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Women's Labor Force Participation and the Distribution of the Gender Wage Gap

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Non-Technical Summary

Many modernizing economies are witnessing rapid growth in women's labour force participation, in the way that today's richer countries did. While this is often associated with women's empowerment, simple economic theory suggests that increases in the labour supply of women will tend to depress the wages of women, potentially widening the gender wage gap. The extent to which this happens will depend upon the degree to which men and women are substitutes in the workplace. One of our key observations is that this varies across the wage distribution, in line with the task content of jobs. Recent research has analysed the degree to which machines or technology substitute individuals, documenting a polarization of the labour market with jobs in the middle 'disappearing'. We focus instead on substitutability between men and women.

We use individual data on employment and earnings in Mexico that span more than a quarter of a century, 1989-2014, capturing one of the most rapid contemporary increases in women's labour supply. We find that the polarization of tasks is reflected in opposing effects on the gender wage gap. In particular, in high-paying occupations that are intensive in abstract and analytical skills, there is a high degree of substitutability between women and men. As a result, a large increase in (skilled) women joining the labour force may depress wages in general, but without increasing the gender wage gap. On the other hand, in low-paying occupations in which individuals do manual or routine tasks, we find that women and men are poor substitutes. Thus, increases in (low skilled) women joining the labour force will tend to widen the gender wage gap. While we have highlighted in this discussion the consequences of increases in women's labour supply, the gender wage gap will also depend on whether the demand for male vs female labour is growing. In fact demand trends have favoured women, attenuating the supply-driven downward pressure on women's wages in low-paid occupations, and fully counteracting it in high-paid occupations.

Pulling the supply and demand trends together and accounting for the education of workers and the skill-content of occupations, we find that the gender wage gap in Mexico narrowed between 5 and 18 percent among workers above the 80th percentile, and among workers below the median it widened by 10 to 22 percent.

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Abstract

We analyse how the rising labor force participation of women influences the distribution of the gender pay gap. We formulate an equilibrium model of the labor market in which the elasticity of substitution between male and female labor varies with the task content of occupations. We structurally estimate the parameters using individual data from Mexico through the recent 25 years when women's labor force participation increased by fifty percent. We provide new evidence that male and female labor are closer substitutes in high-paying abstract task-intensive occupations than in lower-paying manual and routine task-intensive occupations. Consistent with this, we find a widening of the gender pay gap at the lower end of the distribution, alongside a narrowing towards the top. We also find that demand side trends favored women, attenuating the supply-driven negative pressure on women's wages, and more so among college-educated workers in abstract-intensive occupations. The paper presents new evidence on the distribution of the gender wage gap, and contributes to a wider literature on technological change, occupational sorting and wage inequality between and within gender.

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

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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 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 (i) create downward pressure on the wages of both men and women and (ii) create greater downward pressure on the wages of women, and hence widen the gender wage gap. The size of these effects 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, 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. Changes in observed wages will be further modified by demand trends, which may also vary by gender and by task-based occupation.

We structurally estimate the elasticity and demand parameters in 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) and Card and Lemieux (2001)). Aggregate production is described by a nested-CES production function in which types of labor defined by their gender, skill and occupation are allowed to be imperfect substitutes. Following Johnson and Keane (2013), we model occupational choice using a random utility framework, incorporating both individual preferences and equilibrium returns to labor in the decision problem. The four types of labor, male vs female and unskilled vs skilled, either choose home production or select among three market occupations. Following Autor et al. (2003), these are occupations intensive in abstract, routine or manual tasks.[1]

The main novelty of this paper lies in its combining the traditional labor demand-supply model with the task-based approach. This synthesis has the additional benefit that it allows us to indirectly look at distributional effects. Our first innovation is to allow the elasticity of substitution between male and female labor to be occupation-specific- no previous study has allowed this and we show that it matters. In fact we are also the first study to allow the elasticity of substitution between skilled and unskilled labor to be occupation-specific. Our second contribution is to allow for differential demand trends across gender, skill and occupation groups. This allows us to quantify the importance for the wage structure of gender, skill, and occupation-biased technical change independently, but within a unified model.

[1]Skill refers to education and we shall define unskilled as having at most secondary education and skilled as having a college education.

We show that this flexibility is important in accounting for the patterns in the data. A third contribution is that we endogenize labor force participation. The standard labor supply and demand model assumes inelastic (short-run) relative labor supply (Katz and Autor, 1999), making it unsuitable to study the dynamics of FLFP.

We apply this framework to investigate impacts of the rapid rise of women's labor force participation on the wage structure in Mexico. Starting from about 1990, Mexico has experienced one of the largest increases in FLFP in the world during the last quarter century (Ñopo, 2012; The World Bank, 2012). FLFP among women aged 25-55 increased 21 percentage points (50%), from close to 40 percent in 1990 to close to 60 percent in 2013, rising from 4.7 to 14.7 million. In this same period, the average real wage fell, and the mean (median) gender earnings gap increased by close to 5 (9.4) percentage points. That the gender earnings gap increased in favor of men is consistent with the increase in the relative supply of women exerting more downward pressure on women's wages than on men's wages.[2]

What motivates the analysis in this paper is that changes in the gender earnings gap varied dramatically across the earnings distribution. The unconditional earnings gap widened by 39 percentage points at the 5th percentile of the wage distribution, while narrowing by 18 percentage points at the 95th percentile of the distribution. This distributional pattern is robust to adjusting for the skill and age composition of the work force, and a decomposition of the gender earnings gap across percentiles of the distribution (following Firpo et al. (2007, 2009)) shows that changes in the gap in the sample period are primarily wage structure changes.[3]

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 abstract task-intensive occupations (elasticity of 2.6) than in the lower-wage manual or routine task-intensive occupations (elasticity of 1.2 in each case). This can explain why the increase in FLFP in Mexico exerted greater downward pressure on earnings at the lower end of the distribution. Our second result is that demand trends favored female workers in general, and more so among college-educated workers in abstract task-intensive occupations, contributing to explaining the narrowing of the gap at the upper end of the distribution (in the top 30% of the distribution). We conduct counterfactual exercises which confirm that supply and demand had strong impacts on the gender earnings gap by occupation, but in opposite directions: Among college educated workers who were most likely to sort into abstract and analytical task-intensive occupations, demand side forces outpaced the impact of changes in relative supply, leading to convergence in earnings between men and

[2] The gender earnings gap is defined here as the logarithm of male earnings per hour minus the logarithm of female earnings per hour. We first log earnings for individuals and then take the mean for each gender.

[3] The decomposition is based on partial equilibrium counterfactuals which do not take into account that changes in relative supplies may affect relative wages. We therefore obtain structural estimates. In the model, we study the gender earnings gap conditional on skill.

women. Among workers with less than a college degree, who were disproportionately more likely to be in routine and manual task based occupations, increases in supply outpaced increases in the demand for female workers, creating divergence in the earnings of men and women.

Our third finding is that the strong downward trend in fertility in Mexico, together with a shallower negative trend in marriage, can together account for about 22% of the increase in FLFP, the rest being explained by preferences. Male labor force participation reacts with the opposite signs: men are more likely to work if they are in a stable relationship or have a young child. Responses to fertility and marriage of both men and women emerge entirely from the less skilled group, the choices of college-educated workers being unresponsive to these demographic covariates.

Our fourth finding is that the elasticity of substitution between skilled and unskilled labor is larger in manual (elasticity 3.6) than in abstract task-intensive occupations (elasticity 1.4). The elasticity for routine tasks (1.6) lies closer to that for abstract tasks. This has the interesting - and hitherto unrecognized- implication that the rise in FLFP has contributed to the decline of the college premium and, thus, to the decline in inequality among men. A counterfactual exercise conducted on the model indicates that the decline in the college premium would have been half the observed decline (10 rather than 20 log points) if FLFP had not risen. The college premium is of particular interest since this is a channel that has been emphasized in the literature on wage inequality in the US (Katz and Autor, 1999; Acemoglu and Autor, 2011).

The rest of this section delineates more carefully our contributions in relation to existing work. We contribute to the literature on the task-based approach (Autor et al., 2003, 2006; Dorn, 2009; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Altonji et al., 2014; Goos et al., 2014; Michaels et al., 2015) in being the first to introduce imperfect substitutability between two types of labor (male and female), with the degree of substitution varying by task-based occupation. This literature has emphasized that the degree of substitutability or complementary between factors of production is determined by the tasks they are employed to perform, but it has typically looked at how the arrival of new technology or capital substitutes for labor in different occupations. We adapt the framework to focus on how the arrival of new female labor substitutes for male labor in different occupations. We provide the first estimates of the elasticity of substitution between male and female labor by task-based occupation– and thus, implicitly, at different points of the earnings distribution.[4]

The literature on the wage structure has tended to be descriptive or partial

[4]Any job requires, to a higher or lesser degree, cognitive, manual, physical, socio-emotional, and interpersonal skills. The relative importance of any subset of skills is then a function of the specific activities that workers are performing. As long as there is some difference in the bundle of skills that men and women supply to the labor market, the substitutability of male and female labor will tend to vary across occupations.

equilibrium in nature (see the discussion in Johnson and Keane (2013)). Among the first equilibrium models, Heckman et al. (1998a,b) distinguish labor by skill (college and secondary), Lee (2005) differentiates labor by skill and occupation (white- vs. blue-collar) and Lee and Wolpin (2006, 2010) allow a fuller differentiation of labor by skill, occupation, gender, and age, but they assume they are perfect substitutes in production. More recently, Johnson and Keane (2013) similarly differentiate different types of labor, and they allow them to be imperfect substitutes. However they do not estimate substitution elasticities by occupation.

The importance of occupation is underlined in Vella and Moscarini (2004), Kranz (2006) and Kambourov and Manovskii (2008, 2009a,b), among others. They argue that occupation is a better measure of skill than education, and that occupational demand shifts are crucial for understanding changes in the wage structure. In line with this, we differentiate (male and female, and skilled and unskilled) labor by occupation and we also allow for occupational demand shifts. Our model does well in predicting changes in the occupational wage structure.[5]

The question of how substitutable female and male labor are is relevant to recent research emphasizing changes in the demand for skills. First, there is evidence of a growing demand for (non-cognitive) social skills (Deming, 2017), and some evidence that women have stronger social skills (Jaimovich et al., 2017). Second, the importance of manual (brawn-intensive) skills in which men have a biologically-rooted comparative advantage has declined (Galor and Weil, 1996; Blau and Kahn, 1997; Weinberg, 2000; Rendall, 2010; Black and Spitz-Oener, 2010; Pitt et al., 2012; Aguayo-Tellez et al., 2013; Rendall, 2013). Third, the marketization of home production has contributed to the growth of service industries including child care and catering (Lup Tick and Oaxaca, 2010; Akbulut, 2011; Olivetti and Petrongolo, 2014; Ngai and Petrongolo, 2017). All of these factors suggest changes in the relative demand for female labor, and changes that are likely to differ across the task distribution.[6]

By allowing the estimated demand trends to vary by occupation, education, and gender, we take forward a literature in which the gender wage gap or the skill premium has been analysed with respect to either task-biased or skill-biased or gender-biased technical change, rather than allowing that all are at play at once. For instance, Bound and Johnson (1992) and Katz and Autor (1999) focus on skill-biased technological change, Pitt et al. (2012) allow for gender-biased technical change, Goos et al. (2014) allow for routine-biased technical change, but we allow for all of these.

[5]More generally, Card and Lemieux (2001), Card and DiNardo (2002), Eckstein and Nagypal (2004), among others, argue that failing to account for the different dimensions of labor including education, gender, and occupation may compromise our understanding of the drivers of changes in the wage structure.

[6]The cited studies tend to analyse demand trends in partial equilibrium- we differ in simultaneously analysing supply and demand. Also, these studies do not look to estimate the elasticity of substitution between male and female labor at all and, in any case, not by occupation.

By endogenizing labor supply in a Katz and Murphy (1992) style model, we provide a new modelling framework for analysis of increases in women's LFP. Relative to the many partial equilibrium studies of factors leading women to join the workforce, we provide estimates of how skilled and unskilled women and men change their labor supply in response to changes in fertility and marriage trends, and our finding that preferences played a large role is in line with Fernández et al. (2004), Fogli and Veldkamp (2011) and Fernández (2013).

By virtue of our analysis of substitutability of skilled and unskilled labor by occupation, we contribute to a growing literature analysing the sharp fall in earnings inequality in Latin America since the late 1990s. This is widely attributed to a fall in skill and experience premia (López-Calva and Lustig, 2010; Levy and Schady, 2013; Lustig et al., 2013; Galiani et al., 2017; Fernández and Messina, 2018), and this work has concentrated on the male earnings distribution. However, this is a significant omission because increases in FLFP have been of such a magnitude that their potential distributional effects are large. Ours is the first study to endogenize FLFP and estimate changes in the skill premia of men and women in a general equilibrium framework. Our results confirm the extant finding that Mexico experienced a significant contraction of the male earnings distribution over the last 25 years, driven by higher wage growth among low-skilled men than among high-skilled men. We add two new insights: First, that sluggish wage growth among high-skilled men in Latin American countries may be partly explained by the incorporation of college educated women into the workforce.[7] Second, that there was no corresponding decline in inequality among women, rather, an increase.

This paper is also related to the literature on immigration, as one may conceptualize impacts of large inflows of women on labor market outcomes in a manner similar to the way that one conceptualizes impacts of immigration. Following introduction of the nested CES framework into the immigration context by Borjas (2003), recent studies have estimated the elasticities of substitution that determine impacts of immigration on the native wage structure. These are the elasticities of substitution between similarly skilled immigrants and natives, and between workers of different skill levels and, as discussed in Borjas et al. (2012), there is considerable disagreement over these elasticities. However this literature tends to estimate relative wages as a function of relative supplies as in equation 2.2 below, using a partial equilibrium framework, and they consider skill, but not occupation. In principle, our more general modelling approach is applicable in the immigration literature.

