Women and Men at Work: Fertility, Occupational Choice and Development*

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Abstract

We investigate how changes in barriers to female labor force participation and in the child penalty affect occupational decisions, fertility and income. We build a general equilibrium model of occupational choice with men and women, human capital investment and fertility. We fit the model to the US and India. Changing gender barriers account for 31% of the US growth between 1960 and 2010 (4.1% for India in 1983-2004). The implications of these barriers for the welfare of female workers with children were even larger, with lower child penalty alone increasing the welfare of this group by 7% in the US.

Keywords: Gender Barriers; Fertility; Occupational Choice; Growth

JEL codes: E25; J13; O10

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1 Introduction

Gender inequality has been declining in many different areas of life in most advanced and some emerging countries. Barriers to female labor force participation (LFP) in some jobs affect the occupational decisions of women and their accumulation of human capital. Individuals in general and women in particular face conflicts between their work and home roles due to limited time and social norms. This is relevant for women with children who might face difficulties in finding a family-friendly arrangement in some occupations. Careers vary by wages and by their flexibility to accommodate family tasks. Consequently, occupations vary by a child penalty, which corresponds to the effects of children on women's careers. Hence, fertility and occupational choices are joint decisions.

We investigate how changes in barriers to female LFP and in the child penalty affect occupational decisions and fertility choices of women in the US and India.[1] To do this, we build a general equilibrium model of occupational choice with men and women, endogenous human capital investment and fertility, in which individuals choose occupations based on their comparative advantage and relative wages (Roy, 1951). Barriers to LFP are occupation-specific, taking the form of a wedge between women's labor productivity and their wage in the chosen occupation. Women with children face also an occupation-specific child penalty.[2] Women also differ in their mothering preference, which could reflect heterogeneity within a society regarding family size.[3] Fertility differs because women have different preferences for family size and also due to differences in the child penalty by occupation. Some women might choose not to have children and the share of childless women varies endogenously across occupations.

[1]While we take these gender distortions as exogenous, Doepke and Tertilt (2009) study how women's economic and legal rights are endogenously extended over the economic development process.

[2]Some jobs with flexible working hours offer a comparative advantage to mothers to balance work's tasks and household chores (eg., Cubas et al., 2021; Goldin, 2014).

[3]Boneva et al. (2021) show that beliefs about the opinions of friends and family are found to be strong predictors of maternal labor supply decisions.

Consistent with our framework, US and Indian data show important heterogeneity in the proportion of women and in the fertility rate across occupations. The fertility rate barely changed in some occupations over more than four decades, while in other occupations fertility experienced a sharp decline.

We estimate the model parameters for the US and India using macro and micro moments of these two economies, including moments related to the labor share, gender gap and fertility by occupation. We then implement counterfactual exercises to calculate the share of growth accounted for by changes in the child penalty and in the barriers to female LFP by occupation in both countries. Changes in these distortions had non-trivial effects in both economies. For the US, movements in both distortions account for 31% of the observed economic growth between 1960 and 2010. Barriers to female LFP account for approximately 96% of the full 31%. We also calculate the welfare implications of changing gender distortions. Female workers in 2010 in the US would need to be compensated with an increase in 33% in their consumption to live in an economy with the 1960 levels of occupational barriers and child penalty. Changes in the child penalty are particularly important for the welfare of female workers with children. The decrease in the child penalty between 1960 and 2010 increased the welfare of female workers with children in the US by approximately 7%. Such welfare measure translates into a lump-sum transfer of approximately $2,880 per year for each woman with children.

Compared to the US, the growth and welfare implications of changes in female labor market frictions and the child penalty in India are quite different. Changes in these wedges account for just 4% of the growth in GDP per person in India between 1983 and 2004. Moreover, changes in these wedges increased the welfare of female workers by only 4.7% in the same period. In addition, the fall in the child penalty between 1983 and 2004 in India increased welfare of female workers with children by only 0.5%.

Related literature. Our framework provides a novel and complementary mechanism for fertility differentials within a society. Fertility is driven by female preferences and the occupation decisions of women, which depend on gender barriers in the labor market and barriers to balance the work and household chores. In a recent survey, Doepke et al. (2022) highlight that new models aiming to understand the causes and consequences of fertility in high income countries should emphasize women's career and family goals as key drivers of fertility.

Our paper is related to different strands of the literature on fertility and development. Most papers in this literature focus on the joint evolution of economic and demographic processes represented by a negative relationship between fertility and income (Barro and Becker, 1989; de la Croix and Doepke, 2003; Doepke, 2015; Galor and Weil, 1996; Mookherjee et al., 2012). Most of these models abstract from occupational choices and explore the quantity-quality tradeoff, which depends on the income elasticity of the quantity and quality of children (Becker, 1960). Our main mechanism for fertility differentials works through the opportunity cost of child-rearing associated with each occupation. We also allow for the possibility of endogenous childlessness among women (Baudin et al., 2015). Adda et al. (2017) estimate a life cycle model of labor supply, fertility, and savings with occupational choices to quantify the life cycle career costs associated with children. Our focus is on how gender barriers affect the allocation of talent, fertility and economic growth. In this respect, our model is close to Hsieh et al. (2019). We extend their theory by introducing extensive- and intensive-margin fertility decisions such that occupational choice, investment in human capital and fertility are jointly determined. Cavalcanti and Tavares (2016) also study the aggregate effects of barriers to female LFP in a model with endogenous fertility, but they abstract from occupational choices. Cuberes and Teignier (2016) and Chiplunkar and Goldberg (2021) investigate the aggregate effects of gender barriers in the labor market in a model of endogenous entrepreneurship but without fertility decisions. Therefore, our paper contributes to the literature by exploring fertility differentials driven by differences in the opportunity cost of child-rearing by occupation and by analyzing the aggregate effects of different gender barriers.

2 Empirical Facts

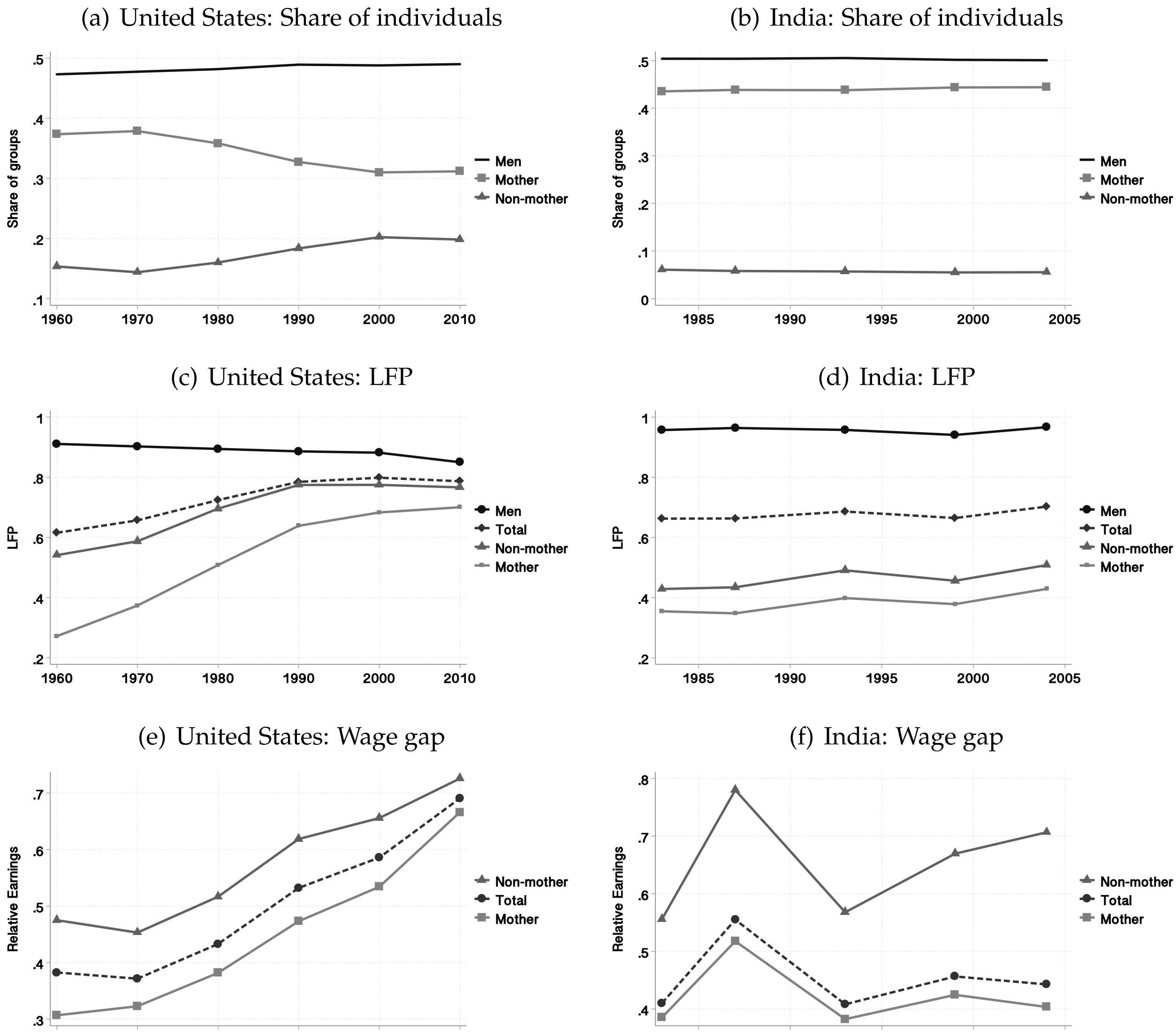
This section presents empirical facts that motivate our work and inspire our modeling strategy. We focus on individuals who have completed their education and before their retirement, restricting our sample for men and women aged between 25 and 54.

Panels (a) and (b) of Figure 1 show the evolution of the share of individuals who are male, female with and without children for the US (1960-2010) and for India (1983-2004). In the 1960s and 1970s, non-mothers accounted for approximately 15% of all working age individuals in the US. This number increased to 20% in 2010. In India in 2004 the share of non-mothers was similar to the one observed in 1983—approximately 8% of all working-age individuals.

