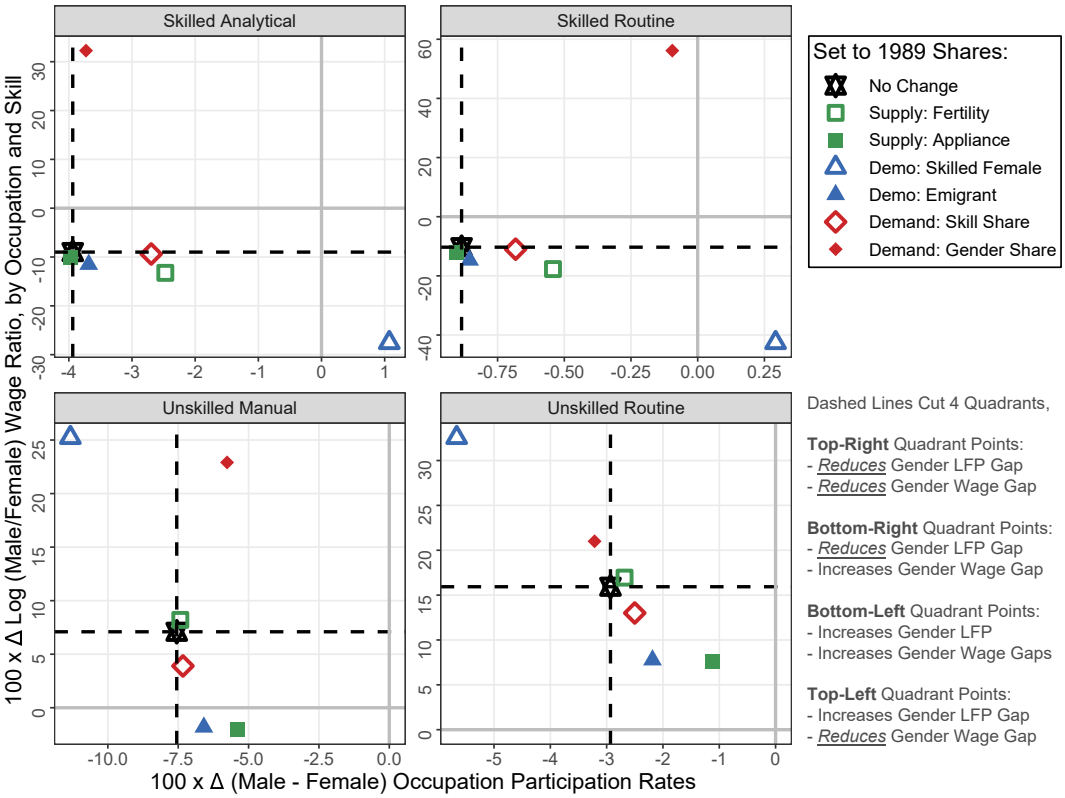
Notes: The panels depict elasticities. It shows the ratio of a percentage change in occupation-specific labor supply—for each gender and skill group—over a percentage increase in an occupation-specific wage. Triangle, circle, and diamond lines represent the elasticity of manual, routine, and analytical labor supplies with respect to different wages. See Figure 8 for aggregate elasticities. See Appendix Table D.5 for average own- and cross-elasticities across the years. See discussions in Section 6.4.

Figure 10: Counterfactual Exercises
Effects of Non-wage Determinants of LFP, Demographics, and Demand Side Parameters on Changes in the Gender LFP and Wages Gaps between C.1992 and C.2012.

(a) Changes in Gender Participation and Wage Gaps: (C.2012 - C.1992)



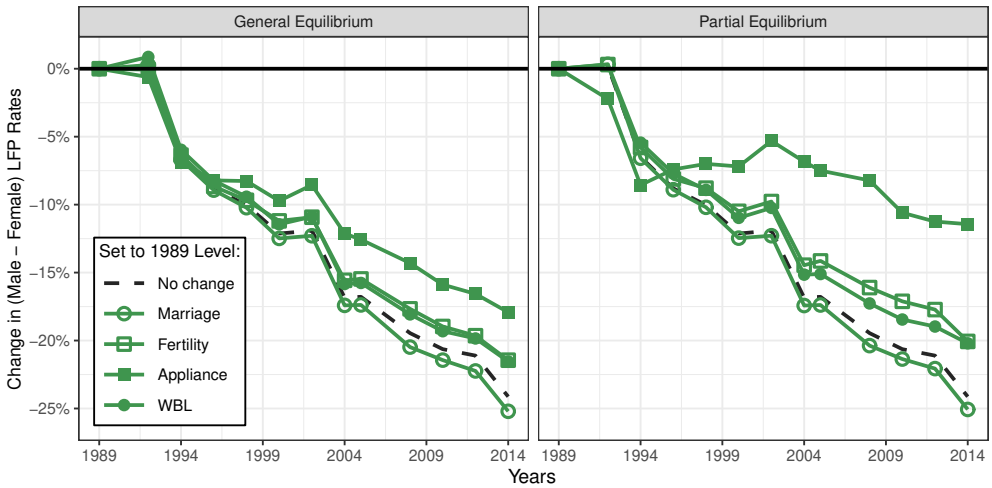
(b) **General Equilibrium** Changes in Participation and Wage Gaps: (C.2012 - C.1992) by Skill/Occ.



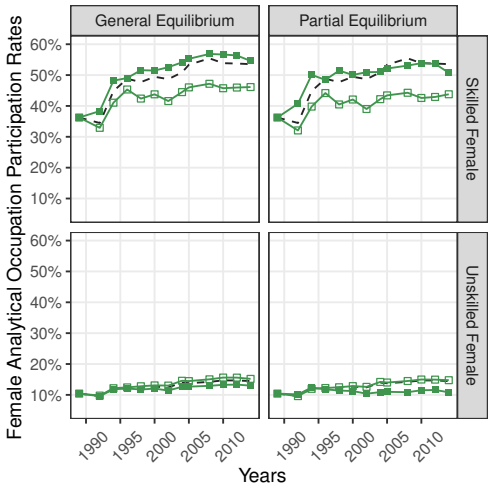
Notes: The Table reports the difference between C.1992 and C.2012 of i) the log (male/female) wage ratio and ii) the change in the (male - female) LFP and occupation rates under different counterfactual scenarios. Figure (a) visualizes results from the "Overall" row in the first two blocks of Tables 6 and 7. Figure (b) visualizes results from the skill/occupation-specific rows in the first two blocks of Tables 6 and 7 (Skilled-manual and unskilled-analytical results are not shown for conciseness). Black-dashed lines mark model predictions, and points indicate predictions under key counterfactual scenarios. Points to the right of the vertical dashed-line reduce gender LFP and occupation participation gaps; points to the top of the horizontal dashed-line reduce the gender wage gaps. Under the counterfactuals, we set the share with under-5 children (Fertility), the share with refrigerator or a washing machine (Appliance), the skilled population female share (Skilled Female), the gender/skill-specific emigrant shares (Emigrant), the skill/occupation-specific demand gender share $\boldsymbol{\alpha_4}$, and occupation-specific demand skill share $\boldsymbol{\alpha_3}$ at their 1989 values, respectively. See discussions in Section 7.

Figure 11: Counterfactual Exercises
Non-wage Determinants of LFP and Occupation Participation Rates

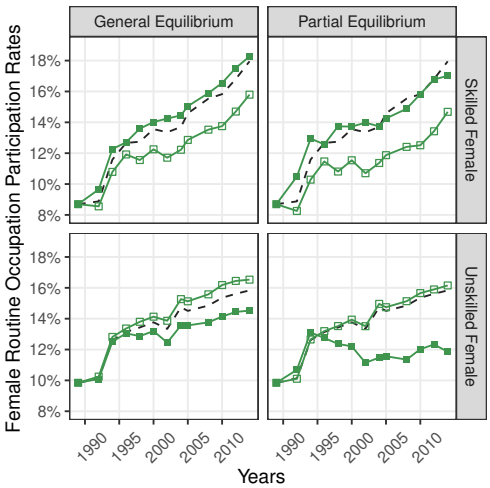
(a) (Male - Female) LFP Gap, Change from 1989



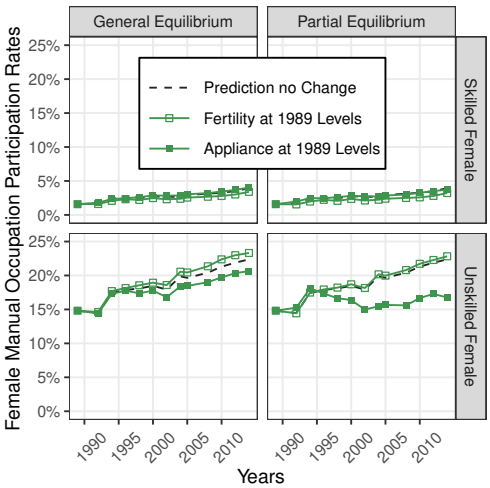
(b) Women Analytical Participation Rates



(c) Women Routine Participation Rates



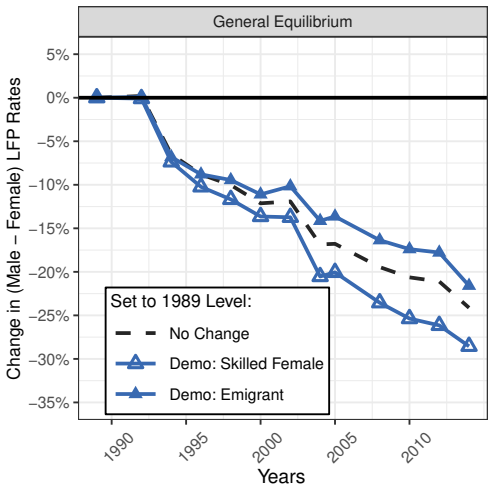
(d) Women Manual Participation Rates



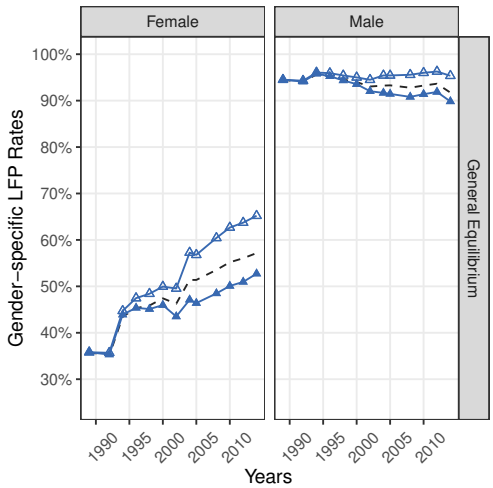
Notes: We set observables for non-wage determinants of LFP at their 1989 values, one at a time. In Panel (a), *appliance* had the largest effect on the aggregate gender participation gap. In Panels (e)-(d), more *appliance* and less *fertility* increased LFP for unskilled and skilled women, respectively. In partial equilibrium, we hold wages as observed. In general equilibrium, we resolve for equilibrium wages given supply curve shifts. See discussions in Section 7.1.

Figure 12: Counterfactual Exercises
Demographics, Demand Parameters, and LFP in **General Equilibrium**

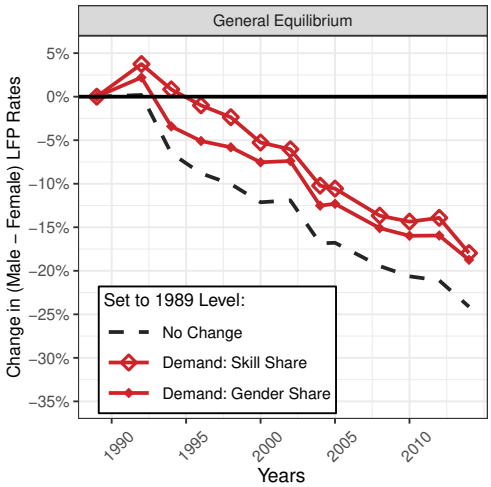
(a) **Demographics**: LFP Gap Change vs. 1989



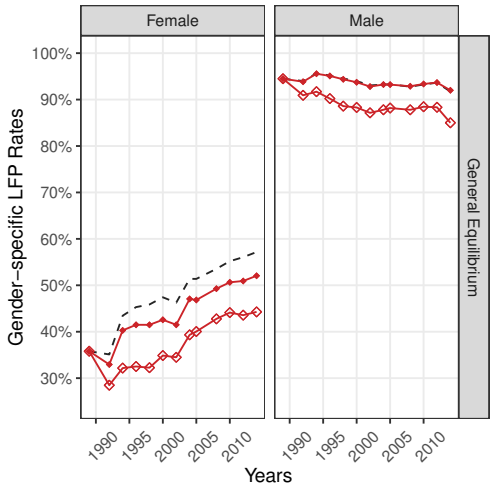
(b) **Demographics**: Gender-specific LFP



(c) **Demand**: LFP Gap Change vs. 1989



(d) **Demand**: Gender-specific LFP



Notes: Panels (a) and (c) show differences between the gender LFP gap in 1989 and each subsequent year under various counterfactuals. Panels (b) and (d) show variations in gender-specific LFP rates over time. In the counterfactuals here, we set the skilled population female share and the gender/skill-specific emigrant shares, and the skill/occupation-specific demand gender share ($\boldsymbol{\alpha_4}$) and occupation-specific demand skill share ($\boldsymbol{\alpha_3}$) parameters at their 1989 values. Figures D.3 and 7 present changes in these variables and parameters over time. See discussions in Sections 7.2 and 7.3.

Table 1: Occupation Groups
Task Structure, Gender Composition, Employment Share, Wage Rank

	Median Percentile of the Task Measure						
ENIGH Principal Group	Analytical	Routine	Manual	Group	Av. Share (x100)	Av. Male Share (x100)	Av. Wage Percentile
Managers	90.0	17.0	27.5	Analytical	2.9	71.3	85.4
Crafts and Trades (Supervisors)	84.0	42.0	62.0	Analytical	1.8	84.2	72.3
Education	83.0	11.0	65.0	Analytical	4.5	38.2	80.2
Professional	83.0	42.0	46.0	Analytical	4.1	62.4	82.3
Technical	71.0	69.0	43.0	Analytical	4.0	59.3	68.6
Arts/Entertainment	66.0	35.0	48.0	Analytical	0.6	76.4	70.4
Sales	61.0	22.5	15.0	Analytical	12.7	46.3	47.5
Crafts and Trades (Laborers)	40.0	82.0	73.0	Routine	14.3	76.4	47.4
Clerical (Supervisors)	61.0	63.0	51.5	Routine	2.5	65.0	77.9
Crafts and Trades (Helpers)	10.5	62.0	60.5	Routine	5.8	80.4	34.8
Machine Operators	16.0	62.0	51.0	Routine	3.6	62.4	48.4
Clerical (Laborers)	41.5	53.0	12.0	Routine	6.6	37.3	60.4
Transport	19.5	21.0	96.0	Manual	5.8	99.0	46.9
Agriculture	32.0	27.0	82.0	Manual	13.2	78.6	20.9
Protective Services	24.5	5.5	76.5	Manual	2.3	93.1	44.4
Domestic Service	9.0	8.0	76.0	Manual	4.1	7.6	27.0
Street Sales	38.0	13.0	64.0	Manual	3.4	44.0	30.3
Service	28.0	25.0	63.0	Manual	7.4	43.4	40.2

Notes: The three task measures were originally constructed for three-digit occupational codes of the U.S. CENSUS by Autor, Levy, and Murnane (2003). For each measure, we first organize the three-digit occupations by percentiles, and then calculate the median percentile within the broader 18 occupational groups of the ENIGH. Each of the 18 occupations is assigned to the group in which the median percentile was highest. See Appendix Section A.3.

Table 2: Labor Force Participation Rates
by Gender, Education and Age: C.1992 and C.2012

	C.1992		C.2012	
	Female Share (x100)	Male Share (x100)	Female Share (x100)	Male Share (x100)
Overall	38.59	96.49	59.59	95.82
Education				
Secondary	35.75	96.58	55.47	95.89
College	71.73	96.00	77.42	95.59
Age				
25-34	40.54	96.82	59.18	95.73
35-44	39.52	97.53	62.63	97.29
45-55	33.52	94.42	56.61	94.26

Notes: The cells report the (conditional) share of the respective column group. For instance, 35.75 percent of the prime-age female population with secondary education (unskilled) participated in the labor force in C.1992. We joined together surveys from 1989, 1992, and 1994 (C.1992), and from 2010, 2012, and 2014 (C.2012) to increase the sample size of the ENIGH data survey. Sample weights used in all calculations.

Table 3: Production Technology Parameter Estimates

	Elasticities of Substitution			
	Estimate	[SE]	Implied Elasticity $(1/(1-\rho))$	95% Conf. Int. $(1/(1-\rho))$
Gender				
$\rho_{4,m}$: male, female (manual)	0.084	[0.066]	1.091	[0.955, 1.273]
$\rho_{4,r}$: male, female (routine)	0.218	[0.067]	1.278	[1.093, 1.540]
$\rho_{4,a}$: male, female (analytical)	0.660	[0.078]	2.941	[2.022, 5.389]
Education				
$\rho_{3,m}$: skilled, unskilled (manual)	0.739	[0.036]	3.831	[3.010, 5.271]
$\rho_{3,r}$: skilled, unskilled (routine)	0.301	[0.110]	1.431	[1.091, 2.078]
$\rho_{3,a}$: skilled, unskilled (analytical)	0.302	[0.125]	1.433	[1.058, 2.220]
Occupation				
ρ_1: analytical, routine and manual	0.031	[0.092]	1.032	[0.869, 1.271]
ρ_2: routine, manual	-0.154	[0.159]	0.867	[0.681, 1.192]

Notes: The table reports the point estimates and standard errors of the elasticities of substitution from the production technology. See estimates discussions in Section 6.2, and estimator discussions in Appendix Section B.3.3.

Table 4: Labor Supply Responses to Wage Changes, Marginal Effects and Elasticities

	Average Marginal Effects and Elasticity Over Time			
	Increase Wages in	Increase Occupation-specific Wages:		
	All Occupations	*Manual Wage*	*Routine Wage*	*Analytical Wage*
Average Marginal Effects on LFP Rates:				
values are in percentage points				
female, unskilled	0.107	0.060	0.026	0.020
female, skilled	0.036	0.003	0.009	0.025
male, unskilled	0.023	0.013	0.008	0.002
male, skilled	0.008	0.001	0.002	0.005
Elasticity of Labor Supply with Respect to Wages:				
values are elasticities				
female, unskilled	0.529	0.099	0.071	0.067
female, skilled	0.341	0.009	0.044	0.160
male, unskilled	0.060	0.025	0.022	0.010
male, skilled	0.062	0.005	0.012	0.041

Notes: Given log wage coefficient $\psi_1 = 0.966$, we show in the top panel the Average Marginal Effects of wages on the gender- and skill-specific LFP rates. In the bottom panel, we show the average elasticities of gender- and skill-specific labor supply with respect to wages. We average over year-specific values. Column 1 shows the the effects of changing all three occupation-specific wages jointly: We evaluate the marginal effects given equi-distance increases in all wages; We evaluate the elasticity given equal-percentage increases in all wages. Columns 2–4 present results when only the wage for one of the three occupations increases. See discussions in Section 6.4.

