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

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

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Abstract

Countries with higher levels of human capital are often more technologically advanced. We study whether formally modeling the importance of human capital for technology adoption decisions can amplify the importance of the former in accounting for cross-country income differences. We document new evidence suggesting that education and technology use are complements in generating income. Motivated by this evidence, we develop a general equilibrium model featuring human capital investment, endogenous occupational choices, and technology adoption. Production occurs in either a traditional sector, where technology adoption is absent, or in a modern sector, where managers choose both the size and quality of their workforce, as well as their technology level. Economies differ in terms of schooling and barriers to technology adoption. These differences together generate a ninefold income gap between the US and the poorest quartile of countries. Schooling alone accounts for a 5.6-fold gap, compared to a 2.9-fold in a one-sector version of the model without technology choice. Our results highlight the importance of modeling the interaction between human capital and technology adoption in understanding global income disparities.

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 – this correlation may be the result of very different causal mechanisms. In this paper, we explore one such mechanism: the extent to which cross-country human capital differences are amplified through their effect on technology adoption. We find this channel is quantitatively relevant in accounting for global income differences.

The inspiring work of Lucas (1988) was the touchstone for an extensive literature determined to understand the relative importance of factors of production 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] In an important contribution to this literature, Erosa, Koreshkova, and Restuccia (2010) showed that if human capital formation requires costly investments beyond time inputs, variations in TFP can be significantly amplified by human capital accumulation, contributing to large cross-country income differences. We build on this insight by proposing a different, but complementary, causal mechanism. We argue that human capital plays a critical role in 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. The model we develop here emphasizes 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. Benhabib, Perla, and Tonetti (2021) study how the interaction between adoption and innovation determines the productivity distribution, and the aggregate growth rate. 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 occupational choices are closely connected to human capital.[3] In turn, such occupational choices condition technology adoption – the set of technological opportunities available to a self-employed street vendor is very different from the one a large corporation manager faces. We model individuals with different innate skills who invest in their human capital and optimally choose occupations. 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. This means the model features two technology adoption margins: (i) an *extensive* margin – the relative size of the modern sector – and (ii) an *intensive* margin – the technology level chosen by modern sector managers.

In our setup, managers with different levels of human capital optimally decide how much and what types of workers (in terms of human capital) to hire, as well as the level of technology to pair with each type. More skilled managers not only adopt better technology (the channel we emphasize), but also operate with a workforce that is, on average, more skilled. This positive assortative matching generates realistic features in terms of the organization of production and labor markets. That is, more productive firms are larger, more technologically advanced, employ more educated workers and pay them more, on average, since such workers earn higher wages. Furthermore, we show that this skill complementarity between managers and workers is of some quantitative importance in accounting for cross-country income disparities.

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 present new micro-level evidence suggesting that human capital and technology use are complements in generating income. To show that, we exploit US individual and business data, as well as establishment-level data from the World Bank Enterprise Surveys, and household data from the India Human Development Survey Panel. 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 characterized by different schooling levels and barriers to technology adoption relative to a leader, calibrated to the US economy, where such adoption barriers are absent. We find that such differences

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

together result in a US output that is 9 times larger than that of the average economy in the lowest quartile of the per capita income distribution. We go on to show that the interaction between education and barriers to technology adoption is quantitatively meaningful: absent technology adoption barriers, differences in schooling only give rise to a 5.6 factor difference, while differences in adoption barriers bring about a factor difference of 2.1 if schooling differences are absent. In addition, the extensive margin is quantitatively important in driving the magnitudes we find, lending support to the inclusion the traditional sector as a transmission channel.

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 2.9 between the output of the richest and poorest simulated economies, compared to a factor of 5.6 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 cross-country differences in human capital, as suggested by recent literature (see e.g., Hendricks and Schoellman, 2018), then the size of technology adoption barriers required 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 themselves work as indirect, but quantitatively meaningful, barriers to technology adoption.

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.

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 focus on the consequences for cross-country income dispersion, as opposed to within-country productivity dispersion.[5]

Finally, our work is also connected to a recent trend in the occupational choice literature that

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

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

emphasizes the importance of distinguishing between different types of self-employed individuals (own-account versus employers) when analyzing different facets of macro-development. For instance, 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 remainder of the paper proceeds 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

We start by presenting 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 sectors and 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 collect microdata from IPUMS-International for a set of 52 countries that vary widely in terms of income levels. Based on Gross Domestic Product (GDP) per capita, the poorest country in our sample is Rwanda, 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 25 years. Throughout the paper we exploit individual-level data including labor earnings, employment status, occupation, and education. For the purpose of 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 compiled in Comin and Hobijn (2004) to create an empirical proxy for cross-country technology adoption. To do this, we consider all the 10 major technologies

[6] Feng, Lagakos, and Rauch (2023) take into account the importance of traditional self-employment in explaining cross-country differences in unemployment; Herreño and Ocampo (2023) study various development policies by focusing on the connection between unemployment risk and self-employment; and Engbom, Malmberg, Porzio, Rossi, and Schoellman (2024) study the relationship between supply of skills, white-collar labor, and firm size. In earlier work, Gollin (2008) documents differences across countries in the labor force fraction that does not work for wages.

used by Comin, Hobijn, and Rovito (2008) in computing technology usage lags across countries. These are mainly production technologies, which were cutting-edge at some point in time according to their analysis.[7] The lags are computed relative to the U.S., 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 all technologies. In our presented results we only include countries that have lag data for at least 5 of the major technologies.

Figure 1: Technology adoption, education, and income

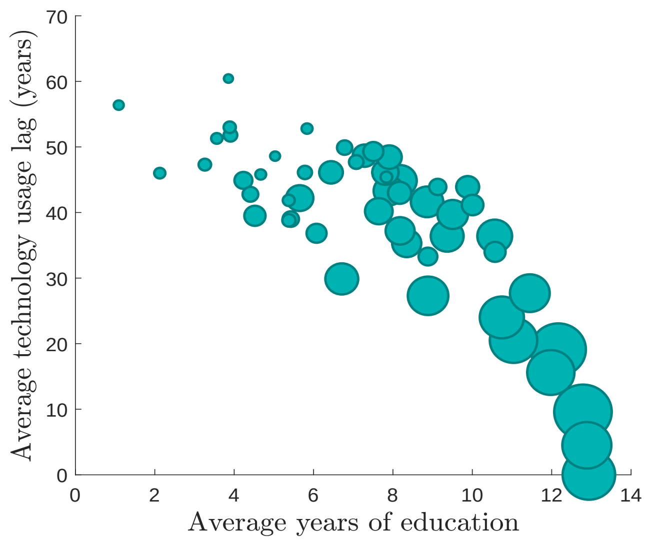


Figure 1 shows a strong and positive cross-country correlation between technology usage, schooling, and incomes (proportional to the circles in the figure). This figure encapsulates the main motivation for our study. These correlations can be the result of different underlying causality mechanisms. The 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). Opportunities for technology adoption are far 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 working on their own *and* who are not managers or professionals according to their occupation; wage or salary workers are individuals who are not employers or self-employed; and employers

[7] The technologies are: internet users per capita, number of PCs per capita, electricity production (kWh per capita), aviation-cargo and aviation-passengers (kilometers per capita), tractors per capita, number of cell phones per capita, number of telephones per capita, number of cars and trucks per capita.

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

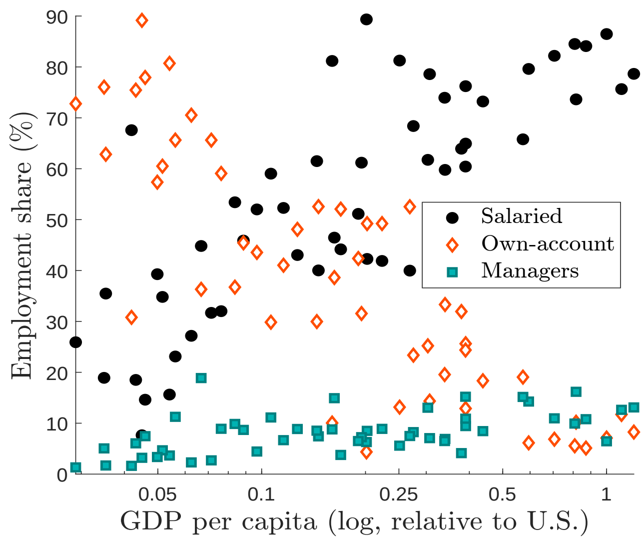


Figure 2 shows the relationship between the distribution of employment status and income per capita across countries. The key observations are that the fraction of own-account workers decreases with income, while the fraction of salaried workers and managers increases, all in a statistically significant fashion. Thus, a key feature of the structural change 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 75 percent, whereas the average share for countries in the poorest quartile is just 29 percent. Most of this difference translates into a much higher share of own-account employment in the poorest economies (66 percent), though the fraction of managers in the poorest quartile is just over 5 percent compared to 12 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.