Panels (c) and (d) of Figure 1 display the male and female LFP rates for the US and India. In the 1980s the participation rates for women with children were 50% and 35% for the US and India, respectively. After 20 years, the participation rate for women with children increased 17 percentage points in the US and 7 percentage points in India. After 40 years, the participation rate for women with children increased 33 percentage points in the US with most of this rise happening between the 1970s and the 1990s. In 2000, LFP rates of women without children were 7 percentage points larger than those with children in the US; in 2004, LFP rates of women without children were 8 percentage points larger than those with children in India.

Panels (e) and (f) of Figure 1 report the evolution of the female to male average wage. The unconditional gender wage gap has converged over time in the US and remained roughly constant in India. In 1960, female workers in the US earned approximately 40% of the average wage of male workers, while in 2010 this ratio had increased to 70%. In 2010, this ratio was 6 percentage points lower for female workers with children than for those without children (67% versus 73%). A different trend was observed for the Indian economy from 1983 to 2004. The difference between mothers and non-mothers in India is larger than the one observed

Figure 1: Share of groups, labor force participation and gender wage gap



Notes. Panels (a) and (b) display the share of working age individuals who are male, female with children and female without children for the US (1960-2010) and India (1983-2004). Panels (c) and (d) display the labor force participation rate for the US (1960-2010) and India (1983-2004). Panels (e) and (f) display the female to male average wage for the US (1960-2010) and India (1983-2004).

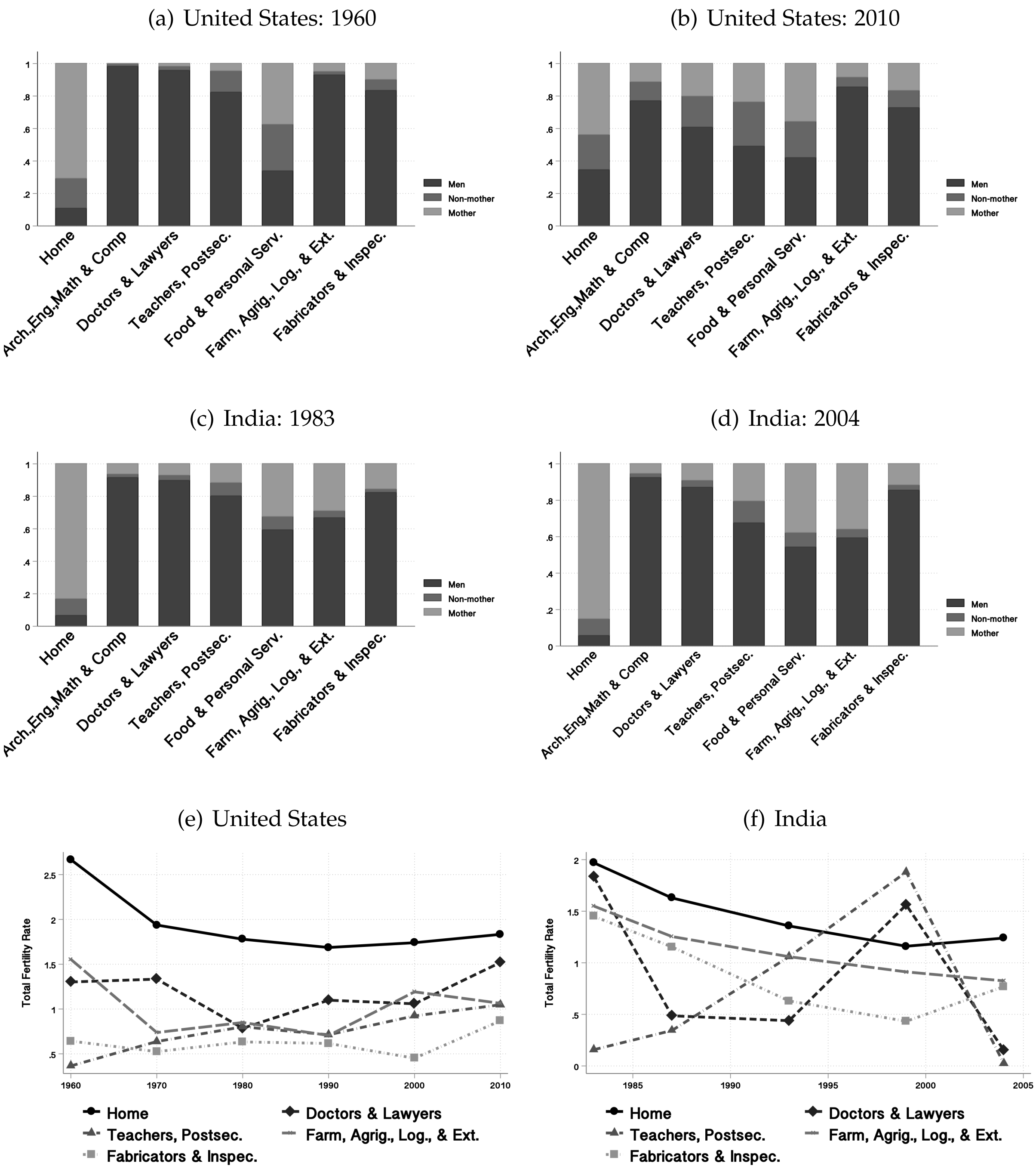
in the US. In India in 2004, mothers earned approximately 40% of the average wage of male workers, while for non-mothers this ratio was 71%.

In sum, the US experienced an increase in the share of female workers who are not mothers; a rise in female LFP for mothers and non-mothers (participation rate among non-mothers is larger than for mothers); and a reduction in the gender wage gap with mothers earning less than non-mothers. In contrast, India saw no increase in the share of female workers who are not mothers; little change in female LFP for mothers and non-mothers (participation rate among non-mothers is larger than for mothers); and no clear trend in the gender wage gap with mothers earning less than non-mothers.

Figure 2 shows the share of workers who are male, female with children and female without children for selected occupations in the US (panels (a) and (b)) and India (panels (c) and (d)). The data for all occupations are shown in the appendix. In 1960 in the US, about 70% of the individuals in the home sector were women with children, 20% were women without children and 10% were men. In 2010, women with children accounted for less than half of the individuals in the home sector and men increased their participation rate in this sector to more than 30%. On the other hand, almost all individuals working as lawyers and doctors were men in 1960 and their participation rate had decreased to approximately 60% in 2010. The share of mothers and non-mothers are roughly the same for lawyers and doctors in 2010 for the US, although mothers correspond to 60% of all female workers in 2010. The distributions of workers by gender and occupation are similar in India in 1983 to those observed in the US in 1960. Moreover, it barely changed between 1983 and 2004.

Finally, panels (e) and (f) of Figure 2 display the fertility rate by occupation in the US from 1960 to 2010 and in India from 1983 to 2004. There are significant differences in fertility rate across occupations in both countries. In 1960 in the US, women who were in the home sector had on average approximately 2 more children than women who were doctors and lawyers. This difference fell to less than one child in 2010. In the 1980s in India, women in the home sector had a similar number of chil-

Figure 2: Share of individuals and fertility for selected occupations



Notes. The figure shows the share of workers (panels (a)-(d)) by selected occupations for the United States (1960-2010) and India (1983-2004). Panels (e) and (f) display the total fertility rate by occupations in the United States (1960-2010) and in India (1983-2004).

dren on average than women who were doctors and lawyers. The fertility rate in India decreased significantly for women in the home sector from 1983 to 2004.

3 The Model

We build a model with men and women, endogenous fertility and occupational sorting. The economy consists of a continuum of measure one of individuals who are either male or female, $g \in \{m, f\}$. Men and women endogenously sort into $i \in \{1, 2, ..., I\}$ occupations, one of which is the home sector. Women choose how many children to have and bear the cost of raising them. Men do not make any fertility decision. Each person possesses an idiosyncratic ability for every occupation.

3.1 Individuals

Individuals live for two periods. In the first period, women and men draw an ability vector $\mathbf{z} = \{z_i\}_{i=1}^{I}$, which determines their productivity for working in each occupation. They make their occupational choice and investment in human capital. Women also choose how many children to have. In the second period, individuals work and consume.

Individuals derive utility from consumption C, leisure, $(1 - s)$, and fertility, n, according to the following utility function:

$$\log(U_g) = \beta \log C + \log(1-s) + [\theta_g + \epsilon] \log(1+n) + \log(x_{ig}), \; g \in \{m, f\}, \quad (1)$$

where s denotes time spent on schooling. Parameters $\beta > 0$ and θ_g control the relative weight of consumption and fertility in the individual's utility. We assume that $\theta_m = 0$, while $\theta_f > 0$. Each woman draws a mothering preference $\epsilon \in \{\epsilon_1, ..., \epsilon_K\}$ from a discrete uniform distribution with $\epsilon_1 < \epsilon_2 < ... < \epsilon_k$, which generates heterogeneity in women's preferences for children. Since men do not make any fertility decision, the male fathering preference is set to zero, such that $\epsilon = 0$ for all men.

Lastly, x_{ig} is the common amenity of all members of group g from working in occupation i.

After choosing occupation i, individuals invest in human capital, which depends on schooling time, s, and on education resources, e. The human capital formation function is given by

$$h_i = s^{\phi_i} e^{\eta}, \quad \phi_i, \eta \in (0, 1). \tag{2}$$

The elasticity of human capital with respect to schooling is sector-specific, ϕ_i, such that each sector exhibits a different return to schooling.