Table 5: Occupational Choice Parameter Estimates

	Estimate	SE	Average Marginal Effect
Fertility			
$\pi_{2,f,u}$: female, unskilled	-0.257	0.135	-0.063
$\pi_{2,f,s}$: female, skilled	2.735	0.810	0.602
$\pi_{2,k,u}$: male, unskilled	-2.281	0.097	-0.132
$\pi_{2,k,s}$: male, skilled	-0.044	0.016	-0.003
Marriage			
$\pi_{3,f,u}$: female, unskilled	-0.265	0.247	-0.065
$\pi_{3,f,s}$: female, skilled	0.267	0.355	0.059
$\pi_{3,k,u}$: male, unskilled	3.017	0.115	0.178
$\pi_{3,k,s}$: male, skilled	0.916	0.050	0.055
Appliance			
$\pi_{4,f,u}$: female, unskilled	-2.075	0.144	-0.508
$\pi_{4,f,s}$: female, skilled	-8.348	0.218	-1.808
$\pi_{4,k,u}$: male, unskilled	0.845	0.440	0.049
$\pi_{4,k,s}$: male, skilled	-3.031	0.025	-0.178
WBL			
$\pi_{5,f,u}$: female, unskilled	-0.514	0.296	-0.126
$\pi_{5,f,s}$: female, skilled	-1.151	0.211	-0.252
$\pi_{5,k,u}$: male, unskilled	0.712	0.522	0.042
$\pi_{5,k,s}$: male, skilled	1.102	0.105	0.066

Notes: For the fertility (share having under-5 children), marriage (share married or having a permanent partner), appliance (share having a refrigerator or a washing machine), and WBL (an index measuring laws and regulations that restrict women's economic opportunities) variables, the Average Marginal Effect is the percentage points increase in leisure probability—averaged across years—given 1 percentage point increase in the respective supply variables, holding all else the same. See estimates discussions in Section 6.5 and estimator discussions in Appendix Section B.3.3.

Table 6: Counterfactual Exercises with Non-wage Determinants of Labor Supply

		Change in Gender Participation and Wage Gaps: C.2012 - C.1992							
		Partial Equilibrium Path of Wages as Observed				**General Equilibrium** Wages Adjust as Supply Curves Shift			
	(1) Model	(2) Fertility	(3) Marriage	(4) WBL	(5) Appliance	(6) Fertility	(7) Marriage	(8) WBL	(9) Appliance
100 × Δ (Male - Female) LFP and Occupation Participation Rates									
Overall	-19.9	-16.5	-20.7	-17.8	-7.5	-17.9	-20.8	-18.5	-14.3
Skilled									
Analytical	-3.9	-2.2	-4.0	-3.5	-3.5	-2.5	-4.0	-3.6	-4.0
Routine	-0.9	-0.3	-0.9	-0.7	-0.8	-0.5	-0.9	-0.8	-0.9
Manual	-0.1	0.0	-0.1	0.0	-0.1	-0.1	-0.1	-0.1	-0.1
Unskilled									
Analytical	-4.5	-4.4	-4.6	-4.1	-1.3	-4.7	-4.7	-4.3	-2.8
Routine	-2.9	-2.5	-3.2	-2.5	0.7	-2.7	-3.2	-2.6	-1.1
Manual	-7.6	-7.1	-7.9	-7.0	-2.6	-7.4	-7.9	-7.2	-5.4
100 × Δ Log (Male/Female) Wage Ratio									
Overall	-6.3	-3.3	-6.1	-6.3	-10.6	-5.6	-5.4	-7.1	-12.2
Skilled									
Analytical	-9.0	—	—	—	—	-13.2	-8.8	-9.8	-10.1
Routine	-10.3	—	—	—	—	-17.7	-10.0	-11.7	-12.2
Manual	-41.5	—	—	—	—	-49.6	-41.2	-43.0	-43.6
Unskilled									
Analytical	3.0	—	—	—	—	3.6	3.8	2.5	-1.8
Routine	15.9	—	—	—	—	16.9	17.3	14.9	7.6
Manual	7.1	—	—	—	—	8.2	8.5	6.0	-2.0
100 × Δ Log (Male/Female) Wage Ratio									
Skilled	-10.4	—	—	—	—	-15.3	-10.2	-11.4	-11.6
Unskilled	9.6	—	—	—	—	10.4	10.8	8.8	2.5
100 × Δ Log (Skilled/Unskilled) Wage Ratio									
Male	-21.5	—	—	—	—	-18.3	-21.5	-21.2	-20.5
Female	-1.4	—	—	—	—	7.5	-0.5	-1.0	-6.4

Notes: The Table reports the difference between C.1992 and C.2012 of i) the log (male/female) wage ratio and ii) the change in the (male - female) gender-specific LFP and occupation participation rates (See Figure 10 and Appendix Figure D.4 for visualizations). The paths of wages are held as observed under PE. Wages adjust given supply curve shifts under GE. Occupation- and skill-specific relative wages are invariant under PE; the overall relative wage ratio shifts under PE due to compositional changes. The first column corresponds to model predictions. The *Fertility* columns correspond to the counterfactual predictions once we set the gender- and skill-specific shares of individuals having a child under the age of 5 to the values of 1989, and constant across the years. This variable is decreasing over time (Panel (a) of Figure D.2). The *Marriage* columns fix the gender- and skill-specific shares of individuals married or having a permanent partner at 1989 levels, and constant across the years. This variable decreases slightly over time (Panel (b) of Figure D.2). The *WBL* columns fix the Women, Business and the Law index at 1989 levels. This variable increases over time (Panel (d) of Figure D.2). The *Appliance* columns fix the gender- and skill-specific shares of individuals with a refrigerator or a washing machine at 1989 levels. This variable increases substantially over-time (Panel (c) of Figure D.2). See discussions in Section 7.1.

Table 7: Counterfactual Exercises with Demographic Variables and Demand Side Parameters

		Change in Gender Participation and Wage Gaps: C.2012 - C.1992							
		Partial Equilibrium Path of Wages as Observed				**General Equilibrium** Wages Adjust as Supply/Demand Curves Shift			
		Demographics		Demand		Demographics		Demand	
	(1) Model	(2) Skilled Female	(3) Emigrant	(4) Gender $\boldsymbol{\alpha_4}$	(5) Skill $\boldsymbol{\alpha_3}$	(6) Skilled Female	(7) Emigrant	(8) Gender $\boldsymbol{\alpha_4}$	(9) Skill $\boldsymbol{\alpha_3}$
100 × Δ (Male - Female) LFP and Occupation Participation Rates									
Overall	-19.9	-17.8	-19.6	—	—	-24.2	-16.7	-16.5	-16.9
Skilled									
Analytical	-3.9	0.9	-4.0	—	—	1.1	-3.7	-3.7	-2.7
Routine	-0.9	0.7	-0.9	—	—	0.3	-0.9	-0.1	-0.7
Manual	-0.1	0.2	-0.1	—	—	0.0	-0.2	0.4	-0.1
Unskilled									
Analytical	-4.5	-5.8	-4.5	—	—	-8.6	-3.2	-4.1	-3.6
Routine	-2.9	-4.3	-2.7	—	—	-5.7	-2.2	-3.2	-2.5
Manual	-7.6	-9.5	-7.4	—	—	-11.3	-6.6	-5.8	-7.3
100 × Δ Log (Male/Female) Wage Ratio									
Overall	-6.3	5.3	-6.3	—	—	9.6	-12.6	17.6	-5.1
Skilled									
Analytical	-9.0	—	—	—	—	-28.6	-11.5	32.3	-9.4
Routine	-10.3	—	—	—	—	-42.6	-14.7	56.2	-11.0
Manual	-41.5	—	—	—	—	-76.8	-46.3	61.3	-42.3
Unskilled									
Analytical	3.0	—	—	—	—	12.6	-1.7	12.1	1.4
Routine	15.9	—	—	—	—	32.6	7.8	21.0	13.0
Manual	7.1	—	—	—	—	25.2	-1.8	22.9	3.9
100 × Δ Log (Male/Female) Wage Ratio									
Skilled	-10.4	—	—	—	—	-31.9	-13.3	35.0	-9.8
Unskilled	9.6	—	—	—	—	23.5	2.7	17.8	6.1
100 × Δ Log (Skilled/Unskilled) Wage Ratio									
Male	-21.5	—	—	—	—	-14.6	-16.9	-6.8	-43.6
Female	-1.4	—	—	—	—	40.8	-1.0	-24.0	-27.7

Notes: The Table reports the difference between C.1992 and C.2012 of i) the log (male/female) wage ratio and ii) the change in the (male - female) gender-specific LFP and occupation participation rates (See Figure 10 for visualization). The paths of wages are held as observed under PE. Wages adjust given supply curve shifts under GE. Occupation- and skill-specific relative wages are invariant under PE; the overall relative wage ratio shifts under PE for demographics counterfactuals due to compositional changes. Participation is invariant under PE for demand counterfactuals. The first column corresponds to model predictions. The *Demographics-Skilled Females* columns keep the female share among skilled population at 1989 levels, while skilled males and gender-specific populations levels increase as observed. The share of skilled workers increased over time, especially for women (Panel (b) of Figure D.3). The *Demographics-Emigrant* columns keep the gender- and skill-specific shares of emigrants in Mexican born population at 1989 levels. The emigrant share in unskilled Mexican born population increased over time, especially for men (Panel (a) of Figure D.3). The *Demand-Gender* $\boldsymbol{\alpha_4}$ and *Demand-Skill* $\boldsymbol{\alpha_3}$ columns set the skill- and occupation-specific demand gender share and occupation-specific demand skill share parameters at 1989 values, respectively. Demand trends favored skilled labor and women (Figure 7). See discussions in Sections 7.2 and 7.3.

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A Data Appendix (online)

A.1 ENIGH Data and Variable Definitions

We compute from the ENIGH survey year-, gender-, skill-, and occupation-specific wages and labor supplies. We have made these data series available for view and download at this link https://github.com/FanWangEcon/PrjLabEquiBFW/blob/main/PrjLabEquiBFW/_data/Dataset1.csv with associated key file.

ENIGH. We use 13 waves of the nationally representative Mexican Household Income and Expenditure Survey (ENIGH), covering 1989-2014. For certain summary statistics, we merged surveys from 1989, 1992, and 1994 (C.1992), and from 2010, 2012, and 2014 (C.2012) to increase sample size and smooth over year-specific changes.

Wage definition. Labor earnings data refer to the monthly monetary remuneration from labor, including wages, salaries, piecework, and any overtime pay, commissions, or tips usually received, but excluding income received from government transfers. We omit earnings of self-employed workers when calculating labor earnings because, for this group, it is not possible to disentangle remuneration from labor from returns to capital or profits, a common problem in the literature; however, our estimates include labor remuneration for formal and informal workers since self-employment and labor informality are distinct categories. We add up earnings from different occupations if the individual has a secondary job. Monthly earnings are converted into hourly wages by dividing monthly earnings by the worker's total hours of work per week in all jobs multiplied by the usual number of weeks in a month. Wage rates are transformed into real 2012 U.S. Dollars using the Mexican Consumer Price Index and the purchasing power parity adjusted exchange rate estimated by the IMF. We removed outliers (less than 1 percent in each year), restricting to hourly rates above \$0.1 and below \$150. The estimates are not sensitive to this.

Full and part time work. We use the sample of workers aged 25 to 55 (prime-age workers). This is done to ameliorate selection problems arising from changes in the educational and retirement choices of younger and older cohorts. Since part-time work is more common among women, to ensure comparability, the wage series in the main analysis is calculated using full time workers only (35 hours or more in the previous week). The share of workers working part-time is 33 to 38 percent for female workers and 10 to 13 percent for male workers. Importantly, the increase in FLFP over the sample period was clearly not driven by part-time work. In fact, the ratio of female to male part-time workers was stable between 1990 and 2004, after which it declined. Nevertheless, we include results for part-time workers and also results accounting for changes in hours in robustness checks.

Participation. We define the labor force participation rate as the proportion of prime-age individuals (25-55 years old) who either worked or sought employment in the previous month relative to the total number of individuals within this age bracket. Our definition of work includes all sectors, occupations, and the informal economy, irrespective of the nature of the activities or if the work complies with the country's formal labor laws and protections (*i.e.* if the job is formal or informal). The survey solely includes individuals residing in the household at the time of data collection, thereby excluding individuals who emigrated, but including immigrants. We have added clarifications of this definition in the updated version of the paper

A.2 Supply Side Variables

We link women's labor force participation decision to fertility trends, marriage patterns, gender discrimination in work-related legislation as captured by the Women, Business and the Law (WBL) index, and home appliance availability. These variables capture potential changes in preferences and the technology of home production over time. Additionally, using the ENIGH survey sample and survey weights, we compute the potential prime-age worker population by gender, skill and year. These potential worker counts are impacted by the emigration of Mexican-born workers, something we discuss below. We have made these potential worker and supply-variable data series available for view and download at this link https://github.com/FanWangEcon/PrjLabEquiBFW/blob/main/PrjLabEquiBFW/_data/Dataset2.csv with associated key file. Trends in supply side variables are visualized in Figures D.2 and D.3.

Fertility and marital status. Fertility is defined as the average number of children under the age of five across women. Marital status refers to being married or having a stable partner. We compute these statistics from the ENIGH dataset directly. We generate aggregate proportions by gender and skill group in each year. The measures of fertility and marriage can only be calculated for a sample restricted to the household head and their spouse or partner; trends for the larger sample used in the estimation are not available. The ENIGH survey started asking the question on marital status to all members of the household in 1996, and the question about the number and age of children since 2004. The sample is restricted to the prime-age population.

WBL. As a measure of women's economic rights, which may also serve as a reverse proxy for discrimination, we use the Women, Business and the Law (WBL) index. The index attempts to capture inequality in legislation against women throughout their working life. Thirty-five legislative issues that correlate with women's economic empowerment were identified and aggregated to construct the index, with higher values indicating a lessening of restrictions on women's economic opportunities. The index can range from 0 to 100 and is increasing in the relative equality of rights between men and women. For a detailed description see Hyland, Djankov, and Goldberg (2020).

Appliance. We compute the share of individuals having home appliances. We consider that an individual has access to home appliance if the individual has either a refrigerator or a washing machine.

Emigration. For purposes of the demographic counterfactual that we construct to analyze changes in the gender-skill composition of potential workers, we use the information on emigrant stocks constructed by Brücker, Capuano, and Marfouk (2013). The authors collected data from 20 OECD member states on the immigrant population aged 25 years and older by gender, educational level, and country of birth between 1980 and 2010. Migration is defined according to country of birth rather than foreign citizenship. The final dataset includes estimated stocks of immigrants coming from 195 countries, including Mexico. Although the information is restricted to migrants going to OECD countries, the Pew Research Center estimates that close to 97.3% of Mexican emigrants go to the Unites States alone. When necessary, we interpolate for emigrants counts in ENIGH survey years.

A.2.1 How Net Migration Impacts Wages and Labor Supplies

Migration enters the model through the effect it has on the number of potential workers in a year, captured by the term $L^{pop}_{gen,t}$ in Equation (2.2) and by the term $L^{pop}_{f,s,t}$ in Equation (5.8). A condition to be included as a potential worker, both in theory and in the data, is that the individual is living in Mexico, so emigration reduces the number of potential workers, and immigration increases it. In particular,

$$L^{pop}_{f,s,t} = L^{nat}_{f,s,t} + L^{imm}_{f,s,t} - L^{emi}_{f,s,t}, \tag{A.1}$$

where $L^{nat}_{f,s,t}$ is the number of prime-age native-born Mexicans of sex f and education s that are alive in year t, irrespective of where they live; $L^{emi}_{f,s,t}$ is number of prime-age native-born Mexicans living abroad; and $L^{imm}_{f,s,t}$ is the number of prime-age foreign-born individuals living in Mexico.

Migration affects the wage structure in the model because overall and occupation-specific labor supplies depend on the number of potential workers. This can be seen in Equation (5.8), which we reproduce below:

$$L^{s}_{f,s,a,t} = L^{pop}_{f,s,t} \times Pr(d_a = 1 \mid f, s, t).$$

For example, a decrease in the net migration of individuals of type (s, f) in year t reduces $L^{pop}_{f,s,t}$ and, in partial equilibrium, $L^{s}_{f,s,a,t}$. By changing relative labor supplies, net migration also affects relative wages and the wage structure.

The survey data that we use in the estimation only includes individuals permanently residing in the household at the time of data collection, thereby excluding individuals who emigrated but including individuals who immigrated. Consequently, our estimate of $L^{pop}_{f,s,t}$ is consistent with our definition of potential workers.

A.3 Division of Occupations into Manual, Routine, and Analytical Task-Intensive Groups

The ENIGH survey uses the Mexican occupation classification system to categorize workers according to the type of tasks they perform in the main job. The system went trough two changes since 1989: first there was an update of the original Clasificación Mexicana de Ocupaciones (CMO) in 1992, and then a full change to the newly introduced Sistema Nacional de Clasificación de Ocupaciones (SINCO) in 2010. These changes make the series incompatible at high levels of disaggregation of the occupational groups, but it is possible to homogenize the SINCO classification to the principal group level of the CMO using the comparability tables produced by INEGI.[A.1] The principal group division has 18 distinct occupational groups that can be consistently followed throughout the period of analysis.

The 18 principal level occupations from the ENIGH are classified into three groups defined by whether the activities done in the jobs are predominantly manual, routine (repetitive and easily codifiable tasks), or analytical intensive. The division is based on the measures constructed by Autor, Levy, and Murnane (2003) from different sets of variables of the 1977 Dictionary of Occupational Titles (DOT)

A.1. http://www.inegi.org.mx/est/contenidos/proyectos/aspectosmetodologicos/clasificadoresycatalogos/sinco.aspx

of the U.S., and then linked to the three-digit occupation codes of the CENSUS. The DOT evaluated highly detailed occupations along 44 objective and subjective dimensions that include physical demands and required worker aptitudes, temperaments, and interests. Autor, Katz, and Kearney (2006) used a subset of those dimensions to generate a simple typology consisting of three aggregates for analytical, routine, and manual tasks. The analytical task measure corresponds to the average from two variables of the DOT: DCP, which measures direction, control, and planning of activities; and GED-MATH, which measures quantitative reasoning requirements. The routine task measure corresponds to an average from two variables of the DOT: STS, which measures adaptability to work requiring set limits, tolerances, or standards; and FINGDEX, measuring finger dexterity. Finally, the manual task measure uses a single variable, EYEHAND, which measures eye, hand, and foot coordination.[A.2]

In practice, we first create a cross-walk between three-digit CENSUS codes in the U.S. and the 18 categories of the principal group occupational division of the ENIGH. This task is facilitated by the fact that both the ENIGH and the U.S. CENSUS follow similar international standards when constructing their own occupation classifications. Since the three task measures are ordinal, there is no direct way to use the actual magnitude of the variables to compare occupations across the three dimensions. For each task measure, we first organize the three-digit occupations by percentiles and then calculate the median percentile of the measure within the broader 18 occupational groups of the ENIGH. Each of the 18 occupations is assigned to the group in which the median percentile was highest (see Table 1).

This procedure generated a balanced division with respect to the overall employment share of each group, and it is also consistent with the broad classification of aggregate occupations used in the literature that follows the task-based framework. Two important caveats should be stressed: First, any attempt to homogenize occupation classification systems from different countries involves some subjective choices. In the cases where we found occupations that do not have an immediate correspondence between the two systems, we had to use our judgement, based on documentation about the description of the occupation, to select a corresponding match. Second, the task measures were created specifically for U.S. economy, and it is likely that there are differences in the intensity in which certain skills are used in given occupations between the U.S. and Mexico. Results should be interpreted with these two caveats in mind.

B Solution, Identification and Estimation of the Model (online)

In this section we discuss model solution, identification and estimation. The theoretical model was presented in Section 5 and the labor market participation and wage data for Mexico were described in Section 3 and Appendix Section A. First, we characterize the labor market equilibrium and describe algorithms for the equilibrium solution in Section B.1. Second, we discuss the identification of demand and supply side parameters in Section B.2. Third, we provide details of the equilibrium estimation routine in Section B.3. Additionally, we provide a Matlab companion code package and website which provides computational examples for our paper.

