Health, Gender Division of Labor, and Productivity

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October 24, 2023

Abstract

This paper examines the role of health in determining aggregate productivity through its effect on the gender division of labor across sectors. A multi-sector general equilibrium model is developed that features a relatively high return to health for men in agriculture, implying a reallocation of female talent toward nonagriculture when health of the general population is improved. Quantitative analysis shows that a health subsidy is more cost-effective than an education subsidy in elevating aggregate productivity, in reducing agricultural employment, and in improving welfare. The general equilibrium effect enhances the impact of the health subsidy while mitigating that of the education subsidy.

Keywords: Health, Gender Division of Labor, Sectoral Labor Allocation, Agriculture, Productivity

JEL classification: E20, I15, I25, O11

*I thank Michelle Rendall, Faisal Sohail, Terry Cheung, Ping Wang, Jan Feld, and Debasis Bandyopadhyay for their useful comments. I also appreciate the comments received at the Econometric Society Asia Meeting and Australasia Meeting, the Society for the Advancement of Economic Theory (SAET) Conference, Macro Development Workshop (Melbourne), and the department seminars at The University of Auckland and Victoria University of Wellington.

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1 Introduction

It has long been a pivotal task in macroeconomics to understand why some countries are rich while others are poor. The wide labor productivity gap in agriculture across countries relative to other sectors is key to understanding the cross-country differences in aggregate productivity (Gollin, Parente, and Rogerson, 2002; Caselli, 2005; Gollin, Lagakos and Waugh, 2014).

Various factors have been explored to explain the low agricultural productivity in low-income countries, including low technical input, high transaction cost, and severe resource misallocation. Among such factors is selection: many workers, women as an exemplified group, who lack a comparative advantage in agriculture, self-select into agriculture as a result of low economy-wide efficiency, subsistence requirements, and factor market distortions (Lagakos and Waugh, 2013; Adamopoulos et al., 2022; Lee, 2016). The misuse of talent then drives down agricultural and aggregate labor productivity.

Health also shapes selection. People in poor countries generally have poor health. They are more likely to suffer from malnutrition, disease, and shorter lifetimes than people in rich countries. This impacts education and sectoral occupational choices. Yet the link between health and aggregate productivity through sectoral labor allocation remains largely uninvestigated. This paper explores this link.

In particular, I examine, in the context of a general equilibrium model, how health affects aggregate productivity through its influences on the *gender* division of labor between agriculture and nonagriculture, based on the fact that the relative return to health across different types of activities differs between genders, as documented by the literature (Pitt, Rosenzweig, and Hassan, 2012; Rendall, 2017). Specifically, improved health increases the physical strength of men considerably more than that of women, implying a higher return to health for men than for women in traditional (brawn-based) agriculture. Health also augments education investment, which raises nonagricultural productivity for both genders comparably. These facts imply that the return to health for women in nonagricultural production is relatively high. Therefore, a general improvement in health can enhance aggregate productivity by allowing more women to self-select into nonagriculture where they have a comparative advantage.

This mechanism is supported empirically. Pitt, Rosenzweig, and Hassan (2012) document that, increases in body mass from improved health and nutrition have substantially larger effects on enhancing physical strength for men than for women, but have larger effects on schooling for women than for men. They find that in a brawn-based economy, big-sized men attend less school and are more likely to engage in energy-intensive activities than small-sized men, while big-sized women are marginally more likely to be in school and participate less in energy-intensive activities than small-sized women. Studies with randomized field experiments in low-income countries also indicate that increased health improved schooling outcomes significantly more for women than for men (Miguel and Kremer, 2004; Bobonis, Miguel, and Puri-Sharma, 2006; Field, Robles, and Torero, 2009) and induced women to shift out of agriculture (Baird et al., 2016). Consistent with the micro-level evidence, cross-country data in Figure 1 shows that controlling for a country's income level, better health, indicated by longer life expectancy (LE) or a lower maternal mortality rate (MMR), is negatively associated with the female share of agricultural employment and positively associated with the female-to-male years of schooling ratio.[1]

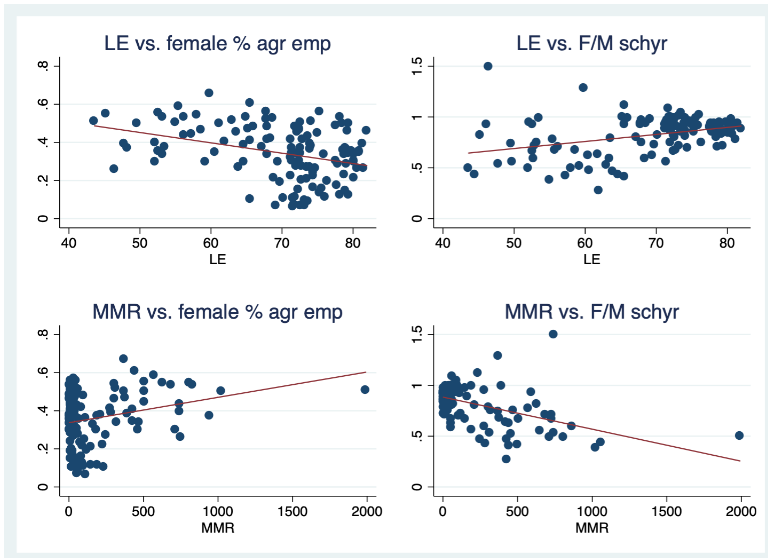

Figure 1. Health versus Female Agricultural Employment and Education

Note: This figure shows cross-country relationships between health and the female share of agricultural employment and the female-to-male years of schooling ratio, controlling for GDP per capita. The maternal mortality rate is defined as the number of maternal deaths per 100,000 live births. Data are for the year 2005. The coefficients of health are statistically significant at 1% for all specifications.

Data source: WDI, FAO, Barro-Lee.

To investigate the macroeconomic implications of the differential health returns based on gender, I construct a two-sector general equilibrium model with overlapping generations of heterogeneous individuals, embedded in an economy described by the Roy (1951) model. Individuals make decisions concerning investment in health and education and, later, the sector to work in (i.e., agriculture versus nonagriculture). They are ex-ante heterogeneous in two dimensions – gender and initial human capital. The direct health effects lie in three dimensions: better health lowers mortality, improves human capital accumulation, and enhances work productivity. The key feature of the model is that agricultural production, for which brawn is the major input, is more health intensive for men than for women; thus, men enjoy a higher return to health in the agricultural sector. This captures the fact

[1]In the Online Appendix, I use cross-sectional individual-level data from the Demographic and Health Surveys for 33 Sub-Saharan African countries and show that the correlation between health and education is larger for women than for men, especially for the population with lower socioeconomic status, and that the correlation between health and nonagricultural employment is also larger for women than for men, regardless of the socioeconomic status.

that improved health increases the physical strength of men more than that of women. In contrast, nonagricultural production requires both health and human capital and its technology does not differ across genders. General health improvements thus elevate women's comparative advantage in nonagricultural work, shifting the allocation of women toward nonagriculture and thereby enhancing aggregate productivity. In addition, women face a barrier of working in nonagriculture, which in turn affects their investment and sectoral choices.[2]

To assess these mechanisms quantitatively, I calibrate the model to match some key moments in the health, education, and economics data of two Sub-Saharan African (SSA) countries. I first calibrate the model to fit the data of Kenya, a typical low-income country in Africa, and use it as the benchmark economy. Then I recalibrate a set of country-specific parameters for Mauritius, a relatively rich SSA country for comparison. My model explains 47% of the agricultural labor productivity gap, 61% of the nonagricultural labor productivity gap, and 52% of the aggregate labor productivity gap observed in the data between the two countries.

The calibrated model is then used for quantitative analysis. I start with comparing the impact of health production efficiency to total factor productivity (TFP). By setting each of these two parameters of Kenya to the Mauritian values, I find that, while the TFP difference is responsible for most of the aggregate labor productivity gap between Kenya and Mauritius, health production efficiency is highly comparable to TFP in explaining differences in agricultural labor productivity and employment share between the two countries. Moreover, improving health production efficiency has a larger impact on reducing female agricultural employment share than improving TFP.

Next, I assess the quantitative importance of modeling an endogenous distribution of idiosyncratic productivities, as opposed to assuming an exogenous distribution. While the literature typically takes the distribution of individual productivities as given when studying sectoral labor allocation (e.g., Lagakos and Waugh, 2013; Lee, 2016), my model endogenizes this distribution through individuals' decisions of health and education investment. To examine the difference, I compare the benchmark model with one in which both health and education decisions are taken as given, when posing a positive TFP or gender barrier shock to both economies. It turns out that the impacts of these shocks on aggregate productivity are considerably smaller in the model with exogenous distribution of individual productivities, compared to the benchmark model. This is essentially because in the exogenous-distribution model, individuals cannot respond to changes in the economic environment by altering health or education investment. This result suggests that studies that assume an exogenous distribution of idiosyncratic productivities potentially underestimate the impact of economic factors such as TFP or labor market frictions.

Furthermore, I explore the sectoral labor productivity gap, a stylized fact in the macro-

[2] Lee (2016) quantifies gender-specific labor market frictions in agriculture and nonagriculture, and finds a negative relation between relative friction against women in nonagriculture and a country's income level.

development literature.[3] I conduct a decomposition analysis to examine the contribution of economic factors – technology, education, innate ability, health, and gender barrier – to the sectoral wage gap. I find that innate ability accounts for most of the sectoral wage differences (40%), followed by technology related to factor intensity (35%) and education (26%). My result is consistent with the literature which finds that selection based on unobserved ability plays a major role in explaining the sectoral wage gap (Herrendorf and Schoellman, 2018; Hamory et al., 2021).

Turn to policy. I concentrate on policies of health and education, the centerpieces of many development policies. I conduct two sets of policy experiments – the first set increases public health expenditure and the second offers a subsidy proportional to individuals' schooling time. Each set consists of experiments implemented on all individuals or target a specific gender;[4] and all policies are under the same budgetary cost. I find that the health subsidy is more cost-effective than the education subsidy in raising aggregate labor productivity, in reducing the agricultural employment share, and in improving general welfare. This is primarily because the health subsidy generates positive labor productivity effects that impact both sectors. On the one hand, better health improves agricultural productivity, which eases subsistence constraints and pushes workers out of agriculture. On the other hand, it enhances nonagricultural productivity, which pulls labor toward nonagriculture. Conversely, the working of the education subsidy mainly hinges on the nonagricultural sector and hence has a limited impact. Additionally, the health subsidy reduces mortality effectively which, combined with its productivity effect, generates a more substantial welfare benefit than the education subsidy. Furthermore, I find that the health subsidy is more effective in raising aggregate labor productivity when offered uniformly to both genders or targeting men, compared to targeting women, while the education subsidy is most effective in raising aggregate labor productivity when targeting women and least effective when targeting men.

Finally, I explore the differences in policy effects between general equilibrium and partial equilibrium analyses. This sheds light on the discrepancy between a nation-wide policy and a local one, such as those in randomized controlled trials (RCTs). My results suggest that, while RCTs find both health and education subsidies effective in improving education and labor market outcomes, when such policies are implemented at the national level the effectiveness of the health policy is enhanced while that of the education policy is diminished.

This paper contributes to the literature in three ways. First, it explores the implications of differential returns to health between genders across activities – a fact documented in the micro-development literature – for the sectoral allocation of labor and for aggregate

[3]The literature documents a large productivity or wage gap between agriculture and nonagriculture in many countries (Gollin, Lagakos, and Waugh, 2014).

[4]This policy design is highly relevant to the real-world policies, many of which have targeted women (see a review in Duflo, 2012).

productivity. Second, by incorporating individual decisions concerning health and education into a Roy-type general equilibrium framework, this paper complements both the macro literature, in which modeling of sectoral allocation typically abstracts from individuals' investment choices, and the empirical literature, which typically neglects the general equilibrium effect. Third, this paper sheds light on the relative importance of health policy in sectoral allocation and structural transformation.

Related literature

This paper draws upon a rich literature in a number of areas. First, it is related to the literature on cross-country productivity differences and, in particular, those in the agricultural sector that overshadow others. Important contributions to this literature include Restuccia, Yang, and Zhu (2008), Chen (2020), Donovan (2021), and Caunedo and Keller (2021) on low level or low quality of technical inputs in agriculture in poor countries; Adamopoulos (2011), Gollin and Rogerson (2010, 2014), Tombe (2015), and Brooks and Donovan (2020) on high transaction, trade, or infrastructure costs; and Adamopoulos and Restuccia (2014), Chen (2017), Chen, Restuccia, and Santaeulalia-Llopis (2021), Adamopoulos et al. (2022), and Chen, Restuccia and Santaeulalia-Llopis (2023) on land misallocation and farm size distortion.

