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THE REVERSAL OF THE GENDER EDUCATION GAP WITH ECONOMIC DEVELOPMENT

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Abstract. Using household surveys covering 83 countries of all income levels, we document that the gender education gap in low-income countries is strikingly large and that it narrows and reverses with economic development. To study the driving forces, we propose a three-sector model in which development features skill-biased structural change and varying levels of educational assortative matching. We calibrate the model to match contrasting labor market outcomes by education and gender groups. The quantitative results suggest that females have a comparative advantage in services. Counterfactual exercises show that skill-biased structural change explains most of the narrowing gender education gap, whereas changing assortative matching plays only a minor role.

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1 Introduction

In almost all industrialized countries, economic development has been accompanied by dramatic progress in gender equality, most notably in educational attainment. To date, among 25- to 34-year-olds, women are more likely to have a tertiary degree than men in all 38 OECD countries (Wolfers, 2021). In low-income countries, however, women are half as likely to have a tertiary degree and half as likely to have a secondary degree as men. Higher education among females is strongly correlated with female empowerment leading to more equitable and desirable gender outcomes.[1] Therefore, investigating the causes of cross-country differences in the gender gap in education is of paramount importance in understanding the progress of gender equality.

Yet it remains an open question in the literature: What are the forces driving the narrowing gender gap in education with economic development? Existing studies link women's rising education rates to fertility behaviors (Rıos-Rull and Sanchez-Marcos, 2002), to divorce risks (Guvenen and Rendall, 2015), to technical change favoring women (Rendall, 2018a), and to women's formal working hours (Reimers, 2020). However, none of these studies provide a systematic cross-country analysis. This paper draws on new evidence and theory to better understand the link between the gender education gap and economic development.

We use nationally representative household surveys from 218 country-year samples covering countries of all income levels to document particularly large variations in the gender education gap across countries. We find that the gender education gap narrows sharply with economic development, and reverses in some high-income countries. In high- and middle-income countries, younger cohorts are making fast progress compared to the older ones, while in low-income countries, even for young cohorts born in the 1990s, women are only 60 percent as likely as men to complete university education. By conducting a shift-share accounting exercise, we find that cross-country gender differences in occupation and employment sector account for around 40 percent of the narrowing gender education gap with development, pointing to labor market outcomes as a crucial contributor to the observed education patterns.

We further show that the well-known U-shaped female labor force participation rate (LFPR) with development is driven by the low-educated females, while the LFPR of the educated females monotonically increases with development. Furthermore, the female intensity, measured by the share of female workers among the total of female and male workers, increases

[1] For example, Lise and Seitz (2011) show that increasing the education levels of women leads to a decrease in consumption inequality within households; Doepke and Tertilt (2018) show that the desired fertility of higher-educated women has a larger impact on realized fertility compared to that of less-educated women.

strongly in the service sector with development, while the service sector itself also grows. These trends highlight the role of *skill-biased structural change* — simultaneous structural transformation (ST) and skill-biased technological change (SBTC), as in Buera et al. (2021) — in narrowing the gender education gap.

In addition to the labor market outcomes, education decisions can also be affected by expectations of household formation (Greenwood et al., 2016). This paper is the first to consider the role of varying assortative matching in gender gaps across countries. To lay the marriage market foundation for our model, we follow Eika et al. (2019) in estimating an educational assortative matching parameter. Consistent with their results, we find that while the assortative matching between *uneducated* women and men marginally increases with development, it sharply decreases between *educated* women and men. This empirical observation is driven in the data by the increasing share of educated women and men with development. The patterns hold both across countries and over time. The decline in assortative matching among the educated decreases both men's and women's incentives to obtain an education as the utility gain from matching decreases. However, the decrease in men's incentives is smaller as they get additional utility from women's home production. Hence, we expect, in isolation, this mechanism to work against narrowing the gender education gap with development.

Motivated by these facts, this paper studies the effects of two mechanisms to understand the narrowing gender education gap with development: (i) skill-biased structural change, and (ii) changing marriage markets. Skill-biased structural transformation leads to a rise in skilled services in which women have a comparative advantage, thus increasing the relative labor demand of educated women. The educational assortative matching process shapes women's incentives to obtain education even when working hours are low because of skewed matching probabilities towards similarly educated men.

To formalize and quantify this idea, we develop a general equilibrium model featuring skill-biased structural transformation and changing assortative matching across economies.[2] Female and male agents are heterogeneous in their cost of obtaining an education as in Rendall (2018a). Agents make education choices to maximize expected utility. Then a male and a female mechanically form a household according to varying levels of educational assortative matching. The household jointly makes female labor force participation and consumption decisions to maximize the household utility subject to the budget constraint. Income is a function of the household education combination and the woman's labor force participation — workers earn a gender- and education-specific wage in equilibrium. Females who are not

[2]We build the model based on the frameworks proposed by Kongsamut et al. (2001), Ngai and Pissarides (2007), Ngai and Petrongolo (2017), Rendall (2018b), and, especially, Buera et al. (2021).

in the labor force produce only home goods by construction.

On the production side, there are three types of firms; they use technologies with potentially different skill and gender intensities to produce agriculture, manufacturing, and service goods. Specifically, the production of each type of firm is modeled as an aggregate constant-elasticity-of-substitution (CES) production function of high- and low-educated labor, and each education type of labor has a CES production function of female and male labor.

To assess the model's quantitative predictions, we parameterize the model by matching key moments in the U.S. data between 1980 and 2005. In particular, the distributions of the education cost of women and men are largely determined by the education shares by gender, while those of the home productivity of the educated and uneducated women are determined by the female LFPR by education. We discipline the consumption parameters and production technologies using the U.S. time series moments including the gender wage gap, labor force shares, wage bill shares of the skilled, sectoral college premia, and sectoral value-added shares. Consistent with the literature, our calibration suggests that i) firms face skill-biased structural change across economies of different development levels and ii) females have a comparative advantage in service production.

Given the calibrated model, we conduct quantitative experiments to estimate the contributions of (i) ST, (ii) sectoral SBTC, and (iii) varying assortative matching in explaining the reversal of the gender education gap in the U.S. We find that while SBTC alone explains one-third of the closing gap, it produces a fall in the LFPR of both educated and uneducated women, contradicting the data. This is because, given men's comparative advantage in a labor market biased towards manufacturing and agriculture, SBTC does not provide sufficient incentive for women to enter the labor market. ST alone can account for over half of the closing gap, but also falls short of producing a reversal. In contrast to the SBTC mechanism, ST incentivizes women to enter the labor market as the opportunity cost of staying at home increases with the growth of services, which affects both educated and uneducated women. Furthermore, we find that SBTC, especially in services, and ST are complements in reversing the gender education gap in the U.S., with a joint explanatory power of around 130 percent. Meanwhile, a fall in assortative matching among the educated attenuates the effects of SBTC and ST on closing the gender education gap in general equilibrium.[3]

We validate the model by assessing its predictions on the gender education gap in other high-income countries between 1980 and 2005. To do so, we vary only sectoral productivity

[3]In the robustness analysis, we also allow for gender-biased technological change and changes in home productivity. The results confirm skill-biased structural change to be the single most important driver in closing the gender education gap.

and skill intensity, which are directly calculated from the data through model identities, across country-year samples, while keeping all the other parameters at the U.S. level in the corresponding year. We find that the model's prediction of the gender education gap explains 86 percent of the variations in the data, providing a satisfactory fit. In particular, skill-biased structural change explains all of the reversal of the gender education gap in Finland and Great Britain, while it explains most of it in Belgium, Japan, and Korea, but none of it in Italy.

To understand cross-country patterns across the economic development spectrum, we take the benchmark parameterized model but allow for different skill-biased structural change and assortative matching across countries. Specifically, we calibrate the sectoral productivity and skill-intensity parameter values to closely match the key female labor market outcomes by income level, as the direct moments to estimate them are not available. We discipline the assortative matching parameter empirically. Our model predictions match well with the gender education gap in high-income countries, but slightly over-predict the gender education gap in middle- and low-income countries by overestimating the share of educated workers in agriculture. Furthermore, variations in the model predictions in the gender education gap across countries are largely driven by skill-biased structural change, while varying assortative matching plays only a minor role.

Related Literature. Our work fits within the literature on cross-country patterns of gender gaps in labor market outcomes. For example, Antecol (2000) discusses the cross-country gender gap in LFPR. More recently, Bridgman et al. (2018) show that while the market hours of women increase strongly with GDP per capita, that of men decreases somewhat; Bento et al. (2021) study the gender gap in entrepreneurship; and Chiplunkar and Kleineberg (2022) investigate the role of gender barriers versus economic forces in driving the gender gaps in employment and wages. Our work complements this literature by being the first to study the causes of the reversal of the gender education gap with economic development across countries.

Our paper builds on the literature trying to understand the link between structural change and economic development (see, for example, Herrendorf et al., 2014; Duarte and Restuccia, 2010, among others). Of particular relevance to our work is Buera et al. (2021), who use a broad panel of advanced economies to study how skill-biased structural transformation can explain the college premium. Porzio et al. (2022) use data on agricultural employment by birth-cohort and education policy reforms to show that human capital growth in the 20th century contributed to the global structural transformation. In addition, Ngai et al. (2022) document patterns of women's and men's working hours over 150 years in the U.S. and relate these patterns to structural transformation; however, they do not touch on education either empirically or theoretically. In this paper, we document the strikingly large gender education gap in low-income countries and show that structural change is a crucial driver of the narrowing gender education gap across countries.

Lastly, our paper is broadly related to the growing literature drawing on detailed micro evidence to document and understand cross-country labor market outcomes. For example, Bick et al. (2018) use household surveys from 80 countries to document that hours worked are higher on average in poorer countries. A few studies use surveys across countries to investigate cross-country patterns of the levels of and transitions between self-employment, unemployment, and wage employment (Feng et al., 2022; Poschke, 2022; Donovan et al., 2022). However, none of these studies focus on the link between the gender education gap and economic development.

The remainder of the paper is organized as follows. Section 2 documents the cross-country patterns in education, labor market outcomes by education, and marriage. Section 3 introduces our benchmark general equilibrium model with endogenous education and labor supply decisions while Section 4 details and validates the quantitative analysis. Section 5 tests the model's prediction across countries for all income levels. Section 6 concludes.

2 Data and Empirical Findings

In this section, we present empirical findings using microdata from 83 countries covering all income levels. We first document a robust narrowing and reversal of the gender education gap with economic development, both across countries and within a country over time. We then show the relevant labor market outcomes and assortative matching patterns across countries and within the U.S. over time.

Data. We draw on household censuses and surveys from *IPUMS International*, which include individual-level information on age, gender, educational attainment, employment status, and industry. For consistency, we keep only samples from 1980 to 2017, which cover 218 country-year censuses and surveys across 83 countries. We also show U.S. time-series patterns using data from 1980 to 2015, which is the period when most of the structural transformation toward services occurred in the U.S. For estimates of GDP per capita, we use output-side real GDP at chained PPPs in 2011 US$ (rgdpo) from the Penn World Table version 9.1 (PWT 9.1).

We restrict attention to prime-age (ages 25-54) women and men throughout. We exclude samples with missing information on educational attainment and those living in group quarters. We use sample weights whenever they are available.

2.1 The gender education gap

We define the gender gap in education as the ratio of the share of females who have acquired education to that of males. Figure 1 plots the gender gaps in university completion and in secondary school completion against log GDP per capita in Panel (a) and (b), respectively. The two dashed vertical lines divides the countries into the bottom, middle, and top terciles of the world income distribution.[4]

Panel (a) of Figure 1 highlights that in the poorest economies women are less than half as likely to obtain a college degree as their male counterparts. This gender education gap narrows quickly with development levels and even reverses in richer economies, where women are more likely than men to have a college degree. Importantly, the cross-country patterns are broadly consistent with the U.S. time series data — the gender gap appears to be large in 1980, but steadily decreases, reaches equality in the 2000s, and has since then reversed. Furthermore, the patterns of the gender gap in completing secondary school with development are similar to that in completing university, as shown in Panel (b) of Figure 1.

Table 1: Regressions of the Gender Education Gap on the Development Level and a Constant

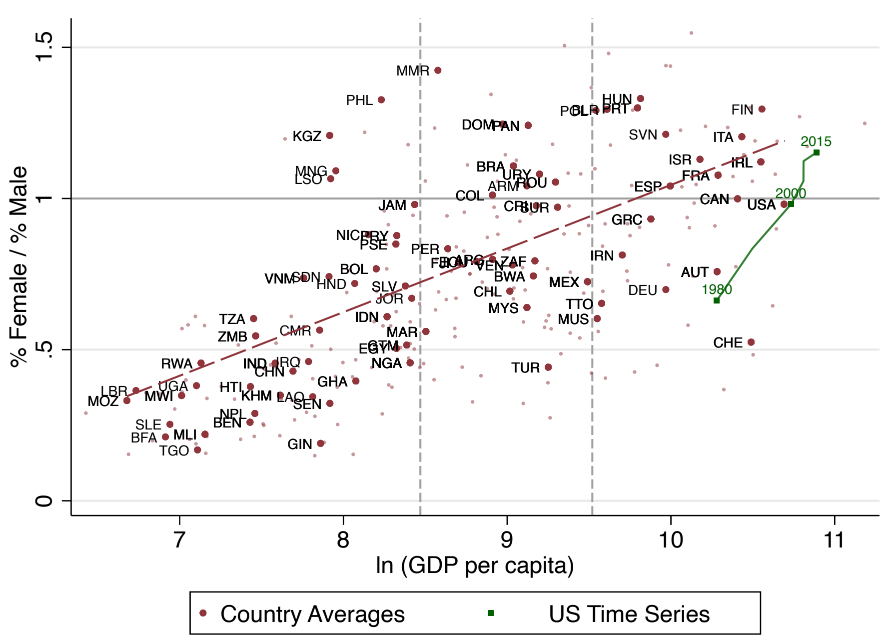
	By University		By Secondary	
	Country-year	Country-average	Country-year	Country-average
ln (GDP per capita)	0.20***	0.21***	0.18***	0.18***
	(0.014)	(0.024)	(0.011)	(0.019)
R^2	0.41	0.44	0.46	0.46
Obs.	218	83	218	83

Note: The gender gap is defined as the share of females who complete university/secondary school divided by that of males. *** indicates statistical significance at the one-percent level. Standard errors are shown in parentheses.