A.2. See the online Appendix in Dorn (2009) for further details. Other papers that have used this measures include Autor, Katz, and Kearney (2006), Goos and Manning (2007), Dorn (2009), Rendall (2013), Autor and Dorn (2013), and Adda, Dustmann, and Stevens (2017).

B.1 Equilibrium Definition and Solution

In this section, we discuss the equilibrium structure and solutions. In Section B.1.1, we discuss denesting the nested-CES problem and solving each sub-nest as a separate but linked demand problem. In Section B.1.2, we characterize the equilibrium solution with a system of nonlinear equations for female occupation-specific wages. In Section B.1.3, we define the competitive labor market equilibrium. In Section B.1.4, we solve for the equilibrium explicitly via nested root search as well as via a faster but less stable contraction algorithm.

B.1.1 Demand Denesting

Given the demand system presented in Section 5, we consider optimal labor demand in a particular sub-nest of the nested-CES demand system. For notational clarity, we ignore skill subscripts in this section. Without loss of generality, the optimal labor demand equations for routine male and female workers are:

$$\begin{aligned} L_{k,r}^{d,*} &= L_r \cdot \left(\alpha_{k,r} + \alpha_{f,r} \cdot \left(\frac{W_{k,r}}{W_{f,r}} \cdot \frac{\alpha_{f,r}}{\alpha_{k,r}} \right)^{\frac{\rho_{4,r}}{1-\rho_{4,r}}} \right)^{\frac{-1}{\rho_{4,r}}} \\ L_{f,r}^{d,*} &= L_r \cdot \left(\alpha_{k,r} \cdot \left(\frac{W_{f,r}}{W_{k,r}} \cdot \frac{\alpha_{k,r}}{\alpha_{f,r}} \right)^{\frac{\rho_{4,r}}{1-\rho_{4,r}}} + \alpha_{f,r} \right)^{\frac{-1}{\rho_{4,r}}} \end{aligned}, \tag{B.1}$$

where $\alpha_{f,r} = 1 - \alpha_{k,r}$ and L_r is the level of aggregate labor demand for this sub-nest. Equation (B.1) contains solutions to the expenditure minimization problem of male and female workers in routine task-intensive occupations for a particular skill group: $\min_{L_{k,r}, L_{f,r}} (L_{k,r} \cdot W_{k,r} + L_{f,r} \cdot W_{f,r})$, such that $L_r = \left(\alpha_k L_{k,r}^{\rho_{4,r}} + \alpha_f L_{f,r}^{\rho_{4,r}} \right)^{\frac{1}{\rho_{4,r}}}$.

The full nested-CES problem presented in Section 5.1 can be solved separately as eleven de-nested problems in the form of Equation (B.1).[D.1] Lower- and higher-level nests are connected via nest-specific aggregate labor demand L_r: L_r is the output quantity requirement for lower-level nests and is the input choice for higher-level nests. L_r captures the effects of upper-nest share and elasticity parameters on choices.

For higher-level nests, given constant returns, the cost of acquiring aggregate labor input is a weighted average of the underlying gender-specific wages from the lowest nests. For example, the routine task-intensive occupation-specific aggregate labor price W_r is equal to:

$$\begin{aligned} W_r =& W_{k,r} \left(\alpha_{k,r} + \alpha_{f,r} \left(\frac{W_{k,r}}{W_{f,r}} \frac{\alpha_{f,r}}{\alpha_{k,r}} \right)^{\frac{\rho_{4,r}}{1-\rho_{4,r}}} \right)^{\frac{-1}{\rho_{4,r}}} \\ &+ W_{f,r} \left(\alpha_{k,r} \left(\frac{W_{f,r}}{W_{k,r}} \frac{\alpha_{k,r}}{\alpha_{f,r}} \right)^{\frac{\rho_{4,r}}{1-\rho_{4,r}}} + \alpha_{f,r} \right)^{\frac{-1}{\rho_{4,r}}} \end{aligned}. \tag{B.2}$$

D.1. Six problems over male and female labor demand for each occupation and skill category, three problems over gender-aggregated skilled and unskilled workers, and two problems over skill-gender-aggregated occupational groups.

B.1.2 System of Equations for Equilibrium Wages

Given the optimal labor supply problem and corresponding aggregate labor supply equations from Section 5.2, at equilibrium, quantity demanded is equal to quantity supplied,

$$L_r \cdot \left(\alpha_{k,r} + \alpha_{f,r} \left(\frac{W_{k,r}}{W_{f,r}} \frac{\alpha_{f,r}}{\alpha_{k,r}} \right)^{\frac{\rho_{4,r}}{1-\rho_{4,r}}} \right)^{\frac{-1}{\rho_{4,r}}} = \frac{L_k^{pop} \cdot \exp\left(\widehat{U}_k \left(r \mid W_{k,r}, \boldsymbol{B}_k \right) \right)}{\sum_{O \in \{a,r,m,h\}} \exp\left(\widehat{U}_k \left(O \mid W_{k,O}, \boldsymbol{B}_k \right) \right)}, \tag{B.3}$$

where $\boldsymbol{B}_k$ represents a vector of exogenous gender (and skill) specific attributes, L_k^{pop} is the gender (and skill) specific population level, and L_r is the aggregate quantity of routine workers demanded of a particular skill level. For notational clarity, we continue to ignore skill subscripts.

Applying some algebra to Equation (B.3) and a symmetric equation for quantity of female workers demanded and supplied, we arrive at two equations where, given aggregate labor demand L_r, the female (male) labor wage in routine occupation is a function of male (female) wages in analytical, routine, and manual occupations:

$$\begin{aligned} W_{f,r} \left(W_{k,a}, W_{k,r}, W_{k,m} \right) &= \left(\left(\frac{L_r}{L_k^s \left(W_{k,a}, W_{k,r}, W_{k,m}; \boldsymbol{B}_k \right)} \right)^{\rho_{4,r}} \frac{1}{\alpha_{f,r}} - \frac{\alpha_{k,r}}{\alpha_{f,r}} \right)^{\frac{\rho_{4,r}-1}{\rho_{4,r}}} \cdot \frac{\alpha_{f,r}}{\alpha_{k,r}} \cdot W_{k,r} \\ W_{k,r} \left(W_{f,a}, W_{f,r}, W_{f,m} \right) &= \left(\left(\frac{L_r}{L_f^s \left(W_{f,a}, W_{f,r}, W_{f,m}; \boldsymbol{B}_f \right)} \right)^{\rho_{4,r}} \frac{1}{\alpha_{k,r}} - \frac{\alpha_{f,r}}{\alpha_{k,r}} \right)^{\frac{\rho_{4,r}-1}{\rho_{4,r}}} \cdot \frac{\alpha_{k,r}}{\alpha_{f,r}} \cdot W_{f,r} \end{aligned} \tag{B.4}$$

Following Equation (B.4), similar results can be arrived at for manual and analytical occupation wages. In all cases, the equilibrium wage for one gender in one occupation is a function of the equilibrium wages of the other gender across all occupations. Overall, within a year, for either skilled or unskilled workers, six equations for the two genders and three occupational categories characterize the equilibrium solution. The equations can be combined. For example, for female analytical work, we have:

$$W_{f,a} = W_{f,a} \Big(W_{k,a} \left(W_{f,a}, W_{f,r}, W_{f,m} \right), W_{k,r} \left(W_{f,a}, W_{f,r}, W_{f,m} \right), W_{k,m} \left(W_{f,a}, W_{f,r}, W_{f,m} \right) \Big).$$

Combining all six equations and given aggregate labor demands L_m, L_r, L_a, we arrive at a system of three equations and three unknowns:

$$\begin{aligned} W_{f,a} &= W_{f,a} \left(W_{f,a}, W_{f,r}, W_{f,m} \right) \\ W_{f,r} &= W_{f,r} \left(W_{f,a}, W_{f,r}, W_{f,m} \right) \\ W_{f,m} &= W_{f,m} \left(W_{f,a}, W_{f,r}, W_{f,m} \right) \end{aligned} \tag{B.5}$$

The solution to the system of equations in Equation (B.5) consists of three female wages. Equation (B.4) leads to male wages given female wages. Equation (B.3) leads to labor quantities given wages. During each model period, we solve Equation (B.5) at the third nest level for skilled and unskilled workers separately.[D.2] The skilled and unskilled equilibrium solutions are linked via aggregate skilled and unskilled labor demands, $L_{s,m}, L_{s,r}, L_{s,a}$ and $L_{u,m}, L_{u,r}, L_{u,a}$.

D.2. Unskilled and skilled workers have separate labor supply problems and belong to separate nests under the demand system.

B.1.3 Competitive Labor Market Equilibrium

In each period, given the aggregate output and productivity ratio $\frac{Y}{Z}$, demand parameter vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$, supply parameters vectors $\boldsymbol{\psi}$ and $\boldsymbol{\pi}$, the vector of gender- and skill-specific supply characteristics $\boldsymbol{B}$, and the vector of gender- and skill-specific potential worker levels $\boldsymbol{L^{pop}}$, the competitive labor market equilibrium consists of wages and aggregate labor quantities, such that,

1. Female wages $\{W_{f,edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$ solve Equation (B.5) for all *edu* groups.

2. Aggregate skill-occupation demands $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$ solve Equation (B.1) given aggregate wages and occupation-specific aggregate demands.[D.3]

The equilibrium definition distinguishes between two separable components of nested-CES equilibrium problems. On the one hand, only the lowest level of demand nests directly face supply-side equations and wages $\{W_{f,edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$. On the other hand, parameters of upper-level nests are linked to the problem at the lowest level of nests via $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$.

For generalizability, in terms of demand, the solution to the equilibrium system is scalable to alternative nested-CES demand systems with additional levels of nests and alternative nesting structures. In terms of supply, the structure here assumes that workers make labor supply decisions for the current period given current wages only.[D.4]

B.1.4 Solving for Market Clearing Wages

Explicit Root Search The system of nonlinear equations in Equations B.5 does not have an analytical solution, but numerical root search routines can be deployed to explicitly solve for equilibrium wages given demand and supply parameters. Specifically, the equilibrium problem can be solved in three nested stages. In stage one, given $W_{f,r}, W_{f,m}$, we solve for the root $W^*_{f,a}$:

$$W^*_{f,a}\left(W_{f,r}, W_{f,m}\right) = \underset{W_{f,a}}{\arg\min} \left| W_{f,a} - W_{f,a}\left(W_{f,a}, W_{f,r}, W_{f,m}\right) \right|. \tag{B.6}$$

In stage two, we solve for the root $W^*_{f,r}$ given $W_{f,m}$:

$$W^*_{f,r}\left(W_{f,m}\right) = \underset{W_{f,r}}{\arg\min} \left| W_{f,r} - W_{f,r}\left(W^*_{f,a}\left(W_{f,r}, W_{f,m}\right), W_{f,r}, W_{f,m}\right) \right|. \tag{B.7}$$

D.3. Aggregate occupation-specific demands at higher tier successively solve Equation (B.1) given $\frac{Y}{Z}$, as well as successively aggregated wages at occupation and skill levels given female skill-occupation specific wages $\{W_{f,edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$.

D.4. Under a dynamic labor supply model, households might make labor decisions based on current wages as well as the path of future wages. Under the assumption of rational expectations, one might iterate over parameters until expectations become self-fulfilling and the expected path of wages conforms to the actual path of wages given aggregate labor supply. This solution concept suffers from the curse of dimensionality when additional dimensions of equilibrium wages are added. In our example here, if workers in 1989 consider the path of wages for the next 25 years in making labor market decisions, Equation (B.5) would become a system of equation that requires solving for a 150-dimensional (3 times 2 times 25) market-clearing root.

In stage three, we arrive at one equation and one unknown:

$$W^*_{f,m} = \underset{W_{f,m}}{\arg\min} \left| W_{f,m} - W_{f,m}\left(W^*_{f,a}\left(W^*_{f,r}\left(W_{f,m}\right), W_{f,m}\right), W^*_{f,r}\left(W_{f,m}\right), W_{f,m}\right)\right|. \tag{B.8}$$

Equation (B.8) can be solved via triply-nested root-search. Given aggregate demands, $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$, Equation (B.8) is solved for skilled and unskilled workers separately and satisfies the first condition for a competitive labor market equilibrium.

Given upper level nest parameters and wage solutions of Equation (B.8), we update $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$. The process iterates until the aggregate skill- and occupation- specific demands are consistent with wage solutions of Equation (B.8). This satisfies the second condition for the competitive labor market equilibrium.

Iterative Wage Contraction In practice, searching for a three dimensional female wage root vector can be slow. To speed up the estimation procedure, we also solve the problem via iterative wage contraction, based on a modified version of the algorithm used in Johnson and Keane (2013).[D.5]

Given $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$, first, we solve for quantity supplied given wages for skilled and unskilled workers following Equation (5.8). Second, given demand-side first-order conditions from Equation (2.1), we solve for relative wages that would be consistent with the quantity supplied. Third, given relative wages, Equation (B.1) solves for the level of female labor demanded, which is proportional to the quantity supplied from the second step. Fourth, given the log odds ratio formulation of the supply equations from Equation (B.25), we solve for the wage levels that support the level of female labor demanded from the third step. Fifth, given female wage levels, we use the relative wages from step three to find male wage levels. Sixth, we update $\{L_{edu,occ}\}_{edu\in\{s,u\},occ\in\{a,r,m\}}$ with new wages, which are the weighted averages of initial wages and new wages computed following Equation (B.2) from step four and five. The process iterates until quantity demanded is equal to quantity supplied.[D.6]

The iterative wage contraction solution algorithm can be fast.[D.7] This algorithm, however, does not guarantee equilibrium convergence. At arbitrary starting points for wages, wage iterations generally converge towards either zero or positive infinity. We start wage iteration at the observed wage levels and solve for converging wages. We check for market clearing in skilled and unskilled nests and across all years separately. When wages do not converge, we reduce the wage updating speed in step six by putting higher weights on wages from prior iterations. In cases where convergence to a fixed-point still fails, we solve explicitly for equilibrium using the explicit root search routine just described in the prior segment of Section B.1.4. On our companion website, we provide as functions both the iterative wage contraction

D.5. Johnson and Keane (2013) does not explicitly solve for demand quantities, but iterates over marginal products given quantities, and quantity supplied given wages.

D.6. Relative wages matter for quantity demanded, but the level of wages matters for quantity supplied given supply parameters. In the second step, period-specific Lagrange multipliers confound the mapping of period-specific aggregate productivity to wage levels. Given marginal products and corresponding relative wages, steps three to five provide a consistent normalization for wage levels given the $\frac{Y}{Z}$ ratio.

D.7. The method solves 12 equilibrium wages during 13 periods in less than one second on a home-PC available in 2021.

algorithm and the exact root search routine, along with associated examples and tutorials.

B.2 Identification of Demand and Supply Parameters

While the nested-CES demand system is commonly estimated in the labor literature, it is perhaps less common to estimate both demand and supply parameters in an equilibrium context. In this paper, we develop an estimation framework. We discuss in the following sections key identification challenges and solutions in our estimation framework. Specifically, in Section B.2.1, we discuss the identification of parameters across nests through relative wages within and across nests. In Section B.2.2, we discuss the necessary data requirement for plausibly jointly identifying ρ and α via equilibrium supply-shifters and the challenge of this approach in our empirical context of biennially aggregated data. In Section B.2.3, we discuss the data requirements for possibly identifying variations in α parameter over-time under polynomial restriction, a standard strategy that we adopt. In Section B.2.4, we discuss the challenge to demand-side only estimation posed by potential mismeasurement of equilibrium wages and number of workers as well as shocks to relative demands. In Section B.2.5, we discuss the challenge to supply-side only estimation in the context of our labor market participation model. Finally, in Section B.2.6, we discuss equilibrium solution based estimation.

B.2.1 One Period Data and Relative Wages Within and Across Nests

Given one period of data, conditional on known $\boldsymbol{\rho}$ values, share parameters $\boldsymbol{\alpha}$ are identified given relative wages within and across nests.

Consider a constant-returns two-level nested-CES problem. Level one combines skilled and unskilled workers, and level two combines male and female workers:

$$\min_{L_{k,s},L_{f,s},L_{k,u},L_{f,u}} \left(L_{k,s}\cdot W_{k,s} + L_{f,s}\cdot W_{f,s} + L_{k,u}\cdot W_{k,u} + L_{f,u}\cdot W_{f,u}\right)$$

$$\text{s.t. } \frac{Y}{Z} = \left(\alpha_s\left(\alpha_{k,s}L_{k,s}^{\rho_s} + (1-\alpha_{k,s})\,L_{f,s}^{\rho_s}\right)^{\frac{\rho}{\rho_s}} + (1-\alpha_s)\left(\alpha_{k,u}L_{k,u}^{\rho_u} + (1-\alpha_{k,u})\,L_{f,u}^{\rho_u}\right)^{\frac{\rho}{\rho_u}}\right)^{\frac{1}{\rho}} \tag{B.9}$$

The problem in Equation (B.9) has eight parameters: $\boldsymbol{\rho} = \{\rho, \rho_s, \rho_u\}$, $\boldsymbol{\alpha} = \{\alpha_s, \alpha_{k,s}, \alpha_{k,u}\}$, and $\{Y, Z\}$. From one period of data, we observe four wages $\{W_{k,s}, W_{f,s}, W_{k,u}, W_{f,u}\}$, and four labor quantities $\{L_{k,s}, L_{f,s}, L_{k,u}, L_{f,u}\}$.

First, it is not possible to separately identify output Y from productivity Z.[D.8] Given $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$, $\frac{Y}{Z}$ is the productivity-scaled aggregate output from the produc-

D.8. It is important to note that CES production function parameters are often estimated in a setting with panels or cross-sections of observed input and output data across many individuals, firms or countries. In those settings, there can be individual-specific productivity shocks Z, with various layers of subscripts. Shocks that are unobserved by the econometrician and wages that are observed by the econometrician jointly drive individual-specific optimal choices, leading to endogeneity between production function inputs and the error term. The central estimation question is to disentangle the endogeneity between inputs and the productivity shock term, which might capture productivity shocks as well as unobserved inputs. In our setting, however, we have an observed time-series of equilibrium wage and quantity data for each occupation and skill cell. Rather than having individual-specific productivity shocks, at each time period, there is a single aggregate productivity shock Z shared across all occupations and all workers. This Z captures both the aggregate productivity variation across time as well as potential unobserved non-labor inputs. Furthermore, we rely on demand optimality conditions in Equation (B.10) to estimate the model, where the $\frac{Y}{Z}$ term does not appear.

tion function, and it determines the levels of optimal demands. Given the output constraint in Equation (B.9), $\frac{Y}{Z}$ is known when $\boldsymbol{\rho}$ and $\boldsymbol{\alpha}$ are known.