[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 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.

Table 1: Distribution of Employment Status by Income Category

	Percentage of Employment		
Quartile	Wage-Salaried	Own-Account	Managers
1	28.7	65.8	5.4
2	49.4	42.5	8.1
3	62.6	30.0	7.4
4	74.9	12.8	12.2
USA	86.5	7.1	6.5

Notes: Income categories are based on GDP per Capita (PPP - constant 2021 international $) from World Bank data. Employment shares are estimated with IPUMS-International data. Categories might 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.

To further support our point, in Appendix A.4, 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 to document evidence that firms, individuals, or households with higher measures of human capital enjoy larger returns from technology use. 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 total sales for observation i; T_i is a variable representing technology usage, which will vary across our data sources; H_i is 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 suggests that measured returns to technology usage increase with human capital.[9]

2.2.1 US evidence: individual and business data

We start by providing US evidence based on individual and business data. We use multiple samples of microdata between 1990 and 2015 obtained from IPUMS-International. To estimate hourly earnings we use individual data on annual earnings, number of weeks worked in a year, and hours worked per week. We restrict the analysis to individuals working full-time (at least 30 hours per week) with positive labor earnings.

We combine this individual-level data with sector-level data from the US Annual Business Survey (ABS) 2019. In particular, we use data on the extent of technology use in employer firms at 2-digit sector level. The ABS data reports the number and percentage of firms (within each sector) that use the following modern technologies: artificial intelligence, cloud-based applications, robotics, specialized equipment, and specialized software. To combine both data sets, we first map the sectors in ABS data to industries in IPUMS data using the description and harmonization documentation of IPUMS. The number of sectors is larger than the number of industries, so for each technology we aggregate to the industry level weighting by the number of reporting firms in each sector.

Next, we define technology intensity at the industry level by estimating the percentage of firms that use modern technologies as the weighted average (based on the number of firms reporting usage) across the five technologies. Finally, we rank industries according to their technology use intensity and we define industries with a high technology usage as those above the average intensity (approximately 30 percent). The industries with the highest intensity based on IPUMS classification include: finance and insurance; health and social work; and business services and real estate. See appendix A.2 for the full ranking of industries based on technology usage.

To estimate regressions based on equation (1), we use hourly earnings as the outcome variable, educational attainment as the human capital variable, and a dummy variable for high technology intensity at the industry level as the measure of technology usage. We control for state of residence, time effects, and potential working experience using 5-year bins. Additionally, we restrict the sample to modern sector workers, either wage/salary workers or employers, to be consistent with the model presented below. The results presented in Table 2 show that returns to education are significantly larger in industries with high technology usage. Based on all modern sector workers, the return to education is 4.1 percentage points larger in an industry with high technology intensity. As a reference, the simple Mincer return to education using hourly earnings is 8.7 percent.

In addition, we estimate a regression using the technology rank of each industry as a categorical measure of technology usage – instead of a dummy variable for low or high intensity – and we also find a positive relationship between technology use and returns to education. Figure 3 presents

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

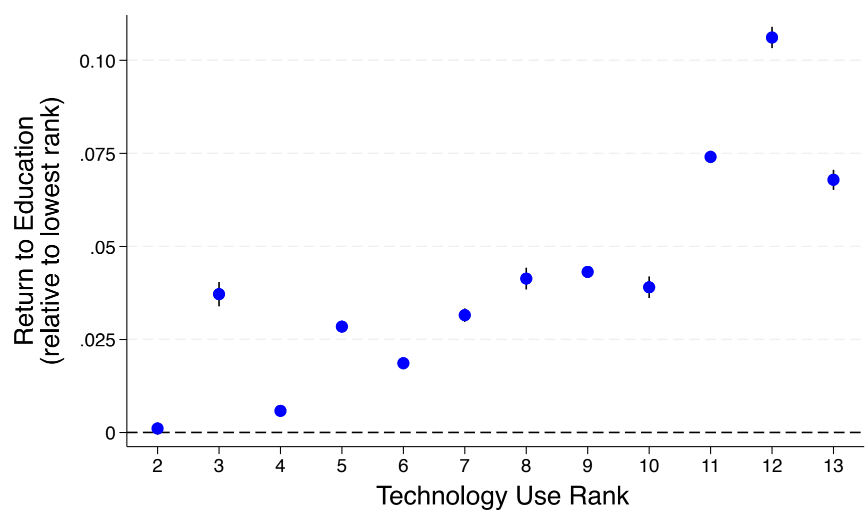
Table 2: Regressions using IPUMS and ABS data from the US

	log(hourly earnings)		
	(1)	(2)	(3)
HighTechUse=1 × EduYrs	0.041***	0.039***	0.065***
	(0.000)	(0.000)	(0.002)
Sample	All	Only wage/salary	Only managers
Observations	5,764,595	5,343,595	421,000

Notes: Column (1) uses all modern sector workers. Columns (2) and (3) use wage/salary workers and managers, respectively. All cases control for state, year, and categories of potential experience using 5-year bins. Robust standard errors are reported. *$p < 0.1$, ** $p < 0.05$, ***$p < 0.01$. Source: Authors' estimations using IPUMS and ABS data.

the estimated coefficients for β_C by industry-rank relative to the industry with lowest technology intensity. It is clear that workers employed in industries with the highest technology intensity have a much larger return to education. Overall, US evidence provides support to the idea that human capital and technology usage are complements in generating income.

Figure 3: Returns to Education and Technology Use Intensity



Notes: This figure presents the estimated returns to education by industry based on their technology use intensity. The industry with the lowest rank is the base category. Source: Authors' estimations using IPUMS and ABS data.

2.2.2 Evidence from a developing country

Next, we provide evidence from a large developing country: India. First, we exploit microdata from the World Bank Enterprise Surveys (WBES). These surveys collect establishment-level data in non-farming sectors, including information about sales, costs, and education of employees. The survey data for India has a relatively large number of observations, and it has available data for variables that are valuable for our analysis. We use the 2014 India survey because we can link it to an innovation module surveyed in that same year. This module provides detailed data on technology usage at the establishment-level for a subset of firms. Due to data constraints, we restrict the analysis to non-service sectors.

To estimate equation (1) using these data, our outcome variable is total sales. We also consider total profits, defined as total sales minus total costs. The latter includes costs of labor, electricity, and materials. The human capital measure is the average years of education of a typical production worker. For technology usage, we use information on the percentage of employees (including management) that use computers on a regular basis.[10] Based on the latter, we construct a high-technology-usage dummy variable that is equal to one if the percentage of workers using computers is larger than the median value (15 percent). In the estimation, we include controls for the age of the establishment (in logs), the size of the locality (four categories based on population), hours of operation per week (in logs), and the sector (e.g., footwear, textiles, or construction).

We also experiment with controlling for establishment size (number of permanent full-time workers in logs) and firm size (number of establishments in logs), though we do not think it is obvious one should control for size variables when evaluating the effects of human capital and technology usage on sales and profits. For instance, in the model we develop below, firms that hire more skilled workers are also larger in size. That said, size controls might serve as a proxy for other unobserved factors.

The results in Table 3 are suggestive of complementarity between human capital and technology usage at the establishment-level. The estimated coefficients are positive and statistically significant in every case. For example, the results in column (1) imply that the return on sales from having a high technology usage among the workforce increases by 18.5 percentage points with an additional year of education of production workers. The returns are lower when controlling for size variables, though again, we do not think is clear that one wants to keep firm size constant when evaluating the complementarity between education and technology usage. We cannot discard the possibility that these estimates are capturing unobserved establishment characteristics, tough these findings suggest that firms with higher human capital derive greater returns from technology usage.