Having delineated our contributions to different strands of research, we now briefly review the findings of studies that address questions similar to ours. Only

[7] Acemoglu et al. (2004) argue that the entry of women into the labor force post-World War II contributed to increasing inequality between secondary and college educated men. Although they do not estimate the elasticity of substitution between men and women by skill or by occupation, they allude to women being closer substitutes to high school men than to men with higher or lower skills.

a few previous studies have investigated impacts of female labor supply on changes in the wage structure. Topel (1994) examined whether the rise in female labor supply contributed to rising inequality in the U.S. during the 1970s and 1980s, concluding that it did, by depressing the wages of low-skilled male workers. Juhn and Kim (1999) challenged this result, arguing that it was dissipated by accounting for changes in relative demand. Instead, they argued, in line with our findings, that college-educated women are close substitutes for college-educated men, so that their entry into the labor market may have tempered the growth in male wage inequality in the 1980s. This resonates with similar debates in the immigration literature.[8]

Only two studies appear to have attempted to directly estimate the elasticity of substitution between male and female labor, both on US data. Exploiting state level variation in U.S. military mobilizations for World War II, Acemoglu et al. (2004), report estimates of the elasticity of substitution between male and female labor of around 3. The authors qualify this finding arguing that this elasticity potentially varies across skill groups, but they do not test that hypothesis. Johnson and Keane (2013) estimate an elasticity of substitution between male and female labor of between 1.85 and 2.2 during 1968 to 1996 in the US. Neither of these studies (or any other) allows the elasticity of substitution between male and female labor to vary by task-based occupation. The range of the elasticities we estimate is consistent with existing estimates but the heterogeneity we find is quantitatively important and has significant distributional consequences.

The speed with which FLFP has recently grown in Mexico is unusual, but there were similarly large increases in female labor force participation rates (of married women) between about 1940 or 1950 and 1980 in the OECD countries. For instance, FLFP increased by about 50% (from around 25% to 52%) between 1940 and 1980 in the US. The average gender pay gap increased in favor of men in this period. It only started to narrow in the late 1970s and this convergence has slowed since 1990 (Bailey and DiPrete, 2016; Blau and Kahn, 2017). We are unaware of any analysis of how increases in FLFP in OECD countries influenced the relative wage of women across the wage distribution, the distribution of gender-specific skill premia and, by implication, the evolution of gender-specific inequality within and between women and men. This study may motivate further analysis in this domain.

The rest of the paper is organized as follows: Section 2 briefly formalizes our main hypothesis using a simplified version of the labor demand-supply model, Section 3 discusses the data, Section 4 presents the main stylized facts, reviewing the evolution of male and female labor force participation rates, and documenting changes in the wage and occupational structure over the last quarter century in Mexico. It also presents a decomposition of the change over time in the gender earn-

[8]For instance, Card (2009) argues that the effects of immigrants on US wages are small, whereas Aydemir and Borjas (2007) argue that recent immigration has reduced US wages, particularly for low-skilled natives.

ings gap across the earnings distribution. In Section 5 we formulate an equilibrium model of the labor market, and describe the empirical strategy used to estimate its parameters. The results are presented in Section 6, and robustness exercises using alternative specifications of the model and different measures of labor supply are in Section 7. Section 8 concludes.

2 Framework

Here we formalize the hypothesis for how increases in FLFP influence the wage structure that was laid out in the Introduction, just to fix ideas. Later, in Section 5, we develop a general equilibrium model. Suppose, for now, that workers in an economy were similar in every respect except for their gender, and that aggregate production could be characterized by a Constant Elasticity of Substitution (CES) function of the form:

$$Y_t = \left[\alpha_t L_{k,t}^{\rho} + (1-\alpha_t) L_{f,t}^{\rho}\right]^{1/\rho}, \tag{2.1}$$

where Y_t is total output at time t; $L_{k,t}$ and $L_{f,t}$ are male and female labor supply respectively; α_t is a *time-varying* 'share' parameter that captures differences in the intensity of labor demand between male and female labor; and $\rho \in (-\infty, 1]$ is a function of the elasticity of substitution (σ_ρ) between male and female labor: $\sigma_\rho \equiv \frac{1}{1-\rho}$. If the economy is operating along the demand curve, wages are equated to marginal productivities and the log (male/female) earnings ratio takes the form:

$$\log\left(\frac{W_{k,t}}{W_{f,t}}\right) = \log\left(\frac{\alpha_t}{1-\alpha_t}\right) - \frac{1}{\sigma_\rho}\log\left(\frac{L_{k,t}}{L_{f,t}}\right), \tag{2.2}$$

where $W_{k,t}$ and $W_{f,t}$ are the wages of male and female workers respectively.

Equation (2.2) shows that the evolution of the wage gap or the log (male/female) earnings ratio depends on two factors: (i) changes in the relative supply of male and female labor $\left(\frac{L_{k,t}}{L_{f,t}}\right)$, scaled by the inverse of the elasticity of substitution (σ_ρ); and (ii) changes in relative demands, captured by time variation of the log ratio of α_t. If male and female labor are not very substitutable in production, that is, if σ_ρ is small, and relative demands are constant, a large increase in female labor supply will impose downward pressure on female wages and, to a lesser extent, on male wages, leading to an increase in the gender earnings gap. If, on the other hand, male and female workers were perfect substitutes, then a rise in female labor force participation would depress *both* male and female wages, with relative earnings remaining constant.

There is no general agreement in the literature about the value of σ_ρ but, using the available estimates of between 1.85 and 3 (Acemoglu et al., 2004; Johnson and Keane, 2013), together with the actual decline in log (male/female) labor supply in Mexico of approximately 50 log points (Table B.2), we would predict an increase in the log (male/female) earnings gap of between 16.7 and 27.7 log points on average, absent any changes in relative demands. In fact, as shown later, relative demands favored women, thus inhibiting the widening of the gap.

In the data we observe labor supply and wages for each group over time but we do not observe relative demand trends or the values of the elasticities of substitution (we explain in Section 5.1 how these are estimated). In Panels (a)-(c) of Figure 4 we show the time series for observed labor supplies and relative wages for each of the three occupation groups. The plots show that as women's labor supply increased the gender earnings gap increased, but only in low-paying routine and manual task-intensive occupations. Between 1989 and 2014, log (male/female) relative supply declined by 44 log points in both abstract and routine task-intensive occupations, and by 69 log points in manual task-intensive occupations. During the same period, the log (male/female) earnings ratio increased 10 log points in manual task-intensive occupations and 2.33 log points in routine task-intensive occupations. In the abstract task-intensive group it fell by 10 log points. In this group, the co-movement of relative supplies and relative wages indicates a role for demand shifts.

The objectives of the full model developed below are threefold: first, to explore if combining the task-based approach with the canonical supply and demand framework is able to recreate the patterns in the Mexican wage structure over the past 25 years; second, to estimate the key structural parameters to test the hypothesis of differential degrees of substitutability between male and female labor across the occupational distribution; finally, to run counterfactual exercises and get quantitative estimates of the effect of the rise of female labor force participation on the gender earnings gap.

3 Data

We use 13 waves of the nationally representative Mexican Household Income and Expenditure Survey (ENIGH), covering 1989-2014. 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 or profits from self-employment work. We add up earnings from different occupations if the individual has a secondary job. Monthly earnings are converted into hourly rates dividing by the worker's total hours of work per week in all jobs multiplied by the usual number of weeks in a month. Earnings are transformed into real U.S. Dollars of 2012 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.

We use the sample of workers age 25-55 (henceforth prime-age workers). This is done to ameliorate selection problems arising from changes in educational and retirement choices of younger and older cohorts. Since part-time work is more common among women, to ensure comparability, the earnings series in the main analysis is for 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. Data on marriage and fertility trends are discussed in section 5.2.

We use the Mexican occupation classification (CMO), containing 18 groups that can be consistently followed through the period of analysis. These occupations are classified into three groups defined by whether the activities performed on the job are predominantly manual, routine, or abstract, following Autor et al. (2003) who used the U.S. 1977 Dictionary of Occupational Titles (DOT). This division will capture the different aptitudes of men and women for different tasks and it also aligns with the earnings distribution. Manual task-intensive occupations place greater demands on physical than abstract or analytical aptitudes, requiring strength and hand, eye, and foot coordination, and these occupations are more often found at the lower end of the pay distribution (agriculture, services, transportation). Abstract task-intensive occupations require skills like quantitative reasoning, direction, control, and planning of activities and are more often found at the top of the pay distribution, the most prominent examples being professionals and managers. Routine task-intensive occupations tend to lie in the middle of the earnings distribution, requiring a mix of physical and analytical skills and aptitudes like adaptability to repetitive work and finger dexterity, examples being clerical, crafts and trades jobs.

Details of the construction of these groups are in Appendix A.1 and the final division used is shown in Table 1. The three occupational groups each representing about a third of the workforce. The Table shows substantial occupational sorting by gender within the three groups. For example, within the abstract task-intensive group, 71 percent of managers and 84 percent of craft and trades supervisors are men but 61.8 percent of education workers are women. Segregation by gender is stronger in manual task-intensive occupations. On average, 99 percent of workers in transport occupations and 93 percent in protective services (such as police and firefighters) are male, while 92.4 percent of workers in domestic services are female. This segregation suggests a lower degree of substitutability between male and female labor in manual occupations.

4 Trends in Women's Labor Supply and Relative Earnings

In 1989, the labor force participation rate of the entire prime-age population in Mexico was about 64.2 percent, the female participation rate (FLFP) was only 36 percent, and women accounted for 29 percent of the workforce. By 2014 this picture had changed drastically: the overall participation rate was 76 percent, the FLFP rate was close to 58 percent, and women represented 41 percent of the workforce (see Panels (a) and (c) Figure 1). This increase of about 50 percent in FLFP during the last 25 years was the largest in the Latin American region (Ñopo, 2012), and one of the largest in the world (The World Bank, 2012).

The preceding statistics are from the ENIGH survey. Using decadal census data corroborates these broad trends, and allows us to depict trends going back to 1960 (see Panels (b) and (d) of Figure 1).[9] Between 1960 and 1990, the FLFP rate increased 11 percentage points, rising from 12 to 23 percent. It accelerated after 1990: between 1990 and 2010 the rate increased by 22 percentage points, reaching 45 percent in 2010.

Three stylized facts characterize the evolution of labor force participation during this period (Table 2). First, most of the increase was of low skilled women (defined as women with at most secondary education), their LFP rising from 35.7 to 55.4 percent between C.1990 and C.2013, while that of high skilled women (defined as college educated) rose from 71.7 to 77.4 percent. While the volume of the increase in FLFP came from low-skilled women, the proportional change in participation of high skilled women was large because the initial share of the female work force with a college-education was only 14.5 percent, rising to 24.0 percent (Table B.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 percent across the period.[10]

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

The following stylized facts underpin this. First, there was an overall tendency for real wages to decline since the early 1990s, associated with 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

[9] Differences in level and trend between the Census and ENIGH data arise from the census only including as economically active individuals whose primary activity was either working or looking for a job. For example, part-time workers whose primary activity was studying are categorized as outside the labor force, leading to census estimates of LFP being lower.

[10] We merged surveys from 1989 and 1992 (C.1990), and from 2012 and 2014 (C.2013) to increase sample size and smooth over year-specific changes.

phenomenon (López-Calva and Lustig, 2010; Levy and Schady, 2013; Lustig et al., 2013; Galiani et al., 2017; Fernández and Messina, 2018). Third, we do not see a similar compression of the female wage distribution. Wage growth for females was ever so slightly u-shaped across the distribution with wages at the bottom and the top performing better than in the middle.

Figure 3 (panel a) shows how the unconditional gender earnings gap evolved across the earnings distribution.[11] The gender gap increased by 10 to 32 percent among workers with below median earnings, and declined by 5 to 18 percent among workers above the 80th percentile. To adjust for skill and experience, we estimate conditional quantile regressions at each percentile in each of the two periods: C.1990 and C.2013. We then report the change in the coefficient of the female dummy in the regression (see Panel (b) of Figure 3).[12] We continue to observe that the change in the gender pay gap is larger at the bottom than at the top- indeed the gap declines monotonically through the distribution. However the changes are small and there is no longer convergence at the top (i.e the composition-adjusted gap at the top still favors men).

4.1 Did the Wage Structure Change? Quantile Decomposition of the Gender Earnings Gap

The wage distribution can change because the characteristics of workers are changing, because the returns to those characteristics are changing, or both.[13] We are concerned with the rise of FLFP but as this was not the only compositional change in the Mexican labor market over this period, it is important to identify the extent to which changes in the skill and age composition of the workforce changed the wage structure. In this section, we first document changes in the characteristics of workers over the sample period. We then explain how we conduct a decomposition of the change in the gender earnings gap to identify the role of characteristics. Figures 2 and 3 which show how much the change in the gender earnings gap varied across the earnings distribution, underline the importance of conducting the decomposition at different percentiles of the distribution.

The lower panel of Table B.1 shows how the age and educational attainment of male and female workers changed between C.1990 and C.2013. The share of prime-age women in the workforce with at least some college education increased from 14.5 to 24.0 percent, while that of men increased more slowly from 15.6 to 20.8 percent. The more rapid growth in the share of skilled women may be an alternative

[11] The series in Panel (a) of Figure 3 is calculated by subtracting the values of the male and female series in Figure 2.

[12] The controls in the regression include dummies for 7 education categories, 6 age categories in five year intervals, and all possible interactions.

[13] In the context of the debate about the rise of income inequality in the United States, Lemieux (2006) shows that a substantial share of the the rise in residual earnings inequality can be accounted by the fact that the earnings of older and more educated workers (the shares of which were rising) tend to be more dispersed. This argument was later controverted by Autor et al. (2008).

explanation for the convergence in earnings at the top of the distribution. Also, the average Mexican worker is becoming older, and more so if they are women (because of the increase in married women's FLFP): the share of workers age 45-55 increased from 20.2 to 28.9 percent in the case of women, and from 23.0 to 29.2 percent in the case of men. If the gender earnings gap increases with age (Barth et al., 2017; Adda et al., 2017), this could also be a factor behind the widening of the mean gender gap.

