Cross-country income dispersion, human capital, and technology adoption

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Abstract

Countries with high levels of human capital also tend to be technologically advanced. We study whether modeling technology adoption can significantly amplify the importance of human capital differences in accounting for cross-country income gaps. We document that schooling is positively and robustly correlated with measures of technology adoption and usage, and negatively correlated with the prevalence of traditional forms of production, where technology adoption is limited, and productivity is lower. Motivated by this, we build a general equilibrium model with human capital investment, endogenous occupational choices, and technology adoption. Production takes place either in a traditional sector, where technology adoption is absent, or in a modern sector, where managers hire a workforce and optimally choose technology. Economies differ in terms of schooling levels by occupation and in the size of barriers to technology adoption. These differences, working together, result in a factor of 6 between US income and that of the bottom quartile of countries. Schooling differences on their own result in a factor of 3.5, compared to a factor of 2 in a one-sector version of the model where technology choices are absent.

Keywords: Human capital; Technology adoption; Cross-country income differences

JEL codes: J24, O11, O33, O41

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1 Introduction

Prosperous, well-educated, countries also tend to be more technologically advanced. While this is an almost self-evident proposition – and one that we confirm with data below – such correlations may be the result of very different causal mechanisms. We study the possibility that cross-country human capital differences may be amplified by technology adoption in a way that is quantitatively relevant in accounting for income differences around the world.

Following the groundbreaking work of Lucas (1988), a large literature ensued determined to understand the relative importance of human capital and total factor productivity (TFP) in accounting for cross-country income dispersion. Its conclusions have ebbed and flowed over the last 3 decades, as more and better data have become available and modeling techniques have evolved.[1] An important turning point in this literature was the argument that when the production of human capital requires significant expenditures (in addition to time inputs), variations in TFP can be significantly amplified by human capital accumulation into large cross-country income differences (see Erosa, Koreshkova, and Restuccia, 2010). We use this complementarity between human capital and TFP as a touchstone, but we study a different causal mechanism by arguing that human capital is crucial for the adoption of more efficient technologies, and that modeling such relationship is important in accounting for cross-country income differences. In other words, variations in education can be significantly amplified when one considers their impact on technology adoption.

While it stands to reason that the adoption of more efficient technologies should be important in accounting for income dispersion, such adoption does not occur in a vacuum; it is the result of a complex mix of factors.[2] Nelson and Phelps (1966) first hypothesized a complementarity between human capital and technological adoption and diffusion: "(...) educated people make good innovators, so that education speeds the process of technological diffusion." This conjecture was later empirically confirmed by Benhabib and Spiegel (1994) using Solow residuals, and more recently by Comin and Hobijn (2004) using more granular measures of technological adoption and diffusion. In the model we develop, we emphasize this channel: managers who accumulate more human capital adopt more

[1] Mankiw, Romer, and Weil (1992) argued physical and human capital differences could account for a large fraction of the cross-country variance in output per capita, leaving only a modest role for cross-country TFP differences. Later, allowing for differences in productivity to be correlated with physical and human capital accumulation, Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999) argued human capital played a much smaller role. In a sort of comeback, Manuelli and Seshadri (2014) argued that building counterparts for human capital stocks using choices of both quantities and quality – as opposed to backing them out using Mincerian returns – goes a long way in returning human capital dispersion to prominence. See Rossi (2018) for a review of the role of human capital in macroeconomic development.

[2] Besides human capital, which is our focus, Comin and Hobijn (2004) find that the type of government, degree of openness to trade, and adoption of predecessor technologies, all play roles in accounting for new technology adoption and diffusion. Buera, Hopenhayn, Shin, and Trachter (2021) highlight the importance of complementarities coming from adoption coordination and how it can significantly amplify existing distortions. Surveying the literature on international diffusion, Keller (2004) finds that imports and foreign direct investment play important roles.

efficient (and more expensive) technologies because the marginal product of technology is increasing in human capital.

Our model economy also reflects the fact that human capital investment choices are closely connected to occupational choices.[3] In turn, such occupational choices condition technology adoption – the set of technological opportunities available to a self-employed street vendor is different from the one large employers face. We model individuals with different innate skills who optimally choose careers that are associated with different amounts of schooling. They can work on their own (what we call own-account) in a *traditional sector*; alternatively, they can become managers, in the Lucas (1978) span-of-control sense, in what we call the *modern sector*; or they can become salaried workers in that same modern sector. Modern sector managers can adopt different technology levels, something traditional sector own-account workers cannot do. With this setup, the model features two margins of technology adoption: an *extensive* margin – the size of the modern sector relative to the traditional one – and an *intensive* margin – the level of technology modern sector managers choose.

The motivation for these modelling choices, and our first contribution, comes from combining microdata from IPUMS-International with technology adoption and diffusion data from the Cross-country Historical Adoption of Technology (CHAT) dataset from Comin and Hobijn (2004). We find that measures of technology adoption and diffusion are strongly, and positively, correlated with schooling, while they are robustly negatively correlated with the share of own-account workers who are not managers or professionals (what we call in the model *traditional sector* workers). We also provide evidence that human capital and technology usage are complements in generating income using household data from the India Human Development Survey-II, and establishment-level data from a large set of countries in various waves of the World Bank Enterprise Surveys. This evidence supports a key mechanism in our model: that returns to technology adoption are increasing in human capital.

In our main model experiment, we simulate and compare counterparts of real-world economies that are characterized by different schooling levels and barriers to technology adoption relative to a leader, calibrated to the U.S. economy, where such adoption barriers are absent. We find that differences in schooling and in adoption barriers generate a factor difference of 6 in output between the US and the average economy in the lowest quartile of the per capita income distribution. We then go on to show that the interaction between education and barriers to technology adoption is quantitatively meaningful: when we shut down schooling differences or differences in adoption barriers one at a time, the output factor differences between the US and the poorest economies are roughly halved. We also find that the extensive margin is quantitatively important in driving the magnitudes

[3] As emphasized, for example, in Mestieri, Schauer, and Townsend (2017) and Hsieh, Hurst, Jones, and Klenow (2019).

we find, lending support to our modeling choice of including the traditional sector.

To further ascertain the quantitative importance of our main mechanism, we create an alternative set of economies where individuals continue to be able to invest in human capital, but they can only become workers or managers in a one-sector economy where technology choices are unavailable. We find that in this alternative setting, differences in schooling can only generate a factor difference of roughly 2 between the output of the richest and poorest simulated economies, compared to a factor of 3.5 in our benchmark economy when we only vary schooling. We conclude that the complementarity between human capital and technology adoption is an important mechanism in the search to fully capture cross-country-income dispersion. Moreover, our quantitative results imply that if there are large differences in human capital levels across countries, as suggested by recent literature (see e.g., Hendricks and Schoellman, 2018), then the size of technology adoption barriers that is needed to rationalize the organization of production in poor economies decreases considerably. A corollary, and policy implication, of our results is that barriers to human capital accumulation can constitute meaningful indirect barriers to technology adoption, especially in poor countries.

Our study shares common elements with various strands of the literature. It fits within the broad development accounting literature surveyed in Caselli (2005) and Hsieh and Klenow (2010) that finds that cross-country dispersion in TFP accounts for the bulk of the cross-country income differences and that this share has been rising over the last 100 years.[4] They emphasize that TFP has important indirect effects for both physical and human capital, while our results suggest that one should not neglect the reverse direction of causality. The quantitative results of our model imply that technology choices amplify the importance of educational attainment in accounting for cross-country income differences.

There is also a smaller, but burgeoning, literature studying how the adoption and operation of more efficient technologies is an important factor in accounting for cross-country growth rate disparities and, ultimately, income dispersion. Porzio (2017) builds a model that can account for a large fraction of the productivity dispersion in poor countries based on the relationship between the efficient allocation of talent and technology adoption. Our model is related in that it also endogenizes technology adoption, but it emphasizes the importance of human capital accumulation in doing so. Moreover, we examine the consequences for cross-country income dispersion, as opposed to within-country productivity dispersion.[5]

Finally, our work is also connected to a very recent trend in the occupational choice literature emphasizing the importance of distinguishing between different types of self-employed individuals (own-account versus employers) when analyzing different facets of macro-development. For instance,

[4] See Gallardo-Albarrán and Inklaar (2021).

[5] See also Comin and Hobijn (2011) and Comin and Mestieri (2018).

Feng and Ren (2023) focus on the connection between financial frictions, skill-biased technological change, and the organization of production.[6] A key contribution of our paper to this literature is that we consider two endogenous margins of technology adoption: a sectoral choice between traditional and modern forms of production, and a choice of technology level within the modern sector.

The rest of the paper is organized as follows. The next section presents motivating evidence connecting human capital with technology adoption and the organization of production. Then, Section 3 introduces a general equilibrium model that builds on the empirical facts, and Section 4 presents the calibration of the model. Finally, Section 5 presents our main quantitative results on cross-country comparisons, and Section 6 concludes the paper.

2 Motivating Evidence

In this section we present cross-country evidence that motivates the quantitative model presented in the next section. We use different sources of microdata at the individual, household and establishment level, as well aggregate data on technology usage across countries, to document the connection between education, technology adoption and the organization of production.

2.1 Education, organization of production, and technology usage lags

We start by using microdata from IPUMS-International for a set of 55 countries that includes high-, middle-, and low-income economies. Based on Gross Domestic Product (GDP) per capita, the poorest country in our sample is Malawi, while the richest one is Switzerland. In most cases the original data sources are population censuses. We use data from the latest available sample in each country, most of them within the last 20 years. Throughout the paper we exploit individual-level data including labor earnings, employment status, occupation, and education. For our analysis it is particularly important that countries have detailed data on the status of employment so that we can distinguish different forms of self-employment, namely, individuals working on their own or firm managers. Following the literature, we restrict the sample to individuals who are relatively more attached to the labor market, especially in poor countries: male population, between 25 and 65 years old, who work in the private sector. See Appendix A.1 for more details.

In addition to this cross-country microdata, we also use aggregate data on technology adoption and diffusion from the CHAT database from Comin and Hobijn (2004) to create an empirical proxy for cross-country technology adoption. To do this, we consider 5 major technologies and follow Comin,

[6] Feng, Lagakos, and Rauch (2023) take into account the importance of traditional self-employment in explaining cross-country differences in unemployment; while Herreño and Ocampo (2023) focus on the connection between unemployment risk and self-employment to study various development policies. In earlier work, Gollin (2008) documents differences across countries in the labor force fraction that does not work for wages.

Hobijn, and Rovito (2008) in computing technology usage lags across countries.[7] These lags are computed with respect to the US, and represent how many years ago these technologies were used in the U.S. with the same intensity as they are used presently in the countries in our sample, averaging over the 5 technologies we consider. In our analysis we only include countries that have lag data in at least 3 of the 5 technologies considered.

