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Why does the schooling gap close while the wage gap persists across country income comparisons? ☆

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ABSTRACT

The schooling gap diminishes because the services sector becomes more pronounced for high-income countries, and the paid hours gap closes. Although gender wage inequality persists across country income groups, differences in schooling years between females and males diminish. We assemble a novel dataset, calibrate a general equilibrium, multi-sector, -gender, and -production technology model, and show that gender-specific sectoral comparative advantages explain the paid hours and schooling gap decline from low- to high-income economies even when the wage gap persists. Additionally, our counterfactual analyses indicate that consumption subsistence and production share heterogeneity across both income groups and genders are essential to explain the co-decline of the schooling and paid hours gaps. Our results highlight effective mechanisms for policies aiming to reduce gender inequality in schooling and suggest that the schooling gap decline and the de-invisibilization of female paid work observed in high-income countries are linked by structural sector movements instead of wage inequality reductions.

1. Introduction

Cross-country data from Barro and Lee (2013) suggest that males in countries in the bottom third of the world income distribution spend 40% more years on average in education than females. In some extreme cases, such as Benin, Mozambique, and Liberia, males spend nearly or even more than twice as many years in school as females. At the same time, when comparing low-, middle-, and high-income countries, female years of schooling increase relatively faster than males', leading to a diminishing schooling gap. Nonetheless, gender wage inequality persists across all country-income groups, and therefore, wage gap differences cannot explain the schooling gap decline observed in cross-country data.

Instead, we show that differences in the sectoral structure of the economies are conducive drivers of the diminishing schooling gap across country income groups. On average, high-income countries exhibit larger modern services sectors than countries in lower income groups. Moreover, females have a sectoral comparative advantage in the services sector compared to other modern production sectors (Ngai and Petrongolo, 2017). Thus, sizeable modern services sectors encourage females to increase their hours of paid work. Because work in modern production is human capital intensive and hours are remunerated accordingly, females have more incentives

☆ The views expressed in this article are those of the authors and do not necessarily reflect the views of the European Central Bank, the Deutsche Bundesbank, or any other Eurosystem central bank.

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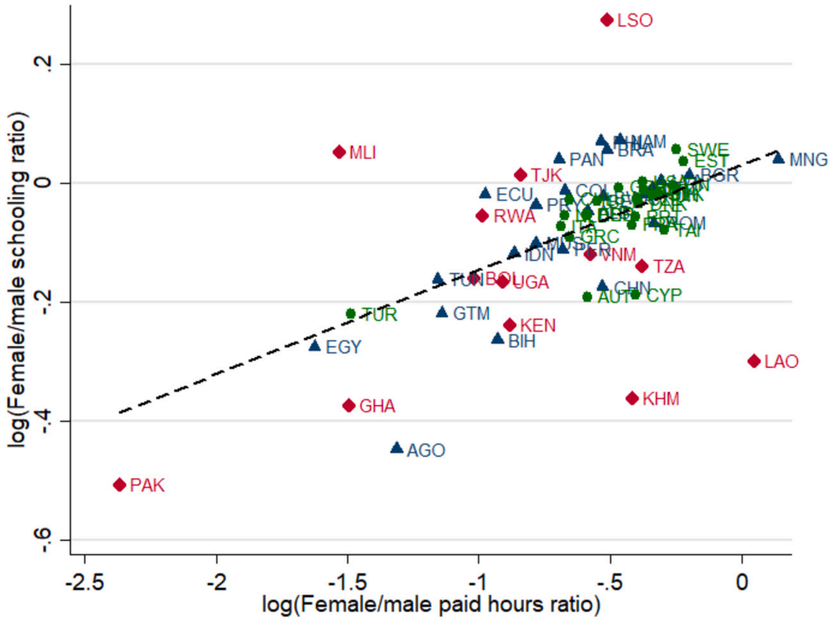

Fig. 1. Female-to-male ratios in years of schooling and paid hours.

to stay longer in school. Males have similar incentives to increase their education as they increase their hours in modern production. However, they have sectoral comparative advantages in the modern agricultural and manufacturing sectors. Since these sectors are less pronounced compared to services in high-income countries, the rates with which male hours of paid work and, thus, schooling years increase are lower than the female rates. Consequently, the structural traits of high-income economies lead to smaller schooling gaps, irrespective of the wage gap.

We assess schooling choices in the context of a general equilibrium, two-gender, three-sector, and two-production technology model of structural change, evaluated for the sectoral compositions of low-, middle-, and high-income economies. Ngai and Petrongolo (2017), whose work we build upon, calibrate their model using US data and have a single commodity production sector. We distinguish between agriculture and manufacturing because we calibrate our model using cross-country data containing many low- and middle-income countries with extensive agriculture and manufacturing sectors.

More importantly, we incorporate gender-specific schooling choices in the model. Restuccia and Vandenbroucke (2014) show that, along what we refer to as the *individual decision margin*, schooling and paid hours choices are closely linked because wages for paid work depend on human capital. Their model suggests that the level of hours in paid work (i.e., the intensive margin in paid hours) drives the extent to which agents can realize the returns to schooling. However, their model does not distinguish by gender and, hence, does not consider the possibility of within-household substitution effects between genders. Instead, our model combines the schooling and paid hours trade-off at a within-household gender level with the structural change model of Ngai and Petrongolo (2017). That is, we assess schooling choices additionally along what we refer to as the *household decision margin*. In conjunction with the dataset we construct, our novelty allows us to examine gender differences in schooling and paid hours choices from this previously unexplored perspective. We find that because female-to-male hours of paid work are greater in high- compared to low-income countries, females have relatively more opportunities to realize the returns to schooling and, consequently, are relatively more incentivized to invest in schooling. As a result, female-to-male years of schooling are greater in high-income countries.

The combination of schooling and gender-biased technological change in our model is motivated by the stylized fact of Fig. 1, depicting the positive correlation between the female-to-male paid hours and schooling ratios. We arrive at this observation by assembling an original cross-country dataset containing information on labor and schooling choices at the household level. Our primary source of paid hours and hourly wages is the cross-sectional micro-dataset of Bick et al. (2018). We calculate paid hours from hours worked by paid employees and employers in modern production schedules (Gollin, 2008; Bick et al., 2022), aggregate at the country-sector-gender level, and compute the wage gaps after controlling for differences in observables (Oaxaca, 1973). Finally, we match the resulting dataset with the country-level female and male schooling data of Barro and Lee (2013).

Our data indicate that males spend more than twice as many hours in paid work than females on average in low-income countries (cf. Bridgman et al., 2018). However, females' hours of paid work increase faster than males' when comparing low- and high-income countries, resulting in a diminishing gender gap in paid hours. The gender gap in years of schooling exhibits a similar pattern. It is large in low-income countries but disappears as females' years of schooling catch up to males' in high-income countries.

Table 1 examines the robustness of the positive correlation between the schooling and paid hours ratios using log-log regressions. Column (1) reports the linear correlation coefficient presented in Fig. 1. Column (2) shows that the elasticity remains positive and statistically significant for the sub-sample of countries with available wage data. The regression of column (3) additionally controls for the wage ratio, the per-capita gross domestic product (GDPPC), and unobservable fundamentals that remain constant across

Table 1
Linear regressions of schooling on paid hours ratios.

Dependent Variable: Female/male schooling ratio	(1)	(2)	(3)	(4)
Paid Hours Ratio	0.18***	0.22***	0.15***	0.16***
	(0.044)	(0.021)	(0.041)	(0.035)
Wage Ratio			0.059	0.18
			(0.13)	(0.14)
GDPPC (in 2005 PPP adj. US $)			-0.035	-0.097
			(0.041)	(0.059)
Share of services in NIPA hours				0.17**
				(0.084)
Income Group FEs	-	-	Yes	Yes
N	60	38	38	38
R^2	0.313	0.629	0.732	0.771

Notes: All variables are in log terms. GDPPC is computed from the Penn World Tables (Feenstra et al., 2015). Parentheses have heteroskedasticity-robust standard errors. *** denote significance on the 1%-level, ** on the 5% and * on the 10%-level.

countries of the same income group. Column (4) further controls for the share of services in hours worked, as measured in the National Income and Product Accounts (NIPA). The paid hours ratio maintains its sign and the 1%-statistical significance in all four regressions. The wage ratio and the GDPPC coefficients are insignificant throughout. Instead, the share of services in NIPA hours has a positive and significant effect at a 5% level, reflecting the females' comparative advantage in the services sector (Ngai and Petrongolo, 2017).

Because of reverse causality, the regressions of Table 1 do not provide conclusive evidence for the positive relationship between the paid hours and schooling ratios. Instead, our approach introduces a general equilibrium model that explicitly accounts for endogeneity in schooling and hours choices. Moreover, its general equilibrium solutions qualitatively reproduce, keeping wages constant, the positive elasticity of the schooling and paid hours ratios reported in Table 1.

Our data granularity allows us to distinguish between modern and traditional production technologies, each comprising three sectors (agriculture, manufacturing, and services). We follow this specification in our model. Further, we distinguish between modern and traditional forms of production. Traditional production is small-scale and occurs on the household level using basic technologies. This form of production, namely own-account unpaid household work, is more pronounced in low-income countries (Gollin, 2008). Modern production occurs on a larger scale by firms using paid laborers and modern technologies. This form of production is prevalent in high-income countries. In our model, the uneven sectoral compositions across country income groups are associated with secular shifts in hours worked both across sectors and from traditional (unpaid) to modern (paid) work.

The main quantitative results of our work are obtained via a benchmark calibration exercise that quantifies the model's qualitative insight on the co-movement of the schooling and paid hours gaps. We calibrate the model using labor, wages, and subsistence targets and predict schooling choices at an individual gender level. Then, we analyze the co-movement of the female-to-male paid hours and schooling ratios. The model predicts that the female-to-male schooling ratio increases by 21.54% from low- to middle-income countries and by 2.52% from middle- to high-income countries, as compared to 12.28% and 2.06% observed in the data. In parallel, the exercise gives a 13.87% increase in female-to-male paid hours from low- to middle- and a 20.0% increase from middle- to high-income countries, closely replicating the 10.35% and 21.59% movements observed in the data. That is, besides accurately predicting schooling choices at the individual level, the model closely replicates the co-rise of the schooling and paid hours ratios observed in the data. We use the benchmark calibration to highlight the differences between the implications of policies and exogenous events affecting the productivity of both genders uniformly and those affecting gender-specific production shares.

Further, we study the fundamental constituents underpinning the mechanics of our model by examining three counterfactual scenarios. The first counterfactual calibration setup does not include any consumption subsistence requirements. A technical novelty in our model is the inclusion of such requirements, which are standard in models of structural change (Herrendorf et al., 2014) but were missing in models of gender-biased structural change. The subsistence term intensifies the household's income trade-off between the years spent in education and working life and, as the counterfactual calibration shows, is catalytic to match the household's schooling choices correctly.

The second counterfactual scenario highlights the role of modern production share gender heterogeneity in the relationship between paid hours, schooling, and wage ratios. Heterogeneity in production shares has a defining influence on the gender-specific sectoral comparative advantages, which shape the structural composition of economic activity and determine the movements of gender ratios across income groups. Without this heterogeneity, the model cannot consolidate the co-movement of the paid hours and schooling ratios under the wage ratio persistence.

The last counterfactual scenario does not allow production shares to change across income groups. In this scenario, the model replicates the wage ratio persistence and predicts increasing schooling years for both genders at an individual level. In contrast with the data, however, not allowing production shares to change with income ties down the gender-specific comparative advantages and results in paid hours and schooling ratios that are approximately constant across all income groups.

The structural change aspect of our work relates to prior literature on gender-biased technological change (Goldin, 1995; Akbulut, 2011; Rendall, 2013; Olivetti and Petrongolo, 2016; Ngai and Petrongolo, 2017; Feng et al., 2023). These articles support that the faster rise of females' hours in paid work is related to changes in the sectoral structure of the economy and, in particular, the rise of the services sector. Females' sectoral comparative advantage lies in services because their production is relatively less intensive in using brawn skills. Structural change results in more prominent services sectors and thus provides more opportunities for females to enter paid work. This pattern arises when sectoral labor productivities are allowed to differ by gender (Ngai and Petrongolo, 2017).

The schooling aspect of our work relates to previous literature on educational choices (Mincer, 1958; Becker, 1962), as our model incorporates an education-driven human capital mechanism. It additionally relates to prior work connecting human capital and labor productivity (Restuccia and Vandenbroucke, 2014; Hiller, 2014; Porzio and Santangelo, 2019). In these studies, labor in modern production is human capital intensive, while in traditional production, it is not. Less stylized assumptions are made by Herrendorf and Schoellman (2018), where human capital intensity is lower in agricultural than in non-agricultural production.

A distinct feature of our approach is its emphasis on the economic rationales explaining the gender gap differences across the country-income spectrum. We find that gender gaps in education are small when gender gaps in hours of paid work are small. Their link is based on the structural traits regarding the economy's sectoral composition. Previous work on gender gaps in education emphasized that discriminating norms and institutions prevent females from investing as much in education (Dollar and Gatti, 1999; Cooray and Potrafke, 2011; Hiller, 2014). Our model calibrations allow the schooling costs to be different across the income groups to account for differences in norms that vary with income (Goldin, 1995, 2006). Therefore, our findings highlight a perspective concerning gender differences in education that integrates previous work on norms and institutions with economic decision-making at the household level.

Much of the previous literature examined the role of the Demographic Transition in explaining income differences across countries. Our analysis does not focus on demographic transition dynamics or use this data feature to explain the gender gap differences across country-income groups. Instead, it highlights the role of sectoral comparative advantages, production share heterogeneity, and consumption subsistence building upon the seminal work of Kongsamut et al. (2001) on non-homothetic preferences. Early work on the relationship between fertility and human capital accentuated the intergenerational savings trade-off between investments in human capital of fewer children versus giving birth to many children (Becker et al., 1990). Galor and Weil (1996) study a dynamic connection between the wage gap and fertility using a joint-household growth model with capital, mental, and physical labor as input factors. They find that capital accumulation closes the wage gap but the improvements in female relative wages are less than the additional opportunity cost of raising children, reducing the couples' incomes and, in turn, the fertility rate. Moreover, Galor and Weil (2000) and Galor (2011) explain the dynamic relationship between demographics and structural transformation using a microfounded overlapping-generation unified-growth theory incorporating endogenous fertility, educational choices, and human capital. Their findings suggest that technological progress raises educational returns implying educational activities developing human capital become appealing for individuals in technologically advanced economies. In our data, high-income economies tend to have larger services sectors which are more human capital intensive and incentivize time-investments in education. Tamura (2006) and Tamura et al. (2016) focus on diminishing mortality rates and how these are related to human capital accumulation and fertility in periods surrounding Demographic Transitions. A greater stock of human capital reduces the mortality rate of young generations discouraging high fertility because, on average, the younger generation is qualitatively more productive. Tamura et al. (2019) provide evidence based on long historical time series indicating that intergenerational human capital transfers can explain better than Mincerian formulations the long-run growth heterogeneity across countries.