Given the occupational choice, individuals' labor income depends on the product of the wage per efficiency unit in sector i, w_i, their idiosyncratic ability in this sector, z_i, and their acquired human capital for sector i, h_i. Income is split into consumption, C, and expenditures on schooling resources, e. An individual's budget constraint is denoted by:

$$C = (1 - \tau_{ig}^{w}) w_i z_i h_{ig} (1 - (1 + \tau_i^n) \chi_g n) - e. \tag{3}$$

Similarly to Hsieh et al. (2019), distortion τ_{if}^{w} represents barriers to female labor market participation. It corresponds to a wedge faced by women between their labor productivity and their wage in occupation i. We set $\tau_{im}^{w} = 0$ such that men do not face barriers in the labor market. Each child takes a fraction $\chi_f \in (0, 1)$ of their mother's time endowment. For men, $\chi_m = 0$. The wedge τ_i^n corresponds to an occupation-specific child penalty faced by women working in sector i. They supply $(1 - \chi_f n_i)$ hours to the labor market, but they incur a cost $(1 - \tau_i^w) w_i h_{if} \tau_i^n \chi_f n_i$ for having n_i children. This barrier captures the occupation-specific heterogeneity in facilitating women to balance household chores and full-time work. Goldin and Katz (2016) and Goldin (2021) document that flexible jobs offer a comparative advantage to mothers, driving τ_n^i down. Maternity leave policies and provision of childcare can reduce the child penalty τ_i^n. Although τ_i^w is common to all female workers in occupation i, τ_i^n affects only female workers with children.

Given their occupational choice i, individuals choose $\{C, e, s, n\}$ to maximize (1) subject to (2) and (3). The solution is characterized by:

$$s_i^* = \frac{1}{1+\frac{1-\eta}{\beta\phi_i}}, \tag{4}$$

$$n_{ig}^* = \max\left\{ 0\ ,\ \frac{(\theta_g+\epsilon)(1-\eta)-\beta\chi_g(1+\tau_{ig}^n)}{\chi_g(1+\tau_{ig}^n)[(\theta_g+\epsilon)(1-\eta)+\beta]}\right\}, \tag{5}$$

$$e_{ig}^* = \left(\eta(1-\tau_{ig}^w)w_i z_i s_i^{\phi_i}(1-(1+\tau_{ig}^n)\chi_g n_{ig}^*)\right)^{\frac{1}{1-\eta}}. \tag{6}$$

Clearly, $n_{im}^* = 0$. Time spent accumulating human capital, s_i^*, is increasing in ϕ_i, the elasticity of human capital with respect to schooling. Individuals in high ϕ_i occupations acquire more schooling and have higher wages as compensation for time spent on schooling. s_{if}^* is not affected by the female barriers. The number of children, n_{if}^*, is decreasing in the child-rearing parameter, χ_f, and in the child penalty, τ_i^n. Expenditure in human capital is distorted by the barriers, τ_i^w, and the child penalty, τ_i^n.

Fertility can differ because women have distinct preferences for family size, ϵ, and also due to their occupation's child penalty τ_i^n. Occupation and fertility are joint decisions. For a given productivity vector z, a woman with strong preference for a large family (high ϵ) can choose an occupation with a low child penalty τ_i^n. Some women might choose not to have children and the share of childless women can also vary by occupation. Therefore, our framework provides a novel and complementary mechanism for fertility differentials. Fertility is driven by female preferences and the occupation decisions of women, which depend on gender barriers in the labor market and barriers to balance the work demands and household chores.

After substituting the optimal decisions of each individual into (3) and (1), an individual's indirect utility reads:

$$U_{ig}^* = (\bar{\eta}\tilde{w}_{ig}z_i)^{\frac{\beta}{1-\eta}},\quad g\in\{m,f\}, \tag{7}$$

where $\bar{\eta} = \eta^\eta(1-\eta)^{1-\eta}$,

$$\tilde{w}_{ig} = (1-\tau_{ig}^w)w_i(s_i^*)^{\phi_i}(1-s_i^*)^{\frac{1-\eta}{\beta}}(1-(1+\tau_{ig}^n)\chi_g n_{ig}^*)(1+n_{ig}^*)^{\frac{[\theta_g+\epsilon](1-\eta)}{\beta}}x_{ig}^{\frac{1-\eta}{\beta}}.$$

Increases in τ^w represent higher barriers for female LFP, which lowers women's indirect utility. Fertility n^*_{if} is non-increasing with the child penalty τ^n_i and therefore the indirect utility is also non-increasing in τ^n_i.

3.1.1 Occupational Skills

In the first period of life, each individual draws a vector of idiosyncratic abilities, $\mathbf{z} = \{z_i\}_{i=1}^I$, from a multivariate Fréchet distribution:

$$F(z_1, \ldots, z_I) = \exp\left[-\sum_{i=1}^{I} z_i^{-\lambda}\right],\ \lambda > 0.$$

The parameter λ governs the dispersion of individual productivity across occupations, with a higher λ implying smaller dispersion.

3.1.2 Occupational Choice

Individuals choose the occupation which maximizes their indirect utility and labor supply is determined by ability-driven self-selection. Unlike men, women are heterogeneous both in their labor productivity across sectors and in their fertility preference $\epsilon \in \{\epsilon_1, ..., \epsilon_K\}$. The following result can be derived:

Proposition 1 *Let $p_{ig}(\epsilon)$ denote the fraction of individuals in occupation i of each group $g \in \{m, f\}$ and fertility preference ϵ. Aggregating across people, the solution to the individual's occupational choice problem leads to*

$$p_{ig}(\epsilon) = \frac{\tilde{w}^{\lambda}_{if}(\epsilon)}{\sum_{s=1}^{I} \tilde{w}^{\lambda}_{sf}(\epsilon)}. \tag{8}$$

Proof. See Appendix A.1. ■

For all men, $\epsilon = 0$ and therefore $p_{im}(\epsilon) = p_{im}$. Since women differ on fertility preference ϵ, the total share of women in a given occupation i is $p_{if} = \sum_{r=1}^{K} \mu(\epsilon_r) \times p_{if}(\epsilon_r)$, where $\sum_r \mu(\epsilon_r) = 1$ denotes the measure of females that have drawn ϵ_r as their mothering preference.

Given the properties of the Fréchet distribution and the endogenous occupational sorting, we can calculate the average quality of workers in an occupation for each group, given their fertility preference.

Proposition 2 *The average quality of workers in each occupation for each group $g \in \{m, f\}$ and fertility preference ϵ is*

$$\mathbb{E}[h_{ig} z_i](\epsilon) = (s_i^*)^{\frac{\phi_i}{1-\eta}} \left(\eta(1-\tau_{ig}^w) w_i (1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon)) \right)^{\frac{\eta}{1-\eta}} p_{ig}(\epsilon)^{-\frac{1}{\lambda(1-\eta)}} \ \bar{\Gamma} \tag{9}$$

where $\bar{\Gamma} = \Gamma\left(1 - \frac{1}{\lambda}\frac{1}{1-\eta}\right)$ is the Gamma function evaluated at the constant $1 - \frac{1}{\lambda}\frac{1}{1-\eta}$.

Proof. See Appendix A.2. ■

3.1.3 Occupational Wages

The average wage for each group in a given occupation is the model counterpart to what we observe in the data.

Proposition 3 *Let $\overline{wage}_{ig}(\epsilon)$ denote the average earnings in occupation i by group g and fertility preference ϵ. Its value satisfies*

$$\overline{wage}_{ig}(\epsilon) = \frac{\hat{\eta} \ \bar{\Gamma} \ \left[\sum_{s=1}^{I} \tilde{w}_{sg}^{\lambda}(\epsilon)\right]^{\frac{1}{\lambda}\frac{1}{1-\eta}}}{[x_{ig}(1-s_i)(1+n_{ig}(\epsilon))^{\theta_g+\epsilon}\ ]^{\frac{1}{\beta}}(1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon))} \tag{10}$$

where $\hat{\eta} = \eta^{\frac{\eta}{1-\eta}}$ and $\bar{\Gamma} = \Gamma\left(1 - \frac{1}{\lambda}\frac{1}{1-\eta}\right)$.

Proof. See Appendix A.3. ■

Average earnings for a given group differ across occupations because of differences in x_{ig}, s_i, n_{ig} and the occupation-specific child barrier τ_{ig}^n. The variation in average earnings for men is unaffected by the fertility variables. Therefore, for men, $\overline{wage}_{im}(\epsilon) = \overline{wage}_{im}$; while for women, $\overline{wage}_{if} = \sum_{r=1}^{K} \mu(\epsilon_r) \times \overline{wage}_{if}(\epsilon_r)$.

In human capital-intensive occupations—those in which schooling is more productive—average wages are higher. Sectors with high common disutility (low x) also have higher wages as compensation. Occupations with strong child barriers (high τ^n) feature relatively higher earnings for women through a similar compensation mechanism.

3.2 Firms

The production sector is summarized by a representative firm, which produces aggregate output Y from labor in each occupation:

$$Y = \left(\sum_{i=1}^{I} (A_i H_i)^\rho \right)^{\frac{1}{\rho}}, \tag{11}$$

where H_i denotes the total efficiency units of labor in sector i. A_i is the exogenous productivity of occupation i.

The representative firm takes w_i as given and hires an amount H_i of efficiency units of labor in each occupation to maximize profits:

$$\max_{H_i} \quad \left(\sum_{i=1}^{I} (A_i H_i)^\rho \right)^{\frac{1}{\rho}} - \sum_{i=1}^{I} w_i H_i. \tag{12}$$

The solution of this problem gives the labor demand for each sector i.

In turn, H_i is defined in equilibrium as

$$H_i = \sum_{g \in \{m,f\}} q_g p_{ig} \mathbb{E}[h_{ig} z_i \mid \text{person chooses } i], \tag{13}$$

where q_g denotes the total measure of individuals in group g, which is 1/2 for males and females. H_i is the product of average human capital and the number of people in the occupation, summed over groups.

3.3 Equilibrium

A competitive equilibrium consists of individual choices $\{C, s, e, n\}$, occupational choices, total efficiency units of labor by group and occupation H_{ig}, final output Y and wages w_i such that:

- Individuals maximize their utility according to equations (4)-(6).
- Individuals choose the occupation that maximizes their indirect utility (7).
- The representative firm maximizes profits, according to (12).
- The occupational wage w_i clears the labor market for each occupation (13).
- The final good market clears.