Figure 1: Technology adoption, education, and income

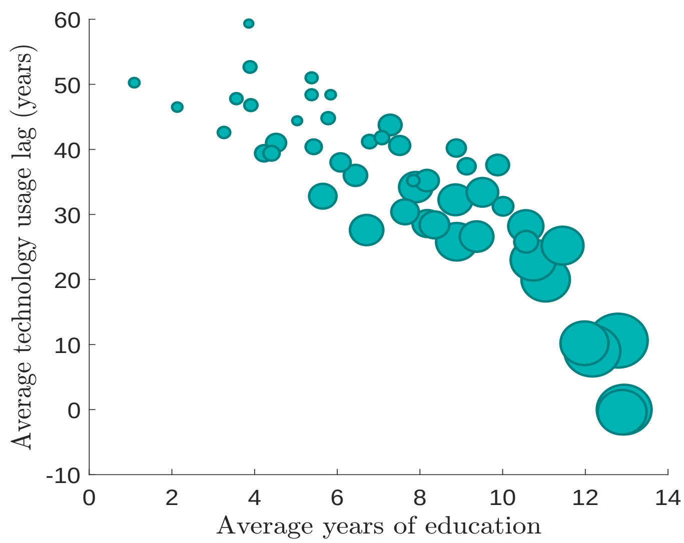


Figure 1 shows a strong and positive cross-country correlation between technology adoption, schooling, and incomes (proportional to the circles in the figure). This figure encapsulates the main motivation for our study. These correlations can be the result of different underlying causality mechanisms. The ones we are emphasizing here are twofold: (i) more educated countries adopt more productive technologies and become richer; and (ii) countries with lower barriers to forms of organization of production that are more conducive to technology adoption also become richer. Here, specifically, we have in mind the distinction between small traditional enterprises largely characterized by self-employment (e.g., a street vendor) and more formal and modern forms of production organization (e.g., a plant). The idea being that the opportunities for technology adoption are much more limited in the former than in the latter.

To formalize the distinction between these different production opportunities, we start by constructing three employment categories from the IPUMS-International data: (i) own-account workers, (ii) wage or salary workers, and (iii) employers. Own-account workers are self-employed individuals who report to be working on their own *and* who are not managers or professionals according to their

[7]We consider internet users per capita, number of PCs per capita, electricity production (kWh per capita), aviation-cargo (kilometers per capita), and tractors per capita.

occupation; wage or salary workers are individuals who are not employers or self-employed; and employers are self-employed individuals who report to be employers *or* whose occupation is manager or professional. These categories of employment, especially the distinction between own-account workers and employers (henceforth managers), will be consistent with the sorting in terms of skills in the model presented below.[8]

Figure 2: Occupational choice and income

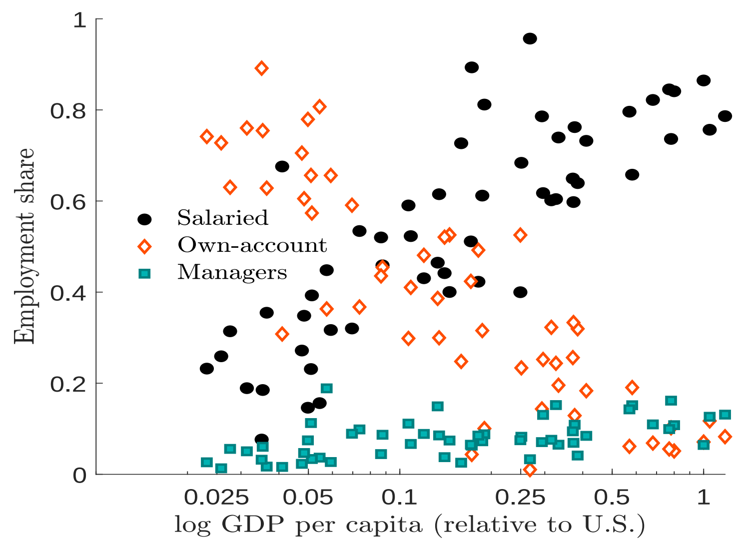


Figure 2 shows the relationship between the distribution of employment status and income per capita across countries. The key observations are that the fraction of own-account workers decreases with income, while the fraction of salaried workers and managers increases, all in a statistically significant fashion. Thus, a key feature of the structural change that economies experience as they grow is the transition from small traditional enterprises, mostly run by a single individual, to larger modern firms where workers and managers generate output together. In our model, we emphasize the importance of self-employment as a traditional form of production that is prevalent in poor countries and where technology adoption is limited.

Next, Table 1 presents a summary of the distribution of employment status by income quartile, including the U.S. as a reference. For countries in the top quartile of the income distribution, the average share of wage or salary workers is 76 percent, whereas the average share for countries in the poorest quartile is just 27 percent. Most of this difference translates into a much higher share of own-account employment in the poorest economies (nearly 70 percent), though the fraction of

[8]The basic idea is that self-employed individuals who are in the top 3 ISCO (International Standard Classification of Occupations) occupations are relatively skilled individuals who would tend to work in modern firms. Those 3 ISCO categories include managers, professionals and associate professionals which, according to the classification, are occupations that tend to require a high level of education and the performance of complex and technical tasks.

managers in the poorest quartile is just over 4 percent compared to 11 percent in the richest quartile. Note that the U.S. has a particularly high share of salaried workers and lower shares of own-account workers and managers compared to other rich economies.

Table 1: Distribution of Employment Status by Income Category

	Percentage of Employment		
Quartile	Wage-Salaried	Own-Account	Managers
1	27.4	68.4	4.3
2	48.5	43.1	8.4
3	66.4	25.4	8.2
4	75.7	13.6	10.8
USA	86.5	7.1	6.5

Notes: Income categories are based on GDP per Capita (PPP - constant 2017 international $) from Word Bank data. Employment shares are estimated with IPUMS-International data. Categories do not add up to 100 due to rounding.

While there is an overall increase in the fraction of own-account employment as incomes fall, it is worth noting that the fraction of own-account employment increases drastically from the second to the first quartile. It is the poorest countries in the world that cannot seem to make significant progress into more modern forms of production organization.

In section A.2 in the appendix we present additional cross-country evidence on the relationship between own-account employment and education. There, we also run simple regressions of own-account employment shares on technology usage lags for the various technologies in Comin, Hobijn, and Rovito (2008), confirming a robust relationship.

2.2 Micro evidence on human capital and technology usage

The data in Figure 1 show a positive relationship between education and technology adoption based on aggregate measures of technology usage. In this section, we use microdata to provide additional empirical support to the idea that human capital and technology usage are complements in generating income. The main goal in the following exercises is documenting evidence that individuals, households, or firms with higher measures of human capital obtain larger returns to technology usage. To do that, we estimate regressions of the following generic form:

$$\log Y_i = \beta_0 + \beta_T T_i + \beta_H H_i + \beta_C (T_i \times H_i) + \beta_z Z_i + \epsilon_i, \tag{1}$$

where Y_i is an outcome variable such as hourly earnings or profit margins for observation i; T_i is a proxy representing technology usage, such as the use of computers or email communications; H_i is

Table 2: Regressions using household data from India

	log(hourly earnings)		log(income per adult)	
	(1)	(2)	(3)	(4)
ComputerUse=1 × EduYrs	0.055***		0.032***	
	(0.006)		(0.006)	
MobileUse=1 × EduYrs		0.026***		0.024***
		(0.002)		(0.002)
Observations	49,604	49,604	72,387	72,387

Notes: Columns (1) and (2) use individual earnings from wage/salary jobs. Columns (3) and (4) use household income from all work-related sources (business and paid jobs). All cases control for sex, state, and a quadratic in age. Robust standard errors are reported. $^{*}p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$.
Source: Authors' estimations using IHDS data.

a measure of human capital, such as years of schooling or percentage of workers with high school completed; Z_i are control variables, such as age of individuals or firms; and ϵ_i is a classic error term. The coefficient of interest for our purposes is β_C, which captures the interaction, or complementarity, between technology use and human capital. A positive and significant value of that coefficient implies that measured returns to technology usage increase with human capital.[9]

We start by providing evidence from household data using the India Human Development Survey-II, 2011-2012 (IHDS II). This is a nationally representative survey of 42,152 households in 1,420 villages and 1,042 urban neighborhoods. The information in these surveys includes *individual* data on education years, labor income, and hours worked, as well as *household* data on business income. Importantly, the data has information on the use of computers and mobile phones for every household member. The latter is key for our estimation following equation 1. We consider two outcome variables: individual hourly earnings from wage and salary jobs, and household income per adult from all work-related sources (farming and non-farming business and wage or salary jobs). For technology usage we consider two dummy variables representing use of computer or use of mobile phone at the individual level. Lastly, we control for a quadratic in age, sex, and state of residence in our estimations, and we focus on adult household members who worked at least part time during the year.

The results in Table 2 show that the coefficients on the interaction between education years and technology usage are positive and statistically significant in every case. For instance, the results in column (1) imply that the measured return on hourly earnings to computer usage increases by 5.5 percentage points with an additional year of education. As a reference, the raw return on hourly earn-

[9]In all estimations presented below, the outcome variables are winsorized at the 2% and 98% levels to lessen the influence of extreme values.

Table 3: Regressions using enterprise surveys

	log(profit margin)		
	(1)	(2)	(3)
Website or Internet=1 × HighEdu=1	0.101**		
	(0.043)		
Website or Email=1 × HighEdu=1		0.097**	
		(0.046)	
Internet or Email=1 × HighEdu=1			0.325***
			(0.082)
Observations	70,387	70,441	40,032

Notes: HighEdu equals one if percentage of full-time workers with high school completed is over 75. Technology variables refer to using high-speed internet, having own website, or using emails for business communications. All cases control for age and size of establishment, size of locality, sector, and country-year fixed effects. The estimation takes into account the survey design: strata and weights. Differences in number of observations are due to data availability. $^{*}p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$.
Source: Authors' estimations using WBES data.

ings to an additional year of education is equal to 5.6% in these data. The coefficients in regressions based on household income per adult are smaller, but still sizable. Thus, household data from a large low-income country provides evidence that human capital and technology usage are complements in generating income.

Next, we present evidence based on firm data from a large number of countries. The data come from the World Bank Enterprise Surveys (WBES). These surveys collect establishment-level data in non-farming sectors, including information about sales, costs, technology use, and education of employees. The latest standardized dataset covers over 150 countries, mostly low- and middle-income economies, between 2006 and 2023. On average, each country has 2 surveys in the data.

To estimate equation 1 using these data, our outcome variable is profit margin defined as: (total sales minus total costs)/total sales. The human capital measure is a dummy variable that equals one if the percentage of full-time workers with high school completed is larger than 75. We think this represents a fairly high value of human capital in the workforce of an establishment for most countries in our sample. For technology usage we construct dummy variables that capture combinations of the following: using high-speed internet, having own website, and using email for communications with clients and suppliers. These three variables are chosen based on data availability. As control variables, we include the age and size of the establishment (in logs), size of locality (four categories based on population), sector (manufacturing or services), and country-year fixed effects.