Second, we provide evidence from household panel data using the India Human Development Survey Panel, 2005, 2011-2012. This is a nationally representative survey of 42,152 households in 1,503 villages and 971 urban neighborhoods across India. The information in these surveys includes individual-level data on education years, labor income, and hours worked, as well as household-level

[10] The question in the survey is: "*Currently, what percentage of this establishment's employees regularly uses computers in their jobs, including management?*".

Table 3: Regressions using enterprise surveys from India

	log(sales)		log(profits)	
	(1)	(2)	(3)	(4)
HighTechUse=1 × AvgEduyrs	0.185***	0.069**	0.200***	0.085**
	(0.044)	(0.033)	(0.051)	(0.041)
Size Controls	No	Yes	No	Yes
Observations	2,366	2,366	2,366	2,366

Notes: 'HighTechUse' is equal to one if the percentage of workers using computers is larger than the median value. 'AvgEduyrs' are the average education years of a production worker. All cases control for age of establishment, size of locality, hours of operation per week, and sector. Size controls include number of full-time permanent workers and number or establishments in the firm. Robust standard errors are reported. $*p < 0.1$, ** $p < 0.05$, $***p < 0.01$. Source: Authors' estimations using WBES data.

data on business income.[11] Importantly, the data has information on the use of computers for every household member. The latter is important for our estimation following equation (1), though it is worth mentioning that we do not know if the individual uses a computer for their job.

We consider two outcome variables: individual hourly earnings from wage and salary jobs, and household income per working adult from all work-related sources (farming and non-farming business and wage or salary jobs). For technology usage we consider a dummy variable representing use of computer at the individual level. In our estimations, we control for sex, state of residence, year, household size, and age effects using 10-year bins. In regressions that use total income per adult, we also control for the total number of hours worked across all activities during the year. We focus on adult (16 years or older) household members who report working hours during the year and we only consider income from businesses that report hired labor. This is done to focus on business activities that do not resemble an own-account occupation, which is consistent with the model introduced in the next section.

The results presented in columns (1) and (3) of Table 4 show that the interaction between education years and computer use is positive and statistically significant. For instance, the results in column (1) imply that the return to computer usage in hourly earnings increases by 5 percentage points with an additional year of education. As a reference, the simple return to an additional year of education in hourly earnings is equal to 6.4% in these data. In the regression based on household income per working adult, the relevant coefficient is smaller but still sizable.

The panel data allows us to control for time-invariant individual characteristics, such as general

[11]In the panel, some individual observations have impossible or implausible changes in education and age over time, such as decreasing values or changes that exceed the time between survey waves. We allow for a one-year discrepancy relative to plausible values; otherwise, the observation is excluded from the analysis. For example, if reported years of education decrease by one year in the second wave, we retain the observation and assign the second wave value. The second wave is prioritized because is considered to have better-quality data.

Table 4: Regressions using household data from India

	log(hourly earnings)		log(income per adult)	
	(1)	(2)	(3)	(4)
ComputerUse=1 $\times$ EduYrs	0.057^{***}	0.027^{**}	0.037^{***}	0.024^{*}
	(0.007)	(0.014)	(0.008)	(0.014)
Individual Fixed Effects	No	Yes	No	Yes
Observations	53,582	53,582	83,240	83,240

Notes: Columns (1) and (2) use individual earnings from wage and salary jobs. Columns (3) and (4) use household income per working adult from all work-related sources (business and paid jobs). All cases include controls for sex, state of residence, year, household size, and age effects. Robust standard errors are reported. Regressions are clustered at the household level. $*p < 0.1$, $**\ p < 0.05$, $***p < 0.01$. Source: Authors' estimations using IHDS data.

unobserved ability, by including individual fixed effects. This allows us to exploit variation in educational attainment and computer usage at the individual level over time. The results presented in columns (2) and (4) show that the coefficient becomes smaller and less statistically significant when individual fixed effects are included. That said, it is worth emphasizing that the estimated coefficients are still large relative to their means and significant at the 90 percent confidence level or higher. Taken together, the results using household data from a large low-income country provide evidence that human capital and technology usage are complements in generating income.

Having documented a link between human capital and technology adoption using different sources of microdata and aggregate data, we now propose a model where this connection is an important income determinant and differences in the determinants of human capital and technology levels from one country to another are therefore major drivers of the income differences between those countries.

3 Model

Environment and household problem

The economy is populated by a unit mass of individuals who derive utility from consumption and from occupation-specific taste shocks according to a utility function to be detailed below. There is a single consumption good that can be produced in one of two *sectors*. Individuals optimally select into one of three possible *occupations* indexed by j.

They can become self employed in the *traditional sector* and produce the consumption good on their own, an occupation we call *own-account* and denote by $j = o$. Alternatively, they can join the *modern sector* as *managers* (denoted by $j = m$). In this case, they manage an establishment where they make a decisions regarding the level of technology to use and produce by hiring salaried workers – the final occupation, which we denote by $j = w$.

In the spirit of Roy (1951), individuals are endowed with a known level of ability ($z \in \mathbb{Z} \subseteq \mathbb{R}_+$)

that is distributed according to $\log z \sim N(\mu, \sigma)$. The mean of this ability distribution is determined by the average schooling in the economy, a statistic we observe directly from the data. Letting s denote years of schooling in the economy, we assume $\mu = \phi \log s$, where $\phi > 0$ modulates the importance of educational attainment for human capital.

In addition to occupational decisions, individuals also choose the level of educational expenditures, e, as in Erosa, Koreshkova, and Restuccia (2010). These expenditures can be thought of as schooling quality or access to professional networks. They get combined with ability (itself a function of schooling) in the production of human capital. Such human capital, in turn, is an important income determinant: in a trivial way in the traditional sector but in a much more interesting way in the modern sector, where we will allow for sorting between workers and managers. We think of human capital as defining manager and worker *types*. As in Eeckhout and Kircher (2018), managers face a trade-off between hiring more versus better worker types. The resulting equilibrium wages are worker-type specific and clear the corresponding worker-type specific labor markets.

Because life-cycle implications are not the main focus of the paper, we model individuals as living for only one period, so all decisions are made at once. Individuals make their choices after observing their occupation-specific taste shocks ε_j. These shocks are *i.i.d.* and independent of z, and follow a type-I extreme value (Gumbel) distribution with location parameter 0 and scale parameter $\lambda > 0$. The occupational choice problem is:

$$V(z) = \max_j \left\{ V_j(z) + \varepsilon_j | j \in \{o, m, w\} \right\}, \tag{2}$$

where $V_j(z)$ are the optimal occupational utilities. An individual who has chosen occupation $j \in \{o, m, w\}$, solves the following problem:

$$\begin{aligned} V_j(z) = \max_{c_j, e_j} \quad & \log(c_j) \\ s.t. \quad & c_j = I_j(h_j; \boldsymbol{\omega}) - e_j, \\ & h_j = z e_j^{\theta}, \quad \theta > 0 \end{aligned}$$

where $\boldsymbol{\omega}$ is a wage vector composed of wages for each worker type h_w, and occupation-specific incomes $I_j(h_j; \boldsymbol{\omega}) \in \{\Pi_o(h_o), \omega(h_w), \Pi_m(h_m; \boldsymbol{\omega})\}$ are discussed below.

Before proceeding, a word is in order regarding the concurrent use of both individual ability shocks and taste shocks. In the absence of occupational taste shocks, and under sensible parameter values, individuals would sort into different occupations based exclusively on pecuniary returns, resulting in two ability thresholds. Individuals above a certain ability threshold $\overline{z}$ would choose to be managers, those below a lower threshold $\underline{z}$ would be self-employed, and those in-between would be salaried workers. The presence of heterogeneous taste shocks weakens such sorting on ability across occupations. This modeling choice is a common strategy in the literature (see Poschke 2018, for example), backed by evidence that non-pecuniary motives play an important role in occupational choices.[12] Incorporating taste shocks also helps discipline the distribution of employment across establishments in a manner consistent with the data, as explained below.