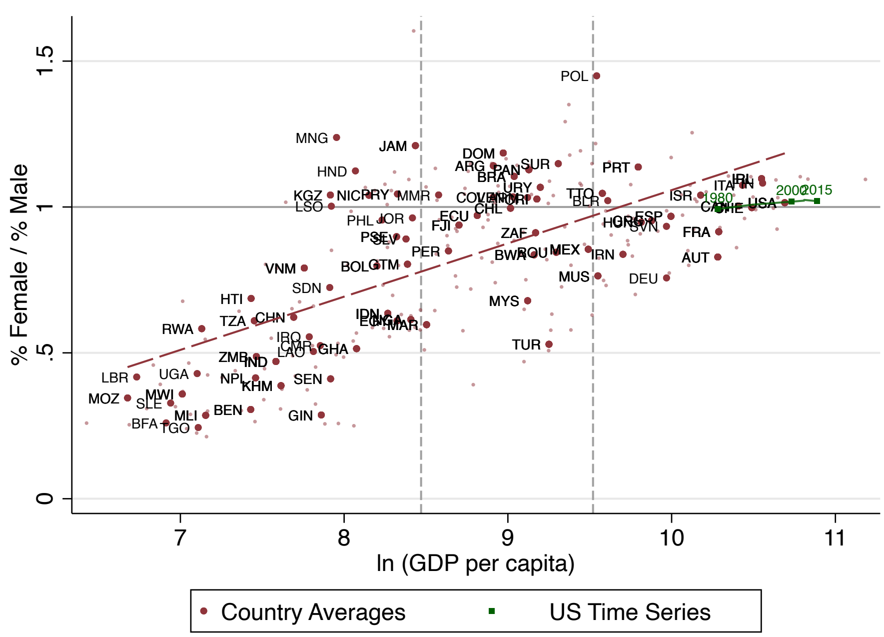
[4] Based on country-average GDP per capita from 1980 to 2017 for all countries in the PWT 9.1, the intervals for low- (bottom third of the world's income distribution), middle- (middle third), and high-income (top third) countries are $\leq \$4,776$, between \$4,776 and \$13,652, and $\geq \$13,652$, respectively. These thresholds are close to the World Bank's published thresholds for lower-middle-, upper-middle- and high-income countries.

Figure 1: Gender Gaps in Education

(a) University Completed



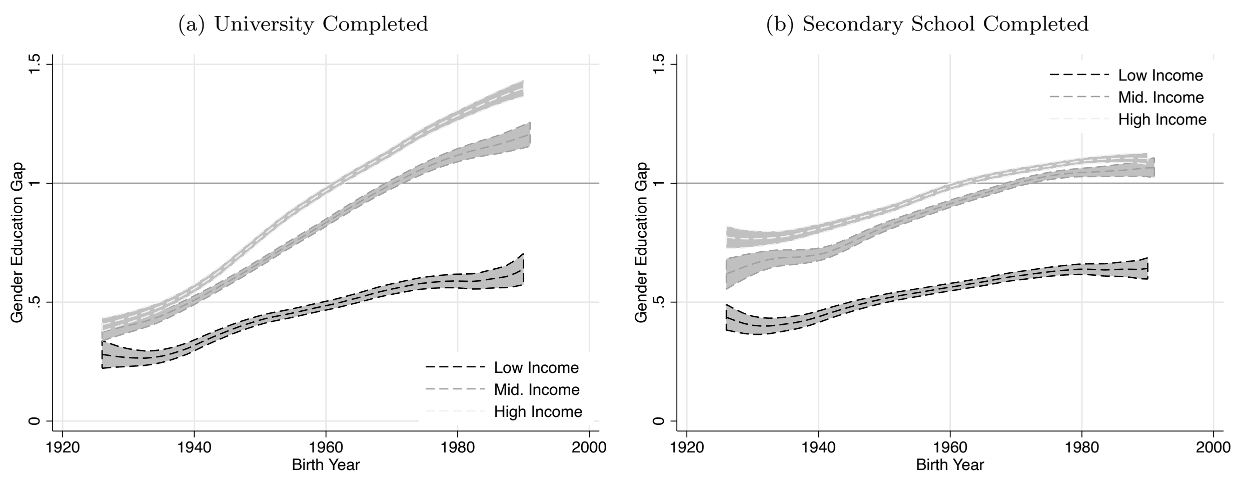
(b) Secondary School Completed



Note: This figure plots the female-to-male population shares of completing university and secondary school against log GDP per capita for each country-year sample (light red dot) and country averages (dark red dot). Red lines represent linear fitted lines of country averages. Green data points show the U.S. time trends.

Table 1 reports the slope coefficients of regressing the ratio of women's to men's share of completing university and secondary school on log GDP per capita and a constant using different cuts of the data. When we include all 218 country-year samples separately for the gender gap in university completion, the slope coefficient is 0.20, which is close to the slope of using country averages at 0.21, as shown in Figure 1. We then consider the gender education gap in completing secondary school; the slope coefficients are 0.18 for both the country-year and country-average regressions. All four slopes are statistically significant at the one percent level.

Figure 2: Gender Education Gap by Cohort



Note: This figure plots the average gender education gap with the 95% confidence intervals by birth-year cohorts in low-, middle-, and high-income countries.

We further explore how gender education gaps evolve over time by comparing cross-sectional cohorts in all country-year samples. Figure 2 plots the gender education gap by birth-year cohorts in low-, middle-, and high-income countries. In middle-and high-income economies, gender education gaps disappear starting from cohorts born in the 1970s and 1960s, respectively. The low-income economies, however, still lag far behind. In low-income countries, the gender education gap narrows, but even for cohorts born in the 1990s, females are only about 60 percent as likely as males to complete college or secondary school education. The empirical results for university completion and secondary school completion are similar. Hereafter, we report the results for university completion as the education threshold in the benchmark analysis.

Composition Effects. How much of the narrowing gender education gap with development can be accounted for by cross-country gender differences in demographic compositions? To answer this question, we conduct a shift-share accounting exercise to find the composition effects of age, sector, and occupation using 204 country-year surveys with available information.[5]

Consider the share of educated females or males in country c at year t, $E^g_{ct}, g = f, m$, which can be written as the weighted average of the educated share across demographic groups $d \in D$ such that $E^g_{ct} = \sum_{d \in D} w^g_{dct} E^g_{dct}$, where w^g_{dct} is the population share of group d for gender g and E^g_{dct} is the corresponding educated share. To estimate the composition effects resulting from variations in w^g_{dct}, we construct a counterfactual aggregate educated share for each country-year observation by gender, $\tilde{E}^g_{ct}$, using the fixed weights $\bar{w}^g_{dct}$ of the global average across all country-year samples. Thus the counterfactual educated share is calculated as $\tilde{E}^g_{ct} = \sum_{d \in D} \bar{w}^g_{dct} E^g_{dct}$. Recall that our benchmark analysis regresses the aggregate gender education gap on log GDP per capita and a constant, $Gap_{ct} \equiv E^f_{ct}/E^m_{ct} = \alpha + \beta log(y_{ct}) + \epsilon_{ct}$. We can now instead regress the counterfactual gender education gap $\tilde{Gap}_{ct}$ on GDP per capita and a constant, $\tilde{Gap}_{ct} \equiv \tilde{E}^f_{ct}/\tilde{E}^m_{ct} = \tilde{\alpha} + \tilde{\beta} log(y_{ct}) + \tilde{\epsilon}_{ct}$. As a result, the composition effect of a set of demographic factors is given by the relative change in the estimates between the benchmark and counterfactual regressions, $1 - \frac{\tilde{\beta}}{\beta}$.

Table 2: Demographic Composition Accounting for the Aggregate Gender Education Gap

Factor	Age	Sector	Occupation
Accounting Share (%)	-6	30	43
Factors	Sector × Occupation	Age × Sector × Occupation	
Accounting Share (%)	44	40	

Note: This table reports the percentage of the coefficient of regressing the gender education gap on log GDP per capita and a constant that is explained by cross-country gender differences in distributions of age, employment sector, occupation, and combinations of the above three factors using a shift-share accounting decomposition exercise.

As shown in Table 2, controlling for the age distribution slightly decreases the slope coefficient, while the sector and occupation distributions have sizable explanatory power of 30 percent and 43 percent, respectively. The decomposition exercise points to labor market outcomes as a potentially strong driving force behind the narrowing gender education gap across countries.

[5] *Age* is categorized into five-year age bins from 25 to 54; *Sector* includes agriculture, manufacturing, service, and the null; *Occupation* uses ISCO code and includes 10 categories and the null.

2.2 Labor market outcomes by gender and education

To motivate our modeling choice of skill-biased structural transformation, we now turn to indicators of the labor market by gender and education attainment. As shown in Appendix Figure A1, we find that the LFPR of women who have completed university increases with development from around 70–80 percent, while the LFPR of women who did not complete university is U-shaped. The pattern of aggregate female LFPR is dominated by the low-educated, resulting in an average LFPR of 56 percent, 49 percent, and 66 percent, respectively, for countries with available data in the bottom, middle, and top terciles of the world income distribution. In contrast, men's LFPR remains high for both education groups throughout different development levels. The aggregate males' LFPR is 90 percent, 91 percent, and 92 percent, respectively, for the three terciles of the world income distribution.

To further understand the link between the rise in women's educational attainment and structural transformation, we investigate the sectoral "female intensity" in the aggregate and by education levels. Specifically, we measure female intensity by female labor force shares within the agricultural, manufacturing, and service sectors, respectively. Appendix Table A1 reports the slope coefficients of regressing sectoral female intensity on log GDP per capita and a constant in the aggregate and by education levels. We find that, as the development level increases across countries, female intensity strongly decreases in the agricultural sector, increases in services with the labor share of women surpassing that of men, and remains the least intensive and relatively stable at around 20 percent in manufacturing. Furthermore, the sectoral female intensity patterns are completely driven by the low-educated. Among the educated labor force, in contrast, female intensity is increasing in log GDP per capita for all three sectors, with the largest magnitude observed in services.

To sum up, this section describes the patterns of labor force participation by gender and education, the rise of women's employment in the service sector, and the rise of educated women's employment in all sectors with development. These facts highlight the importance of considering *skill-biased* structural transformation in understanding the narrowing education gap.

2.3 Assortative household formation by education

Education decisions are influenced by not only labor market outcomes but also household formation expectations. If educated individuals are more likely to marry educated and thus higher-income spouses, then education decisions are affected by the extent of assortative matching. In this section, we document the empirical regularities of assortative matching across development levels to mechanically discipline our quantitative model.

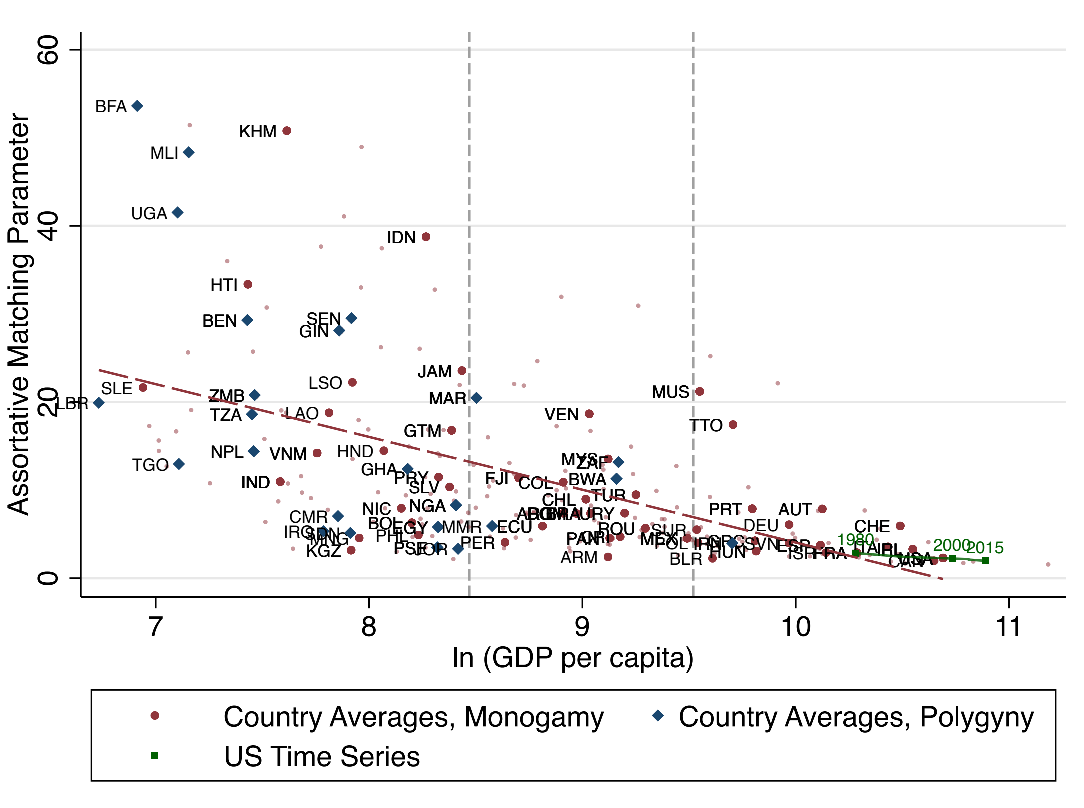
We follow Eika et al. (2019) in measuring the educational assortative matching parameter as the probability ratio of the likelihood of an educated individual marrying an educated spouse relative to the likelihood of the pairing if matches were random. Suppose an economy consists of married households indicated by (j, j'), where the husband's education is j and the wife's education is j'. Denote by $\lambda_{ef}, \lambda_{em}$ the share of educated females and males, respectively. Under the assumption of random matching, the share of households where both the female and the male are educated is given by $\lambda_{ef}\lambda_{em}$. To mechanically account for the distribution of household education types, we denote by α the assortative matching parameter such that the observed share of households where both the female and the male are educated is $\alpha\lambda_{ef}\lambda_{em}$. Using the accounting identities, we have the shares of households with education levels of $\{EE, EN, NE, NN\}$ given by

$$\begin{aligned}
\%(EE) &= \alpha\lambda_{ef}\lambda_{em}, \\
\%(EN) &= \lambda_{em}(1-\lambda_{ef}) + (1-\alpha)\lambda_{em}\lambda_{ef}, \\
\%(NE) &= (1-\lambda_{em})\lambda_{ef} + (1-\alpha)\lambda_{em}\lambda_{ef}, \\
\%(NN) &= (1-\lambda_{em})(1-\lambda_{ef}) + (\alpha-1)\lambda_{em}\lambda_{ef}.
\end{aligned}$$

Consistent with Eika et al. (2019), we find that the U.S. assortative matching parameter α on university decreases from 2.85 in 1980 to 1.97 in 2015. Although we only use α for educated workers to discipline household formation in the benchmark model, we can test whether the model produces consistent values of the assortative matching parameter for the uneducated α_N. Denote by $\lambda_{nf}, \lambda_{nm}$ the share of uneducated females and males, respectively. By construction, $\alpha_N \equiv \frac{\%NN}{\lambda_{nf}\lambda_{nm}} = \frac{(1-\lambda_{ef})(1-\lambda_{em})}{\lambda_{nf}\lambda_{nm}} + \frac{(\alpha-1)\lambda_{ef}\lambda_{em}}{\lambda_{nf}\lambda_{nm}}$, which is pinned down by α and the education shares by gender. We will assess whether our model's prediction on α_N is consistent with the data in the quantitative analysis in Sections 4.1 and 5.