The results in Table 3 are once again suggestive of complementarity between human capital and technology usage at the establishment-level. The estimated coefficients are relatively large and statistically significant in every case. For example, the results in column (1) imply that the measured return on profit margins from using technologies, a website or high-speed internet in that case, increases by 10.1 percentage points if a large fraction of workers have completed high school. To put this number in context, the average profit margin estimated in the data is 52%. Therefore, establishment-level data across a large set of countries provides strong support for the notion that returns to technology usage are larger for firms with higher measures of human capital.

In the next section we propose a model that builds on the link between human capital and technology adoption documented in this section using different sources of microdata and aggregate data.

3 Model

Environment and household problem

The economy is populated by a unit mass of individuals who derive utility from consumption according to a utility function to be detailed below. There is a single consumption good that can be produced in one of two sectors. In the *traditional sector*, individuals with own-account businesses, which we denote by o, produce the consumption good on their own. In the *modern sector*, managers, which we denote with an m, produce with the help of hired salaried workers (which we denote with a w) and also decide on the level of technology to use.

In the spirit of Roy (1951), individuals are endowed with abilities in the different occupations $j \in \{o, w, m\}$ according to the triple $z = \{z_o, z_w, z_m\} \in \mathbb{Z} \subseteq \mathbb{R}^3_+$ and optimally choose one of the three possible occupations in a way detailed below. The z_j are independently and identically distributed according to $\log z_j \sim N(0, \sigma)$. The use of unobserved occupation ability helps us capture the residual income dispersion remaining after we account for observed differences – schooling and education expenditures, in our case, as spelled out below.

We assume that each occupation requires a specific amount of schooling years s_j. That is, the occupational choice and schooling choice are a joint decision. One interpretation for this assumption is that, given differences in occupational income, individuals choose careers based on their abilities, and each career requires a certain level of education, in a similar spirit to Hsieh, Hurst, Jones, and Klenow (2019). As we make explicit below, production only takes place outside of school, so while individuals in occupations that require more schooling have higher average human capital, their income is also discounted more because they spend less time working over their lifetime.

In addition to occupational decisions, individuals also choose the level of human capital expenditures, e, as in Erosa, Koreshkova, and Restuccia (2010). Such expenditures get combined with schooling time to produce human capital h. To keep things as simple as possible, we model individuals as living for only one period, so all decisions are made at once.

Solving backwards, an individual who has already chosen occupation $j \in \{o, w, m\}$, solves the following problem:

$$
\begin{aligned}
V_j(z) = \max_{c,e} \quad & \log(c) \\
s.t. \qquad & c = I_j(z, h_j; \omega) - e, \\
& I_j(z, h_j; \omega) \in \{(1 - s_w)\omega z_w h_w, \Pi_o(z_o h_o), \Pi_m(z_m h_m; \omega)\}, \\
& h_j = s_j^{\phi} e^{\theta},
\end{aligned}
$$

where human capital h_j is produced with the schooling time required by the chosen occupation s_j and the chosen level of educational spending e. In such production, $\phi > 0$ governs the return to years of schooling and $\theta > 0$ is the elasticity of human capital with respect to expenditures on education.

Income I_j is occupation-specific: workers receive wage earnings proportional to their efficiency units in the modern sector for the time they actually spend at work (outside of school). We call $z_j h_j$ *occupation-specific* human capital, and the earnings of the own-account workers and managers are given by $\Pi_o(z_o h_o)$ and $\Pi_m(z_m h_m; \omega)$, respectively, in a way to be detailed below. Finally, given the solution to this problem for every $j \in \{o, w, m\}$, occupational choice is then determined by the maximum value over $V_j(z)$.

Traditional sector production

Production in the traditional sector is characterized by the absence of technological adoption, even if human capital plays a role. An agent that chooses to become a traditional sector entrepreneur, given individual ability z_o, and general human capital h_o, produces:

$$
\Pi_o(z_o h_o) = (1 - s_o)\psi \left(z_o h_o\right)^{\rho}
$$

where $\psi > 0$ governs sectoral productivity and $\rho > 0$ determines returns to human capital in the traditional sector. Note, again, that production only takes place outside of school and is therefore scaled by $(1 - s_o)$.

Modern sector production

In the modern sector, in contrast, technology adoption is possible, but costly. An agent that has decided to become a modern sector manager, given their sectoral human capital $z_m h_m$, takes the wage rate ω as given and chooses efficiency units of labor l and technology v to maximize profits:

$$\Pi_m(z_m h_m; \omega) = \max_{v,l} (1 - s_m) v l^\alpha (z_m h_m)^{1-\alpha} - \omega l - (1+\tau)\frac{v^\eta}{\eta}, \tag{2}$$

where $\alpha \in (0,1)$ governs the share of income accruing to labor; $\eta > 1$ determines the marginal cost of adopting more productive technologies; and $\tau \geq 0$ represents potential barriers to technology adoption in the modern sector in the spirit of Parente and Prescott (2002). This stands for more than the simple pecuniary costs and should also be interpreted to include deeper impediments to technology adoption, whether they be institutional or regulatory.

In Appendix A.4, we show that manager value can be expressed as:

$$\Pi_m(z_m h_m; \omega) = (z_m h_m)^{\frac{\eta(1-\alpha)}{\eta(1-\alpha)-1}} C(\omega; \tau, s_m),$$

which will imply increasing returns in sectoral human capital, $z_m h_m$, since our calibration below implies $\eta(1-\alpha) > 1$.[10] The optimal technology adoption in the modern sector also displays increasing returns to scale in sectoral human capital:

$$v(z_m h_m; w) = \left(\frac{(1-s_m)(z_m h_m)^{1-\alpha}}{\left(\frac{w}{\alpha}\right)^\alpha (1+\tau)^{1-\alpha}} \right)^{\frac{1}{\eta(1-\alpha)-1}},$$

since in our calibration below $\frac{1-\alpha}{\eta(1-\alpha)-1} > 1$.

The central idea we are highlighting in this study is how differences in human capital get amplified into differences in incomes through technology adoption. The parameter η, regulating the marginal cost of technology adoption, is key in quantitatively determining this amplification. Using the solution to the profit maximization problem, the elasticity of optimal technology levels with respect to sector-specific human capital is:

$$\frac{\partial \log v}{\partial \log(z_m h_m)} = \frac{1-\alpha}{\eta(1-\alpha)-1},$$

implying that a lower value of η, all else the same, results in a stronger amplification of human capital differences through technologies choices. The idea that returns to technology adoption are increasing in human capital was also motivated with microdata evidence in Section 2.2.

Equilibrium

We restrict our analysis to steady-state equilibria. There are only two markets in this economy, a goods market and a labor market, so it is enough to guarantee the latter clears. The equilibrium

[10] Where $C(\omega; \tau, s_m) = \left[\frac{(1+\tau)\omega^{\eta\alpha}}{(1-s_m)^\eta}\right]^{\frac{1}{1+\eta(\alpha-1)}} \left[\left(\frac{\eta-1}{\eta}\right)\left(\frac{1}{\alpha}\right)^{\frac{\alpha\eta}{1+\eta(\alpha-1)}} - \left(\frac{1}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}}\right]$.

wage rate ω^* clears the modern labor market, when labor demand by managers - who live in a set denoted by $\Omega_m \subseteq \mathbb{Z}$ - equals the efficiency units supplied by all workers in a set denoted by $\Omega_w \subseteq \mathbb{Z}$:

$$L^d(\omega^*) :- \int_{\Omega_m} l^d(z_m h_m; \omega^*) dz = \int_{\Omega_w} (1 - s_w) z_w h_w dz -: L^s(\omega^*),$$

where we show, in appendix A.4, that

$$l^d(z_m h_m; \omega^*) = \left(\frac{\alpha}{\omega}\right)^{\frac{\eta - 1}{\eta(1-\alpha)-1}} \left(\frac{\left[(1 - s_m)(z_m h_m)^{1-\alpha}\right]^{\eta}}{1 + \tau}\right)^{\frac{1}{\eta(1-\alpha)-1}}.$$

Figure 3: Optimal policies

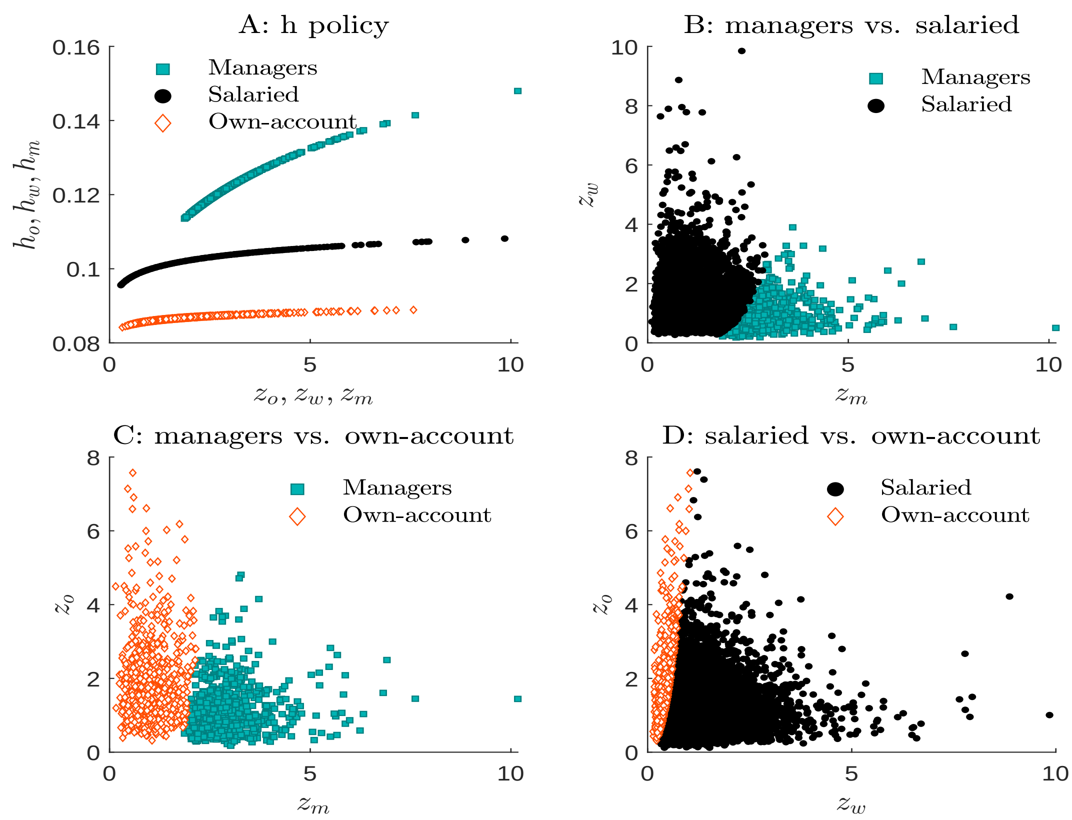


Figure 3 illustrates the optimal policies associated with the household problem for a sample of 10,0000 individuals whose abilities $z = \{z_o, z_w, z_m\}$ are drawn from the distribution described above.[11] Conditional on occupational choice, school time s is independent of abilities z by assumption, but the

[11] The parameter values underlying the figure are the ones in the calibration below.

resources spent on education, e, are not. As a result, human capital ultimately depends on z both through e and through occupational choices. Panel A shows that this relationship is increasing and concave, something we can also show analytically. Note that the impact of managerial skills z_m on human capital is much stronger than that of z_o or z_w, reflecting the fact that the return to managerial specific human capital, $z_m h_m$, is higher as it interacts with technology adoption v. Because of this, managers also spend considerably more resources on education, regardless of ability level, leading to higher levels of human capital.