The studies most relevant to this paper are Lagakos and Waugh (2013) and Lee (2016). The former paper develops a general equilibrium Roy model in which heterogeneous workers self-select into the agricultural sector or the nonagricultural sector. The authors find that the presence of the subsistence requirement and low economy-wide efficiency alone can explain a substantial part of the relatively low agricultural labor productivity in poor countries by inducing a large fraction of unproductive workers into agriculture. In particular, the large share of female employment in agriculture in low-income countries supports their theory. Following their study, Lee (2016) focuses on the impact of gender-specific labor market frictions on cross-country productivity differences and finds that the larger frictions faced by females in nonagriculture account for a considerable part of the low agricultural labor productivity in low-income countries.

My paper is similar to their papers in that they all use a Roy general equilibrium model to study the allocation of heterogeneous workers between agriculture and nonagriculture and draw implications for aggregate productivity. My paper, however, differs from their papers in two essential ways. First, I focus on the role of health in the gender division of labor which is absent in their papers. To my best knowledge, this is the first paper that investigates the impact of health on aggregate productivity through its effect on the gender division of labor across sectors. Second, while their papers take the distribution of workers' productivities as given, my paper allows this distribution to be endogenous, depending on individuals' investments in education and health. I find that estimates of the impact of economic factors such as TFP and labor market frictions can be biased when such investment decisions are neglected.

Another related strand of literature emphasizes the role of unobservable innate ability in selection and the sectoral productivity gap (e.g., Young, 2013). Herrendorf and Schoellman (2018) document large sectoral gaps in wages and school years for a sample of 13 countries. They show that Mincer returns to schooling are higher in nonagriculture than in agriculture and argue that this is mostly explained by workers with higher abilities selecting into nonagriculture, rather than by nonagricultural technology featuring greater human capital intensity. Harmory et al. (2021) use individual-level panel data on Indonesia and Kenya and find that, in both countries, the sectoral wage gap can be significantly reduced when individual fixed effects are included. Both papers, using a small subsample of "movers" from agriculture to nonagriculture, find that the individual gain in earnings by switching the sector is modest, and thus conclude that the reallocation barrier is small.

My paper, on the other hand, integrates a health channel, with two key elements differing from their papers. First, my paper highlights the gender and sectoral differences in the health intensity in production technologies, which are ignored in their papers (though Herrendorf and Schoellman (2018) recognize the differences in the human capital intensity across sectors). These differences can be important in explaining the sectoral productivity gap for an economy heavily populated with less-healthy, agricultural workers (and, in particular, female agricultural workers). Second, my paper considers a gender-specific nonagricultural barrier, while their papers ignore the heterogeneity in the reallocation barrier. As a result, their estimated "barrier" using the wage data of movers may be biased downward due to a selection issue.

This paper is also closely connected to the literature on gender differences in human capital, health, and productivity, and their implications for economic development. In particular, it is well recognized that women have less physical strength than men but have comparable intellectual abilities. The study most relevant to my paper in this line is Pitt, Rosenzweig, and Hassan (2012). They not only document evidence on differential returns to health on schooling and on different types of work between genders, but also construct a Roy-type model with a similar structure as mine to guide their estimation. The main difference between my paper and theirs is that, they concentrate on estimating the gender differences in the impact of body-mass endowment on physical strength, and on education and occupational choices at the individual level. My study is motivated by theirs but switches the focus toward the aggregate implications. By embedding individuals' decisions on health, education, and sectoral occupation in a general equilibrium framework, my paper generates predictions on cross-sectional labor allocation and aggregate productivity. Moreover, the quantitative model is useful for evaluating various policies and for providing insight into how the gender-health channel shapes policy effects on the aggregate economy. My counterfactual analysis indicates that the policy effects in general equilibrium versus in partial equilibrium can diverge.

Other research along this line includes Galor and Weil (1996) who model gender differences in the same two dimensions of labor inputs (i.e., brawn and brain) and argue that capital accumulation raises women's relative wages, since capital is more complementary to intellectual inputs than to physical inputs. Rendall (2017) develops a quantitative general equilibrium model that features women's comparative advantage in the brain dimension and shows that technical changes that lead to an increased demand for intellect along with an increased demand for higher education explain much of the rise in the female labor force participation, the reversal of the gender education gap, and the closing of the gender wage gap in the US over the past decades.[5]

Other studies focusing on gender inequality and economic growth indicate a negative and two-way relationship between the two (Goldin, 1990; Lagerlöf, 2003; Doepke and Tertilt, 2009; Esteve-Volart, 2009). Hsieh et al. (2019) claim that the improved allocation of talent in the US, thanks to reductions in labor market frictions and education barriers against women and blacks, accounts for roughly two-fifths of the growth of aggregate output per person over the last five decades.[6]

Furthermore, this paper is linked to the literature on structural transformation and, particularly, to the studies that document the role of education policy in this process (Caselli and Coleman II, 2001; Porzio, Rossi, and Santangelo, 2022; Cheung and Yao, 2023). I also owe insights to research on the role of women's empowerment policies in economic development (see a review in Duflo, 2012). My paper adds to this literature by comparing the cost-effectiveness of a variety of health and education policies, and by shedding light on the choice between a gender-specific policy and a universal policy.

The paper proceeds as follows. Section 2 presents the general equilibrium model featuring the gender division of labor. Section 3 presents the calibration of the model, followed by counterfactual analysis in Section 4 and policy experiments in Section 5. Section 6 concludes.

2 Model

To investigate the aggregate implications of the differential returns to health by gender, I construct a two-sector general equilibrium model with overlapping generations of heterogeneous individuals who make decisions concerning investment in health and education as well as the employment sector. Good health lowers mortality, improves learning, and raises workers' productivity. Individuals are heterogeneous in gender and initial human capital endowment. The agricultural technology is more health intensive for men than for women, implying a higher return to health for men in agriculture. In addition, I assume that women

[5] Moreover, Becker et al. (2010) find that it is primarily differences in the distribution of noncognitive skills between men and women that explain the overtaking of men by women in higher education in the last few decades, rather than a larger benefit of college for women.

[6] See also Blau and Kahn (2017) for a review of explanations of the gender wage gap.

face a nonagricultural gender barrier.

2.1 Environment

2.1.1 Preferences and demographics

Individuals live for three periods. In the young period, they invest in health and education; in the adult period, they choose between agriculture and nonagriculture and work; and in the old period, they continue to work in the same sector.[7] Individuals derive lifetime utility from consumption of both agricultural and nonagricultural goods:

$$U = u(c_{a,0}, c_{n,0}) + \beta\delta_g(h)u(c_{a,1}, c_{n,1}) + \beta^2\delta_g(h)^2u(c_{a,2}, c_{n,2}) \tag{1}$$

where

$$u(c_{a,t}, c_{n,t}) = \nu\log(c_{a,t} - \bar{c}) + (1-\nu)\log(c_{n,t}) \tag{2}$$

is the flow utility at period t,[8] $c_{a,t}$ ($c_{n,t}$) is consumption of agricultural (nonagricultural) goods, ν indicates relative preferences for agricultural goods, and the subscript $t = 0, 1, 2$ denotes the period of life. In equation(1), β is the discount factor and $\delta_g(h)$ the survival probability (conditional on survival in the previous period) which depends on health capital (h) and satisfies $\delta_g'(h) > 0$. I allow $\delta_g(h)$ to differ across genders (where the subscript g denotes the gender: $g \in \{M, F\}$) to capture factors other than health that cause differential life expectancy between men and women.

I normalize the population size of each generation at the young period to one, of which half is male and half female, and then only a fraction, $\delta_g(h)$ and $\delta_g(h)^2$, of the population will survive into the adult and old periods for each gender. I also assume the total time endowment of an individual at each period to be one.

2.1.2 Health and human capital formation

Individuals build up their health capital, h, during the young period. Let x_P denote the private health investment made by an individual and x_E denote the public health investment received by the individual, during the young period (all goods investments are in units of nonagricultural goods). Health production takes the Cobb-Douglas form, where private and public health expenditures are complementary. While in reality the two may be substitutes in some cases, public health investment plays a crucial role in promoting medicine technology, developing medical professionals, and building healthcare facilities and sanitization services, which cannot be easily substituted by private investment. Moreover, in developing countries where infectious diseases are pervasive, effective public

[7] I divide an individual's lifetime into three periods instead of two for quantitative purposes; the three periods refer to ages 0–20, 21–40 and 41–60.

[8] In the calibration, I set a sufficiently large scale of TFP to ensure flow utility to exceed zero, so that longevity increases lifetime utility.

health measures can generate large positive externalities in curbing disease transmission, enhancing private investments. Thus, I specify an individual's health capital as

$$h = h_0 \left[B x_E^{\alpha_1} (b + x_P)^{\alpha_2} \right] \tag{3}$$

In equation(3), h_0 is the initial endowment of health capital which is assumed to be homogeneous across individuals. $B > 0$ determines the efficiency of health production, which can be affected not only by the medicine technology available to a country, but also by environmental factors such as geography and climate, and by social norms, policies and institutions, including the way public health funding is allocated across programs and the degree of corruption. α_1, $\alpha_2 > 0$; and $\alpha_1 + \alpha_2 < 1$ implies diminishing returns to health investment. $b > 0$ captures the notion that, even if private health expenditure is zero (which may be common in poor countries), an individual would still benefit from public health investment.[9]

Human capital (or skill), also formed during the young period, is given by

$$z = z_0(1 + \rho h^{\theta_1} e^{\theta_2} m^{\theta_3}) \tag{4}$$

where z_0 indicates the initial (non-health) human capital which is heterogeneous across individuals and is drawn from a distribution with *cdf* $F(z_0)$; e denotes the amount of time allocated to education and m the goods investment in education during the young period. Equation(4) says that human capital formation requires three complementary inputs, health (h), time (e), and goods (m), where ρ measures the efficacy of human capital investment. $\theta_1, \theta_2, \theta_3 \in (0, 1)$, and $\theta_1 + \theta_2 + \theta_3 < 1$ captures diminishing returns to the investment. The inclusion of both time and goods inputs in human capital production is common in the macro literature (e.g., Manuelli and Seshadri, 2014; Cordoba and Ripoll, 2013), as the time input captures the opportunity cost of education (i.e., foregone wages) and the goods input captures an intertemporal tradeoff in consumption. Some studies also include health capital in the human capital accumulation model to highlight its indispensable role in learning (e.g., Ashraf, Lester, and Weil, 2008; Manuelli and Yurdagul, 2021).

2.1.3 Production

There are two production sectors in the economy, agriculture (a) and nonagriculture (n). While an adult can choose the sector, a young individual is only allowed to work in agriculture.[10] I abstract from labor force participation decisions for the adult and old periods by assuming that all individuals work from middle age. A middle-age adult's output when

[9] Alternatively, b can be thought of as the part of subsistence consumption necessary for life.

[10] This restriction well applies to low-income countries such as those in Africa, which are the focus of this paper. According to an International Labour Organization (ILO) report (2017), child labor in Africa works predominantly in agriculture.

working in each sector is given by

$$a : y_{a,g,1} = A\zeta_g h^{\phi_g} \tag{5}$$

$$n : y_{n,1} = Ah^{\mu} z^{1-\mu} \tag{6}$$

Note that health capital enters the production function of both sectors because better health converts to higher labor productivity in different dimensions, namely, physical strength and mental health. While the former directly contributes to agricultural productivity, the latter is more relevant to nonagriculture. In equations (5) and (6), A denotes economy-wide efficiency (TFP) and ζ_g gender-specific agricultural productivity, with the subscript g indicating gender. I assume that agriculture is brawn-based, and thus only requires health capital as the input. This assumption is motivated by the fact that, in low-income economies, traditional technology is widely used in agriculture for which brawn is the major input.[11] Important features of the agricultural technology include the following. First, men enjoy higher productivity than women (i.e., $\zeta_M > \zeta_F$), conditional on the health factor, reflecting the absolute advantage of men in agricultural work due to larger physical strength.[12] Second, the health intensity of production is higher for men than for women (i.e, $\phi_M > \phi_F$), motivated by the evidence from Pitt, Rosenzweig, and Hassan (2012) that improved health implies increased physical strength for men more than for women. This agricultural technology implies that a general improvement in health would raise both the absolute and the comparative advantages of men in agricultural production.[13] In addition, I assume that ϕ_M, $\phi_F \in (0, 1)$, implying diminishing returns to scale in agriculture, given a fixed supply of production factors such as land. Nonagricultural technology, on the other hand, exhibits constant returns to scale (CRS); it requires both health and human capital and is assumed independent of genders. I use nonagricultural goods as the numeraire and thus investments in health and education are both in units of nonagricultural goods.

For young individuals, agricultural productivity is a fraction $\eta \in (0, 1)$ of that of a comparable adult, since the young generally have less physical strength than adults and are more vulnerable to exploitation.[14] In addition, let ψ denote the total amount of time available for a young individual to work or study; $\psi < 1$ because a very young child can do neither. Hence, $\psi - e$ is the time allocated to work once the decision on e is made. A

[11] In order to generalize this study to higher-income economies, the agricultural technology should reflect the demand for other factors, such as capital and education.

[12] Pitt, Rosenzweig and Hassan (2012) document that, in Bangladesh, 40% of men in a random sample of adults had a stronger grip than the strongest woman, and that the average female-to-male grip strength ratio is about 0.65.