The remaining article is organized in the following manner. Section 2 contains the theoretical analysis of the article. It introduces the model, presents semi-analytical expressions of its equilibria, and establishes in the form of a proposition the main equilibrium relationship between paid hours and schooling ratios that the model induces. Section 3 describes our data, and presents the calculated comparative advantages. Section 4 presents the quantitative results from our assessment, predictions, and counterfactual calibrations. Finally, section 5 concludes.

2. Model

Time is continuous. At any given time point, a household is born, consisting of two individuals with distinct genders f and m. We use $g = f, m$ to denote the gender in expressions that are not f- or m-specific. The analysis in this section applies to households with pairs that do not comply with the binary gender classification as long as the self-identifications of genders in the couple are distinct.[1] Both individuals live to the age of T. Their lives can be divided into two parts. In the first part, individuals consume, enjoy leisure, provide labor for traditional forms of production, and go to school to accumulate human capital. After schooling is completed, human capital remains fixed. In the second part of their lives, individuals consume, enjoy leisure, and provide labor to both, traditional and modern forms of production.

The economy is comprised of three sectors; agriculture (denoted using A), manufacturing (M), and services (S). We use subscripts $i, j = A, M, S$ to denote abstract sectors. Ngai and Petrongolo (2017) do not emphasize the distinction between agricultural and manufacturing commodities. For our analysis, this distinction is relevant because our cross-sectional data contains information from low-, middle-, and high-income economies with very different sectoral compositions. Production occurs using two different technologies. Traditional production takes place in the household, without any possibility to trade, while modern production is organized by firms and its outputs are traded in the market. Human capital accumulation is only relevant in modern production

[1] The empirical analysis and model calibrations focus on female and male households only because we do not observe households with alternative gender compositions in our data (but cf. Siminski and Yetsenga, 2022).

technology. We use the subscript h to indicate variables relating to traditional, and r to modern production technology. We denote abstract technologies using $s, q = h, r$.

2.1. The firms' decision problem

In each sector, there is a representative, price-taking, profit-maximizing firm having access to a modern production technology described by the production function

$$y_{ir} = Z_{ir} l_{ir}, \tag{2.1}$$

$$l_{ir} = \left(\xi^f_{ir} \left(\delta(s^f) H(s^f) l^f_{ir} \right)^{\frac{\eta-1}{\eta}} + \xi^m_{ir} \left(\delta(s^m) H(s^m) l^m_{ir} \right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{2.2}$$

where y_{ir} is the modernly produced output in sector i, Z_{ir} the technology's total factor productivity of sector i, l_{ir} the firm's composite labor demand, l^g_{ir} the firm's demand for gender g's labor, and η the elasticity of cross-gender labor substitution. Further, $\xi^g_{ir} \in (0, 1)$ denote the two labor factors' production shares and sum up to one.

The function $\delta(s) = T - s$ for $s \in [0, T]$ is the remaining-lifetime, which implies that $\delta(s^g)$ gives the working-lifespan of gender g. Following Bils and Klenow (2000), human capital as a function of schooling is given by

$$H(s^g) = \exp\left(\frac{\zeta}{1-\nu} (s^g)^{1-\nu} \right), \qquad g = m, f. \tag{2.3}$$

Human capital enhances the labor productivity of hours worked in modern production. Labor productivities are gender-specific and shape how genders allocate their productive time across sectors (cf. Ngai and Petrongolo, 2017).

2.2. The household's decision problem

The household represents a single decision unit comprised of two individuals with distinct genders f and m. The common objective of the household's members is to choose their consumption c, leisure ℓ and years of schooling s^m, s^f to maximize their preferences represented by the lifetime utility

$$U(c, \ell, s^f, s^m) = \int_{t=0}^{T} \mathrm{e}^{-\rho t} \left(\log(c - \bar{c}) + \varphi \log(\ell) - \beta^f \mathbb{1}_{t \le s^f} - \beta^m \mathbb{1}_{t \le s^m} \right) \mathrm{d}t, \tag{2.4}$$

where $\mathbb{1}_{t \le s^f}$, $\mathbb{1}_{t \le s^m}$ are indicator functions, β^f, $\beta^m > 0$ represent the flow costs of schooling as in Bils and Klenow (2000); Heckman et al. (2006), but cf. Oreopoulos and Salvanes (2011), $\varphi > 0$ is a constant scaling flow leisure utility, and $\bar{c} > 0$ is the subsistence term.

Consumption c is a nested composite of three different consumption types produced with two distinct technologies combined via constant elasticity of substitution (CES) aggregators. The cross-sector aggregator is

$$c = \left(\sum_{i=A,M,S} \omega_i c_i^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{2.5}$$

with c_A denoting agricultural, c_M manufacturing, and c_S services consumption, ε the elasticity of cross-sector consumption substitution, and $\omega_i > 0$ the sectoral consumption weights summing up to one. The within-sector aggregator is

$$c_i = \left(\psi_i (c_{ir})^{\frac{\sigma-1}{\sigma}} + (1 - \psi_i)(c_{ih})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2.6}$$

where c_{ir} and c_{ih} represent sector i's consumption produced using the modern and traditional technologies, σ is the elasticity of within-sector consumption substitution, and $\psi_i \in (0, 1)$ is modern production technology's weight in sector i.

We limit our attention to cases with $\varepsilon < 1$ and $\sigma > 1$. This assumption is not required for our theoretical results, but it plays a central role when calibrating the model as it generates sectoral labor shifts when technology productivities change unevenly across sectors (Herrendorf et al., 2014; Ngai and Petrongolo, 2017; Moro et al., 2017).

In a similar fashion, leisure ℓ is a CES-composite of the individual leisure times ℓ^f and ℓ^m, given by

$$\ell = \left(\xi^f_l (\ell^f)^{\frac{\eta_l-1}{\eta_l}} + \xi^m_l (\ell^m)^{\frac{\eta_l-1}{\eta_l}} \right)^{\frac{\eta_l}{\eta_l-1}}, \tag{2.7}$$

where η_l is the elasticity of cross-gender leisure substitution and $\xi^g_l \in (0, 1)$ for $g = f, m$ are leisure gender-shares summing up to one.

Traditional production takes place throughout the entire household's lifetime. In contrast, modern production is mutually exclusive with education. While individuals are still in education during the initial part of their lives, they do not participate in the modern production's labor market. Participation in the labor market begins after the education cycle is completed. The couple's traditional production function is

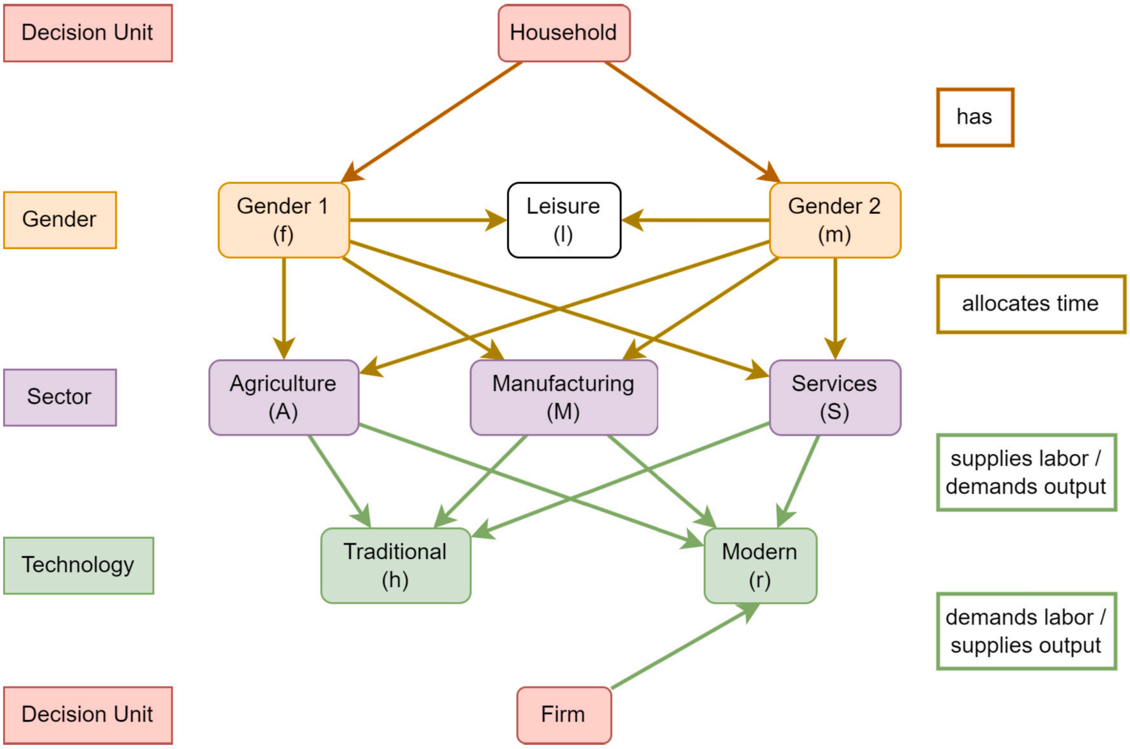

Fig. 2. Telescopic view of household's working-life and firm choices.

$$c_{ih} = Z_{ih}\left(\xi_{ih}^{f}\left(L_{ih}^{f}\right)^{\frac{\eta-1}{\eta}} + \xi_{ih}^{m}\left(L_{ih}^{m}\right)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}. \tag{2.8}$$

The terms L_{ih}^{g} denote gender g's sectoral labor inputs, $\xi_{ih}^{g} \in (0,1)$ are traditional production shares summing up to one, and η is as in eq. (2.2).

Fig. 2 summarizes the flow choices of the household at the working stage of the lives of its members. The two household individuals allocate time to leisure and supply labor to the traditional and modern production of agriculture, manufacturing, and services. The total time allocated to leisure and labor equals the time available to each individual, namely

$$L^{g} = \sum_{i=A,M,S}\left(L_{ih}^{g} + L_{ir}^{g}\right) + \ell^{g}. \tag{2.9}$$

There are no labor and output markets on the side of traditional technology, the production of which takes place in autarky. Instead, there are labor and output markets for the modern production technology.

The household choices are subject to the lifetime budget constraint

$$\int_{t=0}^{T} \mathrm{e}^{-\rho t}\sum_{i=A,M,S} p_{ir}c_{ir}\mathrm{d}t = \sum_{g=m,f}\int_{t=s^{g}}^{T} \mathrm{e}^{-\rho t}M^{g}w^{g}H(s^{g}),\mathrm{d}t, \tag{2.10}$$

where p_{ir} denotes the price of c_{ir}, w^{g} the wage of gender g, and M^{g} denotes the gender g's total labor allocation to modern production, i.e.,

$$M^{g} = L^{g} - \ell^{g} - \sum_{i=A,M,S} L_{ih}^{g}. \tag{2.11}$$

We abstract from explicitly modeling asset accumulation choices, but the lifetime budget constraint encapsulates implicit intergenerational borrowing. The implicit intergenerational contract in this economy is that the young generations' consumption of firm commodities is provided by the working generations. We assume that the implicit rate of interest is equal to the rate of time preference ρ so that both sides of eq. (2.10) are expressed in present value terms. The left-hand side is the present value of the household's lifetime expenditures for acquiring output produced by firms. The right-hand side is the present value of earnings that both household members accumulate from work in the labor market. Schooling choices directly affect earnings via two channels with opposing effects; the positive effect comes from human capital $H(s^{g})$, while the negative stems from the working-life discounter $\int_{t=s^{g}}^{T} \mathrm{e}^{-\rho t}\mathrm{d}t$ (i.e. the lower duration of the working stage).

2.3. General equilibrium

The two individuals of each household jointly (i) choose the consumption of modernly produced outputs ($\{c_{ir}\}_{i=A,M,S}$); (ii) allocate each member's time in traditional and modern production ($\{L^f_{ih}, L^m_{ih}, L^f_{ir}, L^m_{ir}\}_{i=A,M,S}$) and in leisure ($\ell^f, \ell^m$); and (iii) choose the years each member stays in school $\{s^f, s^m\}$. Firms choose labor demand units for each gender ($\{l^f_{ir}, l^m_{ir}\}_{i=A,M,S}$) and produce output using the modern technology ($\{y_{ir}\}_{i=A,M,S}$).

A *competitive equilibrium* is a collection of prices $\{p_{ir}\}_{i=A,M,S}$, wages $\{w^f, w^m\}$, consumption and labor supply allocations $\{c_{ir}, L^f_{ih}, L^m_{ih}, L^f_{ir}, L^m_{ir}\}_{i=A,M,S}$, leisure $\{\ell^f, \ell^m\}$ and schooling choices $\{s^f, s^m\}$, and labor demand and output choices $\{l^f_{ih}, l^m_{ih}, y_{ir}\}_{i=A,M,S}$ such that

1. households maximize their preferences in eq. (2.4) subject to their budget and time constraints in eqs. (2.9) and (2.10), the human capital eq. (2.3), and the traditional production technology eq. (2.8);
2. firms maximize their profits subject to modern production technology eqs. (2.1) and (2.2);
3. agricultural, manufacturing, and services markets clear ($c_{ir} = y_{ir}$ for $i = A, M, S$);
4. traditional production is in autarky ($c_{ih} = Z_{ih} L_{ih}$ for $i = A, M, S$); and
5. labor markets clear ($l^g_{ir} = L^g_{ir}$ for $i = A, M, S$ and $g = f, m$).

2.4. Necessary conditions

On the firm side, the first-order conditions take the form

$$l^g_{ir} : w^g = p_{ir} Z_{ir} \xi^g_{ir} \left(\delta(s^g) H(s^g)\right)^{-\frac{1}{\eta}} \left(l^g_{ir}\right)^{-\frac{1}{\eta}} l_{ir}^{\frac{1}{\eta}}. \qquad (i = A, M, S; \qquad g = f, m) \tag{2.12}$$

The first-order conditions of the household problem are

$$c_{ir} : \frac{\partial U}{\partial c_{ir}} = \lambda d(0) p_{ir}, \qquad (i = A, M, S; \qquad g = f, m) \tag{2.13}$$

$$L^g_{ih} : \frac{\partial U}{\partial c_{ih}} \frac{\partial c_{ih}}{\partial L^g_{ih}} = \lambda w^g d(s^g) H(s^g), \qquad (i = A, M, S; \qquad g = f, m) \tag{2.14}$$

$$\ell^g : \frac{\partial U}{\partial \ell^g} = \lambda w^g d(s^g) H(s^g), \qquad (g = f, m) \tag{2.15}$$

$$s^g : -\beta^g d'(s^g) = -\lambda w^g M^g \left(d(s^g) H'(s^g) + d'(s^g) H(s^g)\right), \qquad (g = f, m) \tag{2.16}$$

where λ is the Lagrange multiplier of the budget constraint, and the function $d(s) = \int_{t=s}^{T} \mathrm{e}^{-\rho t} \mathrm{d}t$ for $s \in [0, T]$ is the remaining-lifetime discounter. With this notation, $d(0)$ gives the total-lifetime discounter and $d(s^g)$ gives gender g's working-life discounter.