Panels B, C, and D illustrate optimal occupational choices as a function of z. Let i, j, k be any occupations in $\{o, w, m\}$ such that they are all different from each other. Then, there are cutoffs in ability in occupation i, $\bar{z}_i(z_j)$, conditional on the ability level in a third occupation, z_k, such that an individual prefers occupation i over j if, and only if, $z_i \geq \bar{z}_i(z_j)$. These cutoffs are increasing in z_j: if $z_j^2 > z_j^1$, then $\bar{z}_i(z_j^2) \geq \bar{z}_i(z_j^1)$. This follows from the fact that V_m, V_w, and V_o are all strictly increasing in their own occupation's ability.

4 Calibration

This section presents how we take the model to the data. We assume that the counterpart of the *leading* economy, where barriers to technology adoption are absent ($\tau = 0$), is the U.S. economy. We choose this as our benchmark not only because of data availability, but also because the U.S. is commonly used as benchmark in the macro-development literature. Moreover, Comin, Hobijn, and Rovito (2008) find the U.S. leads in adoption and usage of most technologies they consider – in fact, they measure adoption lags relative to the U.S.

We estimate schooling years by occupation directly from the IPUMS-International microdata and calibrate the remaining model parameters to relevant data moments of the U.S. economy. Below, we explain and discuss why we choose these particular moments, since such choices are not, in general, innocuous in the context of calibration. See Appendix A.1 for more details on the data used in the calibration.

We start by setting some parameters exogenously. As mentioned, we set schooling time by occupation by directly matching the IPUMS-International data on years of schooling and assuming a 70 year lifetime: $s_o = 11.9/70$, $s_w = 12.9/70$, and $s_m = 14.2/70$. Furthermore, we set α such that the labor share of value added in the modern sector, which in the leading economy is given by $\alpha\left(\frac{\eta}{\eta-1}\right)$, is equal to two-thirds (subject to η, which we set below).

This leaves 6 parameters $(\eta, \theta, \phi, \psi, \rho, \sigma)$ to target 6 moments. An important facet of the economy we need to capture is the occupational distribution. This is a central feature of the model economy, as it drives both the extensive margin of technology adoption, as well as the human capital investment

Table 4: Calibration

Parameters	**Targets**
$\alpha = 0.335$	Labor income share: 67%
$s_o = 0.170$	Years of schooling (own-account): 11.9
$s_w = 0.184$	Years of schooling (workers): 12.9
$s_m = 0.203$	Years of schooling (managers): 14.2
$\eta = 2.002$	Share of salaried workers: 86.5%
$\phi = 1.192$	Mincer return (modern): 9.1%
$\psi = 0.009$	Share of own-account workers: 7.1%
$\rho = 0.503$	Mincer return (traditional): 3.2%
$\sigma = 0.567$	Variance of log-earnings: 0.43
$\theta = 0.034$	Education spending: 6.6% of GDP

decisions. To do this, we match the share of traditional sector producers in the model to the share of own-account individuals in the U.S. economy (7.1%) and the share of modern sector managers in the model to the share of managers in the U.S. economy (6.4%) – the remaining 86.5% are salaried workers.

Next, we must pin down the cost/benefit trade-off behind human capital investment choices. As Erosa, Koreshkova, and Restuccia (2010) make clear, the input split in human capital production between schooling time and educational expenditures is a margin that has particularly important quantitative implications, and therefore needs to be credibly pinned down. Moreover, since our main experiment below involves changing schooling across countries according to the data, it had better be the case that the impact of schooling on earnings is credible. Otherwise, our claims that changes in education are amplified by technology choices could be coming about simply because the model overestimates the impact of education on earnings. To make sure this is not a problem, we estimate a Mincer regression using the microdata to obtain sector-specific returns to schooling: one for own-account workers, whose hourly earnings increase by 3.2% for an additional year of schooling, and one for individuals working in the modern sector (salaried workers and managers together), whose hourly earnings increase by 9.1% (see appendix A.1 for more details). We then compute these counterparts in the model using a discrete approximation and make sure they match these two values. On the cost side, beside the fact that the opportunity cost of time is captured by the forgone income from time spent in school, we match the GDP share of educational expenditures in the U.S. (6.6%).[12]

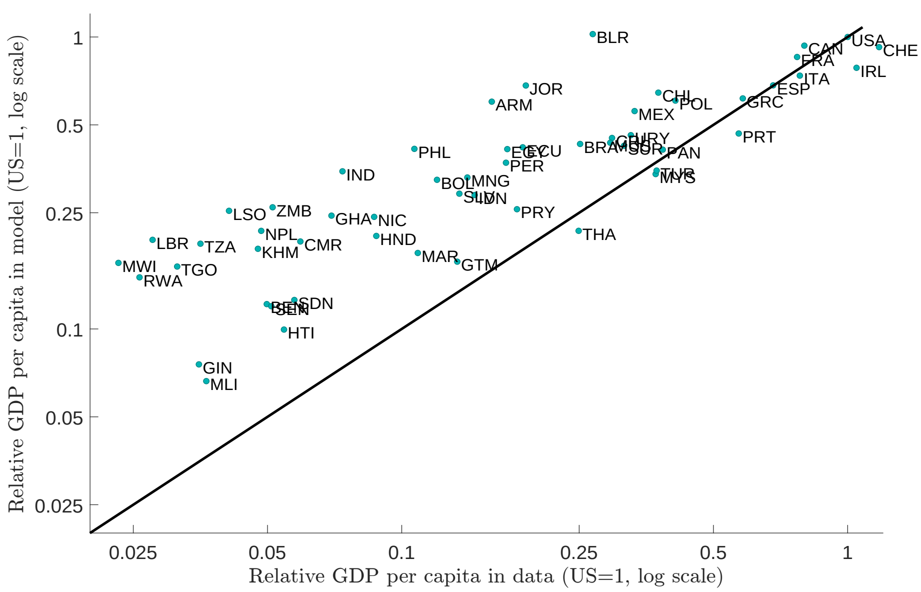
[12] This is the average, from 1995 to 2010 of educational expenditures (public and private) as a share of U.S. GDP. See OECD (2013), Table B2.1.

Finally, in models where there is considerable earnings dispersion owing to both innate talent and occupational choices, it is important to discipline both sources. We already pinned down the distribution of occupations, but we also discipline the overall earnings inequality by matching the variance of log earnings in the U.S. economy (0.43).[13] The complete calibration is summarized in Table 4.

5 Results

Model economies may differ from the US benchmark either because of different occupation-specific schooling, or because of higher barriers to technology adoption (by construction they cannot be lower). These two "shocks" work through various margins: (i) less educated workers acquire less human capital and are consequentially less productive; (ii) less educated workers and/or higher adoption barriers lead modern establishments to adopt lower levels of technology and; (iii) they also lead to lower wages and lower managerial earnings, in turn driving more individuals to select into the traditional sector. Our main thesis is that (ii) and (iii) – what we termed the *intensive* and *extensive* margins of technology adoption – amplify the impact of education on output, and that this amplification is quantitatively meaningful.

Figure 4: Model and data, country-by-country



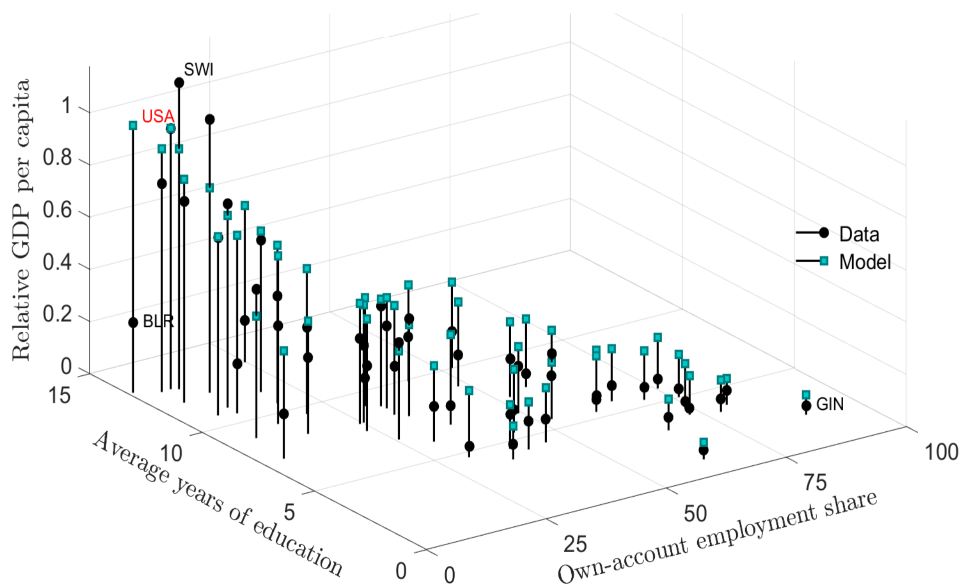
To show this, we create model counterparts for each country in our sample. Each laboratory econ-

[13]The targeted variance of log hourly earnings represents the residual variation after controlling for age, state of residence, state of birth, urban location, and time effects.

omy matches two characteristics of their real-world counterparts: (i) the average years of schooling in each of the three occupations, s_j, and (ii) the share of individuals working in the traditional sector (see Appendix A.1). The former is directly estimated from the microdata for each country, while the latter is matched by varying barriers to technology adoption τ. As adoption barriers increase, more individuals find it worthwhile to pursue a career in the traditional sector.

Figure 4 shows the results of this experiment for all 55 countries in our sample, comparing relative outputs in the model to the data. For a summary measure, letting $\hat{y}$ denote relative output in the model and y its data counterpart, $1 - \frac{\sum |\hat{y}-y|}{\sum |1-y|}$, is the share of the fall in output (relative to the U.S.) that is captured by the model. In this case, schooling and adoption barrier differences – working through the model mechanisms – account for 79 percent of income disparities relative to the U.S. The model not only does well for the average country, but it is also apt at capturing the performance of very poor countries. The poorest country in our sample is Malawi (MWI), for whom the model accounts for 85 percent of the shortfall relative to the U.S. level.