The decomposition methodology we adopt is based on Firpo et al. (2007, 2009), and we provide full details in Appendix A.2. As a starting point, consider a transformed wage-setting model of the form:

$$RIFq_{\tau,gen,t} = X'_{gen,t}\gamma_{gen,t} + \epsilon_{gen,t}, \tag{4.1}$$

where subscript gen indicates if the worker is male ($gen = k$) or female ($gen = f$); the subscript t indicates the period, either initial ($t =$C.1990) or final ($t =$C.2013); $RIFq_{\tau,gen,t}$ represents the value of the RIF[14] corresponding to the τ'th quantile of the earning distribution at time t and for gender gen; X is a vector of socio-demographic characteristics including dummies for 7 education categories, dummies for 6 age categories in five year intervals, and all possible interactions; and $\epsilon_{gen,t}$ is the error term assumed to have zero conditional mean. We can estimate Equation (4.1) for each gender and period separately by OLS, and then express the estimated difference over time of the expected value of the earnings quantile $\hat{q}_\tau$ as:

$$\Delta_t\hat{q}_{\tau,gen} = \underbrace{\left(\overline{X'}_{gen,\text{C}.2013} - \overline{X'}_{gen,\text{C}.1990}\right)\hat{\gamma}_{gen,P}}_{\Delta_t\hat{q}_{X,\tau,gen}} + \underbrace{\overline{X'}_{gen,P}\left(\hat{\gamma}_{gen,\text{C}.2013} - \hat{\gamma}_{gen,\text{C}.1990}\right)}_{\Delta_t\hat{q}_{S,\tau,gen}}, \tag{4.2}$$

where overbars denote averages, and $\hat{\gamma}_{gen,P}$ and $\overline{X}_{gen,P}$ correspond to the estimated vectors of parameters and the explanatory variables of a wage-setting model in which observations are pooled across the two periods.[15] Here, $\Delta_t\hat{q}_{X,\tau,gen}$ corresponds to the composition effect, which captures the part of the change in the τ'th earnings quantile that is accounted for by changes in the average skill-demographic composition of workers, given that we set the returns at their (weighted) average over the two periods. $\Delta_t\hat{q}_{S,\tau,gen}$ is the wage structure effect, capturing how changes in returns are affecting earnings at the quantile τ, given that the observable characteristics are

[14]See Appendix A.2 for the definition of the RIF in the context of Firpo et al. (2007, 2009) extension of the Oaxaca-Blinder decomposition.

[15]This specific counterfactual allows us to analyse composition and wage structure effects relative to a baseline defined by the (weighted) mean returns and (weighted) mean characteristics over the two periods, eliminating the interaction term present in other decompositions (Oaxaca and Ranson, 1994).

fixed to be equal to their (weighted) average over time.

Since we are interested in the effects of composition and price changes on the gender earnings gap, we construct the following measures at 19 different percentiles:

$$\underbrace{\Delta_t\hat{q}_{\tau,k} - \Delta_t\hat{q}_{\tau,f}}_{\text{Overall}} = \underbrace{(\Delta_t\hat{q}_{X,\tau,k} - \Delta_t\hat{q}_{X,\tau,f})}_{\text{Composition}} + \underbrace{(\Delta_t\hat{q}_{S,\tau,k} - \Delta_t\hat{q}_{S,\tau,f})}_{\text{Wage Structure}}. \tag{4.3}$$

The results of the decompositions for 5 selected percentiles are shown in Table 3. We see that wage structure effects are quantitatively more important than compositional effects. Estimated wage structure effects contribute 63 percent of the observed rise in the gender earnings gap at the 5th percentile, and close to 90 percent at the 25th percentile. 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).

The relative importance of composition and wage structure effects in the evolution of the gender wage gap at the 19 percentiles is visualized in Figure 5. Wage structure effects are the dominant factor, lining up with observed relative wages across the distribution. The figure also shows that if the wage structure had remained constant at the average levels over the two periods, compositional effects would have led to a larger gender earnings gap. This suggests that changes in the skill and age of the workforce contributed to widening of the gap at the lower tail, and have impeded further convergence at the top of the distribution.[16]

5 Theoretical Model

5.1 Demand Side

Aggregate production in the economy is a function of the labor that imperfectly substitutable types of workers supply to the market. Agents are divided into 4 types according to their gender and their skill. We label workers with at most secondary education unskilled and workers with at least some college education as skilled. To maintain a tractable number of parameters in the model, we do not differentiate worker types by age, and this is not unreasonable given that we showed that the increase in FLFP that we focus upon modelling the effects of was fairly uniform across the sample age range of 25-55. In the next sub-section we model how each type of agent chooses between either staying in home production or entering the workforce in one of three market occupations: abstract, routine or manual task-intensive.

[16] 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 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 technology is described by a three-level nested constant elasticity of substitution (CES) function, with the nests corresponding to occupation, education, and gender. At the top level, output is produced by a CES combination of labor in the three types of market occupations:

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

Y_t is total output at time t; Z_t is a scale parameter that is allowed to vary in time to capture skill-neutral technological change; $L_{a,t}$, $L_{r,t}$, and $L_{m,t}$ are the total supplies of labor in abstract, 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-abstract (routine and manual) vs abstract task-intensive occupations ($\sigma_{\rho_1} \equiv \frac{1}{1-\rho_1}$); and $\rho_2 \in (-\infty, 1]$ is a function of the elasticity of substitution (σ_{ρ_2}) between labor in routine vs manual task-intensive occupations ($\sigma_{\rho_2} \equiv \frac{1}{1-\rho_2}$).[17]

The parameter $\alpha_{1,t}$ is a time-varying share parameter that captures the relative demand for non-abstract vs abstract task-intensive occupations. Similarly, $\alpha_{2,t}$ captures differences in relative demand in routine vs manual task-intensive occupations. Examples of sources of shifts in relative demand include non-neutral technical change (e.g. routine-biased technical change as in Goos et al. (2014); variations in non-labor input demands through capital skill complementarity as in Krusell et al. (2000); product market demand shifts through changes in the external demand for commodities as in Fernandez and Messina (2017); trade and outsourcing generating incentives to modernize the production processes as in Juhn et al. (2014), and increasing competition with local industries as in Autor et al. (2016).

In the second level of the production technology, labor in each occupation is divided into two groups, skilled (s) and unskilled (u).

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

where the parameters have an analogous interpretation to those in Equation (5.1).

Finally, at the third level of the production technology, labor is disaggregated in each occupation-education group by gender. This is done using a productivity weighted CES combination of female workers, indexed by f, and male workers, indexed by k. That is:

[17] Note that, by assumption, the elasticity of substitution between male and female labor in abstract vs manual task-intensive occupations is the same as the elasticity of substitution between abstract vs routine task-intensive occupations. This seems a natural way of organizing the three occupational groups since we observe them align this way in the earnings distribution as low vs. high paying occupations. However, importantly, we shall investigate alternative specifications in the robustness checks section.

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

where the parameters have an analogous interpretation to those in Equation (5.1). Note that elasticities of substitution between male and female labor are allowed to vary between occupations and also between skill groups, but not within both occupation and skill group at once. To test how sensitive the results are to the ordering of the levels in the production technology, we report results using alternative model specifications.

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 relative productivities or demand shifters 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), 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. For example, the parameter $\alpha_{1,t}$ is allowed to change according to:

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

As is clear from equation 2.2 the elasticities of substitution are identified by movements in relative supply (specified in the next section), but the demand trends are identified residually. In particular, any changes in relative wages that are not explained by movements in relative supplies are absorbed by the relative demand parameters. In total, the demand side of the model has 56 parameters that we need to estimate.[18]

5.2 Occupational Choice on the Supply Side

Male and female workers sort themselves into different market occupations based on preferences about job flexibility and earning's profiles (Goldin, 1984, 1986; Adda et al., 2017); societal expectations and attitudes towards female work (Brown et al., 1980; Goldin, 1984, 2006); and as a function of gender specific comparative advan-

[18]This include 8 elasticities of substitution and 48 coefficients associated with the third order polynomials of α shares.

tage associated with differences in physical, sensory, motor, and spatial aptitudes (Galor and Weil, 1996; Black and Juhn, 2000; Rendall, 2010, 2013; Baker and Cornelson, 2016). Comparative advantage will reflect in marginal productivity and hence in wages, and influence occupational sorting through wages. The model attempts to incorporate both individual preferences and equilibrium returns to labor in the decision problem of the agents.

As in Johnson and Keane (2013), we model occupational choice using a random utility framework where agents of different types choose between the four alternatives according to which provides the highest utility. We model these utilities as linear functions that depend on pecuniary and non-pecuniary rewards from each choice. In particular, the utility that a worker of a given type receives from choosing to enter the workforce in one of the three market occupations at time t is

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

where $\psi_{gen,edu,occ}$ are time-invariant parameters capturing non-pecuniary rewards (such as job flexibility, or the mission-orientation of a job) that a worker gets from choosing occupation occ at time t; and ψ_1 measures the weight in utility terms that a worker gives to labor earnings ($W_{gen,edu,occ,t}$). $\epsilon_{gen,edu,occ,t}$ 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.

The utility from home production is modelled symmetrically for men and women. The literature has linked movements of women into the labor market to changes in contraceptive technology and fertility(Katz and Goldin, 2000; Costa, 2000; Cruces and Galiani, 2007); marriage markets (Grossbard-Shechtman and Neuman, 1988; Fernández and Wong, 2014; Greenwood et al., 2016); social norms and attitudes towards women's work (Rindfuss et al., 1996; Costa, 2000; Fernández et al., 2004; Goldin, 2006; Fernández, 2013); and improvements in technology and capital (e.g. appliances) used for home production (Costa, 2000; Greenwood et al., 2005; de V. Cavalcanti and Tavares, 2008; Coen-Pirani et al., 2010).

We do not specify how the underlying mechanisms that explain the rise of female labor force participation interact with the demand side of the model. What we do is to condition the decision to remain in home production on variables linked to fertility choice and marriage patterns, while capturing changes in preferences and technical change in home production using trends. Both fertility and marriage declined through the sample period- see Figure 6 which plots these trends conditional on education and gender. In 1989, the percentage of each group with under-5 children was between 45 and 55 percent, falling by 2014 to between 25 and 35 percent, a substantial fall of close to 20 percentage points. Changes in the marriage market were less pronounced: in 1989, between 86 and 94 percent of each group was married or partnered and, by 2014, these numbers had fallen 3 to 8 percentage points, with the largest decline among the college educated (7.4 and 8 percentage points for males and females respectively).

The utility from choosing home production, denoted by h, takes the form:

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

where $\pi_{1,gen}$ and $\pi_{2,gen}$ are the intercept and slope of a gender-specific linear trend that captures both changes in preferences for home production over time, and changes in the technology used in home production activities; $Pr(\text{child} = 1 \mid gen, edu, t)$ is the probability that the agent has a child under the age of 5, which, since the level of aggregation is at the gender-education level, corresponds to the proportion of the population from a given group that has at least one child under the age of five at time t; and $Pr(\text{married} = 1 \mid gen, edu, t)$ is the probability that the worker is married or has a permanent partner. Finally, $\epsilon_{gen,edu,h,t}$ is a idiosyncratic taste shock assumed to be independent and identically distributed extreme value.

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

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

We can 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 abstract task-intensive occupations is

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

Where $L_{f,s,t}$ is the total number of female workers with college education at time t, which we take as given. As the example shows, we condition on the schooling level of the agents, but we assume that educational choices are taken before the age of 25, the starting age for an agent to become part of the sample. The supply side of the model has a total of 25 parameters that we need to estimate.

5.3 Equilibrium and Estimation

Labor demand for agents of a given gender and skill in a specific market occupation at a given time is denoted $L^d_{gen,edu,occ,t}$, and determined by the equilibrium condition that wages are equal to marginal productivities:

$$W_{gen,edu,occ,t} = \frac{\partial Y_t}{\partial L^d_{gen,edu,occ,t}}. \tag{5.9}$$

Also, in equilibrium, wages are set to equate the supply and demand for the different types of labor :

$$L^d_{gen,edu,occ,t} = L^s_{gen,edu,occ,t} \quad \text{for} \quad occ = a, r, m, \tag{5.10}$$

while the total supply in home production can be recovered residually.

A solution to the model is then obtained by finding the vector of wages for which Equations (5.9) and (5.10) are satisfied by each type of agent in each occupation. For a given vector of parameters, this can be accomplished in an iterative way using a fixed-point algorithm: (i) start with an arbitrary wage vector W^0 and find the total supply of workers from each type in each occupation, which can be calculated using Equations (5.7) and (5.8). (ii) Plug the estimated supply of workers of each type into the marginal productivity function defined by Equation (5.9) and calculate the new vector of wages W^1. (iii) If $W^0 = W^1$, we have a solution for this set of parameters. If $W^0 \neq W^1$, set $W^0 = W^1$ and go back to step (i).

The model generates a prediction of the wage and labor supply of the four worker types in the four occupations (including home production) in every time period. With 13 years of data there are $(12 + 16) \times 13 = 364$ predictions in total that are a function of the 81 parameters.[19]

For every prediction there is a corresponding observed value in the data. We assume a simplified error structure such that the differences between predictions and data are assumed to follow a normal distribution centred at zero. We then fit the model to the data using the method of moments, targeting observed labor shares and wages. Following Johnson and Keane (2013), we construct the weight matrix from the score of the log-likelihood function. Details of the estimation technique are presented in Appendix A.3.

[19] Wages: 4 types of workers in three market occupation leads to 12 predictions per year. Supplies: 4 types of workers in 4 possible occupations leads to 16 predictions per year.

6 Results

6.1 Model Fit to the Data

Figure 7 shows the fit of the model with respect to the data. We show the relative earnings and relative supply series by occupation groups, and the participation rates for women and men, estimated as the inverse of labor supplied to home production. The plots show that the model predictions consistently track the long-term trends in the data. The model is less successful at capturing short-term variations, especially those related to temporary spikes in the data. This is likely to be because we fit a smooth function for the α shares. Table B.3 shows observed and predicted mean wages and occupation shares for all groups at the start and end of the period. The predictions are good with the exception of small-cell cases such as college-educated workers in manual and routine task-intensive occupations C.1990, especially among women, but these groups represent less than 1 percent (between 0.05 and 0.63 percent) of the prime-age population.[20]

6.2 Parameter Estimates

6.2.1 Demand Side

Elasticities of substitution by occupation: gender and skill. See Table 4. The elasticities of substitution between male and female labor are estimated to be around 1.2 in manual and routine task-intensive occupations. In abstract task-intensive occupations the point estimate is 2.6. Table 4 reports the confidence intervals. These results support our hypothesis that the elasticity of substitution between male and female labor varies across occupation groups, with male and female labor being closer substitutes in occupations that rely more on abstract or analytical skills, occupations which tend to lie towards the upper end of the earnings distribution.

To get a sense of what these values represent, we performed some back-of-the-envelope calculations. In manual task-intensive occupations, log (male/female) relative supply fell between about 1990 and 2013 by 56.4 log points (see Table B.2), so an elasticity of 1.2 implies that the log (male/female) earnings ratio should have increased, other things equal, by 46.5 log points. This is considerably larger than the observed 6.4 log point increase. In routine and abstract task-intensive occupations, log (male/female) relative supply fell by 38.9 log points, so the implied elasticities predict an increase in the gender earnings gap of 31.9 and 14.7 log points respectively, also significantly higher than the observed 1 and -13 log point changes. There are two main takeaways from these calculations: first, the increase in FLFP exerted substantial downward pressure on the wages of female workers, especially in manual occupations towards the bottom of the distribution of earnings. Second, relative

[20] The model generates a mean wage in each group. We plot the logarithm of this.

demand trends must have been strongly favorable to women, otherwise the gender earnings gaps would be much higher everywhere.