Second, one period of data does not allow for the joint identification of $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$. However, given $\boldsymbol{\rho}$ values, $\boldsymbol{\alpha}$ values are identified. Specifically, three optimality conditions link respective optimal relative labor demands to relative wages:

$$\begin{aligned}
\log\left(\frac{W_{k,s}}{W_{f,s}}\right) &= \underbrace{\log\left(\frac{\alpha_{k,s}}{1-\alpha_{k,s}}\right) + (\rho_s - 1)\cdot\log\left(\frac{L_{k,s}}{L_{f,s}}\right)}_{\text{Relative wage between skilled males and females}}, \\
\log\left(\frac{W_{k,u}}{W_{f,u}}\right) &= \underbrace{\log\left(\frac{\alpha_{k,u}}{1-\alpha_{k,u}}\right) + (\rho_u - 1)\cdot\log\left(\frac{L_{k,u}}{L_{f,u}}\right)}_{\text{Relative wage between unskilled males and females}}, \\
\text{and } \log\left(\frac{W_{k,s}}{W_{k,u}}\right) &= \underbrace{\log\left(\frac{\alpha_s}{1-\alpha_s}\left[\frac{\alpha_{k,s}\cdot L_{k,s}^{\rho_s-1}\cdot O_u^{\rho_u}}{\alpha_{k,u}\cdot L_{k,u}^{\rho_u-1}\cdot O_s^{\rho_s}}\right]\right) + \rho\cdot\log\left[\frac{O_s}{O_u}\right]}_{\text{Relative wage between skilled males and unskilled males}},
\end{aligned} \tag{B.10}$$

where $O_s = \left(\alpha_{k,s}L_{k,s}^{\rho_s} + (1-\alpha_{k,s})\,L_{f,s}^{\rho_s}\right)^{\frac{1}{\rho_s}}$ and $O_u = \left(\alpha_{k,u}L_{k,u}^{\rho_u} + (1-\alpha_{k,u})\,L_{f,u}^{\rho_u}\right)^{\frac{1}{\rho_u}}$. The first two equations of Equations (B.10) determine $\alpha_{k,s}$ and $\alpha_{k,u}$, which determine the values inside the square brackets of the third equation and identify α_s. Since $\log\left(\frac{\alpha}{1-\alpha}\right) : (0,1) \to \mathcal{R}$, there exists $\boldsymbol{\alpha}$ to fit any positive wages vectors.

Third, using Equation (B.2), α_s is alternatively identifiable by

$$\log\left(\frac{W_s}{W_u}\right) = \log\left(\frac{\alpha_s}{1-\alpha_s}\right) + \rho\cdot\log\left(\frac{O_s}{O_u}\right), \tag{B.11}$$

where W_s and W_u are aggregate wages for O_s and O_u. In problems with additional layers of nesting, by applying Equation (B.11) iteratively upward, a $\boldsymbol{\alpha}$ vector of up to $2^N - 1 = \sum_{i=0}^{N-1} 2^{N-i-1}$ parameters can be identified given 2^N pairs of wage and labor quantity data.

In the context of our empirical problem, the literature does not provide us with occupation-specific gender elasticities nor occupation-specific skill elasticities. If such values existed, following the above procedure, year-specific demand share parameters might potentially be found that fit the observed data series perfectly.

B.2.2 Two Periods Data and Equilibrium Supply-shifters

Given two periods of data, if equilibrium changes in wages and labor quantities are driven by equilibrium supply-shifters only, then demand parameters that do not vary over the two periods can be identified. We consider estimation issues related to shocks to relative demands in Appendix Section B.2.4.

Given data from $t = \tau$ and $t = \tau + 1$, time-subscripted Equations (B.10) provide six equations for identifying the six $\boldsymbol{\rho}$ and $\boldsymbol{\alpha}$ parameters. Each pair of nest-specific and time-invariant α and ρ values is pinned down by linearly matching the relative wages and labor quantity in both periods. In this and the following sections, for notational clarity, we ignore the skill and task-intensive occupation subscripts.

It might not, however, be possible to explain observed equilibrium changes with only equilibrium supply-shifters. For any one particular nest, there exists a continuum of α and ρ combinations that can explain observed relative wages and quantities

in a period. We can express α as a function of ρ:

$$\widehat{\alpha}_t(\rho) = \frac{\left(\frac{W_{k,t}}{W_{f,t}}\right) \cdot \left(\frac{L_{k,t}}{L_{f,t}}\right)^{1-\rho}}{1 + \left(\frac{W_{k,t}}{W_{f,t}}\right) \cdot \left(\frac{L_{k,t}}{L_{f,t}}\right)^{1-\rho}} \ , \tag{B.12}$$

where the hat and the time sub-script indicate that $\widehat{\alpha}_t$ is a function of observables at period t. Between periods $t = \tau$ and $t = \tau + 1$, a condition for the existence of an equilibrium supply-shifter is that there must be a $\rho^\star \in (-\infty, 1]$, where

$$\widehat{\alpha}_t(\rho^\star) = \widehat{\alpha}_{t+1}(\rho^\star) \ . \tag{B.13}$$

Equation (B.13) simplifies to

$$\log\left(\frac{W_{k,\tau}W_{f,\tau+1}}{W_{f,\tau}W_{k,\tau+1}}\right) \cdot \left(\log\left(\frac{L_{k,\tau+1}L_{f,\tau}}{L_{f,\tau+1}L_{k,\tau}}\right)\right)^{-1} > 0 \ . \tag{B.14}$$

Equation (B.14) is a necessary condition for the existence of equilibrium supply-shifters,[D.9] and it simply requires that relative wages must shift in the opposite direction as relative labor quantities.

For a nested-CES problem, variations in ρ and α in any sub-nest impact demands across all nests. Hence, to use an equilibrium supply-shifters identification strategy, observable changes for all lowest-layer sub-nests must satisfy Equation (B.14). For Mexico, if there are episodes of supply-only policy shifts and corresponding short-interval ex-ante and ex-post observed equilibrium wages and labor quantities, demand parameters can plausibly be identified during each episode and compared over time without parametric assumptions.

Empirically, given our biennially aggregated data, we do not find any data segments during which changes in labor quantities and wages satisfy Equation (B.14) across all level three sub-nests. It is perhaps natural that over the course of 2 to 4 years, there would be sufficient changes in demand-side parameters that can substantially impact equilibrium, precluding the use of supply-shifter only instruments for identification.

B.2.3 Three and More Periods Data and Demand Share Polynomials

With three or more periods of data, we follow the literature and allow for demand-side share parameters to vary over t under polynomial restrictions. This means both demand and supply parameters can vary over time. Here, we consider one sub-nest. The logic for identification across nests follows from the discussions in Section B.2.1.

We express the logarithm of α_t as a Mth degree polynomial:

$$\log\left(\frac{W_{k,t}}{W_{f,t}}\right) = \log\left(\frac{\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}{1 - \exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}\right) + (\rho - 1) \cdot \log\left(\frac{L_{k,t}}{L_{f,t}}\right) \ . \tag{B.15}$$

D.9. Because Equation (B.13) is a function of relative wages and quantities, it does not relate to how the aggregate output to productivity ratio $\frac{Y_t}{Z_t}$ might or might not be changing over time. Additionally, as a necessary condition, satisfying Equation (B.14) does not mean that observed changes in wages and quantities are only driven by supply-shifters.

$T \geq M+2$ periods of data are needed to identify the $M+1$ polynomial coefficients, $\{a_0, a_1, \ldots, a_M\}$, and ρ.[D.10] In practice, polynomial coefficients can be found by regressing $\{\log(\widehat{\alpha}_t(\rho))\}_{t=1}^{T}$ on the time matrix $\{1, t, t^2, \ldots, t^M\}_{t=1}^{T}$. To analyze data requirements for identification, we provide an explicit characterization for data variations that identifies each a_i.

Polynomial coefficients can be identified via differences of $\log(\widehat{\alpha}_t(\rho))$. With data vector $\{\log(\widehat{\alpha}_t(\rho))\}_{t=\tau}^{\tau+M}$, starting at any $\tau \in [1, T-M]$, the coefficient for the highest polynomial term. a_M, is equal to:

$$a_M = \frac{1}{M!} \cdot \sum_{i=0}^{M} \underbrace{\left((-1)^i \frac{M!}{(M-i)!i!}\right)}_{\text{Alternating binomial coeff.}} \times \underbrace{\log\left(\widehat{\alpha}_{(\tau+M-i)}(\rho)\right)}_{\text{All data: } \widehat{\alpha}_\tau, \ldots, \widehat{\alpha}_{(\tau+M)}}, \tag{B.16}$$

where the sum is equal to the Mth difference over time of $\log(\widehat{\alpha}_t(\rho))$.[D.11] Specifically, when $M=3$, given $T>4$ periods of data available, the coefficient for the highest polynomial is equal to:

$$\alpha_3\left(\rho, \left\{\frac{W_{k,t}}{W_{f,t}}, \frac{L_{k,t}}{L_{f,t}}\right\}_{t=\tau}^{\tau+3}\right) = \frac{1}{3 \cdot 2} \cdot \underbrace{\log\left(\frac{\widehat{\alpha}_{\tau+3}(\rho) \cdot \widehat{\alpha}_{\tau+1}(\rho) \cdot \widehat{\alpha}_{\tau+1}(\rho) \cdot \widehat{\alpha}_{\tau+1}(\rho)}{\widehat{\alpha}_{\tau+2}(\rho) \cdot \widehat{\alpha}_{\tau+2}(\rho) \cdot \widehat{\alpha}_{\tau+2}(\rho) \cdot \widehat{\alpha}_{\tau}(\rho)}\right)}_{3^{rd} \text{ difference given wage and quantities at } \tau, \tau+1, \tau+2}, \tag{B.17}$$

for any $\tau \in [1, T-3]$. The log relative ratios of the $\hat{\alpha}_t$ across time segments, which are a function of relative wages and labor quantities as shown in Equation (B.12), determine the polynomial coefficients.

Given coefficients for higher order polynomials, coefficients for the $m < M$ lower order polynomials are equal to, for all starting dates $\tau \in [1, T-m]$:

$$a_m = \sum_{i=0}^{m} \left((-1)^i ((m-i)!i!)^{-1}\right) \cdot \underbrace{\left(\log(\widehat{\alpha}_{\tau+m-i}(\rho)) - \sum_{j=0}^{M-m-1} a_{M-j} \cdot t^{M-j}\right)}_{\text{Difference out higher than } m^{th} \text{ polynomial terms}}. \tag{B.18}$$

Equation (B.18) identifies a_m from the mth difference over time of $\log(\widehat{\alpha}_t(\rho))$, after first differencing out the contribution to $\widehat{\alpha}_t(\rho)$ from higher than m^{th} order polynomial terms as shown in Equation (B.18).

Despite the flexibility of a Mth order polynomial, intuitively, identification is potentially possible because the Mth derivative of a Mth order polynomial is, by design, time-invariant. This time-invariance restriction allows for iteratively solving for the coefficients for lower order polynomial terms through differencing.

Following the discussion in Section B.2.2 for two periods of data, in the multi-period context, it is also possible that there exist no combinations of polynomial coefficients, $\{a_0, a_1, \ldots, a_M\}$ and ρ that could plausibly explain observed equilibrium

D.10. In Equation B.15, we assume that patterns of changes in α_t are smooth and not subject to shocks, an assumption we relax in Section B.2.4.

D.11. The first difference is $(\widehat{\alpha}_t - \widehat{\alpha}_{t-1})$, the second difference is $(\widehat{\alpha}_{t+1} - \widehat{\alpha}_t) - (\widehat{\alpha}_t - \widehat{\alpha}_{t-1})$. The Mth difference is based on differencing data from over $M+1$ periods. The number of occurrences of each $\widehat{\alpha}_t$ term in the mth difference follows the $(m+1)^{th}$ row of Pascal's Triangle and is expressed in Equation (B.16) as a finite alternating series with binomial coefficients.

outcomes. The discussion in Section B.2.2 could be viewed as an analysis under 0th order polynomial assumption with $M = 0$.

In the absence of mismeasurement and shocks to relative demands, if the polynomial coefficients generated from Equations (B.16) and (B.18) based on different segments of data with different τ starting points vary, that indicates a violation of the time-invariance assumption of the Mth derivative of the Mth order polynomial. Empirically, given the possibility of mismeasurement and relative demand shocks, estimates based on different τ starting points would not be the same. However, large deviations in coefficients computed based on Equations (B.16) and (B.18) for different data segments might be indicative that the time-invariance assumption given the current order of polynomial is not satisfied (or it might also be indicative of the presence of significant mismeasurement or shocks, see the next section). An increase in M might be needed, with requisite increase in T data availability. In this paper, we model changes in relative demand trends in each sub-nest with 3rd degree polynomials.

B.2.4 Demand Estimation, Mismeasurement, and Shocks

Mismeasurement and Shocks Let $\{W_{k,t}, W_{f,t}, L_{k,t}, L_{f,t}\}$ and $\left\{\widehat{W}_{k,t}, \widehat{W}_{f,t}, \widehat{L}_{k,t}, \widehat{L}_{f,t}\right\}$ represent data with and without mismeasurement respectively. Assuming that mismeasurement is classical and log normal, we have

$$\begin{aligned} \log(W_{gen,t}) &= \log(\widehat{W}_{gen,t}) + \epsilon_{gen,t} \\ \text{and } \log(L_{gen,t}) &= \log(\widehat{L}_{gen,t}) + \eta_{gen,t} \ , \end{aligned} \tag{B.19}$$

where $\epsilon_{gen,t} \sim \mathcal{N}\left(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon^2\right)$ and $\eta_{gen,t} \sim \mathcal{N}\left(-\frac{\sigma_\eta^2}{2}, \sigma_\eta^2\right)$. As in prior sections, for notational clarity, we continue to ignore skill- and task-intensive occupation subscripts.

Additionally, changes in α_t over time might not be smooth, and there could be relative productivity shocks ν_t to skill- and gender-biased technological changes:

$$\log\left(\frac{\alpha_t}{1-\alpha_t}\right) = \log\left(\frac{\widehat{\alpha}_t}{1-\widehat{\alpha}_t}\right) + \nu_t \ , \tag{B.20}$$

where the log of $\widehat{\alpha}_t$ follows a smooth polynomial over time. Given Equation (B.20), α_t is a positive fraction for any ν_t draws along the real line, meaning that $\alpha_t\left(\widehat{\alpha}_t, \nu_t\right) : (0,1) \times \mathcal{R} \to (0,1)$.[D.12] For ease of exposition, we assume ν_t to be normal: $\nu_t \sim \mathcal{N}\left(-\frac{\sigma_\nu^2}{2}, \sigma_\nu^2\right)$.

Scenario One We now consider four possible scenarios based on varying assumptions on σ_ϵ^2, σ_η^2, and σ_ν^2. In the first scenario, suppose $\sigma_\epsilon^2 > 0$, but $\sigma_\eta^2 = 0$ and

D.12. Given Equation (B.20), for any $\nu_t \in \mathcal{R}$, we have

$$\alpha_t\left(\widehat{\alpha}_t, \nu_t\right) = \widehat{\alpha}_t \cdot \left(\frac{\exp\left(\nu_t\right)}{1 + \widehat{\alpha}_t \cdot \left(\exp\left(\nu_t\right) - 1\right)}\right) \in (0,1) \ .$$

This is because

$$\lim_{\nu_t \to -\infty} \left(\frac{\exp\left(\nu_t\right)}{1 + \widehat{\alpha}_t \cdot \left(\exp\left(\nu_t\right) - 1\right)}\right) = 0 \text{ and } \lim_{\nu_t \to \infty} \left(\frac{\exp\left(\nu_t\right)}{1 + \widehat{\alpha}_t \cdot \left(\exp\left(\nu_t\right) - 1\right)}\right) = \frac{1}{\widehat{\alpha}_t} \ .$$

$\sigma_\nu^2 = 0$, Equation (B.15) becomes:

$$\log\left(\frac{W_{k,t}}{W_{f,t}}\right) = \log\left(\frac{\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}{1-\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}\right) + (\rho-1)\cdot\log\left(\frac{L_{k,t}}{L_{f,t}}\right) + (\epsilon_{k,t} - \epsilon_{f,t}) \ . \tag{B.21}$$

Under Equation (B.21), mismeasurement is on the left-hand-side. The identification discussions for ρ and polynomial coefficients is the same as before,[D.13] but now there can be gaps between model predictions and the data.

Scenario Two In the second scenario, suppose $\sigma_\epsilon^2 > 0$ but $\sigma_\eta^2 > 0$ and $\sigma_\nu^2 = 0$, but ρ is known from prior literature, we have:

$$\log\left(\frac{W_{k,t}}{W_{f,t}}\frac{L_{k,t}}{L_{f,t}}^{1-\rho}\right) = \log\left(\frac{\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}{1-\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}\right) + (\epsilon_{k,t} - \epsilon_{f,t}) + (1-\rho)\cdot(\eta_{k,t} - \eta_{f,t}) \ . \tag{B.22}$$

Under Equation (B.22), polynomial share coefficients remain identifiable. A challenge is that as the data-generating true ρ tends away from perfect substitution ($\rho = 1$) and toward complementarity ($\rho \to -\infty$), the mismeasurement is magnified. Lower ρ values reduce the precision of polynomial share estimates given the same span of data.

Scenario Three In the third scenario, suppose $\sigma_\epsilon^2 > 0$, $\sigma_\eta^2 > 0$ and $\sigma_\nu^2 = 0$, and ρ is not known, we have:

$$\begin{aligned}\log\left(\frac{W_{k,t}}{W_{f,t}}\right) = &\log\left(\frac{\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}{1-\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}\right) + (\rho-1)\cdot\log\left(\frac{L_{k,t}}{L_{f,t}}\right) + \\ &(\epsilon_{k,t} - \epsilon_{f,t}) + (1-\rho)\cdot(\eta_{k,t} - \eta_{f,t}) \ .\end{aligned} \tag{B.23}$$

In Equation (B.23), the log relative labor ratio is correlated with the error term. Hence, there is standard classical errors-in-variable attenuation bias. As in the second scenario, mismeasurement can be magnified by lower values for data-generating true ρ.

In terms of the measurement errors, for developed economies such as the U.S., there might be administrative records of income and wages as well as detailed firm-level employment data by industry and occupation. In our context, mismeasurement is of greater concern. We compute wages and the number of workers based on aggregating the ENIGH survey data from a full sample of 87,826 housing units. Our focus on occupation leads to 16 occupation-skill-gender data cells. In each survey year, for some cells (e.g., routine-unskilled-men) the sample size is substantial, but for other cells (e.g., manual-skilled-women) the sample size is limited and suffers from sampling error. Additionally, there might be mismeasurement in the underlying reported wage/earning and labor market participation decisions.

D.13. Without mismeasurement, given M^{th} order polynomial and $T \geq M+2$ periods of data, any $M+1$ segment of data will generate the same exactly identified demand parameters using Equations (B.16) and (B.18). With mismeasurement, the best-fit is in effect obtained from an averaging of the results from each $M+1$ data segment.

Scenario Four In the fourth scenario, suppose $\sigma_\epsilon^2 > 0$, $\sigma_\eta^2 > 0$ and $\sigma_\nu^2 > 0$, and ρ is not known, we have:

$$\log\left(\frac{W_{k,t}}{W_{f,t}}\right) = \log\left(\frac{\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}{1-\exp\left(\sum_{i=0}^{M} a_i \cdot t^i\right)}\right) + (\rho-1)\cdot\log\left(\frac{L_{k,t}}{L_{f,t}}\right) + (\epsilon_{k,t}-\epsilon_{f,t}) + (1-\rho)\cdot(\eta_{k,t}-\eta_{f,t}) + \nu_t \ . \tag{B.24}$$

In Equation (B.24), α_t is a function of ν_t, and α_t impacts the labor demand curve. In our setting, when labor supply is elastic with respect to wages (i.e. $\psi_1 > 0$), the equilibrium relative labor ratio $\frac{L_{k,t}}{L_{f,t}}$ is endogenous to ν_t. Hence, when directly estimating Equation (B.24), in addition to issues related to mismeasurement, bias can also come from the correlation between ν_t and $\frac{L_{k,t}}{L_{f,t}}$.

It is important to note that even when labor supply is inelastic with respect to wages (i.e. $\psi_1 = 0$), bias can still arise if demand shocks ν_t are correlated with supply shocks—technological shocks might impact both demand and supply curves. However, in both cases ($\psi_1 = 0$ and $\psi_1 > 0$) it might be possible to identify shocks that only shift supply curves as instruments for estimating Equation (B.24). For example, demographic changes might shift the x-intercepts of the labor supply curves without impacting labor demand. One problem is that in most studies like ours that exploit aggregate time-series variation, an IV estimator will likely perform poorly because of the small sample sizes and the difficulty of finding variables that strongly impact aggregate labor supplies in the short run. We compare the performance of the Equilibrium, OLS, and IV estimators in Appendix Section C.