Figure 5: Model and data, matching the targets

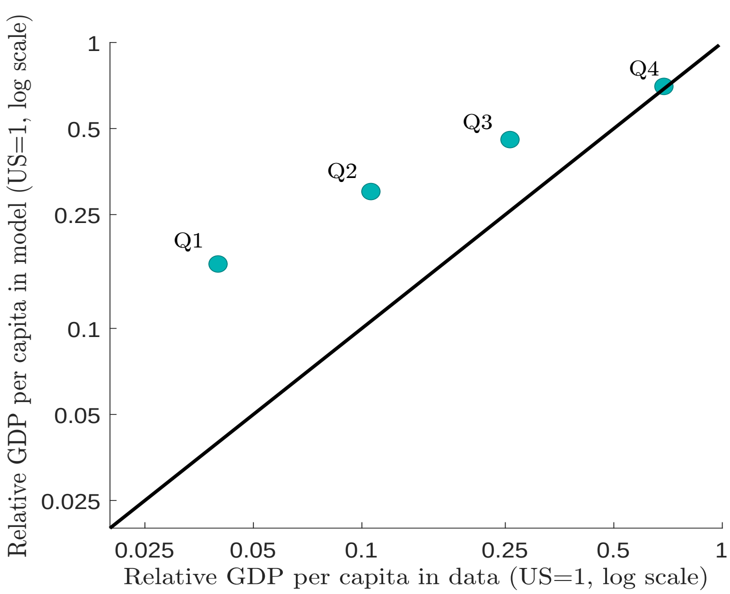


In Figure 5 we present a different perspective on the same data, designed to capture the model's limitations. Each country is represented by a stem with two markers whose heights are the output in the model (or the data) relative to the U.S. We report relative output as a function of the share of individuals in the traditional sector and the average years of schooling in the data. To be clear, since we are only matching schooling years in each occupation and the share of individuals in the traditional sector, average years of schooling in the model and in the data may differ. This happens because we are not targeting the shares of salaried workers or managers, which vary endogenously. In practice though, the difference between years of schooling in the data and the model only averages 1.2 percentage points across our sample.

This perspective is informative about what the model can and cannot do. By construction, the model cannot fully account for the output of countries, like Switzerland, which have a higher GDP per capita than the U.S. despite lower average schooling and higher own-account employment share. In addition, the model also does a poor job for a country like Belarus, who exhibits much lower GDP per capita than the U.S. despite reporting higher average schooling and lower traditional sector employment. The explanation behind Belarus's relatively low output lies elsewhere and not in the mechanisms we emphasize. Crucially though, there are not many outliers such as these two countries, and the model does a good job of capturing cross-country income dispersion.

To gloss over outliers and assess the performance of the model across income levels more systematically, we group countries into quartiles of the income distribution. A country in the top quartile (ex-US) averages 64% of the U.S. GDP per capita, while a country in the bottom quartile averages only 4%. We then repeat the exercise, matching average years of schooling in each occupation for each quartile, and changing barriers to technology adoption to match the average share of individuals in the traditional sector in each quartile. The results appear in Figure 6 (note the log-log scale).

Figure 6: Model and data, by quartiles



The model puts the poorest quartile's income at 16.8% of the U.S., implying it is able to capture about 87% ($1 - \frac{0.168-0.04}{1-0.04}$) of the output difference. An equivalent, but admittedly less impressive, way to put this is that the model can generate a factor difference of 6, between the U.S. and the poorest quartile's average output, compared to a factor of 25 in the data.[14]

One question that immediately comes to mind is whether the model is generating this large output drop on the back of unrealistically large barriers to technology adoption. The poorest quartile's τ in the model is 1.08, implying that technology adoption is roughly twice $(1+\tau)$ as expensive in the world's poorest countries compared to the U.S. This strikes us as entirely reasonable; an underestimation of true barriers if anything, both compared to other models in the literature, as well as in the context of cross-country data estimates of different types of business costs. For example, in Parente and Prescott (2002) a barrier size twice as high as this is necessary to generate a fall in output similar to what we get.[15] World Bank (2020a) reports that the cost of starting a business in Guinea is roughly half as high as in the U.S. (measured in USD), but since Guinea's income is 25 times smaller, this means startup costs in Guinea are 12.5 times larger than in the U.S., a magnitude much larger than what our model requires. Business setup costs are, of course, different from technology adoption costs, but we think this helps drive our point across that assuming technology adoption costs in poor countries are double what they are in the U.S. is most definitely not an overestimation.

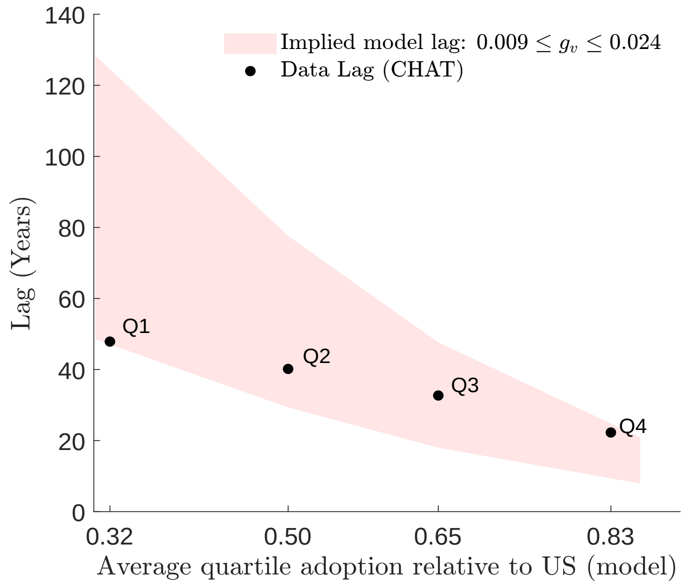
Another way to independently corroborate the reasonability of the model's technology adoption outcomes is to compare them to the empirical measures of the technological lags in Comin, Hobijn, and Rovito (2008). Recall that these lags represent how many years ago a set of important technologies were used in the U.S. with the same intensity as they are presently used in other countries. Our model is not a dynamic one, but the thought experiment we have in mind is of a world where technology usage in different countries may rise over time as barriers fall and education improves. Letting a given quartile's average technology choice in the model be denoted by v_Q and the corresponding US object be v_{US} then, for a particular average annual growth rate of technology adoption, g_v, the number of years it takes for this quartile to catch up to the US, N_Q, is implicitly given by $v_{US} = v_Q(1+g_v)^{N_Q}$.

The question is then, can the levels of v we get from the different quartiles in the model generate model-implied lags that resemble the Comin, Hobijn, and Rovito (2008) lags for *reasonable* technology adoption growth rates? The average lags (in years) from Comin, Hobijn, and Rovito (2008) run from 18.8 in the richest quartile to 48.2 in the poorest. They show up as the black dots in Figure 7. Can these lags be rationalized by the model for realistic growth rates? The shaded area represents the years it would take for the adoption level, v_Q, in each model quartile to reach the U.S. level, v_{US}, for yearly rates of growth between 0.9% (top contour) and 2.5% (bottom contour). How *reasonable* is this interval for growth rates of technology adoption? The best empirical proxies available for a wide

[14] High-income countries are under-represented in our 55-country sample. As a result, average relative incomes by quartile in our sample are lower than in a more representative sample of 183 countries in the Penn World Tables, Feenstra, Inklaar, and Timmer (2015), from the first to the third quartile. Nonetheless, the bottom quartile's relative average incomes are very similar, at 0.04 in our sample and 0.044 in the PWT. See Table 6 in the appendix.

[15] Model details also matter, of course, and the cost of adoption function in Parente and Prescott (2002) is different from ours. But still a useful approximation, we think.

Figure 7: Implied model lags vs. data



variety of countries are estimates of measured TFP growth.[16] In the U.S., according to the database associated with Fernald (2012), TFP growth has averaged 1.2% annually since 1948. To look at a wider set of countries, we use the Penn World Tables, Feenstra, Inklaar, and Timmer (2015), and compute estimates of TFP growth rates for 15 year intervals from 1980 to 2019 for a sample of 103 countries. We find that 95% of the observations lie between -4.1% and 2.7%, an interval that contains the one we use in Figure 7. We view this thought experiment and the model implied lags, which were in no way targeted, as corroborating evidence in favor of the model.

The interaction between education and barriers to adoption

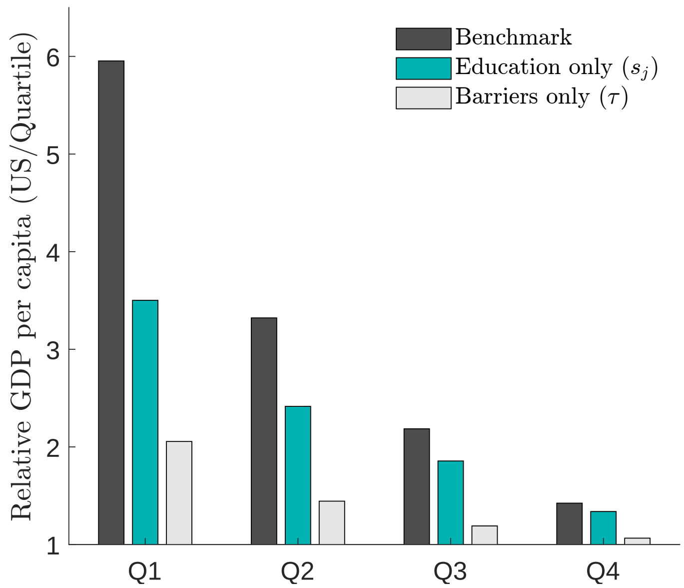
To better understand the quantitative importance of the interaction between education and technology adoption, we shut down one shock at a time. First, to quantify the impact of education in isolation, we keep the costs of technology adoption at U.S. levels ($\tau = 0$) and change average years of schooling in each occupation, for each quartile, to match the data. Next, to single out the effects of technology adoption barriers, we keep average years of schooling in the different occupations at U.S. levels, and we change the cost of technology adoption for each quartile by the same magnitude as in our benchmark experiment (e.g., $\tau = 1.08$ for the poorest quartile).

Figure 8 shows that our benchmark, which interacts the two shocks, results in output differences that are larger than the sum of the parts, with the amplification rising as incomes drop. This is one

[16]Measured TFP changes reflect a gamut of factors beyond technology adoption, but they are widely available.

our main quantitative results: the complementarity between education and barriers to technology adoption is quantitatively meaningful for cross-country income dispersion.

Figure 8: Shock decomposition



An alternative way to assess the importance of the interaction is to fix education at U.S. levels and raise barriers to match the share of employment in the traditional sector in each quartile (instead of increasing barriers to the same level as in the benchmark). In this case, τ needs to go up to 2.8 (as opposed to 1.08) for the poorest quartile and the output factor for this quartile is 3 (as opposed to 2 in the "barriers only case" in Figure 8). Importantly, this result is also relevant for the literature that looks at the size of barriers or distortions needed to explain the composition of the economy (e.g., large informal sector) in poor countries.[17] Indeed, our results imply that once we account for the importance of education and its complementarity with technology adoption in modern firms, the barriers needed to rationalize the data are much smaller.