To our knowledge, there are no comparable estimates of the elasticity of substitution between male and female labor for Mexico or indeed any country other than the U.S. (see Acemoglu et al. (2004); Johnson and Keane (2013) discussed in Section 1). These earlier estimates are broadly in line with ours but they are a constant for the entire economy, ignoring important heterogeneities that have significant distributional effects.

Elasticities of substitution by occupation and skill. We also depart from available studies in estimating elasticities of substitution between skilled and unskilled labor by occupation. Our estimates are 1.4 in abstract 1.6 in routine and 3.6 in manual task-intensive occupations. Consistent with intuition, skilled and unskilled workers are closer substitutes in occupations where abstract analytical skills are less important. These results support the hypothesis that the sharp educational upgrading in Mexico contributed to the fall in earnings inequality among men. Our estimates for the elasticities of substitution between skilled and unskilled labor lie in a range that incorporates the values that other studies have found in Latin America and the US. Estimates for five Latin American countries during the 1990s range from 1.25 Fernández and Messina (2018) to 3 Manacorda et al. (2010)) and for the US the elasticity is close to 1.5 Katz and Murphy (1992); Ciccone and Peri (2005); Johnson and Keane (2013).

Demand trends by occupation, gender and skill. Figure 8 shows the model predictions for the evolution of the share parameters which capture changes in labor demand (see Equation (5.4)). We show the evolution of demand for male relative to female labor by skill and occupation. Moving up one nest, we then show the evolution of overall demand by skill and occupation. Estimates for the uppermost nest show demand trends aggregated by occupation. We also show estimated total factor productivity trends. To facilitate interpretation, each series shown is normalized to take the value of zero in 1989.

The estimated trends show that the demand for female relative to male labor increased through the last quarter century. This holds in every skill-occupation group[21], but it is clear that demand favored women most in the group of college-educated workers sorting into abstract-intensive occupations. For this group, the model predicts that demand trends alone would lead the log (male/female) earnings ratio to have fallen by 58 log points. For workers with at most secondary, relative demand alone predicts a decline in the log (male/female) earnings ratio of 14 log points in both abstract and routine occupations, and by 25 log points in manual occupations.

The coefficients of the relative demand polynomials are estimated residually,

[21] Every curve showing the ratio of male to female demand is declining. The exception is college x manual occupation in panel (b) but as noted earlier this is a group containing very few people.

so we are not able to pinpoint exactly what the main drivers behind the observed patterns are. There is considerable agreement in the literature that structural changes faced by most economies in the last decades have been favorable to female labor, with jobs in which women have a comparative advantage or no disadvantage gaining ground in the economy. As discussed in the Introduction, some studies emphasize labor reallocation from goods to service industries (Lup Tick and Oaxaca, 2010; Akbulut, 2011; Olivetti and Petrongolo, 2014; 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, 2010; Black and Spitz-Oener, 2010; Aguayo-Tellez et al., 2013; Rendall, 2013; Juhn et al., 2014; Deming, 2017; Jaimovich et al., 2017).

Abstracting from gender, relative demand trends have evolved to favor labor with more schooling, and labor in abstract task-intensive occupations (panels (c) and (d) of Figure 8). 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 et al., 2007; Caselli, 2012) and the growth of foreign direct investment (Feenstra and Hanson, 1997) in this period.

This result confirms that Mexico experienced skill and routine-biased technical change, a phenomenon that has been widely argued to explain rising income inequality in developed economies. Nevertheless, in contrast to many OECD countries, Mexico experienced a compression of wage inequality among men, with educational upgrading more than offsetting the increasing demand for skill. An additional insight provided by our fairly unique focus on women in this discussion is that the relative demand for skill favored women and, among women, we see no offset, in fact no marked change in wage inequality despite even greater educational upgrading among women.

6.2.2 Supply Side

Estimates of the parameters from the supply side of the model are shown in Table 5 with standard errors. For the key parameters, we also report the average marginal effects.[22]

As we may expect, we find that an increase in the wage in a given market occupation raises the probability that an agent will choose that occupation, but the wage elasticity of labor supply is small. For example, take the case of a college-educated female worker choosing among the three market occupations or home production. If

[22] Average marginal effects of the fertility and marital status variables are calculated by taking the numerical derivative of the probability of choosing home production with respect to the given variable. In the case of the pecuniary rewards (ψ_1), the reported average marginal effect is calculated by finding the numerical derivative of the probability that a labor type chooses a given market occupation with respect to the wage. We calculate the derivatives in each year and for every possible labor type and occupation combination separately, and then take the average across all the values.

the hourly wage for her group in the abstract task-intensive occupation increases by 10 percent (from 6.5 to 7.15), then the probability of her choosing that occupation is predicted to increase by 1.43 percentage points. Since the individual probabilities are in a one-to-one correspondence with the occupation shares, the share of college-educated female workers in abstract task-intensive occupation would also be predicted to increase by 1.43 percentage points. This illustrates that, conditional on education and sex, wage dynamics were not a major driver in the choice of participation or occupation. While this is of interest, it is not entirely surprising given that we allow the agent just four occupational choices; the wage elasticity is likely to be higher within our occupational categories, as most individuals will tend to move within rather than across the broad occupational class.

Our estimates show that the decline of fertility and marriage has had a significant bearing on the LFP decision, but only for unskilled women (with at most secondary schooling). The percentage of prime-age unskilled women with young children fell by 18.9 percentage points from 1989 to 2014 (Figure 6), and our model predicts that this is associated with a rise in labor force participation of 3.3 percentage points, which is about 17 percent of the total observed change. We find no statistically significant effect of having children under the age of five on the LFP decision of college educated women. The percentage of unskilled women in stable partnerships fell by 6 percentage points (Figure 6)and our estimates predict that this would generate an increase in FLFP of 1 percentage point, about 5 percent of the observed change. As for fertility, marital status has no impact on the decision of college educated women to enter the labor market.

Together, the fertility transition and changes in marital status explain close to 22 percent of the overall rise in female labor force participation among women with at most secondary education, the group for which we observe the largest movement into the workforce. The other 78 percent is explained by changes in preferences for home production and/or advances in home production technology, which we capture with the linear trend in Equation (5.6). This suggest that changes in cultural and social norms regarding female work (Fernández et al., 2004; Fogli and Veldkamp, 2011; Fernández, 2013) may have been a major driver behind the increase in FLFP.

We also obtained estimates of participation parameters for men. We find that both marital status and fertility influence the decision to participate in the labor market though, as for women, only among men with at most secondary schooling. Interestingly, the direction of the effects is the opposite to that of females. Having children under the age of five and being married or with a permanent partner is associated with higher labor force participation, although the average marginal effects are small. Neither of the two variables is statistically significant in the case of college educated men.

6.3 Counterfactual Exercises

Using the parameter estimates of the model, we can quantify the impact of relative supply and demand changes on the occupation and wage structure. We run four counterfactual excercises, 'turning off' a channel that directly affects either the participation and occupation choice, or the marginal product of labor. We then run the model under these alternative scenarios and compute the counterfactual equilibrium wages and occupation shares.

In the first scenario, we set the the linear, quadratic, and cubic coefficients of all the demand trends (α shares) to zero. This allows us to quantify the estimated impact of demand side forces on the occupation and wage structure. In the second and third scenarios, the share of individuals with children under the age of 5 and the share in a stable partnership (respectively), in each of the four labor groups is set equal to its level in 1989 and constant across the years. This allows us to quantify the estimated impact of changes in fertility and partnership decisions respectively. In the fourth scenario, the linear trends ($\pi_{2,f}, \pi_{2,k}$) in the home production utility function are set equal to zero. This exercise allows us to quantify the estimated impact of changes in preferences and home production technology.

Results are in Table 6. Each cell reports the difference between males and females of the changes over the period in the occupation shares and log mean wages for each group. The first two columns show the data and the prediction of the baseline model. Columns 4-6 report the results from the different counterfactual scenarios.

Switching off demand confirms and quantifies our earlier inference that relative demand trends favored female labor. Holding demand constant, the model predicts a significantly higher gender earnings gap in all occupations and skill groups. For example, the gender earnings gap among college educated workers in abstract task-intensive occupation is predicted to increase by 29.3 log points in this scenario when in fact it decreased by -8.5 log points. For unskilled workers in manual occupations the gender earnings gap is predicted to increase by as much as 30.9 log points when in fact it increased by 11.4 log points. Thus it is clear that demand trends mitigated impacts of the change in the gender composition of labor supply. However, differences in occupational choices of men and women, especially participation rates, were mostly unaffected by how demand evolved, which is due to the fact that the wage elasticity of labor supply is low.

The second and third counterfactuals capture the equilibrium effects of declines in fertility and partnership. They show that these changes, while they did have some explanatory power for the decision to enter the workforce among unskilled workers, were not of sufficient magnitude to generate changes in relative earnings or participation rates.

The story is quite different when we look at the final counterfactual that switches off the linear trends in the utility of home production. Now the rise in FLFP is much lower: 6 percentage points predicted instead of the 22 percentage points observed. This scenario delivers strong convergence in (male/female) relative earnings in all occupations and skill groups. For example, it predicts that the gender earnings gap in manual task-intensive occupations among unskilled workers would have declined by 18 log points, while the full (baseline) model predicts a 8.8 log point increase (and the actual was an 11.4 log point increase). For abstract task intensive occupations, shutting down trends in home production predicts that the gender earnings gap among college educated workers in abstract occupations would have declined more (by 20.7 log points) than the baseline prediction (a decline of 13.5 log points, and the actual was a decline of -8.5 log points). These results provide a clear statement of the influence of rising FLFP on the gender wage gap across the distribution.

The third block of Table 6 reports the results of the same counterfactuals but aggregating across the three occupations. We aggregate using a weighted average of the groups, where the weights are equal to the respective occupation shares. It is clear from the first and fourth counterfactuals that demand and supply trends had strong impacts on the gender earnings gap, but in opposite directions: Among higher-educated workers, demand side forces outpaced the impact of changes in relative supply, so there was convergence in earnings between men and women. Among lower-educated workers, supply side forces outpaced the impact of changes in relative demand, so there was divergence in earnings between men and women.

The last block of Table 6 reports the results for the four counterfactuals focusing on changes in the skill (college/high) school premium by sex. The impact of rising FLFP on the college premium is of particular interest since this is the channel that most of the literature on wage inequality has ignored. The baseline model predicts a decline in the skill premium of -20.4 log points but, once we limit the rise of FLFP through the fourth counter-factual, the decline in the premium halves to -9.8 log points. The implication is that the movement of women into the workforce was also a driver in the contraction of the male wage distribution. This is a direct consequence of the finding that the elasticity of substitution between male and female labor is high in occupations with a concentration of high-skilled individuals. No previous work has recognized that the rise of FLFP is potentially an important driver of the documented fall in income inequality in most countries in Latin America during the past quarter century.

7 Robustness Checks

As discussed in section 3, the earnings series used for the baseline estimates included only incomes of full-time workers. We now report estimates including income from part-time workers. We also produce estimates replacing the head count measure of labor supply with the total number of hours worked by each group. For the latter exercise, since we do not have a measure of hours worked in home production, we impute those values. We assign each person in home production the average number of hours worked by workers in market occupation with the same age, gender and level of schooling.

Table B.4 reports the point estimates and standard errors of the different elasticities of substitution using these alternative measures. The rank-size of the values in each of the levels (nests) is maintained. Once we include income from part-time workers the elasticity of substitution between male and female labor in manual and routine task-intensive occupations is lower, down from 1.2 in the baseline model to 0.8 and 0.97 respectively. This reinforces our conclusions from the previous section that increasing female labor supply led to downward pressure that was particularly large among female workers in these lower-paying occupations.[23]

Using the intensive margin measure of labor supply does not change the estimates in any meaningful way. The corresponding estimates of the parameters from the supply side of the model under the alternative earnings and supply measures are shown in Table B.5. These results are essentially unchanged compared to the baseline. As discussed, demand is estimated residually and we restrict relative productivities to follow a cubic trend in their natural logarithm. The cubic trends provided the best fit of the model to the data. 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; results available upon request.

When modeling the structure of the production technology, two decisions were made that could influence the results but are not grounded on a solid theoretical basis: First, in the three nests, labor is first divided by education and then by gender. This division changes the number of relative demands that are estimated in each dimension, but it should not alter the main results in a significant way. Second, the model assumes that the elasticity of substitution between abstract and routine task-intensive occupations is the same as that between abstract and manual-task intensive occupations. The way the model is set-up implies that at least one occupational group will have a common elasticity with the other two; we choose the abstract task-intensive occupation since it leads to a natural division between high and low-paying jobs, but it did not have to be that way.

Table B.6 presents point estimates and standard errors of the elasticities of substitution in the production technology under three revised model specifications, alongside the baseline estimates: (i) switch the order of the second and third nests

[23]This suggests that if part-time work were rising disproportionately more for women than for men, this would tend to widen the gender earnings gap in favor of men in the occupations that absorb part-time workers. However, this was not the case in Mexico: the share of women in part-time work relative to the share of men in part-time work was fairly stable between about 1990 and 2002, after which it declined (see Figure B.1).

of the production technology; (ii) impose that the occupational group that has the common elasticity with the other two is the routine task-intensive; and (iii) impose, instead, that the occupational group that has the common elasticity with the other two is the manual task-intensive. We find that the rank-size of the values of the elasticities of substitution between male and female labor is maintained in all cases: in manual and routine task-intensive occupations these elasticities are between 0.7 and 1.2, while in abstract task-intensive occupations the elasticity is between 1.9 and 2.6. The corresponding estimates of the parameters from the supply side of the model under the alternative model specifications are shown in Table B.7. Results are essentially unchanged compared to the baseline.

8 Conclusions

We develop an equilibrium model of the labor market to investigate whether rising female labor supply can explain the evolution of the wage structure. In a departure from previous work on gender earnings gaps, the model follows the task-based approach, allowing the elasticity of substitution between male and female labor to vary depending on the task content of occupations. Furthermore, labor supply is endogeneously determined. Using data from 1990 to 2013, our main findings are summarized as follows:

1. The gender earnings gap widened at the lower tail of the earnings distribution, while contracting at the top. This has implications for inequality, and for identifying relevant mechanisms. Studying average changes in the gap would conceal this variation.[24]

2. We estimate an elasticity of substitution between male and female labor in manual and routine task-intensive occupations of 1.2. This relatively low elasticity contributes to explaining the widening of the gender earnings gap in these relatively low-paid jobs. Counterfacutals show that, absent the rise in FLFP, the gender gap at the lower tail would have contracted.