4 Calibration and Model Fit

This section describes how we discipline the model parameters. The calibration is country- and time-specific. We use micro-level Census data from the Integrated Public Use Micro-data Series (IPUMS) for the US and India. Appendix A contains the source and definition of the variables used, as well as the 20 sectors we analyze. While we can externally set some parameters, most of them are model-specific and were internally calibrated such that the model matches key data moments.

External Calibration. For the time cost of raising a child, χ, Kleven et al. (2019) estimated the long-run female time cost of raising a child to be 0.097 in Denmark. We use their estimate and set $\chi_f = 0.097$.

We follow Hsieh et al. (2019) to estimate η and β. Parameter η corresponds to the fraction of output spent on education. From the OECD, we collect information on the public spending on education as a share of GDP and normalize it by the LFP rate to calculate this fraction. η is set at

0.08 for the US and at 0.06 for India.[4] To calibrate β, we assume that the pre-market period lasts 25 years so that $s_i = (\text{years of education})/25$. The average wage of group g in occupation i is proportional to $(1 - s_i)^{-1/\beta}$. We choose $\beta = 0.633$ for the US and $\beta = 0.27$ for India to match the Mincerian return to schooling across occupations, which averages 12.7% across the six decades in the US, and 18.1% across the two decades in India.[5]

We calibrate λ taking the average of two different strategies. In the first, we estimate $\lambda(1 - \eta)$ using micro-data on individual wages to fit the distribution of residuals from a cross-sectional regression of earnings on occupation-group-age dummies in each year for each country. We then match the coefficient of variation of occupation residual wages.[6] In the second strategy, we estimate the same regression and use MLE to obtain an estimate for $\lambda(1 - \eta)$.[7] Taking the average number from these two methods, we set $\lambda = 2.47$ (2.19) for the US (India).

Parameter ρ governs the elasticity of substitution across occupations and is set to $2/3$, the value used by Hsieh et al. (2019). We also assume that the home occupational preference for all groups is equal to one, such that $x_{1g} = 1$. Table C4 in Appendix C summarizes the value of the externally calibrated parameters.

Internal Calibration. The remaining parameters are disciplined by solving the model and targeting certain data moments. In a general equilibrium setting a change in any parameter might affect all targets. However, some data moments are more sensitive to certain parameters. In particular, the female fertility weight in utility θ_f is set to match the fertility of

[4]Public education spending as a share of GDP in the US averaged 4.95% over the years 1995, 2000, 2005, and 2010. For India, public education spending as a share of GDP over the same period was 3.6%. See http://www.oecd.org/education/eag2013.htm.

[5]The Mincerian return $\psi \pm 1$ year around mean schooling $\bar{s}$ satisfies $e^{2\psi} = \left(\frac{1-\bar{s}+0.04}{1-\bar{s}-0.04}\right)^{-1/\beta}$ so $\beta = \ln\left(\left(\frac{1-\bar{s}+0.04}{1-\bar{s}-0.04}\right)/2\psi\right)$.

[6]The coefficient of variation of wages within an occupation-group in the model satisfies: $Variance/Mean^2 = \Gamma(1 - 2/\lambda(1-\eta))/(\Gamma(1 - 1/\lambda(1-\eta)))^2$.

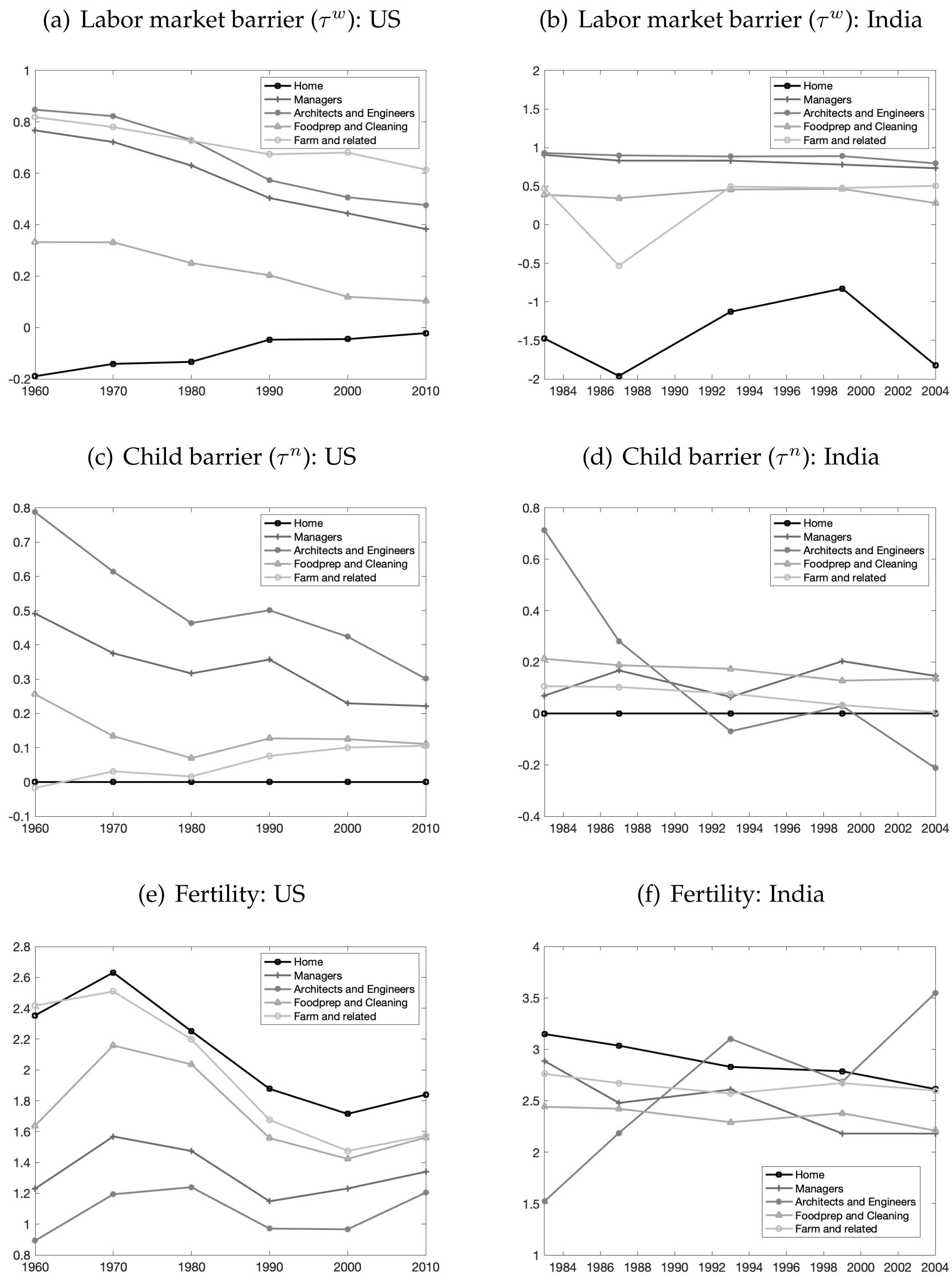
[7]The resulting estimates for $\lambda(1-\eta)$ are similar to those estimates reported in Hsieh et al. (2019). They range from a low of 1.26 in 1980 to a high of 1.44 in 2000, and average 1.38 across years.

women working in the home sector. The child barrier τ_i^n are calibrated to match the occupation-specific fertility rates. The male common amenity parameter, x_{im}, is set to match the average wage by occupation. We set the occupation-specific technology parameter A_i to fit male occupational shares exactly. The productivity of female workers in the home sector and the proportion of women working in each occupation are used to discipline the amenity parameter x_{if}.

The support for the discrete uniform distribution governing the mothering preference, ϵ, is calibrated to match the standard deviation of fertility. The parameter for the time elasticity of human capital, ϕ_i, targets occupation-specific male education. The labor market distortion τ_i^w for each occupation is chosen to match the female wage gap by occupation.

Panels (a) and (b) of Figure 3 show the labor market wedge for selected occupations for the US (1960-2010) and India (1983-2004). The labor market wedge fell substantially in most occupations in the US, while in India there was not a clear trend. Figure C1 in Appendix C reports the values for the average labor market wedge and child penalty for the US and India. It also displays the value for θ_f and the support of ϵ for both economies.

Figure 3: Baseline economies: US (1960-2010) and India (1983-2004). Labor market friction, child penalty and fertility by occupations



Notes. Panels (a) and (b) display the labor market friction, τ_i^w, for selected occupations in the US and India. Panels (c) and (d) display the child penalty, τ_i^n, for selected occupations in the US and India. Panels (e) and (f) display the fertility rates by occupations for selected occupations in the US and India.

Panels (c) and (d) of Figure 3 display the child penalty for selected occupations for the US (1960-2010) and India (1983-2004). In the US, the child penalty fell by more than half from 1960 to 2010 for architects and engineers. Consistent with Kleven (2022), who empirically estimated child penalties in the US, most of the decline in this wedge occurred until the 1990s—see also Figure C1(a) in Appendix C. In India, for the period from 1983 to 2004, we also observe for architects and engineers a substantial reduction in the child penalty. There were no major changes in the child penalty in other occupations in India. Since the fertility weight in utility θ_f is set to match the fertility of women working in the home sector, this affects the fertility rate of all women. The fertility rates by occupation generated in the model are displayed in panel (e) for the US and panel (f) for India. The fertility weight fell over time in the US, which decreased the average fertility in the home sector. The average fertility in other occupations could have changed differently due to the occupation-specific child penalty and this is what we observe for some occupations in the US. The average fertility among architects and engineers remained roughly constant over this period. Interestingly, in India the average fertility rate among architects and engineers increased substantially from 1983 to 2004.

Model Fit. We targeted the proportion of men and women by occupations and the fertility rate by occupations. Figures C2 and C3 in Appendix C show that the model matches the allocation of workers by occupations and the fertility by occupations almost exactly in both the US and India.

5 Quantitative Analysis

5.1 Aggregate Effects

We now perform different counterfactual exercises. We first calculate the share of growth accounted for by changes in the child penalty and in the barriers to female LFP. To do this, we keep distortions τ_i^w and τ_i^n at their initial calibrated values (1960 for the US and 1983 for India) and calculate the counterfactual output in the final year of the sample for each country with all the other parameters fixed. We also run counterfactual exercises in which we keep just one of the wedges at their initial value.