[13] Studies show that there is a gender labor division *within* agriculture. For example, Foster and Rosenzweig (1996) document that, in many developing countries, most men do the plowing, while most women do the weeding. I abstract from within-sector labor division and focus on sectoral aggregates.

[14] One may also think of the relatively low productivity of the young in terms of health capital, h, which is not fully developed before the end of the young period.

young individual's agricultural output is thereby

$$y_{a,g,0} = (\psi - e)\eta A \zeta_g h^{\phi_g} \tag{7}$$

An old individual continues to work in the same sector, but the output is a fraction $\gamma \in (0, 1]$ of what is produced in middle age as health and human capital depreciates:[15]

$$a : y_{a,g,2} = \gamma A \zeta_g h^{\phi_g} \tag{8}$$

$$n : y_{n,2} = \gamma A h^{\mu} z^{1-\mu} \tag{9}$$

In the steady state, the aggregate output of the two sectors at a given time period is as follows:

$$Y_a = \int y_{a,g,0,i} di + \int_{i\in\Omega_a} \delta(h_i) y_{a,g,1,i} di + \int_{i\in\Omega_a} \delta(h_i)^2 y_{a,g,2,i} di \tag{10}$$

$$Y_n = \int_{i\in\Omega_n} \delta(h_i) y_{n,i} di + \int_{i\in\Omega_n} \delta(h_i)^2 y_{n,i} di \tag{11}$$

where $\Omega_a(\Omega_n)$ denotes the set of the population working in agriculture (nonagriculture).

2.1.4 Barrier, income and budget

Wage income depends on marginal revenue product. Women, however, face a barrier in the nonagricultural sector, which is modeled as a wedge of income. This can be viewed as a tax on women's nonagricultural income with the tax revenue discarded. The assumption of a nonagricultural gender barrier is motivated by the broad literature on gender inequality and discrimination against women in the labor market, and, in particular, by Lee (2016), who finds that the relative friction against women in the nonagricultural sector is negatively associated with a country's income level. Using nonagricultural goods as the numeraire and denoting the price of agricultural goods in period t as $p_{a,t}$, the wage income at period t ($t = 1, 2$) for worker i of gender g is

$$w_{g,t} = \begin{cases} p_{a,t} y_{a,g,t} & \text{if } i \in \Omega_a \\ y_{n,t}(1 - \kappa \cdot \mathbf{1}_{g=F}) & \text{if } i \in \Omega_n \end{cases} \tag{12}$$

where $\kappa \in [0, 1]$ measures the degree of the nonagricultural gender barrier, and $\mathbf{1}_{g=F}$ is the indicator of being female. For the young, since they can only work in agriculture when not going to school, they receive the wage income $w_{g,0} = p_{a,t} y_{a,g,0}$. As the sectoral wage depend on gender, age, health and human capital, I denote them as $w_{a,g,t}(h)$ and $w_{n,g,t}(h, z)$ for

[15] I do not model the depreciation of health and human capital directly but allow it to be captured by a productivity loss measured by γ. The assumption that $\gamma \in (0, 1]$ may only apply to low-income countries where people have low life expectancy on average, and their productivity may depreciate relatively quickly after middle age, while in high-income countries, such as the US, an average worker typically reaches peak lifetime income in his/her early 50s (Lagakos et al., 2018).

agriculture and nonagriculture.

Moreover, I assume that public health expenditures are financed through a lump sum tax, τ, and that there is no intertemporal borrowing constraint. Thus, the intertemporal budget constraint for an individual in the steady state equilibrium (where $p_{a,t} = p_a$ for all t) is

$$x_P + m + p_a c_{a,0} + c_{n,0} + \delta(h)\frac{p_a c_{a,1} + c_{n,1}}{1+r} + \delta(h)^2 \frac{p_a c_{a,2} + c_{n,2}}{(1+r)^2} = w_0 - \tau + \frac{\delta(h) w_1}{1+r} + \frac{\delta(h)^2 w_2}{(1+r)^2} \tag{13}$$

(I omitted the subscript g here to ease the notational burden.) That is, the discounted present value of lifetime consumption plus goods investments in health and education equal the discounted present value of lifetime (after-tax) income.

2.2 Optimization and equilibrium

2.2.1 Optimization

In this model economy, an individual maximizes lifetime utility by choosing the level of health and education investments in the young period and the sector in which to work in the adult period, as well as consumption of agricultural and nonagricultural goods in all periods. The problem can be solved in two steps. First, solve for the optimal level of health and education investment and consumption, *given* the sectoral decision of an individual with initial ability z_0, and derive the lifetime utility $V(z_0; a)$ and $V(z_0; n)$ associated with each sector. Second, compare $V(z_0; a)$ and $V(z_0; n)$ to determine the optimal sector.[16] The full characterization of the model is presented in the Online Appendix. Below, I examine an individual's decision-making in the adult period to offer some insight on sectoral choice.

In the adult period, the individual chooses the sector, given health and human capital. He/she chooses nonagriculture if and only if

$$w_{n,1} + \frac{\delta(h) w_{n,2}}{1+r} > w_{a,1} + \frac{\delta(h) w_{a,2}}{1+r}, \tag{14}$$

where $w_{a,t}$ ($w_{n,t}$) denotes the agricultural (nonagricultural) wage. In the steady state equilibrium, where prices are constant, equation(14) is equivalent to $w_{n,1} > w_{a,1}$; that is,

$$h^{\mu} z^{1-\mu}(1 - \kappa \cdot \mathbf{1}_{g=F}) > p_a \zeta_g h^{\phi_g}, \tag{15}$$

which can be rewritten as

$$\frac{z^{1-\mu}}{h^{\phi_g - \mu}} \geq \frac{p_a \zeta_g}{1 - \kappa \cdot \mathbf{1}_{g=F}}. \tag{16}$$

Equation(16) is intuitive. For a given individual, the left-hand side reflects (non-health)

[16] I assume that an individual stays in agriculture when he/she is indifferent between the sectors.

human capital relative to health capital (when $\phi_g > \mu$), and the right-hand side reflects price- and barrier-adjusted relative agricultural productivity. Thus, when $\phi_g > \mu$, the individual chooses nonagriculture if his/her human capital is sufficiently high relative to health capital, while when $\phi_g < \mu$, an improvement in health capital increases the likelihood of choosing nonagriculture. For women, the lower the barrier in nonagriculture, the more likely they are to select that sector.

Then in the young period, conditional on the decision rules in the adult period, the individual invests in health and education that maximizes lifetime utility given by equation(1), subject to the budget constraint and technologies of health and human capital formation (equations (13), (3), and (4)). It turns out that individuals with higher initial endowment of human capital, z_0, are more likely to work in nonagriculture, due to their advantage (both absolute and comparative) in accumulating human capital.

2.2.2 Market clearing conditions

Assuming that agricultural goods can only be used for consumption, whereas nonagricultural goods can be used for both consumption and investment, the goods market clearing conditions in a steady state equilibrium can be written as

$$\int c_{a,0,i}di + \int \delta(h_i)c_{a,1,i}di + \int \delta(h_i)^2 c_{a,2,i}di = Y_a \tag{17}$$

and

$$\int (c_{n,0,i} + x_{Pi} + m_i)di + \int \delta(h_i)c_{n,1,i}di + \int \delta(h_i)^2 c_{n,2,i}di + x_E = Y_n \tag{18}$$

The labor market clearing condition of the two sectors are

$$N_a = \int (\psi - e_i)di + \int_{i\in\Omega_a} \delta(h_i)di + \int_{i\in\Omega_a} \delta(h_i)^2 di \tag{19}$$

and

$$N_n = \int_{i\in\Omega_n} \delta(h_i)di + \int_{i\in\Omega_n} \delta(h_i)^2 di, \tag{20}$$

where N_a and N_n denote the demand for labor in agriculture and nonagriculture, respectively.

2.2.3 Steady state equilibrium

Definition: A *steady state competitive equilibrium* is a set of allocations for each individual $\{(c_{a,t}, c_{n,t})_{t=0,1,2},\ x_P,\ m,\ e\}$ and a set of prices $\{p_a, w_{a,g,t}(h), w_{n,g,t}(h,z)\}$ such that, given prices, human capital and health capital formation technology (equations(4) and (3)), and the distribution of initial human capital $F(z_0)$:

i) each individual chooses $\{(c_{a,t}, c_{n,t})_{t=0,1,2},\ x_P,\ m,\ e\}$ and sector to maximize lifetime utility given by equation(1);

ii) the goods market and labor markets clear; that is, equations(17)–(20) hold;
iii) the government budget is balanced; that is, $x_E = \tau$; and
iv) the distributions of (h, z, g) within and across sectors are stationary.

3 Calibration

I now calibrate the model for Kenya, a typical SSA country, which is used as the benchmark economy in this study. Then I recalibrate a set of country-specific parameters for Mauritius, a relatively rich SSA country for comparison. I calibrate both economies in steady state equilibrium.

3.1 Baseline Calibration

The main strategy for calibrating the benchmark economy is to first set the values of some parameters directly using estimates from the literature or data, and then to calibrate the remaining parameters within the model, which is simulated for 100,000 individuals of each gender to match key data moments of Kenya. The three periods of an individual's life refer to ages 0–20, 21–40, and 41–60. Below are the main steps for calibrating the Kenyan economy.

To calibrate the distribution of the initial endowment of human capital, first, I assume that the initial human capital z_0 follows a Weibull distribution with *cdf* $F(z_0) = 1 - e^{-z^{\sigma}}$, where σ is the shape parameter with a smaller value indicating a larger dispersion of initial ability.[17] I assume that the distribution is identical for both genders. Ideally, σ would be calibrated to fit the wage distribution of Kenyan data. However, given that such data are unavailable for using as a wage distribution for this study,[18] I set $\sigma = 2.7$ to match the variance of log wages of about 0.2, estimated from the US wage distribution by Lagakos and Waugh (2013), since income distribution (measured by Gini coefficient) is highly comparable between the US and Kenya.[19] Next, given $F(z_0)$, I discretize the space of z_0, assume the minimum z_0 to be 0.01 and the maximum 2.05, which is the value at the 99.9 percentile of the distribution, and set the interval of the z_0 space to be 0.01. This gives 205 values of z_0 in total. Then I simulate this distribution for 100,000 individuals of each gender and use them as the agents of the model economy.

For health and mortality parameters, I normalize the initial health capital h_0 to one and assume the gender-specific survival function to be $\delta_g(h) = \sqrt{1 - \frac{D_g}{h}}$, where D_g $(g \in \{F, M\})$ are to be calibrated within the model. Note that D_g captures mortality risk from causes other than health capital; it is not only heterogeneous across genders due to biological or

[17] Extreme value distributions are widely used for income, wealth, ability, or productivity distributions in the economics literature.
[18] The individual-level data used by Harmory et al. (2021) contain too large a fraction of nonagricultural workers (85% in KLPS-2) and is therefore unsuitable for drawing a wage distribution for this study.
[19] The Gini coefficient of income is 41.2 and 40.8, respectively, for the US and Kenya (based on 2015 data from the World Bank).

behavioral differences, but also heterogeneous across countries as a result of differential social environments, availability of life-saving technology, culture-related behavior, and so forth. The functional form of δ implies that the adult mortality rate (AMR) is equal to $\frac{D_g}{h}$ for an individual of gender g and health h. Turning to the health formation parameters in equation(3), I normalize $B = 1$ and set $\alpha_2 = 0.133$, the latter corresponding to the elasticity of body mass endowment (i.e., weight-to-height ratio) to calorie intake estimated by Pitt, Rosenzweig, and Hassan (2012); this value is also consistent with Hall and Jones (2007), who estimate the elasticity of health status to health input to be 0.042–0.4. I leave α_1, the elasticity of health capital to public health expenditure, to be calibrated in the model. I also set $b = 1$; that is, for individuals whose private health expenditures are zero, health capital is determined as $h = h_0 B x_E^{\alpha_1}$.

For the human capital production function, I calibrate θ_1, elasticity of human capital production to health capital, based on Ashraf, Lester, and Weil (2008), who estimate the response of human capital accumulation to the decline of adult mortality rates using data from Sri Lanka. Specifically, they estimate that when the adult (annual) mortality rate falls from 0.00972 to 0.00393 (which corresponds to a fall of AMR from 0.356 to 0.162 as defined in my study), the implied change in schooling is 0.386 years, and the implied change in human capital is 3.90% for countries with initial years of schooling in the range [4, 8], which is the case for most SSA countries, including Kenya. I also back out the percentage change in health capital, h, from the change in AMR, and then compute $\theta_1 = 0.0328$.[20] I set $\theta_2 = 0.428$ and $\theta_3 = 0.488$, based on the estimates from Manuelli and Yurdagul (2021), and leave ρ to be calibrated in the model.

For the preference parameters, I set the annual discount factor to 0.985, broadly consistent with the literature; converting it into 20 years gives $\beta = 0.739$. For ν, I follow Restuccia, Yang, and Zhu (2008) and Lagakos and Waugh (2013) and set $\nu = 0.005$, which implies a long-run agricultural employment share of about 0.5%.