We further document that, across countries, the qualitative pattern of α decreasing with development also holds, and the magnitudes become much larger. Figure 3 plots the benchmark estimates of α in all country-year samples when using university completion as the education threshold. The median value of α decreases from 16.8 in low-income countries to 4.0 in high-income countries for university-educated households. We also show in Appendix Figure A3 that the assortative matching between the *uneducated* women and men marginally increases with development, consistent with the time-series patterns of high-income countries documented in Eika et al. (2019). We will incorporate the large variation in α across development levels in the model to investigate its role in explaining the narrowing gender

Figure 3: Educational Assortative Matching



Note: This figure plots α values against log GDP per capita for each country-year sample (light red dot) and country averages (blue diamond for countries that have polygamous unions and dark red dot for the rest). Observations with α values larger than the country-average 95th percentile value of 53.62 are dropped in this figure.

education gap with development.[6]

3 The model

This section introduces our benchmark general equilibrium model with endogenous education and labor supply decisions. In our setup, large agricultural sectors in poor economies can be generated by either differential productivity growth rates by sector or income effects.

[6]In the benchmark results, we follow the weighting mechanism in Eika et al. (2019) to include the single households when calculating the share of households where both the male and female are educated so that the reported α's are conservative estimates. Appendix Figure A4 plots the results when we restrict the sample to only married households, where the α estimates are larger by construction. The patterns remain similar to our benchmark results.

3.1 Households

There is a mass one of both females and males, heterogeneous in their cost of education ($a \in \mathbb{R}_+$). Individuals face a discrete education choice: to obtain an education or not. Those choosing an education must pay a utility cost, a, which follows the distribution $\Gamma(a)$. Individuals also face a discrete occupation choice: to work in the agricultural sector, B, the goods sector, G, or the service sector, S. Individuals, if working, supply one unit of labor to the market. Let $\mathbb{O} = \{NS, ES, NG, EG, NB, EB\}$ describe the set of education-occupation possibilities. We assume free mobility across sectors; hence, wages by gender and education are equal across sectors.

Individuals make education decisions to maximize expected utility. After completing education, households composed of one male and one female are formed according to a mechanical assortative matching process. Households then make consumption and labor supply decisions to maximize utility. Given a household (j, j') with $j, j' \in \{E, N\}$ representing the male's and female's education, respectively, let the household utility function be $u_{jj'}(c)$. The total consumption, c, consists of both home consumption, c_H, and market consumption.

Education decisions. For gender $g = f, m$, the expected utilities of completing and not completing education are $\mathbb{E}_E^g\left(u_{jj'}(c)\right) - a$ and $\mathbb{E}_N^g\left(u_{jj'}(c)\right)$, respectively. Hence, an individual with an education cost of a will obtain education if and only if $a < \mathbb{E}_E^g\left(u_{jj'}(c)\right) - \mathbb{E}_N^g\left(u_{jj'}(c)\right) \equiv a^{*g}$. Therefore, females and males choose to acquire education if $a < a^{*g}$. The educated shares of females and males are $\Gamma\left(a^{*f}\right)$ and $\Gamma\left(a^{*m}\right)$, respectively.

Households' consumption and labor supply. We assume males inelastically supply one unit of labor. Home production is performed only by women and it takes a value drawn from the distribution $ln(x) \sim \mathcal{N}_j(\mu_j, \sigma_j^2), j = E, N$. The household consumes home-production output $c_H = x$ if the female does not work in the labor market, but consumes $c_H = \psi_j x$ if she works in the labor market, where $\psi_j < 1, j = E, N$. With technological progress, home production of food and goods disappears and only home production of services remains (Ngai and Pissarides, 2008). Hence, we assume that home production is only substitutable to services as commonly assumed in the literature. Let the composite of service consumption be

$$\hat{c}_S = \left(c_H^{\frac{\sigma-1}{\sigma}} + c_S^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where c_S is the consumption of market services, and σ governs the elasticity of substitution between market and home-produced services. The household's total consumption is a CES function of

$$c = \left(\phi_G^{\frac{1}{\nu}} c_G^{\frac{\nu-1}{\nu}} + \phi_S^{\frac{1}{\nu}} \hat{c}_S^{\frac{\nu-1}{\nu}} + \phi_B^{\frac{1}{\nu}} (c_B - \underline{B})^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}, \tag{2}$$

where c_G, c_B are goods and agricultural sector-specific consumption, $\underline{B}$ is a constant subsistence level of consumption, and ν is the elasticity of substitution between consumption of all sectors.

Households (j, j') maximize,

$$\max_{c_G, c_S, c_B, c_H(l^f_{jj'})} u_{jj'}(c) \tag{3}$$

s.t.

$$\sum_{i=G,S,B} p_i c_i \leq w^m_j + w^f_{j'} l^f_{jj'} \equiv y_{jj'W}, \tag{4}$$

where p_i denotes the goods price of sector $i = G, S, B$, $w^f_{j'}$ and w^m_j denote the wage income for the female and male, respectively, and $l^f_{jj'} = 1$ if the woman works and zero otherwise. We set $W = l^f_{jj'}$ to be the index of whether the female works in the market for a household type (j, j'). Hence, there are eight types of households characterized by {jj'W}.

Since we consider only the extensive margin of labor market participation, without loss of generality, we focus on the case where home and market services are perfect substitutes $\sigma \to \infty$ or equivalently $\hat{c}_S = (c_H + c_S)$, which allows us to obtain the closed form solution for all household decisions. In Appendix C.1, we also show the results when there is imperfect substitution between market and home production. The main effect of imperfect substitution is that a woman's labor force participation will also depend on her husband's wage. Given that we have two types of husbands, educated or uneducated, with two distinct incomes, allowing for substitutability has little effect on our benchmark calibration results.[7]

Given market income $(y_{jj'W})$ and home production (c_H), households maximise total consumption c. Let $\Omega = p_S \left(\frac{\phi_s}{p_s}\right)^\nu + p_B \left(\frac{\phi_B}{p_B}\right)^\nu + p_G \left(\frac{\phi_G}{p_G}\right)^\nu$, which we can interpret as the aggregate price index of the consumer. Then we can solve for the market consumption as

$$c_{jj'W} = \left(y_{jj'W} - p_B \underline{B} + p_S c_H\right) (\Omega)^{\frac{1}{\nu - 1}}. \tag{5}$$

Therefore, a female enters the labor market if

$$u(c|c_H = \psi_j x) \geq u(c|c_H = x) \Rightarrow w^f_j \geq p_S x \,(1 - \phi) \equiv \underline{w}^f_j(x). \tag{6}$$

That is, market income needs to be large enough to compensate for any lost value-add of home production. In particular, women's employment choices are independent of male wages, as long as the spousal male's wage exceeds the subsistence level. A female also works

[7] In the literature, estimates for the elasticity typically range between 1.8 and 2.5.

if the male's wage does not cover the subsistence requirement in agricultural goods:

$$w_j^m < p_B \underline{B}. \tag{7}$$

We denote $\underline{x}_j^f$ as the cutoff of home production such that $\underline{w}_j^f(\underline{x}_j^f) = w_j^f$. In the case of households below the subsistence level, we set $\underline{x}_j^f \to +\infty$ if $w_j^m < p_B \underline{B}$. Therefore, the shares of women in the labor force by education level are given by

$$L_E^f = \mathcal{N}_E(\underline{x}_E^f)\Gamma(a^{*f}) \tag{8}$$

$$L_N^f = \mathcal{N}_N(\underline{x}_N^f)\big(1 - \Gamma(a^{*f})\big). \tag{9}$$

3.2 Firms' production

There are three types of representative firms hiring labor to produce agriculture, goods, and service outputs. The production functions for all three sectors are

$$Y_k = A_k H_k, \text{ for } k = G, S, B.$$

The total sectoral labor input, H_k, is a CES function of educated and uneducated labor:

$$H_k = \left(\chi_k H_{Ek}^{\frac{\theta-1}{\theta}} + (1-\chi_k) H_{Nk}^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}, \text{ for } k = G, S, B,$$

where θ is the elasticity between educated and uneducated labor. Educated and uneducated labor inputs are CES functions of female and male labor,

$$H_{jk} = F\left(H_{jk}^f, H_{jk}^m\right) = \left(\zeta_{jk}(H_{jk}^f)^{\frac{\eta-1}{\eta}} + (1-\zeta_{jk})(H_{jk}^m)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \text{ for } j = E, N,$$

where η is the elasticity between female and male labor.

We denote total labor force participation for gender g and education j by $H_j^g = \sum_k H_{jk}^g$. Because labor is perfectly mobile across sectors but not education levels, in equilibrium $w_{Ek}^f = w_E^f$, $w_{Nk}^f = w_N^f$, $w_{Ek}^m = w_E^m$ and $w_{Nk}^m = w_N^m$. Firms choose labor inputs to maximize profit:

$$\max_{\{H_{jk}^g\}} p_k Y_k - \sum_{jg} w_j^g H_{jk}^g.$$

Labor are paid their marginal products, hence we can solve the gender wage gaps by education level:

$$x_j = \frac{w_j^f}{w_j^m} = \frac{\zeta_{jk}}{1-\zeta_{jk}} \left(\frac{H_{jk}^f}{H_{jk}^m} \right)^{-\frac{1}{\eta}}, j = E, N. \tag{10}$$

Furthermore, the college wage premium for women and men is given by:

$$\pi^f = \frac{w_E^f}{w_N^f} = \pi_k \frac{\zeta_{Ek}}{\zeta_{Nk}} \left(\frac{H_{Ek}}{H_{Ek}^f} \frac{H_{Nk}^f}{H_{Nk}} \right)^{\frac{1}{\eta}}, \text{ and} \tag{11}$$

$$\pi^m = \frac{w_E^m}{w_N^m} = \pi_k \frac{1-\zeta_{Ek}}{1-\zeta_{Nk}} \left(\frac{H_{Ek}}{H_{Ek}^m} \frac{H_{Nk}^m}{H_{Nk}} \right)^{\frac{1}{\eta}}, \text{ where} \tag{12}$$

$$\pi_k = \frac{p_{Ek}}{p_{Nk}} = \frac{\chi_k}{1-\chi_k} \left(\frac{H_{Ek}}{H_{Nk}} \right)^{-\frac{1}{\theta}}, k = G, S, B. \tag{13}$$

Note that π_k is the sector-specific relative price of college to non-college labor, which in turn is a composite of women's and men's labor.

3.3 Equilibrium

A competitive equilibrium is defined by education choices (a^{*m}, a^{*f}), market wages $(w_N^m, w_E^m, w_N^f, w_E^f)$, market prices (p_G, p_S, p_B), consumption $\{c_{jj'WB}, c_{jj'WG}, c_{jj'WS}, c_{jj'WH}\}_{j,j'=E,N;W=0,1}$, and labor allocation $\{H_{Ek}^g\}_{g=f,m;k=G,S}$ and $\{H_{Nk}^g\}_{g=f,m;k=G,S,B}$, such that:
(i) individuals make optimal education choices where men with $a < a^{*m}$ and women with $a < a^{*f}$ obtain an education, while others do not; and females make optimal labor force participation choices where they work if $x > \underline{x}_j^f, j = E, N$.
(ii) the representative firms maximize profits, subject to technology in Section 3.2; and individuals maximize utility (3), subject to the budget constraint (4);
(iii) given the optimal choices of firms and households, output prices clear the goods market in each sector, and market wages clear the labor market for each education-gender group:

$$\sum_{jj'=EE,EN,NE,NN;W=0,1} c_{jj'Wk} = Y_k, k = B, G, S; \tag{14}$$

$$H_{EB}^g + H_{EG}^g + H_{ES}^g + NL_E^g = \Gamma(a^{*g}), g = f, m; \tag{15}$$

$$H_{NB}^g + H_{NG}^g + H_{NS}^g + NL_N^g = 1 - \Gamma(a^{*g}), g = f, m. \tag{16}$$

Model Predictions. We focus on two mechanisms that qualitatively narrow the gender education gap in our model. The mechanism is skill-biased structural transformation, which is a combination of SBTC within sectors (an increase in $\chi_k, k = B, G, S$) and structural transformation (ST) due to a higher growth rate of A_B, A_G compared to A_S. The second mechanism concerns changes in educational assortative matching (captured by varying α).

For the mechanism of skill-biased technological transformation, consider the empirically relevant case where females have a comparative advantage in producing services, $\zeta_{Sk} > \zeta_{G,k}, \zeta_{B,k}$, which will be confirmed later in our model calibration section. Disproportionately more females than males are drawn into the growing service sector due to ST. Furthermore, the increase in females' employment in the labor market incentivizes females to obtain more education due to SBTC, which narrows the gender education gap with development.

Our model predicts that an increase in assortative matching narrows the gender education gap. When α increases, educated females benefit from a higher probability of marrying an educated and thus higher-earning spouse. Meanwhile, the net benefits for educated males are lower; their utility increases with the educated spouse's higher income but decreases as the educated spouse is likely to opt-out of full-time home production. Given the empirical observation of α decreasing with development, our model predicts that variations in assortative matching actually widen the gender education gap in favor of men with development as a counter-force.

4 Quantitative Analysis

We investigate quantitatively the extent to which our model can account for the patterns of the gender education gap. In this section, we calibrate the model to match the key features of the U.S. time series data. Using the calibrated model, we then conduct counterfactual exercises for the U.S. to quantify the role of technological change and assortative matching in reversing the gender education gap. Furthermore, we assess the model's performance in predicting the variations in the gender education gap over time across high-income economies from the World KLEMS data.

4.1 Calibration

We calibrate the model to replicate two equilibria at different points in time: the 1980 and the 2005 U.S. economies.[8] In the benchmark calibration, all preference parameters are imposed to be the same in the two equilibria, except for the levels of SBTC, sectoral TFP, and assortative matching.

[8]We choose 2005 as the terminal year following Buera et al. (2021) because this is the last period that is consistently available across KLEMS datasets.

We begin by directly assigning some parameter values following the literature. We first normalize TFP in the three market sectors to be one in 1980. We assume that the distributions of home productivity do not change over time as Bridgman (2016) finds evidence that there was no home productivity change between 1980 and 2005. Home productivity differences between working and non-working women, $\psi_j, j = E, N$, are set to differ by home production hours. Using data from Ramey and Ramey (2010), we find that among educated females, those who are working spend 47 percent as much time in home production as those who are not working; Among uneducated females, the corresponding figure is 54%. Hence, we set $\psi_E = 0.47$ and $\psi_N = 0.54$.

Next, we set all elasticities outside the model using estimates from the literature. The elasticity of substitution between sector-specific consumption, ν, has been estimated in numerous studies. For the benchmark calibration, we follow the recent estimates (see, for example, Herrendorf et al., 2014) using consumption value-added data and relative prices, which suggest a relatively low value of 0.002. The elasticity of substitution between educated and uneducated labor, θ, is set to 1.53 following Buera et al. (2021). This value is close to the estimates in the earlier literature. The elasticity of substitution between female and male labor, η, is set to 2.27, following Ngai and Petrongolo (2017) who match the response in hours ratios to changes in the wage ratio.