Traditional sector production

Production in the traditional sector is characterized by the absence of technological adoption and only depends on human capital. An individual that chooses to become a traditional sector entrepreneur, given human capital h_o, produces:

$$\Pi_o(h_o) = \psi h_o^\rho$$

where $\psi > 0$ governs sectoral productivity and $\rho > 0$ determines returns to human capital in the traditional sector. The latter allows for the possibility that human capital is less valuable in the traditional sector than in the modern sector.

Modern sector production

In the modern sector, in contrast, technology adoption plays an important role. Managers choose the optimal technology level by trading off higher total factor productivity for a higher (convex) cost. A modern manager's production can be thought of as an aggregate of multiple divisions or stations, each indexed by the type of worker employed. In each division, manager and worker human capital (productivity) get combined according to a constant returns to scale, constant elasticity of substitution (CES), *quality* aggregate. This, in turn, is combined withe the *quantity* of that type of labor, which yields decreasing returns to scale, and the total factor productivity term introduced earlier. As in Eeckhout and Kircher (2018), we allow for interactions between a manager and different worker types, but not between different worker types.

To formalize the problem, let x and y index the different types of workers and managers (as defined by their different human capital levels h_w and h_m, respectively). Then, an individual of type y that chooses to be a modern sector manager takes worker-type wages $\omega(x)$ as given, and optimally decides what technology level to adopt $v(x)$ for each worker type, and the labor demand for each type $l(x)$:

$$\Pi_m(y;\boldsymbol{\omega}) = \max_{v(x),l(x)} \int_x \left(v(x) \left[\alpha_m h_m(y)^p + (1-\alpha_m) h_w(x)^p\right]^{1/p} l(x)^\alpha - l(x)\omega(x) - (1+\tau)\frac{v(x)^\eta}{\eta} \right) dx, \qquad (3)$$

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). These stand 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.

[12] See Hamilton (2000), or Hurst and Pugsley (2011), for examples.

Letting $f(x,y) := [\alpha_m h_m(y)^p + (1-\alpha_m)h_w(x)^p]^{1/p}$ denote the sectoral human capital component of modern production, in Appendix A.6, we show that optimal manager profits can be expressed as:

$$\Pi_m(y;\boldsymbol{\omega}) = \int_x f(x,y)^{\frac{\eta}{\eta(1-\alpha)-1}} C(\omega(x),\tau)dx,$$

which turns out to imply increasing returns to human capital since in our calibration below, $\eta(1-\alpha) > 1$.[13] Then, the optimal technology adoption in the modern sector by manager type y for workers of type x also displays increasing returns to scale in sectoral human capital:

$$v(x,y) = \left[\left(\frac{\alpha}{\omega(x)}\right)^{\alpha} \frac{f(x,y)}{(1+\tau)^{1-\alpha}}\right]^{\frac{1}{\eta(1-\alpha)-1}}. \tag{4}$$

The main goal of our study, in light of the motivation from the microdata evidence presented in Section 2.2, is to understand how differences in human capital can be amplified into differences in incomes through technology adoption. The parameter η – which governs 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 sectoral human capital is:

$$\frac{\partial \log v}{\partial \log f(x,y)} = \frac{1}{\eta(1-\alpha)-1}, \tag{5}$$

implying that a lower value of η, all else the same, results in a stronger amplification. Our sensitivity analysis confirms the importance of this parameter in amplifying human capital differences into income differences across countries.

Equilibrium

We restrict our analysis to steady-state equilibria. This economy has as many labor markets as there are $x-$types of workers. In addition, there is a goods market. For general equilibrium it is therefore enough to guarantee that all labor markets clear.

Given our extreme-value distribution assumption on the taste shocks, the occupational shares conditional on ability level z are given by:

$$\pi_j(z) \coloneqq \frac{e^{(V_j(z)/\lambda)}}{\sum_k e^{(V_k(z)/\lambda)}}, \qquad \text{for } j,k \in \{o,m,w\},$$

where λ, the scale parameter controlling the dispersion of the shocks, plays a prominent role. A larger λ, raises the importance of the taste shocks relative to the pecuniary motives and muddles the ability thresholds that become *fuzzier*. Since the support of the taste shocks is the whole real line, individuals of any ability z have a non-zero probability of picking any of the three occupations. In

[13] Where $C(\omega(x),\tau) = \left[\frac{1}{(1+\tau)\omega(x)^{\eta\alpha}}\right]^{\frac{1}{\eta(1-\alpha)-1}} \left[\left(\frac{\eta-1}{\eta}\right)\alpha^{\frac{\alpha\eta}{\eta(1-\alpha)-1}} - \alpha^{\frac{\eta-1}{\eta(1-\alpha)-1}}\right]$, for each worker type x.

section 4 below, we explain how we discipline λ, bringing in information on occupational shares, as well as earnings and establishment size dispersion. The total supply of labor in each occupation j is then:

$$L_j^s \coloneqq \int_z \pi_j(z) dF(z),$$

where $F(z)$ denotes the cumulative probability distribution of ability z.

From profit maximization (see appendix A.6), the optimal demand for workers of type x by a manager of type y is:

$$l^d(x,y) = \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x,y)^\eta}{1+\tau}\right)^{\frac{1}{\eta(1-\alpha)-1}}. \tag{6}$$

The right-hand side of this equation implies that, given labor wages $\omega(x)$, managers of higher type y demand a larger quantity of every worker type. Therefore, establishment size increases with managerial human capital $h_m(y)$. Moreover, for any manager of type y, the ratio of demand for workers of type x_1 to that for workers of type x_0 is given by:

$$R(y, x_1/x_0) \coloneqq \frac{l^d(x_1,y)}{l^d(x_0,y)} = \left(\frac{w(x_0)}{w(x_1)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x_1,y)}{f(x_0,y)}\right)^{\frac{\eta}{\eta(1-\alpha)-1}}. \tag{7}$$

It is possible to show that for any pair of worker types such that $h_w(x_1) > h_w(x_0)$, the value of $R(y, x_1/x_0)$ is increasing in human capital of managers $h_m(y)$ if $\rho < 0$. This allows us to summarize an important equilibrium property:

Proposition 1. *If $\eta(1-\alpha) > 1$ and $\rho < 0$, then, given the wage schedule $\omega(x)$, modern managers with higher human capital $h_m(y)$:*

(i) operate larger firms and adopt more productive technologies; and

(ii) employ a larger share of workers with high human capital $h_w(x)$.

Part (i) of the proposition follows directly form equations (4) and (6) above. The proof of part (ii) is standard and involves showing that managers and workers are complements in sectoral human capital (see appendix A.6). If the latter is true, as it is the case in our quantitative application below, workers of high type x will be more likely to work for managers of high type y. To reiterate, proposition 1 implies that, in equilibrium, larger firms are characterized by managers and workers with high levels of human capital and, consequently, by more productive technology choices.

The equilibrium wage rate vector $\boldsymbol{\omega}^*$ clears the modern-sector labor markets when labor of type x demanded by managers - who live in a set denoted by $\Omega_m(x) \subseteq \mathbb{Z}$ - equals the supply of type-x workers in a set denoted by $\Omega_w(x) \subseteq \mathbb{Z}$. Note that both these sets are themselves dependent on the wage vector $\boldsymbol{\omega}$ through optimal occupational choices. Letting $\phi(z)$ denote the measure of individuals over these two sets, labor market clearing in market x is given by

$$L^d(\omega^*(x)) := \int_{\Omega_m(x)} l^d(x,y)\phi(z)dz = \int_{\Omega_w(x)} \phi(z)dz =: L^s(\omega^*(x)).$$

The properties of the equilibrium wage schedule depend not only on the degree of complementarity between worker and manager productivity, but also on the (endogenous) relative scarcity of workers and managers. To our knowledge, at this level of generality, the equilibrium wage schedule does not admit a closed-form solution and needs to be solved for using numerical methods.