In discussing the four scenarios above, we have clarified the conditions under which bias might arise when demand-side parameters are estimated from demand-side relative optimality conditions alone. In Appendix Sections B.2.6 and B.3, we discuss how equilibrium solution based estimation can resolve the challenges posed by scenarios three and four.

B.2.5 Supply Estimation and Wage Endogeneity

Following Equations (2.2), (5.5), and (5.6), the difference in indirect utility from choosing one of the three occupational categories and leisure is:

$$\begin{aligned} & U(occ \mid gen, edu, t) - U(h \mid gen, edu, t) \\ = \ & \underbrace{(\psi_{gen,edu,occ} - \pi_{1,gen} - \pi_{2,gen} t)}_{\text{Time-varying intercepts}} - \underbrace{\boldsymbol{\pi}'_{gen,edu}\boldsymbol{B}_{gen,edu,t}}_{\text{Time-varying observables}} \\ & + \underbrace{\psi_1 \log\left(W_{gen,edu,occ,t}\right)}_{\text{Wage effects}} + \underbrace{\left(\epsilon_{gen,edu,occ,t} - \epsilon_{gen,edu,h,t}\right)}_{\text{Residual}} \ . \end{aligned} \tag{B.25}$$

Given the extreme value aggregate probability formulation shown in Equation (5.7), we could potentially estimate the parameters of Equation (B.25) via OLS by replacing the left-hand-side of Equation (B.25) with $\log\left(L^s_{gen,edu,O,t}/L^{pop}_{gen,edu,t}\right) - \log\left(L^s_{gen,edu,h,t}/L^{pop}_{gen,edu,t}\right)$, which represents log differences in observed aggregate labor shares.

In partial equilibrium discrete choice supply (or demand) estimation settings, the potential endogeneity of prices with the error term might require the use of instruments. In the context of the equilibrium model here, equilibrium wage solutions

capture all time-varying and occupation-specific share and productivity differences from the demand-side.

B.2.6 Mismeasurement, Shocks, Equilibrium Solution, and Estimation

To conduct the counterfactual analysis of interest, we need both demand- and supply-side parameters. For estimating demand parameters, equilibrium estimation avoids potential bias that might arise from demand-only estimation discussed in Appendix Section B.2.4. For estimating supply parameters, equilibrium estimation provides wages endogenously.

At each t, given vectors of demand parameters $\left\{\widehat{\boldsymbol{\alpha}}_{4,t}, \widehat{\boldsymbol{\alpha}}_{3,t}, \widehat{\alpha}_{2,t}, \widehat{\alpha}_{1,t}, \frac{Y_t}{Z_t}, \boldsymbol{\rho}\right\}$, supply parameters $\{\boldsymbol{\psi}, \boldsymbol{\pi}\}$, gender- and skill-specific supply-side variables $\boldsymbol{B}_t$, gender- and skill-specific total potential worker count $\boldsymbol{L}_t^{pop}$, and relative productivity shocks $\boldsymbol{\nu}_t$ (see Appendix Section B.2.4), one could solve for vectors of equilibrium wages $\widehat{\boldsymbol{W}}$ and labor quantities $\widehat{\boldsymbol{L}}$ across twelve occupation-gender-skill categories. Given vectors of measurement error draws $\{\boldsymbol{\epsilon}_t, \boldsymbol{\eta}_t\}$ (see Appendix Section B.2.4), model predictions could be matched to observed wages $\boldsymbol{W}$ and labor quantities $\boldsymbol{L}$. In a specific gender, skill, and occupation cell, we have, for equilibrium labor quantity,

$$\log\left(L_{gen,skl,occ,t}\right) = \log\left(\widehat{L}_{gen,skl,occ,t}\left(\underbrace{\widehat{\boldsymbol{\alpha}}_{4,t}, \widehat{\boldsymbol{\alpha}}_{3,t}, \widehat{\alpha}_{2,t}, \widehat{\alpha}_{1,t}, \frac{Y_t}{Z_t}, \boldsymbol{\rho}}_{\substack{\text{Demand}\\\text{Parameters}}}, \underbrace{\boldsymbol{\nu}_t}_{\substack{\text{Dem.}\\\text{Shocks}}}, \underbrace{\boldsymbol{\psi}, \boldsymbol{\pi}}_{\substack{\text{Supply}\\\text{Param.}}}, \underbrace{\boldsymbol{B}_t, \boldsymbol{L}^{pop}{}_t}_{\substack{\text{Supply}\\\text{Observed}}}\right)\right) + \eta_{gen,skl,occ,t}\ , \tag{B.26}$$

and a parallel equation for equilibrium wage.

Following the discussions in Appendix Section B.2.4, for demand only estimation under Equation (B.23), observed relative wages are regressed on observed relative labor quantities, leading to potential bias. Under Equation (B.26), observed wages and labor quantities are both on the left-hand-side of Equation (B.26) and are matched against model equilibrium predictions that are solved at given vectors and parameters, observables, and potential shock draws.

In addition to the identification of supply- and demand-side parameters previously discussed, the variances of relative demand shocks and measurement errors are potentially identifiable as well. On the one hand, $\boldsymbol{\nu}_t$ impacts both $\widehat{\boldsymbol{L}}(\boldsymbol{\nu}_t)$ and $\widehat{\boldsymbol{W}}(\boldsymbol{\nu}_t)$, which allows $\boldsymbol{\nu}_t$ to help explain the residual covariance between $\boldsymbol{L}(\boldsymbol{\nu}_t)$ and $\boldsymbol{W}(\boldsymbol{\nu}_t)$ not explained by the smooth demand trends and supply-side observables. On the other hand, measurement errors for wages ($\boldsymbol{\epsilon}_t$) and labor quantities ($\boldsymbol{\eta}_t$) are uncorrelated by assumption and help explain uncorrelated residual differences between model predictions and data.

To jointly identify the variances of these unobservables, given the distributional assumptions from Appendix Section B.2.4, we could repeatedly solve for equilibrium outcomes $\widehat{\boldsymbol{L}}(\boldsymbol{\nu}_t)$ and $\widehat{\boldsymbol{W}}(\boldsymbol{\nu}_t)$ given vectors of $\boldsymbol{\nu}_t$ draws, and find the vectors of $\boldsymbol{\epsilon}_t(\boldsymbol{\nu}_t)$ and $\boldsymbol{\eta}_t(\boldsymbol{\nu}_t)$ draws that explain the residual differences between model predictions and data using Equation (B.26). These residual differences can be inputs for a simulated maximum likelihood estimator. This approach imposes high computational burdens: given a specific set of parameter values, equilibrium solution needs to be resolved a large number of times to construct one simulated likelihood; the simulated likelihood

needs to be reconstructed a large number of times as the estimator searches across the large parameter space.

In Appendix Section B.3, we solve the model along smooth polynomial trends and set $\boldsymbol{\nu_t} = \mathbf{0}$. This means that the differences between model predictions and observables are potentially explained by measurement (sampling) errors as well as random demand shocks that deviate from polynomial trends. Our Monte Carlo exercises (see Section C) demonstrate that the Equilibrium Estimator performs well in the presence of demand shocks.

B.3 Estimation

We discuss our equilibrium estimation strategy in the following sections. We discuss the estimation parameter space in Section B.3.1. We discuss initializing starting values for estimation in Section B.3.2. We discuss the error structure in Section B.3.3.

B.3.1 Estimation Parameter Space

Let Θ be the 94×1 vector of all parameters of the model. This includes 11 supply-side $\boldsymbol{\psi}$ parameters,[D.14] 18 supply-side $\boldsymbol{\pi}$ parameters, 8 demand-side elasticity parameters, 44 demand-side share polynomial coefficients, and 13 year-specific demand-side output-productivity ratios.

Let $\Theta^{\rho} = \left\{ \{\rho_{4,O}, \rho_{3,O}\}_{O \in m,r,a}, \rho_1, \rho_2 \right\}$ be the 8×1 vector of elasticity parameters. Let $\mathcal{O}$ be some estimation objective function that is a function of the differences in model prediction and observed data. Let $p(\Theta)$ be the 312×1 vector of equilibrium wage and labor-quantity predictions of the model. Let q be the observed vector of wages and labor-quantity data taken from ENIGH. Finally, let subscripts i in q_i and p_i denote any time, gender, skill, and occupation specific data and predictions.

The equilibrium estimation problem searches for optimal constrained elasticity parameters, given unconstrained non-elasticity parameters that provide best fit conditional on the elasticity parameters:[D.15]

$$\min_{\Theta^{\rho} \in (-\infty, 1]^8} \left\{ \min_{\Theta \setminus \Theta^{\rho}} \mathcal{O}\left(\{q_i - p_i(\Theta)\}_i\right) \right\}. \tag{B.27}$$

Given the large parameter space, it is important to initialize estimation at good starting values. Given a particular combination of Θ^{ρ} values, we initialize the estimation of demand- and supply-side parameters at parameters that provide best-fit under demand- and supply-side only estimation. Specifically, given Θ^{ρ}, we minimize:

$$\min_{\Theta \setminus \Theta^{\rho}} \mathcal{O}\left(\left\{q_j^L - p_j^L\left(\Theta \mid q^W\right)\right\}_j\right), \tag{B.28}$$

where p^L is the combined vector of labor quantities predicted by demand and supply equations given data wage vector q^W, and q^L is the data vector of labor quantities to match. We estimate demand-side parameters via nonlinear least-square, which we

D.14. There are 13 $\boldsymbol{\psi}$ parameters, however, 2 of them can not be separately identified from gender-specific $\pi_{1,gen}$ parameters.

D.15. Θ^{ρ} values are constrained between perfect substitutability and perfect complementarity. All other parameters can take on any positive or negative values.

provide details for in the next section, and supply-side parameters via linear least-square. We use the resulting estimates as starting parameter values for equilibrium estimation in Equation (B.27).

B.3.2 Initializing demand-side parameters

We discuss here the estimation routine to generate starting values for all 56 non-elasticity demand-side parameters. The strategies here follow from the identification discussions in Section B.2.

Given our parametric assumptions on share parameter trends from Equation (5.4), Equation (B.1) for optimal male and female labor demand can be rewritten as:

$$\begin{aligned} L_k^{d,*} =& L\left(1+\left(1-\exp\left(\sum_{j=0}^{3} a_j t^j\right)\right)\left(\left(\frac{W_k}{W_f}\cdot\frac{1-\exp\left(\sum_{j=0}^{3} a_j t^j\right)}{\exp\left(\sum_{j=0}^{3} a_j t^j\right)}\right)^{\frac{\rho}{1-\rho}}-1\right)\right)^{\frac{-1}{\rho}} \\ L_f^{d,*} =& L\left(1+\exp\left(\sum_{j=0}^{3} a_j t^j\right)\left(\left(\frac{W_f}{W_k}\cdot\frac{\exp\left(\sum_{j=0}^{3} a_j t^j\right)}{1-\exp\left(\sum_{j=0}^{3} a_j t^j\right)}\right)^{\frac{\rho}{1-\rho}}-1\right)\right)^{\frac{-1}{\rho}} \end{aligned} . \tag{B.29}$$

Conditional on the elasticity parameter ρ and given data on relative prices $\left\{\frac{W_{k,t}}{W_{f,t}}\right\}_{t=1}^{T}$ and gender-specific labor demands $\{L_{g,t}\}_{t=1}^{T}$, the share trend parameters of Equation (B.29) can be estimated via Equation (B.30):

$$\min_{\{a_j\}_{j=0}^{3},\{L_t\}_{t=1}^{T}} \sum_{t=1}^{T}\sum_{g\in\{k,f\}} \tau_{g,t}\cdot\left(L_{g,t}-L_{g,t}^{d,*}\left(L_t,\{a_j\}_{j=0}^{3},\rho;t,\frac{W_{k,t}}{W_{f,t}}\right)\right)^2, \tag{B.30}$$

where $\tau_{g,t}$ are potential estimation weights.[D.16]

In Equation (B.30), in addition to unknown share trend parameters, time-varying aggregate labor demand $\{L_t\}_{t=1}^{T}$ for the sub-nest under consideration are also unknown. These $\{L_t\}_{t=1}^{T}$ values can first be found as best fitting proportional scalars: slopes estimates with the origin as the y-intercept. Let $\Omega_{g,t}\left(\{a_j\}_{j=0}^{3},\rho\right)=L_{g,t}^{d,*}/L_t$, at each t, the best fitting L_t value is:

$$\widehat{L}_t=\frac{\Omega_{k,t}\cdot L_{k,t}+\Omega_{f,t}\cdot L_{f,t}}{\Omega_{k,t}^2+\Omega_{f,t}^2}. \tag{B.31}$$

Given Equation (B.31) and ignoring weights, the optimization problem from Equation (B.30) can be rewritten as:

$$\min_{\{a_j\}_{j=0}^{3}} \sum_{t=1}^{T}\left(\left(\frac{L_{k,t}-L_{f,t}\left(\frac{\Omega_{k,t}}{\Omega_{f,t}}\right)}{1+\left(\frac{\Omega_{k,t}}{\Omega_{f,t}}\right)^2}\right)^2+\left(\frac{L_{f,t}-L_{k,t}\left(\frac{\Omega_{f,t}}{\Omega_{k,t}}\right)}{1+\left(\frac{\Omega_{f,t}}{\Omega_{k,t}}\right)^2}\right)^2\right), \tag{B.32}$$

D.16. For example, $\tau_{g,t}=\frac{Q_{g,t}}{\sum_{\hat{t}=1}^{T}\sum_{\hat{g}\in\{m,f\}}Q_{\hat{g},\hat{t}}}$.

where $\{\Omega_{g,t}\}_{g\in\{k,f\}}$ are only functions of the share trend parameters $\{a_j\}_{j=0}^{3}$. Equation (B.32) assumes a parametric functional form for share parameters, nonparametrically fits L_t, and assumes that ρ is fixed over time. Equation (B.32) is estimated via non-linear least square.[D.17]

The $\{L_t\}_{t=1}^{T}$ generated initially from Equation (B.32) are best-fitting for the current sub-nest, however, they are not consistent with parameters from higher layer nests. To generate consistent aggregate outputs requirements at lower nests, we repeat the just described estimation procedure but now perform it at higher layers of the nested-CES demand system: we use aggregate wages generated following Equation (B.2) and fit higher layer nest aggregate labor choice predictions against the $\{L_t\}_{t=1}^{T}$ just generated from lower layer nests.

In this fashion, we estimate Equation (B.32) repeatedly as we move iteratively upwards along each branch of the nested-CES problem. This generates polynomial share parameters along each branch of each nest layer. At the highest nest layer, estimating Equation (B.32) generates best-fitting predictions for the aggregate $\left\{\frac{Y_t}{Z_t}\right\}_{t=1}^{T}$ ratios. Equipped with all demand-side parameters, we generate $\{L_t\}_{t=1}^{T}$ aggregate output requirements for the lowest nest layer. This overall procedure can be repeated several times until the $\left\{\frac{Y_t}{Z_t}\right\}_{t=1}^{T}$ ratio across iterations converge. The demand-side estimation routine discussed in this section is linearly-scalable to nested-CES problems with additional layers and branches. Conditional on Θ^{ρ}, we use the estimates from this section as the starting parameter values for equilibrium estimation under Equation (B.27).

B.3.3 Error Structure, Weight Matrix, and Standard Errors

In this section, we discuss the estimation objective function $\mathcal{O}$. We assume a simplified error structure to facilitate estimation. The presence of the error term follows from our discussions in Section B.2.4 on potential mismeasurement due to misreporting or sampling errors. For any given prediction i, we assume that the error term, e_i, at the true parameter vector, Θ^*, follows a normal distribution centered at zero that is independent across i.[D.18] That is,

$$e_i = q_i - p_i(\Theta^*) \ , \tag{B.34}$$

where $f(e_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(\frac{e_i^2}{2\sigma_i^2}\right)$. The log-likelihood function takes the form

$$\log \mathcal{L}(\Theta) = \sum_i \log f(e_i) = \sum_i \log f(q_i - p_i(\Theta)) \ , \tag{B.35}$$

D.17. Given ρ, for the nest-specific nonlinear data-fitting procedure, starting values for polynomial share coefficients is obtained by estimating the following linear equation:

$$\log\left(\frac{\left(\frac{W_k}{W_f}\right)\cdot\left(\frac{L_k}{L_f}\right)^{1-\rho}}{1+\left(\frac{W_k}{W_f}\right)\cdot\left(\frac{L_k}{L_f}\right)^{1-\rho}}\right) = \alpha_0 + a_1 t + a_2 t^2 + a_3 t^3. \tag{B.33}$$

This follows from the discussions in Section B.2.3.

D.18. The normality assumption for the error terms follows from the Central Limit Theorem. We compute sample averages from the micro-data. All but 5 of the gender-skill-occupation-year sub-nest have at least 35 observations based on which sample means are computed.

and the respective score function, $s(\Theta)$, is:

$$s(\Theta) = \frac{\partial \log \mathcal{L}(\Theta)}{\partial \Theta} = \sum_i \frac{\partial \log f(q_i - p_i(\Theta))}{\partial \Theta} = \sum_i \frac{1}{\sigma_i^2} \frac{\partial p_i(\Theta)}{\partial \Theta}(q_i - p_i(\Theta)) \ , \quad \text{(B.36)}$$

which we can write more compactly in vector form as

$$s(\Theta) = W'(\Theta)(q - p(\Theta)) \ . \quad \text{(B.37)}$$

Here, $W(\Theta)$ is 312×94 weight matrix that depends on the derivatives of the vector of predictions with respect to each of the parameters, and the variance of each prediction error σ_i^2.

Note that $m(\Theta) = q - p(\Theta)$ is a vector such that, at the true parameter values, $E(q - p(\Theta^*)) = 0$. We can use these moment conditions in the estimation. Suppose $W(\Theta) = W$ is fixed. We can obtain a consistent estimator of Θ^* by GMM:

$$g(\hat{\Theta}_{gmm}) = W'(q - p(\hat{\Theta}_{gmm})) = W' m(\hat{\Theta}_{gmm}) = 0 \ , \quad \text{(B.38)}$$

In our setup, we have more moment conditions (312) than parameters to be estimated (94), so Equation (B.38) will usually not be satisfied. We then find the values that minimize the weighted square sum of prediction errors,

$$\hat{\Theta}_{gmm} = \text{argmin} \ \ m(\Theta)' \Omega m(\Theta), \ . \quad \text{(B.39)}$$

with $\Omega \equiv WW'$ being a positive definite weighting matrix.

W is not known. An efficient GMM estimator can be obtained by choosing a weight matrix that is asymptotically equivalent to the one that would result from the maximum likelihood estimator using the score vector in Equation (B.37). We follow an iterative process. We start from a plausible set of initial values of the parameters (Θ_0) and use them to estimate the vector of partial derivatives $\frac{\partial \hat{p}_i(\Theta_0)}{\partial \Theta_0}$. The estimates of the variance of each error, $\hat{\sigma}_{i,0}^2$, are calculated as the square of the estimated error from this initial set of parameter values. Both of these estimates are then used to construct an initial weight matrix, which allows us to solve the minimization problem.[D.19] The estimates obtained after this first iteration[D.20] are used to update the weight matrix, and the process continues until the parameter vector converges to a stable point.