Furthermore, these results are useful to isolate the importance of education for both income gaps and differences in the organization of production across countries. For instance, changing only education levels by occupation results in an income gap of around 3.5 between the U.S. and the poorest quartile, and the share of own account workers increases by over 20 percentage points in those poor economies relative to the U.S. value. Thus, education gaps alone can account for a large fraction of the difference in the share of own-account workers between rich and poor economies.

[17]For example, see Restuccia and Rogerson (2017) for a recent review of the misallocation literature.

Importance of the extensive and intensive margins of technology adoption

As we have been pointing out, technology adoption affects output through two main margins (setting aside general equilibrium effects): an intensive and an extensive one. The former operates as modern-sector managers optimally decide to use better or worse technologies, while the latter operates through the occupational choices that determine the relative sizes of the modern and traditional sector (where no technology choice is available, and schooling tends to be lower.) An important motivation for including the latter type of sector, stems from the well-known facts that informal sectors are very large in poor economies, and that informal firms are smaller, less productive, and use less human capital than their formal counterparts.[18] Moreover, the Informal Sector Enterprise Surveys from the World Bank, a subset of WBES (2023), also show that informal firms use much less basic technologies such as computers (or even the internet) compared to formal firms. Nonetheless, it important to ask how much this extensive margin contributes to the differences in income we find in Figure 6. To do this, let sh_o denote the share of individuals working in the traditional sector and define $y_o := \int_{\Omega_o} \Pi_o dz$ to be total output in that sector, and $\bar{y}_o := \frac{y_o}{sh_o}$ be average output. In addition, let $y_m := \int_{\Omega_m} \Pi_m dz + \omega L^d(w^*)$ denote (net) output in the modern sector, and $\bar{y}_m := \frac{y_m}{1-sh_o}$ the corresponding average net output. Then, we can express the economy's (net) output as $y = sh_o\bar{y}_o + (1 - sh_o)\bar{y}_m$.

To assess the contribution of the extensive margin, we compute a counterfactual income in the poorest quartile where we keep the intensive margin, represented by the net output change in the modern sector, constant. That is, we compute $sh_o\Big|_{Q1}\bar{y}_o\Big|_{Q1} + (1 - sh_o)\Big|_{Q1}\bar{y}_m\Big|_{US}$. It turns out that this counterfactual output is 2.35 times smaller than the U.S. output. Given that the benchmark experiment resulted in a factor of 5.95, this implies the extensive margin accounts for a non-trivial fraction of the income gap generated in the model. We conclude that models that ignore the fact that in the poorest of economies most of the economic activity is done in settings where the possibility of adopting better technologies is largely absent, are going to miss a significant part of the interaction between education and technology adoption.

An economy without technology adoption

In the *Education only* experiment shown in Figure 8, even if barriers are not changing, there is still some interaction between an economy's human capital and technology adoption. This is because as we move to lower quartiles and schooling falls, less educated managers, who face a less educated workforce, optimally decide to adopt lower levels of technology, so the intensive margin of technology adoption is still operating. Moreover, the extensive margin is still at play, with a larger share of individuals optimally selecting into the traditional sector as they face lower equilibrium wages in

[18] See Porta and Shleifer (2014) among many others.

the modern sector. To remove these channels altogether, we consider a one-sector economy where individuals continue to build human capital as in our benchmark economy, but unlike what happens there, they can only choose to be workers or managers, and the latter do not get a technology choice.

This economy is also populated by a unit mass of individuals who derive utility from consumption, but they are endowed with abilities in only two different occupations: workers and managers $j \in \{w, m\}$ according to the tuple $z = \{z_w, z_m\} \in \mathbb{R}^2_+$. Like before, the z_j are independently and identically distributed according to $\log z_j \sim N(0, \sigma)$. We also continue to assume that each of the two occupations requires a specific amount of schooling years, s_j, and that in addition to occupational decisions, individuals also choose the level of non-schooling education expenditures, e, which together with schooling time, s_j produce human capital h_j.

Given ability z and the choice of occupation j, the individual's problem in this simplified economy can be expressed as:

$$
\begin{aligned}
V_j(z) = \max_{c,e} \quad & \log(c) \\
s.t. \qquad & c = I_j(z, h_j; w) - e, \\
& I_j(z, h_j; \omega) \in \{(1 - s_w)\omega z_w h_w, \Pi_m(z_m h_m; \omega)\}, \\
& h_j = s_j^{\phi} e^{\theta},
\end{aligned}
$$

where ϕ and θ play the same roles as before. Occupational income I_j continues to depend on individual-specific ability z, human capital h_j, and the wage per efficiency unit ω. Workers receive wage earnings proportional to their efficiency units, for the time they actually spend at work (outside of school). The managerial earnings are given by $\Pi_m(z_m h_m; \omega)$ in a way to be detailed below.

The single good in the economy is produced by managers and workers working together, where the former are the residual claimants, and the latter are salaried. An individual that has decided to become a manager, given their sectoral human capital, $z_m h_m$, takes the wage rate, ω, as given and chooses efficiency units of labor, l, to maximize profits:

$$
\Pi_m(z_m h_m; \omega) = \max_l (1 - s_m) l^{\alpha} (z_m h_m)^{1-\alpha} - \omega l,
$$

where $\alpha \in (0, 1)$.

To calibrate the model, we use the same schooling-related moments as above, and a subset of the targets used before, all shown in Table 5. Most of the parameters except α are close to what they were in our benchmark economy. The reason α is higher is that we are not setting its value such as to match the labor income share and instead pick it, together with the 3 other parameters, to match the 4 targets on the lower half of the table (note that in this model α modulates both the labor share and the span-of-control in production). As a result, this economy does have a counterfactually high labor income share.[19]

Table 5: Calibration (human capital economy)

Parameters	**Targets**
$s_w = 0.184$	Years of schooling (workers): 12.9
$s_m = 0.203$	Years of schooling (managers): 14.2
$\alpha = 0.913$	Share of salaried workers: 86.5%
$\phi = 1.660$	Mincer return: 9.1%
$\sigma = 0.672$	Variance of log-earnings: 0.43
$\theta = 0.064$	Education spending: 6.6% of GDP

The experiment now simply consists of varying the average years of schooling in each of the two occupations to match the ones observed in each of the quartiles of the income distribution. The results in Figure 9 show that reducing schooling to match the data in the average poorest quartile country decreases output by a factor of two only, compared to a factor of 3.5 in our benchmark economy when only education is changing. We argue that this large difference owes to the interaction between human capital and technology choices in our benchmark model.

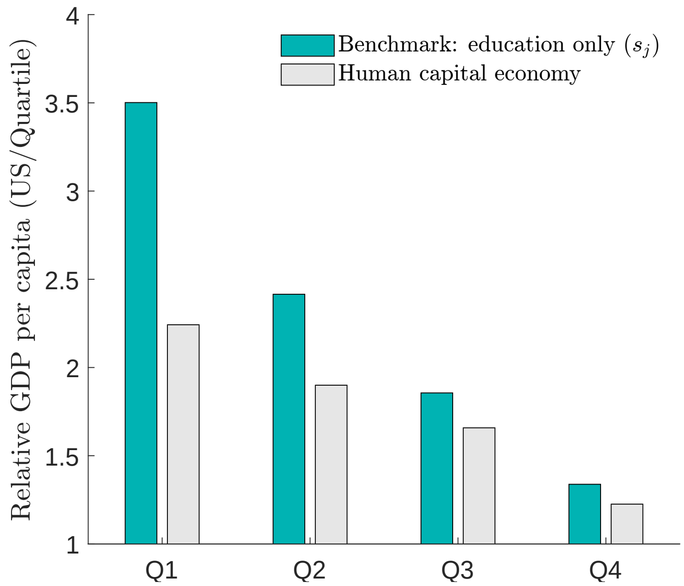
This is not to say that changes in education cannot have a stronger effect on output than this. In more detailed models of human capital, like Erosa, Koreshkova, and Restuccia (2010), the importance of human capital can be much higher. Our conjecture is that if human capital is allowed to interact with technology adoption in the context of those models, then that effect would be even higher.

Adjusting for education quality

There is a large literature arguing that cross-country cognitive skills are more strongly related to income than school attainment is. Hanushek and Kimko (2000), for example, find that direct measures of labor-force quality from international mathematics and science test scores are strongly related to growth. Additionally, Schoellman (2012) shows that differences in education quality can increase the importance of schooling in accounting for income difference across countries. Our individual-level measure of schooling years from IPUMS-International is not quality-adjusted. To assess the robustness of our results we adjust years of schooling for quality using harmonized test scores from major international student achievement testing programs. This is the same harmonization process

[19] If we set the value of α to match a labor share of income equal to two-thirds, as in the benchmark economy, the model overestimates the share of managers, but the cross-country income comparisons are basically unaffected.

Figure 9: Comparison to human capital economy



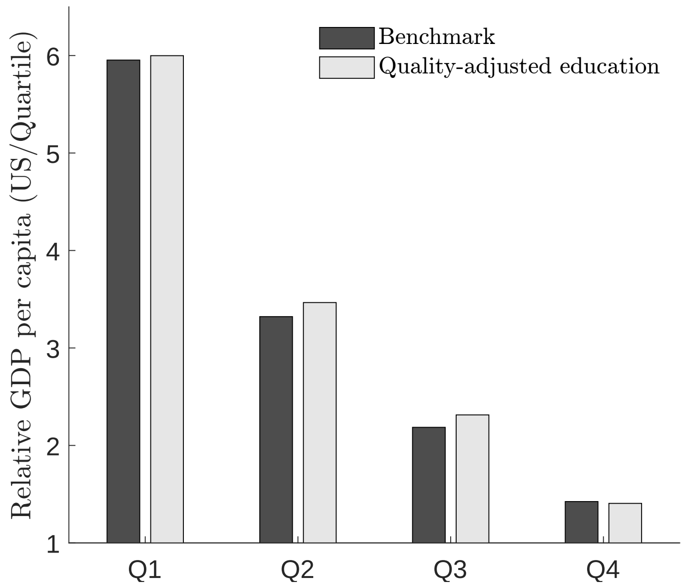
the World Bank uses in computing its Human Capital Index.[20] These test scores adjustment factors are country-specific, independent of occupation, and are shown in Table 9 in the appendix. Poorer countries suffer a stronger adjustment, on average, putatively because of their lower education quality.

We recalibrate the model for the US economy using the adjusted schooling years, and then re-run our quartile experiment. Note that in the model, schooling years play two roles: they serve as inputs into the production of human capital, and they also represent the time individuals spend outside the market, not working. We use the quality-adjusted years for the former, and the unadjusted for the latter. This way, differences in education quality affect the contribution of schooling time to human capital formation, but time spent away from the labor market is independent of education quality. The larger differences in adjusted schooling between the US and lower quartiles mean that the barrier size τ that is needed to match the share of own-account individuals in the poorest economies is only half as large as before (at 0.51 versus 1.08). Nonetheless, the income factor differences that come out of the model are robust to this adjustment. A little larger, if anything, as Figure 10 shows.