Note that given strict decreasing returns to scale to labor of each type, all types with strictly positive labor supply will be hired by any operating establishment. In general, there could be types with zero labor supply (if they decide to be modern managers or self-employed in the traditional sector.) Not so in our case, thanks, once again, to the occupation preference shocks that guarantee a full support for worker types.

4 Calibration

This section details the mapping from 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 US 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 that country.

We estimate schooling years directly from the IPUMS-International microdata and calibrate the remaining model parameters to relevant data moments of the US 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 that show up on the top panel of Table 5. As mentioned, we set schooling time by directly matching the IPUMS-International data on years of schooling assuming a maximum of 16 years: $s = 12.9/16$. 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).

Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018) estimate the same CES production function we use for the modern sector on NAICS major sector moments derived from matched employer-employee data from the Longitudinal Employer-Household Dynamics Program of the U.S. Census Bureau, vacancy data from the Job Openings and Labor Turnover Survey from the U.S. Bureau of Labor and Statistics, and sectoral productivity data from the Bureau of Economic Analysis' Annual Industry Accounts. They estimate the worker's productivity's share in output to be 0.364, so we set the manager's share to $\alpha_m = 1 - 0.364 = 0.636$. They also find that positive assortative matching is a

Table 5: Calibration

Parameters	Targets matched
$\alpha = 0.224$	Labor income share: 67%
$s = 0.806$	Average Years of schooling: 12.9
$\alpha_m = 0.636$	Estimated by Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018)
$p = -0.208$	Estimated by Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018)
$\eta = 1.502$	Share of modern managers: 6.4%
$\lambda = 0.497$	Std. dev. of log employment: 1.3
$\phi = 0.486$	Mincer return (total): 8.9%
$\psi = 0.187$	Share of own-account workers: 7.1%
$\rho = 0.849$	Mincer return (traditional): 3.2%
$\sigma = 0.458$	Variance of log-earnings: 0.46
$\theta = 0.027$	Education spending: 6.6% of GDP

prominent feature of the US labor market, and estimate the elasticity of substitution between worker and employer productivity $\sigma = 1/(1-p)$ to be 0.828. Accordingly, we set $p = 1 - 1/0.828 = -0.208$, meaning that modern sector production is supermodular.[14]

This leaves 7 parameters $(\eta, \lambda, \phi, \psi, \rho, \sigma, \theta)$ to target 7 moments that appear in the bottom panel of Table 5. A feature of the economy we need to target is the occupational distribution, as it drives both the extensive margin of technology adoption, as well as the human capital investment decisions. To do this, we match the share of traditional sector producers in the model to the share of own-account individuals in the US economy (7.1%) and the share of modern sector managers in the model to the share of managers in the US 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 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 Mincer regressions using the IPUMS data. We find that for the average individual, one additional year of schooling results in a 8.9% increase in hourly

[14] In the Appendix section A.5.2 we conduct sensitivity analysis with respect to the complementarity in production parameter p.

earnings (the relevant counterpart to model earnings since we don't have an intensive margin). Next, to make sure we capture the different impact of education between the two sectors, we also perform an estimate for own account workers separately, and find that their hourly earnings increase only by 3.2% for an additional year of schooling. We then compute these counterparts in the model using a discrete approximation and make sure they match these two values. On the cost side, we match the GDP share of educational expenditures in the U.S. (6.6%).[15]

The allocation of human capital across occupations is a key mechanism in our model. While human capital is a function of innate ability, sorting is further confounded by occupation-specific taste shocks. The dispersion of the ability and taste shocks distributions have direct implications not only for the earnings distribution, but also for the distribution of productivity (human capital) and employment across establishments. Everything else being the same, more talented managers, with larger spans of control, operate larger establishments. But the dispersion in taste shocks means that everything else is not the same and blunts this effect. Some talented would-be managers (and workers) will select into a different occupation for large enough shocks. On the other hand, this can lead individuals that in the absence of taste shocks would chose to be workers say, to become managers instead, and open relatively small establishments.[16]

To discipline the two effects described in the previous paragraph, besides the occupational shares we already covered, we bring in moments from the earnings distribution – the variance of log earnings in our overall US IPUMS sample is 0.46 – and the establishment size distribution – the standard deviation of log-employment across establishments in the US economy is 1.3.[17] In Appendix A.5.1, we show the each of our internal calibration targets is especially sensitive to specific parameters in the model, as suggested by Table 5.[18]

5 Results

5.1 Characterizing the benchmark economy

In characterizing the benchmark economy, it is perhaps instructive to start with downstream decisions, specifically with the modern sector, which is the more consequential in our setting.

In solving their worker quality-quantity hiring problem, managers have an answer: the more productive a manager is (measured by human capital h_m), the more workers (panel A of Figure 4) and the better workers (panel C) they hire, on average. That is, the modern sector exhibits positive assortative matching: even though all managers hire all worker types (recall our decreasing returns to

[15]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.

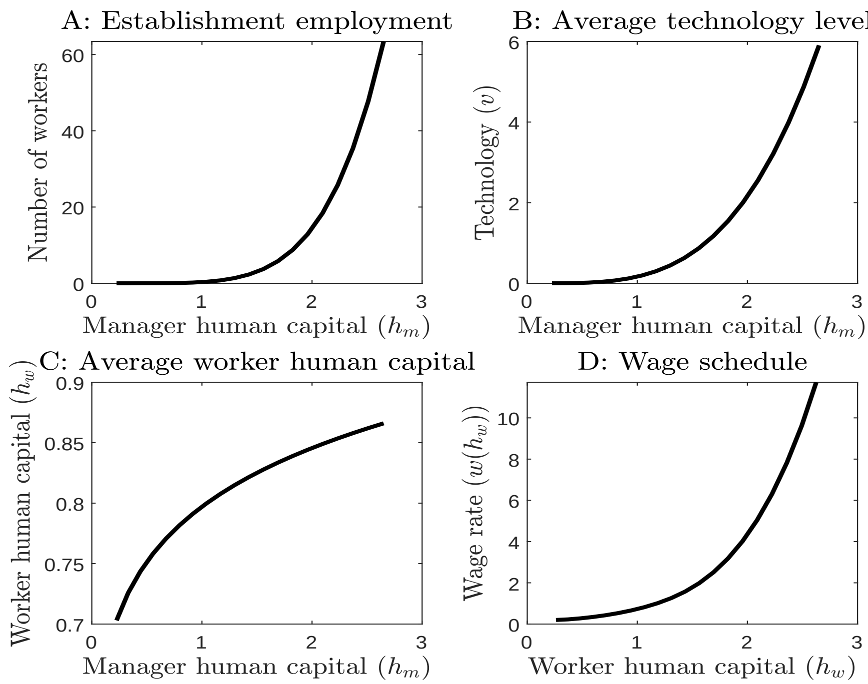
[16]In the Appendix A.5.4 we conduct sensitivity analysis with respect to the preference shock scale parameter λ.

[17]This number was calculated using the 2022 County Business Patterns from the Census Bureau. Poschke (2019) finds a similar number using the Global Entrepreneurship Monitor survey.

[18]The fraction of modern managers is particularly sensitive to the value of η, which is a key parameter for the amplification of human capital differences (see equation 5). In Appendix A.5.3, we present sensitivity analysis with respect to that parameter.

scale assumption in quantities of work), the weighted average of worker quality is clearly increasing in manager productivity (see equation 7). This, together with the supply of work of different types (to be discussed below) results in an equilibrium wage schedule in which better-quality workers receive higher pay. Not only are the largest establishments operated by more productive managers and employ a higher quality workforce, but beyond this, and importantly for our purposes, they also feature more productive technology (panel B). The convexity in this relationship comes from equation 5.

Figure 4: Modern sector policies



Moreover, Panel D in Figure 4 shows that the equilibrium wage schedule is convex in worker human capital h_w. We think this aligns with the evidence presented in Section 2.2, which suggests that the return to human capital for modern managers and workers increases with technology use. In particular, the model captures the non-linearity in worker human capital due to the complementarity between managers and workers in sectoral human capital, as well as the increasing returns to technology adoption in modern production. That is, high-human capital workers receive higher returns because they tend to work with high-human capital managers who adopt more productive technologies that those workers can use.