3. We estimate an elasticity of substitution between male and female labor in abstract task-intensive occupations of 2.6. This contributes to explaining the contraction of the gender earnings gap at the upper end of the earnings distribution, where these occupations lie.

4. Relative demand trends favored women in all occupations and skill groups, but this trend was strongest among college educated workers in abstract task-

[24]This was the result of the following underlying patterns in changes in male and female earnings inequality. The male wage distribution contracted, with wages at the low end of the earnings distribution growing more rapidly than at the top. Changes in female wages were more uniform across the distribution, but with slight relative gains at both tails compared to the middle.

intensive occupations. This contributes further to explaining the better relative earnings of women towards the top of the distribution.

5. We estimate that 22 percent of the 20 percentage point increase in female labor force participation in Mexico since 1989 can be explained by changes in marital status and fertility. The rest is explained by unobservables that we interpret as changes in preferences, for instance, shifting cultural norms and attitudes towards women's work.[25]

6. We propose that the large rise in FLFP contributed to the decline of the skill premium for men.

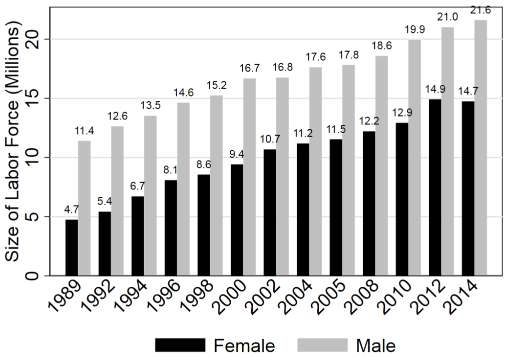
[25] The LFP of men responds in the opposite direction to marriage and fertility- men who are in stable relationships or who have a young child are more likely to work. The responses of both men and women to marriage and fertility are driven by the unskilled.

Tables and Figures

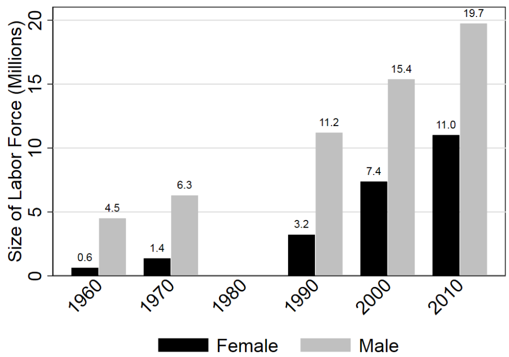
Figure 1: Labor Force Participation by Gender

Absolute Numbers

(a) Survey Data

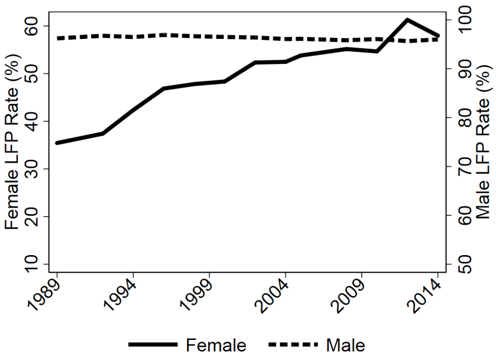


(b) Census Data



Participation Rates

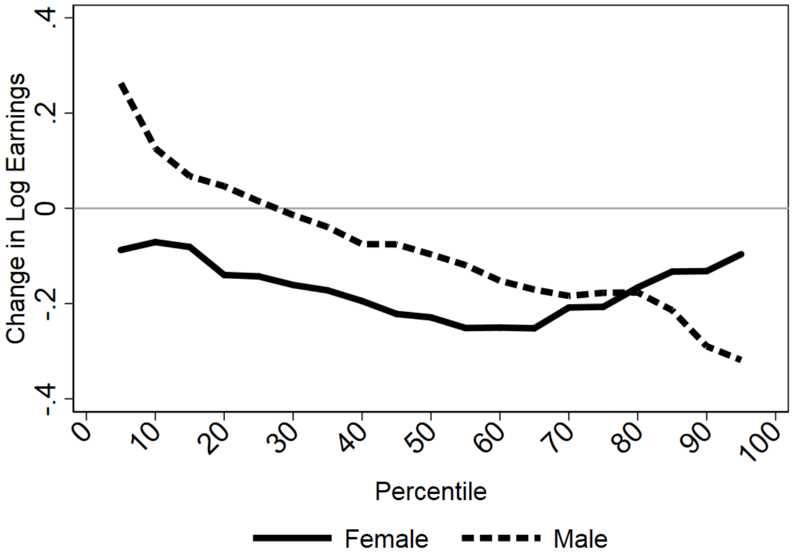
(c) Survey Data



(d) Census Data

Notes: Participation refers to prime-age population either working or actively searching for a job. The differences between the census and survey data (ENIGH) arise because the census only includes as economically active those individuals whose primary activity was either working or looking for a job. For example, part-time workers whose primary activity was studying are categorized as outside the labor force, leading to an underestimation. Sample weights used in all calculations.

Figure 2: Distribution of Changes in Log Hourly Earnings by Gender between C.1990 and C.2013

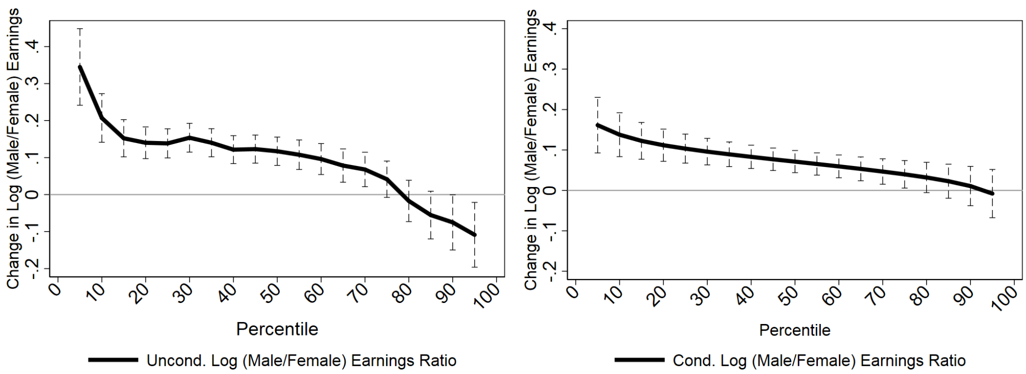


Notes: The series are constructed by computing the change in real log hourly earnings between C.1990 and C.2013 at each percentile of the distribution. Sample restricted to prime-age population working more than 35 hours a week. To increase sample size we joined together surveys from 1989 and 1992 (C.1990), and from 2012 and 2014 (C.2013). The plot shows that wages in Mexico have tended to decrease over the period. Wage changes for men and women diverge at the two ends of the distribution.

Figure 3: Distribution of Changes in the Gender Earnings Gap

(a) Uncond. Change: C.1990-C.2013

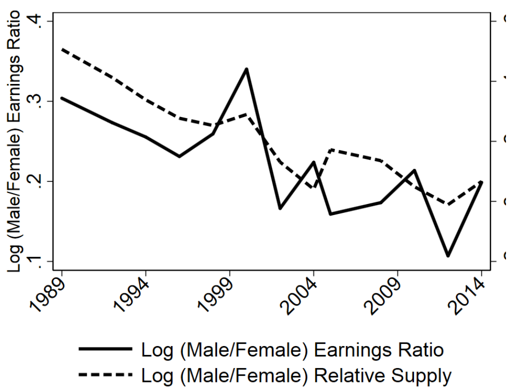
(b) Conditional: C.1990-C.2013



Notes: Panel (a) shows the change in log (male/female) hourly earnings by percentile between C.1990 and C.2013. Panel (b) shows a similar statistic using changes in the conditional wage distributions. We do this by running conditional quantile regression at each percentile in two periods: C.1990 and C.2013. We then report the change in the coefficient of the female dummy in the regression. The controls in the regression include: dummies for 7 education categories, dummies for 6 age categories in five year intervals, and all possible interactions. Sample is restricted to prime-age population that reported working for more than 35 hours a week. Vertical bars correspond to 95 percent confidence intervals. Sample weights used in all calculations.

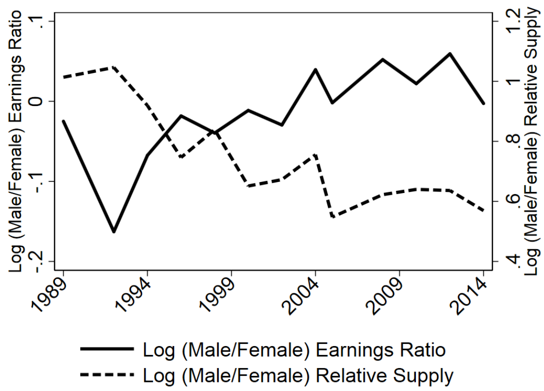
Figure 4: Co-movement of Gender Earnings Gap and Relative Supplies by Occupation Groups

(a) Abstract Occupations



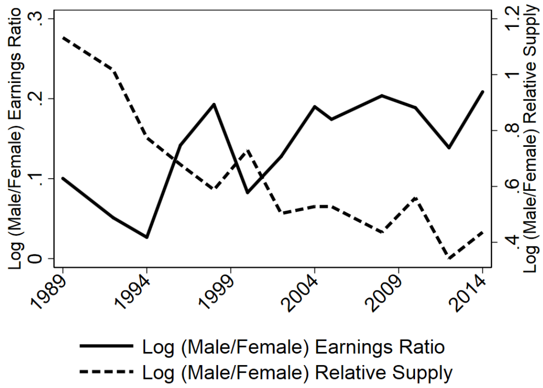
$d\ln(L_k/L_f) \approx -44$; $d\ln(W_k/W_f) \approx -10$

(b) Routine Occupations



$d\ln(L_k/L_f) \approx -44$; $d\ln(W_k/W_f) \approx 2.3$

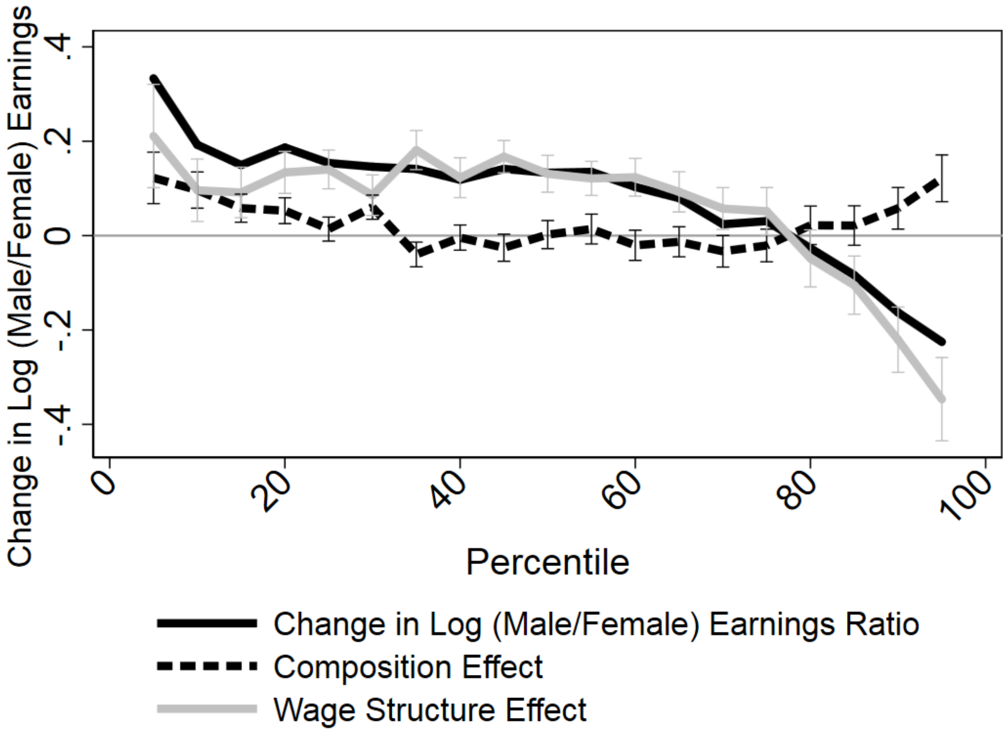
(c) Manual Occupations



$d\ln(L_k/L_f) \approx -69$; $d\ln(W_k/W_f) \approx 10$

Notes: We plot log (male/female) earnings and log (male/female) labor supply over the period of analysis. Legends below each plot report the log point changes in the relative wages and supplies. The sample for the earnings series is restricted to prime-age population that reported working for more than 35 hours a week. The sample for the relative supply series includes all workers in the labor force (including part time) between the ages of 25 and 55. Sample weights used in all calculations.

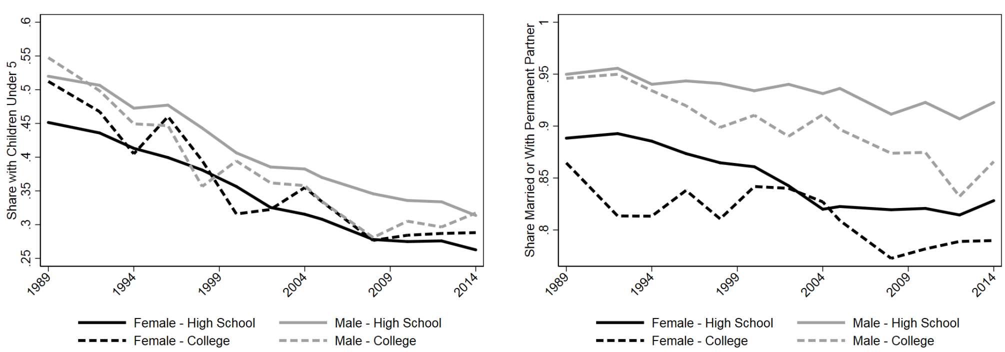
Figure 5: Decomposition of the Gender Earnings Gap by Percentile of the Distribution



Notes: The Figure shows results of the Oaxaca-Blinder decomposition of the unconditional change in the log (male/fermale) earnings ratio between C.1990 and C.2013 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.