Turning to production, I normalize TFP, A, to 10 and gender-specific agricultural productivity for males, ζ_M, to 1, leaving the female agricultural productivity parameter, ζ_F, to be calibrated in the model.[21] I set η, the relative child labor productivity in agriculture, to 0.5, as the International Labour Office (ILO, 2007) documents that the child labor wage relative to adults' ranges from 1/6 to 2/3 in the surveyed countries. I set $\psi = 0.7$, since the age for starting schooling in Kenya and many other countries is around six, which is also about the age when children in low-income countries start to share the household work burdens. For the relative productivity of the elderly, I set $\gamma = 1$, as Lagokos et al. (2018) estimate that the lifecycle wage profile is quite flat after the middle age in low-income

[20]Specifically, using numbers from Ashraf, Lester and Weil (2008), we have $\frac{h_2-h_1}{h_1} = \frac{\frac{D}{AMR_2}-\frac{D}{AMR_1}}{\frac{D}{AMR_1}} = \frac{\frac{1}{AMR_2}-\frac{1}{AMR_1}}{\frac{1}{AMR_1}} = 1.1903$ and $\frac{z_2-z_1}{z_1} = 0.101 * 0.386 = 0.0390$. Thus, $\theta_1 = \frac{z_2-z_1}{z_1} / \frac{h_2-h_1}{h_1} = 0.0328$.

[21]Note that we need a sufficiently large scale of TFP to ensure flow utility exceeds zero, so that longevity enhances lifetime utility.

countries.

Now 11 parameters remain to be calibrated within the model: $\bar{c}$, D_M, D_F, ρ, x_E, α_1, ζ_F, ϕ_M, ϕ_F, μ and κ. They are calibrated jointly to match a set of 11 targeted moments for Kenya: the agricultural employment share of the workforce ($agremp$) and of the female workforce ($agremp_F$), the nonagriculture-to-agriculture wage ratio ($\frac{w_n}{w_a}$), agricultural gender wage gap ($\frac{w_{a,F}}{w_{a,M}}$), public and private health expenditure to GDP ratios ($\frac{X_P}{Y}$, $\frac{X_E}{Y}$), adult mortality rates of the two genders (AMR_F, AMR_M), education expenditure-to-GDP ratio ($\frac{M}{Y}$), and average years of schooling of the two genders ($schyr_F$, $schyr_M$).

Some targeted moments deserve explanations. First, the sectoral wage gap ($\frac{w_n}{w_a}$) is computed based on Hamory et al. (2021), who estimate nonagricultural wage premium, $\frac{w_n}{w_a}$, to be 1.6 using Kenyan longitudinal data. Second, regarding the agricultural gender wage gap, there are no micro-data based estimates for Kenya; there are, however, estimates for other developing countries. For example, Hertz et al. (2008) estimate that the gender wage ratio (defined as female-to-male wage ratio) in the rural areas to be 0.56 for Ghana, 0.70 for Malawi, and 0.87 for Nigeria; Mahajan (2017) estimates the agricultural gender wage ratio to be 0.70–0.74 in India. In addition, Pitt, Rosenzweig, and Hassan (2012) estimate that the female-to-male grip strength ratio is 0.65. Based on these estimates, I choose the targeted agricultural gender wage ratio to be 0.7 for Kenya. Third, average years of schooling for each gender are taken from the Barro-Lee education attainment dataset for the year 2005 (for population above age 25), and all the remaining targeted moments are sourced from WDI.

While the 11 parameters are calibrated jointly, some of them are more relevant to a certain set of targets. For example, $\bar{c}$ is calibrated particularly to target the agricultural employment share and κ targets the agricultural employment share of female; ϕ_F and ϕ_M matter a great deal for gender sectoral employment share and wage gap; ρ is calibrated to education expenditure share, and α_1 and x_E to the private and public health expenditure shares.

Table 1 presents the parameterization. Notably, agricultural technology exhibits higher return to health for men than for women, with the share of health in agricultural production being 0.64 for men and only 0.21 for women. This aligns with empirical evidence from Pitt, Rosenzweig, and Hassan (2012), which indicates that improved health results in considerably greater increases in physical strength for men than for women. The gender disparity in health intensity in agriculture, combined with the lower female-specific agricultural productivity ($\zeta_F = 0.67$), implies that men possess both a comparative and absolute advantage in agricultural production. Furthermore, the nonagricultural health share is lower than the agricultural health share for men but higher than the agricultural health share for women. This parameterization implies that improved health can lead to marginal increases in women's nonagricultural employment more than for men's, which is consistent with the empirical evidence mentioned in Section 1.

Two further remarks are in order. First, the share of health in agriculture (gender average) is 0.43, closely aligning with Restuccia, Yang and Zhu (2008) and Adamopoulos et al. (2022), who assign 0.42 and 0.46, respectively, as the agricultural labor share. Second, my estimate of the elasticity of health production to public health expenditure, denoted α_1, is equal to 0.23, which is near the lower bound of estimates from Hall and Jones (2007) for the very young and middle-aged.

Table 2 compares the targeted moments between the model and the data, demonstrating a good fit of the model. Specifically, the model predicts that the majority of the Kenyan workforce (58%) is engaged in agricultural production, and this proportion is even larger among females (64%). The sectoral wage ratio is approximately 1.6, and the agricultural gender wage ratio is around 0.7. Men have more years of schooling than women but also have a higher adult mortality rate.

Table 1. Parameterization of the Benchmark Model

A. Predetermined

parameter	value	target
discount factor	$\beta = 0.739$	preset
utility weight of agr. cons.	$\nu = 0.005$	literature
initial h.c. distribution	$\sigma = 2.7$	literature
health production	$B = 1$, $\alpha_2 = 0.133$	normalized; literature
human capital production	$\theta_1 = 0.033$, $\theta_2 = 0.428$, $\theta_3 = 0.488$	literature, computed
TFP	$A = 10$	normalized
male agr. productivity	$\zeta_M = 1$	normalized
youth/elderly production	$\psi = 0.7$, $\eta = 0.5$, $\gamma = 1$	literature

B. Calibrated within the Model

parameter	value	target
subsistence cons.	$\bar{c} = 2.72$	
mortality	$D_M = 0.31$, $D_F = 0.25$	jointly match $agremp$,
human capital production	$\rho = 0.43$	$agremp_F$, $\frac{w_n}{w_a}$, $\frac{w_{a,F}}{w_{a,M}}$,
health production	$\alpha_1 = 0.23$, $x_E = 0.45$,	$\frac{X_P}{Y}$, $\frac{X_E}{Y}$, $\frac{M}{Y}$, AMR_F,
agr. production	$\phi_M = 0.64$, $\phi_F = 0.21$, $\zeta_F = 0.67$	AMR_M, $schyr_F$, $schyr_M$
nonagr. production	$\mu = 0.31$	
gender barrier	$\kappa = 0.28$	

Table 2. Model Fit: The Benchmark Economy

target	data	model
$agremp$	0.58	0.58
$agremp_F$	0.65	0.64
$\frac{w_n}{w_a}$	1.60	1.62
$\frac{w_{a,F}}{w_{a,M}}$	0.70	0.69
$\frac{X_P}{Y}$ (%)	2.73	2.73
$\frac{X_E}{Y}$ (%)	2.52	2.52
$\frac{M}{Y}$ (%)	6.22	6.18
AMR_M, AMR_F	0.43, 0.37	0.43, 0.38
$schyr_M$, $schyr_F$	6.97, 4.71	8.33, 4.17

3.2 Calibration of the Mauritian economy

Based on the calibration above, I recalibrate a set of 7 country-specific parameters for Mauritius, a relatively rich country in the SSA, taking values of other parameters and the initial distribution of idiosyncratic human capital endowment from the benchmark economy.[22] The country-specific parameters are TFP (A), health production efficiency (B), public health expenditure (x_E), human capital production efficacy (ρ), sectoral gender barrier (κ), and mortality parameters (D_M, D_F). They are calibrated jointly to match the following seven targeted moments of Mauritius: agricultural employment share ($agremp$) and that of female workers ($agremp_F$), public health expenditures as a share of GDP ($\frac{X_E}{Y}$), education expenditure to GDP ratio ($\frac{M}{Y}$), average years of schooling ($schyr$) and adult mortality rates of the two genders (AMR_F, AMR_M).

Table 3 displays the parameterization of the Mauritius model. When comparing the two countries, note that Mauritius has a TFP more than double that of Kenya; it also has higher health production efficiency and higher public health expenditure, but lower human capital production efficacy and higher exogenous mortality. Table 4 demonstrates that, with these parameters, the model fits the data well.

[22]Mauritius is one of the richest countries in SSA, with GDP per capita about six times that of Kenya. Its most important industries include financial and business services, and information and communication technology. Moreover, I do not use other relatively rich SSA countries, such as South Africa or Botswana, for this analysis because both countries experienced severe HIV/AIDS epidemics during the 1990s and 2000s, which led to a dramatic increase in mortality among young adults. Such an epidemic has distinct implications for youth behavior, health, and mortality compared to other diseases, making it less suitable for use in this research (see, for example, Yao (2022) that focuses on HIV/AIDS and women's fertility and education in Africa).

Table 3. Parameterization of the Mauritius Model

parameter	value	target
TFP	$A_{MU} = 24.28$	
health production	$B_{MU} = 3.72$, $x_{E,MU} = 1.24$	jointly match *agremp*,
human capital production	$\rho_{MU} = 0.12$	$agremp_F$, $\frac{X_E}{Y}$, $\frac{M}{Y}$, *schyr*,
mortality	$D_{F,MU} = 0.33$, $D_{M,MU} = 0.80$	AMR_F, AMR_M
gender barrier	$\kappa_{MU} = 0.46$	

Table 4. Model Fit: The Mauritius Economy

target	data	model
agremp	0.10	0.15
$agremp_F$	0.09	0.09
$\frac{X_E}{Y}$ (%)	1.77	1.72
$\frac{M}{Y}$ (%)	3.63	3.40
schyr	7.84	8.53
AMR_M, AMR_F	0.22, 0.11	0.22, 0.10

3.3 Model validity

To check the validity of the calibrated model, I compare the model-based Mauritius-to-Kenya labor productivity ratio to the data, since they are not targeted moments for my calibration. Specifically, I compute the ratios of agricultural output per worker, nonagricultural output per worker, and GDP per worker between the two countries from the model and compare them with the data in Table 5. As can be seen, the model explains 47% of the agricultural labor productivity difference, 61% of the nonagricultural labor productivity difference, and 52% of the aggregate labor productivity difference between the two countries.

Table 5. Productivity Differences: Data vs. Model

	data	model	% explained
agriculture	9.52	4.50	47
nonagriculture	4.62	2.81	61
aggregate	7.04	3.63	52

Note: The aggregate productivity difference ($\frac{y_{MU}}{y_{KE}} \equiv \frac{p_{a,MU}y_{qa,MU}+y_{qn,MU}}{p_{a,KE}y_{qa,KE}+y_{qn,KE}}$) is defined as the ratio of GDP per worker between Mauritius and Kenya. Sectoral productivity differences ($\frac{y_{qa,MU}}{y_{qa,KE}}$ and $\frac{y_{qn,MU}}{y_{qn,KE}}$) are the ratios of sectoral output (i.e., quantity) per worker. GDP per worker data (aggregate and sectoral) are taken from WDI; the sectoral output per worker ratios are computed from sectoral GDP per worker ratios adjusted with the ratio of agricultural-to-nonagricultural relative prices of the two countries. The agricultural-to-nonagricultural price ratios are taken from Lagakos and Waugh (2013), who construct the data from the food producer price data in FAO.

To further validate my model, I proceed by utilizing empirical research to extract useful moments for comparison with my model's predictions. Two empirical studies are used. The first one is Jayachandran and Lleras-Muney (2009), who estimate the effect of MMR reductions on girls' educational attainment in Sri Lanka. They argue that MMR is greatly influenced by public health policies, as increases in hospital beds, ambulance services, midwives provisions as well as other prenatal and postnatal care services can effectively reduce MMR (and thereby the female adult mortality rate). To mimic the natural experiment setting used in their paper, I conduct an experiment that increases public health expenditure x_E for women only, which improves their health and lowers their AMR. In order to compare my estimate with Jayachandran and Lleras-Muney (2009), I choose an increase in x_E that leads to a one-year increase in female life expectancy. To estimate the corresponding change in AMR, I compute the cross-country correlation between female AMR and life expectancy using WDI data. This correlation is -0.011, meaning that a one-year increase in female life expectancy is associated with a 0.011 decrease in AMR. I then search for the value of x_E that leads to such a decrease in female AMR in my model economy; it turns out that an increase in public health expenditure of about 7% is needed to achieve an additional year of female life expectancy.