While the model is calibrated to match the overall dispersion in establishment employment, it also does a reasonable good job at capturing other, untargeted, features of the establishment size distribution. The average establishment in the U.S. employs about 16 workers, while in our model it employs 14.[19] In the US economy, most establishments are small, but most workers are employed by

[19]All of the data on establishment size described in this section is from the Census Bureau's 2024 County Business Patterns dataset U.S. Census Bureau (2022).

large establishments. The model has no trouble capturing the former feature, as 61% of establishments employ less than 10 people (it's 73% in US data), but it falls short in capturing the latter. In the model, 16% of the people work in establishments larger than 50 workers, while in the data it's 60%. The reason for this is that the model's establishment size right tail is not quite long enough. It does have a fair number of establishments that employ over 50 workers (3.5%, as compared to 5.3% in the data), but it does not have any establishments employing more than 100 workers, which constitute 2.3% of the data.

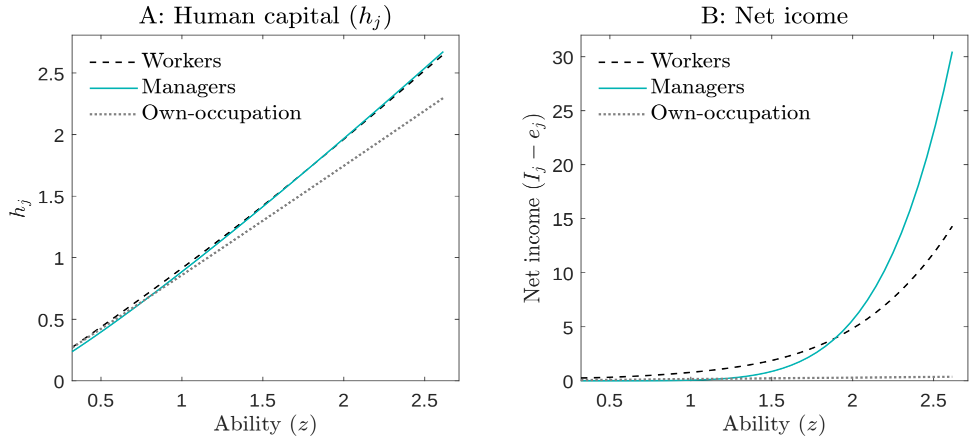
Part of the reason why the calibration fails to capture the share of large establishments is that were these establishments to exist in the model, the earnings of their managers would be very high and push the earnings dispersion up above its target. Why is it then that establishment size and earnings distributions do not align in the model as they do in the data? The fundamental difference is that the mapping between the model's manager earnings and their data counterpart is imperfect. In the model managers are residual claimants, so all the establishment's equity accrues to them, whereas their data counterparts are mostly salaried professional managers, and the equity accrues to shareholders. Given this disconnect there is a tension between the model's moments and their data counterparts. We opted for a conservative calibration by not targeting the share of very large establishments. This would have necessitated very productive managers in our benchmark economy and would have ultimately resulted in an even larger cross-country income dispersion.

Taking a step back allows us to focus on the individual decisions made before entering the labor market: those regarding human capital and occupational choices. Recall that individual ability, z, is combined with education expenditures to produce human capital h_j in a way detailed above. Our calibrated values for ψ and ρ imply the traditional sector is relatively unproductive and the return to human capital there is fairly low. As a result, it is optimal for own-account individuals to invest very little in education, resulting in low levels of human capital, as panel A in Figure 5 shows. In contrast, for a sufficiently high ability level, workers and managers invest more in education, resulting in higher levels of human capital.

Furthermore, occupational choices are made taking into account income net of educational expenditures $I_j - e_j$ and the idiosyncratic occupational taste shocks. Panel B of Figure 5 shows the former, for each occupation. For modern sector workers, this is just the wage schedule we saw above in panel D of Figure 4 minus the respective education expenditures. Notice that while there is a clear crossing point between worker and manager value, there is none between workers, and own-occupied individuals: absent taste shocks all individuals would be better off being a modern sector worker than working on their own in the traditional sector. We are abusing language here, since that is not the right counterfactual. Absent taste shocks, the calibrated parameter values would be different, and such a crossing point would necessarily have to exist since we are targeting a strictly positive share of own-account individuals.

Given the calibrated dispersion of the taste shocks, Figure 6 makes clear the occupational choices of individuals with different abilities. Panel A shows the overall density by ability and splits it into

Figure 5: Pre-labor market policies



the three occupational groups whose sizes are used as targets in our calibration. Workers are not only the largest occupational group (86.5 percent) in the economy, but also span most of the ability support, something that is confirmed in panel C, which focuses exclusively on the distribution of workers across abilities. At the highest ability levels the measure of workers is (essentially) zero since it takes an extremely large, and therefore unlikely, taste shock draw to overcome such a large difference in net incomes.

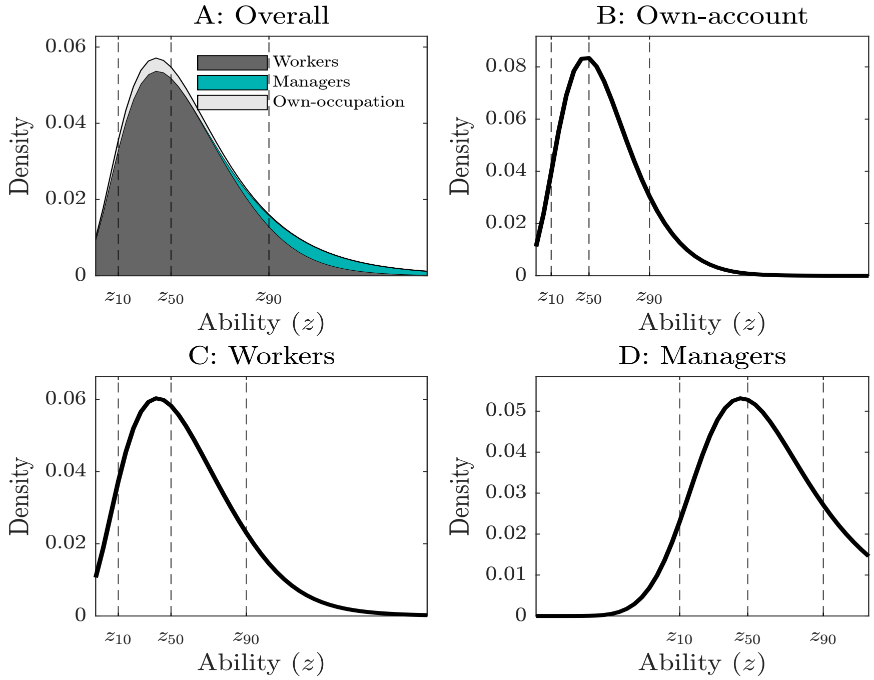
Own-account individuals are the group that has, on average, the lowest ability: the 90th percentile own-account ability level is below the 10th percentile manager ability level, as can be seen in panels B and D. It is mostly at low abilities that the difference between worker net income and own account net income is low enough that it can be overturned by a large enough taste shock draw. Finally, individuals of high ability mostly select into modern sector management, as the large difference between manager net income and worker net income dominates any taste shocks in that part of the ability support.

5.2 Main experiment

Model economies may differ from the US benchmark we just looked at either because they feature more or less schooling, or because they are subject to 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.

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

Figure 6: Ability and occupations



omy matches two characteristics of their real-world counterparts: (i) the average years of schooling and, (ii) the share of individuals working in the traditional sector (see Appendix A.1). The former represents a direct, exogenous change (in s) to the distribution of human capital, while the latter is matched by varying barriers to technology adoption τ. As these barriers increase, more individuals find it optimal to work in the traditional sector. Both moments are obtained from the microdata for each country.