Finally, the standard errors of the parameter estimates are calculated by applying the method of moments formula. We presented standard errors of demand- and supply-side parameter estimates in Tables 3 and 5 as well as Appendix Table D.6. Let Γ be the matrix of partial derivatives of the sample moments $\bar{m}(\hat{\Theta}_{gmm})$ with respect to the parameters. The ith row correpsonds to:

$$\Gamma_i(\hat{\Theta}_{gmm}) = \frac{\partial \bar{m}_i(\hat{\Theta}_{gmm})}{\partial \hat{\Theta}_{gmm}} \ , \quad \text{(B.40)}$$

so the variance-covariance matrix can be calculated using:

$$\hat{Var}(\hat{\Theta}_{GMM}) = \left[\Gamma(\hat{\Theta}_{gmm})' \hat{Var}[\bar{m}(\Theta_{gmm})]^{-1} \Gamma(\hat{\Theta}_{gmm})\right]^{-1}. \quad \text{(B.41)}$$

D.19. The parameter search is done using the interior-point algorithm in Matlab.

D.20. Note that even though the weight matrix is a function of the parameters, it remains fixed during the parameter search.

C Equilibrium Estimator Monte Carlo Exercises (online)

C.1 Monte Carlo Simulations with Demand Shocks

In Appendix section B.2.4, we discussed measurement errors and demand shocks as two potential drivers of the differences between model predictions and observed outcomes. In this section, we describe Monte Carlo exercises designed to evaluate the equilibrium estimator. We estimate the model parameters with simulated data generated with varying magnitudes of demand shocks. We demonstrate that even small demand shocks lead to bias in OLS estimation, which proceeds by regressing relative wages on relative quantities. We confirm that IV is median unbiased but has very high variance, such that the mean is not close to the true value. We highlight the poor finite-sample properties of IV and the likelihood of weak instruments. Given the equilibrium data-generating process, we can evaluate the OLS and IV estimators compared to true elasticity parameter values. Previous discussions have focused on the robustness of the elasticity estimate to specific modeling choices, like the functional form assumption on relative demand trends (Borjas, Grogger, and Hanson 2012).

By demand shocks (ν_t), we mean shocks that induce random variations in the patterns of relative demands across occupation, skill, and gender cells that deviate from the patterns that would be generated by the smooth polynomial assumed under Equation 5.4. Following the formulation from Equation B.20, the demand shocks induce random normal proportional deviations from the polynomial share parameters.

The Monte Carlo exercises proceed in the following steps. First, for each simulation, we draw (11×13) i.i.d. demand shocks across subnests and years and solve for equilibrium outcomes; we use estimated model parameters for all simulations. Second, we draw different sets of shocks to generate 300 simulated datasets. Third, we repeat these equilibrium simulations under four scenarios with increasing magnitudes of demand shocks in standard deviations (σ_ν). The four scenarios map to demand-side share parameters that are, on average, the same as share parameters under polynomial trends, but with proportional deviations that have 0.2, 2, 4, and 9 percent standard deviations respectively.[E.1] Fourth, for each of the (300×4) simulated datasets under the four scenarios, we estimate model parameters following Appendix Section B.3 by matching model equilibrium predictions based on polynomial demand trends to the "observed" simulated data.

C.2 Equilibrium Estimator Performance

For each demand shock size, we compute parameter-specific statistics using the 300 estimates for each one of the 94 parameters. First, we compute *the proportional deviation*, which is the ratio of the estimated sample-mean for each parameter and the true parameter value, minus one. Second, we compute *the standardized bias*, which is equal to the distance between the estimated sample mean and the true parameter value in units of the standard deviation of the sample estimate distribution. Third, we construct *indicators for whether each true parameter value falls within the confidence interval around the estimated sample mean.* Given the differing scales of the 94 parameters that we estimate, these three statistics jointly provide information on the performance of the equilibrium estimator.

E.1. These are the effects of the demand shocks on the gaps between model and predictions.

The distribution of parameter estimates for all parameters from the Monte Carlo exercise with the second and third highest magnitudes of demand shocks in Figures D.6 and D.7. The vertical line marking the middle of the estimates distribution is generally close to the vertical line marking the true parameter value both in levels as well as in units of the standard deviation of each parameter's estimates. There is a general widening of the estimates distribution in Figure D.6 compared to Figure D.7. In addition, all parameter-specific statistics for each scenario is available at at this link: https://github.com/FanWangEcon/PrjLabEquiBFW/blob/main/PrjLabEquiBFW/_esti/mc_ee_esti_stats.csv.

For most parameters, estimated sample means are close to the true parameter values, with the gap increasing as the standard deviation of demand shocks increases. Specifically, first, under the four scenarios with rising demand shocks, proportional deviations are less than 1 percent for 100, 83, 54, and 38 percent of parameters, and are less than 10 percent for 100, 94, 88, and 87 percent of the parameters, respectively. Second, under the four scenarios and focusing on standardized bias, 74, 57, 29, and 23 percent of estimates-sample-means are within 0.1 standard deviations of the true parameter values. Additionally, 91 (98), 81 (100), 62 (96), and 51 (89) percent are within 0.2 (0.5) standard deviations of the true values. Third, given the magnitudes of the standardized bias and a sample size of 300, we find that 71 (84), 57 (68), 41 (52), and 22 (37) percent of the true parameter values are within the 90 (99) percent confidence intervals constructed around estimated sample means. Overall, the equilibrium estimator performs well for most parameters, and there is evidence for statistically significant but small bias for a substantial subset of parameters, especially at larger levels of demand shocks.

An exception is that the equilibrium estimator performs relatively poorly in estimating ρ_1 (substitutability between aggregate analytical labor and the routine and manual labor aggregate), ρ_2 (substitutability between aggregate routine labor and aggregate manual labor), $\rho_{3,a}$ (substitutability between skilled and unskilled analytical workers). At the extreme, from the scenario with the largest demand shocks, the estimated sample median and mean for ρ_1 (true value 0.031) are -0.135 and -1.410 (s.d. 3.17). The estimates-sample median and mean for ρ_2 (true value -0.154) are -0.084 and -6.613 (s.d. 62.0). The estimates-sample median and mean for $\rho_{3,a}$ (true value 0.302) are -0.118 and -0.493 (s.d. 1.50). Additionally, the estimates for $\alpha_{1,0}$, $\alpha_{1,1}$, $\alpha_{1,2}$, and $\alpha_{1,3}$ (the vector of polynomial share parameters for aggregate analytical labor vs. the routine and manual labor aggregate) to have 26%, 63%, -52%, and -17% percent proportional deviations from the true share parameters. As discussed in Appendix Section B.2, the identification of higher-level CES demand parameters relies on variations in aggregate relative prices and quantities, which are functions of lower nest estimated parameters and observed lowest-layer facing wages and quantities. In our setting, these Monte Carlo results indicate that there is insufficient aggregate variation to provide precise estimates for the highest-layer CES parameters at high levels of demand shocks. We do not expect this to have major implications for our results since variation in the data is very limited at this aggregate level, and our focus is on lies at the occupation-specific parameters for elasticity and labor share that lie at lower nests, which are well estimated. The aggregate relative productivity across occupations is of less importance.

C.3 Comparison of the Equilibrium Estimator with the OLS and IV Estimators

In this section, we use our Monte Carlo simulations to compare the distributions of gender substitutability parameters $\rho_{4,r}$, $\rho_{4,m}$, and $\rho_{4,a}$ from the equilibrium estimator (EE) and from OLS and IV estimators. Our overall finding is that, in our empirical setting and given the simulation scenarios, OLS results suffer from high bias, IV results suffer from high variance, and equilibrium estimator results have a comparative low bias as well as low bias. The comparison of estimation results are visualized in Figure D.8.

As discussed in the main text, there is a long tradition of estimating the elasticity of substitution across worker types (e.g., male or female workers, immigrants, and native workers) based on the log-linear CES demand optimal equation. Equation B.24 offers the possibility of obtaining gender-elasticity parameters by regressing the time series of log relative wages and log relative labor quantities. In this setting, to account for shifts in relative demands over time, researchers commonly control for time polynomials of different orders. As discussed in Appendix Section B.2.4, IVs can also be used in this setting, although far less frequently (Havranek et al. 2022), to correct for bias arising from demand shocks that are not captured by relative demand time-trends or attenuation bias due to mismeasurements on quantities.

For the OLS and IV estimations, for each occupation group, we run separate regressions to estimate the occupation-specific gender elasticities using relative wages and labor quantities across time. For the IV, we use the level of gender- and skill-specific potential prime-age workers (see Figure D.3) as the instrument. Under the equilibrium data generating process, the population size and composition are exogenous inputs.

An important aspect of the reduced-form estimation is the polynomial order used to approximate relative demand trends. The reduced-form econometrics literature has found that the elasticity of substitution estimates are sensitive to assumptions on the order of polynomials that is used to approximate the time trend (Borjas, Grogger, and Hanson 2012). In our setting, we use the simulations from the scenario with the smallest amount of demand shocks to explore the order of polynomials under which mean elasticity estimates are the closest to the true parameter values of the data generating process. We found this to be a fifth order polynomial time trend, which we use in all OLS and IV estimations.[E.2]

In panel (a) of Figure D.8, we show the distributions of $\rho_{4,r}$, $\rho_{4,m}$, and $\rho_{4,a}$ estimates from the scenario with the lowest magnitudes of demand shocks (0.1% s.d.). Unsurprisingly, estimated sample means from IV, OLS, and EE are all close to the true parameter values. However, as can be seen in the figure, even with this very small magnitude of demand shocks, OLS and IV estimates have larger variance, and their sample means are relatively further away compared to EE.

In panels (b) and (c) of Figure D.8, under scenarios with higher magnitudes of demand shocks, we find a similar pattern where the distributions of EE estimates are more centered around the true parameter values. In panel (b), with 2% s.d. demand shocks, the difference in OLS sample means and true gender-substitutability parameter values are between 0.09 to 0.10. These are between 13 to 61 larger than the corresponding sample bias gaps for EE estimates. At the same time, while

E.2. We should note that although we used third order polynomials to model the log of the demand share parameters, the log relative demand shares—the intercept term in Equation B.24—is not itself a third order polynomial but a function of third order polynomials.

IV and EE estimates have similar bias, IV estimates are less precise, with sample standard deviations that are between 2.4 to 3.2 times larger than those for EE. In panel (c), at 5% s.d. demand shocks, OLS sample bias increases to 0.43, 0.47, and 0.40 for $\rho_{4,r}$, $\rho_{4,m}$, and $\rho_{4,a}$, while EE sample bias remains less than 0.06. At the same time, the variability for IV estimates widens further, and IV sample standard deviations are now between 3.5 to 7.7 times larger than EE.

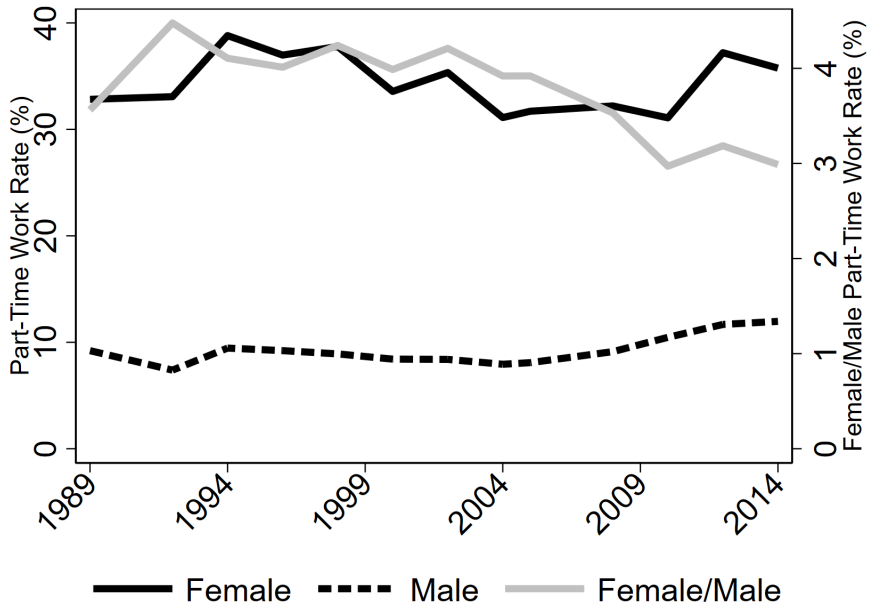
In panel (d) of Figure D.8, at the highest level of demand shock scenario, the IV and OLS estimates both retain very limited information due to exploding range of estimates. Approximately 25, 50, and 90 percent of the OLS estimates for $\rho_{4,m}$, $\rho_{4,r}$, and $\rho_{4,a}$ are higher than the perfect substitutability threshold of 1, respectively. At the same time, IV estimates for $\rho_{4,m}$, $\rho_{4,r}$, and $\rho_{4,a}$ have standard deviations of 14.8, 6.1, and 7.7 along with minimum to maximum ranges of -21 to 119, -40 to 181, and -79 to 54, respectively. In contrast, the EE estimates for $\rho_{4,m}$, $\rho_{4,r}$, and $\rho_{4,a}$ have means (s.d.) of 0.289 (0.270), 0.148 (0.193), and 0.639 (0.201), which fall comparatively much more tightly around the true parameter values.[E.3]

It is important to point out that the improved performance of the EE estimator comes at the cost of additional equilibrium assumptions required to generate equilibrium wages and labor quantities as outcomes of the structural equilibrium model. The elasticity interpretation of the IV and OLS estimations also requires the structural assumptions of CES aggregation between male and female labor, but OLS and IV estimations do not require the specification of a full equilibrium model. However, as we have demonstrated, the structure of the equilibrium model, in particular, the elasticity of LFP on equilibrium wages as well as the source of deviation between first-order optimality predictions and observed data are important determinants of whether reduced form strategies can be usefully applied in empirical settings.

E.3. We include additional distributional statistics for the OLS, IV, and EE estimates across the four scenarios and for the three gender-substitutability parameters at this link: https://github.com/FanWangEcon/PrjLabEquiBFW/blob/main/PrjLabEquiBFW/_esti/mc_ee_iv_ols.csv.

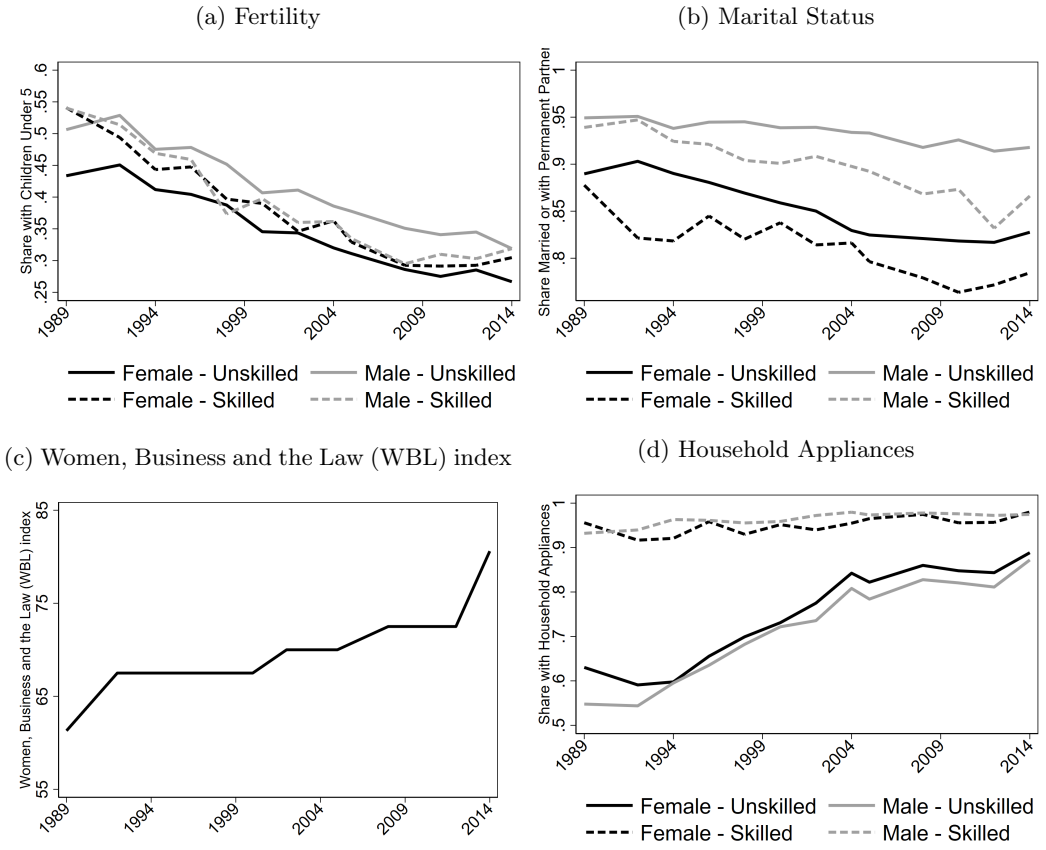
D Additional Figures and Tables (online)

Figure D.1: Share of Part-Time Workers by Sex



Notes: An individual is defined as working part-time if he/she reported working less than 35 hours a week. See discussions in Section 8.

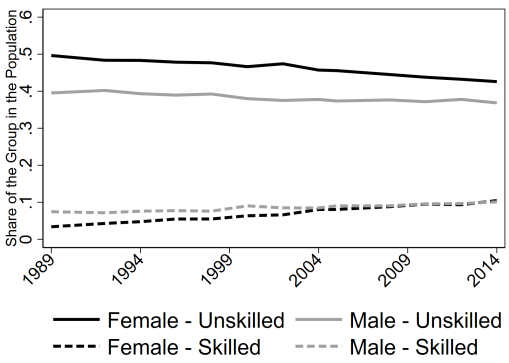
Figure D.2: Trends in Fertility, Marriage, Appliances and Norms Regarding Women's Work



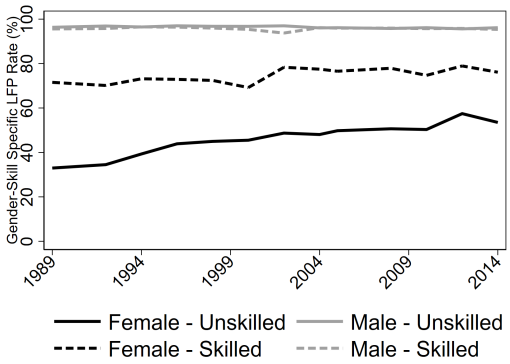
Notes: Panel (a) depicts the share of each group with children under the age of 5, Panel (b) depicts the share of each group that is married or has a permanent partner, Panel (c) shows the value of the Women, Business and the Law (WBL) index, Panel (d) shows the share of each group that has both a refrigerator or a washer in the household. The measures of fertility and marriage can only be calculated for a sample restricted to the household head and their spouse or partner; trends for the larger sample used in the estimation are not available. The ENIGH survey started asking the question on marital status to all members of the household in 1996, and the question about the number and age of children since 2004. The sample is restricted to the prime-age population. See discussions in Section 3, Section 7.1, and Appendix Section A.2.