Part I, Panel (a) of Table 1 displays results for the US. We calculate the impact of the wedges on GDP per person and per hours worked. The movements in both wedges together accounted for 31% of the US growth in market GDP per person in the period and the labor market frictions alone accounted for approximately 96% of the overall effect. When we consider only the role of the child penalty on the change of the GDP per hours worked, then the growth contribution of this wedge is larger. It accounts for about 2.4% of the growth in GDP per hours worked from 1960 to 2010 in the US or 1.68% when we consider home production—approximately 12% of the overall impact of both frictions on growth of total output per hours worked. The reduction in the child penalty leads to a rise in fertility, as shown by the decrease of the female LFP when only this distortion is changed.

Part I, Panel (b) of Table 1 contains similar analyses for India for the period from 1983 to 2004. Results are sharply different from the US. In India, both wedges accounted for only 4.1% of the change in the GDP per person between 1983 and 2004. The labor market frictions alone contributed for the majority of the overall effect. For total GDP per hours worked, the fall in the child penalty alone accounted for approximately 1.19% of the growth in this variable from 1983 to 2004. This corresponds to about 36% of the overall effect of the two wedges on total GDP per hours worked.

Welfare. Part II of Table 1 displays a welfare analysis for the changes in barriers to female LFP and in the child penalty. We report an average of the welfare gains for all women in the economy and for women with and without children separately. Changing wedges increase the average welfare for all women in the US by 33% in consumption equivalent terms. That is, female workers in 2010 in the US would, on average, need to be compensated by an increase in 33% of their consump-

Table 1: Output and welfare implications of changing frictions

Part I: Output	Share of growth accounted for by		
	τ_w and τ_n	τ_n only	τ_w only
Panel (a): United States, 1960-2010			
Mkt GDP per person	31.2%	0.76%	30.1%
Labor force participation	71.0%	-4.75%	65.2%
Home + mkt GDP per person	13.3%	-0.14%	12.7%
Mkt GDP per hours worked	32.7%	2.44%	30.6%
Home + GDP per hours worked	14.1%	1.68%	12.4%
Panel (b): India, 1983-2004			
Mkt GDP per person	4.1%	-0.08%	4.1%
Labor force participation	-84.9%	0.32%	-98.6%
Home + mkt GDP per person	1.9%	0.03%	1.8%
Mkt GDP per hours worked	5.9%	1.31%	4.3%
Home + mkt GDP per hours worked	3.3%	1.19%	1.9%
Part II: Welfare	Welfare impact of frictions		
	τ_w and τ_n	τ_n only	τ_w only
Panel (a): United States, 1960-2010			
Female workers, all	33.47%	4.71%	28.39%
Female workers with children	35.10%	7.04%	27.75%
Female workers without children	30.59%	0.63%	29.78%
Female workers, switchers	97.11%	77.28%	90.14%
Male workers, all	0.94%	0.08%	0.93%
Male workers, stayers	-1.27%	-0.12%	-1.20%
Panel (b): India, 1983-2004			
Female workers, all	4.73%	0.54%	3.94%
Female workers with children	4.76%	0.53%	3.92%
Female workers without children	4.67%	0.55%	4.03%
Female workers, switchers	58.50%	65.67%	57.34%
Male workers, all	0.50%	-0.15%	0.62%
Male workers, stayers	-0.50%	-0.25%	-0.44%

tion to live in an economy with the 1960 levels of female barriers and child penalty—instead of those observed in 2010. Most of the contribution comes from changes in female labor market frictions—about 86% of the overall welfare effect. For women that would have switched jobs with lower barriers, the welfare gain is even larger: 97%. Changes in the child penalty are important for the welfare of female workers with children. Lower child penalty increased welfare of female workers with children by about 7% and, for those who switched jobs by 77%. The average annual 2010 US mother's income is $41,109. Therefore, such welfare measures translate into a lump-sum transfer of approximately $2,880 per year for each woman with children and $31,000 per year for those mothers who choose to switch occupations.

We also calculate the the impact on welfare of men from changing female wedges. Changes in female wedges affect the welfare of male workers in two different channels: one possible negative channel comes from more competition in some occupations; and another positive channel from improving aggregate efficiency and wages. For the US the overall welfare effect is positive for all men, since there is an average welfare gain of about 0.9% in consumption equivalent terms. The competition channel is more relevant for those male workers who remain in their original sector facing more competition from female workers. For stayer male workers, there is an average welfare loss of about -1.31%.

For India the welfare implications of changes in female labor market frictions and in the child penalty are smaller than in the US. The average welfare gain for female workers in India is 4.7% in consumption equivalent terms when we consider the 2004 economy with the 1983 wedges. About 12% of this 4.7% rise in average welfare is due to improvements in the child penalty across occupations, τ_i^n. The fall in the child penalty from 1983 to 2004 increased the welfare of female workers with children by approximately 0.5% of consumption in 2004. For stayer male workers, the average welfare loss of changing both wedges is 0.5%.

5.2 Sectoral Effects

To understand the underlying mechanisms behind the aggregate output and welfare results, we now investigate the sectoral effects, focusing on how changes in the wedges affected female workers by occupations.

Panel (a) of Figure 4 presents a scatter plot with the share of female workers by occupations in the US in the counterfactual with wedges observed in 1960 and in the 2010 baseline economy. If distortions did not affect female occupational choices, the point simulations would lie along the 45 degree line. This is not what we observe. We do not report the share of female labor in the home sector, which is the only point above the 45 degree line. The proportion of women in the home sector would be approximately 2.5 times higher in the counterfactual than in 2010. All the other points are below the 45 degree line, implying that the share of female labor in each occupation would be lower in the counterfactual than in 2010. For some occupations, the share of female labor would be almost null in an economy in 2010 with the 1960 distortions. Results for India, considering the period from 1983 to 2004, do not show major changes in occupations due to changes in the gender wedges, Figure 4(b).

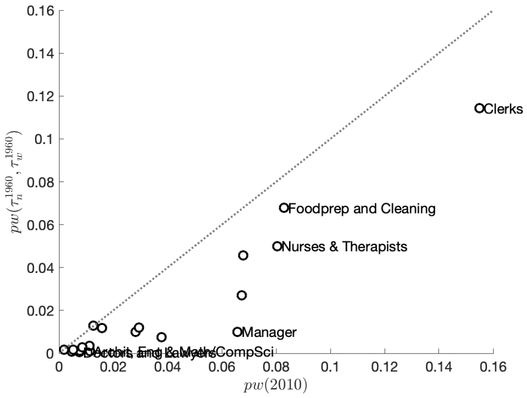
Panels (c) and (e) of Figure 4 display similar results but keeping just one of the wedges at their initial value, $\tau_n^{i,1960}$ and $\tau_w^{i,1960}$, respectively. Most of the female labor reallocation in the US from 1960 to 2010 was driven by the labor market wedge. Panels (d) and (f) of Figure 4 contain results for each of the wedges for India. The share of female labor for most of occupations were quite low in India in 1983 and in 2004 and therefore it is hard to observe a major role of the wedges in changing female labor in India.

6 Concluding Remarks

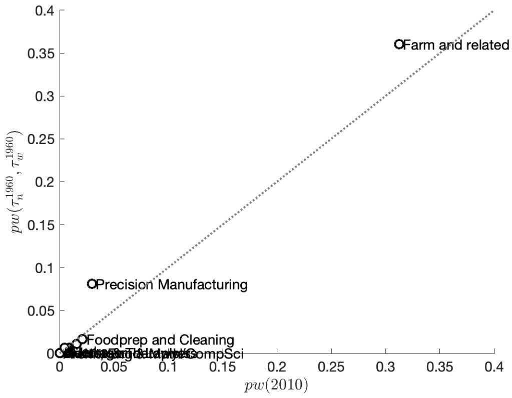
Our work contributes to a growing literature documenting the macroeconomic effects of gender barriers. By incorporating fertility choices, labor market distortions and child penalties in the occupational choice

Figure 4: Sectoral effects for the United States economy: Share of female workers by occupation for each counterfactual

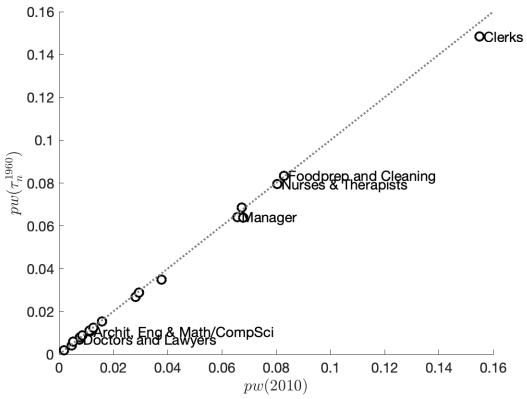
(a) Female labor share, US: 2010 baseline and counterfactual with τ_n^{1960} and τ_w^{1960}



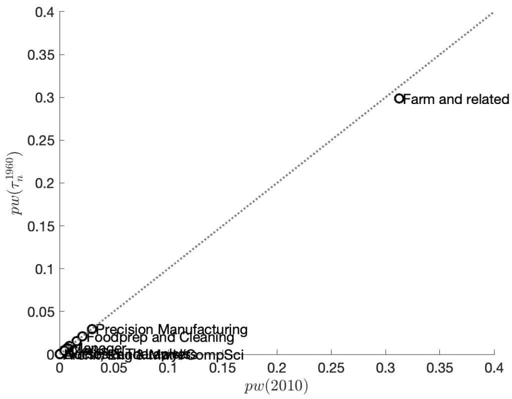
(b) Female labor share, India: 2004 baseline and counterfactual with τ_n^{1983} and τ_w^{1983}



(c) Female labor share, US: 2010 baseline and counterfactual with τ_n^{1960}

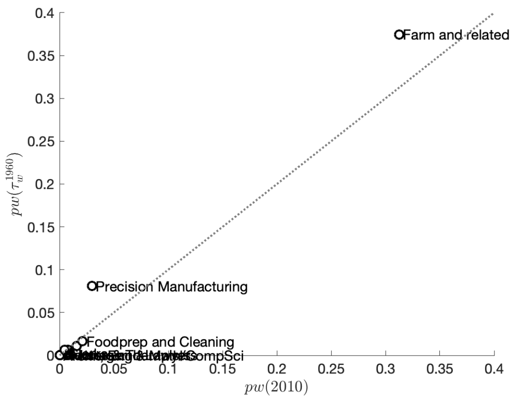


(d) Female labor share, India: 2004 baseline and counterfactual with τ_n^{1983}



(e) Female labor share, US: 2010 baseline and counterfactual with τ_w^{1960}

(f) Female labor share, India: 2004 baseline and counterfactual with τ_n^{1983} and τ_w^{1960}



model of Hsieh et al. (2019), we show how the joint decline in barriers to female labor market participation and child penalties changed fertility, occupational choices and aggregate efficiency. We fit the model to the US and India and quantify gender distortions' aggregate and welfare effects. Changes in barriers to female LFP and in the child penalty accounted for approximately 31% of the US GDP growth over 1960-2010 and 4.1% of India GDP growth over 1983-2004. The decline in labor market frictions accounted for most of the output growth in both countries.