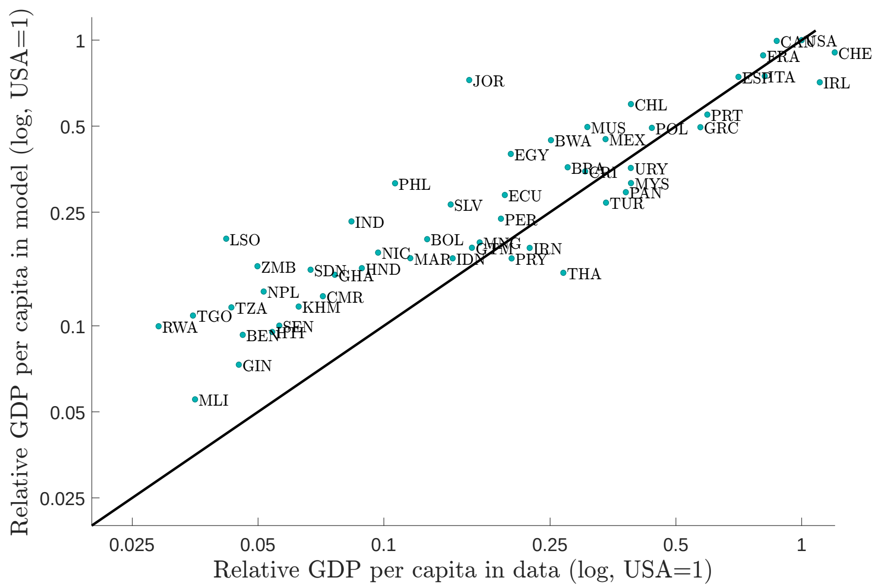
Figure 7 shows the results of this experiment for all 52 countries in our sample, comparing relative outputs in the model to the data. For a summary measure, letting $\hat{y}$ denote relative output in the model and y its data counterpart, $1 - \frac{\sum |\hat{y}-y|}{\sum |1-y|}$, is the share of the 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 86 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. If we take the 10 percent poorest countries in our sample, the model accounts for 92 percent of their income shortfall relative to the US level.[20]

In Figure 8 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 US economy. 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.

This perspective is informative about what the model can and cannot do. By construction, the

[20]These are Tanzania, Lesotho, Mali, Togo, and Rwanda.

Figure 7: Model and data, country-by-country



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 Jordan, who exhibits much lower GDP per capita than the U.S. despite reporting similar schooling and traditional sector employment levels. The explanation behind Jordan'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.

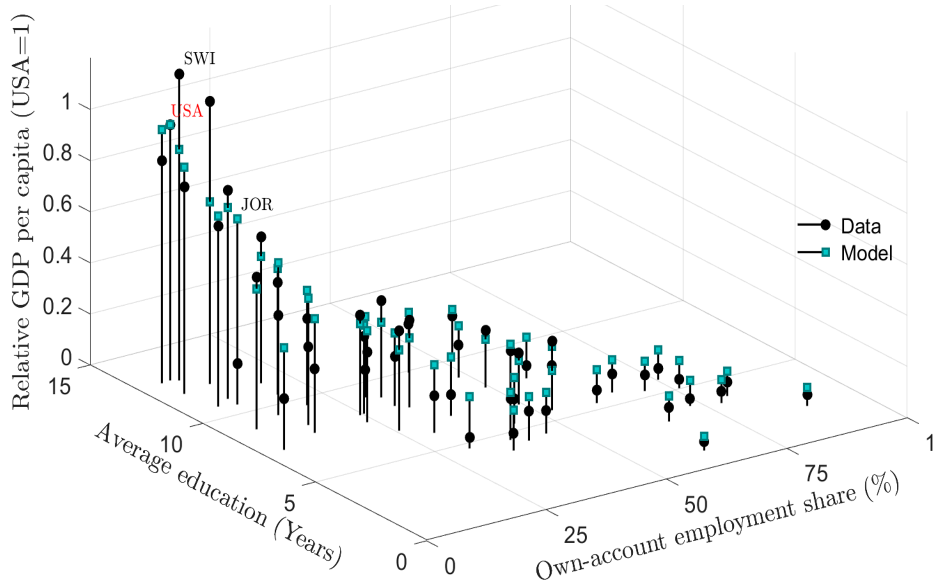
To gloss over outliers and assess the performance of the model across income levels more systematically, we group countries into quartiles of the income distribution. A country in the top quartile (ex-US) averages 71.4% of the U.S. GDP per capita, while a country in the bottom quartile averages only 4.7%. We then repeat the exercise, matching average years of schooling 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 9.

The model puts the poorest quartile's income at 11.2% of the U.S., implying it is able to capture about 93% $\left(1-\frac{0.112-0.047}{1-0.047}\right)$ of the output difference. An equivalent way to put this is that the model can generate a factor difference of 9, between the U.S. and the poorest quartile's average output, compared to a factor of 21 in the data.[21]

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

[21] High-income countries are under-represented in our 52-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 (PWT), Feenstra, Inklaar, and Timmer (2015), from the first to the third quartile. Nonetheless, the bottom quartile's relative average incomes are very similar, at 0.047 in our sample and 0.044 in the PWT. See Table 7 in the appendix.

Figure 8: Model and data, matching the targets



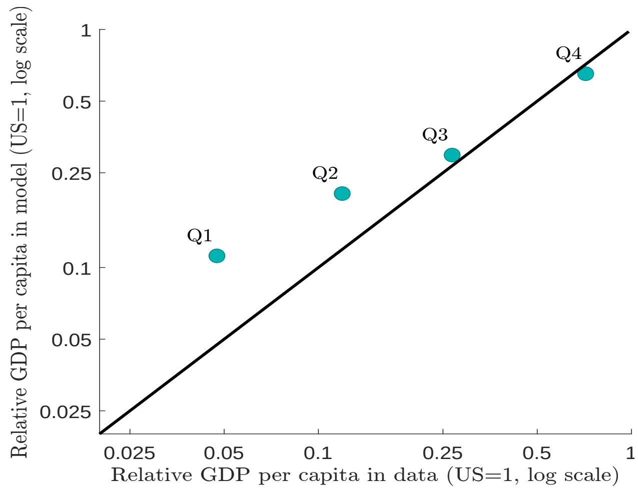
the model is 0.4, implying that technology adoption is roughly 40 percent more expensive in the world's poorest countries compared to the U.S. This strikes us as entirely reasonable; an underestimation of true barriers if anything, both compared to other models in the literature, as well as in the context 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.[22] World Bank (2020a) reports that the cost of starting a business in Mali, one of the poorest countries in our sample, is roughly two-thirds as high as in the U.S. (measured in USD), but since Mali's income is roughly 25 times smaller, this means startup costs in Guinea are 16 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 our implied technology adoption costs in poor countries are most definitely not an overestimation.

We already discussed how the model fits the US establishment distribution in section 5.1, but another way to scrutinize the model is to ask what kind of change does it predict for the establishment distribution as schooling falls and barriers to technology adoption rise – something the model was not designed to capture. While establishment data is hard to come by for a large cross-section of countries, it is well-established that average firm size and firm size dispersion are positively associated with income. Using data from the Global Entrepreneurship Monitor, Poschke (2018) reports that the elasticity of average employment with respect to income is 0.65.[23] Regressing log average establishment size on log income for our sample of 52 synthetic countries results in a coefficient of

[22] 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.

[23] This number excludes the self-employed and is therefore a better fit for our model. See Table 3 in Poschke (2018).

Figure 9: Model and data, by quartiles



0.15, implying the model can account for almost a quarter of the cross-country variation in average establishment size. Regarding establishment size dispersion, Poschke (2018) reports that the semi-elasticity of the standard deviation of log employment with respect to income is 0.17, while we find 0.15 (coincidentally) using our synthetic country sample, or almost 90 percent of the variation in dispersion.