Table 3: Benchmark Parameters Values

Parameter	Value
Panel A: Pre-Assigned Parameters	
ν - Elasticity of substitution between sector-specific consumption	0.002
θ - Elasticity of substitution between educated and uneducated labor	1.53
η - Elasticity of substitution between female and male labor	2.27
$\{A_B^{US}, A_G^{US}, A_S^{US}\}_{t=0}$ - Sector-specific technology	$\{1, 1, 1\}$
Panel B: Data Identified Parameters	
$\{A_B^{US}, A_G^{US}, A_S^{US}\}_{t=T}$ - Sector-specific technology	$\{3.78, 2.00, 1.36\}$
$\{\chi_{B,0}, \chi_{G,0}, \chi_{S,0}, \chi_{B,T}, \chi_{G,T}, \chi_{S,T}\}$ - Educated productivity	$\{0.28, 0.31, 0.45, 0.36, 0.47, 0.60\}$
$\{\zeta_{EB}, \zeta_{NB}, \zeta_{EG}, \zeta_{NG}, \zeta_{ES}, \zeta_{NS}\}$ - Female productivity	$\{0.25, 0.25, 0.24, 0.29, 0.37, 0.40\}$
$\{\alpha_0, \alpha_T\}$ - Educational assortative mating	$\{2.85, 2.17\}$
$\{\psi_E, \psi_N\}$ - Relative home productivity	$\{0.467, 0.536\}$
Panel C: Calibrated Parameters	
$\{\mu_m, \mu_f, \sigma_m, \sigma_f\}$ - Education cost distribution	$\{3.86, 0.25, 7.46, 1.28\}$
$\{\mu_E, \mu_N, \sigma_E, \sigma_N\}$ - Home productivity distribution	$\{-3.78, -2.84, 1.84, 0.27\}$
$\left(\frac{p_{B,0}}{Y_0}\underline{B}\right), \phi_B, \phi_G$ - Consumption parameters	$\{0.024, 1.16 \times 10^{(-7)}, 0.37\}$

Note: The table reports the values and interpretations of the parameters of the quantitative model under the benchmark calibration to match key moments in the U.S. data.

We then estimate a number of parameters that our model analytically identifies from the observed data moments. The data-identified parameters include the technology parameters, $\{A_B^{US}, A_G^{US}, A_S^{US}\}_{t=T}$, $\{\zeta_{EB}, \zeta_{NB}, \zeta_{EG}, \zeta_{NG}, \zeta_{ES}, \zeta_{NS}\}$, $\{\chi_{B,0}, \chi_{G,0}, \chi_{S,0}, \chi_{B,T}, \chi_{G,T}, \chi_{S,T}\}$, and the marriage parameters, $\{\alpha_0, \alpha_T\}$. First, we estimate the rise in sector-specific TFP through real labor productivity growth in each sector from the KLEMS data, following Ngai and Petrongolo (2017) and references therein. The resulting 2005 TFP values are, $A_{B,T} = 3.78$, $A_{G,T} = 2.00$ and $A_{S,T} = 1.36$, which translate into compounded annual growth rates of 0.055 for agriculture, 0.028 for industry and 0.012 for services.[9] Second, gender-specific productivities $\{\zeta_{EG}, \zeta_{NG}, \zeta_{ES}, \zeta_{NS}, \zeta_{EB}, \zeta_{NB}\}$ are determined by eight moments in the data given Equation (10), we solve for ζ_{jk} for a given η,

$$\zeta_{jk} = \frac{x_j \left(\frac{H_{jk}^f}{H_{jk}^m}\right)^{\frac{1}{\eta}}}{\left(1 + x_j \left(\frac{H_{jk}^f}{H_{jk}^m}\right)^{\frac{1}{\eta}}\right)}.$$

The eight data moments are the two gender wage gaps by education type x_j in 1980 and the six sectoral labor force participation ratios for educated and uneducated service and goods workers, $\frac{H_{jk}^f}{H_{jk}^m}$ for $j = E, N$ and $k = B, G, S$. In the sensitivity analysis, we also allow ζ's to change over time. We then compute the six input shares of educated labor, $\{\chi_G, \chi_S, \chi_B\}_{t=0,T}$, by solving π_k. Skill-specific productivity for a given θ, in each time period, is:

$$\chi_k = \frac{1}{1 + (\pi_k)^{\frac{1-\theta}{\theta}} \left(I_{Ek}^{-1} - 1\right)^{\frac{1}{\theta}}}, \text{ where } I_{Ek} \equiv \frac{\pi_k H_{Ek}}{\pi_k H_{Ek} + H_{Nk}}, \text{ and } k = G, S, B.$$

This estimation requires us to use the six sectoral educated wage bill shares (I_{Ek}) and the six sector-specific relative college-to-non-college prices, (π_k), in 1980 and 2005, which are a function of gender-specific productivity and gender-specific wages:

$$\pi_k = \frac{\left[\zeta_{Ek}^{\eta}(w_E^f)^{1-\eta} + (1-\zeta_{Ek})^{\eta}(w_E^m)^{1-\eta}\right]^{\frac{1}{\eta-1}}}{\left[\zeta_{Nk}^{\eta}(w_N^f)^{1-\eta} + (1-\zeta_{Nk})^{\eta}(w_N^m)^{1-\eta}\right]^{\frac{1}{\eta-1}}}.$$

We also directly calculate the educational assortative matching parameter α to be 2.85 in 1980 and 2.17 in 2005 using the ratio of the share of couples who are both high-educated to the share of high-educated females multiplied by that of males. The resulting decrease in α over time is consistent with Eika et al. (2019) who show a robust decline in educational

[9] Ngai and Petrongolo (2017) report a differential growth rate of 1.2 percent for manufacturing relative to services from 1970 to 2006, which is consistent with the 1.6 percent we obtain from 1980 to 2005.

assortative matching among the educated.[10] We report values of these 17 parameters in Panel B of Table 3.

Lastly, Panel C of Table 3 reports values of the 11 remaining parameters to be calibrated: (i) the distribution of education cost by gender, $\{\mu_m, \mu_f, \sigma_f, \sigma_m\}$, (ii) the distribution of female home productivity by education level, $\{\mu_E, \mu_N, \sigma_E, \sigma_N\}$, and (iii) consumption weights and the non-homotheticity in preferences, $\{\phi_s, \phi_g, \underline{B}\}$. We use the simulated method of moments (SMM) by minimizing the distance between data targets and model moments to calibrate the 11 parameters with 12 moments concurrently.[11]

Even though the parameters in Panel C of Table 3 are jointly estimated, it is useful to discuss the intuitions of how certain moments inform specific parameters. The distribution of education cost by gender, $ln(a) \sim \mathcal{N}_j(\mu_g, \sigma_g^2)$, $g = f, m$, is captured by four parameters, $\{\mu_m, \mu_f, \sigma_f, \sigma_m\}$, which are largely governed by four moments in the data: the shares of educated females and males in $t = 0$ and $t = T$ or $\Gamma\left(a^{*f}\right)_{t=0,T}$ and $\Gamma\left(a^{*m}\right)_{t=0,T}$. The distribution of home productivity by gender, $ln(x) \sim \mathcal{N}_j(\mu_j, \sigma_j^2)$, $j = E, N$ are captured by $\{\mu_E, \mu_N, \sigma_E, \sigma_N\}$, which are informed by the shares of women not in the labor force by education level in $t = 0$ and $t = T$. Lastly, consumption weights and the non-homothetic term in preferences, $\{\phi_s, \phi_g, \underline{B}\}$, are mostly identified by four data moments of the initial and terminal value-added shares in goods and food.

Table 4 reports each data moment and its model counterpart. Panels A and B report the moments used in the direct estimation of parameters and the resulting model predictions in equilibrium. In particular, the model predicts that the gender wage gap is higher for the educated (0.70) than for the uneducated (0.66), compared to the values of 0.69 and 0.63, respectively, in the data. The model also predicts that the female intensity is the highest in services (0.67), compared to goods (0.16) and agriculture (0.18), closely matching the data. Yet the model slightly overpredicts the female intensity among the uneducated in each sector.

Panel B in Table 4 shows that the model matches the wage bill share by sector fairly well, both in 1980 and 2005. Meanwhile, the model slightly overestimates the π_k's, the relative college-to-non-college price by sector, in the initial year 1980 as the productivity parameters are estimated directly from the data and the benchmark model does not perfectly match gender wage gaps or employment shares. Nevertheless, the relative increases in π_k for the

[10]The benchmark estimates of α include singles in the calculation. When we restrict our sample to those who are married, α is estimated to be 3 in 1980 and 2 in 2005, which coincide with the results in Eika et al. (2019).

[11]See McFadden (1989). We adopt the TikTak algorithm to search for the global optimizer, which is shown by Arnoud et al. (2019) to be the strongest performer among a series of global optimization algorithms.

Table 4: Moments Targeted in the Model vs Data

Moment	Target	Model
Panel A: Moments identifying ζ's		
Educated gender wage gap (x_E) in $t = 0$	0.69	0.70
Uneducated gender wage gap (x_N) in $t = 0$	0.63	0.66
Educated female/male service labor ratio in $t = 0$	0.69	0.67
Educated female/male goods labor ratio in $t = 0$	0.16	0.16
Educated female/male agriculture labor ratio in $t = 0$	0.19	0.18
Uneducated female/male service labor ratio in $t = 0$	1.17	0.98
Uneducated female/male goods labor ratio in $t = 0$	0.39	0.32
Uneducated female/male agriculture labor ratio in $t = 0$	0.25	0.21
Panel B: Moments identifying χ's		
Educated service wage bill share (I_{ES}) in $t = 0, T$	$\{0.38, 0.56\}$	$\{0.36, 0.54\}$
Educated goods wage bill share (I_{EG}) in $t = 0, T$	$\{0.20, 0.36\}$	$\{0.20, 0.34\}$
Educated agriculture wage bill share (I_{EB}) in $t = 0, T$	$\{0.17, 0.22\}$	$\{0.16, 0.20\}$
Relative college service price (π_S) in $t = 0, T$	$\{1.30, 1.96\}$	$\{1.57, 2.40\}$
Relative college goods price (π_G) in $t = 0, T$	$\{1.20, 2.02\}$	$\{1.48, 2.38\}$
Relative college agriculture price (π_B) in $t = 0, T$	$\{1.26, 2.03\}$	$\{1.56, 2.52\}$
Panel C: Jointly Target Moments in Calibration		
Male educated shares in $t = 0, T$	$\{0.24, 0.28\}$	$\{0.24, 0.28\}$
Female educated shares in $t = 0, T$	$\{0.16, 0.30\}$	$\{0.16, 0.30\}$
Educated women in LF in $t = 0, T$	$\{0.76, 0.81\}$	$\{0.77, 0.82\}$
Uneducated women in LF in $t = 0, T$	$\{0.61, 0.72\}$	$\{0.60, 0.70\}$
Goods value-added share (y_G) in $t = 0, T$	$\{0.32, 0.22\}$	$\{0.36, 0.29\}$
Food value-added share (y_B) in $t = 0, T$	$\{0.03, 0.01\}$	$\{0.04, 0.01\}$

Note: This table reports the moments used in the benchmark calibration and the corresponding model predictions.

benchmark model are consistent with the data, with an increase of 52 percent versus 52 percent for services, 61 percent versus 68 percent in goods, and 61 percent versus 60 percent in agriculture, respectively. Importantly, regarding the matching market, our model predicts that α_N is 1.11 and 1.20 in 1980 and 2005, respectively, similar to the data values of 1.10 and 1.11. This result again confirms that our model is robust to different types of specifications to characterize the varying assortative matching over time.

As shown in Panel C in Table 4, the model matches well the desired moments in the SMM calibration routine. The model perfectly matches the education shares by gender in the data, which increases from 24% to 28% for males and from 16% to 30% for females. The model predicts that female LFPR increases from 77 percent to 82 percent among the educated and from 60 percent to 70 percent among the uneducated, closely matching the data. Lastly, the goods and food value-added shares decrease by seven and three percentage points in the model, respectively, compared to 10 and two percentage points in the data.

The fact that estimates of female productivity weights in services (ζ_{ES}, ζ_{NS}) are 23-67 percent larger than that in food and goods confirms that females have comparative advantages in services. The estimates of productivity weights on the educated workers (χ_k) strongly increase in all three sectors over time, suggesting that skill-biased technological change is an aggregate phenomenon in the U.S. We also find that SBTC is more pronounced in the goods and agricultural sectors than the service sector, consistent with Buera et al. (2021). For preferences, the non-homothetic term ($\underline{B}$) has a value of 0.02, and is significantly different from zero. Consistent with the literature, we find a very low value for the consumption weight of food and much larger weights of 0.38 and 0.62 for goods and services, respectively. The average home productivity for educated females is lower than that for uneducated females; this difference is partially driven by the higher LFP for educated females. In addition, our calibration implies that females have a lower average education cost of 0.25 compared to the value of 3.78 for males, even though males have higher college-educated shares in 1980. This difference in education costs is consistent with the evidence found in Becker et al. (2010).

4.2 U.S. Benchmark Results

As reported in the top panel in Table 5, by construction, our calibrated model matches well the data variations over time in the gender education gap and female LFPR by education level. In particular, the gender education gap narrows by 39.4 percentage points between 1980 and 2005 in the U.S., and by 39.5 percentage points in the model. Meanwhile, our model predicts that among females, university graduates and non-university graduates' LFPR increase by 5.3 and 10.5 percentage points, respectively, corresponding closely to the data moments.

Based on the calibrated benchmark model, we now conduct a quantitative decomposition exercise. Table 5 reports the quantitative importance of ST and SBTC in explaining the narrowing gender education gap and the increasing female labor force participation rates. Row (i) of the bottom panel shows the model predictions when we allow only for ST in the model, by varying A_k^{US} between 1980 and 2005 but keeping χ_k and α at the 1980 level.

Table 5: U.S. Benchmark Decomposition between 1980 and 2005

		Female Labor Force Participation	
	Gender Edu. Gap	University	Non-University
Δ P.P. in Data	-39.4	5.0	10.6
Δ P.P. in Model	-39.5	5.3	10.5
Contributions to Empowering Women in Model			
(i) Only ST	56.5%	182.3%	378.3%
(ii) Only SBTC	31.7%	-144.3%	-413.5%
(iii) SBTC in Services	33.6%	-86.4%	-325.6%
(iv) ST and SBTC	132.0%	93.0%	152.3%

Note: The top panel of this table reports the data and the model percentage point change in the gender education gap and in the LFPRs for females who are university and non-university graduates, respectively, between 1980 and 2005 in the U.S. The bottom panel reports the model predictions in percent of the benchmark prediction when we only allow selected mechanisms to vary over time.

ST alone accounts for 57 percent of the benchmark model changes in the gender education gap over time, but it over-predicts the change in female LFPR. Allowing only for SBTC, on the other hand, contributes to 32 percent of the narrowing gender education gap, but it reverses the female LFPR over time, as a result of males' comparative advantage in the production process without ST, which is skewed toward manufacturing and agriculture. Consequently, ST and SBTC are highly complementary in incentivizing women to obtain education and participate in the labor market. To further highlight this point, row (iii) reports a counterfactual of allowing only for SBTC in the service sector, which accounts for 34 percent of the narrowing gender education gap, which is two percentage points higher than that of the counterfactual allowing for SBTC in all sectors. The corresponding values for a counterfactual of allowing for SBTC only in goods or agriculture are nine percent and one percent, respectively (not shown in Table 5). This result confirms that SBTC in services is the only sectoral SBTC that matters for the narrowing gender education gaps. By combining SBTC and ST in row (iv), our model produces the required technological change to induce more women than men to become educated, and at the same time correctly predicts that the female LFPR increases less for the university-educated than the uneducated, although it slightly over-predicts the magnitudes. Further adding the decreasing assortative matching parameter, α, matches the model's quantitative predictions with the data.