We solve the model for both genders' schooling, labor supply, and leisure choices. The online appendix contains an extensive derivation of a system of three equations that the wage ratio w^f/w^m and schooling choices s^f and s^m should satisfy in equilibrium. For brevity, we next focus on reformulations of eq. (2.13) to eq. (2.16) that describe (i) how schooling and labor choices are connected to gender-specific sectoral comparative advantages, and (ii) how the schooling and modern (i.e. paid) hours gaps are endogenously related in equilibrium.

2.5. Schooling, labor supply, and leisure

Cross-gender time allocation ratios constitute the basis for calculating the model's equilibria. There are three types of time allocation ratios; namely ratios for traditional production, modern production, and leisure. We focus on the first two for our exposition.

Cross-gender relative labor allocation ratios for hours in traditional production are obtained by dividing the household problem's necessary conditions for each gender's traditional labor. This gives

$$\frac{L^f_{ih}}{L^m_{ih}} = \left(\frac{\xi^f_{ir}}{\xi^m_{ir}}\right)^{\eta} \left(\frac{\xi^f_{ir} d(s^f) H(s^f)}{\xi^m_{ir} d(s^m) H(s^m)}\right)^{-\eta} = \tilde{\xi}^{\eta}_{ih} \left(\tilde{w} \tilde{d} \tilde{H}\right)^{-\eta}. \tag{2.17}$$

We use the shorthand tilde notation to denote ratios of gender f to gender m variables. For example, $\tilde{\xi}_{ih}$ denotes the ratio ξ^f_{ih}/ξ^m_{ih}. We use the same notation to denote ratios of functions with schooling choices as arguments. As an example, $\tilde{H}$ is used to denote the ratio $H(s^f)/H(s^m)$. For modern labor hours, we divide the firm problem's necessary conditions for each gender's labor and use the labor market-clearing conditions to get

$$\frac{L^f_{ir}}{L^m_{ir}} = \frac{l^f_{ir}}{l^m_{ir}} = \tilde{\xi}^{\eta}_{ir} \tilde{w}^{-\eta} \left(\tilde{\delta} \tilde{H}\right)^{-1}. \tag{2.18}$$

Modern labor ratios depend on the productivity ratios $\tilde{\xi}_{ir}$, on the wage ratio $\tilde{w}$ and, through the ratio $\tilde{\delta} \tilde{H}$, on the household's schooling choices. As a working hypothesis, suppose that the productivity and wage ratios are equal to one. Then, eq. (2.18) implies that the modern labor ratio is decreasing to the schooling ratio for any interval in which $\delta(s^g)H(s^g)$ is increasing in s^g. In short, as long as the individuals are young enough and their returns to investing in education are high, a decline in the schooling gap makes the modern labor allocation ratios of the genders more balanced. This is the first hint as to our model's implications for co-movements of the paid hours and schooling ratios. We return to this point in section 4 to quantitatively substantiate the mechanics at play in a fully calibrated model.

2.5.1. Relative (implicit) prices

Following Ngai and Petrongolo (2017), we use cross-sector labor mobility to obtain expressions for relative prices of modernly produced outputs. For two distinct modern production sectors $i \neq j$ this gives the relative prices of c_{ir} and c_{jr}:

$$\frac{p_{ir}}{p_{jr}} = \frac{Z_{jr}}{Z_{ir}} \left(\frac{\xi^f_{jr}}{\xi^f_{ir}} \right)^{\frac{\eta}{\eta-1}} \left(\frac{I^f_{ir}}{I^f_{jr}} \right)^{\frac{1}{\eta-1}}, \tag{2.19}$$

where I^f_{ir} denotes the female sectoral wage-bill shares in modern production.[2] Additionally, we define implicit prices for the traditionally produced outputs by the corresponding household's marginal utilities. For each c_{ih}, we require that implicit prices satisfy $\frac{\partial U}{\partial c_{ih}} = \lambda d(0) p_{ih}$. Relative prices between c_{ih} and c_{jh} are then given by

$$\frac{p_{ih}}{p_{jr}} = \frac{Z_{jr}}{Z_{ih}} \left(\frac{\xi^f_{jr}}{\xi^f_{ih}} \right)^{\frac{\eta}{\eta-1}} \left(\frac{I^f_{ih}}{I^f_{jr}} \right)^{\frac{1}{\eta-1}} \frac{d(s^f)H(s^f)}{d(0)}. \tag{2.20}$$

Relative prices between traditionally and modernly produced outputs depend on the technology ratio Z_{jr}/Z_{ih}. The more advanced is modern compared to traditional technology, the greater modern compared to the traditional marginal product and, so, the lower the relative price of the modern commodity. Therefore, via the ratio Z_{jr}/Z_{ih}, relative prices reflect the economy's modernization level.[3]

The key distinction between eq. (2.19) and eq. (2.20) is related to the term $d(s^f)H(s^f)/d(0)$. It acts to adjust relative prices for differences in the marginal products due to education. The term does not enter eq. (2.19) because schooling choices affect the marginal products of modern production uniformly across sectors. In contrast, it appears in eq. (2.20) because schooling affects only modern, and not traditional production. For usual parameterizations of the discounting and human capital functions, which we return to in section 3, this has the following implication: Schooling intensifies the impact of modernization on relative prices. Compared to Ngai and Petrongolo (2017), this schooling channel is central in our work as it further affects both genders' labor and supply choices.

2.5.2. Relative expenditures

In equilibrium, the marginal rate of substitution (MRS) between any combination of consumption types should be equal to the relative (potentially implicit) prices. Using the equilibrium condition and the homogeneity properties of the constant elasticity consumption aggregators we calculate the relative expenditures between all consumption types. We present the expressions for the relative expenditures between sector i's modernly and traditionally produced output (E_{irih}), between the modernly produced output of sectors i and j (E_{irjr}), and between modern sector i and leisure (E_{irl}). The remaining cases can be implicitly calculated via these three expressions.

Relative expenditures for a fixed sector i and distinct production technologies are given by

$$E_{irih} = \frac{p_{ir}c_{ir}}{p_{ih}c_{ih}} = Z_{irih}^{\sigma-1} \left(\left(\frac{\xi^f_{ir}}{\xi^f_{ih}} \right)^{\frac{\eta}{\eta-1}} \left(\frac{I^f_{ih}}{I^f_{ir}} \right)^{\frac{1}{\eta-1}} \frac{d(s^f)H(s^f)}{d(0)} \right)^{\sigma-1}, \tag{2.21}$$

where, for brevity, we have used

$$Z_{irih} = \frac{Z_{ir}}{Z_{ih}} \left(\frac{\psi_i}{1-\psi_i} \right)^{\frac{\sigma}{\sigma-1}}. \tag{2.22}$$

[2] For example, the gender f's leisure and sectoral wage bill shares are

$$I^f_{ih} = \frac{w^f d(s^f)H(s^f)L^f_{ih}}{\sum_g w^g d(s^g)H(s^g)L^g_{ih}},\ I^f_{ir} = \frac{w^f \delta(s^f)H(s^f)L^f_{ir}}{\sum_g w^g \delta(s^g)H(s^g)L^g_{ir}},\ \text{and}\ I^f_l = \frac{w^f d(s^f)H(s^f)\ell^f}{\sum_g w^g d(s^g)H(s^g)\ell^g}.$$

[3] Ngai and Petrongolo (2017) and Bridgman et al. (2018) use the term marketization and their distinction between home and firm production follows the US-based NIPA definition. Following Bick et al. (2022), we use the term modern production because our calibration analyses account for the provision of home services such as cooking and child-caring, which are not included in NIPA calculations. In particular for low-income countries, these activities are important to accurately describe both genders' allocations of labor.

Further, we derive E_{irjr} as

$$E_{irjr} = \frac{p_{ir}c_{ir}}{p_{jr}c_{jr}} = Z_{irjr}^{\varepsilon-1}\left(\frac{\xi_{ir}^{f}}{\xi_{jr}^{f}}\right)^{\frac{\eta(\varepsilon-1)}{\eta-1}}\left(\frac{I_{jr}^{f}}{I_{ir}^{f}}\right)^{\frac{\varepsilon-1}{\eta-1}}\left(\frac{1+E_{ihir}}{1+E_{jhjr}}\right)^{\frac{\sigma-\varepsilon}{\sigma-1}}, \tag{2.23}$$

where

$$Z_{irjr} = \frac{Z_{ir}}{Z_{jr}}\left(\frac{\omega_i}{\omega_j}\right)^{\frac{\varepsilon}{\varepsilon-1}}\left(\frac{\psi_j}{\psi_i}\right)^{\frac{\sigma}{1-\sigma}}. \tag{2.24}$$

The term $d(s^f)H(s^f)/d(0)$ appears in eq. (2.21) but cancels out in eq. (2.21). This is a consequence of schooling intensifying the impact of modernization on relative prices. It thereby intensifies the secular shifts in relative expenditures in favor of modern sectors.

The third expression relates modern consumption of sector i to leisure and is given by

$$E_{irl} = \frac{p_{ir}c_{ir}}{p_l\ell} = \frac{1}{\varphi}\left(1-\frac{\bar{c}}{c}\right)^{-1}\frac{E_i}{1+E_{ihir}}. \tag{2.25}$$

Here, E_i is the share of expenditures on sector i in total expenditure. It enters E_{irl} because the relative expenditures of c_{ir} with leisure capture trade-offs not only between c_{ir} and leisure but every consumption output available to the household. Thus, increasing the leisure time allocation has an income effect impacting all types of consumption. The subsistence share of consumption $\bar{c}/c$ appearing in eq. (2.25) makes the income effect in the trade-off between consumption and leisure more severe when the household's lifetime income is low.

2.5.3. Individual time allocation choices

The equilibrium ratio of g-labor allocations L_{is}^{g} and L_{jq}^{g} are

$$\frac{L_{is}^{g}}{L_{jq}^{g}} = E_{isjq}\frac{I_{is}^{g}}{I_{jq}^{g}}\left(\frac{d(s^g)}{d(0)}\frac{\delta(0)}{\delta(s^g)}\right)^{\mathbb{1}_{s=r}-\mathbb{1}_{q=r}}. \tag{2.26}$$

When $s=r=q$, eq. (2.26) gives the relative labor supply for the modern sectors i and j, which depends on the household's consumption preferences via relative expenditures E_{isjq} and on the relative g-production shares via the ratio of wage bills I_{is}^{g} and I_{jq}^{g}. The term $d(s^g)\delta(0)/d(0)\delta(s^g)$ adjusts the allocation ratio for schooling choices and is relevant for gender decisions when $s \neq q$. In this case, one of the two labor allocations in eq. (2.26) is used in the modern production function and benefits from schooling, because the effective wage increases as the gender g's human capital increases by staying longer in education. The labor allocation going to traditional production is unaffected by schooling and, so, the schooling adjustment vanishes when $s=h=q$. Lastly, the term disappears when $s=r=q$ because both time allocations are affected by schooling choices in the same way.

2.5.4. Schooling choices

From the necessary conditions of the household's decision problem, the *individual decision margin* of gender g' schooling choices are described by

$$-\beta^g d'(s^g) = \frac{M^g}{L_{ih}^{g}}G(s^g)\delta(0)\left(1-\frac{\bar{c}}{c}\right)^{-1}\frac{E_i}{1+E_{irih}}I_{ih}^{g}. \tag{2.27}$$

The function $G(s^g) = \frac{H'(s^g)}{H(s^g)} + \frac{d'(s^g)}{d(s^g)}$ is the marginal effect (logarithmic derivative) of schooling on lifetime income and captures the schooling trade-off introduced by Becker (1962) and Mincer (1958).[4] The left-hand side of (2.27) is the marginal schooling cost, and the right-hand side is the marginal benefit of schooling measured in sector i's terms (i.e., L_{ih}^{g}, E_i, E_{irih}, and I_{ih}^{g}). The marginal schooling benefit stems from human capital. Schooling increases human capital, makes modern production more efficient, and increases productive wages. Individuals have greater lifetime incomes, which translates to more consumption. Additionally, eq. (2.27) shows that along the individual decision margin, the marginal schooling benefit increases in hours of paid work because hours multiplicatively act on the relative marginal effect of schooling on lifetime income. Described simply, higher paid hours raise the extent to which agents can realize the returns from higher schooling.

The *household decision margin* is obtained by the combination of the schooling equations of the two genders, i.e.,

$$\frac{\beta^f}{\beta^m}\tilde{d}' = \frac{M^f}{M^m}\tilde{w}\tilde{d}\tilde{H}\frac{G(^f)}{G(s^m)}, \tag{2.28}$$

and relates females' and males' marginal costs and marginal benefits of schooling. It reveals that optimal individual decisions are compatible with optimal household behavior if the ratio of individual schooling benefits equals the rate of substitution between

[4] The term $d(s^g)H(s^g)$ in the budget constraint eq. (2.10) measures the added value of schooling to lifetime income, conditional on hours in modern work M^g and wages w^g. Its derivative $d(s^g)H'(s^g) + d'(s^g)H(s^g)$ measures the marginal contribution of schooling to lifetime income. A marginal increase in years of schooling raises human capital but shortens the remaining life span during which agents can engage in modern work.

female and male schooling costs. On the one hand, when females and males opt for higher schooling, they contemplate and compare the utility cost they would each incur. On the other hand, they contemplate and compare the marginal benefit that schooling has on each of their lifetime incomes. In doing so, they take into account that they face different wages and that they spend different amounts of hours in paid work.

Equation (2.28) captures the positive relationship between the female-to-male paid hours and the schooling ratios we observe in Fig. 1. Our model entails heterogeneity in gender specific production shares ξ_{is} allowing it to describe equilibria with different labor allocations and schooling years across genders and a constant wage ratio; similar to what we observe in the data. The household explicitly chooses the levels of labor and schooling and the model mechanics imply that for small equilibrium perturbations their ratios have a positive relationship. We summarize the main result here in the form of a proposition and we give the proof in appendix A.

Proposition 1. *Suppose that $\zeta < ((1-\nu)/\rho)^{\nu-1}$. Along equilibrium paths with allocations for which wages are constant, the elasticity of the paid hours ratio with respect to the ratio of schooling is positive.*

For usual parameterizations of the human capital function found in the literature, the condition of Proposition 1 is satisfied. For instance, setting $\zeta = 0.32$, $\nu = 0.58$, and $\rho = 0.04$ as in Bils and Klenow (2000); Restuccia and Vandenbroucke (2014) gives $((1-\nu)/\rho)^{\nu-1} = 0.37 > \zeta$, implying that the paid hours elasticity with respect to schooling is positive. Proposition 1 indicates that when wages do not adjust to account for the decreasing gap in schooling between f and m, then the gender receiving the lower wage overcompensates in terms of paid hours work. As a result, the paid hours work differential between f and m closes.