Effects on female welfare were larger, and particularly so for women with children. The average welfare gain in the US for mothers and non-mothers were about 35% and 31%, respectively, from the changes in gender distortions between 1960 and 2010. For India, changing wedges implied welfare gains of 4.8% and 4.5% for mothers and non-mothers, respectively, in the period 1983-2004.

Our results suggest that flexibility of working-time arrangements, taxation and support to families with young children can effectively reduce gender distortions and therefore have important macroeconomic consequences.

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Appendix

A Data Appendix

We use census microdata from the Integrates Public Use Micro-data Series (IPUMS) for The United States and India. For the United States, we use data from the 1960-1990 decennial Censuses and the 2000 and 2010 American Community Surveys (ACS). Data for India comes from the 1983-2004 Socio-Economic Survey (Employment survey produced by the National Sample Survey Organization).

In order to focus on individuals who have completed their education and before their retirement, we restricted our sample for men and women aged between 25 and 54 (inclusive). We excluded those individuals who reported being unemployed (not working but searching for work), on active military duty, and in undefined occupations.

We are interested in two groups: men and women. Women are divided into mothers and non-mothers. Mothers are classified as women (of any age or marital status) with at least one children residing in the household. We classify a person as being in the home sector if they are not currently employed or work less than ten hours per week. Those individuals who are employed but usually work between ten and thirty hours per week are classified as part-time workers. We split the sampling weight of part-time workers equally between the home sector and the occupation in which they are working. Individuals working more than thirty hours per week are considered to be full-time workers in a market occupation.[8] We consider 20 market occupations[9], including the home sector. The occupations are listed in Table A1.

[8]For India we do not observe worked hours, so we classify a person as being in the home sector if she is not currently employed and there is only full time workers.

[9]We follow the 20 broad occupational groups defined by Hsieh et al. (2019). We Harmonize Standard Occupational Classification (SOC) codes from US Census data to Indias's National Classification Ocupation (NCO) system. We also experimented with a more detailed classification of 67 occupations, but we don't observe mothers in some of these occupations.

Table A1: List of Occupations

1.	Home
2.	Executives, Administrative, and Managerial
3.	Management Related
4.	Architects, Engineers, Math, and Computer Science
5.	Natural and Social Scientists, Recreation, Religious, Arts, Athletes
6.	Doctors and Lawyers
7.	Nurses, Therapists, and Other Health Service
8.	Teachers, Postsecondary
9.	Teachers, Non-Postsecondary and Librarians
10.	Health and Science Technicians
11.	Sales, All
12.	Administrative Support, Clerks, Record Keepers
13.	Fire, Police, and Guards
14.	Food, Cleaning, and Personal Services and Private Household
15.	Farm, Related Agrigulture, Logging, and Extraction
16.	Mechanics and Construction
17.	Precision Manufacturing
18.	Manufacturing Operators
19.	Fabricators, Inspectors, and Material Handlers
20.	Vehicle Operators

All variables are defined separately for each occupation-group-year. For ease of exposition, we will refer to the occupation-group-year as a “cell”. The variables are the following:

Women with children: women of any age or marital status with at least one child residing in the household (own children).

Income: We measure earnings as the sum of labor, business, and farm income in the previous year for the United States and earnings in the previous month for India. We compute the average annual earnings for each full time working individual in that cell (for the US, we follow Hsieh et al. (2019) and compute earning only for those who are currently working, who worked 48 weeks during the prior year, and had at least $1000 of income (in 2010 dollars)).

Education: The average years of schooling for all individuals in that cell.

Fertility: Average number of children living in the household for women between 35-45 years old.

Below, we present the share of individuals and for all occupations:

Table A2: Share of individuals by occupation in the US

Occupation	1960			2010		
	Men	Non-mother	Mother	Men	Non-mother	Mother
Home	0.11	0.18	0.71	0.34	0.22	0.44
Executives, Administrative, and Managerial	0.87	0.07	0.06	0.59	0.18	0.23
Management Related	0.84	0.10	0.06	0.44	0.26	0.31
Architects, Engineers, Math, and Computer Science	0.98	0.01	0.01	0.77	0.12	0.11
Natural and Social Scientists, Recreation, Religious, Arts, Athletes	0.78	0.14	0.08	0.49	0.26	0.25
Doctors and Lawyers	0.96	0.02	0.02	0.61	0.19	0.20
Nurses, Therapists, and Other Health Service	0.19	0.36	0.44	0.14	0.32	0.55
Teachers, Postsecondary	0.82	0.13	0.05	0.49	0.27	0.24
Teachers, Non-Postsecondary and Librarians	0.33	0.35	0.32	0.22	0.30	0.47
Health and Science Technicians	0.71	0.15	0.15	0.53	0.20	0.28
Sales, All	0.66	0.14	0.20	0.55	0.20	0.25
Administrative Support, Clerks, Record Keepers	0.36	0.33	0.31	0.27	0.30	0.43
Fire, Police, and Guards	0.98	0.01	0.01	0.79	0.09	0.12
Food, Cleaning, and Personal Services and Private Household	0.34	0.29	0.37	0.42	0.22	0.36
Farm, Related Agriculture, Logging, and Extraction	0.93	0.02	0.05	0.85	0.06	0.08
Mechanics and Construction	0.99	0.00	0.00	0.97	0.01	0.02
Precision Manufacturing	0.80	0.08	0.12	0.66	0.14	0.20
Manufacturing Operators	0.71	0.11	0.18	0.71	0.11	0.19
Fabricators, Inspectors, and Material Handlers	0.83	0.07	0.10	0.73	0.11	0.17
Vehicle Operators	0.99	0.00	0.01	0.90	0.04	0.06

Table A3: Share of individuals by occupation in India

	1983			2004		
Occupation	**Men**	**Non-mother**	**Mother**	**Men**	**Non-mother**	**Mother**
Home	0.11	0.18	0.71	0.34	0.22	0.44
Executives, Administrative, and Managerial	0.87	0.07	0.06	0.59	0.18	0.23
Management Related	0.84	0.10	0.06	0.44	0.26	0.31
Architects, Engineers, Math, and Computer Science	0.98	0.01	0.01	0.77	0.12	0.11
Natural and Social Scientists, Recreation, Religious, Arts, Athletes	0.78	0.14	0.08	0.49	0.26	0.25
Doctors and Lawyers	0.96	0.02	0.02	0.61	0.19	0.20
Nurses, Therapists, and Other Health Service	0.19	0.36	0.44	0.14	0.32	0.55
Teachers, Postsecondary	0.82	0.13	0.05	0.49	0.27	0.24
Teachers, Non-Postsecondary and Librarians	0.33	0.35	0.32	0.22	0.30	0.47
Health and Science Technicians	0.71	0.15	0.15	0.53	0.20	0.28
Sales, All	0.66	0.14	0.20	0.55	0.20	0.25
Administrative Support, Clerks, Record Keepers	0.36	0.33	0.31	0.27	0.30	0.43
Fire, Police, and Guards	0.98	0.01	0.01	0.79	0.09	0.12
Food, Cleaning, and Personal Services and Private Household	0.34	0.29	0.37	0.42	0.22	0.36
Farm, Related Agriculture, Logging, and Extraction	0.93	0.02	0.05	0.85	0.06	0.08
Mechanics and Construction	0.99	0.00	0.00	0.97	0.01	0.02
Precision Manufacturing	0.80	0.08	0.12	0.66	0.14	0.20
Manufacturing Operators	0.71	0.11	0.18	0.71	0.11	0.19
Fabricators, Inspectors, and Material Handlers	0.83	0.07	0.10	0.73	0.11	0.17
Vehicle Operators	0.99	0.00	0.01	0.90	0.04	0.06

B Derivations and Proofs

B.1 Proof of Proposition 1 – Occupational Shares

For a given level of mothering preference ϵ, the individual's utility from choosing a particular occupation, $U(\tau_{ig}, w_i, z_i)$, is proportional to $(\tilde{w}_{ig}(\epsilon)z_i)^{\frac{\beta}{1-\eta}}$, where $\tilde{w}_{ig}(\epsilon) = \frac{w_i(s_i^*)^{\phi_i}(1-s_i^*)^{\frac{1-\eta}{\beta}}(1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon))^{\alpha}(n_{ig}^*(\epsilon))^{\frac{\theta_g(1-\eta)}{\beta}} x_{ig}^{\frac{1-\eta}{\beta}}}{\tau_{ig}}$.

Without loss of generality, consider the probability that the individual of group g chooses occupation 1 and denote this by p_{1g}. Then

$$\begin{aligned} p_{1g}(\epsilon) &= \Pr[\tilde{w}_{1g}(\epsilon)z_1 > \tilde{w}_{sg}(\epsilon)z_s], \quad \forall s \neq 1 \\ &= \Pr[\tfrac{\tilde{w}_{1g}(\epsilon)z_1}{\tilde{w}_{sg}(\epsilon)} > z_s], \quad \forall s \neq 1 \\ &= \textstyle\int F_1(z, \upsilon_2 z, \ldots, \upsilon_J z).dz \end{aligned}$$

where $F_1(\cdot)$ is the derivative of the cdf with respect to its first argument and $\upsilon_i \equiv \tilde{w}_{1g}(\epsilon)/\tilde{w}_{ig}(\epsilon)$.