Yet the benchmark model predicts the untargeted gender wage gap in 2005 to be 0.57 and 0.67 for the educated and uneducated, respectively, in contrast to the values of 0.70 and 0.78 in the data. While the model can generate convergence in the gender wage gap for the uneducated, the large influx of educated female workers widens the gender wage gap for the educated.[12] To fix this prediction, we consider an alternative calibration where we allow for gender-biased technological change (GBTC) in the model. Specifically, in addition to the three existing over-time variations in the benchmark model, we follow the same procedure as before to directly estimate the gender-specific productivity parameters by education level (ζ's) for 2005. Appendix D contains the details on the results and shows that the model closely matches the target moments. The alternative calibration generates the gender wage gap to be 0.72 and 0.83 in 2005 for the educated and uneducated, respectively, more closely matching the data. Furthermore, Table A6 shows that when all four mechanisms are present, allowing for GBTC alone explains only nine percent of the total model narrowing in the gender education gap, while the other quantitative decomposition results remain similar to the benchmark case.

We conclude that SBTC, especially in services, combined with ST are the main drivers of the narrowing gender education gap in the U.S. and the result is robust to model specifications with and without GBTC.

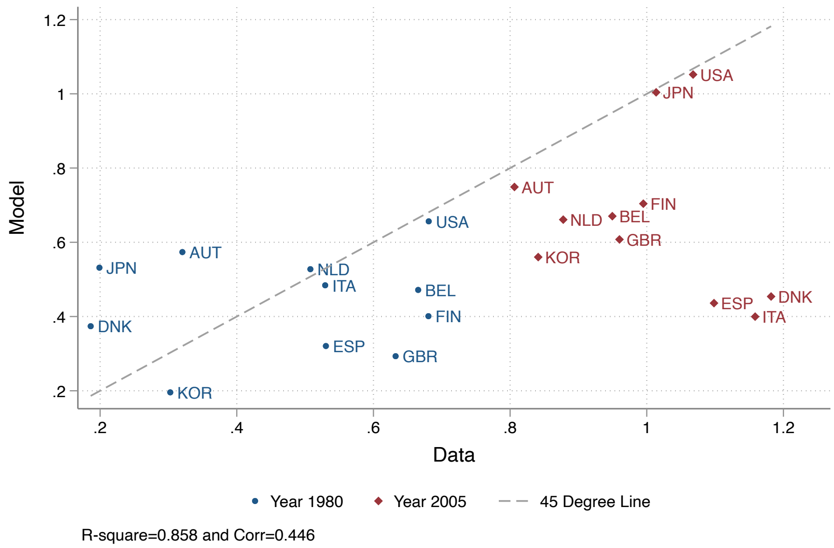
4.3 Model Predictions for High-Income Countries

In this section, we validate the model by assessing its performance of predicting the *untargeted* variations in the gender education gap over time and across high-income economies from the KLEMS data. We start with the benchmark parameter values but re-calculate only the values of data-identified A's and χ's for each country-year sample using the same estimation procedure as for the U.S. Appendix Table A3 reports the estimates that we use for the exercise.[13] Figure 4 then plots the model's predictions of the gender education gaps against the data, where data moments are computed using the educated population size by sex and age groups from Barro and Lee (2013). The R-square shows that our model accounts for 86 percent of the variation in the gender education gap over time across KLEMS countries. The correlation between the education gaps in the data and the model is 0.45.

[12] This is a common feature of such models. See also Ngai and Petrongolo (2017).

[13] Ideally, we would also like to use the actual estimated assortative matching parameter for each country-year sample. Unfortunately, this moment is not available in the KLEMS data; very few desired samples have household surveys where the α can be identified in both time periods. Hence, we have to use the estimated α for the U.S. in the corresponding year.

Figure 4: Base Model Predictions on the Gender Education Gap Across KLEMS Countries



Note: This figure plots the gender education gap in the base model against that in the data. It also reports the R-square of regressing one on the other, and the correlation coefficient between the two.

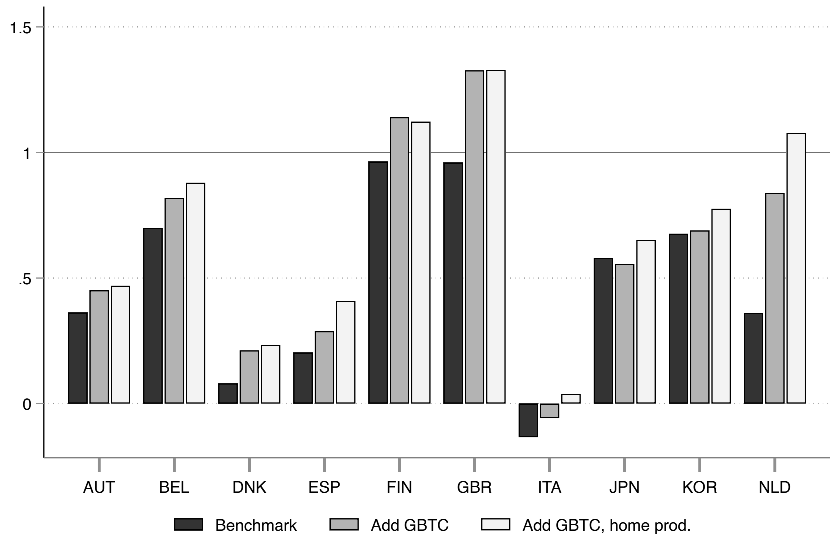
We also assess the baseline model's predictions on LFPR. Because we fix the home productivity distribution to the same as in the U.S., the model can account for only 68 percent of the variations in LFPR in KLEMS countries with a model-data correlation of 0.17, as plotted in Panel (a) of Appendix Figure A5.[14] However, we can match the LFPR perfectly by calibrating a scale parameter A_h in each country-year sample such that home productivity x follows the distribution $ln(x) \sim \mathcal{N}_j(A_h\mu_j, \sigma_j^2), j = E, N$. Panel (b) of Appendix Figure A5 plots the model predictions of the gender education gap both in the benchmark model and in the alternative model that perfectly matches LFPRs. By further matching the LFPR, our model explains only an additional four percentage points of the data variation in gender education gaps.

Figure 5 shows the degree of the change in the gender education gap between 1980 and 2005 that can be explained by our baseline model for each KLEMS country. Our mechanism of skill-biased structural transformation accounts well for the evolution in Finland, the UK, Belgium, and Korea, with an average explanatory power of 82 percent, while it explains little of the patterns in Denmark, Spain, or Italy.[15] For the latter set of countries, there must be

[14] LFPR are taken from OECD.Stat covering all 25–54 year old women and men.

[15] Specifically, Denmark is an outlier for the particularly large decrease in the gender education gap, with the ratio of female to male educated share increasing by one, compared to the average value of 0.5. It also experienced a relatively small SBTC. Italy is also unique in the sense that service productivity decreased rather than increased from 1980 to 2005. Spain is a mix of the experience of these two countries.

Figure 5: Share of the Change in the Gender Education Gap Explained by the Model



Note: This figure plots the share of the gender education gap in each KLEMS country that is explained by i) the benchmark model, ii) an alternative model additionally allowing for GBTC, and iii) another alternative model additionally allowing both for GBTC and varying home productivity across these countries.

mechanisms other than skill-biased structural change that pushes down the gender education gap over time. For example, such mechanisms could include changing social norms or gender discrimination, which is consistent with the decline in gender barriers found in Chiplunkar and Kleineberg (2022) using data from 13 countries.

Figure 5 also plots the explanatory power of two alternative models. The second set of columns shows the effect of additionally allowing for GBTC in this subset of countries. Overall, GBTC has again only a small effect on narrowing gender education gaps, with the exception of Great Britain and the Netherlands. The third set of columns presents the model predictions of further allowing for home productivity variation to match the LFPR; however, the additional explanatory power is generally small with the exception of the Netherlands. Therefore, we conclude that although GBTC and home productivity variations may be important for the model's performance in predicting the gender education gap and labor force participation across countries, they are not crucial for the model's quantitative power in explaining the narrowing gender education gap across countries. Due to the lack of available data to identify these parameters in less-developed economies, we fix the gender-biased technology and home productivity parameters at the U.S. level for model predictions across income levels.

5 Cross-Country Calibration Across Income Levels

We have developed and validated a model of gender education gaps that matches the key characteristics of the advanced economies from 1980 to 2005. In this section, we test the model's predictions on the gender education gap over the full range of the world income distribution. To do so, we fix all the parameters but allow for exogenous variations in three dimensions: (i) sectoral productivity A_B, A_G, A_S, (ii) sectoral skill intensity χ_B, χ_G, χ_S in the three market sectors, and (iii) educational assortative matching α in the marriage market, to match key features of labor markets in low-, middle, and high-income countries. We then test the model predictions on the gender education gap across development levels.

As we consider the full spectrum of the world income distribution, it is crucial to match women's labor market characteristics, in particular, the high LFPR and high agriculture share in low-income countries, which are distinct from the high-income economies we have discussed thus far. Therefore, we target only female moments and assess the model's predictions with men's labor market characteristics as an out-of-sample test. As the direct moments for identification are not available in developing economies, we calibrate the economy-wide parameters (A_S, A_G, A_B) and (χ_S, χ_G, χ_B) to match the median values of the six female moments: (i) LFPR, (ii) employment shares of agriculture and services, and (iii) shares of educated workers in each sector. The assortative matching parameter is directly identified by the shares of the four types of couples by education level in the data as before.

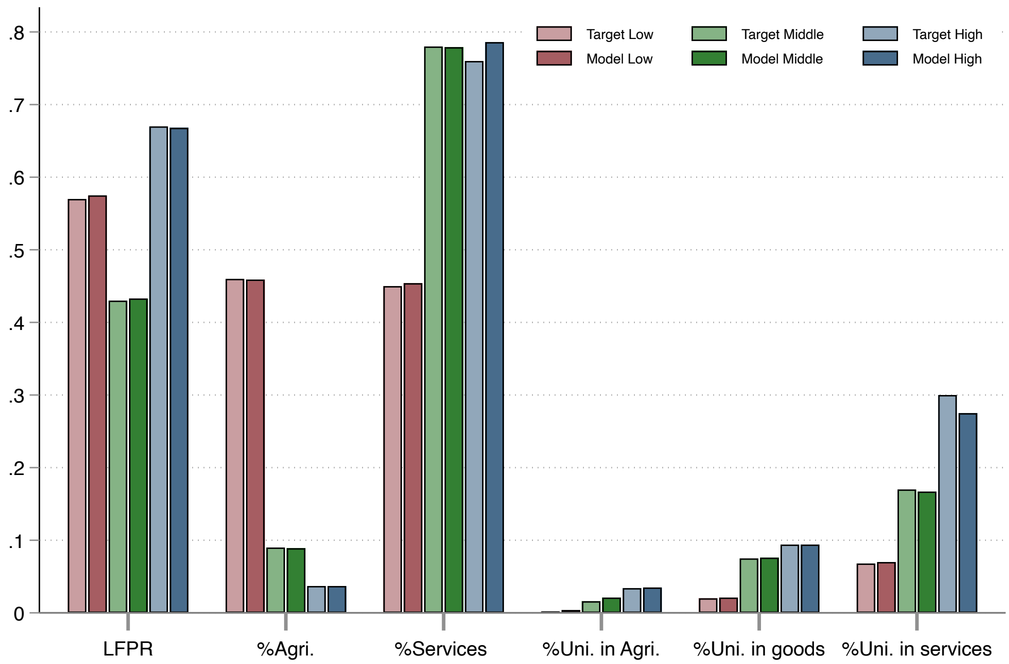
Table 6: Parameter Values by Income Tercile

Calibrated Parameter	Value
$\{A_B, A_G, A_S\}_{high}$	$\{0.45, 1.47, 1.14\}$
$\{A_B, A_G, A_S\}_{middle}$	$\{0.20, 1.47, 0.84\}$
$\{A_B, A_G, A_S\}_{low}$	$\{0.052, 1.47, 0.63\}$
$\{\chi_B, \chi_G, \chi_S\}_{high}$	$\{0.27, 0.47, 0.54\}$
$\{\chi_B, \chi_G, \chi_S\}_{middle}$	$\{0.22, 0.47, 0.46\}$
$\{\chi_B, \chi_G, \chi_S\}_{low}$	$\{0.10, 0.22, 0.27\}$
Estimated Parameter	Value
$\{\alpha\}_{high,middle,low}$	$\{3.98, 7.38, 16.78\}$

Note: The table reports the values of the parameters varying across the median low-, middle-, and high-income countries.

Table 6 presents the values of the calibrated technological parameters and the estimated assortative matching parameter in high-, middle, and low-income countries. Consistent with the literature, we find that productivity growth is the highest in agriculture and the lowest in services, which implies ST across countries. Meanwhile, we also find evidence of SBTC within all three sectors across countries, as indicated by larger estimates of χ's in more-developed economies. In addition, while α decreases with development, the magnitudes of decline across countries are much bigger than that in the U.S. over time.

Figure 6: Targeted Moments in the Model and the Data by Income Tercile

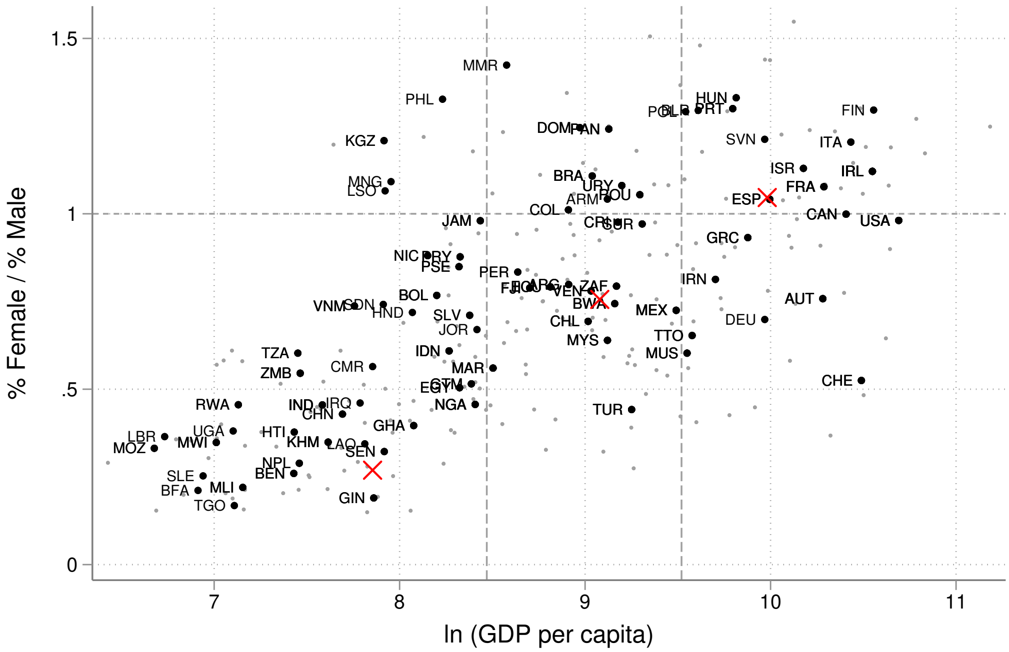


Note: This figure plots the moments targeted in the cross-country calibration and the corresponding model predictions in the median low-, middle-, and high-income countries.