Figure D.3: Share of Each Gender-Skill Group in the Prime-Age Population, Gender-Skill Specific Participation Rates, and Share of Emigrants in the Mexican Born Prime-Age Population

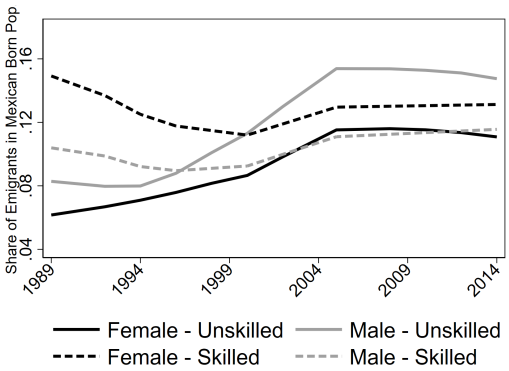
(a) Share of the Gender-Skill Group in Prime-Age Population



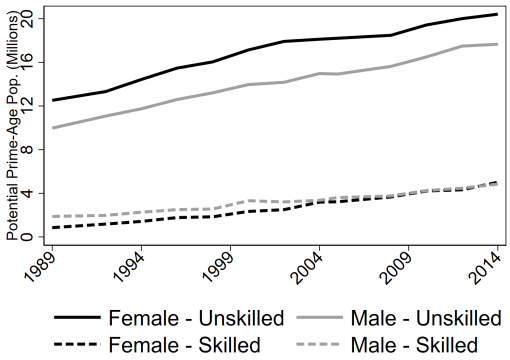
(b) Gender-Skill Specific LFP Rate



(c) Share of Emigrants in Mexican Born Population



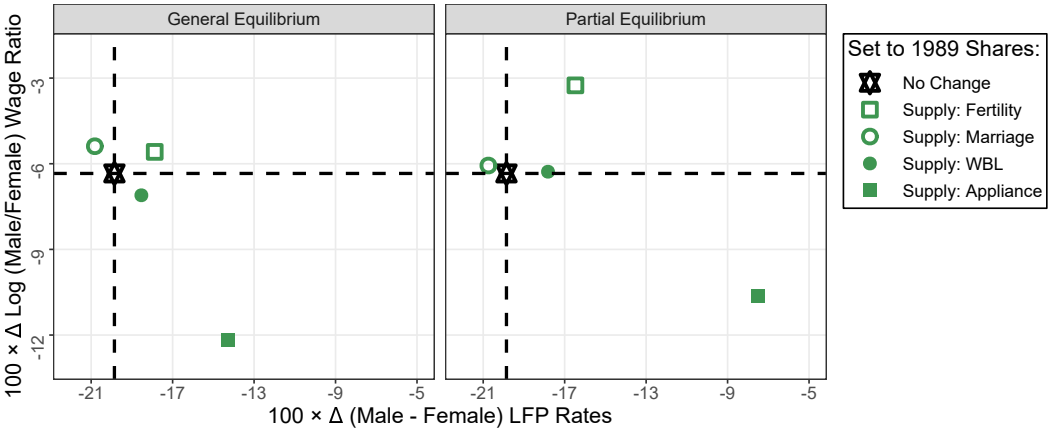
(d) Potential Workers (Excluding Emigrants)



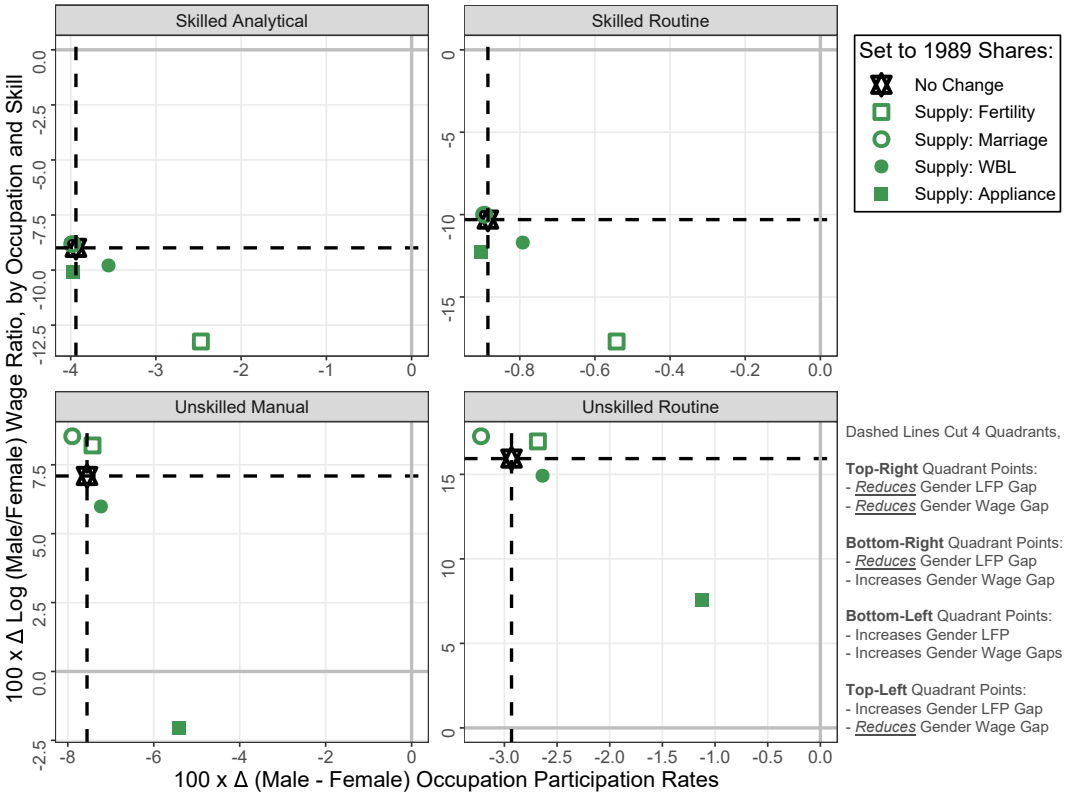
Notes: Panel (a) depicts the share of each gender-skill group in the prime-age population. Panel (b) depicts the gender-skill specific participation rates. Panel (c) depicts the share of emigrants in the total Mexican born population, conditional on gender, skill group, and being prime-age. Panel (d) depicts the total number of potential prime-age workers by gender and skill group (excluding emigrants). The number of emigrants by skilled group are taken from Brücker, Capuano, and Marfouk (2013). See discussions in Section 3, Section 7.1, and Appendix Section A.2.

Figure D.4: Counterfactual Exercises
Effects of Non-wage Determinants of LFP on Changes in the Gender LFP and Wages Gaps between C.1992 and C.2012.

(a) Changes in Gender Participation and Wage Gaps: C.2012 - C.1992



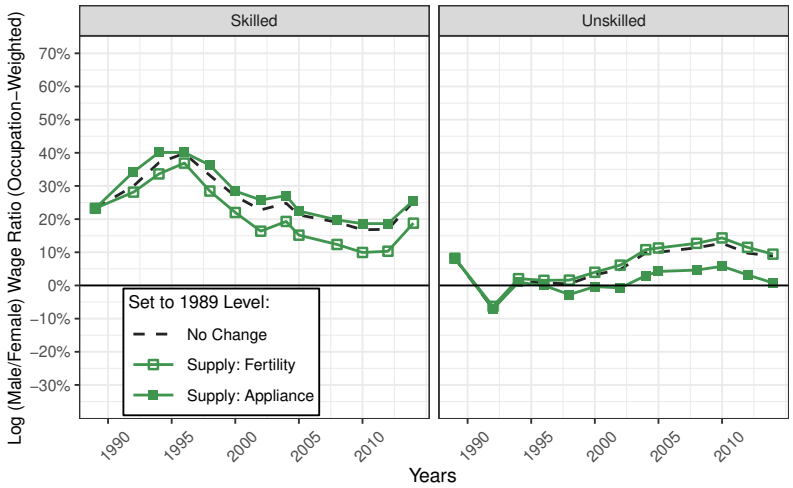
(b) **General Equilibrium** Changes in Participation and Wage Gaps: C.2012 - C.1992 by Skill/Occ.



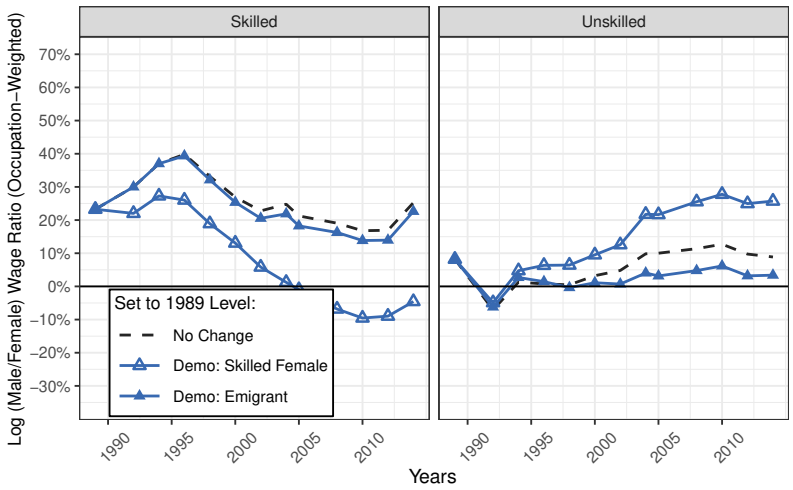
Notes: The Table reports the difference between C.1992 and C.2012 of i) the log (male/female) wage ratio and ii) the change in the (male - female) LFP and occupation rates under different supply variable counterfactual scenarios. Figure (a) visualizes results from the "Overall" row in the first two blocks of Table 6. Figure (b) visualizes results from the skill- and occupation-specific rows in the first two blocks of Table 6 (skilled-manual and unskilled-analytical results are not shown for conciseness). Black-dashed lines mark model predictions, and points indicate predictions under key counterfactual scenarios. Points to the right of the vertical dashed-line reduce gender LFP and occupation participation gaps; points to the top of the horizontal dashed-line reduce gender wage gaps. Under the counterfactuals, we set the share with under-5 children (Fertility), the share married or having a permanent partner (Marriage), the WBL index (capturing laws and regulations that restrict women's economic opportunities), and the share with a refrigerator or a washing machine (Appliance) at their 1989 values, respectively. Figure D.2 presents changes in these variables over time. See discussions in Section 7.1.

Figure D.5: Counterfactual Exercises, **General Equilibrium** Log (Male/Female) Wage Ratio by Skill

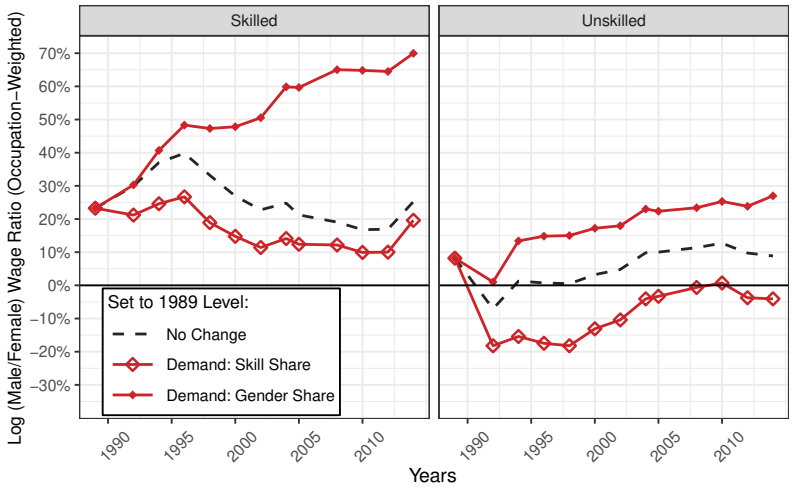
(a) **Non-Wage Determinants of LFP**



(b) **Demographics**

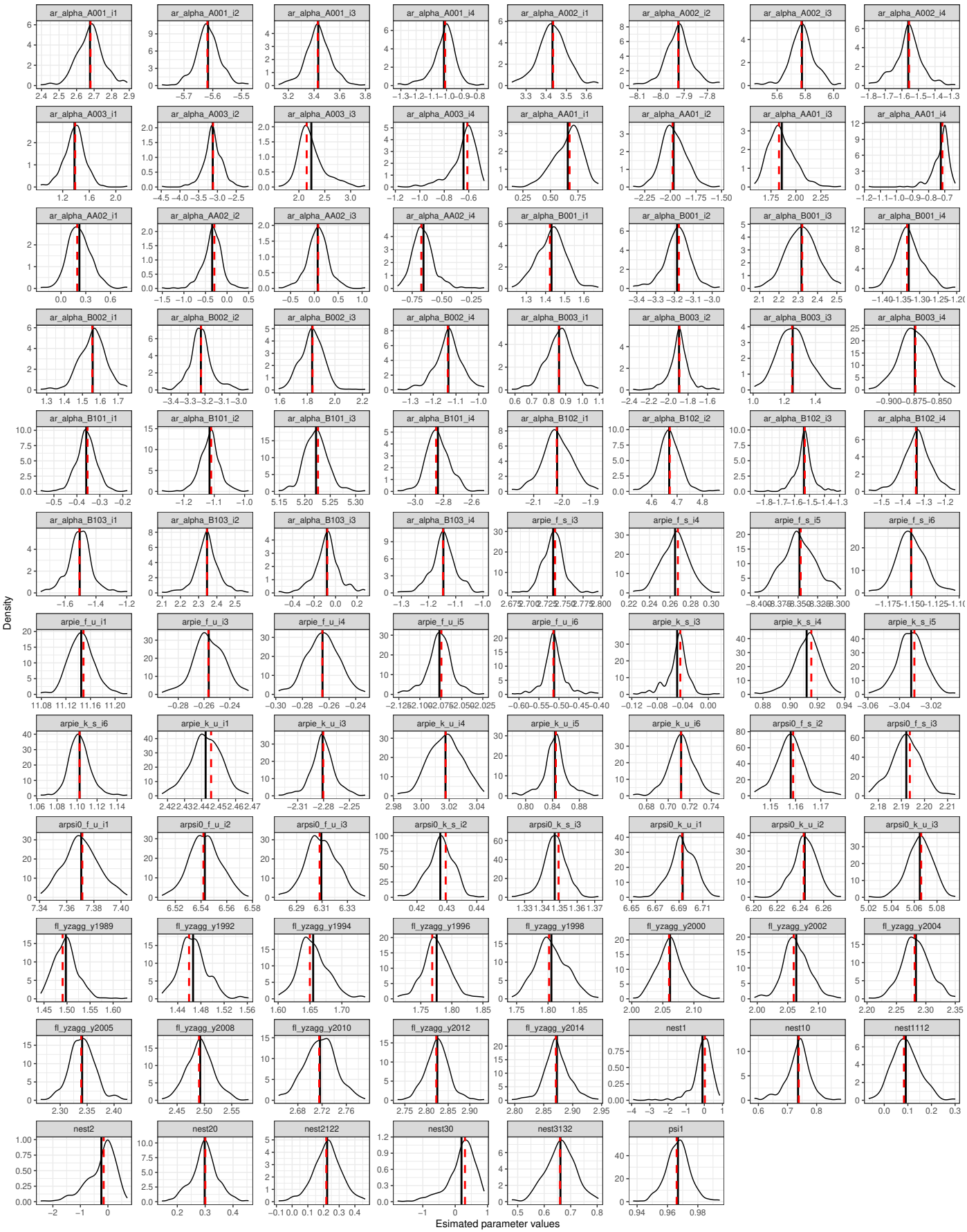


(c) **Demand Parameters**



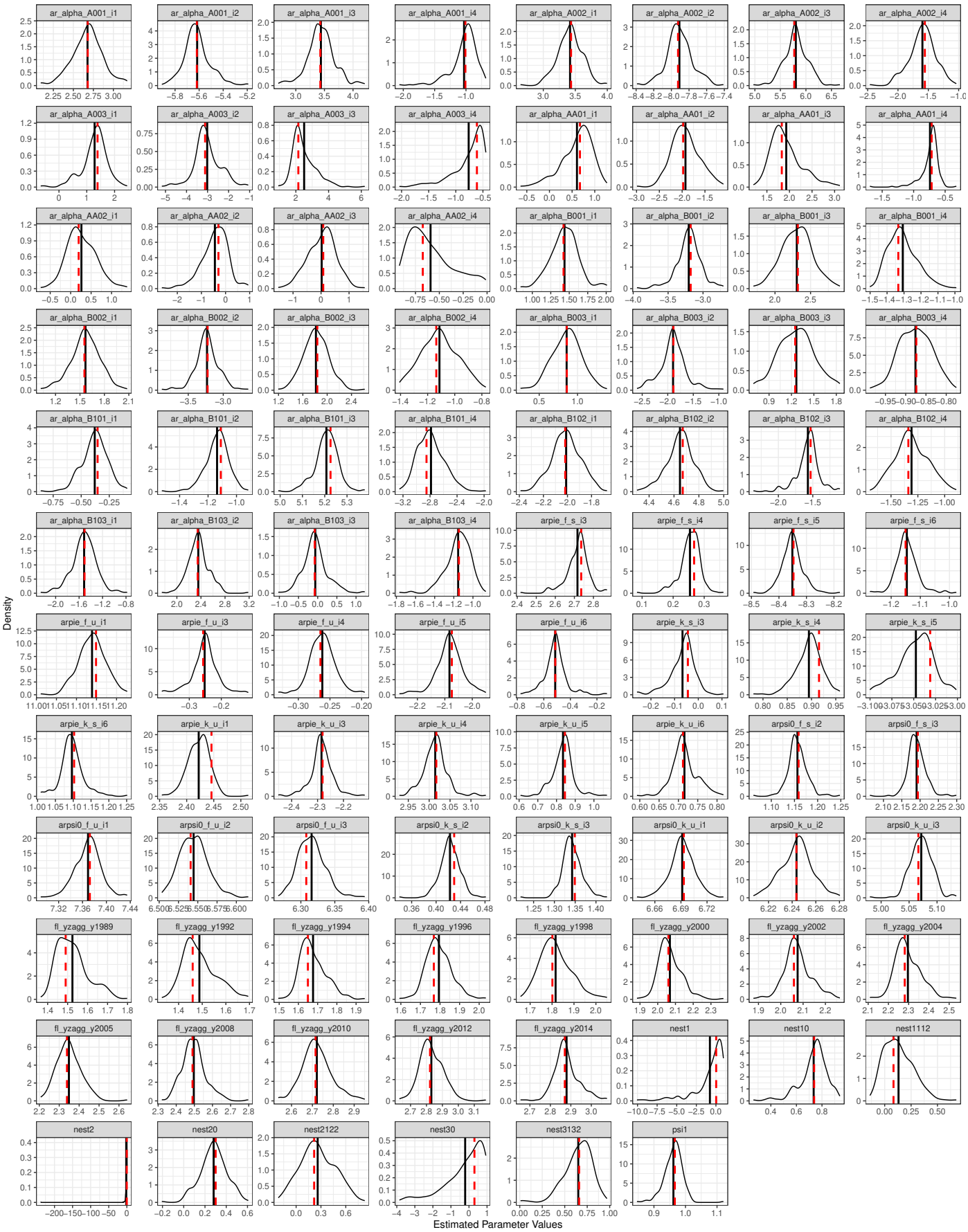
Notes: Panels (a), (b), and (c) show variations in the log (male/female) wage by skill groups under non-wage determinants of LFP, demographic, and demand counterfactuals, respectively. In the counterfactuals, we set the share with under-5 children (Fertility) and with a refrigerator or a washing machine (Appliance), the gender-specific skilled worker share (Skilled Female) and the gender/skill-specific emigrant (Emigrant) shares, and the skill/occupation-specific demand gender share ($\boldsymbol{\alpha_4}$) and occupation-specific demand skill share ($\boldsymbol{\alpha_3}$) parameters at their 1989 values. Figures D.2, D.3, and 7 present changes in these variables and parameters over time.

Figure D.6: Equilibrium Estimator Monte Carlo Exercise with 2% Demand Trend Proportional Shocks



Notes: Given observables and estimates, we draw 300 sets of i.i.d. demand shocks (2% s.d. demand trend proportional shocks) and solve for 300 sets of equilibrium data. For each simulated dataset, we estimate 94 parameters using the equilibrium estimator. Each subplot presents the sample distribution of 300 estimates for one parameter. Black vertical lines mark sample averages, red dashed lines mark the true parameter values. See discussions in Section C.2. See link for label translations.