Recall that

$$F(z_1, \ldots, z_J) = \exp\left[\sum_{j=1}^{I} z_j^{-\lambda}\right]$$

Taking the derivative with respect to z_1 and evaluating at the appropriate arguments gives

$$\begin{aligned} F_1(z, \upsilon_2 z, \ldots, \upsilon_J z) &= \lambda z^{-\lambda-1}\exp[-\textstyle\sum_{s=1}^{I}\upsilon_s^{-\lambda}z^{-\lambda}] \\ &= \lambda z^{-\lambda-1}\exp[-\bar{\upsilon}z^{-\lambda}], \quad \text{where } \bar{\upsilon} \equiv \textstyle\sum_{j=1}^{J}\upsilon_j^{-\lambda} \end{aligned}$$

p_{1g} is now:

$$\begin{aligned} p_{1g}(\epsilon) &= \int_0^{\infty} \lambda z^{-\lambda-1}\exp[-\bar{\upsilon}z^{-\lambda}]dz \\ &= \int_0^{\infty} \lambda z^{-\lambda-1}\exp[-(\bar{\upsilon}^{\frac{-1}{\lambda}}z)^{-\lambda}]dz \end{aligned}$$

We proceed with integration by change of variables $z' = \bar{\upsilon}^{\frac{-1}{\lambda}} z$ e $dz' = \bar{\upsilon}^{\frac{-1}{\lambda}} dz$:

$$
\begin{aligned}
p_{1g}(\epsilon) &= \int_0^\infty \lambda(\bar{\upsilon}^{\frac{1}{\lambda}} z')^{-\lambda-1} \exp[-(z')^{-\lambda}] \bar{\upsilon}^{\frac{1}{\lambda}} dz' \\
&= \bar{\upsilon}^{-1} \int_0^\infty \lambda(z')^{-\lambda-1} \exp[-(z')^{-\lambda}] dz' \\
&= \bar{\upsilon}^{-1} \int_0^\infty dF(z') \\
&= \bar{\upsilon}^{-1} \\
&= \frac{1}{\sum_{s=1}^{I} \upsilon_s^{-\lambda}} \\
&= \frac{\tilde{w}_{1g}^{\lambda}(\epsilon)}{\sum_{s=1}^{I} \tilde{w}_{sg}^{\lambda}(\epsilon)}
\end{aligned}
$$

More generally,

$$
p_{ig} = \frac{\tilde{w}_{ig}^{\lambda}(\epsilon)}{\sum_{s=1}^{I} \tilde{w}_{sg}^{\lambda}(\epsilon)}, \quad \forall i \in \{1, \ldots, J\}
$$

B.2 Proof of Proposition 2 – Average Quality of Workers

Efficiency units of labor of an individual in occupation i is given by $h_{ig} = s^{\phi_i} e^{\eta}$. Using the results from the individual's optimization problem, we have that:

$$
\begin{aligned}
h_{ig} z_i &= (s_i^*)^{\phi_i} \left(\frac{\eta(1-\tau_{ig}^w) z_i w_i (1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon))^{\alpha} (s_i^*)^{\phi_i}}{(1+\tau_i^h)} \right)^{\frac{\eta}{1-\eta}} z_i \\
h_{ig} z_i &= (s_i^*)^{\phi_i} \left(\frac{\eta(1-\tau_{ig}^w) w_i (1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon))^{\alpha} (s_i^*)^{\phi_i}}{(1+\tau_i^h)} \right)^{\frac{\eta}{1-\eta}} z_i^{\frac{1}{1-\eta}}
\end{aligned}
$$

The average of efficiency units of labor in an occupation is given by:

$$
\mathbb{E}[h_{ig} z_i \mid \text{choose occ } i] = (s_i^*)^{\phi_i} \left(\frac{\eta(1-\tau_{ig}^w) w_i (1-(1+\tau_{ig}^n)\chi_g n_{ig}^*(\epsilon))^{\alpha} (s_i^*)^{\phi_i}}{(1+\tau_i^h)} \right)^{\frac{\eta}{1-\eta}} \mathbb{E}[z_i^{\frac{1}{1-\eta}}]
$$

The next step is to calculate $\mathbb{E}[z_i^{\frac{1}{1-\eta}} \mid \text{choose occ } i]$. Let's calculate $\mathbb{E}[z^x \mid$

choose occ i]. As shown during the derivations of occupational share, the new conditional distribution of z_i given that workers sorts into occupation i is given by $G(z) = F(\upsilon_1 z, \upsilon_2 z, \ldots, \upsilon_J z) = \exp(-\sum_{j=1}^{J} \upsilon_j^{-\lambda} z^{-\lambda}) = \exp(-\frac{1}{p_j} z^{-\lambda})$. So we now have the following:

$$\begin{aligned}
\mathbb{E}[z_i^x] &= \int_0^\infty z^x dG(z) \\
&= \int_0^\infty \lambda \frac{1}{p_j} z^{-\lambda-1+x} \exp(-\frac{1}{p_j} z^{-\lambda}) dz
\end{aligned}$$

Let $y = \frac{1}{p_j} z^{-\lambda}$, so that $\mathbb{E}[z_i^x]$ simplifies to:

$$\begin{aligned}
\mathbb{E}[z_i^x] &= \frac{1}{p_j}^{\frac{x}{\lambda}} \int_0^\infty y^{-\frac{x}{\lambda}} e^{-y} dy \\
&= p_j^{-\frac{x}{\lambda}} \, \Gamma\left(1 - \frac{x}{\lambda}\right)
\end{aligned}$$

So for $x = \frac{1}{1-\eta}$, we have:

$$\mathbb{E}[z_i^{\frac{1}{1-\eta}}] = p_j^{-\frac{1}{\lambda(1-\eta)}} \, \Gamma\left(1 - \frac{1}{\lambda} \frac{1}{1-\eta}\right)$$

Therefore, average quality is given by:

$$\mathbb{E}[h_{ig} z_i](\epsilon) = (s_i^*)^{\phi_i} \left(\frac{\eta(1-\tau_{ig}^w) w_i (1-(1+\tau_{ig}^n)\chi_g n_{ig}^*)^\alpha (s_i^*)^{\phi_i}}{(1+\tau_{ig}^h)} \right)^{\frac{\eta}{1-\eta}} p_{ig}(\epsilon)^{-\frac{1}{\lambda(1-\eta)}} \, \bar{\Gamma}$$

where $\bar{\Gamma} = \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta})$ is the Gamma function evaluated at the constant $1 - \frac{1}{\lambda}\frac{1}{1-\eta}$.

B.3 Proof of Proposition 3 – Average Earnings

For a given ϵ, let $\overline{wage}_{ig}(\epsilon)$ denote the average earnings in occupation i by group g. Its value satisfies

$$\overline{wage}_{ig}(\epsilon) = (1 - \tau^w_{ig})w_i \cdot \mathbb{E}[h_{ig}z_i](\epsilon)$$

From the previous proposition, we have the expression for the average quality. Therefore,

$$\overline{wage}_{ig}(\epsilon) = \frac{\hat{\eta}\ \bar{\Gamma}\ \left[\sum_{s=1}^{I} \tilde{w}^{\lambda}_{sg}(\epsilon)\right]^{\frac{1}{\lambda}\frac{1}{1-\eta}}}{x_{ig}^{\frac{1}{\beta}}(1-s_i)^{\frac{1}{\beta}}(1-(1+\tau^n_{ig})\chi_g n^*_{ig}(\epsilon))^{\alpha}(n^*_{ig}(\epsilon))^{\frac{\theta_g}{\beta}}}$$

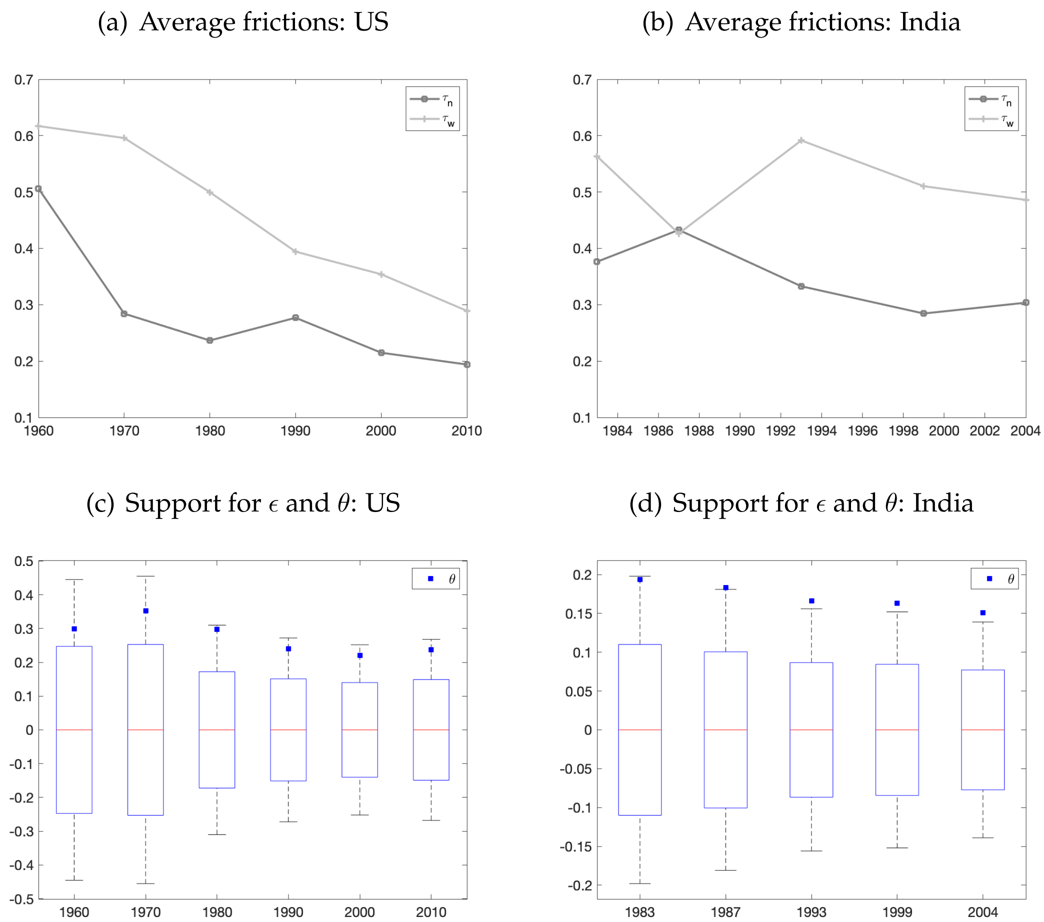
where $\hat{\eta} = \eta^{\frac{\eta}{1-\eta}}$ and $\bar{\Gamma} = \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta})$.