My model predicts that a reduction in MMR equivalent to a one-year gain in female life expectancy would lead to a relative improvement in women's health and education outcomes, reducing their agricultural employment and raising aggregate labor productivity, albeit modestly. In particular, women's average years of schooling would increase by 0.12 years, or 2.9%, which is very close to the estimates of Jayachandran and Lleras-Muney (2009), who find the corresponding figures to be 0.11 years (or 3%).

The second empirical study that I turned to is Porzio, Rossi, and Santangelo (2022) who, based on a school construction program in Indonesia, estimate the effect of increases in years of schooling on sectoral employment.[23] Given that there are no direct model parameters equivalent to the policy changes introduced by the reform, I conduct an experiment that offers an education subsidy to young individuals, holding prices constant, where the amount of the subsidy is set to be proportional to their schooling time.[24] My simulation shows that an extra year of schooling leads to a 6.3 percentage point reduction in the agricultural employment share of the total workforce. This closely aligns with Porzio, Rossi, and Santangelo (2022), who estimate that an additional year of schooling reduces the probability of agricultural employment by 6.3 percentage points.

[23]Their research essentially follows the seminal work of Duflo (2001). The INPRES school construction program in Indonesia built 61,000 primary schools between 1974 and 1978.

[24]In this experiment, for each unit of time an individual spends in school, they receive a subsidy equal to the average agricultural wage of a young worker.

4 Counterfactual Analysis

To further explore the health – gender division of labor – productivity mechanism underscored in the model, I now present three sets of counterfactual analysis. First, I look into the impact of health production efficiency on sectoral labor allocation and aggregate productivity and compare it to that of TFP. Second, I assess the differences between modeling an *endogenous* distribution of individual productivities and simply assuming an exogenous distribution which is typically done in the literature. Third, I examine the contribution of various factors to the sectoral wage gap with a decomposition analysis.

4.1 The impact of health production efficiency vs. TFP

How does the efficiency of health production shape health, education, sectoral labor allocation, and aggregate productivity in Kenya? And how do these effects compare to TFP? To address these questions, I set the health production efficiency parameter (B) and TFP (A), one at a time, of Kenya equal to the corresponding values of Mauritius, and compare their effects on a number of variables. Table 6 (columns 3–4) shows that, while setting health production efficiency or setting TFP to the Mauritian values have a comparable effect on the agricultural employment share in Kenya, the former has a larger impact on reducing *female* agricultural employment share. This is unsurprising provided that improved health enhances women's comparative advantage in nonagriculture and men's in agriculture.

In addition, while an increase in TFP raises both private health expenditure and education expenditure as a share of GDP, due to increased returns to both health and education, an increase in B raises education expenditure share but lowers health expenditure share. The former is mainly driven by labor reallocation to nonagriculture where education has a higher return, while the latter occurs because higher health production efficiency means relatively low investment is needed given the same return to health. Regarding the gender gap, increases in both TFP and B slightly improve men's health relative to women's health but reduce the gap in (non-health) human capital.

Turning to labor productivity, while the difference in TFP is responsible for most of the nonagricultural and aggregate labor productivity gap between Kenya and Mauritius, health production efficiency is very close to TFP in explaining the agricultural labor productivity gap between the two countries. These results are primarily driven by the facts that agricultural production is relatively health intensive compared to nonagriculture, especially for men, and that the increase in TFP induces greater education investment which benefits nonagricultural production.

Furthermore, I experiment with setting the public health expenditure, x_E, of Kenya to the Mauritian value (see last column of Table 6). This turns out to have a qualitatively similar (though quantitatively smaller) effect as the increase in B; and this variable will be a key component in the policy experiments in Section 5.[25]

Table 6. Counterfactual: TFP and Health

variables	BM	TFP (%)	B (%)	x_E (%)
$agremp$	0.575	-57.8	-59.4	-12.2
$agremp_F$	0.638	-65.4	-84.6	-18.1
$\frac{X_P}{Y}$	2.73%	145.2	-2.2	-0.1
$\frac{M}{Y}$	6.18%	134.7	100.9	17.4
$\frac{h_{M,ave}}{h_{F,ave}}$	1.077	1.44	1.2	0.6
$\frac{z_{M,ave}}{z_{F,ave}}$	1.188	-4.31	-7.8	-1.0
$\frac{y_{qa,MU}}{y_{qa,KE}}$	4.50	-63.7	-62.6	-12.1
$\frac{y_{qn,MU}}{y_{qn,KE}}$	2.81	-66.8	-37.8	-6.8
$\frac{y_{MU}}{y_{KE}}$	3.63	-72.9	-51.2	-11.2

Note: This table shows the results of counterfactual experiments (in percentage change relative to the benchmark values) when setting the values of A, B, or x_E of Kenya to the values for Mauritius. Column 2 shows the values of the variables in the benchmark economy and columns 3–5 show the counterfactual results. Rows 2–3 show sectoral employment shares of the workforce and of females; rows 4–5 show private health expenditure and education expenditure to GDP ratios; rows 6–7 show male-to-female average health capital and human capital ratios; and the last three rows show the Mauritius-to-Kenya ratios of agricultural output per worker, nonagricultural output per worker, and GDP per worker (PPP-adjusted using Kenyan benchmark prices).

4.2 Endogenous vs. exogenous distribution of idiosyncratic productivities

One distinct feature of my model is that the distribution of idiosyncratic productivities is endogenous, which depends on individuals' choices of health and education investment, in addition to initial endowment of ability. This differs from former macro studies on sectoral allocations which take such distributions as given (e.g., Lagakos and Waugh, 2013; Lee, 2016). In this section, I investigate what differences an endogenous distribution of individual productivities makes by comparing some counterfactual results between the benchmark model ("Model 1") with a model that assumes exogenous distribution of idiosyncratic productivities ("Model 2"). In the latter model, all individuals' human capital (z) and health capital (h) are fixed to their values of the benchmark economy; individuals only choose

[25] One might be concerned that once taking into account the labor force participation (LFP) rate (which is assumed to be one for the middle- and old-aged in the current model), the counterfactual results may change since cross-country data indicate that the female-to-male LFP ratio and countries' income level have a U-shaped relation. To address this concern, I show in the Online Appendix the results of the above counterfactual experiments, when the female-to-male LFP ratio is assumed to vary with an economy's income level. The results are very close to those in Table 6, with a very modest increase in sectoral and aggregate labor productivity, suggesting that LFP is unlikely to be an important margin for inclusion in this study.

sectors, taking their productivities as given. Then I set TFP of Kenya to the Mauritian value, or set the gender barrier (κ) to zero in the two models, and compare their impacts on the two model economies.

The results in Table 7 indicate that the differences between the two types of models are considerable. When TFP of Kenya increases to the Mauritian value, the agricultural employment share of Kenya drops by 58% in Model 1 but 48% in Model 2. The aggregate labor productivity of Kenya would increase by nearly three-fold in Model 1 but only by 141% in Model 2. When κ is zero, the agricultural employment share drops by 8% and that of females by 40% in Model 1, compared with respective drops of 3% and 13% in Model 2; the increase in GDP per worker is 12% in Model 1 compared to only 0.4% in Model 2.

These results are not difficult to explain when we look into the variables related to health and education in rows 3–6 of Table 7. In Model 1, individuals respond to the increase in TFP or the decrease in the gender barrier by raising both health and education investments, generating a large positive feedback to the positive shock, while in Model 2, there is no such feedback (the reductions in health- and education-expenditure-to-GDP ratios are purely driven by an increase in GDP). My results suggest that, by ignoring part of behavioral responses, studies employing an exogenous distribution of idiosyncratic productivities underestimate the impact of economic factors, such as TFP or labor market frictions, on sectoral allocation and aggregate productivity.

Table 7. Counterfactual: Endogenous vs. Exogenous Distribution

variables	BM	TFP (%)		κ (%)	
		endo.	*exog.*	*endo.*	*exog.*
$agremp$	0.575	-57.8	-47.5	-7.8	-2.6
$agremp_F$	0.638	-65.4	-48.1	-39.7	-12.7
$\frac{X_P}{Y}$	2.73%	145.2	-55.9	46.6	-9.4
$\frac{M}{Y}$	6.18%	134.7	-55.9	30.2	-9.4
$\frac{h_{M,ave}}{h_{F,ave}}$	1.077	1.44	0.0	-1.6	0.0
$\frac{z_{M,ave}}{z_{F,ave}}$	1.188	-4.31	0.0	-23.9	0.0
y_{qa}	6.31	175.6	96.9	12.6	2.1
y_{qn}	13.92	201.1	97.3	5.3	-2.5
y	9.48	278.6	141.2	11.7	0.4

Note: This table shows the results of counterfactual experiments (in percentage change from the benchmark values) when setting TFP to the Mauritian value or setting the gender barrier (κ) to zero in the two types of models (columns 3–6). The results of Model 1 are shown in columns 3 and 5, and those of Model 2 are shown in columns 4 and 6; column 2 shows the benchmark values of the variables. See an explanation of the variables in the note for Table 6. The last three rows show agricultural and nonagricultural output per worker, and GDP per worker (PPP-adjusted using Kenyan benchmark prices).

To further understand whether investment in education or in health plays a greater role in distinguishing the endogenous distribution from exogenous distribution of individual productivities, I conduct additional experiments that only fix individuals' human capital (z) *or* health capital (h) to their benchmark values, and see how these partial-endogenous-distribution models respond to the TFP or κ shock.

Table 8 shows the results regarding agricultural employment share and labor productivity in models with different types of idiosyncratic productivity distributions. It appears that, under both shocks, the model with an exogenous distribution of z generates an outcome closer to the one with a full exogenous distribution, while the model with an exogenous distribution of h tends to be closer to the one with an endogenous distribution of individual productivities. The reason lies in the fact that nonagricultural production is more skill intensive; thus, when an economy encounters a shock that favors labor reallocation toward nonagriculture, say a positive productivity shock or a reduction in distortions, the response in education investment matters more for labor allocation and productivity than the response in health investment.[26] This result suggests that compared to endogenizing health, endogenizing education may be a more important dimension for modeling sectoral allocation and productivity.

Table 8. Exogenous Distribution of z *vs.* h

	TFP (%)				κ (%)			
	endo	*exog*	*exog-z*	*exog-h*	*endo*	*exog*	*exog-z*	*exog-h*
$agremp$	-57.8	-47.5	-49.5	-53.6	-7.8	-2.6	-3.9	-7.9
$agremp_F$	-65.4	-48.1	-50.7	-56.7	-39.7	-12.7	-15.5	-46.0
y_{qa}	175.6	96.9	103.0	151.9	12.6	2.1	3.9	6.3
y_{qn}	201.1	97.3	105.3	176.6	5.3	-2.5	-3.0	-6.1
y	278.6	141.2	152.5	241.9	11.7	0.4	1.3	1.7

Note: This table shows the results of the counterfactual experiments (in percentage change relative to the benchmark values) that assume either the distribution of human capital z (columns 4 and 8) or the distribution of health capital h (columns 5 and 9) is exogenous, when TFP is set to the Mauritian value (columns 2–5) or when κ is set to zero (columns 6–10), and compares the results to models with the endogenous distribution (columns 2 and 6) and the exogenous distribution (columns 3 and 7) of individual productivities.

[26] An exception is the change in nonagricultural output per worker (y_{qn}) under the κ shock, where the model with the exogenous h distribution generates a more negative effect on y_{qn} than the model with the exogenous z distribution. This is due to a composition effect. When the gender barrier is removed and education response is allowed for, a large proportion of female workers switch to nonagriculture, including less productive ones. This drives down the average labor productivity in nonagriculture.

4.3 Decomposition of the sectoral wage gap

A stylized fact highlighted in the macro-development literature is that a sectoral wage gap, or nonagricultural wage premium, exists for many countries, and that the gap is especially large for developing countries. Gollin, Lagakos, and Waugh (2014) argue that, even with better measures of sectoral labor inputs (such as measures taking into account hours worked and human capital per worker) and value added, a sizable sectoral wage gap remains. Herrendorf and Schoellman (2018) consider observed and unobserved differences in workers' abilities and sectoral differences in human capital intensities in a multi-sector model. Using the wage changes of US switchers, they find that the "selection view" (i.e., workers with higher unobserved abilities select into nonagriculture), rather than the "technology view" (i.e., nonagricultural production is more human capital intensive), explains most of the observed differences in sectoral wages in the US data. More recently, Hamory et al. (2021) use long-run individual-level panel data from Indonesia and Kenya and find that accounting for individual fixed effects leads to a large reduction (67%–92%) in sectoral productivity gaps.