Figure 6 plots the moments targeted in the data and model. Our calibrated model perfectly matches the U-shaped female LFPR, declining agriculture employment, and rising services employment across countries. For the share of educated labor in each sector's labor force, our model also closely matches the increasing skill intensity among female workers in all three sectors. As an out-of-sample test, Appendix Table A2 reports the corresponding aggregate moments in the model and data, which are not targeted. All moments match closely except a modest over-prediction of the share of university workers in the agricultural sector in low- and middle-income countries. In addition, our cross-country model predicts that α_N, the assortative matching parameter between uneducated women and men, increases from 1.1 in a low-income country to 1.5 in middle- and high-income countries, which is broadly consistent with the trends and values shown in Figure A3.

What is the degree to which our model can explain the narrowing gender education gap with development across countries? As plotted in Figure 7, our model predicts that females

Figure 7: Gender Education Gap in the Model and the Data



Note: This figure plots the gender education gap against log GDP per capita. Each black dot represents one country as in Panel (a) of Figure 1, and the red X is the prediction of the quantitative model.

are 105 percent as likely as males to obtain a college degree in the median high-income country. The model also predicts that the gender education gap decreases by 29 percentage points when we move from the median high-income country to the median middle-income country, and by 78 percentage points when we move from the median high-income country to the median low-income country. In the data, the corresponding declines are 21 and 56 percentage points. The model's over-predictions are partially due to the over-prediction of the share of the educated female labor force in the agricultural sector, particularly in the median low-income country, as shown in Figure 6. Because females have less incentive relative to males to obtain an education if they are primarily working in the agricultural sector, overshooting the importance of education in agriculture leads to an over-prediction of the gender education gap in middle and low-income countries.[16]

We further test whether or not the model's predictions of the *untargeted* female intensity by sector and education level are consistent with the empirical pattern. Table 7 reports the difference between high- and low-income countries in female intensity by sector in the aggregate and by education level in the data and the model. Without targeting the moments,

[16] See Ngai et al. (2022) for a framework that explicitly models the family farm. Hence, in equilibrium, the framework attenuates the importance of educated workers in the agricultural sector.

Table 7: The Female Intensity Difference between High- and Low-Income Country

	Aggregate		**Non-University**		**University**	
	Data	Model	Data	Model	Data	Model
Agriculture	-5.5	-6.9	-6.1	-10.4	11.6	13.3
Manufacturing	-1.1	-5.9	-1.5	-12.7	10.2	12.0
Services	9.1	-1.0	9.4	-14.5	22.6	25.0

Note: This table reports the percentage point value of the female intensity in the median high-income country less that in the median low-income country. We report this statistic in the aggregate and by education level for each sector in the model and in the data.

our model correctly predicts the aggregate decline in the female intensity in agriculture and manufacturing, although it fails to generate the aggregate increase of female intensity in services. Furthermore, consistent with the data, the model predicts that the aggregate patterns are driven by uneducated workers in each sector. Most importantly, the model perfectly predicts the rising female intensity among educated workers, with an increase of 13, 12, and 25 percentage points in agriculture, manufacturing, and services, respectively, between the high- and low-income countries, closely matching the magnitudes of 12, 10, and 22 percentage points in the data.

Table 8: Decomposition of the Mechanisms of Cross-country Predictions

	Female LFPR		**Gender Edu. Gap**	
Difference	High - Middle	High - Low	High - Middle	High - Low
Data P.P.	25.4	12.2	21.0	55.9
Benchmark P.P.	23.5	9.3	29.0	77.7
Contributions to Empowering Women in Model				
Only ST	131.1%	-204.3%	80.7%	73.2%
Only SBTC	-49.8%	-336.6%	23.4%	57.8%
Only SBTC services	-43.8%	-310.8%	16.2%	42.2%
Only ST and SBTC	106.4%	117.2%	93.8%	82.0%

Note: The top panel of this table reports the percentage point difference of the female LFPR and the gender education gap in the data and in the model between the median high-income country and the median- or low-income country. The bottom panel reports the model predictions in percent of the benchmark prediction when we only allow selected mechanisms to vary across countries.

We can now decompose the role of the different mechanisms in the benchmark cross-country model in Table 8. To do so, we allow only the selected mechanism to vary across economies, while fixing other parameters at the level of a median high-income country for model predictions. Consistent with our findings for the U.S. over time, the difference in the gender education gap between high- and middle-income countries are jointly explained by ST and SBTC, leaving a minor effect of six percentagen points that is explained by assortative matching. Meanwhile, just as for the time series pattern in the U.S., the difference in female LFPRs is solely explained by ST, while SBTC and varying assortative matching predict a contrasting pattern from the data.

When we compare high- and low-income countries, either ST or SBTC alone contributes significantly to the narrowing gender education gap, with a joint explanatory power of 82 percent of the benchmark prediction, which is close to the data moment. In addition, varying assortative matching between median high- and low-income countries plays a larger role in the model's prediction of a narrowing of the gender education gap because of the larger difference in α (17 versus 4), and it accounts for an additional 18 percent of the benchmark prediction relative to the counterfactual of allowing only for ST and SBTC. As LFPRs are high in low-income countries, a rise in ST does not lead to a rise in the LFPR, in contrast to the high- to middle-income countries and U.S. time series patterns. Instead, with ST, women will exit the labor market as they do not need to contribute to subsistence consumption. SBTC alone also leads to a fall in the LFPR in low-income countries because men still have a strong comparative advantage in the labor market. Thus, only skill-biased structural transformation can explain the initial relative fall and subsequent rise (U-shaped pattern) of the female LFPR.

6 Conclusions

In this paper, we focus on understanding the gender education gap across countries both empirically and theoretically. We start by documenting the strikingly large gender education gap in low-income countries, where females are only half as likely as males to complete university or secondary school. Meanwhile, in almost all industrialized countries nowadays, females obtain more education than males.

To investigate the causes of the sharp decrease in the gender education gap with economic development, we develop a three-sector model featuring skilled-biased structural change, assortative household formation, and endogenous education and female labor supply decisions. We validate the model by testing its prediction on a large set of out-of-sample developed countries. The model also matches the *untargeted* difference in female intensity between high- and low-income countries in the aggregate and by education level.

Through the lens of our calibrated model, skilled-biased structural transformation towards services complemented by SBTC in services is the most important factor driving the narrowing gender education gap with economic development. In contrast, SBTC in sectors where women do not hold a comparative advantage leads to a slight increase of the gender education gap. We also show that varying assortative matching plays a minor role in explaining the decrease in the gender education gap with development.

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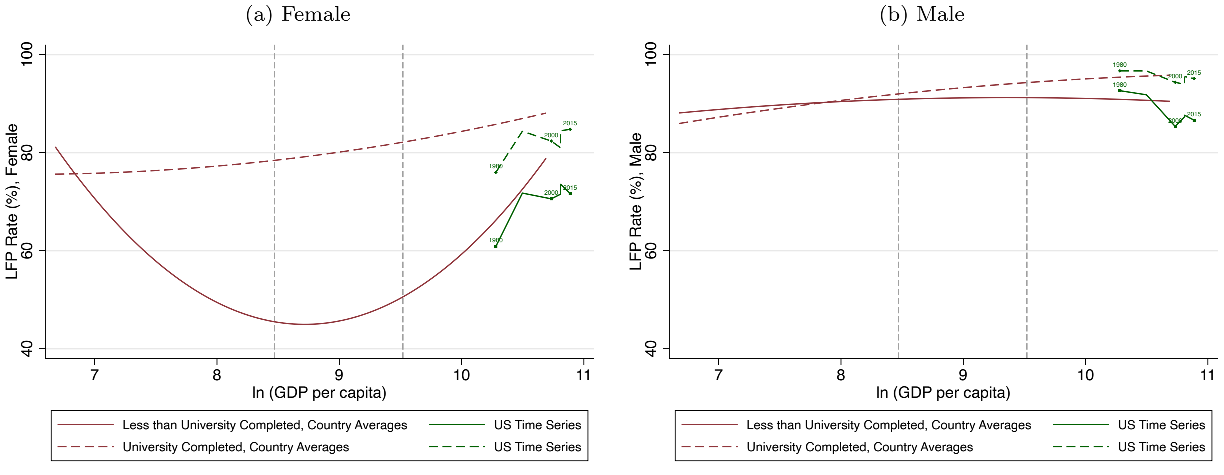
Appendices

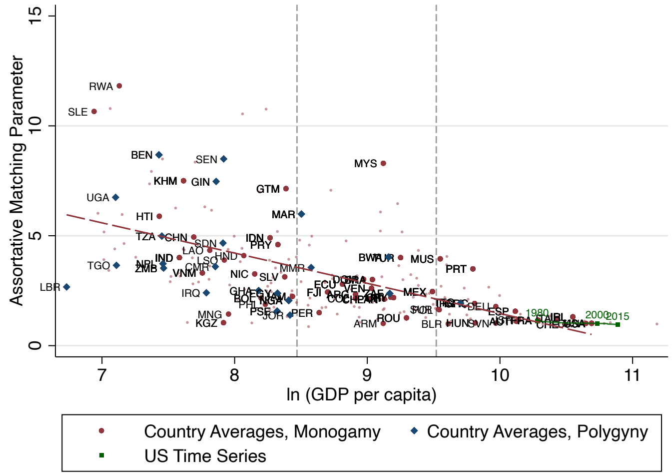
A Additional Figures and Tables

Figure A1: Labor Force Participation Rate (%) by Gender and Education



Note: Red lines represent quadratic fitted lines of country-average labor force participation rates against log GDP per capita by gender and education level. We use the employment status variable (*empstat*) to classify all employed and unemployed individuals as being in the labor force, and all others as not being in the labor force.

Figure A2: Educational Assortative Matching, Secondary School Threshold

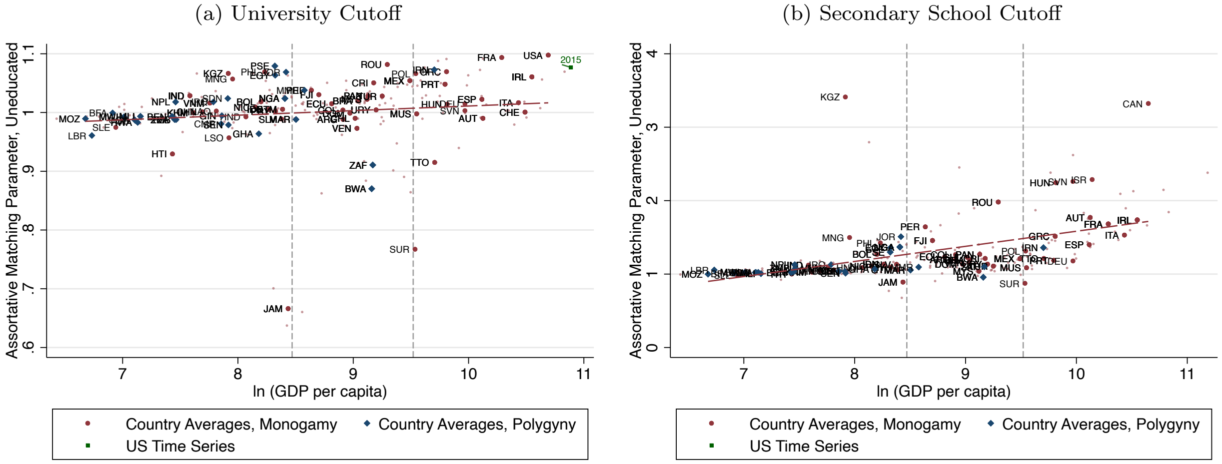


Note: This figure plots α values against log GDP per capita for each country-year sample (light red dot) and country averages (blue diamond for countries that have polygamous unions and dark red dot for the rest). Observations with secondary-school α values larger than the country-average 95th percentile value of 11.82 are dropped in this figure.

Figure A3: Educational Assortative Matching among Uneducated

(a) University Cutoff

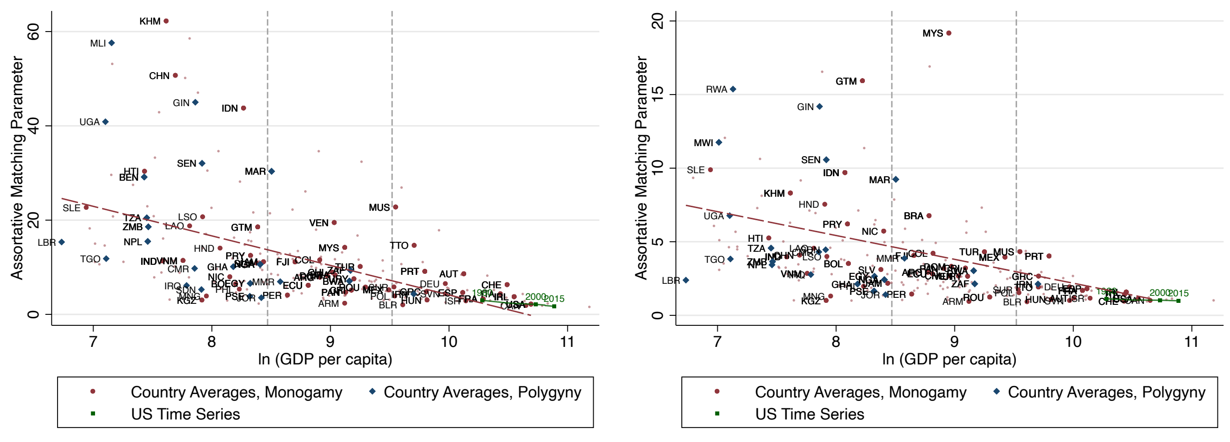
(b) Secondary School Cutoff



Note: This figure plots α_N values against log GDP per capita for each country-year sample (light red dot) and country averages (blue diamond for countries that have polygynous unions and dark red dot for the rest). Observations larger than the country-average 95th percentile are dropped.