That is, our model yields equilibrium mechanics supporting the main motivating data artifact. Even though wage ratios are on average constant, the paid hours and schooling ratios co-move across country income groups. In addition, this result has policy implications for cases of regulation affecting the production shares ξ_{is}^{g} (e.g., via setting gender-specific labor market participation quotas). We postpone discussing the policy implications until section 4, where we present the quantitative results from the main calibration of the model.

2.6. Calculating equilibria

Finding equilibria is reduced to finding solutions to a system of three equations that the wage ratio $\tilde{w}$ and the schooling choices s^f, s^m should satisfy. The genders' schooling equations, i.e., eq. (2.27) for $g = f$ and $g = m$, are two of the system's conditions. The third condition ensures that the household's time and budget constraints are simultaneously satisfied. In the online appendix, we show how to combine the two constraints by rewriting them in terms of their implications for the share of female time allocated to the traditional production of services. The resulting equation represents a fundamental recurring equilibrium mechanism: For any equilibrium pair of household schooling choices, relative wages adjust so that the labor choices are compatible with the constraints of the household's decision problem and the market-clearing conditions. Labor shares are chosen so that they satisfy the time constraint and make the consumption choices affordable under the equilibrium market prices.

3. Data and calibration

For the empirical analysis, we use a novel dataset combining information on hours in paid and household work by females and males, information on their relative wages, and information on both genders' schooling years. The dataset contains 15 low-, 27 middle- and 23 high-income countries and allows us to assess how hours, wages and schooling years of females and males differ per country income group.[5]

3.1. Data

We aggregate hours of work from the household-level data collected and harmonized by Bick et al. (2018). The authors collect surveys surrounding the year 2005 and satisfying sufficient criteria to compute hours worked and, whenever work is paid, hourly wages in a comparable way across a large sample of countries. For cases when a time-use module is not included in Bick et al. (2018), we augment our data with time-use information obtained from the Multinational Time-Use Study (Gershuny and Fisher (2014), henceforth MTUS). For the full list of countries and respective surveys used, see Table B.1 in appendix B.

The resulting dataset encompasses substantially more low-income countries than previous studies (e.g., Folbre, 2014). When data allow, we include individuals aged less than 15 years, which is the usual cut-off age for studies focusing on hours worked by adults in developed economies. Firstly, this is to maintain consistency with the timing in the model, where life starts with schooling. Secondly and more importantly, schooling often ends and working life begins prior to 15 years of age in low-income countries.[6]

[5] We divide countries into low-, middle-, and high-income groups depending on their position in the global income distribution. We calculate the threshold levels for each income group based on the world distribution of real 2005 PPP-adjusted per capita GDP, which we compute from the Penn World Tables (Feenstra et al., 2015). These thresholds constitute the benchmarks we use to classify country data compiled pre/post 2005).

[6] In most low-income countries, the labor module is asked to individuals aged 5 or older (7 or 10 years in middle- and high-income countries). For some countries, the labor module is only asked to individuals aged 15 or above. However, except for three of those cases mean years of schooling are 9 years or higher, so that if kids start school at age 6, then the 15 year age limit is not binding on average.

(a) Weekly hours in paid work (b) Relative hourly wages

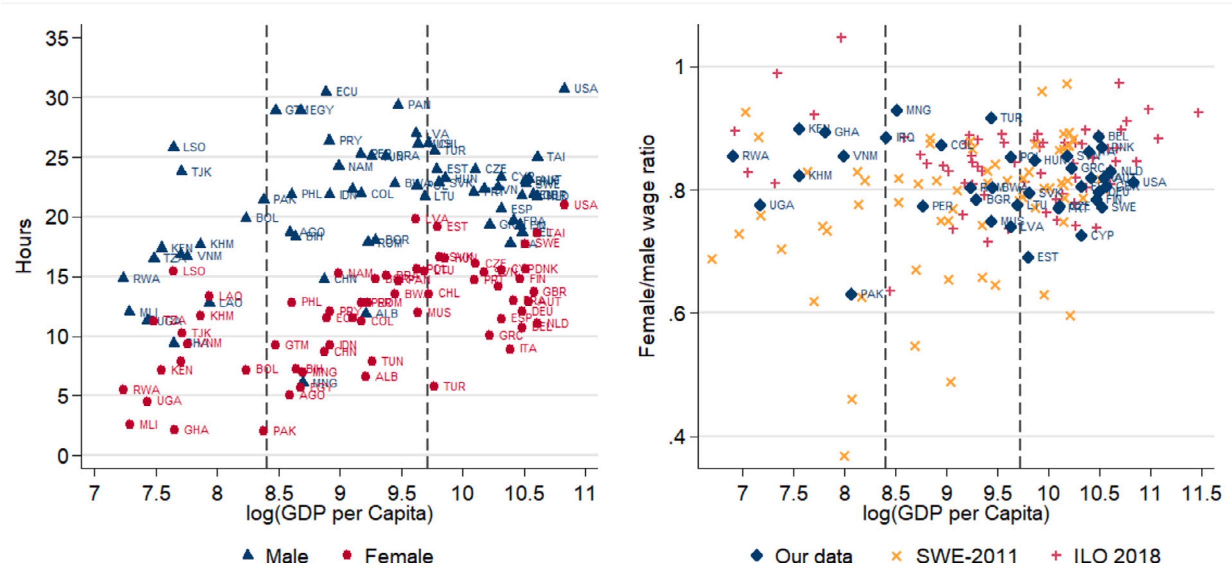

Fig. 3. Paid hours in paid work and relative wages.

3.1.1. *Hours in paid work*

For 60 of the 65 countries, we measure hours in paid work by focusing on individuals who report not being enrolled in education. We classify all non-enrolled who report in their primary occupation to be in paid employment or to be an employer as paid workers. Based on this classification, we compute the mean hours worked per week and per person in paid work for each gender. Fig. 3a displays the dispersion of paid hours per person over income for the countries in our data. Mean paid hours of females rise from low- to middle- and from middle- to high-income countries (from an average of 7.9 hours in low-income countries to 11.5 in middle- and 14.1 in high-income countries). Males' hours are higher than females in all country income groups. In low-income countries, the mean of male paid hours is more than twice as high as the female's mean (16.9 hours). Females' paid hours rise relatively faster than males', so the female-to-male paid hours ratio rises from 0.47 in low- to 0.62 in high-income countries. We cross-validate these patterns against the paid-hours data reported by Herrendorf and Schoellman (2018). Their estimates have similar implications for the rise of females' relative paid hours, which increase from 0.46 in low- to 0.59 in high-income countries.

3.1.2. *Measuring hours in unpaid work*

For hours worked in unpaid/family/household work and self-employment without employees, we use the sample of all females and males, irrespective of enrollment in education. We distinguish paid versus unpaid workers by capturing whether someone engages in a larger-scale, modern production schedule (that requires human capital), or in a smaller-scale, basic production schedule. This abstracts from the possibility that part of the traditional output is sold in a (black) market. We are limited to this approach because we do not observe non-official market transactions in the data.

We include time-use data on hours spent producing household services such as cooking or cleaning at home, childcare, shopping or collecting water and firewood (particularly relevant in low-income countries) to hours in unpaid services. We use two sources to calculate the hours spent on such activities. Whenever available in the surveys by Bick et al. (2018), the hours spent in household services are compiled using the information on the reported labor hours. For the remaining countries, we augment our calculations with the values reported in the Multinational Time Use Studies (Gershuny and Fisher, 2014). The value added from hours in these activities is not accounted for in NIPA and thus typically excluded in measures of hours worked (cf. Folbre, 2014). However, they form a substantial part of total productive time (Freeman et al., 2005; Aguiar and Hurst, 2007; Bridgman et al., 2018).

Moreover, much of the increase in female hours of paid work can be attributed to reducing hours in the production of unpaid household services (Bar and Leukhina, 2011; Ngai and Petrongolo, 2017). Therefore, the inclusion of the time spent producing unpaid household services is a central component for the analysis of gender-specific total productive time. From the time-use modules or studies, we observe how many hours are spent cooking, cleaning, in childcare, shopping or collecting water and firewood only for 7 low-, 7 middle- and 8 high-income countries.[7] In some countries, we do not observe hours in all five time-use activities. For these cases, we calculate mean hours in the production of all those household services together, by country income group. Following Bick et al. (2018), we proceed in three steps. First, we calculate the mean hours worked per adult for each activity available in a country. Second, we average hours worked per adult in each activity across low-, middle-, and high-income countries. Third, we sum these averages to form mean total hours in household services by country income groups.

[7] For two low- and three middle-income countries, we observe hours in household services, but we cannot disaggregate NIPA-hours to paid and unpaid hours.

Table 2
Schooling, labor and leisure allocations in the data.

Country Income Group	Agric. L^g_{Ah}	L^g_{Ar}	Manuf. L^g_{Mh}	L^g_{Mr}	Services L^g_{Sh}	L^g_{Sr}	Leisure ℓ^g	School. s^g
Females								
Low	9.14	2.41	0.70	1.41	32.91	4.07	61.36	5.0
Middle	3.15	0.53	0.42	2.15	33.32	8.82	63.61	8.0
High	0.48	0.26	0.11	2.50	26.76	11.38	70.51	10.4
All	4.26	1.07	0.41	2.02	31.00	8.09	65.16	7.8
Males								
Low	10.08	4.87	0.84	2.94	14.17	9.08	70.02	6.0
Middle	5.00	3.24	0.65	5.53	11.29	13.53	72.76	8.6
High	0.86	0.88	0.68	8.80	10.94	12.87	76.98	10.8
All	5.31	3.00	0.72	5.75	12.13	11.83	73.26	8.5

Notes: Labor, leisure, and schooling data used in the calculations of calibration targets and fixed model parameters. Labor and leisure allocations are measured as shares of total time. All values are averages over the countries in the respective country income groups. The values are rounded to two decimal digits. We compute leisure as the difference between total time (assuming that one needs 8 hours of sleep per day, total time is 112 hours per week) and hours in paid and unpaid work. Schooling is measured in years.

3.1.3. *Measuring leisure hours*

Finally, we calculate leisure hours as the difference between the total time available per week and the sum of hours in paid and unpaid work. We assume that one needs on average 8 hours of sleep per day resulting in a total time of 112 hours per week for this calculation. Table 2 documents the average hours allocated in labor and leisure decomposed by gender, sector, and production technology. The columns L^g_{Ah}, L^g_{Mh}, L^g_{Sh} are sectoral averages of hours worked per person in traditional production for the entire population of our data's labor force modules (where possible aged 5 or above). Similarly, the columns L^g_{Ar}, L^g_{Mr}, L^g_{Sr} are sectoral averages of hours worked per person in modern production for the entire population of the modules that is not enrolled in education.

3.1.4. *Relative wages: a Blinder-Oaxaca application*

To compute the relative wages of females, we apply the Blinder-Oaxaca (1973) decomposition to the micro-level hourly wage data compiled in Bick et al. (2018). Our approach follows the conventional process for the gender-decomposition of wages in the literature and is based on the premise that differences in the mean wages of females and males can, at least in part, be attributed to differences in mean characteristics of both genders (Weichselbaumer and Winter-Ebmer, 2005). In our case, accounting for differences in characteristics is crucial because, in low-income countries, a considerable share of the females that select into paid work have more than secondary education. Left unaccounted, this would erroneously suggest that female wages are substantially higher than males' and that female wages decline from low- to high-income countries. Our analysis focuses on the part that cannot be explained by differences in observable characteristics, namely the unexplainable gender difference in mean wages. By construction, one can refer to it as the wage gap that would persist if females and males had the same observable characteristics on average. We compute the wage gap at the country level by applying the decomposition to the samples of paid female and male employees using the specification

$$\log w_i = c^g + \beta^g_1 \times \text{age}_i + \beta^g_2 \times \text{age}^2_i + \beta^g_3 \times \mathbb{1}_{\text{Married}_i} + \sum_{k=M,S} \beta^g_k \times \mathbb{1}_{\text{Sec}_i=k} + \sum_{e=s,m} \beta^g_e \times \mathbb{1}_{\text{Educ}_i=e} + \epsilon_i \tag{3.1}$$

where $g = f, m$ and where w_i is the individual's hourly wage, $\mathbb{1}_{\text{Sec}_i=k}$ indicates the individual's industry (agriculture being the baseline), and $\mathbb{1}_{\text{Educ}_i=e}$ indicates the individual's education level (less than secondary being the baseline, compared to secondary completed or more than secondary schooling).

We visualize the relative wages implied by the decomposition of the gaps in Fig. 3b. It suggests that female relative wages remain broadly constant in our cross-section of countries, around 0.81 to 0.82. Given the low number of countries, we perform permutation tests (10^4 iterations) for the difference in relative wages between low- and high-income countries. The results substantiate our finding on the persistence in females' relative wages, with the mean difference amounting only to 0.01. We also compare our relative wage estimates to those reported by Schober and Winter-Ebmer (2011) for data from 1975-94 and to those reported in the ILO (2018) Global Wage Report. Both of the cross-validation sources report estimates that control for differences in both genders' observable characteristics, but the estimates therein exhibit higher variation and provide mixed evidence. For instance, according to the estimates reported by Schober and Winter-Ebmer (2011), female-to-male relative wages in low-income countries are 0.06 lower than in high-income countries, while in the ILO (2018)'s estimates they are 0.066 higher. Finally, performing permutation tests on each dataset we cannot reject the hypothesis that females' relative wages are persistent across income groups.

Table 3
Preferences and human capital parameters.

Parameter		Description	Source
ϵ	0.002	Cross-sector consumption substitution	
σ	2	Within-sector consumption substitution	Ngai and Petrongolo, 2017
η, η_ℓ	2.27	Cross-gender labor/leisure substitution	
ρ	0.04	Rate of time preference	As Restuccia and Vandenbroucke, 2014
ν	0.58	Human capital Mincerian returns	Bils and Klenow, 2000
ζ	0.32	Human capital scale	
	50	Life expectancy, low income countries	
T	60	Middle income countries	World Development Indicators
	69	High income countries	

3.1.5. Years of schooling

Information on the number of years of schooling is not available in the survey micro-data of many of our countries. The only relevant information in the survey data is the individuals' educational levels, which we make use of in the decomposition of wages. Hence, we merge the data we construct from the micro-surveys with the dataset constructed by Barro and Lee (2013). The latter is assembled from census data and provides the mean years of schooling of females and males. For four observations in our dataset, there is no information available in Barro and Lee (2013). Instead, we retrieve years of schooling from the database of the United Nations Development Programme (UNDP, 2019).[8]

Table 2 reports mean years of schooling (and time allocations) by country income group. It shows that in low-income countries, there exist considerable differences in female and male years of schooling. Females in low-income countries have an average of 5 years of schooling, while males exhibit an average of 6 years of schooling (about 20% more). Schooling values in low-income countries are, thus, about as high as those that prevailed in today's OECD countries about 100 years ago (Grant and Behrman, 2010). Schooling levels increase as countries become richer, which is in line with Evans et al. (2020). Specifically, female and male years of schooling increase to 8.0 and 8.6 for middle-income countries. In high-income countries, schooling is 10.4 years for females and 10.8 years for males. Overall, years of schooling more than double for females, while for males they increase by 80%.