Figure 6: Trends in Fertility and Marriage

(a) Changes in Fertility (b) Changes in Marital Status

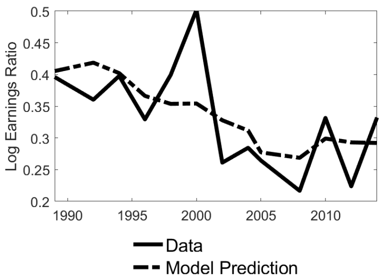


Notes: Panel (a) depicts the share of each group with children under the age of 5, and Panel (b) depicts the share of each group that is married or has a permanent partner. The measures of fertility and marriage can only be calculated for a sample restricted to the household head and their spouse or 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. Sample weights used in all calculations.

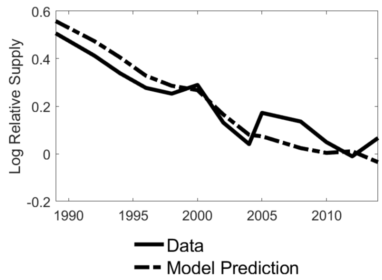
Figure 7: Model Fit:
Data and Model Predictions for Relative Earnings, Relative Supplies and Participation Rates

Abstract Occupations

(a) Log (Male/Female) Earnings Ratio

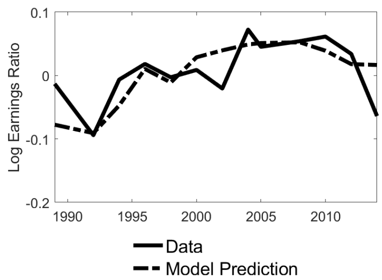


(b) Log (Male/Female) Relative Supply

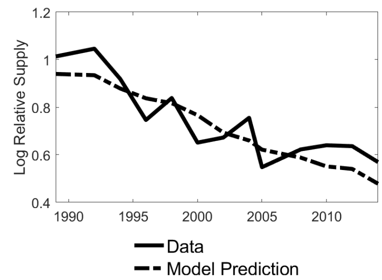


Routine Occupations

(c) Log (Male/Female) Earnings Ratio

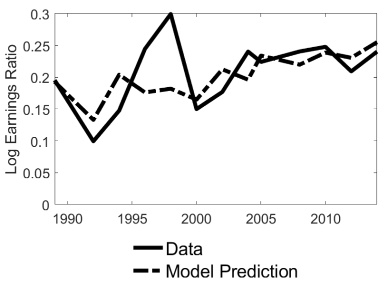


(d) Log (Male/Female) Relative Supply

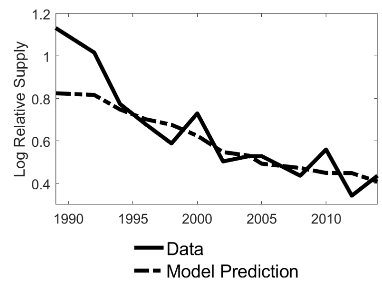


Manual Occupations

(e) Log (Male/Female) Earnings Ratio

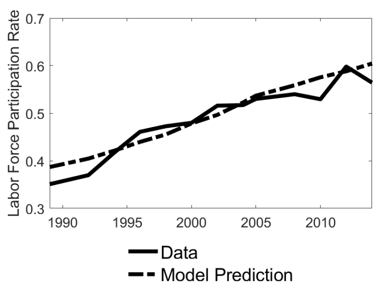


(f) Log (Male/Female) Relative Supply

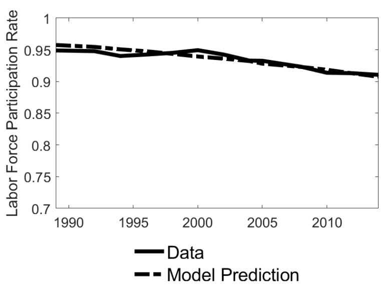


Participation Rates

(g) Female



(h) Male

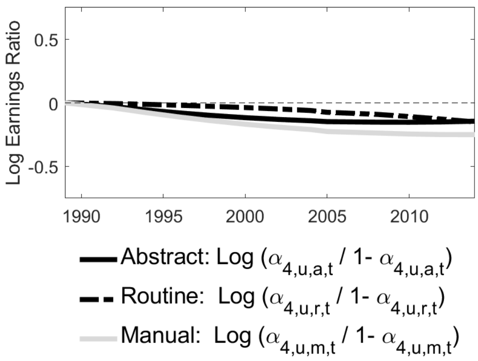


Notes: The different panels depict the series of log (male/female) relative earnings, log (male/female) relative supplies, and labor force participation rates from both the raw data and as predicted from the model, showing a close fit.

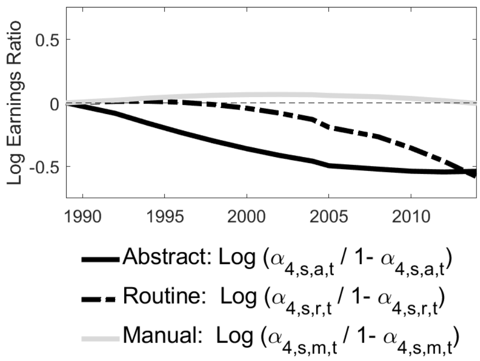
Figure 8: Estimates of the Relative Demand Indexes and Total Factor Productivity

Production Technology: Level III

(a) Male vs. Female (Secondary)

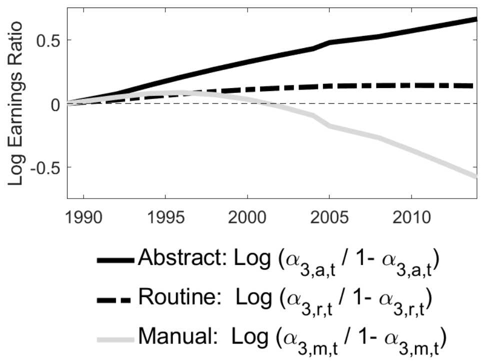


(b) Male vs. Female (College)



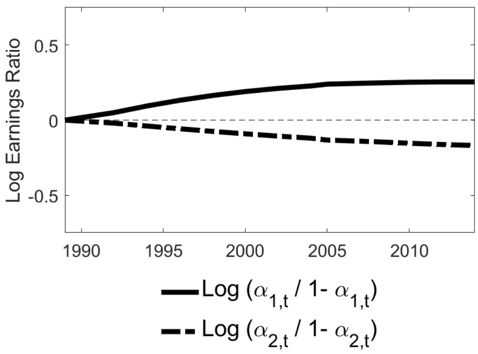
Production Technology: Level II

(c) College vs. Secondary

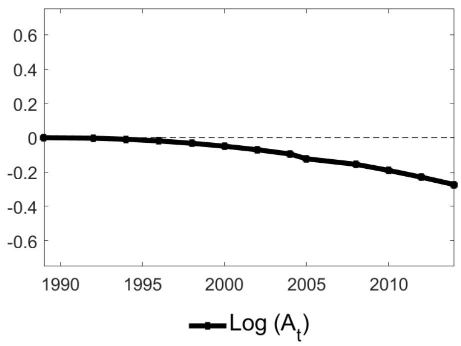


Production Technology: Level I

(d) Analytical vs. Routine and Manual; and Routine vs. Manual



(e) Total Factor Productivity



Notes: Panels (a)-(d) show the estimated change in the relative demand indexes captured by the log ratio of the α shares. Panel (e) shows the estimated change of log total factor productivity. The changes in total factor productivity and the α shares are estimated using a cubic time trend in their natural logarithm. To facilitate interpretation, each series is normalized to zero in 1989.

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

ENIGH Principal Group	Median Percentile of the Task Measure: Abstract	Routine	Manual	Group	Av. Share (x100)	Av. Male Share (x100)	Av. Earnings Percentile
Managers	90.0	17.0	27.5	Abstract	2.9	71.3	85.4
Crafts and Trades (Supervisors)	84.0	42.0	62.0	Abstract	1.8	84.2	72.3
Education	83.0	11.0	65.0	Abstract	4.5	38.2	80.2
Professional	83.0	42.0	46.0	Abstract	4.1	62.4	82.3
Technical	71.0	69.0	43.0	Abstract	4.0	59.3	68.6
Arts/Entertainment	66.0	35.0	48.0	Abstract	0.6	76.4	70.4
Sales	61.0	22.5	15.0	Abstract	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 et al. (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. Further details are presented in Appendix A.1.

Table 2: Labor Force Participation Rates:
by Gender, Education and Age: C.1990 and C.2013

	C.1990		C.2013	
	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 female population with secondary school participated in the labor force in C.1990. We joined together surveys from 1989 and 1992 (C.1990), and from 2012 and 2014 (C.2013) to increase sample size of the ENIGH data survey. Sample weights used in all calculations.

Table 3: Decomposition of the Gender Earnings Gap for Selected Percentiles

	P5		P25		P50		P75		P95	
	Est.	[S.E.]	Est.	[S.E.]	Est.	[S.E.]	Est.	[S.E.]	Est.	[S.E.]
Observed Change	0.333	[0.054]	0.154	[0.021]	0.133	[0.021]	0.031	[0.027]	-0.225	[0.045]
Overall Wage Structure	0.211	[0.056]	0.140	[0.021]	0.131	[0.020]	0.052	[0.026]	-0.347	[0.045]
Overall Composition	0.122	[0.028]	0.014	[0.013]	0.002	[0.015]	-0.021	[0.018]	0.121	[0.025]

Notes: The table shows results of the Oaxaca-Blinder decomposition of the unconditional change in the log (male/fermale) earnings ratio by percentiles. The standard errors in brackets are calculated via bootstrap with 500 replications. Sample weights used in all calculations.

Table 4: Parameter Estimates: Production Technology

	Elasticities of Substitution			
	Estimate	[SE]	Implied Elasticity $(1/(1-\rho))$	95% Conf. Int. $(1/(1-\rho))$
Gender				
$\rho_{4,m}$: female, male (manual)	0.175	[0.181]	1.212	[0.84, 2.12]
$\rho_{4,r}$: female, male (routine)	0.179	[0.129]	1.219	[0.93, 1.76]
$\rho_{4,a}$: female, male (abstract)	0.622	[0.099]	2.646	[1.75, 5.43]
Education				
$\rho_{3,m}$: college, secondary (manual)	0.722	[0.067]	3.594	[2.44, 6.81]
$\rho_{3,r}$: college, secondary (routine)	0.355	[0.041]	1.549	[1.38, 1.77]
$\rho_{3,a}$: college, secondary (abstract)	0.276	[0.121]	1.382	[1.04, 2.05]
Occupation				
ρ_1: abstract, routine and manual	0.031	[0.094]	1.032	[0.87, 1.27]
ρ_2: routine, manual	-0.141	[0.183]	0.877	[0.67, 1.28]

Notes: The table reports the point estimates and standard errors of the elasticities of substitution from the production technology.

Table 5: Parameter Estimates: Occupational Choice

	Occupational Choice		
	Estimate	SE	Average Marginal Effect
Earnings			
ψ_1: earnings	0.154	[0.009]	0.022
Fertility/Children			
$\pi_{3,f,u}$: female, secondary	0.712	[0.127]	0.174
$\pi_{3,f,s}$: female, college	-0.139	[0.229]	-0.025
$\pi_{3,k,u}$: male, secondary	-0.367	[0.182]	-0.022
$\pi_{3,k,s}$: male, college	0.122	[0.219]	0.008
Marriage			
$\pi_{4,f,u}$: female, secondary	0.589	[0.107]	0.144
$\pi_{4,f,s}$: female, college	0.267	[0.134]	0.047
$\pi_{4,k,u}$: male, secondary	-0.524	[0.155]	-0.032
$\pi_{4,k,s}$: male, college	0.026	[0.196]	0.002
Non Pecuniary Rewards/Tastes			
$\pi_{1,f}$: female, home production	0.961	[0.078]	
$\pi_{2,f}$: female, home production trend	-0.059	[0.003]	
$\pi_{1,k}$: male, home production	-0.716	[0.127]	
$\pi_{2,k}$: male, home production trend	0.054	[0.005]	
$\psi_{f,u,m}$: female, secondary, manual	0.036	[0.048]	
$\psi_{f,u,r}$: female, secondary, routine	-0.437	[0.046]	
$\psi_{f,u,a}$: female, secondary, abstract	-0.555	[0.044]	
$\psi_{f,s,m}$: female, college, manual	-0.756	[0.130]	
$\psi_{f,s,r}$: female, college, routine	-0.362	[0.088]	
$\psi_{f,s,a}$: female, college, abstract	0.508	[0.080]	
$\psi_{k,u,m}$: male, secondary, manual	0.541	[0.063]	
$\psi_{k,u,r}$: male, secondary, routine	0.296	[0.064]	
$\psi_{k,u,a}$: male, secondary, abstract	-0.682	[0.066]	
$\psi_{k,s,m}$: male, college, manual	-0.347	[0.073]	
$\psi_{k,s,r}$: male, college, routine	-0.347	[0.092]	
$\psi_{k,s,a}$: male, college, abstract	0.581	[0.083]	

Notes: The table shows the point estimates, standard errors and average marginal effects of the main parameters from the supply side of the model. Average marginal effects of the fertility and marital status variables are calculated by taking the numerical derivative of the probability of choosing home production with respect to the given variable. We calculate this derivative in each year separately and then take the average across all years. In the case of the pecuniary rewards (ψ_1), the reported average marginal effect is calculated by finding the numerical derivative of the probability that a labor type chooses a given market occupation with repect to the wage. Ie calculate this derivative in each year and for every possible labor type-occupation combination separately and then take the average across all the values.