Figure A4: Educational Assortative Matching, Upper Estimates

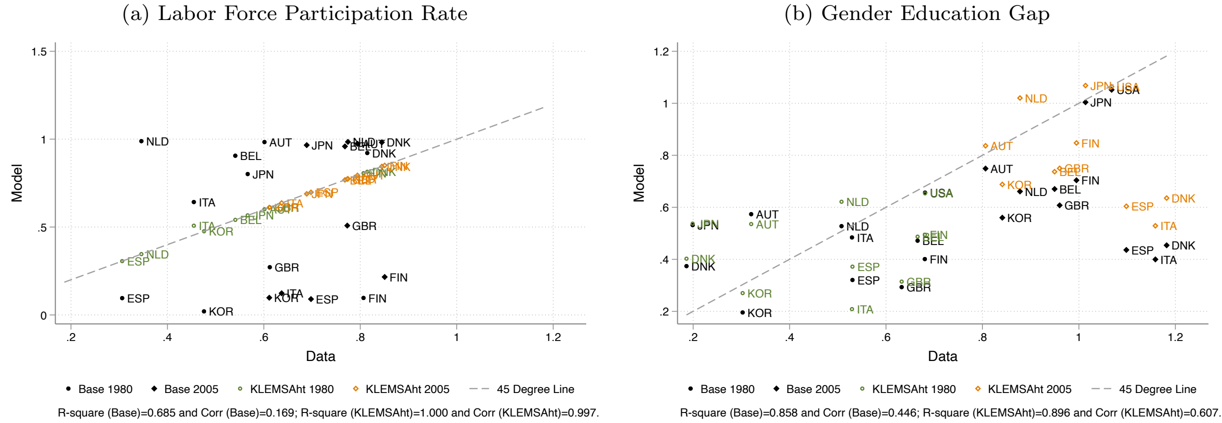
(a) University Completion (b) Secondary School Completion



Note: Restricting each sample to married households, this figure plots α values against log GDP per capita for each country-year sample (light red dot) and country averages (blue diamond for countries that have polygynous unions and dark red dot for the rest). Observations larger than the country-average 95th percentile are dropped.

Figure A5: Model Predictions Adding GBTC and Varying Home Prod.

(a) Labor Force Participation Rate (b) Gender Education Gap



Note: This figure plots the model-predicted gender education gaps and LFPR in all KELMS samples using data-identified A's, χ's, and ζ's while adding GBTC and calibrating home productivity to match LFPR to the baseline model.

Table A1: Slope of Female Labor Force Share within Sector (%) on log GDP per capita

		By Education Group	
	Aggregate	Non-University	University
Agriculture	-5.39***	-5.50***	4.25***
	(1.46)	(1.46)	(0.98)
Manufacturing	-0.46	-0.73	3.81***
	(.84)	(.86)	(.74)
Services	3.53***	3.19**	8.07***
	(1.07)	(1.15)	(1.00)
Obs.	83	83	83

Note: ***, ** and * indicate statistical significance at the one-percent, five-percent and 10-percent levels. Standard errors are shown in parentheses. We use the industry variable (*indgen*) for classification. The agricultural sector includes agriculture, fishing, and forestry; the manufacturing sector includes mining, extraction, manufacturing, construction, and utilities; the service sector includes wholesale and retail trade, hotels, restaurants, transportation, storage, communications, financial services, insurance, public administration, defense, services not specified, business services, real estate, education, health, social work, other services, and private household services.

Table A2: Model Predictions on Agg. Cross-country Moments vs the Data

Moment Median	Untargeted Data			Model		
Income Level	Low	Middle	High	Low	Middle	High
Female LFPR	0.57	0.43	0.67	0.55	0.41	0.65
%Agri Employment	0.46	0.09	0.037	0.44	0.09	0.037
%Services employment	0.45	0.78	0.76	0.47	0.78	0.78
%Uni. in Agri	0.002	0.016	0.034	0.007	0.021	0.034
%Uni. in goods	0.020	0.075	0.094	0.023	0.078	0.092
%Uni. in services	0.068	0.17	0.30	0.076	0.18	0.30

Note: The table reports the aggregate moments that are *untargeted* in the cross-country parameterization of the quantitative model and the model's predictions for each moment.

Table A3: Calibrated Parameters for KLEMS Countries

Country	$\{A_B, A_G, A_S\}_{1980}$	$\{A_B, A_G, A_S\}_{2005}$	$\{\chi_B, \chi_G, \chi_S\}_{1980}$	$\{\chi_B, \chi_G, \chi_S\}_{2005}$
AUT	$\{1.15, 0.82, 0.93\}$	$\{2.50, 1.97, 1.11\}$	$\{0.04, 0.14, 0.26\}$	$\{0.20, 0.23, 0.36\}$
BEL	$\{0.92, 0.77, 0.96\}$	$\{2.23, 1.70, 1.14\}$	$\{0.09, 0.20, 0.31\}$	$\{0.17, 0.32, 0.39\}$
DNK	$\{0.59, 0.72, 0.80\}$	$\{2.54, 1.14, 1.06\}$	$\{0.12, 0.11, 0.23\}$	$\{0.11, 0.19, 0.31\}$
ESP	$\{0.30, 0.48, 0.55\}$	$\{1.00, 0.78, 0.61\}$	$\{0.06, 0.20, 0.41\}$	$\{0.24, 0.35, 0.55\}$
FIN	$\{0.85, 0.54, 0.68\}$	$\{2.22, 1.72, 0.87\}$	$\{0.37, 0.36, 0.48\}$	$\{0.47, 0.48, 0.60\}$
GBR	$\{0.58, 0.49, 0.68\}$	$\{1.30, 1.38, 0.98\}$	$\{0.15, 0.17, 0.31\}$	$\{0.27, 0.36, 0.48\}$
ITA	$\{0.38, 0.46, 0.58\}$	$\{1.36, 0.70, 0.53\}$	$\{0.04, 0.09, 0.24\}$	$\{0.12, 0.12, 0.38\}$
JPN	$\{1.08, 1.08, 1.10\}$	$\{2.27, 2.66, 1.90\}$	$\{0.25, 0.31, 0.40\}$	$\{0.37, 0.43, 0.51\}$
KOR	$\{0.23, 0.24, 0.43\}$	$\{1.11, 1.62, 0.67\}$	$\{0.45, 0.46, 0.58\}$	$\{0.59, 0.55, 0.66\}$
NLD	$\{1.00, 1.17, 1.39\}$	$\{2.22, 1.85, 1.75\}$	$\{0.02, 0.13, 0.28\}$	$\{0.29, 0.25, 0.36\}$

Note: The table reports the estimates of the sectoral productivity and the sectoral skill-intensity parameters in each available KLEMS country in 1980 and 2005.

B Proofs of the theoretical results

B.1 Consumption

Given market income agents maximize market consumption. We can ignore the home production choice and solve consumption conditional on income, $y_{Wjj'}$. Substituting the budget constraint for c_S, $c_S = \frac{y_W jj' - p_B c_B - p_G c_G}{p_S}$, FOCS are:

$$\frac{\partial c}{\partial c_B} = c^{\frac{1}{\nu}} \left[\phi_B^{\frac{1}{\nu}} (c_B - \underline{B})^{\frac{-1}{\nu}} - \phi_S^{\frac{1}{\nu}} (\hat{c}_S)^{\frac{-1}{\nu}} \frac{p_B}{p_S} \right] = 0 \tag{17}$$

$$\frac{\partial c}{\partial c_G} = c^{\frac{1}{\nu}} \left[\phi_G^{\frac{1}{\nu}} (c_G)^{\frac{-1}{\nu}} - \phi_S^{\frac{1}{\nu}} (\hat{c}_S)^{\frac{-1}{\nu}} \frac{p_B}{p_S} \right] = 0 \tag{18}$$

Using the two first-order conditions and the budget constraint we can derive the following relative consumption choices and consumption of market services with the assumption that home production and market services are perfect substitutes:

$$\frac{c_H + c_S}{c_B - \underline{B}} = \left(\frac{\phi_S}{\phi_B} \right) \left(\frac{p_B}{p_S} \right)^{\nu}, \tag{19}$$

$$\frac{c_H + c_S}{c_G} = \left(\frac{\phi_S}{\phi_G} \right) \left(\frac{p_G}{p_S} \right)^{\nu} \tag{20}$$

$$c_S = \frac{y_j^g - p_B \underline{B} - c_H \left(p_B \left(\frac{\phi_B}{\phi_S} \right) \left(\frac{p_S}{p_B} \right)^{\nu} + p_G \left(\frac{\phi_G}{\phi_S} \right) \left(\frac{p_S}{p_G} \right)^{\nu} \right)}{p_S + p_B \left(\frac{\phi_B}{\phi_S} \right) \left(\frac{p_S}{p_B} \right)^{\nu} + p_G \left(\frac{\phi_G}{\phi_S} \right) \left(\frac{p_S}{p_G} \right)^{\nu}}. \tag{21}$$

Note that relative consumption, Equations (19) and (20), do not depend on education-occupation status. Given $\Omega = p_S \left(\frac{\phi_s}{p_s} \right)^{\nu} + p_B \left(\frac{\phi_B}{p_B} \right)^{\nu} + p_G \left(\frac{\phi_G}{p_G} \right)^{\nu}$ and Equations (19)-(21), total consumption (the composite of market and home consumption) is

$$c = (y_W jj' - p_B \underline{B} + p_S c_H) \, \Omega^{\frac{1}{\nu - 1}}. \tag{22}$$

B.2 Production

The marginal products of labor are

$$
\begin{aligned}
w_{Ek}^f &= p_k A_k H_k^{\frac{1}{\theta}} \chi_k H_{Ek}^{-\frac{1}{\theta}+\frac{1}{\eta}} \zeta_{Ek} (H_{Ek}^f)^{-\frac{1}{\eta}}, \text{ for } k = S, G; \\
w_{Nk}^f &= p_k A_k H_k^{\frac{1}{\theta}} (1-\chi_k) H_{Nk}^{-\frac{1}{\theta}+\frac{1}{\eta}} \zeta_{Nk} (H_{Nk}^f)^{-\frac{1}{\eta}}, \text{ for } k = S, G; \\
w_{Ek}^m &= p_k A_k H_k^{\frac{1}{\theta}} \chi_k H_{Ek}^{-\frac{1}{\theta}+\frac{1}{\eta}} (1-\zeta_{Ek}) (H_{Ek}^m)^{-\frac{1}{\eta}}, \text{ for } k = B, S, G; \\
w_{Nk}^m &= p_k A_k H_k^{\frac{1}{\theta}} (1-\chi_k) H_{Nk}^{-\frac{1}{\theta}+\frac{1}{\eta}} (1-\zeta_{Nk}) (H_{Nk}^m)^{-\frac{1}{\eta}}, \text{ for } k = B, S, G.
\end{aligned}
\tag{23}
$$

Define wage bill shares by gender as:

$$
I_{jk}^f = \frac{w_k^f H_{jk}^f}{w_k^f H_{jk}^f + w_k^m H_{jk}^m}, \text{ where } j = E, N, \text{ and } k = B, G, S, \tag{24}
$$

and by education type as:

$$
I_{Ek} = \frac{p_{Ek} H_{Ek}}{p_{Ek} H_{Ek} + p_{Nk} H_{Nk}}, \text{ where } k = B, G, S, \tag{25}
$$

where $I_{Nk} = 1 - I_{Ek}$ and education-specific factor prices are:

$$
p_{Ek} = p_k A_k H_k^{\frac{1}{\theta}} \chi_k \left(H_{Ek}\right)^{-\frac{1}{\theta}},
$$

$$
p_{Nk} = p_k A_k H_k^{\frac{1}{\theta}} (1-\chi_k) \left(H_{Nk}\right)^{-\frac{1}{\theta}}.
$$

Using (10) and (13) the wage bill shares are:

$$
I_{jk}^f = \left[1 + x_j^{\eta-1} \left(\frac{1-\zeta_{jk}}{\zeta_{jk}}\right)^{\eta}\right]^{-1}, \tag{26}
$$

$$
I_{Ek} = \left[1 + \pi_k^{\theta-1} \left(\frac{1-\chi_k}{\chi_k}\right)^{\theta}\right]^{-1}, \tag{27}
$$

and

$$
I_{Nk} = 1 - I_{Ek} = \left[\pi_k^{\theta-1} \left(\frac{1-\chi_k}{\chi_k}\right)^{\theta}\right] \left[1 + \pi_k^{\theta-1} \left(\frac{1-\chi_k}{\chi_k}\right)^{\theta}\right]^{-1}. \tag{28}
$$

From the above two equations and the production functions, we obtain

$$\frac{H_{jk}}{H^f_{jk}} = \left(\frac{\zeta_{jk}}{I^f_{jk}}\right)^{\frac{\eta}{\eta-1}}, \tag{29}$$

$$\frac{H_k}{H_{Ek}} = \left(\frac{\chi_k}{I_{Ek}}\right)^{\frac{\theta}{\theta-1}}, \tag{30}$$

and

$$\frac{H_k}{H_{Nk}} = \pi_k^{-\theta}\left(\frac{\chi_k}{1-\chi_k}\right)^{\theta}\left(\frac{\chi_k}{I_{Ek}}\right)^{\frac{\theta}{\theta-1}} = \left(\frac{1-\chi_k}{I_{Nk}}\right)^{\frac{\theta}{\theta-1}}, \tag{31}$$

and the output in terms of relative wage bills

$$Y_k = A_k H_{Ek}\left(\frac{\chi_k}{I_{Ek}}\right)^{\frac{\theta}{\theta-1}}, \tag{32}$$

$$Y_k = A_k H_{Nk}\left(\frac{1-\chi_k}{I_{Nk}}\right)^{\frac{\theta}{\theta-1}}, \tag{33}$$

$$Y_k = A_k H^f_{Ek}\left(\frac{\zeta_{Ek}}{I^f_{Ek}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{\chi_k}{I_{Ek}}\right)^{\frac{\theta}{\theta-1}}, \tag{34}$$

$$Y_k = A_k H^f_{Nk}\left(\frac{\zeta_{Nk}}{I^f_{Nk}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{1-\chi_k}{I_{Nk}}\right)^{\frac{\theta}{\theta-1}}. \tag{35}$$

Since wages by gender equal across sectors in equilibrium, using marginal products and the above four equations, we have

$$\frac{p_S}{p_G} = \frac{A_G}{A_S}\left(\frac{\chi_G}{\chi_S}\right)^{\frac{\theta}{\theta-1}}\left(\frac{\zeta_{EG}}{\zeta_{ES}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{I_{ES}}{I_{EG}}\right)^{\frac{1}{\theta-1}}\left(\frac{I^f_{ES}}{I^f_{EG}}\right)^{\frac{1}{\eta-1}} \tag{36}$$

or

$$\frac{p_S}{p_G} = \frac{A_G}{A_S}\left(\frac{1-\chi_G}{1-\chi_S}\right)^{\frac{\theta}{\theta-1}}\left(\frac{\zeta_{NG}}{\zeta_{NS}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{I_{NS}}{I_{NG}}\right)^{\frac{1}{\theta-1}}\left(\frac{I^f_{NS}}{I^f_{NG}}\right)^{\frac{1}{\eta-1}} \tag{37}$$

and

$$\frac{p_B}{p_S} = \frac{A_S}{A_B}(1-\chi_S)^{\frac{\theta}{\theta-1}}\left(\frac{\zeta_{NS}}{\zeta_{NB}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{1}{I_{NS}}\right)^{\frac{1}{\theta-1}}\left(\frac{I^f_{NB}}{I^f_{NS}}\right)^{\frac{1}{\eta-1}}. \tag{38}$$