3.2. Calibration

3.2.1. Fixed calibration parameters

Table 3 presents the model parameters we take from prior research. We follow Ngai and Petrongolo (2017) with $\epsilon = 0.002$, and $\sigma = 2.0$. Consumption and services from different sectors forming the composite c are, thus, hard to substitute, while modern and traditionally produced versions of the same sector can be easily substituted. Following the aforementioned authors', we set η and η_ℓ equal to 2.27. Consequently, female and male labor and leisure constitute good substitutes in their respective composite formation. For the parameterization of human capital $H(s)$, we rely on Bils and Klenow (2000). The former authors estimate $\nu = 0.58$ from a cross-country regression of the Mincerian returns estimated by Psacharopoulos (1994) on years of schooling. They then set $\zeta = 0.32$ to match the average Mincerian return across countries. With this parametrization, the marginal return of schooling on human capital is positive and decreasing.

Life expectancy T is the same for both genders but differs across country income groups. We compute it based on the data on life expectancy at birth from the World Bank (2007) (WDI). Data begin in 1960, but most of our country datasets include individuals who were born before that year. For each country, we regress life expectancy (in logs) on the year of birth using the post-1960 data and predict life expectancy at birth for all individuals in each country survey. The resulting average life expectancy amounts to 50 years in low-, 60 years in middle-, and 69 years in high-income countries.

3.2.2. The materialization of comparative advantages in the data

Given the baseline parameters, our data, and closed-form expressions derived from our model, we can directly infer the seven model parameters governing the female production shares. We do so by applying the calculated life expectancies, the wage ratios, and the time allocation data of Table 2 to eqs. (2.17) and (2.18).[9] Having the production shares, we pin down the sectoral comparative advantages ($\tilde{\xi}_{Ar}$, $\tilde{\xi}_{Mr}$, $\tilde{\xi}_{Sr}$, $\tilde{\xi}_{Ah}$, $\tilde{\xi}_{Mh}$, $\tilde{\xi}_{Sh}$, and $\tilde{\xi}_l$). We give their values in Table 4.

In low-income countries, the female sectoral comparative advantage within the traditional production sectors lies with traditional services. This is because the value of $\tilde{\xi}_{Sh}$ (1.11) is greater than the values of $\tilde{\xi}_{Ah}$ and $\tilde{\xi}_{Mh}$. There is no clear female sectoral comparative advantage among the modern production sectors, because the $\tilde{\xi}_{Ar}$, $\tilde{\xi}_{Mr}$, and $\tilde{\xi}_{Sr}$ have almost equal values (between 0.54-0.56). However, the granularity of our data allows us to see that there exists a pronounced female advantage in services among the modernly produced sectors (cf. Goldin, 1995; Rendall, 2013; Akbulut, 2011; Olivetti and Petrongolo, 2016; Ngai and Petrongolo,

[8] Timor-Leste and China in 2005, Bosnia-Herzegovina (2011), and Angola (2014), and with schooling years for ages 25+. Accessed in Feb. 2020. Database discontinued, but the values are also reported here.

[9] For the equation describing the female leisure share, we refer to the online appendix.

Table 4
Calculated comparative advantages.

	Traditional Techn.			Modern Techn.			Leisure
Country Income Group	$\tilde{\xi}_{Ah}$	$\tilde{\xi}_{Mh}$	$\tilde{\xi}_{Sh}$	$\tilde{\xi}_{Ar}$	$\tilde{\xi}_{Mr}$	$\tilde{\xi}_{Sr}$	$\tilde{\xi}_{l}$
Low	0.73	0.71	1.11	0.56	0.55	0.54	0.72
Middle	0.65	0.65	1.28	0.36	0.52	0.66	0.75
High	0.62	0.36	1.18	0.47	0.46	0.76	0.77
All	0.72	0.61	1.19	0.50	0.50	0.67	0.75

Notes: Female comparative advantages calculated by eqs. (2.17) and (2.18), the analog expression for leisure, and using our data on hours, schooling, and relative wages as reported in Table 2.

Table 5
Grouped calibration targets and predictions.

Used in	Setup	Calibration Notes	Labor Group (I) L^f_{ArAh}, L^f_{MrMh}, L^f_{SrSh}, L^f_{ArSr}, L^f_{MrSr}, L^f_l	Subsistence Group (II) $\bar{c}/c$	Wages Group (III) $\tilde{w}$	Schooling Years Group (IV) s^f, s^m
Schooling Predictions	Benchmark	Main calibration	targeted	targeted	targeted	predicted
Counterfactual Analyses	A	No consumption subsistence ($\bar{c}/c = 0$)	targeted	-	targeted	predicted
	B	No modern production share gender heterogeneity ($\xi^f_{Sr} = 0.5 = \xi^m_{Sr}$)	targeted	targeted	targeted	predicted
	C	Fixed low income production shares across all income groups	targeted	targeted	targeted	predicted

2017), but that it materializes only in middle- and high-income countries (as $\tilde{\xi}_{Sr}$ rises to 0.66 and then to 0.76). These results tie well into the discussion about female labor force participation and the rise of the service sector in high-income countries.

Moreover, $\tilde{\xi}_{Mh}$ indicates that males have a strong sectoral comparative advantage in traditional manufacturing in high-income countries. The comparative advantages are calculated from the labor time allocation values of Table 2. The average hours of males allocated to traditional production remain fairly stable from low- to high-income countries, while those of women start with a small value in low-income countries and decline strongly with income. This indicates that the modernization of manufacturing is gender biased. For example, this can occur when traditional manufacturing production is greatly segmented across genders; e.g., females specialize in the production of clothing, while males specialize in furniture and housing construction and maintenance work. The pattern of traditional manufacturing time allocations of Table 2, and thus the male comparative advantage suggested by $\tilde{\xi}_{Mh}$, can occur when the rates with which modernization takes place differ across the segmented traditional manufacturing activities as countries become richer. For example, most of the production of clothing is modernized, while much of the minor housing maintenance is performed within the household in high-income economies.

3.2.3. Targets and distance-minimizing parameters

The results of section 4 are obtained via a benchmark and three counterfactual model calibrations. For all the calibration exercises, we use up to 8 distance-minimizing model parameters and up to 8 data targets. In all cases, the number of distance-minimizing parameters is equal to the number of targets. The following discussion conceptually distinguishes the parameters, targets, and predictions into four groups to facilitate the presentation. Table 5 summarizes how these four groups are used in the various calibration setups.

Group (I) concerns labor and leisure statistics. It suffices to target labor and leisure statistics for one of the two genders because any combination of relative wages and schooling choices that ties down the equilibrium labor and leisure allocation of gender f also ties down the allocation of gender m. Thus, we target the female labor allocation ratios L^f_{ArAh}, L^f_{MrMh}, L^f_{SrSh}, L^f_{ArSr}, L^f_{MrSr} and the female leisure share L^f_l. The targeted ratio values can be computed from Table 2. The distance-minimizing parameters corresponding to this target group are the Z^f_{ArAh}, Z^f_{MrMh}, Z^f_{SrSh}, Z^f_{ArSr}, Z^f_{MrSr}, and φ.

The parameters of the form Z_{isjq} in eqs. (2.22) and (2.24) combine elements of the household's preferences (ψ_i, ω_i) with the productivities in traditional and modern technologies (Z_{is}, Z_{jq}). Thus, the calibrated values for Z_{isjq} cannot be directly interpreted as productivities. Moreover, without making additional structural assumptions about the form of Z_{isjq} or targeting additional statistics from data with household preferences' variation, it is impossible to disentangle 12 parameters of the form ψ_i, ω_i, and Z_{is} from 6 parameters of the form Z_{isjq}.

Group (II) concerns the consumption subsistence. In section 4, we use counterfactual A to illustrate that the inclusion of subsistence requirements greatly improves the accuracy of predictions for the household's schooling choices. For the benchmark calibration and the two remaining counterfactual cases (counterfactuals B and C), we target $\bar{c}/c$ using values from Table 6. In the online ap-

Table 6
Subsistence share and wage ratio targeted values.

Target	Low Income	Middle Income	High Income	All Countries
$\gamma = \bar{c}/c$	0.23	0.06	0.02	0.10
$\tilde{w}$	0.8190	0.8157	0.8133	0.8160

Notes: For the subsistence share values, we retrieve from the World Bank the necessary daily budget required to finance the minimum amount of consumption to survive in 2005 and scale it at a yearly level (\$1.25 × 365 days, in international and real 2005 terms). We divide this value by each country's level of real PPP-adjusted per capita GDP and average across country income groups. Wages ratios are calculated by averaging per income group the data of Fig. 3b.

pendix, we show how to derive the subsistence share parameter $\gamma = \bar{c}/c$ as a function of a composite parameter $\hat{c}_i = \omega_i^{\frac{\epsilon}{1-\epsilon}} \psi_i^{\frac{\sigma}{1-\sigma}} \bar{c}$ that we use in the benchmark and counterfactuals B and C.

Group (III) concerns the female-to-male wage ratio. The wage ratio data targets are documented in Table 6. We do not specify any calibrated parameter corresponding to the wage ratio. In all setups, the wage ratio is calculated so that labor markets clear.

Group (IV) concerns the household's schooling choices. The female and male schooling years are not targeted either in the benchmark calibration or in counterfactuals A to C. Instead, schooling years are predicted per country income group. The calibrated parameter corresponding to this group is the female flow cost of schooling β^f. We fix $\tilde{\beta}$ equal to the value obtained from the data according to the right-hand side of eq. (2.28).[10] The male flow cost of schooling is then obtained by the identity $\beta^m = \beta^f / \tilde{\beta}$.

3.2.4. Other calibration details

All calibrations took place in the computing cluster of SAFE Leibniz Institute.[11] The calibration methodology is the same for all setups of Table 5. The model is calibrated using a nested procedure with two levels. At the outer level, the distance between targets and model predictions is minimized. The inner level numerically approximates model equilibria as solutions to a system of three equations on three unknowns (s^f, s^m, $\tilde{w}$).[12]

The distance minimization is implemented using *Nelder-Mead* with error tolerance equal to 10^{-4}. Distances are calculated using the $\mathcal{L}^1$ norm. The equilibrium system is solved using Newton's method. The solver approximates solutions with range and domain error tolerances equal to 10^{-8}. The Jacobian of the system is obtained via numerical differentiation using symmetric difference quotients with adaptive stepping. Furthermore, the root finder iterations use a dampening parameter to regulate Jacobian steps pointing outside the domain for which the equilibrium system is well defined.

We originally initialized the calibration minimizer with values calculated from the expressions of section 2, by substituting the labor shares, schooling years, and wage ratios retrieved from the data. The initial values for the parameters of the form Z_{isjq} were obtained from eqs. (2.21) and (2.23), φ from eq. (2.24), and $\hat{c}_i$ from the equation that solves for $\bar{c}/c$ (which we derive in the appendix). The nested root finder initializes the wage ratio and the schooling years by their corresponding data values.[13]

4. Results and discussion

We use the benchmark calibration to quantify the qualitative insight of section 2 and Proposition 1. The model can quantitatively replicate data averages at both, individual and household decision margins, predict schooling choices accurately within each income group, and support the co-movements of schooling and paid hours ratios across income groups. Further, we use three counterfactual scenarios to examine the role of (i) consumption subsistence (counterfactual A), (ii) labor production share heterogeneity across genders within each country income group (counterfactual B), and (iii) across country income groups (counterfactual C) on the relationship between the paid hours and schooling gaps.

4.1. Schooling predictions

The benchmark calibration examines the model's capacity to predict schooling choices accurately. The setup has 8 data targets and 8 calibrated parameters. Schooling years are not targeted; instead, the model is calibrated only using the remaining targets, and the equilibrium schooling choices are backed out from the model's fit.

Table 7 provides a detailed overview of the calibration results. The first 8 columns ($\hat{c}$ to β^f) give the calibrated parameters. The values for the β^m column are calculated by eq. (2.28). The last three columns give the model's equilibrium values for the wage ratio and the years of schooling.

Most calibrated parameters change monotonically across country income groups. It is not clear how to interpret the changes across income for the values of $\hat{c}_S$ and Z_{isjq} because they are composite expressions of both preferences and productivity parameters. The

[10] We calculate 0.4110 for the low-, 0.4330 for the middle-, 0.5219 for the high-income group and 0.4597 for the complete sample.

[11] We performed all calculations using a multi-socket system with two AMD EPYC 7763 64-Core CPUs and hyperthreading (in total 256 logical processors).

[12] See online appendix eqs. (D.23), (E.2) and (E.3).

[13] More details about the calibration procedure are available in the online appendix. The source code for the model's calibrations is distributed as free software under the Expat license. The online appendix documents how the code repository can be accessed.

Table 7
Distance-minimizing calibrated parameters.