Figure D.7: Equilibrium Estimator Monte Carlo Exercise with 4.5% s.d. Demand Trend Proportional Shocks

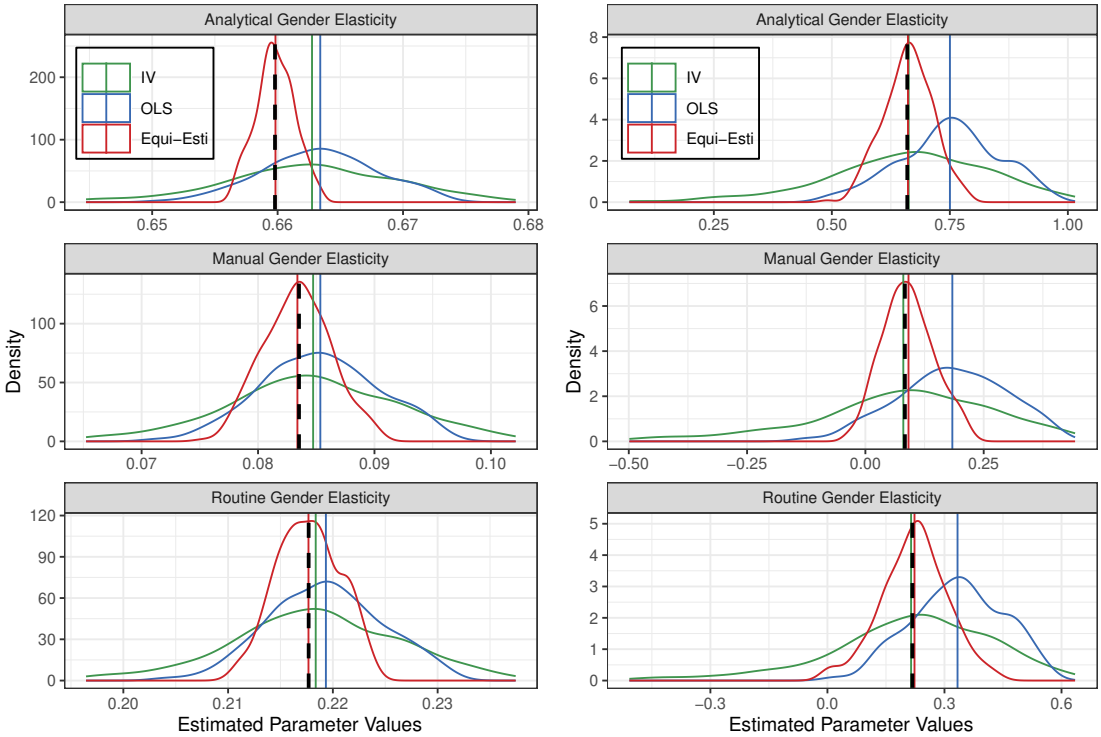


Notes: Given observables and estimates, we draw 300 sets of i.i.d. demand shocks (4.5% s.d. demand trend proportional shocks) and solve for 300 sets of equilibrium data. For each simulated dataset, we estimate 94 parameters using the equilibrium estimator. Each subplot presents the sample distribution of 300 estimates for one parameter. Black vertical lines mark sample averages, red dashed lines mark the true parameter values. See discussions in Section C.2. See link for label translations.

Figure D.8: OLS, IV, Equilibrium-Estimator Monte Carlo Comparisons

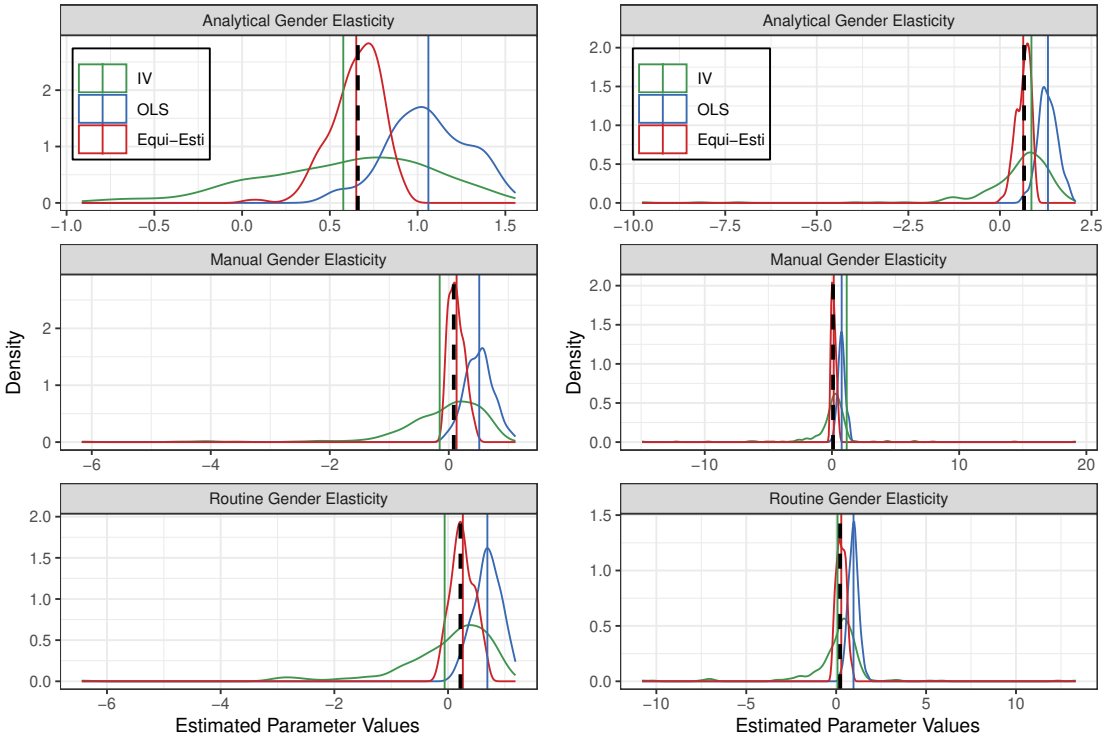
(a) 0.1% s.d. Demand Trend Proportional Shocks

(b) 2% Demand Trend Proportional Shocks



(c) 4.5% s.d. Demand Trend Proportional Shocks

(d) 7.5% s.d. Demand Trend Proportional Shocks



Notes: Given observables and estimates, we draw 300 sets of i.i.d. demand shocks. We do this four times, with 0.1%, 2%, 4.5% and 7.5% s.d. of demand trend proportional shocks. We solve for (4×300) sets of equilibrium data. With each simulated dataset, we use OLS and IV to estimate $\rho_{4,m}$, $\rho_{4,r}$, and $\rho_{4,a}$. We compare these with estimates for the same parameters provided by the equilibrium estimator. Each subplot presents the distribution of estimates for one parameter from the three estimators. Colored vertical lines mark sample averages for each estimator, black dashed lines mark the true parameter values. Given large variance for results in panel (d), for visibility, we cut out the top 1 and bottom 1 percentile of estimates. See discussions in Appendix Section C.3.

Table D.1: Changes in the Composition of the Labor Force between C.1992 and C.2012

	C.1992			C.2012			Dif. in Dif.
	Female Share (x100)	Male Share (x100)	$\Delta_{c.1992}$ (Male - Female)	Female Share (x100)	Male Share (x100)	$\Delta_{c.2012}$ (Male - Female)	$\Delta_{c.2012}$ - $\Delta_{c.1992}$
Prime-Age Population							
Participation Rate	38.59	96.49	57.89	59.59	95.82	36.24	-21.66
Education							
Secondary (unskilled)	92.09	84.27	-7.82	81.24	79.05	-2.18	5.64
College (skilled)	7.91	15.73	7.82	18.76	20.95	2.18	-5.64
Age							
25-34	44.63	43.61	-1.02	35.74	36.36	0.62	1.64
35-44	32.34	32.84	0.50	34.16	33.97	-0.20	-0.69
45-55	23.02	23.55	0.52	30.09	29.67	-0.42	-0.95
Prime-Age Workforce							
Education							
Secondary (unskilled)	85.48	84.37	-1.11	76.00	79.19	3.19	4.29
College (skilled)	14.52	15.63	1.11	24.00	20.81	-3.19	-4.29
Age							
25-34	46.48	43.58	-2.90	34.96	36.03	1.08	3.97
35-44	33.31	33.38	0.07	36.18	34.72	-1.46	-1.53
45-55	20.21	23.04	2.83	28.87	29.25	0.39	-2.44

Notes: The table reports participation rates of the prime-age population in the first row. The following rows show shares of the prime-age population (first panel) and shares of the prime-age work force (second panel) in each gender-education and gender-age group. For example, in C.1992, 92.09 percent of the female population had at most a secondary schooling, and 7.91 percent had a college degree. As fractions of the work force these shares were 85.45 and 14.52 percent. Sample weights used in all calculations. See discussions in Section 4.

Table D.2: Model Fit
Data and Model Predictions for Occupation Participation Rates and Wages

	C.1992				C.2012			
	Female Data	Female Model	Male Data	Male Model	Female Data	Female Model	Male Data	Male Model
Mean Wages								
College								
Analytical	7.17	6.16	10.25	8.77	6.26	6.37	8.11	8.17
Routine	6.11	4.33	8.29	5.47	4.84	5.58	5.59	6.11
Manual	3.17	2.55	5.23	4.30	3.17	3.70	3.39	4.10
Secondary								
Analytical	3.94	3.21	4.66	3.77	2.73	3.43	3.30	4.15
Routine	3.40	2.58	3.11	2.34	2.41	2.88	2.55	3.05
Manual	1.92	1.59	2.16	1.85	1.74	1.73	2.21	2.16
Occupation Shares (x100)								
College								
Analytical	1.61	2.24	5.00	5.31	5.24	5.14	6.36	6.16
Routine	0.41	0.62	1.23	1.26	1.65	1.60	1.92	1.83
Manual	0.08	0.05	0.65	0.39	0.35	0.42	0.85	0.89
Home Production	2.05	1.24	0.53	0.45	2.52	2.60	0.65	0.90
Secondary								
Analytical	5.19	5.47	6.75	6.45	6.31	6.24	5.64	5.62
Routine	5.29	4.87	13.76	13.55	6.74	6.62	13.64	13.38
Manual	7.59	6.82	17.21	17.58	9.44	9.84	15.28	15.05
Home Production	30.69	31.60	1.96	2.11	20.71	20.50	2.70	3.21

Notes: The table reports average wages and occupation participation rates (among all potential workers) in C.1992 and C.2012 both from the raw data and predicted by the model. For this table, the occupation participation rates are not conditional on gender and skill groups, i.e. the female and male columns sum up to 100. See discussions in Section 6.1.

Table D.3: Levels and Changes of Real Hourly Wages
by Sex, Education, and Occupation. C.1992 and C.2012

	C.1992				C.2012				Dif. in Dif.	
	Female Wages	Male Wages	Log Gap Wages	Log Gap Supplies	Female Wages	Male Wages	Log Gap Wages	Log Gap Supplies	Δ Log Gap Wages	Δ log Gap Supplies
Education										
Skilled	7.03	9.81	33.31	86.54	5.74	7.01	20.08	19.62	-13.23	-66.92
	[0.17]	[0.16]	[2.97]	[0.00]	[0.10]	[0.13]	[2.54]	[0.00]	[3.91]	[0.00]
Unskilled	3.11	2.95	-5.34	77.88	2.25	2.48	9.85	37.96	15.19	-39.92
	[0.04]	[0.02]	[1.44]	[0.00]	[0.02]	[0.02]	[1.39]	[0.00]	[2.09]	[0.00]
Occupation										
Analytical	5.34	7.59	35.12	41.75	4.70	5.84	21.58	2.87	-13.55	-38.88
	[0.11]	[0.12]	[2.59]	[0.00]	[0.09]	[0.11]	[2.47]	[0.00]	[3.68]	[0.00]
Rotuine	3.81	3.64	-4.61	98.93	3.00	2.89	-3.66	60.21	0.95	-38.73
	[0.07]	[0.04]	[2.10]	[0.00]	[0.05]	[0.03]	[2.16]	[0.00]	[2.94]	[0.00]
Manual	1.93	2.23	14.41	95.12	1.82	2.25	20.78	38.75	6.36	-56.37
	[0.04]	[0.03]	[2.37]	[0.00]	[0.03]	[0.02]	[1.82]	[0.00]	[3.01]	[0.00]
Educ.-Occ.										
Skilled										
Analytical	7.35	10.37	34.40	85.46	6.30	8.15	25.86	16.15	-8.53	-69.31
	[0.21]	[0.19]	[3.36]	[0.00]	[0.13]	[0.18]	[2.96]	[0.00]	[4.50]	[0.00]
Rotuine	6.27	8.88	34.79	70.18	4.88	5.25	7.39	13.86	-27.40	-56.32
	[0.32]	[0.34]	[6.62]	[0.00]	[0.16]	[0.16]	[4.57]	[0.00]	[8.23]	[0.00]
Manual	3.75	5.27	35.14	214.06	3.15	3.31	5.15	63.92	-30.00	-150.14
	[0.65]	[0.41]	[18.96]	[0.01]	[0.23]	[0.14]	[8.31]	[0.00]	[20.50]	[0.01]
Unskilled										
Analytical	3.95	4.66	16.64	16.00	2.67	3.12	15.72	-9.71	-0.92	-25.72
	[0.10]	[0.09]	[3.22]	[0.00]	[0.07]	[0.08]	[3.62]	[0.00]	[4.85]	[0.00]
Routine	3.42	3.10	-9.58	102.09	2.41	2.52	4.32	68.98	13.90	-33.11
	[0.06]	[0.03]	[1.90]	[0.00]	[0.04]	[0.02]	[1.86]	[0.00]	[2.63]	[0.00]
Manual	1.92	2.16	11.77	93.58	1.73	2.18	23.18	37.40	11.40	-56.19
	[0.04]	[0.03]	[2.37]	[0.00]	[0.03]	[0.02]	[1.72]	[0.00]	[2.96]	[0.00]

Notes: The table reports the average real hourly wages, the average log (male/female) wages gap, and the log (male/female) relative supply by skill, occupation, and year. Sample is restricted to prime-age workers. The sample for the construction of the wages series is restricted to include only full-time workers. Standard errors are in brackets. Sample weights used in all calculations. See discussions in Section 6.2.

Table D.4: Aggregate Average Marginal Effects of Wages Decomposition

	$\sum_{t=1}^{T} \frac{1}{T} \frac{dPr(work\|gen,t)}{d\boldsymbol{w}}$		Occupation-specific: $\sum_{t=1}^{T} \frac{1}{T} \frac{\partial Pr(d_O=1\|gen,edu,t)}{\partial w_O}$		
	Increase Wages in		Increase Occupation-specific Wages:		
	All Occupations		*Manual Wage*	*Routine Wage*	*Analytical Wage*
Average Marginal Effects with Respect to Gender- and Skill-specific:					
LFP Rates					
female, secondary	0.107	|	0.060	0.026	0.020
female, college	0.036	|	0.003	0.009	0.025
male, secondary	0.023	|	0.013	0.008	0.002
male, college	0.008	|	0.001	0.002	0.005
Manual Occupation Participation Rates					
female, secondary	—	|	0.090	-0.009	-0.007
female, college	—	|	0.008	-0.001	-0.002
male, secondary	—	|	0.120	-0.054	-0.017
male, college	—	|	0.018	-0.003	-0.006
Routine Occupation Participation Rates					
female, secondary	—	|	-0.015	0.041	-0.005
female, college	—	|	-0.001	0.022	-0.010
male, secondary	—	|	-0.075	0.083	-0.014
male, college	—	|	-0.004	0.024	-0.014
Analytical Occupation Participation Rates					
female, secondary	—	|	-0.015	-0.006	0.033
female, college	—	|	-0.004	-0.013	0.037
male, secondary	—	|	-0.033	-0.021	0.033
male, college	—	|	-0.013	-0.020	0.025

Notes: Values are in percentage points. Given log wage coefficient $\psi_1 = 0.966$, we compute the Average Marginal Effects of wages over time for gender and skill groups. Average Marginal Effect in columns 2–4 are the partial derivatives of occupation participation rates—averaged across the years—with respect to wage. Column 1 shows the total derivative of overall LFP rates with respect to all three wages, evaluated towards the direction of equi-distance increases in all wage levels. The table presents a decomposition: in the first block, the values from each row in the first column is the sum of the values from columns 2 to 4; each value from columns 2 to 4 in the first block is the sum of the values in the same cell in subsequent panels. See discussions in Section 6.4.

Table D.5: Elasticity of Aggregate and Occupation-specific Labor Supply to Wage

	Average Wage Elasticities Over Time			
	Increase Wages in	Increase Occupation-specific Wages:		
	All Occupations	*Manual Wage*	*Routine Wage*	*Analytical Wage*
Elasticity of Gender- and Skill-specific Labor Supply to Wages:				
Aggregate Labor Supply				
female, secondary	0.529	0.099	0.071	0.067
female, college	0.341	0.009	0.044	0.160
male, secondary	0.060	0.025	0.022	0.010
male, college	0.062	0.005	0.012	0.041
Manual Labor Supply				
female, secondary	—	0.148	-0.015	-0.012
female, college	—	0.025	-0.002	-0.007
male, secondary	—	0.235	-0.106	-0.032
male, college	—	0.076	-0.011	-0.027
Routine Labor Supply				
female, secondary	—	-0.042	0.114	-0.014
female, college	—	-0.006	0.113	-0.051
male, secondary	—	-0.201	0.224	-0.039
male, college	—	-0.024	0.150	-0.090
Analytical Labor Supply				
female, secondary	—	-0.048	-0.021	0.108
female, college	—	-0.026	-0.083	0.238
male, secondary	—	-0.128	-0.081	0.129
male, college	—	-0.111	-0.169	0.217

Notes: Values are elasticities. Given log wages coefficient $\psi_1 = 0.966$, we compute the elasticities of wages for gender and skill groups. Column 1 presents the ratio of a percentage change in aggregate labor supply over a concurrent and equal-percentage increase in wages for all three occupation-specific wages. Averages across the years are shown in the table; Figure 8 visualizes these aggregate elasticities year by year. Columns 2–4 present occupation-specific elasticities—averaged across the years—of aggregate and occupation-specific labor supplies with respect to wages. Appendix Figure 9 visualizes these occupation-specific elasticities year by year. See discussions in Section 6.4.

Table D.6: Additional Supply Side Parameter Estimates

	Estimate	SE
Non Pecuniary Rewards/Tastes		
$\psi_{f,u,m}$: female, unskilled, manual	18.514	0.159
$\psi_{f,u,r}$: female, unskilled, routine	17.687	0.181
$\psi_{f,u,a}$: female, unskilled, analytical	17.453	0.170
$\psi_{f,s,r}$: female, skilled, manual	11.145	0.143
$\psi_{f,s,r}$: female, skilled, routine	12.304	0.185
$\psi_{f,s,a}$: female, skilled, analytical	13.338	0.168
$\psi_{k,u,m}$: male, unskilled, manual	9.139	0.126
$\psi_{k,u,r}$: male, unskilled, routine	8.690	0.118
$\psi_{k,u,a}$: male, unskilled, analytical	7.511	0.125
$\psi_{k,s,r}$: male, skilled, manual	2.446	0.078
$\psi_{k,s,r}$: male, skilled, routine	2.875	0.100
$\psi_{k,s,a}$: male, skilled, analytical	3.795	0.107

Notes: The table shows the point estimates and standard errors of additional supply side parameters. These parameters are "intercepts" that are specific to each gender and skill group for each one of the three work occupations. See estimates discussions in Section 6.5 and estimator discussions in Appendix Section B.3.3.

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