C Calibration Details and Model Fit

Table C4: Baseline Parameters and Identifying Assumptions

Parameter	Definition	Determination	Value (USA)	Value (India)
λ	Frechét shape parameter	Coefficient of variation in earnings	2.47	2.19
η	Goods elasticity of human capital	Education Spending	0.08	0.06
β	Consumption weight in utility	Mincerian return to education	0.633	0.271
χ	Child-rearing penalty	Child penalty in terms of hours supplied	0.097	0.097
ρ	Elasticity of substitution across occupations	Hsieh et al. (2019)	2/3	2/3

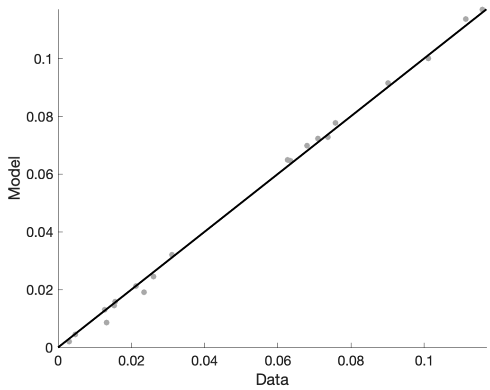
Figure C1: Baseline economies: US (1960-2010) and India (1983-2004).



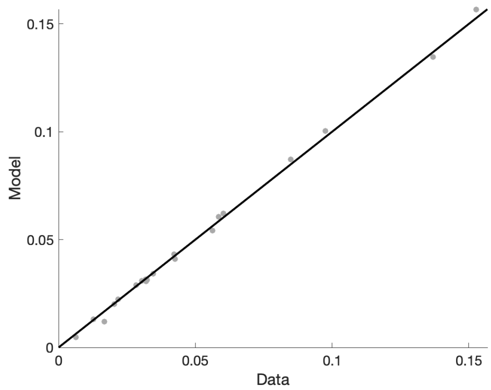
Notes. Panels (a) and (b) display the average labor market friction, τ_i^w, and the average child penalty for the US and India, respectively. Panels (c) and (d) display the value for θ_f (solid square) and the support for ϵ for the US and India, respectively.

Figure C2: Model fit for the United States economy: Share of workers and fertility rate by occupation in the data (x-axis) and in the model (y-axis), 1960 and 2010

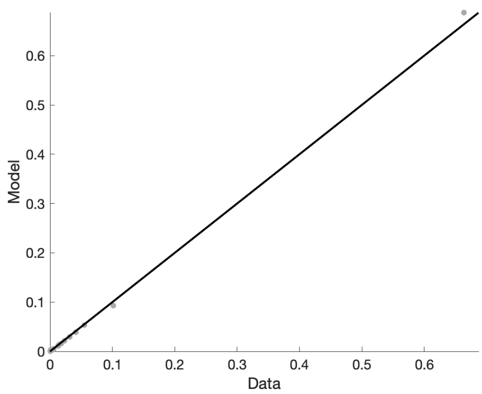
(a) Male workers (%) by occupation, 1960



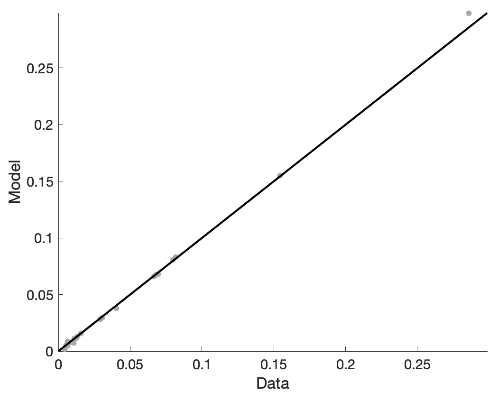
(b) Male workers (%) by occupation, 2010



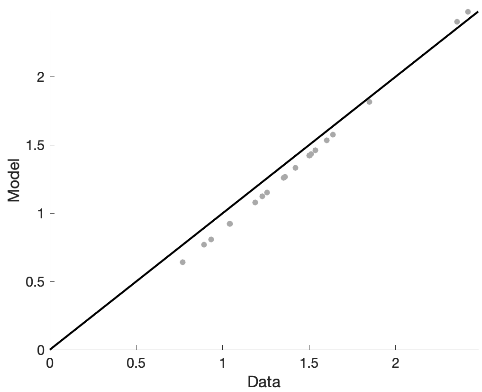
(c) Female workers (%) by occupation, 1960



(d) Female workers (%) by occupation, 2010



(e) Fertility rate by occupation, 1960



(f) Fertility rate by occupation, 2010

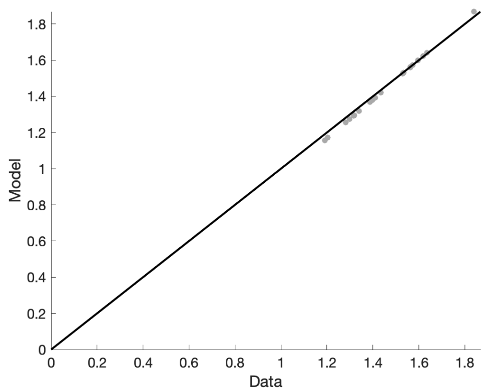
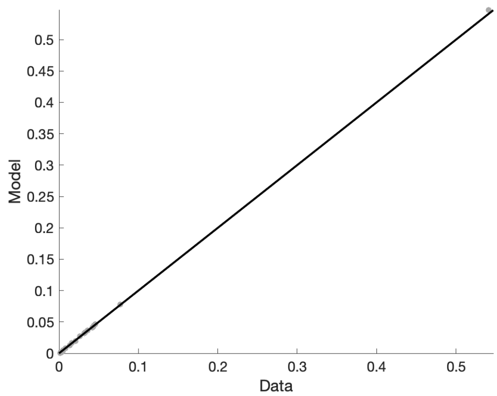
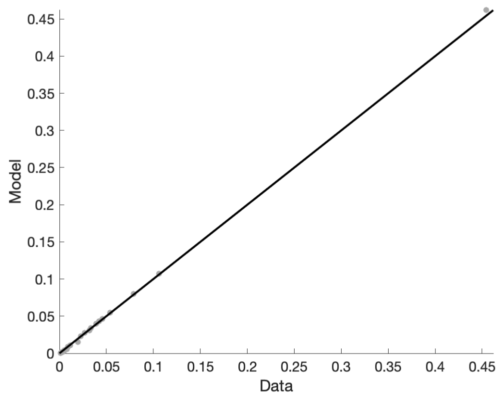


Figure C3: Model fit for the India economy: Share of workers and fertility rate by occupation in the data (x-axis) and in the model (y-axis), 1983 and 2004

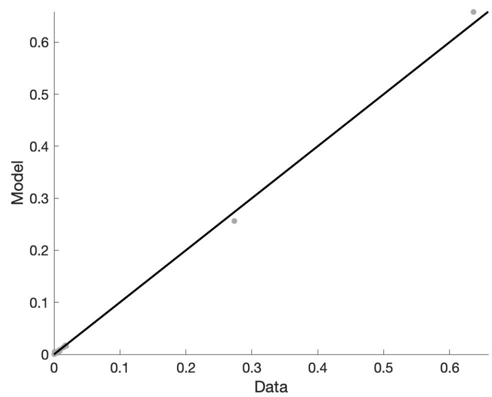
(a) Male workers (%) by occupation, 1983



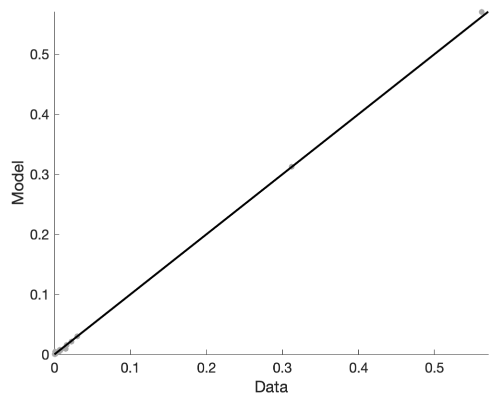
(b) Male workers (%) by occupation, 2004



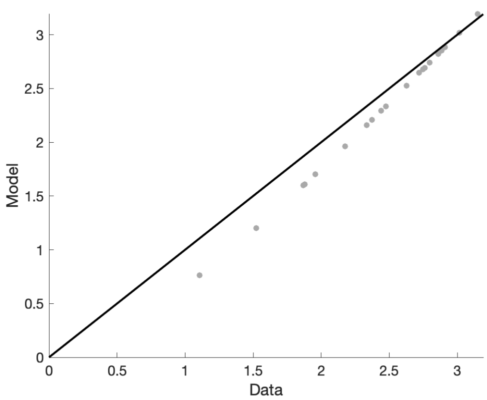
(c) Female workers (%) by occupation, 1983



(d) Female workers (%) by occupation, 2004



(e) Fertility rate by occupation, 1983



(f) Fertility rate by occupation, 2004