Group	$\hat{c}_S$	φ	Z_{ArAh}	Z_{MrMh}	Z_{SrSh}	Z_{ArSr}	Z_{MrSr}	β^f	β^m	$\tilde{w}$	s^f	s^m
Benchmark: Schooling predictions												
low	11.0410	1.8370	0.0922	0.9547	0.1620	0.9066	12.7088	0.3673	0.8938	0.8188	5.7369	7.5522
middle	6.1257	1.7262	0.1256	2.0985	0.1660	5.6320	13.5258	0.4225	0.9756	0.8157	7.7332	8.3759
high	4.7037	1.3765	0.2315	4.1683	0.1956	26.9880	8.0076	0.5783	1.1082	0.8133	9.8589	10.4155
all	14.1069	1.6241	0.1244	2.0423	0.1520	5.5207	12.3555	0.4486	0.9759	0.8480	7.5019	8.9182

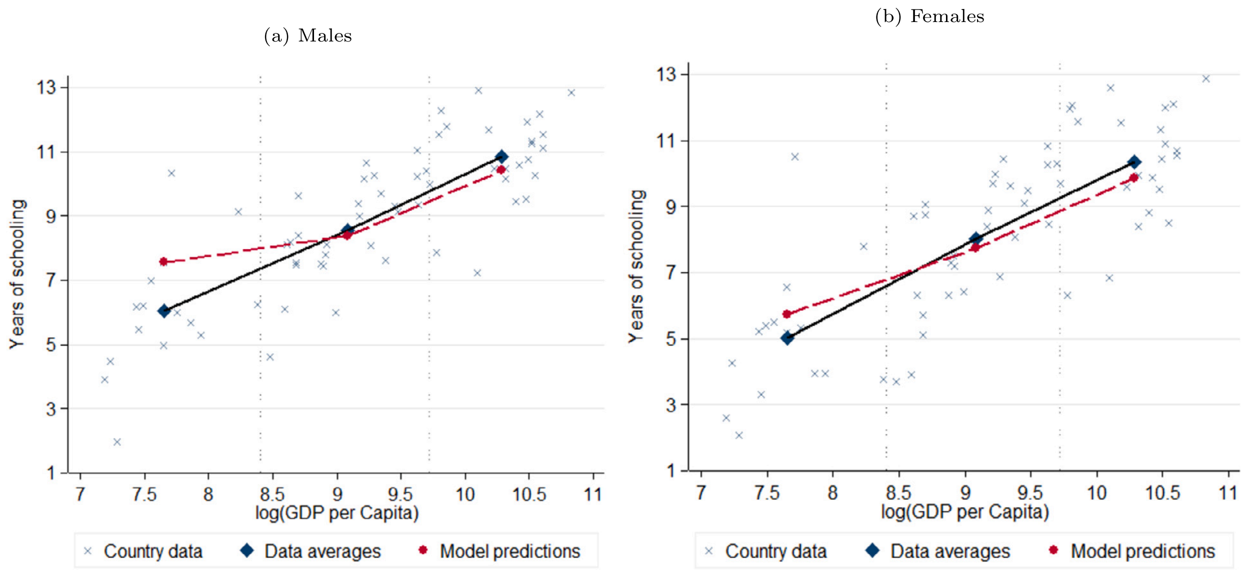

Fig. 4. Individual margin: predictions for years of schooling.

leisure preferences parameters decline with income. Households in high-income countries have more consumption opportunities as they produce at a greater productivity level. Thus, the opportunity cost in terms of foregone consumption when increasing leisure is greater. At the same time, greater productivity increases the households' lifetime income and reduces the share of income allocated to subsistence needs.

The calibrated schooling costs (β^f and β^m) increase with the income group. This can ostensibly be counter-intuitive, in particular, if one does not consider how different the context of education is across income levels. Low-income economies are based on less sophisticated technologies which, besides requiring less time to master, are more easily accessible. Ceteris paribus, acquiring the skills that are relevant to engage in paid work, which prevails in high-income economies employing more sophisticated technologies, is more difficult to achieve (cf. Spitz-Oener, 2006). Female schooling costs are consistently lower than male schooling costs, but the gap closes across income groups. The higher the income of the economy, the less the differences in the flow costs of education between females and males. This result is not related to opportunity costs of paid labor because the model explicitly accounts for this trade-off (see Proposition 1). Instead, the differences in schooling preferences can be interpreted as an amalgamation of (self-fulfilling) beliefs and norms about female and male education that is captured by the data for different income groups. For instance, the diminishing of schooling cost differences can reflect that in high-income countries socially based, explicit or implicit, entry barriers to female education are relatively less intense than in low-income countries.

Fig. 4 consolidates the model predictions for female and male years of schooling. The model performs well in matching female and male schooling choices at the individual decision margin. For females, the model predicts 5.74, 7.73, and 9.86 for low-, middle-, and high-income countries, closely missing the data averages (5.03, 8.02, and 10.35). The largest error occurs for male schooling in low-income countries, where the model predicts 7.55 years, whereas the data average is 6.03 (1.52 years difference). For middle- and high-income countries, male schooling predictions are 8.38 and 10.42 years, missing the data averages 8.57 and 10.84 by 0.19 and 0.42 years.

Fig. 5 displays the model-predicted labor and leisure allocations and the corresponding data averages per income group. Across all income groups, the model predicted leisure time allocation shares (ℓ^f, ℓ^m) for both genders are approximately 60% implying that individuals allocate slightly more than half of their active part of the day to non-work activities. The model replicates the decline of traditional hours (N^f, N^m) and the rise of hours in paid work (M^f, M^m) from low- to high-income countries for both genders.

More importantly, although years of schooling are not targeted the model replicates the co-movement of the paid hours and schooling ratios across income groups, and it does so while keeping the wage ratio constant. This quantitatively validates the theoretical insight of Proposition 1, which we derived from the equation describing the household decision margin. In Table 8, we

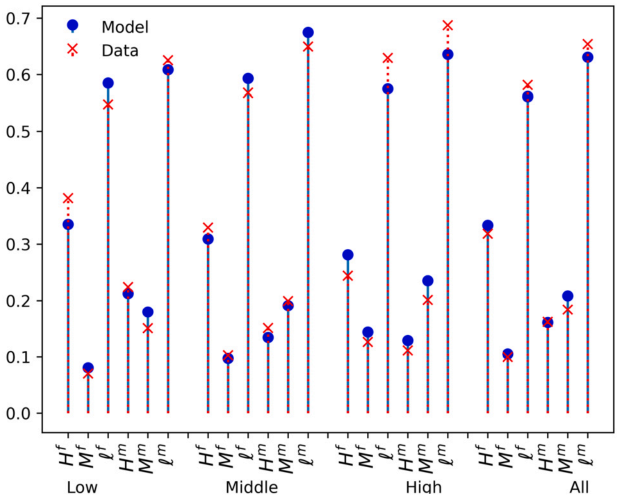

Fig. 5. Individual margin: labor and leisure allocation predictions.

Table 8
Household margin: schooling and paid hours predictions.

Variable	Income Group			Relative Difference	
	Low	Middle	High	Middle-Low	High-Middle
Data					
$\tilde{w}$	0.8190	0.8157	0.8133	-0.41%	-0.29%
$\tilde{M}$	0.4673	0.5156	0.6269	10.35%	21.59%
$\tilde{s}$	0.8339	0.9363	0.9556	12.28%	2.06%
Benchmark: Schooling predictions					
$\tilde{w}$	0.8188	0.8157	0.8133	-0.38%	-0.29%
$\tilde{M}$	0.4479	0.5094	0.6113	13.75%	20.00%
$\tilde{s}$	0.7596	0.9233	0.9466	21.54%	2.52%

compare the movements of the three ratios across income groups as observed in the data to those predicted by the model. The wage ratio persistence is replicated with negligible errors for both the movement from low-to-middle and middle-to-high-income countries. The more pronounced error is in the low-to-middle difference of the schooling ratio, as the model over-predicts the change by 12.3 pp. The error for the low-to-middle difference of the paid hour ratio is of a smaller scale, about 3.4 pp. Remarkably, considering that schooling levels are not targeted in the benchmark, the errors in the differences of paid hours and schooling ratios from middle- to high-income countries are less 1.6 pp.

4.2. Model mechanics

This section investigates the model mechanics using two partial equilibrium exercises. The first exercise examines the model's local responses under a productivity factor shock in the modern service sector of the economy. An example of such a shock can be the introduction of a novel artificial intelligence tool that enhances the productivity of white-collar workers irrespective of their gender. The second exercise examines the model's predicted responses when the female production share in modern services changes. For instance, this could arise as the government introduces policies aiming to increase female labor participation in the modern service sector of the economy.

Fig. 6 displays the partial equilibrium impact on labor, leisure and schooling of a change in the productivity factor of modern services (Z_{Sr}). Each variable's response is calculated assuming that the other parameters remain constant.[14] The horizontal axes measure relative changes of Z_{Sr} from the value for which the general equilibrium is calculated ranging from -10% to 10%. The vertical dash lines indicate the starting value from the calibration. Productivity improvements scale production uniformly for the two genders and, thus, the f and m-wage bills (I^f_{Sr} and I^m_{Sr}) remain unaffected. Moreover, a positive Z_{Sr} shock increases the marginal product of modern services for both genders equally. As a result, the adjustments in labor allocations are approximately parallel for the two genders. As a response to a productivity shock, modern service labor shares (L^f_{Sr}/L^f and L^m_{Sr}/L^m) increase. This puts

[14] Figs. 6 and 7 use the calibrated parameters of the benchmark when averages for all the countries are targeted. The resulting figures when only low-, middle-, or high-income countries are targeted exhibit similar qualitative response patterns.

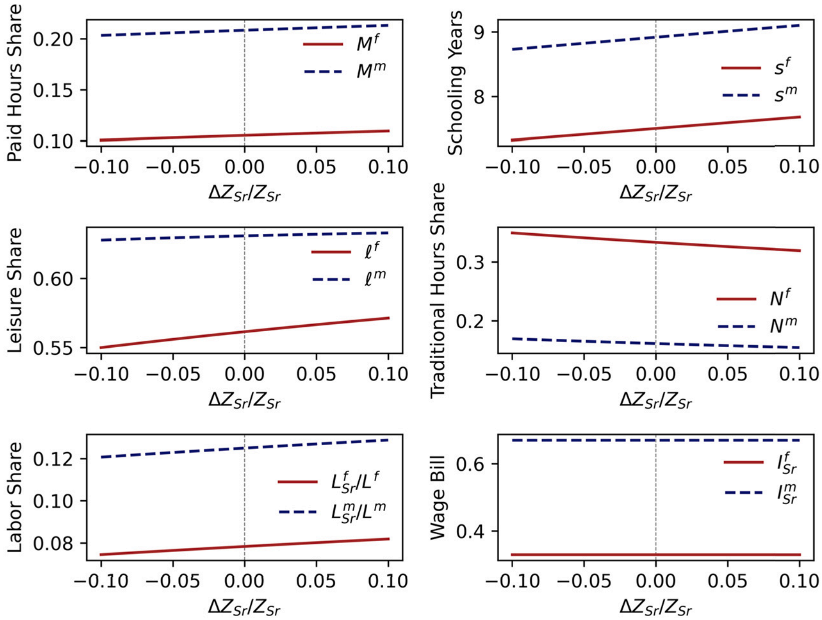

Fig. 6. Impact of productivity changes.

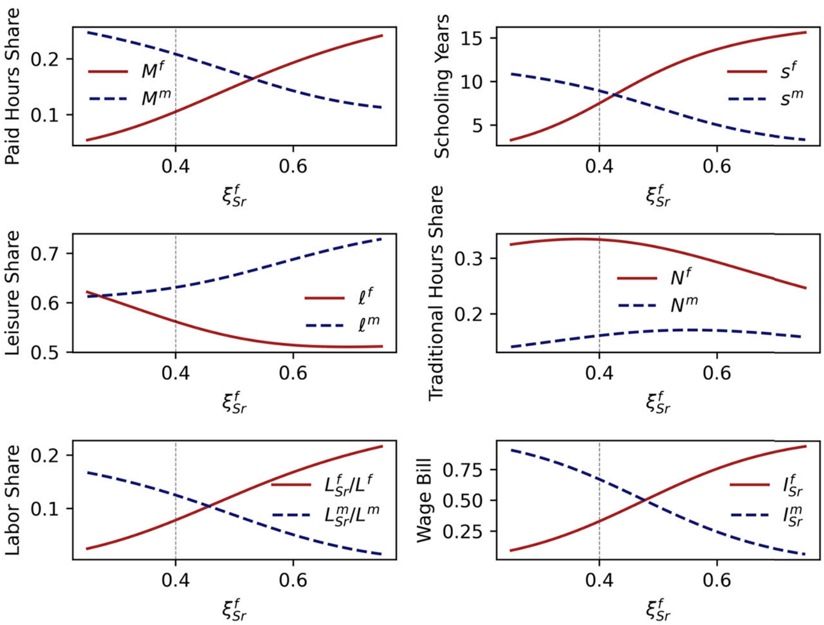

Fig. 7. Impact of gender production share changes.

upward pressure on hours in paid work (M^f and M^m), while in parallel traditional hours (N^f and N^m) decrease. Additionally, a productivity shock in the modern services sector increases the labor compensation for both genders and, because the modern sector scales with human capital, incentivizes both genders to increase their years of schooling.

While productivity factors affect only the household decision margins, changes in production shares have implications for the individual decision margins. When the two genders commonly reach household decisions, relative production shares govern production substitutability and drive how time is allocated across genders.

Fig. 7 displays the partial equilibrium impact on labor, leisure, and schooling of changes in gender f's labor production share in modern services' production. Each variable's response is calculated assuming that the other parameters, such as the wage ratio, remain constant. The horizontal axes measure the value of ξ^f_{Sr} and the vertical dash lines indicate the calibrated values of the benchmark setup (all countries). Gender f's wage bill for modern services increases as its production share increases, while gender m's decreases as the wage bill shares sum up to one. An increase in ξ^f_{Sr} increases the marginal product of gender f in modern

Table 9
Counterfactual calibrations.

Group	s^f	s^m	$\tilde{s}$	$\tilde{w}$	$\tilde{M}$	$\frac{\Delta\tilde{s}}{\tilde{s}}$	$\frac{\Delta\tilde{w}}{\tilde{w}}$	$\frac{\Delta\tilde{M}}{\tilde{M}}$
Counterfactual A: Without subsistence								
low	4.3673	5.9168	0.7381	0.8190	0.4432			
middle	7.0367	7.6910	0.9149	0.8155	0.5059	0.2395	-0.0043	0.1413
high	10.6680	11.0597	0.9646	0.8133	0.6214	0.0543	-0.0027	0.2285
Counterfactual B: Without modern services production share heterogeneity								
low	8.2732	5.9288	1.3954	0.8190	0.8844			
middle	14.4496	2.7289	5.2950	0.3757	1.6838	2.7945	-0.5413	0.9039
high	15.4972	5.7828	2.6799	0.5088	1.2619	-0.4939	0.3543	-0.2505
Counterfactual C: With fixed labor production shares across income								
low	5.7369	7.5522	0.7596	0.8188	0.4479			
middle	9.6693	12.8170	0.7544	0.8156	0.4310	-0.0069	-0.0038	-0.0376
high	14.3816	19.1179	0.7523	0.8316	0.4635	-0.0029	0.0196	0.0754

services. At the same time, the marginal product of gender m decreases because $\xi^m_{Sr} = 1 - \xi^f_{Sr}$ decreases. Therefore, the household substitutes L^m_{Sr}/L^m with L^f_{Sr}/L^f. As a result, gender f allocates more time to paid work (M^f increases) but less time to leisure (ℓ^f decreases). The mirror image of this happens for the leisure and paid hours allocations of gender m. The opposite movements of labor allocations create different schooling incentives for the two genders. As more time is allocated to paid work, schooling becomes more appealing for gender f. However, the labor substitution effect decreases time in paid work for gender m, making schooling less attractive.