Using Equation (20) from the consumer's problem, relative prices Equations (36) or (37), output Equations (32) and (34) from the producer's problem, and goods market clearing conditions, we have

$$\frac{Y_S}{Y_G} = \left(\frac{\phi_S}{\phi_G}\frac{p_G}{p_S}\right)^{\nu}, \tag{39}$$

$$\frac{A_S}{A_G}\frac{H_{ES}}{H_{EG}}\left(\frac{\chi_S}{\chi_G}\right)^{\frac{\theta}{\theta-1}}\left(\frac{I_{EG}}{I_{ES}}\right)^{\frac{\theta}{\theta-1}} = \left(\frac{\phi_S}{\phi_G}\frac{p_G}{p_S}\right)^{\nu}, \tag{40}$$

$$\frac{H_{ES}}{H_{EG}} = \frac{A_G}{A_S}\left(\frac{\phi_S}{\phi_G}\frac{p_G}{p_S}\right)^{\nu}\left(\frac{\chi_S}{\chi_G}\right)^{\frac{-\theta}{\theta-1}}\left(\frac{I_{EG}}{I_{ES}}\right)^{\frac{-\theta}{\theta-1}}, \tag{41}$$

$$\frac{H_{ES}}{H_{EG}} = \left(\frac{A_G}{A_S}\right)^{1-\nu}\left(\frac{\phi_S}{\phi_G}\right)^{\nu}\left(\frac{\zeta_{ES}}{\zeta_{EG}}\right)^{\frac{\eta\nu}{\eta-1}}\left(\frac{\chi_G}{\chi_S}\right)^{\frac{\theta(1-\nu)}{\theta-1}}\left(\frac{I_{ES}}{I_{EG}}\right)^{\frac{\theta-\nu}{\theta-1}}\left(\frac{I^f_{EG}}{I^f_{ES}}\right)^{\frac{\nu}{\eta-1}}. \tag{42}$$

Next, using consumption decisions and market clearing conditions, we can solve again for the equilibrium. But now we need to add the agricultural sector, which includes the non-homotheticity condition/assumption.

$$Y_S = \left(\frac{\phi_S}{\phi_B}\frac{p_B}{p_S}\right)^{\nu}\left(Y_B - \underline{B}\right), \tag{43}$$

$$A_S H_{NS}\left(\frac{1-\chi_S}{I_{ES}}\right)^{\frac{\theta}{\theta-1}} = \left(\frac{\phi_S}{\phi_B}\frac{p_B}{p_S}\right)^{\nu}\left(A_B H_{NB} - \underline{B}\right), \tag{44}$$

$$A_S H_{NS}\left(\frac{1-\chi_S}{I_{ES}}\right)^{\frac{\theta}{\theta-1}} = \left(\frac{\phi_S}{\phi_B}\frac{A_S}{A_B}(1-\chi_S)^{\frac{\theta}{\theta-1}}\left(\frac{\zeta_{NS}}{\zeta_{NB}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{1}{I_{NS}}\right)^{\frac{1}{\theta-1}}\left(\frac{I^f_{NB}}{I^f_{NS}}\right)^{\frac{1}{\eta-1}}\right)^{\nu}$$
$$\left(A_B H_{NB} - \underline{B}\right), \tag{45}$$

$$A_S H^f_{NS}\left(\frac{\zeta_{NS}}{I^f_{NS}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{1-\chi_S}{I_{ES}}\right)^{\frac{\theta}{\theta-1}} = \left(\frac{\phi_S}{\phi_B}\frac{A_S}{A_B}(1-\chi_S)^{\frac{\theta}{\theta-1}}\left(\frac{\zeta_{NS}}{\zeta_{NB}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{1}{I_{NS}}\right)^{\frac{1}{\theta-1}}\left(\frac{I^f_{NB}}{I^f_{NS}}\right)^{\frac{1}{\eta-1}}\right)^{\nu}$$
$$\left(A_B H^f_{NB}\left(\frac{\zeta_{NB}}{I^f_{NB}}\right)^{\frac{\eta}{\eta-1}} - \underline{B}\right). \tag{46}$$

Lastly, using the zero-profit condition, we can solve for prices as function of wage rates. Goods and service prices are

$$p_k = \frac{1}{A_k}\left\{\chi_k^{\theta} p_{Ek}^{1-\theta} + (1-\chi_k)^{\theta} p_{Nk}^{1-\theta}\right\}^{\frac{-1}{\theta-1}} \tag{47}$$

or equivalently

$$p_k = \frac{1}{A_k}\left\{\chi_k^\theta\left[\zeta_{Ek}^\eta (w_E^f)^{1-\eta} + (1-\zeta_{Ek})^\eta (w_E^m)^{1-\eta}\right]^{\frac{\theta-1}{\eta-1}} + (1-\chi_k)^\theta\left[\zeta_{Nk}^\eta (w_N^f)^{1-\eta} + (1-\zeta_{Nk})^\eta (w_N^m)^{1-\eta}\right]^{\frac{\theta-1}{\eta-1}}\right\}^{\frac{-1}{\theta-1}}. \tag{48}$$

C Alternative Setup for Home Production

C.1 Home production as imperfect substitutes for services

In this section, we present a model where home production is an imperfect substitute for service consumption. The household's aggregate market and home consumption is a CES of

$$c = \left(\phi_G c_G^{\frac{\nu-1}{\nu}} + \phi_S \hat{c}_S^{\frac{\nu-1}{\nu}} + \phi_B (c_B - \underline{B})^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}} \tag{49}$$

where c_G and c_B are sector-specific consumption and $\underline{B}$ is a constant as in the benchmark model. But $\hat{c}_S$ is a composite service consumption made up of home and market consumption. Given the discrete employment choices, service consumption is

$$\hat{c}_S = \left(c_H^{\frac{\sigma-1}{\sigma}} + c_S^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{50}$$

Households maximize utility:

$$\max_{c_G, c_S, c_B, c_H, l^f} U(c, c_H) \tag{51}$$

s.t.

$$\sum_{i=G,S,B} p_i c_i \leq w_j^m + w_{j'}^f l_{jj'}^f \equiv y_{jj'W}. \tag{52}$$

Given market income, households maximize market consumption c. Substituting the budget constraint for c_S, $c_S = \frac{y_j - p_B c_B - p_G c_G}{p_S}$, FOCS are:

$$\frac{\partial c}{\partial c_B} = c^{\frac{1}{\nu}}\left[\phi_B (c_B - \underline{B})^{\frac{-1}{\nu}} - \phi_S (\hat{c}_S)^{\frac{\nu-\sigma}{\sigma\nu}} c_S^{\frac{-1}{\sigma}} \frac{p_B}{p_S}\right] = 0, \tag{53}$$

$$\frac{\partial c}{\partial c_G} = c^{\frac{1}{\nu}}\left[\phi_G (c_G)^{\frac{-1}{\nu}} - \phi_S (\hat{c}_S)^{\frac{\nu-\sigma}{\sigma\nu}} c_S^{\frac{-1}{\sigma}} \frac{p_G}{p_S}\right] = 0. \tag{54}$$

Then

$$c_B = \left(\frac{\phi_B}{\phi_S}\frac{p_S}{p_B}\right)^{\nu} \left(\left(\frac{A_w}{c_S}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)^{\frac{\sigma-\nu}{\sigma-1}} c_S + \underline{B}, \tag{55}$$

$$c_G = \left(\frac{\phi_G}{\phi_S}\frac{p_S}{p_G}\right)^{\nu} \left(\left(\frac{A_w}{c_S}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)^{\frac{\sigma-\nu}{\sigma-1}} c_S, \tag{56}$$

$$c_S + \left[p_B\left(\frac{\phi_B}{\phi_S}\frac{p_S}{p_B}\right)^{\nu} + p_G\left(\frac{\phi_G}{\phi_S}\frac{p_S}{p_G}\right)^{\nu}\right] \left(\left(\frac{A_w}{c_S}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)^{\frac{\sigma-\nu}{\sigma-1}} c_S = y_j - p_B\underline{B}. \tag{57}$$

Equation (57) solves for c_S and Equations (55) and (56) solve for the remaining consumption allocation. A female enters the labor market if $w_j^m < p_B\underline{B}$ or if

$$\left(\Omega^{\frac{1}{\nu-1}}\right)^{\frac{\sigma-1}{\sigma}} \left[\left(w_j^f + w_j^m - p_B\underline{B}\right)^{\frac{\sigma-1}{\sigma}} - \left(w_j^m - p_B\underline{B}\right)^{\frac{\sigma-1}{\sigma}}\right] \geq x^{\frac{\sigma-1}{\sigma}},$$

$$w_j^f \geq \left[\left(\Omega^{\frac{1}{\nu-1}}\right)^{-\frac{\sigma-1}{\sigma}} x^{\frac{\sigma-1}{\sigma}} + \left(w_j^m - p_B\underline{B}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - \left(w_j^m - p_B\underline{B}\right) \equiv \underline{w}_j^f(x, w_j^m).$$

D Allowing for GBTC in the U.S. Over Time

Table A4: Calibrated Parameters, adding GBTC

Parameter	Value
Panel A: Pre-Assigned Parameters	
Same as benchmark	
Panel B: Data-Identified Parameters	
$\{A_B^{US}, A_G^{US}, A_S^{US}\}_{t=T}$ - sector-specific technology	$\{3.78, 2.00, 1.36\}$
$\{\chi_{B,0}, \chi_{G,0}, \chi_{S,0}, \chi_{B,T}, \chi_{G,T}, \chi_{S,T}\}$ - educated productivity	$\{0.28, 0.31, 0.45, 0.36, 0.46, 0.60\}$
$\{\zeta_{EB,0}, \zeta_{NB,0}, \zeta_{EG,0}, \zeta_{NG,0}, \zeta_{ES,0}, \zeta_{NS,0}\}$ - female productivity	$\{0.25, 0.25, 0.24, 0.29, 0.37, 0.40\}$
$\{\zeta_{EB,T}, \zeta_{NB,T}, \zeta_{EG,T}, \zeta_{NG,T}, \zeta_{ES,T}, \zeta_{NS,T}\}$ - female productivity	$\{0.31, 0.30, 0.32, 0.31, 0.42, 0.46\}$
$\{\alpha_0, \alpha_T\}$ - educational assortative mating	$\{2.85, 2.17\}$
Panel C: Calibrated Parameters	
$\{\mu_m, \mu_f, \sigma_m, \sigma_f\}$ - education cost distribution	$\{3.61, 0.37, 6.90, 1.29\}$
$\{\mu_E, \mu_N, \sigma_E, \sigma_N\}$ - home productivity distribution	$\{-3.97, -2.86, 2.07, 0.41\}$
$\left(\frac{p_{B,0}}{Y_0}\underline{B}\right), \phi_B, \phi_G$ - consumption parameters	$\{0.02, 1.13 \times 10^{(-7)}, 0.36\}$

Note: The table reports the values and interpretations of the parameters of the quantitative model under the calibration further adding GBTC.

Table A5: Moments Targeted in the Model vs Data, adding GBTC

Moment	Target	Model
Panel A: Moments identifying $\{\mu_m, \mu_f, \sigma_f, \sigma_m\}$		
Male educated shares in $t = 0, T$	$\{0.24, 0.28\}$	$\{0.24, 0.28\}$
Female educated shares in $t = 0, T$	$\{0.16, 0.30\}$	$\{0.16, 0.30\}$
Panel B: Moments identifying $\{\mu_E, \mu_N, \sigma_E, \sigma_N\}$		
Educated women in LF in $t = 0, T$	$\{0.76, 0.81\}$	$\{0.77, 0.83\}$
Uneducated women in LF in $t = 0, T$	$\{0.61, 0.72\}$	$\{0.60, 0.70\}$
Panel C: Moments identifying $\{\phi_s, \phi_g, \underline{B}\}$		
Goods value-added share (y_G) in $t = 0, T$	$\{0.32, 0.22\}$	$\{0.36, 0.28\}$
Food value-added share (y_B) in $t = 0, T$	$\{0.03, 0.01\}$	$\{0.04, 0.01\}$
Panel D: Moments identifying ζ's		
Educated gender wage gap (x_E) in $t = 0, T$	$\{0.69, 0.70\}$	$\{0.70, 0.72\}$
Uneducated gender wage gap (x_N) in $t = 0$	$\{0.63, 0.78\}$	$\{0.69, 0.89\}$
Educated female/male service labor ratio in $t = 0, T$	$\{0.69, 1.12\}$	$\{0.67, 1.04\}$
Educated female/male goods labor ratio in $t = 0, T$	$\{0.16, 0.42\}$	$\{0.16, 0, 38\}$
Educated female/male agriculture labor ratio in $t = 0, T$	$\{0.19, 0.36\}$	$\{0.18, 0.34\}$
Uneducated female/male service labor ratio in $t = 0, T$	$\{1.17, 1.26\}$	$\{0.98, 0.98\}$
Uneducated female/male goods labor ratio in $t = 0, T$	$\{0.39, 0.30\}$	$\{0.32, 0.23\}$
Uneducated female/male agriculture labor ratio in $t = 0, T$	$\{0.25, 0.26\}$	$\{0.21, 0.20\}$
Panel E: Moments identifying χ's		
Educated service wage bill share (I_{ES}) in $t = 0, T$	$\{0.38, 0.56\}$	$\{0.36, 0.54\}$
Educated goods wage bill share (I_{EG}) in $t = 0, T$	$\{0.20, 0.36\}$	$\{0.20, 0.33\}$
Educated agriculture wage bill share (I_{EB}) in $t = 0, T$	$\{0.17, 0.22\}$	$\{0.16, 0.20\}$
Relative college service price (π_S) in $t = 0, T$	$\{1.30, 1.96\}$	$\{1.60, 2.40\}$
Relative college goods price (π_G) in $t = 0, T$	$\{1.20, 2.02\}$	$\{1.50, 2.54\}$
Relative college agriculture price (π_B)in $t = 0, T$	$\{1.27, 2.03\}$	$\{1.59, 2.55\}$

Note: The table reports the moments targeted in the calibration further adding GBTC of the quantitative model and the model's predictions for each moment.

Table A6: Decomposition of the U.S. with Calibration Adding GBTC

			Female Labor Force Participation	
		Gender Edu. Gap	University	Non-University
	Δ P.P. in Data	-39.4	5.0	10.6
	Δ P.P. in Model	-40.0	5.4	10.4
	Contributions to Empowering Women in the Model			
(i)	Only GBTC	9.0%	14.6%	28.1%
(ii)	GBTC and ST	62.3%	170.7%	375.4%
(iii)	GBTC and STBC	33.0%	-105.4%	-363.2%
(iv)	ST and STBC	116.9%	81.2%	108.2%
(v)	GBTC, ST, and SBTC	120.7%	97.0%	137.8%

Table A6 reports the quantitative decomposition results, similar to that of Table 5. When all four mechanisms are present, allowing for GBTC alone explains only nine percent of the total model variations. Adding ST and STBC improves the explanatory power by 53 and 24 percentage points, respectively. Lastly, allowing for GBTC, ST, and SBTC together accounts for 122 percent of the total model variation, which is slightly smaller than the 133 percent that is accounted for by combining ST and STBC in the benchmark. Therefore, we conclude that GBTC contributes minimally to the gender education gap evolution in the U.S.