Table 6: Counterfactual Excercises

	Change in Supply and Wage Gaps: C.2013 - C.1990					
	Data	Model	I Demand	II Fertility	III Marriage	IV Preferences
100 × Δ Log (Male/Female)Earnings Ratio						
College						
Abstract	-8.5	-13.5	29.3	-13.2	-13.5	-20.7
Routine	-27.4	0.5	51.5	0.6	0.1	-13.2
Manual	-29.0	30.0	-11.0	30.6	29.9	12.1
Secondary						
Abstract	-0.9	3.1	12.9	0.9	2.4	-10.3
Routine	13.9	14.2	26.9	10.0	12.8	-11.3
Manual	11.4	8.8	30.9	4.4	7.3	-18.0
100 × Δ Male - Female Occ. Share						
College						
Abstract	-2.1	-2.0	-0.4	-2.1	-2.0	-0.9
Routine	-0.4	-0.8	-0.2	-0.8	-0.7	-0.5
Manual	0.1	-0.3	0.0	-0.3	-0.3	-0.1
Home Production	-0.8	-0.2	-0.3	-0.1	-0.2	-1.7
Secondary						
Abstract	-1.5	-2.4	-2.1	-2.1	-2.3	-0.5
Routine	-2.0	-3.0	-3.0	-2.6	-2.9	-0.9
Manual	-6.0	-3.5	-3.8	-3.0	-3.3	-0.4
Home Production	13.0	12.4	12.6	11.1	12.0	5.3
100 × Δ Log (Male/Female)Earnings Ratio						
College	-13.2	-11.7	29.9	-11.4	-11.7	-20.4
High School	15.2	14.6	27.1	10.8	13.3	-8.2
100 × Δ Log (College/Secondary)Earnings Ratio						
Male	-16.3	-20.4	-25.7	-19.8	-20.2	-9.8
Female	12.1	5.8	-28.6	2.4	4.8	-6.6

Notes: The Table reports the difference between C.1990 and C.2013 of i) the log (male/female) earnings ratio and ii) the change in the occupational shares by sex and iii) the the log (college/secondary) earnings ratio under alternative scenarios. The first two columns correspond to the data and model predictions. Column I corresponds to the counterfactual estimates once all the linear, quadratic, and cubic coefficients of the α shares (demand) are set to zero. Column II corresponds to the counterfactual estimates once we set the probability of having a child under the age of 5 to the values of 1989, and constant across the years. Column III corresponds to the counterfactual estimates once we set the probability of being married or having a permanent partner to the values of 1989, and constant across the years. Finally, column IV correspond to the counterfactual estimates once we set the coefficients of the linear trends $(\pi_{2,f}, \pi_{2,k})$ in the home production utility function to zero.

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A Appendix

A.1 Division of Occupations into Manual, Routine, and Abstract 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.[26] 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 in three groups defined by whether the activities done in the jobs are predominantly manual, routine (repetitive and easily codifiable tasks), or abstract intensive. The division is based on the measures constructed by Autor et al. (2003) from different sets of variables of the 1977 Dictionary of Occupational Titles (DOT) 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 et al. (2006) used a subset of those dimensions to generate a simple typology consistent of three aggregates for abstract, routine, and manual tasks. The abstract 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, foot coordination.[27]

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

[26] `http://www.inegi.org.mx/est/contenidos/proyectos/aspectosmetodologicos/clasificadoresycatalogos/sinco.aspx`

[27] See the online Appendix in Dorn (2009) for further details. Other papers that have used this measures include Autor et al. (2006); Goos and Manning (2007); Dorn (2009); Rendall (2013); Autor and Dorn (2013); Adda et al. (2017).

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 follow 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 that an occupation didn't have an immediate correspondence between the two systems, we had to use my 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 this two caveats in mind.

A.2 Using RIF to Decompose Changes in Distributional Statistics beyond the Mean

Firpo et al. (2007, 2009) allow extending the traditional Oaxaca-Blinder decomposition to distributional statistics beyond the mean. This is achieved through the use of influence functions (IF). Influence functions measure the effect that an infinitesimal amount of "errors" have on a given estimator (Cowell and Victoria-Feser, 1996), but they also have properties that allows us to model the sensitivity of a given unconditional wage quantile to a change in a set of covariates. To see this, let $q_\tau(F_W)$ be τth quantile of the distribution of wages, expressed in terms of the cumulative distribution $F_W(w)$. Define the following mixture distribution:

$$G_{W,\epsilon} = (1-\epsilon)F_W + \epsilon H_W \quad for \quad 0 \leq \epsilon \leq 1 \tag{A.1}$$

where H_W is some perturbation distribution that only puts mass at the value w. In that case, $G_{W,\epsilon}$ is a distribution where, with probability $(1-\epsilon)$, the observation is generated by F_W, and with probability ϵ, the observation takes the arbitrary value of the perturbation distribution. By definition, the influence function corresponds to:

$$IF(w; q_\tau, F_W) = lim_{\epsilon \to 0} \ \frac{q_\tau(G_{W,\epsilon}) - q_\tau(F_W)}{\epsilon} \tag{A.2}$$

where the expression is analogous to the directional derivative of q_τ in the direction of H_W. Analytical expressions for influence functions have been derived for many distributional statistics.[28] The influence function in the case of the τth quantile takes the form:

$$IF(w; q_\tau, F_W) = \frac{\tau - \mathbb{1}[w \leq q_\tau]}{f_W(q_\tau)} \tag{A.3}$$

where $\mathbb{1}[\cdot]$ is an indicator function and f_W is the PDF.[29] Using some of the properties of influence functions, a direct link with the traditional Oaxaca-Blinder approach can be established. In particular, a property that is shared by influence functions is that, by definition, the expectation is equal to zero.

$$\int_{-\infty}^{+\infty} IF(w; q_\tau, F_W) dF(w) = 0 \tag{A.4}$$

Firpo et al. (2009) propose a simple modification in which the quantile is added back to the influence function, resulting in what the authors call the Recentered Influence Function (RIF).

$$RIF(w; q_\tau, F_W) = q_\tau + IF(w; q_\tau, F_W) \tag{A.5}$$

The importance of this transformation lies in the fact that the expectation of the RIF is precisely the quantile q_τ. With this result, Firpo et al. (2009) show that we can model the conditional expectation of the RIF as a linear function of the explanatory variables.

$$E[RIF(w_t; q_\tau, F_{W,t}|X_t)] = X_t'\gamma_t \tag{A.6}$$

Moreover, if we apply the law of iterated expectations to Equation A.6, the end result is an expression that directly relates the impact of changes in the expected values of the covariates on the unconditional quantile q_τ. Note that this result is all that is required to extend the Oaxaca-Blinder decomposition to quantiles, since the basic components of the method are all present in Equation (A.6).

Estimation of Equation (A.6) can be done by OLS, and only requires replacing the dependent variable, $\log w_t$ in the original wage setting model with the RIF of the quantile q_τ. The interpretation of the estimates $\widehat{\gamma}_t$ can be thought of as the effect of a small change in the distribution of X on q_τ, or as linear approximation of the effect of large changes of X on q_τ (Firpo et al., 2007).

[28] Essama-Nssah and Lambert (2011) provides a comprehensive list of influence functions for different distributional statistics.

[29] Note that the influence function in this case depends on the density. In order to obtain the empirical density the authors propose non-parametric kernel density estimation.

A.3 Estimation of the Model: Error Structure, Weight Matrix, and Standard Errors

We assume a simplified error structure to facilitate estimation. Let Θ be the 81×1 vector of parameters to be estimated. Let $p(\Theta)$ by the 364×1 vector of wage and supply predictions of the model as function of the parameters. Finally, let q be the observed vector of wages and labor shares taken directly from the ENIGH data. For any given prediction i, we assume that the error term, e_i, at the true parameter vector, Θ^*, follows a normal distribution centred at zero that is independent across i. That is,

$$e_i = q_i - p_i(\Theta^*), \tag{A.7}$$

where $f(e_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} exp(\frac{e_i^2}{2\sigma_i^2})$.

The log-likelihood function takes the form

$$\log \mathcal{L}(\Theta) = \sum_i \log f(e_i) = \sum_i \log f(q_i - p_i(\Theta)), \tag{A.8}$$

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

$$s(\Theta) = \frac{\partial \log \mathcal{L}(\Theta)}{\partial \Theta} = \sum_i \frac{\partial \log f(q_i - p_i(\Theta))}{\partial \Theta} = \sum_i \frac{1}{\sigma_i^2} \frac{\partial p_i(\Theta)}{\partial \Theta}(q_i - p_i(\Theta)), \tag{A.9}$$

which we can write more compactly in vector form as

$$s(\Theta) = W'(\Theta)(q - p(\Theta)). \tag{A.10}$$

Here, $W(\Theta)$ is 364×81 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. At the maximum likelihood estimate, $\hat{\Theta}_{ml}$, the score vector of the log likelihood is set to zero:

$$s(\hat{\Theta}_{ml}) = W'(\hat{\Theta}_{ml})(q - p(\hat{\Theta}_{ml})) = 0. \tag{A.11}$$

We use $m = q - p(\Theta)$ as a vector of population moments such that $E(q - p(\Theta)) = 0$, and obtain a a consistent estimator of Θ^* by GMM:

$$g(\hat{\Theta}_{gmm}) = W'(q - p(\hat{\Theta}_{gmm})) = 0, \tag{A.12}$$

where W' is a fixed positive definite matrix of instruments. Efficient GMM estimator can be obtained by choosing instruments that are asymptotically equivalent to the weights $W'(\hat{\Theta}_{ml})$ in Equation (A.10). The problem is that we would need to have a consistent initial estimate of Θ^*. Given that we do not have those initial consistent estimates, we follow a 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, $\hat{\sigma}^2_{i,0}$, 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.[30] The estimates obtained after this first iteration[31] are used to update the weight matrix, and the process continues until the parameter vector converges to a stable point.

Since it is usually not possible to satisfy Equation (A.12), we estimate the parameters of the model using the quadratic form:

$$\hat{\Theta}_{gmm} = \text{argmin}[q - p(\Theta)]'W(\Theta)W'(\Theta)[q - p(\Theta)]. \tag{A.13}$$

Finally, the standard errors of the parameter estimates are calculated applying the standard method of moments formula. 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:

$$\Gamma_i(\hat{\Theta}_{gmm}) = \frac{\partial \bar{m}_i(\hat{\Theta}_{gmm})}{\partial \hat{\Theta}_{gmm}}, \tag{A.14}$$

so the variance-covariance matrix can be calculated using:

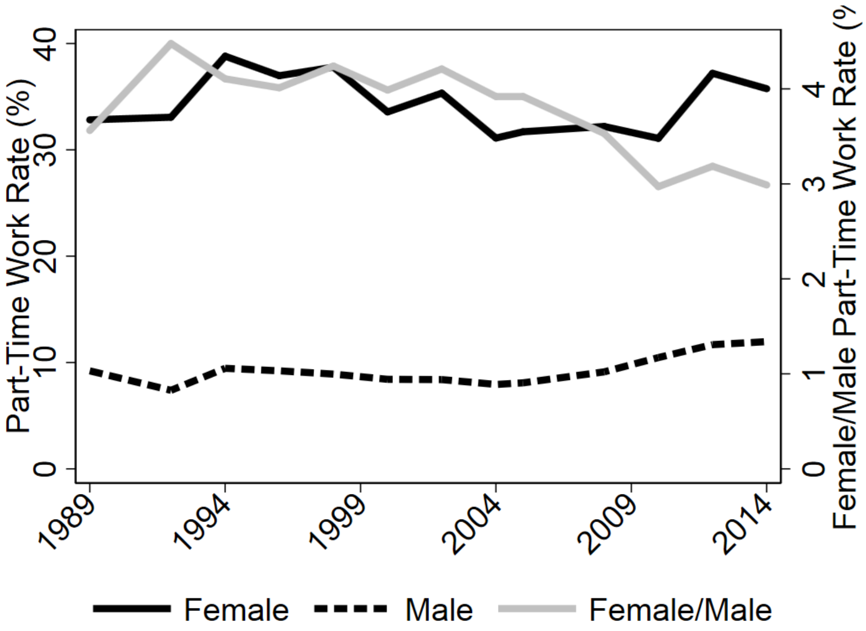
$$\hat{Var}(\hat{\Theta}_{GMM}) = \left[\Gamma(\hat{\Theta}_{gmm})'\hat{Var}[\bar{m}(\Theta_{gmm})]^{-1}\Gamma(\hat{\Theta}_{gmm})\right]^{-1}. \tag{A.15}$$

[30] The parameter search is done using the interior-point algorithm in Matlab.

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

B Online Appendix

Figure B.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.

Table B.1: Changes in the Composition of the Labor Force between C.1990 and C.2013

	C.1990			C.2013			Dif. in Dif.
	Female Share (x100)	Male Share (x100)	$\Delta_{c.1990}$ (Male - Female)	Female Share (x100)	Male Share (x100)	$\Delta_{c.2013}$ (Male - Female)	$\Delta_{c.2013}$ - $\Delta_{c.1990}$
Prime-Age Population							
Participation Rate	38.59	96.49	57.89	59.59	95.82	36.24	-21.66
Education							
Secondary	92.09	84.27	-7.82	81.24	79.05	-2.18	5.64
College	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	85.48	84.37	-1.11	76.00	79.19	3.19	4.29
College	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.1990, 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.

Table B.2: Levels and Changes of Real Hourly Earnings:
by Sex, Education, and Occupation. C.1990 and C.2013

	C.1990				C.2013				Dif. in Dif.	
	Female Earnings	Male Earnings	Log Gap Earnings	Log Gap Supplies	Female Earnings	Male Earnings	Log Gap Earnings	Log Gap Supplies	Δ Log Gap Earnings	Δ log Gap Supplies
Education										
College	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]
Secondary	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										
Abstract	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.										
College										
Abstract	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]
Secondary										
Abstract	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 earnings, the average log (male/female) earnings gap, and the log (male/female) relative supply by education, occupation, and year. Sample is restricted to prime-age workers. The sample for the construction of the earnings series is restricted to include only full-time workers. We joined together surveys from 1989 and 1992, and from 2012 and 2014 to increase sample size. The standard errors in brackets are calculated via bootstrap with 500 replications. Sample weights used in all calculations.

Table B.3: Model Fit:
Data and Model Predictions for Occupation Shares and Wages

	C.1990				C.2013			
	Female Data	Female Model	Male Data	Male Model	Female Data	Female Model	Male Data	Male Model
Mean Wages								
College								
Abstract	7.35	6.45	10.37	9.51	6.30	6.14	8.15	7.92
Routine	6.27	6.80	8.88	7.68	4.88	4.80	5.25	5.46
Manual	3.75	8.00	5.27	6.39	3.15	2.27	3.31	2.45
Secondary								
Abstract	3.95	3.58	4.66	4.26	2.67	2.68	3.12	3.29
Routine	3.42	3.12	3.10	2.89	2.41	2.44	2.52	2.60
Manual	1.92	1.77	2.16	2.08	1.73	1.74	2.18	2.24
Occupation Shares (x100)								
College								
Abstract	2.26	1.72	5.30	4.58	5.22	5.32	6.14	6.18
Routine	0.63	0.77	1.27	1.38	1.66	1.81	1.90	1.67
Manual	0.05	0.61	0.39	1.12	0.49	0.83	0.92	1.05
Home Production	1.26	1.09	0.45	0.33	2.55	1.95	0.93	0.99
Secondary								
Abstract	5.45	5.36	6.39	6.77	6.27	6.44	5.69	5.43
Routine	4.89	5.64	13.58	14.63	6.69	7.00	13.34	12.98
Manual	6.90	7.34	17.59	16.47	10.35	10.08	15.04	15.68
Home Production	31.49	30.37	2.12	1.83	19.59	19.35	3.23	3.25

Notes: The Table reports average wages and occupations shares in C.1990 and C.2013, both from the raw data and predicted by the model.