To summarize, when an exogenous event or a government policy increases the gender f's production share of ξ^f_{Sr}, the paid hours and schooling year gaps ($\tilde{M}$ and $\tilde{s}$) co-close, even if the wage ratio $\tilde{w}$ persists. Fig. 7 locally encapsulates the qualitative result of Proposition 1 around the vertical dashed lines in each plot. In the neighborhood of the starting value of ξ^f_{Sr} for which the general equilibrium of the benchmark is calculated, an increase of ξ^f_{Sr} leads to a simultaneous rise of the female-male ratios in paid hours and years of schooling.

Evidence from previous literature suggests that fertility variations across countries in different stages of the Demographic Transition can contribute to heterogeneity in Mincerian returns to human capital (Becker et al., 1990; Galor and Weil, 2000; Tamura, 2006; Tamura et al., 2016, 2019). While our analysis does not specifically focus on fertility, our calibration indirectly endorses lower mortality rates in high-income countries by assigning different T values to distinct income groups. In our dataset, we observe an increase in T from low- to high-income countries. This implies that, in line with previous literature, our model's returns to schooling will be greater in high-income countries even when the human capital parameters ν and ζ are constant and households allocate a fixed share of their life span to education. This is because a constant share of lifespan allocated to education translates to (i) more years in education and (ii) more years in working life with a greater stock of human capital.

Life-expectancy differences across income groups are one aspect that can contribute to Mincerian returns heterogeneity. Another contributing factor is direct heterogeneity in human capital accumulation dynamics over the country-income distribution, such as variations in the parameters ν and ζ, due to institutional or cultural differences. These additional factors become particularly relevant when exploring policy implications, such as the impact of norm homogenization due to globalization or the reduction of cultural and social barriers in female education. The lack of granularity in the schooling dimension of our data limits our capacity to quantitatively explore these policy implications. To prevent overfitting, our calibrations use at least as many targets as the number of parameters in distance minimization. However, the lack of additional schooling information prevents us from expanding the number of calibration targets to match targets and fitted parameters, despite our model's capacity to accommodate heterogeneous human capital parameters across country income groups. Nevertheless, we identify this aspect and its policy implication as a promising direction for future research.

4.3. Counterfactual analyses

We calibrate the model using three counterfactual hypotheses to investigate the relevance of non-homotheticities in consumption preferences as well as production share heterogeneity across gender and income in our findings. Table 9 presents the main results for the three counterfactual cases.

4.3.1. Without subsistence requirements

Counterfactual A explores a scenario where consumption subsistence is shut down ($\hat{c} = 0$). The presence of subsistence requirements in the household's preferences introduces non-homotheticities intensifying the income effect channel of the model. The exclusion of the subsistence term from the calibration exercise reduces the quality of the model's fit and schooling predictions, indicating that the neglected income effects have a significant role when schooling choices are formed.

At the individual level and for low- and middle-income countries, the model without subsistence predicts lower schooling years than in the data. This is because the presence of subsistence-based income effects reinforces the individuals' incentives to stay longer in education when resources are scarce. Thus, in low- and middle-income countries subsistence requirements are more stringent in relative terms and increase the household's marginal utility for every consumption level.[15] When subsistence requirements are present, the individuals of the household desire to consume more and, thus, have a greater incentive to stay in education, increase their human capital, earn greater productive wages during their working life, and eventually, meet their aspired consumption level.

The impact of switching off the subsistence requirements on the wage ratio predictions is minimal. Further, the qualitative insight underpinning Proposition 1 holds in this counterfactual scenario. However, the model's ability to replicate the actual schooling and labor choices is hindered compared to the benchmark setup. Most importantly, calibrating without subsistence widens the prediction errors of the differences in $\tilde{M}$ and $\tilde{s}$ across income groups. In particular, it severely overestimates the middle- to high-income schooling ratio difference as 5.43% (compared to 2.52% in the benchmark setup and 2.06% in the data).

4.3.2. No gender heterogeneity in labor shares of modern services

In counterfactual B, we calibrate the model without heterogeneity in the modern production services' gender shares ($\xi^{f}_{Sr} = 0.5 = \xi^{m}_{Sr}$). Compared to the calibrated values of the benchmark ($\xi^{f}_{Sr} = 0.35, 0.40, 0.43$ for low-, middle-, and high-income countries), the hypothesized symmetry greatly increases gender f's comparative advantage in producing modern services.

The counterfactual calibration fails to replicate the wage ratio persistence, but still replicates the co-movement of the schooling and paid hours ratios across income groups. Nonetheless, the predicted schooling years are quantitatively and qualitatively very distant from the data. For instance, the predicted female years of schooling are greater than the predicted male years of schooling for every income group, and the female-to-male schooling ratios are 1.40, 5.3, and 2.68.

The enhanced comparative advantage of f in modern services intensifies the main mechanic our model predicts. Greater comparative advantages in modern services induce greater incentives to engage in that sector and to increase total hours in paid work. In turn, this makes it optimal for the individual enjoying these comparative advantages to stay more years in schooling, increase his/her human capital and receive greater productive wages from paid work. The labor contribution in modern services of the partner of the individual enjoying the comparative advantage is substituted out and the incentives to stay in education diminish. This exercise further highlights quantitatively the potential implications of policies targeting production shares (see also Fig. 7).

4.3.3. With fixed gender production shares across income

The last counterfactual scenario we present (counterfactual C) restricts the extent to which the labor production shares change across country income groups. Specifically, when calibrating middle- and high-income countries, this counterfactual sets the gender production shares to be equal to their values for the low-income group. The scenario still allows, via Z_{ip}, labor productivity to increase from low- to high-income countries in each sector i and technology p, but only in a uniform way across the two genders.

The calibration produces persistence in the wage ratio across income groups. Moreover, it yields schooling years predictions at an individual level that increase across income groups for both genders; albeit overestimating the levels. However, without allowing production share heterogeneity to change across levels, the resulting schooling and hours of paid work ratios remain approximately constant across income groups, which is qualitatively very different from the stylized facts derived from our data.

The results suggest that the production and leisure shares and the substitution patterns they induce within the household decision unit have a central role in producing the co-movement of the schooling and paid hours gaps we observe in cross-country data. Without gender share differences across income groups, female and male labor substitution does not occur because the comparative advantages of the two genders do not change. Due to increased productivity, both genders still have incentives to increase hours of paid work and years of schooling in economies with greater income. However, these incentives are uniform across genders and, thus, the schooling years grow at a similar pace, implying that the schooling ratio remains constant.

5. Conclusion

We construct a novel cross-country dataset by combining micro-survey data from Bick et al. (2018) and schooling data from Barro and Lee (2013). Our dataset allows us to examine the relationship between gender differences in hours of paid work, wages, and schooling choices. The data indicate that the difference in years of schooling between females and males declines from low- to high-income countries. Nonetheless, the gender differences in hourly wages, after controlling for differences in observable characteristics, persist across all country income groups. Instead, we observe that parallel to the decline of the schooling gap, gender differences in hours of paid work tend to diminish, too.

Beginning from this stylized fact, we introduce a general equilibrium, multi-sector, -gender, and -production technology model extending the work of Ngai and Petrongolo (2017) by including schooling choices as in Restuccia and Vandenbroucke (2014). We use our data to calculate each gender's sectoral comparative advantage in the modern sectors, which are human-capital intensive, and in the traditional production sectors. The data suggest that compared to the other modern sectors, females' comparative advantage lies in services. High-income countries exhibit larger service sectors, providing more opportunities for females to take advantage of their sectoral comparative advantage by allocating more time to paid work.

[15] The marginal utility of $\log(c - \bar{c})$ is increasing in $\bar{c}$ for fixed c.

The gender heterogeneity of our model allows us to investigate how decisions at the individual gender level result in relationships in paid hours and schooling gaps at the household decision margin. We show that, when relative wages are held constant, the equilibrium elasticity of the female-to-male paid hours ratio with respect to the corresponding schooling ratio implied by the model is positive. That is, the model formalizes the stylized relation of the three gaps in the data. Furthermore, we quantify the model's schooling predictions by calibrating it to replicate the persistence in female-male relative wages. The model accurately predicts both the levels and co-movements of the paid hours and schooling ratios across country income groups.

We examine the contribution of three central constituents of our model by performing counterfactual analyses. First, we show that non-homotheticities stemming from consumption subsistence intensify the income effect driving the choices of schooling. As such, they are crucial to obtain precise quantitative schooling predictions. Second, we show that gender heterogeneity in labor production shares is essential for replicating the schooling ratio and labor ratio differences we observe in the data across country-income groups. Thirdly, we illustrate that if sectoral comparative advantages in middle- and high-income countries were as in low-income countries, then the gender gaps in paid hours and years of schooling would remain constant across country income groups.

Our empirical and theoretical analyses suggest that the pronounced prevalence of the modern service sectors in high-income countries, combined with the rise of females' sectoral comparative advantage in services, is closely linked with the diminishing schooling gap. In high-income countries, females allocate more time to modern (i.e., paid) work, which incentivizes staying longer in education. The production of modern services is human capital intensive, and more hours of paid work offer more opportunities to realize greater returns to schooling via greater productive wages. Males have similar incentives, but their years of schooling increase less across income. Males' sectoral comparative advantages are found in modern manufacturing and agriculture, which are less prevalent in high-income economies. Due to this, the schooling gap is smaller in high-income countries even though, on average, the wage gap persists across all country income groups. Our finding is robust against costs of schooling that increase from low-, to middle-, and high-income countries.

Our work provides an economic rationale strongly suggesting that analysis and policy planning concerning the equality of opportunities in schooling should be examined in the same context as the equality of labor market access opportunities. Conversely, our result emphasizes that the observed gender differences in education across the country-income spectrum are less conducive to the observed wage gap differences. Instead, continuing efforts towards de-invisibilizing female labor and improving labor market access can help reduce gender educational differences.

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Appendix A. Proof of Proposition 1

For brevity, let

$$F(s) = \frac{G(s)d(s)H(s)}{d'(s)} = H'(s)\frac{d(s)}{d'(s)} + H(s).$$

We solve eq. (2.28) for relative paid hours ($\tilde{M}$) and calculate its elasticity with respect to relative schooling choices ($\tilde{s}$)

$$\left.\frac{\partial \log \tilde{M}}{\partial \log \tilde{s}}\right|_{\tilde{w}} = \left.\frac{\partial \log\left(\tilde{\beta}/\tilde{w}\tilde{F}\right)}{\partial \log \tilde{s}}\right|_{\tilde{w}} = -\left.\frac{\partial \log F(s^f)}{\partial \log \tilde{s}}\right|_{\tilde{w}} + \left.\frac{\partial \log F(s^m)}{\partial \log \tilde{s}}\right|_{\tilde{w}}.$$

Using the inverse mapping theorem, we get

$$\begin{aligned}\left.\frac{\partial \log \tilde{M}}{\partial \log \tilde{s}}\right|_{\tilde{w}} &= -\frac{F'(s^f)}{F(s^f)}\left(\frac{\partial \log \tilde{s}}{\partial s^f}\right)^{-1} + \frac{F'(s^m)}{F(s^m)}\left(\frac{\partial \log \tilde{s}}{\partial s^m}\right)^{-1} \\ &= -\frac{F'(s^f)}{F(s^f)}s^f - \frac{F'(s^m)}{F(s^m)}s^m.\end{aligned}$$

Since $F(s) < 0$ for any $0 < s < T$, when both s^g with $g = f, m$ satisfy $F'(s^g) > 0$, the elasticity is positive. We have

$$\begin{aligned}F'(s) &= H''(s)\frac{d(s)}{d'(s)} + H'(s)\frac{(d'(s))^2 - d(s)d''(s)}{(d'(s))^2} + H'(s) \\ &= H(s)\zeta s^{-2\nu}\left(\zeta - \nu s^{\nu-1}\right)\frac{d(s)}{d'(s)} + H(s)\zeta s^{-\nu}\left(2 + \rho\frac{d(s)}{d'(s)}\right) \\ &= H(s)\zeta s^{-\nu}\left(e^{-\rho(T-s)} + 1\right)\left(s^{-\nu}\left(\zeta - \nu s^{\nu-1}\right)\frac{1}{\rho}\frac{e^{-\rho(T-s)} - 1}{e^{-\rho(T-s)} + 1} + 1\right) \\ &= H(s)\zeta s^{-\nu}\left(e^{-\rho(T-s)} + 1\right)\left(s^{-\nu}\left(\zeta - \nu s^{\nu-1}\right)\frac{1}{\rho}\tanh\left(-\frac{1}{2}\rho(T-s)\right) + 1\right).\end{aligned}$$

Define the functions

$$
\begin{aligned}
g(s) &= s^{-\nu}\left(\zeta - \nu s^{\nu-1}\right)\\
h(s) &= \frac{1}{\rho}\tanh\left(-\frac{1}{2}\rho(T-s)\right)\\
f(s) &= g(s)h(s) + 1.
\end{aligned}
$$

Since $H(s)\zeta s^{-\nu}\left(e^{-\rho(T-s)}+1\right) > 0$, the term $F'(s)$ is positive if and only if $f(s) > 0$. We will derive a lower bound for f.

The function g is strictly concave in $(0,T)$, positive for $s > s_0 = (\nu/\zeta)^{1/(1-\nu)}$, and has a maximum at $s_1 = (1/\zeta)^{1/(1-\nu)}$, which is equal to $g(s_1) = \zeta^{1/(1-\nu)}(1-\nu)$. The function h is negative and greater than $-1/\rho$ for all $s \in (0,T)$. We distinguish two cases. Firstly, for any $s \le s_0$, the product $g(s)h(s)$ is positive and $f(s)$ is positive. Secondly, for any $T > s > s_0$, we have

$$
f(s) > 1 - \frac{g(s_1)}{\rho}.
$$

The lower bound is non-negative if $\zeta < ((1-\nu)/\rho)^{\nu-1}$.

Appendix B. Data sources

Table B.1
Survey overview.