We conclude that accounting for education quality reinforces our findings, and even helps highlighting the fact that, in our model, education differences can be substantially amplified with relatively small differences in barriers to adoption across countries. These results also imply that as we increase the differences in human capital stocks across countries, the adoption barriers needed to rationalize the data are smaller. That is because individuals self-select into sectors based on their human capital, which reduces the importance of misallocations associated with such barriers as an explana-

[20] See World Bank (2020b).

Figure 10: Adjusting for education quality



tion of cross-country differences in income. Instead, our results suggest that barriers associated with lower human capital accumulation can be key in accounting for income gaps and differences in the organization of production across countries.

6 Conclusion

While human capital has been shown to be an important factor behind cross-country output differences, less is known about its complementary effects on other, equally important, determinants of such differences. This study argues that the extent to which countries adopt better, more efficient technologies, is related to their human capital level in a way that is quantitatively important in accounting for cross-county income differences. We think of technology adoption as occurring along two margins: an intensive margin, with modern firms adopting more or less efficient technology; but also an extensive margin, with managers optimally choosing to operate in a modern sector, where technology adoption choices depend on their human capital level, or a traditional self-employment sector where technology adoption is absent. This is intended to capture the fact that informal, self-employment activities, which are much more prevalent in developing countries, are associated with more limited technological adoption choices.

We use microdata to both motivate and discipline our general equilibrium model along educational and occupational choice margins. The model is built to capture income differences between economies that differ both in terms of schooling as well as in terms of barriers to technology adoption. Our benchmark economy can capture over 85% of the income differences between the U.S. and the average country in the bottom quartile of the world income distribution. Comparatively, a model where individuals acquire education but where technology adoption is absent, can only generate around half of the income differences between the U.S. and the average bottom quartile country. We conclude that the interaction between education and technology adoption is quantitatively meaningful in accounting for the cross-country income dispersion.

A Appendix

A.1 Data appendix

This section provides more details on the microdata (IPUMS-International) used in the paper. We focus on countries that have individual data on education, employment status, and occupation. We use the latest available sample for each country based on these data requirements. Every sample is from a year within the last two decades (2000 or later) and the original data source is either a census or a survey. We map educational attainment to education years - between 0 and 16 - following Lagakos, Moll, Porzio, Qian, and Schoellman (2018). Employment status in the data refers to individuals being categorized mainly as employers, own-account workers, wage/salary workers, or unpaid workers. Occupations are based on 1-digit codes following the ISCO. In all cases, we restrict our analysis to male individuals who work in the private sector and are between 25 and 65 years old. The latter is done to take into account life-time education.

As explained in the main text, one of our main goals is to combine data on occupations and employment status to create three categories of employment that are consistent with occupational choices in our model. For our cross-country analysis in Section 2, we use data from countries for which it is possible to distinguish self-employment status as own-account employment, employee, or another category. That is because countries which only have a generic category for self-employment are not useful for our analysis as we cannot distinguish between traditional and modern forms of entrepreneurship.[21] Moreover, we do not consider individuals who are categorized as unpaid workers, who are working for the armed forces, or who have an unspecified occupation.

Table 6 presents aggregate summary statistics of our data by region of the world. These are unweighted statistics for each region calculated by taking the average across the values obtained for each country. The table highlights that we have a good number of developing and poor economies in our data.

Table 6: Aggregate Summary Statistics

Region	No. Countries	Education Years	Share of Wage/Salary Workers
Africa	17	4.9	0.37
Asia	11	8.0	0.52
Europe	9	11.4	0.79
Latin America	16	7.4	0.55
USA/Canada	2	12.9	0.85

Source: Authors' estimations using IPUMS-International data.

Table 7 presents more detailed summary statistics by country, together with the data on technology usage lags from Comin, Hobijn, and Rovito (2008). These are the country-level estimates used in figures of Section 2.1 and in the calibration of the model for cross-country comparisons.

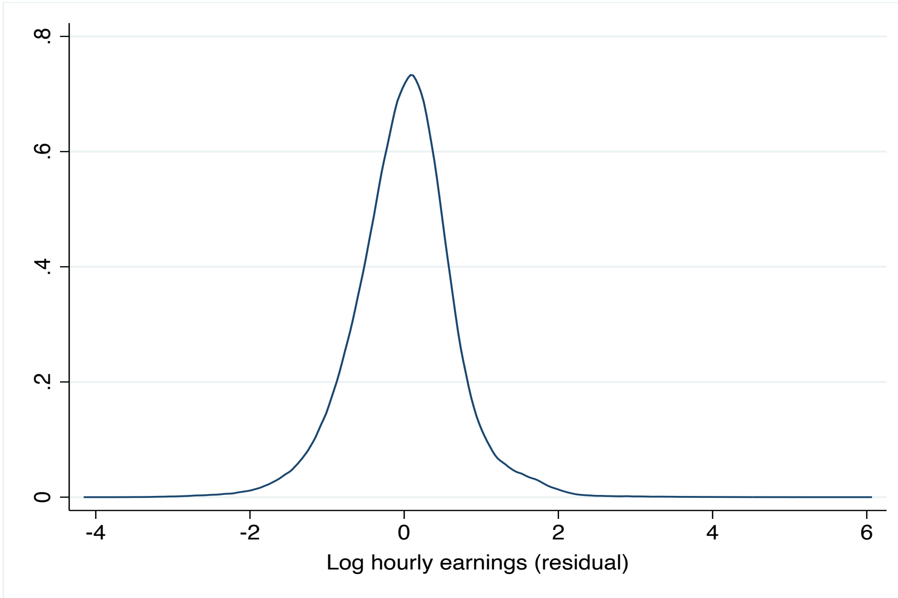
[21] A particular case is the United States. This country reports data for self-employment based on incorporated and unincorporated status. Then, to include the United States as our key reference, we split self-employment based on the occupation dimension (managers/professionals vs the rest) as explained in the main text.

Table 7: Summary Statistics by Country

Country	GDP pc	N_o	N_w	N_m	s_o	s_w	s_m	Tech. Lag
CHE	1.18	0.08	0.79	0.13	12	13	13	10.6
IRL	1.05	0.12	0.76	0.13	10	12	13	9.0
USA	1.00	0.07	0.86	0.06	12	13	14	0.0
CAN	0.80	0.05	0.84	0.11	12	13	13	-0.4
ITA	0.78	0.10	0.74	0.16	10	11	12	20.0
FRA	0.77	0.06	0.85	0.10	11	12	13	10.2
ESP	0.68	0.07	0.82	0.11	9	11	11	23.0
GRC	0.58	0.19	0.66	0.15	10	12	13	25.2
PRT	0.57	0.06	0.80	0.14	6	9	9	25.8
POL	0.41	0.18	0.73	0.08	9	11	12	28.2
PAN	0.38	0.32	0.64	0.04	7	10	12	32.2
CHL	0.38	0.13	0.76	0.11	7	9	12	26.6
TUR	0.37	0.33	0.60	0.07	5	9	9	34.2
MYS	0.37	0.26	0.65	0.09	4	7	8	27.6
MEX	0.33	0.20	0.74	0.06	8	10	12	33.4
URY	0.33	0.24	0.60	0.15	7	8	10	
SUR	0.32	0.32	0.60	0.08	8	9	10	
CRI	0.30	0.25	0.62	0.13	7	8	11	28.6
MUS	0.29	0.14	0.79	0.07	7	9	9	28.4
BLR	0.27	0.01	0.96	0.03	13	13	14	
BRA	0.25	0.23	0.68	0.08	6	8	11	30.4
THA	0.25	0.53	0.40	0.07	4	8	7	32.8
JOR	0.19	0.10	0.81	0.09	9	11	11	25.8
ECU	0.19	0.32	0.61	0.07	7	8	11	35.2
PRY	0.18	0.49	0.42	0.09	5	8	10	36.0
EGY	0.17	0.04	0.89	0.06	5	7	10	43.8
PER	0.17	0.42	0.51	0.06	8	11	13	37.6
ARM	0.16	0.25	0.73	0.03	12	14	16	
IDN	0.15	0.53	0.40	0.07	6	9	8	40.6
MNG	0.14	0.52	0.44	0.04	8	12	14	31.2
SLV	0.13	0.30	0.61	0.09	4	7	8	38.0
GTM	0.13	0.39	0.46	0.15	3	5	5	41.0
BOL	0.12	0.48	0.43	0.09	7	10	13	40.2
MAR	0.11	0.41	0.52	0.07	3	5	6	39.4
PHL	0.11	0.30	0.59	0.11	7	10	9	37.4
HND	0.09	0.45	0.46	0.09	3	5	8	39.4
NIC	0.09	0.44	0.52	0.04	4	7	10	40.4
IND	0.07	0.37	0.53	0.10	6	7	10	41.2
GHA	0.07	0.59	0.32	0.09	5	10	8	41.8
CMR	0.06	0.66	0.32	0.03	4	9	9	44.8
SDN	0.06	0.36	0.45	0.19	2	5	4	46.8
HTI	0.05	0.81	0.16	0.04	3	10	9	52.7
ZMB	0.05	0.57	0.39	0.03	6	10	11	35.2
SEN	0.05	0.66	0.23	0.11	2	7	4	42.6
BEN	0.05	0.78	0.15	0.07	2	9	7	47.8
NPL	0.05	0.61	0.35	0.05	4	6	9	48.4
KHM	0.05	0.71	0.27	0.02	4	8	8	51.0
LSO	0.04	0.31	0.68	0.02	3	5	8	
MLI	0.04	0.63	0.35	0.02	1	1	3	50.2
TZA	0.04	0.75	0.19	0.06	5	9	6	48.4
GIN	0.04	0.89	0.08	0.03	2	7	6	46.5
TGO	0.03	0.76	0.19	0.05	4	9	10	44.4
LBR	0.03	0.63	0.31	0.06	4	9	7	
RWA	0.03	0.73	0.26	0.01	3	6	8	59.3
MWI	0.02	0.74	0.23	0.03	4	6	6	

Notes: N_j and s_j refer to employment shares and average education years in each occupation category defined in the main text. Tech. Lag is calculated with data from Comin, Hobijn, and Rovito (2008). We only report lags for countries that have data in at least 3 of the 5 technologies considered. GDP per capita is expressed relative to the US.

Figure 11: Distribution of hourly earnings in the United States



Source: Authors' estimations using IPUMS-International data.

Additionally, for the calibration of the model in Section 4, we use multiple samples for the United States from 1990 to 2015. To the variables described above, we add individual data on annual earnings, number of weeks worked in a year, and hours worked per week. We use these variables to calculate hourly earnings. We restrict the sample to individuals working full-time (at least 30 hours per week) with positive labor earnings and, to reduce the influence of outliers, we exclude earnings in the lowest and highest percentile. Individual earnings are deflated using the GDP deflator from the IMF.