With these findings in mind, I explore, based on my model, the contribution of various factors – technology, innate ability, education, health, and labor market friction – to the sectoral wage gap of Kenya. Specifically, I examine the following six factors, holding individuals' sectoral choices to be the same as in the benchmark economy: (1) factor intensity – setting the factor intensity of nonagriculture to agriculture (that is, $y_{n,g} = Ah^{\phi_g}$); (2) gender-specific productivity – setting the nonagricultural production function to $y_{n,g} = A\zeta_g h^{\mu} z^{1-\mu}$; (3) education – setting the education investment of nonagricultural workers to that of agricultural workers (that is, $e = m = 0$); (4) innate ability – setting the initial human capital endowment (z_0) of nonagricultural workers to the average of agricultural workers; (5) health – setting the health capital of nonagricultural workers to the average of agricultural workers; and (6) gender barrier– setting $\kappa = 0$. For each factor i, I compute the new sectoral wage gap, $\left(\frac{w_n}{w_a}\right)_i$, and its change from the benchmark value, $\triangle_i = \left(\frac{w_n}{w_a}\right)_{BM} - \left(\frac{w_n}{w_a}\right)_i$, and then measure the contribution of that factor to the benchmark sectoral wage gap as $CON_i = \frac{\triangle_i}{\triangle}$, where $\triangle = \sum_i \triangle_i$.

Table 9 (columns 2–3) shows that differences in innate ability of workers between the two sectors explain the largest part of the sectoral wage gap (40%), followed by sectoral differences in technology related to factor intensity (35%), and then by differences in education (26%). Sectoral differences in gender-specific productivity and health capital play a relatively minor role. In addition, the nonagricultural gender barrier has a negative contribution by construction, as its elimination would lead to an increase in the female nonagricultural wage, enlarging the sectoral wage gap.[27] Overall, my findings are consis-

[27]This result is caused by fixing the sectoral labor allocation to the benchmark economy in this experiment. If we re-solve the model in equilibrium, removing the gender barrier would induce more women to nonagriculture and the sectoral wage gap would shrink to 1.53.

tent with the literature that suggests that selection based on innate abilities plays the most important role in explaining the nonagriculture-agriculture wage gap.

Table 9. Decomposition of the Sectoral Wage Gap

	$\left(\frac{w_n}{w_a}\right)_i$	CON_i (%)	F (%)	M (%)
BM	1.62			
1. factor intensity	1.09	34.7	29.0	71.0
2. gender-specific prod.	1.43	12.5	100.0	0.0
3. education	1.22	26.4	26.5	73.5
3. innate ability	1.01	40.3	37.3	62.7
5. health	1.60	0.1	-20.0	120.0
6. friction	1.84	-14.6	100.0	0.0

Note: This table shows the sectoral wage gap (in column 2) for the benchmark economy (row 2) and for the factors (1)–(6) (rows 3–8). Column 3 shows the contribution of each factor to the sectoral wage gap, with its share of female and male wages shown in columns 4 and 5.

Furthermore, given the gender focus of this study, it would be interesting to ask: Which gender's wage distribution matters more for each factor examined above when it comes to the contribution to the overall sectoral wage gap? To answer this question, I recompute the sectoral wage ratio for each factor when fixing the wage distribution of one gender at a time to the benchmark economy. The last two columns of Table 9 show the share of each gender's wage distribution in each factor's contribution to the overall sectoral wage gap. Apart from gender-specific productivity and labor market friction, which are both female-specific factors, male wages play a greater role in all factors' contribution to the sectoral wage gap than female wages. This is unsurprising since, on average, men are better-educated, healthier, and more productive in both sectors than women; therefore, eliminating the sectoral difference of factor intensity, education, innate ability, or health would have a larger effect on men's wages, which in turn generates a greater impact on the sectoral wage gap.

5 Policy Experiments

Health and education have long been the centerpieces of development policies, as they are not only regarded as goals in their own right but also arguably have significant potential benefits for economic growth (United Nations, 2015). In addition, many development policies were specifically designed to target improving the condition of women, such as offering girls' scholarships and setting quotas for women in parliament. While policy makers claimed that such policies, by empowering women and achieving gender equality, could accelerate economic development, empirical research has found mixed effects (Duflo, 2012).

To offer new perspective on policy, I conduct experiments that provide health and education subsidies to individuals, based on my calibrated model. In particular, I compare the impacts of the two types of subsidies to shed light on the relative importance of health policy, which is the focus of this study. To gain insight into the impact of gender-specific policy, I implement experiments that subsidize both genders or a specific gender, and compare their effects. Furthermore, in section 5.2, I investigate the differences in policy effects in general equilibrium versus those in partial equilibrium to gain insight into the discrepancy between a nation-wide policy and a local policy, such as those in RCTs.

5.1 Health subsidy vs. education subsidy

I conduct two sets of policy experiments that focus on health and education subsidies, all at the same budgetary cost. The first set of experiments involves increased public health expenditure (x_E), and the second set of experiments involves subsidized education through an income transfer conditional on school attendance. Since school-attendance-based education subsidies have been widely implemented and studied in the development literature, the latter set of experiments serve as a comparison to evaluate the relative importance of health subsidies. Each set of policies is implemented on three groups of beneficiaries – all individuals, women only, and men only. Although male-specific subsidies are uncommon in practice, their inclusion here allows us to draw richer insights on policy effects.

The first health subsidy experiment involves doubling x_E for all individuals. This sets the budgetary cost for all other experiments, which is around 2% of GDP for each experiment; in the health subsidy experiments, it raises Kenya's public health expenditure-to-GDP ratio to 4–5%. This is a reasonable budget, since it is still below that of some SSA countries and far below the average of OECD countries (which is about 10%). Then in the second (third) healthy subsidy experiment, only women (men) enjoy additional public health benefits (i.e., an increase in x_E). In the education subsidy experiments, I assume that the subsidy is proportional to an individual's education time, e, with the subsidy rate solved in equilibrium to meet the policy budget. In order to focus on the effects of health and education subsidies, I abstract from any substitution or income effects of taxation by assuming that all policies are externally financed (which can be thought of as international humanity funds for health or education).

Table 10 shows the results. In addition to agricultural employment share and labor productivity, it also reports the policy effects on schooling years (by gender) and lifetime utility (by gender and for all). The latter allows us to investigate the welfare implications of the policies. Several results emerge.

First, the health subsidy effectively raises aggregate labor productivity and reduces agricultural employment share, especially for women. An improvement in health not only increases individual labor productivity in both sectors, but also increases women's comparative advantage in nonagriculture, inducing a more efficient allocation of (female) labor.[28] It is noteworthy that women's average years of schooling increases relative to men's in all three experiments, even when only men are subsidized. This is in line with empirical evidence from various studies that find that improved health benefited women's education relative to men's (Pitt, Rosenzweig and Hassan, 2012; Miguel and Kremer, 2004; Bobonis, Miguel, and Puri-Sharma, 2006; Field, Robles, and Torero, 2009; Baird et al., 2016).

The health subsidy is, nonetheless, more effective in raising aggregate labor productivity when offered uniformly to both gender or when targeting men, compared to targeting women. This is primarily because the (absolute) return to health improvement is higher for men due to their higher health share in agriculture. Thus, the effect of the health subsidy on *average* worker productivity is lower when men are excluded as beneficiaries. Additionally, since a health improvement in men results in a considerable increase in agricultural labor productivity, in equilibrium, it eases the subsistence constraint, drives down agricultural price, and pushes more workers to shift out of agriculture.

Second, when policy subsidizes education, it is most effective in raising aggregate labor productivity when targeting women and least effective when targeting men. This is mainly because subsidizing women's education (not men's) plays a similar role as decreasing the gender barrier in nonagriculture and, thus, reduces the distortion in labor allocation, while subsidizing only men's education exerts an opposite effect. Moreover, despite an insignificant effect on the agricultural employment share when the policy subsidizes both genders or women only, women's average years of schooling increases considerably relative to men's. This is consistent with Duflo, Dupas and Kremer (2021), who find that offering secondary school scholarships to qualified students increased their education attainment significantly, but these effects were concentrated among women. In addition, the slight increase in agricultural employment share is mainly due to an equilibrium effect, as better education enhances relative productivity of the nonagriculture sector, driving up the agricultural price. This result also suggests that the education subsidy has a much larger impact on individuals who are on the margin of whether to continue education than those on the margin of whether to commence education.[29]

Third, comparing the two types of subsidies, the health subsidy is more cost-effective than the education subsidy in elevating aggregate labor productivity and in reducing agricultural employment share. The reason is that two forces are at work when health is

[28] Even when health subsidies are limited to men, the policy still increases women's comparative advantage in nonagriculture.

[29] The impact of the education subsidy on aggregate labor productivity and on agricultural employment share may be under-estimated, because of an absence of borrowing constraints in my model. In a study by Cheung and Yao (2023) where they assume that initial financial wealth constrain individuals' borrowing capacity during their schooling period, they find a sizable impact of public education policy on agricultural employment share and aggregate labor productivity. Given that the focus of this paper is to investigate the relative importance of a health subsidy (compared to an education subsidy) and that individuals face the same budget constraint when they make both health and education investment decisions at youth, however, the lack of borrowing constraints is unlikely to alter the results regarding the *relative* importance of health subsidy considerably.

improved that affect both sectors. On the one hand, better health raises agricultural productivity, which eases the subsistence constraint and pushes workers out of agriculture. On the other hand, it enhances nonagricultural productivity (especially for females, relative to their agricultural productivity), which pulls workers into nonagriculture. Conversely, the working of the education subsidy is limited to the nonagricultural sector and thus has a mitigated impact on labor allocation and aggregate productivity.[30]

Finally, turning to welfare, a health subsidy is generally more welfare enhancing than an education subsidy. This is because improved health, versus education, not only has a larger impact on aggregate labor productivity but also reduces mortality. For example, the health subsidy that covers everyone reduces AMR by 14% for both genders, which generates a substantial welfare benefit. Among the three health subsidy experiments, the one that covers both genders is more welfare enhancing at the aggregate level than those targeting a specific gender.

Table 10. Policy Experiments (all in %)

variables	health subsidy			education subsidy		
	all	fe	ma	all	fe	ma
$agremp$	-8.5	-2.8	-10.8	0.1	0.2	2.0
$agremp_F$	-12.2	-4.9	-14.4	3.3	-0.6	10.2
$schyr_F$	18.4	25.2	6.0	31.9	52.7	-6.0
$schyr_M$	1.7	0.0	1.7	3.5	-1.9	8.7
y_{qa}	9.1	3.9	11.4	1.3	2.9	-1.1
y_{qn}	5.1	5.8	3.3	3.0	4.0	1.3
y	10.7	6.5	11.0	2.3	3.5	-0.6
U_F	14.3	24.0	-1.4	4.5	9.8	1.3
U_M	11.6	0.0	17.7	3.3	0.2	4.9
U	12.6	9.3	10.3	3.8	3.9	3.5

Note: This table shows the results of policy experiments (in percentage changes relative to the benchmark values). Columns 2–4 show results of increasing public health expenditure for all, for women only, and for men only; and columns 5–7 show results of subsidizing education for the same three groups. Rows 3–4 show percentage changes in average years of schooling by gender, and the last three rows show percentage changes in average lifetime utility by gender and for all.

5.2 General equilibrium vs. partial equilibrium

This subsection explores differences in the effects of health and education subsidies between general equilibrium (GE) and partial equilibrium (PE). While empirical studies, such as

[30] My finding that a health subsidy is more cost-effective than an education subsidy aligns with Miguel and Kremer (2004). Based on a deworming program among Kenyan school children, they find that mass treatment with deworming drugs is considerably more cost-effective than school subsidies in boosting school participation.

RCTs, suggest a potentially significant impact of health or education subsidies on education and labor market outcomes (Duflo, Dupas and Kremer, 2021; Miguel and Kremer, 2004; Bobonis, Miguel, and Puri-Sharma, 2006; Field, Robles, and Torero, 2009; Baird et al., 2016), whether such subsidization should be implemented nationwide is often debated in poor countries. An essential question is whether the local effect of a subsidy in a randomized field experiment applies to the country level. Understanding the discrepancy in policy effects between GE and PE (where prices are held constant) is crucial for addressing this question.

Table 11 shows the effects of the same health and education subsidies that cover both genders as in Section 5.1, but now by GE and PE. Notably, the impact of the health subsidy on aggregate labor productivity is higher in GE than in PE, while the impact of the education subsidy on aggregate labor productivity is lower in GE than in PE. Such a disparity arises from different labor allocations, resulting from different directions in price changes. In GE, the health subsidy increases the agricultural productivity which drives down the agricultural price, while the education subsidy increases nonagricultural productivity (but not agricultural productivity) that drives up the agricultural price; the former induces labor allocation toward nonagriculture while the latter does the opposite. These effects are absent in PE. Hence, while GE captures the additional benefit of the health subsidy in reducing the agricultural employment share through a price adjustment, it makes the education subsidy less appealing for the same reason (but in opposite direction).

These results suggest that, while local randomized experiments find both health and education subsidies improve individuals' education and labor market outcomes, when implemented at the national level, the effectiveness of the health policy would be further enhanced, while that of the education policy would be mitigated.

Table 11. GE vs. PE (all in %)

variables	health subsidy		education subsidy	
	GE	PE	GE	PE
$agremp$	-8.5	3.2	0.1	-7.9
$agremp_F$	-12.2	-2.7	3.3	-2.6
$schyr_F$	18.4	15.1	31.9	41.9
$schyr_M$	1.7	-10.9	3.5	12.2
y_{qa}	9.1	11.4	1.3	0.2
y_{qn}	5.1	9.5	3.0	0.6
y	10.7	8.6	2.3	4.1

Note: This table compares the effects of health and education subsidies (when covering both genders) in general equilibrium (columns 2 and 4) versus in partial equilibrium (columns 3 and 5).