Country	Year	Survey	Time-Use
Low-Income Countries			
Benin	2010	Enquete Modulaire Integree sur les Conditions de Vie des Menages (EMICOV)	Yes
Bolivia	2005	Encuesta de Hogares (RIGA)	-
Cambodia	2011	Cambodia Socio-Economic Survey (CSES)	-
Ghana	1998	Living Standards Measurement Survey (LSMS)	Yes
Kenya	2005	Kenya Integrated Household Budget Survey	-
Lao PDR	2007	Expenditure and Consumption Survey	-
Lesotho	2008	Integrated Labor Force Survey	Yes
Mali	2010	Permanent Household Survey (EPAM)	Yes
Pakistan	2011	Labor Force Survey	Yes
Rwanda	2011	Enquete Integrale sur les conditions de vie des menages	Yes
Tajikistan	2007	Living Standards Survey (LSMS)	-
Tanzania	2009	National Panel Survey (LSMS)	-
Timor Leste	2007	Living Standards Survey (LSMS)	Yes
Uganda	2010	National Panel Survey (LSMS)	-
Vietnam	2002	Household Living Standards Survey (LSMS)	-
Middle-Income Countries			
Albania	2012	Labor Force Survey	-
Angola	2008	Inquerito Integrado sobre o Bem-Estar da Populacao (IBEP)	-
Bosnia	2001	Living Standards Measurement Survey (LSMS)	-
Botswana	2005	Labor Force Survey	-
Brazil	2009	National Household Sample Survey (PNAD)	-
Bulgaria	2005	European Union Labor Force Survey	-
China	2006	The China Health and Nutrition Survey	Yes
Columbia	2008	Integrated Household Survey (GEIH)	-
Ecuador	2005	Encuesta de Condiciones de Vida (LSMS)	-
Egypt	2006	Labor Market Panel Survey	Yes
Guatemala	2000	Encuesta Nacional Sobre Condiciones de Vida (ENCOVI)	Yes
Indonesia	2010	Sakernas (National Labor Force Survey)	-
Iraq	2007	Household Socio-Economic Survey (LSMS)	Yes
Kazakhstan	1996	Living Standards Measurement Survey (LSMS)	Yes
Latvia	2005	European Union Labor Force Survey	-
Lithuania	2005	European Union Labor Force Survey	-
Mauritius	2010	Continuous Multi Purpose Household Survey (CMPHS)	-
Mongolia	2006	Labor Force Survey	Yes
Namibia	2009	Household Income and Expenditure Survey	-
Panama	2008	Encuesta de Niveles de Vida (ENV) (LSMS)	-
Paraguay	2011	Encuesta de Hogares (Household Survey)	-
Peru	2010	Encuesta Nacional de Hogares (ENAHO)	-
Philippines	2010	Labor Force Survey (Jan, Apr, Jul, Oct)	-
Poland	2005	European Union Labor Force Survey	-
Romania	2005	European Union Labor Force Survey	-
South Africa	2008	Combined Quarterly Labor Force Surveys	MTUS
Tunisia	2010	Enquete Nationale sur la Population et l'Emploi	-

Table B.1 (*continued*)

Country	Year	Survey	Time-Use
High-Income Countries			
Austria	2005	European Union Labor Force Survey	MTUS
Belgium	2005	European Union Labor Force Survey	-
Chile	2009	National Socioeconomic Survey (CASEN)	-
Cyprus	2005	European Union Labor Force Survey	-
Czech Republic	2005	European Union Labor Force Survey	-
Denmark	2005	European Union Labor Force Survey	-
Estonia	2005	European Union Labor Force Survey	-
Finland	2005	European Union Labor Force Survey	-
France	2005	European Union Labor Force Survey	MTUS
Germany	2005	European Union Labor Force Survey	MTUS
Greece	2005	European Union Labor Force Survey	-
Hungary	2005	European Union Labor Force Survey	-
Italy	2005	European Union Labor Force Survey	MTUS
Netherlands	2005	European Union Labor Force Survey	MTUS
Portugal	2005	European Union Labor Force Survey	-
Slovak Republic	2005	European Union Labor Force Survey	-
Slovenia	2005	European Union Labor Force Survey	-
Spain	2005	European Union Labor Force Survey	MTUS
Sweden	2005	European Union Labor Force Survey	-
Taiwan	2011	Labor Force Survey	-
Turkey	2011	Household Labor Force Survey	-
United Kingdom	2008	European Union Labor Force Survey	MTUS
United States	2005	Current Population Survey	MTUS

Notes: For the EULFS countries, hourly wages are retrieved from the EU Statistics on Income and Living Conditions when available. Column 4 indicates whether the respective survey includes a time-use module. If so, it is used to compute hours in household services. Alternatively, we calculate hours in traditional services from MTUS.

Appendix C. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jedc.2023.104805.

References

Aguiar, Mark, Hurst, Erik, 2007. Measuring trends in leisure: the allocation of time over five decades. Q. J. Econ. 122 (3), 969–1006. https://doi.org/10.1162/qjec.122.3.969.

Akbulut, Rahşan, 2011. Sectoral changes and the increase in women's labor force participation. Macroecon. Dyn. 15 (2), 240–264. https://doi.org/10.1017/S1365100510000040.

Bar, Michael, Leukhina, Oksana, 2011. On the time allocation of married couples since 1960. J. Macroecon. 33 (4), 491–510. https://doi.org/10.1016/j.jmacro.2011.04.001.

Barro, Robert J., Lee, Jong Wha, 2013. A new data set of educational attainment in the world, 1950–2010. J. Dev. Econ. 104, 184–198. https://doi.org/10.1016/j.jdeveco.2012.10.001.

Becker, Gary S., 1962. Investment in human capital: a theoretical analysis. J. Polit. Econ. 70 (5), 9–49. https://doi.org/10.1086/258724.

Becker, Gary S., Murphy, Kevin M., Tamura, Robert, 1990. Human capital, fertility, and economic growth. J. Polit. Econ. 98 (5, Part 2), S12–S37. https://doi.org/10.1086/261723.

Bick, Alexander, Fuchs-Schündeln, Nicola, Lagakos, David, 2018. How do hours worked vary with income? Cross-country evidence and implications. Am. Econ. Rev. 108 (1), 170–199. https://doi.org/10.1257/aer.20151720.

Bick, Alexander, Fuchs-Schündeln, Nicola, Lagakos, David, Tsujiyama, Hitoshi, 2022. Structural change in labor supply and cross-country differences in hours worked. J. Monet. Econ. 130, 68–85. https://doi.org/10.1016/j.jmoneco.2022.05.007.

Bils, Mark, Klenow, Peter J., 2000. Does schooling cause growth? Am. Econ. Rev. 90 (5), 1160–1183. https://doi.org/10.1257/aer.90.5.1160.

Blinder, Alan S., 1973. Wage discrimination: reduced form and structural estimates. J. Hum. Resour. 8 (4), 436–455. https://doi.org/10.2307/144855.

Bridgman, Benjamin, Duernecker, Georg, Herrendorf, Berthold, 2018. Structural transformation, marketization, and household production around the world. J. Dev. Econ. 133, 102–126. https://doi.org/10.1016/j.jdeveco.2017.12.009.

Bureau of Economic Analysis. NIPA Handbook: Concepts and Methods of the U.S. National Income and Product Accounts. U.S. Department of Commerce, Washington, D.C. Technical report. https://www.bea.gov/resources/methodologies/nipa-handbook.

Cooray, Arusha, Potrafke, Niklas, 2011. Gender inequality in education: political institutions or culture and religion? Eur. J. Polit. Econ. 27 (2), 268–280. https://doi.org/10.1016/j.ejpoleco.2010.08.004.

Dollar, David, Gatti, Roberta, 1999. Gender inequality, income, and growth: are good times good for women? Working Paper Series 20771. World Bank Group, Washington, D.C. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/251801468765040122/gender-inequality-income-and-growth-are-good-times-good-for-women.

Evans, David K., Akmal, Maryam, Jakiela, Pamela, 2020. Gender gaps in education: the long view. Working Paper 523. Center for Global Developmen, Washington, DC. https://www.cgdev.org/publication/gender-gaps-education-long-view.

Feenstra, Robert C., Inklaar, Robert, Timmer, Marcel P., 2015. The next generation of the Penn World Table. Am. Econ. Rev. 105 (10), 3150–3182. https://doi.org/10.1257/aer.20130954.

Feng, Ying, Ren, Jie, Rendall, Michelle, 2023. The reversal of the gender education gap with economic development. CEPR Press Discussion Paper DP17786. Centre for Economic Policy Research. https://cepr.org/publications/dp17786.

Folbre, Nancy, 2014. The care economy in Africa: subsistence production and unpaid care. J. Afr. Econ. 23 (suppl_1), i128–i156. https://doi.org/10.1093/jae/ejt026.

Freeman, Richard B., Schettkat, Ronald, Duflo, Esther, Jappelli, Tullio, 2005. Marketization of household production and the EU-US gap in work. Econ. Policy 20 (41), 7–50. https://doi.org/10.1111/j.1468-0327.2005.00132.x.

Galor, Oded, 2011. Unified Growth Theory. Princeton University Press. ISBN 978-1-4008-3886-8. https://books.google.de/books?id=qw7XdPAIob8C.

Galor, Oded, Weil, David N., 1996. The gender gap, fertility, and growth. Am. Econ. Rev. 86 (3), 374–387.

Galor, Oded, Weil, David N., 2000. Population, technology, and growth: from Malthusian stagnation to the demographic transition and beyond. Am. Econ. Rev. 90 (4), 806–828. https://doi.org/10.1257/aer.90.4.806.

Gershuny, Jonathan, Fisher, Kimberly, 2014. Multinational time use study. In: Michalos, Alex C. (Ed.), Encyclopedia of Quality of Life and Well-Being Research. Springer, Netherlands, Dordrecht. ISBN 978-94-007-0752-8, pp. 4197–4202.

Goldin, Claudia, 1995. The U-shaped female labor force function in economic development and economic history. In: Paul Schultz, T. (Ed.), Investment in Women's Human Capital and Economic Development. University of Chicago Press. ISBN 978-0-226-74087-4, pp. 61–90.

Goldin, Claudia, 2006. The quiet revolution that transformed women's employment, education, and family. Am. Econ. Rev. 96 (2), 1–21. https://doi.org/10.1257/000282806777212350.

Gollin, Douglas, 2008. Nobody's business but my own: self-employment and small enterprise in economic development. J. Monet. Econ. 55 (2), 219–233. https://doi.org/10.1016/j.jmoneco.2007.11.003.

Grant, Monica J., Behrman, Jere R., 2010. Gender gaps in educational attainment in less developed countries. Popul. Dev. Rev. 36 (1), 71–89. https://doi.org/10.1111/j.1728-4457.2010.00318.x.

Heckman, James J., Lochner, Lance J., Todd, Petra E., 2006. Earnings functions, rates of return and treatment effects: the mincer equation and beyond. In: Hanushek, Eric A., Welch, Finis (Eds.), Handbook of the Economics of Education, vol. 1. Elsevier, pp. 307–458.

Herrendorf, Berthold, Schoellman, Todd, 2018. Wages, human capital, and barriers to structural transformation. Am. Econ. J. Macroecon. 10 (2), 1–23. https://doi.org/10.1257/mac.20160236.

Herrendorf, Berthold, Rogerson, Richard, Valentinyi, Ákos, 2014. Growth and structural transformation. In: Aghion, Philippe, Durlauf, Steven N. (Eds.), Handbook of Economic Growth. In: Handbook of Economic Growth, vol. 2. Elsevier, pp. 855–941.

Hiller, Victor, 2014. Gender inequality, endogenous cultural norms, and economic development. Scand. J. Econ. 116 (2), 455–481. https://doi.org/10.1111/sjoe.12056.

ILO, 2018. Global Wage Report 2018/19: what lies behind gender pay gaps. International Labor Office Publications. https://www.ilo.org/global/publications/books/WCMS_650553/lang--en/index.html.

Kongsamut, Piyabha, Rebelo, Sergio, Xie, Danyang, 2001. Beyond balanced growth. Rev. Econ. Stud. 68 (4), 869–882. https://doi.org/10.1111/1467-937X.00193.

Mincer, Jacob, 1958. Investment in human capital and personal income distribution. J. Polit. Econ. 66 (4), 281–302. https://doi.org/10.1086/258055.

Moro, Alessio, Moslehi, Solmaz, Tanaka, Satoshi, 2017. Does home production drive structural transformation? Am. Econ. J. Macroecon. 9 (3), 116–146. https://doi.org/10.1257/mac.20150109.

Ngai, L. Rachel, Petrongolo, Barbara, 2017. Gender gaps and the rise of the service economy. Am. Econ. J. Macroecon. 9 (4), 1–44. https://doi.org/10.1257/mac.20150253.

Oaxaca, Ronald, 1973. Male-female wage differentials in urban labor markets. Int. Econ. Rev. 14 (3), 693–709. https://doi.org/10.2307/2525981.

Olivetti, Claudia, Petrongolo, Barbara, 2016. The evolution of gender gaps in industrialized countries. Annu. Rev. Econ. 8 (1), 405–434. https://doi.org/10.1146/annurev-economics-080614-115329.

Oreopoulos, Philip, Salvanes, Kjell G., 2011. Priceless: the nonpecuniary benefits of schooling. J. Econ. Perspect. 25 (1), 159–184. https://doi.org/10.1257/jep.25.1.159.

Porzio, Tommaso, Santangelo, G., 2019. Does schooling cause structural transformation? In: Cambridge Working Papers in Economics 1925. Faculty of Economics, University of Cambridge, Cambridge. https://doi.org/10.17863/CAM.38660.

Psacharopoulos, George, 1994. Returns to investment in education: a global update. World Dev. 22 (9), 1325–1343. https://doi.org/10.1016/0305-750X(94)90007-8.

Rendall, Michelle, 2013. The Service Sector and Female Market Work. Europe vs the US. 2013 Meeting Papers 1202. Society for Economic Dynamics, Seoul. https://www.economicdynamics.org/meetpapers/2013/paper_1202.pdf.

Restuccia, Diego, Vandenbroucke, Guillaume, 2014. Explaining educational attainment across countries and over time. Rev. Econ. Dyn. 17 (4), 824–841. https://doi.org/10.1016/j.red.2014.03.002.

Schober, Thomas, Winter-Ebmer, Rudolf, 2011. Gender wage inequality and economic growth: is there really a puzzle?—A comment. World Dev. 39 (8), 1476–1484. https://doi.org/10.1016/j.worlddev.2011.05.001.

Siminski, Peter, Yetsenga, Rhiannon, 2022. Specialization, comparative advantage, and the sexual division of labor. J. Labor Econ. 40 (4), 851–887. https://doi.org/10.1086/718430.

Spitz-Oener, Alexandra, 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. 24 (2), 235–270. https://doi.org/10.1086/499972.

Tamura, Robert, 2006. Human capital and economic development. J. Dev. Econ. 79 (1), 26–72. https://doi.org/10.1016/j.jdeveco.2004.12.003.

Tamura, Robert, Simon, Curtis, Murphy, Kevin M., 2016. Black and white fertility, differential baby booms: the value of equal education opportunity. J. Demogr. Econ. 82 (1), 27–109. https://doi.org/10.1017/dem.2015.17.

Tamura, Robert, Dwyer, Jerry, Devereux, John, Baier, Scott, 2019. Economic growth in the long run. J. Dev. Econ. 137, 1–35. https://doi.org/10.1016/j.jdeveco.2018.10.010.

UNDP, 2019. United Nations Human Development Report 2019. United Nations Development Programme. http://report2019.archive.s3-website-us-east-1.amazonaws.com.

Weichselbaumer, Doris, Winter-Ebmer, Rudolf, 2005. A meta-analysis of the international gender wage gap. J. Econ. Surv. 19 (3), 479–511. https://doi.org/10.1111/j.0950-0804.2005.00256.x.

World Bank, 2007. World development indicators. Technical report. World Bank, Washington, DC. https://openknowledge.worldbank.org/handle/10986/8150.