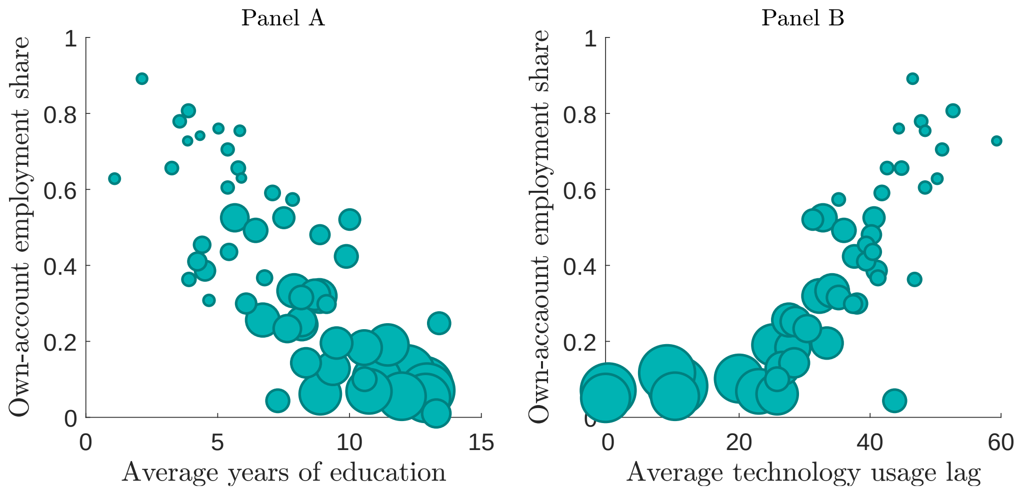
One of the calibration targets in our baseline economy is the variance of log hourly earnings in the United States. To compute this, we first estimate a regression of log hourly earnings on time effects, non-linear age effects, and geography variables (state of residence, state of birth, urban status). The results are presented in Figure 11.

Lastly, in our baseline calibration for the United States, we target returns to education by sector. To compute such returns, we estimate a regression of log hourly earnings on a dummy variable that takes value 1 if the individual is not an own-account worker (part of the modern sector) and zero otherwise, and an interaction between this dummy variable and individual education years, while controlling for time affects and a quadratic in age. We use the coefficients on the interaction (the estimated Mincer returns) as targets for education returns in our calibration.

A.2 Occupational choices, education years, and technology usage lags

This section provides additional evidence on the importance of the organization of production and occupational choices in mediating between education and technology adoption. In Panel A of Figure 12 we show the fraction of own-account employment against average schooling attainment across countries. Unsurprisingly, there is a strong negative correlation between these two variables. It is worth highlighting that the group of countries with large shares of own-account employment and low average education also tend to be poorer – circles are proportional to income per capita.

Figure 12: The importance of occupational choices



Panel B of Figure 12 illustrates the strong positive relationship between average technology usage lags and the fraction of own-account employment across countries. Note how countries that have around half or more of their labor force in own-account production tend to have a technology usage lag of more than 40 years.

Table 8: Own-account Employment and Technology Usage Lags

	Average	Internet users	PCs	Electricity	Aviation-Cargo	Tractors per capita
Own-account (%)	0.429	0.154	0.204	0.891	0.460	0.393
	(0.0482)	(0.0159)	(0.0287)	(0.0915)	(0.0868)	(0.0766)
Observations	48	47	46	48	39	48

Notes: Standard errors are in parenthesis. Employment shares are estimated with IPUMS-International data and technology usage lags are obtained from Comin et al. (2008). We only include countries that have data in at least 3 of the 5 technologies considered. GDP per capita is expressed relative to the US value.

In Table 8, we confirm the strength and statistical significance of this relationship by running simple cross-country regressions of own-account employment shares on technology usage lags for each of the 5 technologies that we consider. The positive correlation between both variables is weaker for more modern technologies, like the Internet, but still meaningful (and always statistically significant).

This relationship leads us to think of the organization of production as an extensive margin in technology adoption. This feature is incorporated in the model presented in the main text, which sports a modern sector where managers hire workers and decide on the technology level they choose to adopt, and a traditional sector, where self-employed individuals do not decide on technology adoption and their productivity depends exclusively on their innate skills and education.

A.3 Education quality adjustment

Table 9 presents the differences between raw years of schooling and quality-adjusted years of schooling for the United States and each income quartile. This is the data used in the exercise presented in Figure 10 in the main text.

We follow the same harmonization process the World Bank uses in computing its Human Capital Index in World Bank (2020b). These are harmonized scores across major international student achievement testing programs measured in Trends in International Mathematics and Science Study (TIMSS)-equivalent units from Patrinos and Angrist (2018), where 300 is minimal attainment and 625 is advanced attainment. In computing the adjustment factor, we normalize by 625. We do this for each country in our sample and then average the values in each quartile.

Table 9: Raw and quality-adjusted years of schooling

	Raw schooling years				Adjusted schooling years		
Group	Own-account	Workers	Managers	Adjustment	Own-account	Workers	Managers
USA	11.90	12.90	14.20	0.82	9.70	10.52	11.58
4th quartile	7.16	9.28	10.76	0.71	5.14	6.62	7.65
3rd quartile	5.76	8.33	9.71	0.64	3.73	5.37	6.26
2nd quartile	3.70	7.37	7.48	0.60	2.25	4.46	4.52
1st quartile	3.23	7.42	7.32	0.59	1.88	4.38	4.31

A.4 Profit maximization in modern production

Recall from (2) that the problem of a modern sector manager is:

$$\Pi_m(z_m h_m;\omega) = \max_{v,l}(1-s_m)vl^{\alpha}(z_m h_m)^{1-\alpha} - \omega l - (1+\tau)\frac{v^{\eta}}{\eta},$$

The F.O.C. w.r.t. v is:

$$(1-s_m)l^{\alpha}(z_m h_m)^{1-\alpha} = (1+\tau)v^{\eta-1},$$

and therefore,

$$v = \left(\frac{(1-s_m)l^{\alpha}(z_m h_m)^{1-\alpha}}{1+\tau}\right)^{\frac{1}{\eta-1}}. \tag{3}$$

Plugging this back into the objective:

$$\Pi_m(z_m h_m;\omega) = \max_{l}\left(\frac{\left[(1-s_m)l^{\alpha}(z_m h_m)^{1-\alpha}\right]^{\eta}}{1+\tau}\right)^{\frac{1}{\eta-1}} - \omega l - \frac{1}{\eta}\left(\frac{\left[(1-s_m)l^{\alpha}(z_m h_m)^{1-\alpha}\right]^{\eta}}{1+\tau}\right)^{\frac{1}{\eta-1}};$$

$$\Pi_m(z_m h_m;\omega) = \max_{l}\frac{\eta-1}{\eta}\left(\frac{\left[(1-s_m)l^{\alpha}(z_m h_m)^{1-\alpha}\right]^{\eta}}{1+\tau}\right)^{\frac{1}{\eta-1}} - \omega l$$

Taking the F.O.C.:

$$\omega = \alpha \left(\frac{\left[(1-s_m)(z_m h_m)^{1-\alpha}\right]^{\eta}}{1+\tau} \right)^{\frac{1}{\eta-1}} l^{\frac{1+\eta(\alpha-1)}{\eta-1}}$$

Solving for labor:

$$l = \left(\frac{\omega}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}} \left(\frac{1+\tau}{[(1-s_m)(z_m h_m)^{1-\alpha}]^{\eta}} \right)^{\frac{1}{1+\eta(\alpha-1)}} \tag{4}$$

Plugging this back into the objective once more:

$$\begin{aligned}\Pi_m(z_m h_m; \omega) =& \frac{\eta-1}{\eta} \left(\frac{\left[(1-s_m)(z_m h_m)^{1-\alpha}\right]^{\eta} \left(\frac{\omega}{\alpha}\right)^{\frac{\alpha\eta(\eta-1)}{1+\eta(\alpha-1)}} \left(\frac{1+\tau}{[(1-s_m)(z_m h_m)^{1-\alpha}]^{\eta}}\right)^{\frac{\alpha\eta}{1+\eta(\alpha-1)}}}{1+\tau} \right)^{\frac{1}{\eta-1}} \\ & -\omega \left(\frac{\omega}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}} \left(\frac{1+\tau}{[(1-s_m)(z_m h_m)^{1-\alpha}]^{\eta}} \right)^{\frac{1}{1+\eta(\alpha-1)}}\end{aligned}$$

To simplify notation, let $p_m = \left[(1-s_m)(z_m h_m)^{1-\alpha}\right]^{\eta}$.

$$\Pi_m(z_m h_m; \omega) = \frac{\eta-1}{\eta} \left(\frac{p_m \left(\frac{\omega}{\alpha}\right)^{\frac{\alpha\eta(\eta-1)}{1+\eta(\alpha-1)}} \left(\frac{1+\tau}{p_m}\right)^{\frac{\alpha\eta}{1+\eta(\alpha-1)}}}{1+\tau} \right)^{\frac{1}{\eta-1}} - \omega \left(\frac{\omega}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}} \left(\frac{1+\tau}{p_m}\right)^{\frac{1}{1+\eta(\alpha-1)}}$$

$$\Pi_m(z_m h_m; \omega) = \left(\frac{(1+\tau)\omega^{\alpha\eta}}{p_m}\right)^{\frac{1}{1+\eta(\alpha-1)}} \left[\left(\frac{\eta-1}{\eta}\right) \left(\frac{1}{\alpha}\right)^{\frac{\alpha\eta}{1+\eta(\alpha-1)}} - \left(\frac{1}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}} \right]$$

Simplifying, note that we can write this as $\Pi_m(z_m h_m; \omega) = (z_m h_m)^{\frac{\eta(1-\alpha)}{\eta(1-\alpha)-1}} C(\omega; \tau; s_m)$, where

$$C(\omega; \tau) = \left[\frac{(1+\tau)\omega^{\eta\alpha}}{(1-s_m)^{\eta}}\right]^{\frac{1}{1+\eta(\alpha-1)}} \left[\left(\frac{\eta-1}{\eta}\right) \left(\frac{1}{\alpha}\right)^{\frac{\alpha\eta}{1+\eta(\alpha-1)}} - \left(\frac{1}{\alpha}\right)^{\frac{\eta-1}{1+\eta(\alpha-1)}} \right].$$

Finally, replacing (4) into (3) we obtain the optimal level of technology adoption:

$$v(z_m h_m; \omega) = \left(\frac{(1-s_m)(z_m h_m)^{1-\alpha}}{\left(\frac{\omega}{\alpha}\right)^{\alpha} (1+\tau)^{1-\alpha}} \right)^{\frac{1}{\eta(1-\alpha)-1}}.$$

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