6 Conclusion

To explore how health affects aggregate labor productivity through its effect on the gender division of labor across sectors, I develop a multi-sector general equilibrium model with heterogeneous individuals who invest in health and education, and choose the sector. A higher return to health for men than for women in agriculture implies that a general improvement in health enhances women's comparative advantage in nonagriculture, inducing greater female nonagricultural employment, increasing aggregate labor productivity. The model is calibrated to two African economies, Kenya and Mauritius; it explains 47% of the agricultural labor productivity gap, 61% of the nonagricultural labor productivity gap, and 52% of the aggregate labor productivity gap between the two economies.

Counterfactual analysis shows that, while TFP is responsible for most of the aggregate labor productivity gap between Kenya and Mauritius, health production efficiency is highly comparable to TFP in explaining differences in agricultural labor productivity and employment share between the two countries. Moreover, increasing health production efficiency has a larger impact on reducing the female agricultural employment share than increasing TFP. Compared to a model with an exogenous distribution of workers' productivities, my model featuring an endogenous distribution of individual productivities based on investment choices predicts a considerably larger impact of TFP and labor market friction on labor allocation and productivity. Furthermore, a decomposition analysis reveals that innate ability accounts for most of the sectoral wage gap of Kenya, followed by sectoral factor intensity and education.

Policy experiments show that a health subsidy is more cost-effective than an education subsidy in raising aggregate labor productivity, in reducing the agricultural employment share, and in improving general welfare. This is primarily because health policy impacts both sectors directly – it increases agricultural productivity, eases the subsistence constraint, and thus pushes workers out of agriculture; and it increases nonagricultural productivity, which attracts more workers to nonagriculture. In contrast, the working of an education subsidy hinges on the nonagricultural sector and thus has a limited impact. In addition, while a health subsidy reduces females' agricultural employment relative to males', it is more effective in improving aggregate labor productivity when covering both genders uniformly or just men, compared to targeting just women. Furthermore, a comparison of policy effects between GE and PE suggests that, while RCTs find both local health and education subsidies effective in improving individuals' schooling and labor market outcomes, when implemented at the national level the effectiveness of the health policy is enhanced while that of the education policy is diminished.

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Online Appendix for "Health, Gender Division of Labor, and Productivity"

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October 24, 2023

This appendix consists of three sections. Section A provides micro-level evidence on the relationship between health and education or sectoral employment, with a particular focus on the gender differences in these relationships. Section B provides a characterization of the model, and Section C shows the results of a number of counterfactual experiments when labor force participation is taken into account.

A. Empirical Evidence

As noted, various empirical studies document that, compared to men, women benefited more from health improvement in terms of education and labor market outcomes (Pitt, Rosenzweig and Hassan, 2012; Miguel and Kremer, 2004; Bobonis, Miguel, and Puri-Sharma, 2006; Field, Robles, and Torero, 2009; Baird et al., 2016). While these studies provided convincing evidence and have motivated this current study, they typically use data based on randomized field experiments or local surveys in an individual country. To complement their analysis, I now look into micro-level data from a broader set of developing countries to investigate gender differences in the relationships between health and education or sectoral employment. In particular, I use data from the Demographic and Health Surveys (DHS) for 33 SSA countries. The dataset contains individual-level information related to education and health, along with other demographics.[1] I employ individuals' body-mass index (BMI) as the measure of health. BMI is a commonly used health measure in development economics and is found to be significantly and positively associated with living standard, including nutritional status, in developing countries (Nubé et al., 1998).[2]

In the following analysis, I run regressions to examine the relationships between health and years of schooling or sectoral employment, with a particular focus on gender differences in these relationships. Since BMI at higher levels can be negatively associated with health, I conduct regressions with samples of different ranges of BMI.

[1] For each country, I select the year nearest to 2005 with data available. The full dataset contains more than 160,000 individuals, of which about three quarters are females.

[2] In rich countries, BMI is often used to define and classify obesity, though.

Note that the cross-sectional nature of my dataset poses two major limitations on this analysis. First, I am unable to draw a causal effect from the regressions. Thus, I interpret the coefficients of health as correlations between health and the dependent variable, rather than a causal effect of health, and focus on gender differences in these correlations. Second, the regressions show the relationship between individuals' *current* BMI and *past* years of schooling. Thus, the BMI measure adopted here can only be viewed as an approximation of individuals' BMI at their school age which may be relevant for their schooling decisions. With these caveats in mind, I explain my regression analysis below.

A.1 Health and education

I begin by examining the relationship between health and education and then compare the results between men and women. I regress years of schooling (in log) on BMI, controlling for country, region, area (i.e., urban or rural) and year fixed effects, as well as age and household wealth. I run these regressions separately for men and women.[3] In addition, I use a sample that contains all levels of BMI and a subsample with BMI below 25, since BMI higher than 25 may be negatively associated with health.[4]

Figure A1 displays the regression coefficients of BMI by gender from the regressions. The point estimates in the top row (labeled "all") indicates that a larger BMI is associated with more years of schooling for both genders, regardless of the BMI range. There is little gender differences in this relation, however, which appears to contradict the theory that improved health leads to a greater increase in women's education.

Since the primary focus of this paper is the impact of health on the gender division of labor between agriculture and nonagriculture, the most relevant population are individuals with relatively low socioeconomic status. Given that they are more likely to face resource constraints that influence their sectoral choices, they are situated on the margins of these decisions. Therefore, I conduct the same regressions using subsamples of individuals with lower socioeconomic status: those with 4 or fewer years of schooling, those with 6 or fewer years of schooling, and those with a household wealth index less than or equal to 3.[5]

The remaining rows of Figure A1 clearly depict a larger coefficient of BMI for women compared to men when the focus is for the less-advantaged group. This suggests a stronger

[3] I dropped observations with age below 20, years of schooling above 20, or BMI above 60, and where women who were pregnant at the time of survey. I include household wealth as a control variable because the correlation between education and BMI can depend on socioeconomic status. One caveat is that household wealth in the dataset is an index with five values (from 1 to 5) and measures an individual's *current* household wealth; thus, for married people, it may not well reflect household wealth at the time of schooling, which is more relevant to their education investment. However, due to the lack of data on income or wealth, I use this wealth index as an approximation for the socioeconomic status of one's household at the time of schooling.

[4] In a population-based cohort study of 3.6 million adults in the UK, Bhaskaran et al. (2018) discovered a J-shaped relationship between BMI and mortality hazard, with the lowest all-cause mortality occurring at a BMI level of around 25.

[5] 4 is the median years of schooling of the full sample and 6 is the years of primary school.

association between health and education for women with low socioeconomic status.

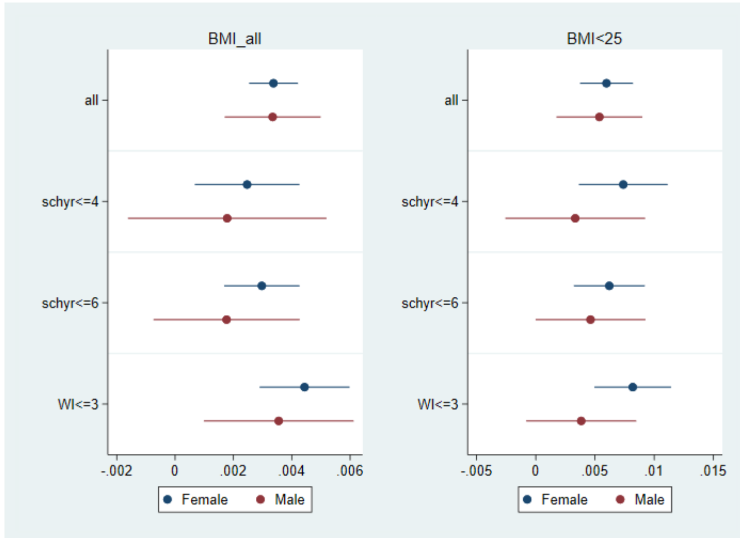

Figure A1. Coefficients of BMI in Schooling Years Regressions

Note: This figure shows the point estimates of the coefficient of BMI (with 95% confidence intervals) from the following regression: $\ln(schyr)_i = \beta_0 + \beta_1 BMI_i + \beta_2 X_i + \varepsilon$, where the dependent variable is the log of individual i's years of schooling, BMI_i is the body mass index, and X_i is a set of control variables: country, region, area, and year fix effects, age, age^2, and the household wealth index. The left panel uses a sample of all levels of BMI, whereas the right panel uses a subsample with BMI below 25. The top row shows the estimates from the sample with all individuals, while the remaining rows show estimates from subsamples of individuals with lower socioeconomic status (i.e., years of schooling no more than 4 or 6, or household wealth index no more than 3). Regression coefficients are presented separately for females and males.

A.2 Health and sectoral employment

I now examine the relationships between health and sectoral employment. Specifically, I run OLS regressions, for men and women separately, of individuals' employment sector (a dummy variable that equals 1 if he/she works in nonagriculture and 0 otherwise) on BMI, controlling for country, region, area and year fixed effects, as well as age, household wealth, and years of schooling. In addition to the full sample, I use subsamples of BMI less than 25 and of different socioeconomic status (measured by years of schooling or household wealth index).

Across nearly all specifications, the coefficient of BMI is larger and has a higher level of significance for women compared to men. This indicates that, controlling for education, healthier women tend to work in nonagriculture, regardless of their socioeconomic status.[6] Combined with the findings in the previous subsection, it suggests that health plays a significant role in shaping the gender division of labor across sectors, both through the education channel and in its own right.

[6]The results are qualitatively similar when years of schooling is excluded from the control variables.

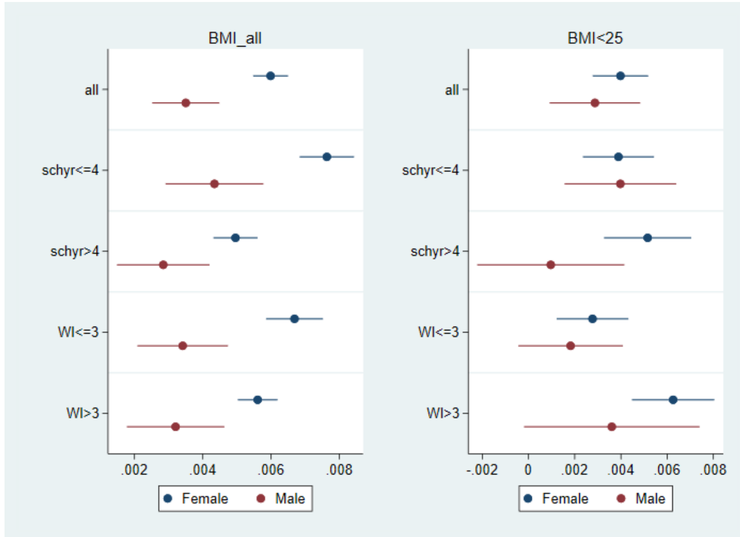

Figure A2. Coefficients of BMI in Sectoral Employment Regressions

Note: This figure shows the point estimates of the coefficient of BMI (with 95% confidence intervals) from the following regression: $occ_{nagr,i} = \beta_0 + \beta_1 BMI_i + \beta_2 X_i + \varepsilon$, where the dependent variable is individual i's employment sector, a dummy variable that equals 1 if the individual works in the nonagricultural sector and 0 otherwise; BMI_i is the body mass index, and X_i is a set of control variables: country, region, area, and year fix effects, and age, age^2, years of schooling and household wealth index. The left panel uses a sample of all levels of BMI, whereas the right panel uses a subsample with BMI below 25. The top row shows the estimates from the sample with all individuals, while the remaining rows show estimates from subsamples of individuals with different socioeconomic status (by years of schooling or household wealth index). Regression coefficients are presented separately for females and males.

In addition, while the regressions above show a significant positive coefficient of years of schooling (not shown in the figure though), the magnitude of this coefficient is smaller for women than for men. This implies that, holding other factors constant, a woman is less likely to work in the nonagricultural sector than a man with the same level of education.[7] This result suggests the presence of a "barrier" that women encounter in entering the nonagricultural sector.

B. Model characterization

This section first derives the optimal conditions for a woman's problem given the sectoral choice and then shows the optimal sectoral choice. For men, these conditions are identical except for the agricultural technology (i.e., ζ_g and ϕ_g) and the nonagricultural gender barrier (i.e., $\kappa = 0$ for men). The analysis below is based on the steady state equilibrium, so prices are constant.

[7]For example, from the regressions using the full sample, the coefficient of years of schooling is 0.012 for women and 0.018 for men, both significant at 1%.