Table B.4: Parameter Estimates: Production Technology. Alternative Supply Measures

	Full-Time Workers			Part-Time Workers			Hours Worked		
	Estimate	SE	Elasticity	Estimate	SE	Elasticity	Estimate	SE	Elasticity
Gender									
$\rho_{4,m}$: female, male (manual)	0.175	[0.181]	1.212	-0.258	[0.152]	0.795	0.161	[0.138]	1.192
$\rho_{4,r}$: female, male (routine)	0.179	[0.129]	1.219	-0.030	[0.110]	0.971	0.355	[0.146]	1.551
$\rho_{4,a}$: female, male (abstract)	0.622	[0.099]	2.646	0.607	[0.121]	2.543	0.666	[0.108]	2.990
Education									
$\rho_{3,m}$: college, secondary (manual)	0.722	[0.067]	3.594	0.771	[0.083]	4.371	0.803	[0.120]	5.081
$\rho_{3,r}$: college, secondary (routine)	0.355	[0.041]	1.549	0.364	[0.073]	1.572	0.342	[0.122]	1.519
$\rho_{3,a}$: college, secondary (abstract)	0.276	[0.121]	1.382	0.151	[0.197]	1.177	0.173	[0.211]	1.209
Occupation									
ρ_1: abstract, routine and manual	0.031	[0.094]	1.032	0.688	[0.167]	3.206	0.621	[0.186]	2.639
ρ_2: routine, manual	-0.141	[0.183]	0.877	-0.519	[0.146]	0.658	-0.246	[0.192]	0.803

Notes: The table shows the point estimates and standard errors of the elasticities of substitution from the production technology using different labor supply measures. Columns 1-3 report the baseline estimates; columns 4-6 report the estimates if income from part-time workers is also included in earnings series; and columns 7-9 report the estimates if we measure labor supply by the total number of hours worked of each group instead of the head-count. Since there is no measure of hours worked for people that are in home production, those values are imputed. We assign each person in home production the average number of hours worked by workers in market occupation with the same level of schooling, sex, and age.

Table B.5: Parameter Estimates: Occupational Choice. Alternative Supply Measures

	Full-Time Workers			Part-Time Workers			Hours Worked		
	Estimate	SE	Av. MFX	Estimate	SE	Av. MFX	Estimate	SE	Av. MFX
Earnings									
ψ_1: earnings	0.154	[0.009]	0.022	0.090	[0.009]	0.013	0.138	[0.012]	0.023
Fertility/Children									
$\pi_{3,f,u}$: female, secondary	0.712	[0.127]	0.174	0.647	[0.214]	0.159	0.661	[0.227]	0.162
$\pi_{3,f,s}$: female, college	-0.139	[0.229]	-0.025	0.158	[0.172]	0.029	0.126	[0.207]	0.022
$\pi_{3,k,u}$: male, secondary	-0.367	[0.182]	-0.022	-0.242	[0.259]	-0.015	-0.238	[0.206]	-0.015
$\pi_{3,k,s}$: male, college	0.122	[0.219]	0.008	0.022	[0.235]	0.002	0.023	[0.263]	0.001
Marriage									
$\pi_{4,f,u}$: female, secondary	0.589	[0.107]	0.144	0.567	[0.146]	0.139	0.574	[0.17]3	0.141
$\pi_{4,f,s}$: female, college	0.267	[0.134]	0.047	0.127	[0.187]	0.023	0.294	[0.179]	0.051
$\pi_{4,k,u}$: male, secondary	-0.524	[0.155]	-0.032	-0.537	[0.182]	-0.034	-0.535	[0.191]	-0.033
$\pi_{4,k,s}$: male, college	0.026	[0.196]	0.002	-0.043	[0.234]	-0.003	-0.045	[0.166]	-0.003
Non Pecuniary Rewards/Tastes									
$\pi_{1,f}$: female, home production	0.961	[0.078]		0.811	[0.116]		0.935	[0.167]	
$\pi_{2,f}$: female, home production trend	-0.059	[0.003]		-0.051	[0.004]		-0.057	[0.004]	
$\pi_{1,k}$: male, home production	-0.716	[0.127]		-0.707	[0.135]		-0.609	[0.165]	
$\pi_{2,k}$: male, home production trend	0.054	[0.005]		0.047	[0.004]		0.048	[0.004]	
$\psi_{f,u,m}$: female, secondary, manual	0.036	[0.048]		-0.041	[0.057]		-0.126	[0.096]	
$\psi_{f,u,r}$: female, secondary, routine	-0.437	[0.046]		-0.420	[0.059]		-0.361	[0.096]	
$\psi_{f,u,a}$: female, secondary, abstract	-0.555	[0.044]		-0.504	[0.061]		-0.455	[0.094]	
$\psi_{f,s,m}$: female, college, manual	-0.756	[0.130]		-0.641	[0.099]		-0.723	[0.107]	
$\psi_{f,s,r}$: female, college, routine	-0.362	[0.088]		-0.263	[0.106]		-0.066	[0.082]	
$\psi_{f,s,a}$: female, college, abstract	0.508	[0.080]		0.721	[0.105]		0.622	[0.089]	
$\psi_{k,u,m}$: male, secondary, manual	0.541	[0.063]		0.577	[0.062]		0.687	[0.124]	
$\psi_{k,u,r}$: male, secondary, routine	0.296	[0.064]		0.385	[0.063]		0.404	[0.123]	
$\psi_{k,u,a}$: male, secondary, abstract	-0.682	[0.066]		-0.497	[0.063]		-0.542	[0.129]	
$\psi_{k,s,m}$: male, college, manual	-0.347	[0.073]		-0.484	[0.116]		-0.355	[0.100]	
$\psi_{k,s,r}$: male, college, routine	-0.347	[0.092]		-0.378	[0.111]		-0.318	[0.102]	
$\psi_{k,s,a}$: male, college, abstract	0.581	[0.083]		0.873	[0.115]		0.727	[0.106]	

Notes: The table shows the point estimates, standard errors and average marginal effects of the main parameters from the supply side of the model using different labor supply measures. Average marginal effects of the fertility and marital status variables are calculated by taking the numerical derivative of the probability of choosing home production with respect to the given variable. We calculate this derivative in each year separately and then take the average across all years. In the case of the pecuniary rewards (ψ_1), the reported average marginal effect is calculated by finding the numerical derivative of the probability that a labor type chooses a given market occupation with repect to the wage. We calculate this derivative in each year and for every possible labor type-occupation combination separately and then take the average across all the values.

Table B.6: Parameter Estimates: Production Technology. Alternative Model Specifications

	Baseline			Nests Order Swap			Routine			Manual		
	Estimate	SE	Elasticity	Estimate	SE	Elasticity	Estimate	SE	Elasticity	Estimate	SE	Elasticity
Gender												
$\rho_{4,m}$: female, male (manual)	0.175	[0.181]	1.212	-0.246	[0.098]	0.802	-0.427	[0.177]	0.701	-0.029	[0.104]	0.972
$\rho_{4,r}$: female, male (routine)	0.179	[0.129]	1.219	-0.278	[0.102]	0.782	-0.095	[0.153]	0.913	0.007	[0.023]	1.007
$\rho_{4,a}$: female, male (abstract)	0.622	[0.099]	2.646	0.466	[0.115]	1.872	0.529	[0.099]	2.121	0.551	[0.099]	2.225
Education												
$\rho_{3,m}$: college, secondary (manual)	0.722	[0.067]	3.594	0.564	[0.045]	2.292	0.454	[0.104]	1.831	0.581	[0.058]	2.385
$\rho_{3,r}$: college, secondary (routine)	0.355	[0.041]	1.549	0.382	[0.054]	1.618	0.380	[0.051]	1.614	0.189	[0.047]	1.233
$\rho_{3,a}$: college, secondary (abstract)	0.276	[0.121]	1.382	0.012	[0.040]	1.012	0.008	[0.048]	1.008	0.446	[0.150]	1.805
Occupation												
ρ_1: abstract, routine and manual	0.031	[0.094]	1.032	0.441	[0.109]	1.788						
ρ_2: routine, manual	-0.141	[0.183]	0.877	-1.816	[0.135]	0.355						
ρ_1: routine, abstract and manual							-0.784	[0.231]	0.560			
ρ_2: abstract, manual							0.332	[0.171]	1.496			
ρ_1: manual, abstract and routine										0.411	[0.134]	1.697
ρ_2: abstract, routine										-0.714	[0.099]	0.583

Notes: The table shows the point estimates and standard errors of the elasticities of substitution from the production technology using different model specification. Columns 1-3 report the baseline estimates; columns 4-6 report the estimates after switching the order of the second (education) and third (gender) nests of the production technology; columns 7-9 show the estimates if the occupational group that has the common elasticity with the other two groups is the routine task-intensive; and columns 10-12 report the estimates if the occupational group that has the common elasticity with the other two groups is the manual task-intensive.

Table B.7: Parameter Estimates: Occupational Choice. Alternative Model Specifications

	Baseline			Nests Order Swap			Routine			Manual		
	Estimate	SE	Av. MFX	Estimate	SE	Av. MFX	Estimate	SE	Av. MFX	Estimate	SE	Av. MFX
Earnings												
ψ_1: earnings	0.154	[0.009]	0.022	0.109	[0.009]	0.018	0.085	[0.008]	0.014	0.098	[0.010]	0.016
Fertility/Children												
$\pi_{3,f,u}$: female, secondary	0.712	[0.127]	0.174	0.805	[0.118]	0.197	0.832	[0.162]	0.206	0.664	[0.050]	0.162
$\pi_{3,f,s}$: female, college	-0.139	[0.229]	-0.025	-0.042	[0.116]	-0.008	-0.126	[0.330]	-0.022	0.022	[0.150]	0.004
$\pi_{3,k,u}$: male, secondary	-0.367	[0.182]	-0.022	-0.162	[0.098]	-0.010	-0.174	[0.240]	-0.009	-0.246	[0.164]	-0.015
$\pi_{3,k,s}$: male, college	0.122	[0.219]	0.008	0.073	[0.113]	0.005	0.061	[0.310]	0.004	-0.050	[0.196]	-0.003
Marriage												
$\pi_{4,f,u}$: female, secondary	0.589	[0.107]	0.144	0.767	[0.115]	0.188	0.500	[0.107]	0.124	0.588	[0.056]	0.144
$\pi_{4,f,s}$: female, college	0.267	[0.134]	0.047	0.318	[0.105]	0.059	0.103	[0.176]	0.018	0.193	[0.093]	0.035
$\pi_{4,k,u}$: male, secondary	-0.524	[0.155]	-0.032	-0.598	[0.115]	-0.037	-0.635	[0.244]	-0.034	-0.577	[0.144]	-0.035
$\pi_{4,k,s}$: male, college	0.026	[0.196]	0.002	-0.145	[0.124]	-0.009	-0.142	[0.299]	-0.010	-0.129	[0.154]	-0.009
Non Pecuniary Rewards/Tastes												
$\pi_{1,f}$: female, home production	0.961	[0.078]		0.822	[0.088]		0.712	[0.105]		0.848	[0.049]	
$\pi_{2,f}$: female, home production trend	-0.059	[0.003]		-0.051	[0.003]		-0.026	[0.003]		-0.054	[0.002]	
$\pi_{1,k}$: male, home production	-0.716	[0.127]		-0.646	[0.098]		-0.971	[0.221]		-0.672	[0.124]	
$\pi_{2,k}$: male, home production trend	0.054	[0.005]		0.045	[0.002]		0.081	[0.005]		0.045	[0.003]	
$\psi_{f,u,m}$: female, secondary, manual	0.036	[0.048]		0.196	[0.050]		0.101	[0.076]		0.019	[0.021]	
$\psi_{f,u,r}$: female, secondary, routine	-0.437	[0.046]		-0.228	[0.052]		-0.208	[0.076]		-0.391	[0.024]	
$\psi_{f,u,a}$: female, secondary, abstract	-0.555	[0.044]		-0.356	[0.052]		-0.525	[0.078]		-0.492	[0.027]	
$\psi_{f,s,m}$: female, college, manual	-0.756	[0.130]		-0.699	[0.063]		-0.804	[0.148]		-0.720	[0.092]	
$\psi_{f,s,r}$: female, college, routine	-0.362	[0.088]		-0.235	[0.061]		-0.126	[0.120]		-0.265	[0.063]	
$\psi_{f,s,a}$: female, college, abstract	0.508	[0.080]		0.739	[0.058]		0.863	[0.123]		0.757	[0.064]	
$\psi_{k,u,m}$: male, secondary, manual	0.541	[0.063]		0.625	[0.025]		0.717	[0.062]		0.631	[0.022]	
$\psi_{k,u,r}$: male, secondary, routine	0.296	[0.064]		0.423	[0.029]		0.527	[0.063]		0.424	[0.023]	
$\psi_{k,u,a}$: male, secondary, abstract	-0.682	[0.066]		-0.522	[0.026]		-0.403	[0.063]		-0.489	[0.033]	
$\psi_{k,s,m}$: male, college, manual	-0.347	[0.073]		-0.591	[0.069]		-0.582	[0.069]		-0.474	[0.064]	
$\psi_{k,s,r}$: male, college, routine	-0.347	[0.092]		-0.149	[0.063]		-0.269	[0.065]		-0.316	[0.058]	
$\psi_{k,s,a}$: male, college, abstract	0.581	[0.083]		0.783	[0.063]		0.895	[0.063]		0.749	[0.071]	

Notes: The table shows the point estimates, standard errors and average marginal effects of the main parameters from the supply side of the model using different model specifications. Columns 1-3 report the baseline estimates; columns 4-6 report the estimates after switching the order of the second (education) and third (gender) nests of the production technology; columns 7-9 show the estimates if the occupational group that has the common elasticity with the other two groups is the routine task-intensive; and columns 10-12 report the estimates if the occupational group that has the common elasticity with the other two groups is the manual task-intensive. Average marginal effects of the fertility and marital status variables are calculated by taking the numerical derivative of the probability of choosing home production with respect to the given variable. We calculate this derivative in each year separately and then take the average across all years. In the case of the pecuniary rewards (ψ_1), the reported average marginal effect is calculated by finding the numerical derivative of the probability that a labor type chooses a given market occupation with repect to the wage. We calculate this derivative in each year and for every possible labor type-occupation combination separately and then take the average across all the values.