Working in agriculture

Suppose a woman with initial human capital z_0 works in agriculture from the adult period. She would not invest in education since its return is zero; thus, $m = e = 0$. The Lagrangian is as follows.

$$\begin{aligned}\mathcal{L}(\mathbf{c}, x_P, h, \lambda_1, \lambda_2) =& U(\mathbf{c}, h) + \lambda_1\{A\zeta_F h^{\phi_F}[\psi p_{a,0}\eta + \frac{\delta(h)p_{a,1}}{1+r} + \frac{\delta(h)^2 p_{a,2}\gamma}{(1+r)^2}] - \tau - x_P \\ & - (p_{a,0}c_{a,0} + c_{n,0}) - \frac{\delta(h)(p_{a,1}c_{a,1} + c_{n,1})}{1+r} - \frac{\delta(h)^2(p_{a,2}c_{a,2} + c_{n,2})}{(1+r)^2}\} \\ & + \lambda_2[h_0 B x_E^{\alpha_1}(b + x_P)^{\alpha_2} - h] \end{aligned} \quad (1)$$

where $\mathbf{c} = \{c_{a,t}, c_{n,t}\}_{t=0,1,2}$, and λ_1 and λ_2 are Lagrangian multipliers associated with the budget constraint and health capital formation, respectively, and $p_{a,0} = p_{a,1} = p_{a,2} = p_a$ (steady state condition). The first-order conditions (FOCs) are as follows.

$$c_{a,0} - \bar{c} = \frac{c_{a,1} - \bar{c}}{\beta(1+r)} = \frac{c_{a,2} - \bar{c}}{\beta^2(1+r)^2},\ c_{n,0} = \frac{c_{n,1}}{\beta(1+r)} = \frac{c_{n,2}}{\beta^2(1+r)^2}, \quad (2)$$

$$\frac{\nu}{p_a(c_a - \bar{c})} = \frac{1-\nu}{c_n} = \lambda_1, \quad (3)$$

$$\lambda_1 = \lambda_2 h_0 B \alpha_2 x_E^{\alpha_1} x_P^{\alpha_2 - 1}, (>\ if\ x_P = 0) \quad (4)$$

$$\begin{aligned}&[\beta\delta'(h) + 2\beta^2\delta(h)\delta'(h)][\nu\log(c_{a,0} - \bar{c}) + (1-\nu)\log(c_{n,0}) + [\beta\delta'(h) + 4\beta^2\delta(h)\delta'(h)]\log[\beta(1+r)] \\ &+ \frac{1-\nu}{c_{n,0}}\{p_a A\zeta_F\phi_F h^{\phi_F - 1}[\psi\eta + \frac{\delta(h)}{1+r} + \frac{\delta(h)^2\gamma}{(1+r)^2} + \frac{h}{\phi_F}\cdot(\frac{\delta'(h)}{1+r} + \frac{2\delta(h)\delta'(h)\gamma}{(1+r)^2})] \\ &-[\beta\delta'(h) + 2\beta^2\delta(h)\delta'(h)][p_a(c_{a,0} - \bar{c}) + c_{n,0}] - [\frac{\delta'(h)}{1+r} + \frac{2\delta(h)\delta'(h)}{(1+r)^2}]p_a\bar{c}\} \\ &= \frac{1-\nu}{c_{n,0}}\cdot\frac{1}{h_0 B\alpha_2 x_E^{\alpha_1}(b + x_P)^{\alpha_2 - 1}}\end{aligned} \quad (5)$$

where the last equation has combined (2)–(4). Equation(2) reflects the intertemporal consumption-saving decisions, equation(3) reflects the relation between agricultural and nonagricultural consumption, equation(4) links the shadow price of health to that of consumption goods through private health investment, and equation(5) equates the marginal benefit (LHS) and marginal cost (RHS) of health. Note that the LHS of equation(5) indicates that health benefits one's life through a number of channels. First, it directly increases lifetime utility by raising longevity (the first line); second, it improves productivity given longevity (associated with the first term in the bracket of the second line); and third, it increases lifetime income net of consumption expenditure through raising longevity (the second term in the bracket of the second line plus the third line).

Using equations (2)–(5), the budget constraint and the health production equation in the paper, we can solve $\mathbf{c}$, x_P and h as well as lifetime utility $V(z_0; a)$ for a woman who works in agriculture.

Working in nonagriculture

Now we derive optimal conditions given that a woman works in nonagriculture from the adult period. The Lagrangian is as follows.

$$\begin{aligned}\mathcal{L}(\mathbf{c}, x_P, m, e, h, \lambda_1, \lambda_2, \lambda_3) = & U(\mathbf{c}, h) + \lambda_1\{(\psi - e)p_a\eta A\zeta_F h^{\phi_F} - \tau + Ah^{\mu}z^{1-\mu}(1-\kappa)[\frac{\delta(h)}{1+r} + \frac{\delta(h)^2\gamma}{(1+r)^2}] \\ & - x_P - m - (p_a c_{a,0} + c_{n,0}) - \frac{\delta(h)(p_a c_{a,1} + c_{n,1})}{1+r} - \frac{\delta(h)^2(p_a c_{a,2} + c_{n,2})}{(1+r)^2}\} \\ & + \lambda_2[h_0 B x_E^{\alpha_1}(b + x_P)^{\alpha_2} - h] + \lambda_3[z_0(1 + \rho h^{\theta_1}e^{\theta_2}m^{\theta_3}) - z]\end{aligned} \tag{6}$$

where λ_1, λ_2 and λ_3 are Lagrangian multipliers associated with the budget constraint, health capital and human capital formation, respectively. We then derive FOCs as follows.

$$c_{a,0} - \bar{c} = \frac{c_{a,1} - \bar{c}}{\beta(1+r)} = \frac{c_{a,2} - \bar{c}}{\beta^2(1+r)^2},\ c_{n,0} = \frac{c_{n,1}}{\beta(1+r)} = \frac{c_{n,2}}{\beta^2(1+r)^2}, \tag{7}$$

$$\frac{\nu}{p_a(c_{a,0} - \bar{c})} = \frac{1-\nu}{c_{n,0}} = \lambda_1, \tag{8}$$

$$\lambda_1 = \lambda_2 h_0 B\alpha_2 x_E^{\alpha_1} x_P^{\alpha_2 - 1}, (> \ if \ x_P = 0) \tag{9}$$

$$\lambda_1 = \lambda_3 z_0\rho\theta_3 h^{\theta_1}e^{\theta_2}m^{\theta_3 - 1}, (> \ if \ m = 0) \tag{10}$$

$$\lambda_1 p_a\eta A\zeta_F h^{\phi_F} = \lambda_3 z_0\rho\theta_2 h^{\theta_1}e^{\theta_2 - 1}m^{\theta_3}, (> \ if \ e = 0) \tag{11}$$

$$\lambda_1 A(1-\mu)h^{\mu}z^{-\mu}(1-\kappa)[\beta\delta(h) + \beta^2\delta(h)^2\gamma] = \lambda_3, \tag{12}$$

$$\begin{aligned}& [\beta\delta'(h) + 2\beta^2\delta(h)\delta'(h)][\nu\log(c_{a,0} - \bar{c}) + (1-\nu)\log(c_{n,0}) \\ & +[\beta\delta'(h) + 4\beta^2\delta(h)\delta'(h)]\log[\beta(1+r)] + \frac{1-\nu}{c_{n,0}}\{(\psi - e)p_a\eta A\zeta_F\phi_F h^{\phi_F - 1} \\ & +A\mu h^{\mu-1}z^{1-\mu}(1-\kappa)[\frac{\delta(h)}{1+r} + \frac{\delta(h)^2\gamma}{(1+r)^2} + \frac{h}{\mu}\cdot(\frac{\delta'(h)}{1+r} + \frac{2\delta(h)\delta'(h)\gamma}{(1+r)^2})] \\ & -[\beta\delta'(h) + 2\beta^2\delta(h)\delta'(h)][p_a(c_{a,0} - \bar{c}) + c_{n,0}] - [\frac{\delta'(h)}{1+r} + \frac{2\delta(h)\delta'(h)}{(1+r)^2}]p_a\bar{c} + \frac{\theta_1}{\theta_3}\cdot\frac{m}{h}\} \\ & = \frac{1-\nu}{c_{n,0}}\cdot\frac{1}{h_0 B\alpha_2 x_E^{\alpha_1}(b + x_P)^{\alpha_2 - 1}}\end{aligned} \tag{13}$$

Compared with the FOCs of the agricultural problem, the additional equations (10)–(13) represent FOCs of m, e, and h. Note that now in addition to enhancing utility (directly) and lifetime income net of consumption expenditure through longevity and productivity, health benefits one's life by improving the efficacy of education investment (last term of the LHS of (13)).

Moreover, we can derive the following conditions using equations (10), (11) and (12):

$$p_a \eta A \zeta_F h^{\phi_F} = \frac{\theta_2}{\theta_3} \cdot \frac{m}{e} \tag{14}$$

$$A(1-\mu)h^{\mu} z^{-\mu}(1-\kappa)[\frac{\delta(h)}{1+r} + \frac{\delta(h)^2\gamma}{(1+r)^2}][z_0 \rho \theta_3 h^{\theta_1} e^{\theta_2} m^{\theta_3 - 1}] = 1 \tag{15}$$

Using (8), (13)–(15), the budget constraint, health capital and human capital production equations in the paper, we can solve $\mathbf{c}$, x_P, m, e, h, and z as well as lifetime utility $V(z_0; n)$ for a woman who works in nonagriculture.

The sectoral choice

Given lifetime utility associated with each sector, a woman chooses the sector in which to work for her adult and old periods at the beginning of life and allocates her budget between consumption and investment in health and education accordingly. Thus, an individual's value function is given by

$$V(z_0) = \underset{\{a,n\}}{max}\{V(z_0; a), V(z_0; n)\} \tag{16}$$

C. Counterfactual experiments with labor force participation

This section attempts to address the concern that, while the labor force participation (LFP) rate is assumed to be one for the middle- and old-aged in the model, the asymmetric relation between LFP and countries' income level between genders observed in the data may otherwise change some of my counterfactual results. To address this issue, instead of building the LFP decision into the model, I estimate the gender LFP ratio from the data for the counterfactual experiments in Section 4.1, and recompute sectoral employment share and labor productivity.

I first run a regression analysis to find the relation between the female-to-male LFP ratio and GDP per capita using cross-country data from ILOSTAT and WDI.[8] The regression model is as follows:

$$LP_{ratio,i} = \beta_0 + \beta_1 gdp_i + \beta_2 gdp_i^2 + \varepsilon$$

where $LP_{ratio,i}$ is the ratio of the female-to-male LFP rate of country i and gdp_i is the log of GDP per capita of country i, and ε is the error term. The estimated coefficients $\hat{\beta}_0$, $\hat{\beta}_1$,

[8] The cross-country data of LFP by gender are taken from ILOSTAT (for the year 2010, which is the earliest data available), and GDP per capita is the 2000–2010 average, taken from WDI. The LFP data of Kenya are unavailable in ILOSTAT but are available in WDI for the year 2019, which I take for estimation.

and $\hat{\beta}_2$ turn out to be 5.129, -0.994, and 0.055, suggesting a U-shaped relationship between the gender LFP ratio and a country's income level.

Next, for each experiment in Section 4.1, I compute GDP per capita in log, convert it to the data scale (denoted by Y_{pc}) and use it to estimate the gender LFP ratio by: $\hat{LP}_{ratio} = \hat{\beta}_0 + \hat{\beta}_1 Y_{pc} + \hat{\beta}_2 Y_{pc}^2$. Then I use $\hat{LP}_{ratio}$ to recompute sectoral employment share and labor productivity for each experiment, assuming that LFP is independent of individual productivity.[9]

The results are shown in Table A1. The gender LFP ratio drops in all experiments as Kenya's GDP per capita rises, with the largest drop occurring in the TFP experiment. The impact on the sectoral employment share and productivity is very modest, though. The slight increase in both sectoral and aggregate labor productivity is unsurprising: since men are on average more productive than women in each sector, reducing women's participation would drive up average labor productivity, given that individual productivity is independent of participation (by assumption). Overall, the results are very close to those without LFP considerations, suggesting the LFP decision is unlikely to change my benchmark results considerably.

Table A1. Counterfactual results with LFP (all in %)

	TFP	B	x_E
$\hat{LP}_{ratio}$	88.6	91.2	98.0
$agremp$	0.54	2.58	-0.04
y_{qa}	1.27	1.09	0.28
y_{qn}	0.42	0.56	0.09
y	0.43	0.49	0.16

Note. This table shows, for each counterfactual experiment of Section 4.1, the estimated female-to-male LFP ratio relative to the benchmark value ($\hat{LP}_{ratio}$), and the percentage change in agricultural employment share ($agremp$), and sectoral and aggregate labor productivity (y_{qa}, y_{qn}, y) from the corresponding results in Section 4.1 (Table 6).

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[9] I fix male's LFP rate to one and compute female's LFP using $\hat{LP}_{ratio}$. Note that since I assume the LFP rate to be one in the benchmark model which implies the gender LFP ratio to be one, I adjust the estimated gender LFP ratio proportionally such that $\hat{LP}_{ratio}$ of the benchmark model equals one.

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