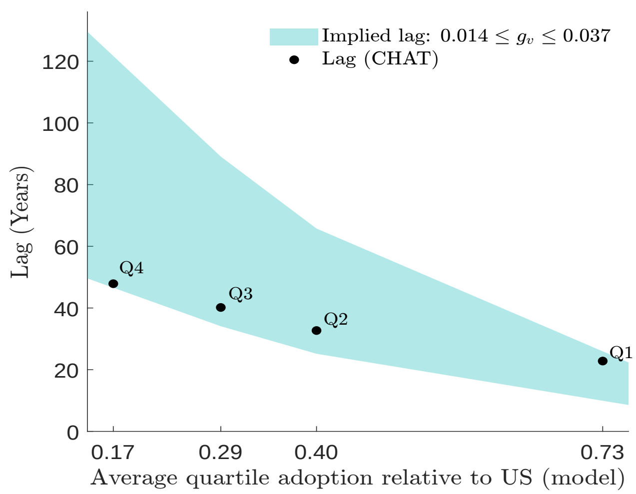
Another way to independently corroborate the reasonability of the model's technology adoption outcomes is to compare them to the empirical measures of the technological lags in Comin, Hobijn, and Rovito (2008). In fairness, these technology usage measures are not the same as the model's technology level v. The lags represent how many years ago a set of relevant technologies were used in the U.S. with the same intensity as they are presently used in other countries, while the model's v is more of a measure of how productive technology is. Nonetheless, we are going to use one as proxy for the other. The goal here is not to use the lags to calibrate the model in any way, but to ask whether there is glaring evidence from the lags that could falsify the model.

The lags depend not only on where other countries find themselves today regarding technology usage, but also on how fast such usage increased in the U.S.. Our model has something to say about the former, but not the latter, since it is not a dynamic one. In any case, 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 v_Q 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? Splitting our country sample into quartiles again, and taking average lags (in years) from the corresponding countries from Comin, Hobijn, and Rovito (2008), the resulting lags run from 22.8 in the richest quartile to 49.2 in the poorest. They show up as the black dots in Figure 10. 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 1.4% (the top contour, and the rate of growth of technology adoption that would be necessary for the top quartile to reach the US level in 22.8 years) and 3.7% (the bottom contour, and the rate that would be necessary for the top quartile to reach the US level in 49.2 years).

How reasonable is this interval for growth rates of technology usage? The best empirical proxies available for a wide variety of countries are estimates of measured TFP growth. We recognize these are not ideal counterparts, since measured TFP changes reflect factors beyond changes in technology – like institutional changes or varying trade patterns – but they are widely available.

Figure 10: Implied model lags vs. data



Looking at the US (since the lags are with respect to past US history), according to data from Fernald (2012), TFP growth (adjusted for utilization) grew at an average of 1.5% from 1947 to 2005, right in line with the lower bound of our interval. The upper bound of our interval does seem to be on the high side in comparison, but there are (at least) two attenuating factors one should consider. The first is that of all processes measured TFP captures, technology is probably one of the fastest-changing, say in relation to something like institutional changes, implying that whatever *pure* measures of technology change are, they should grow faster than measured TFP. The second is that countries in lower quartiles are far from the technological frontier, so they do not need to come up with the blueprints like the U.S. did, by-and-large, and can (and do) supercharge their technological evolution.

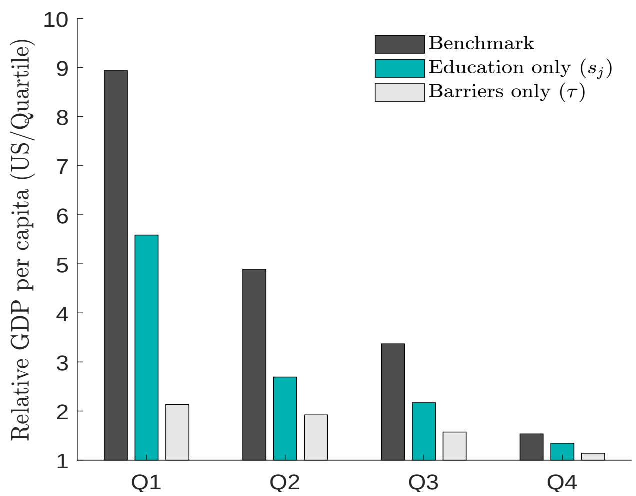
Looking at a wider set of countries, using the Penn World Tables (PWT), Feenstra, Inklaar, and Timmer (2015), we can find numerous examples where measured TFP growth averaged above 3% a year for sustained periods. In fact, half of the countries that report more than 11 years of TFP data had at least one such 10-year period, while a quarter of the countries that more than 21 years of TFP data had at least one such 20-year period. In light of these numbers, we think the growth rate range we find above helps corroborate the quantitative relevance of the model.

5.2.1 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 so as to match the data for each quartile . Next, to single out the effects of technology adoption barriers, we keep average years of schooling 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., $\tau = 0.4$ for the poorest quartile).

Figure 11 illustrates one of our main quantitative results: differences in schooling and barriers to adoption interact and amplify each other in a way that is quantitatively meaningful for cross-country income dispersion. In our benchmark, which interacts the two shocks, the resulting factor difference of 9 is larger than the sum of the factor differences when only education varies (5.6) and the factor difference when only barriers vary (2.1). Moreover, this amplification seems to rise as incomes drop.

Figure 11: Shock decomposition



Furthermore, these experiments are useful to isolate the importance of education for technology adoption and for the organization of production across countries. In both cases the model offers sharp policy implications.

Consider the technology level v averaged over all modern establishments in the model economy. Changing only schooling levels (and keeping barriers constant) results in technology levels that are 3 times smaller in the poorest quartile than in the US economy. This magnitude may be hard to appreciate since we do not have an immediate data counterpart to contrast it to. Nonetheless, the model suggests that the importance of education for technology adoption is at least as much as that of adoption barriers themselves. When we only increase the cost of technology adoption by the same magnitude as in our benchmark for the poorest quartile ($\tau = 0.4$) and leave schooling unchanged at the US level, the average v only drops by a factor of 2.25. If we further consider the fact that educating your workforce is a straightforward and well-understood budget item with plenty of other positive externalities, it is impossible not to arrive at the conclusion that this must be one of the most effective ways of promoting technology adoption.

Looking at the same experiments, but focusing instead on the share of own account workers, the effectiveness of education in eradicating the traditional sector is also apparent. When we change education to the poorest quartile's level and leave barriers unchanged, the share of own account workers increases by over 33 percentage points, from 6.6 percent to 40 percent. In contrast, when we change barriers to $\tau = 0.4$ and leave education at US levels, the share of own account workers only goes up to 22 percent. Education gaps alone (working through technology complementarities) can account for a large fraction of the difference in the share of own-account workers between rich and poor economies.

Finally, while we chose to assess the importance of barriers by moving them by the same amount as we did in the benchmark, an alternative way is to fix education at US 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 1.5 (as opposed to 0.4) for the poorest quartile and the output factor for this quartile is 5.6 (as opposed to 2.1 in the "barriers only case" in Figure 11). 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.[24] 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.

5.2.2 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.[25] 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

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

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

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 9. 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 $sh_o\Big|_{Q1} \bar{y}_o\Big|_{Q1} + (1 - sh_o)\Big|_{Q1} \bar{y}_m\Big|_{US}$. We find that the extensive margin accounts for a little over a quarter 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.

5.3 An economy without technology adoption

In the *Education only* experiment shown in Figure 11, even if barriers are not changing, there is still some interaction between human capital and technology adoption. As we move to lower quartiles and schooling falls, less educated managers – who also hire from 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 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 managers or workers, $j \in \{m, w\}$, and the former do not get to make a technology choice.

As in the benchmark model, this economy is also populated by a unit mass of individuals who derive utility from consumption and an occupation-specific preference shock, and are endowed with known ability ($z \in \mathbb{Z} \subseteq \mathbb{R}_+$) that is distributed according to $\log z \sim N(\mu, \sigma)$. The mean of this ability distribution is determined by the average schooling in the economy, s that determines the mean of the ability distribution: $\mu = \phi \log s$, where $\phi > 0$. Individuals make their choices after observing their occupation-specific taste shocks ε_j, this time only over two occupations $j \in \{m, w\}$. Again, these shocks are *i.i.d.* and independent of z, and follow a type-I extreme value (Gumbel) distribution with location parameter 0 and scale parameter $\lambda > 0$. Individuals also choose the level of non-schooling education expenditures, e, which together with schooling time, s produce human capital h.

The occupational problem is simply:

$$V(z) = \max_j \{V_j(z) + \varepsilon_j | j \in \{m, w\}\}, \tag{8}$$

where $V_j(z)$ are the optimal occupational utilities. Going backwards, an individual who has already chosen occupation $j \in \{m, w\}$, solves the following problem:

$$\begin{aligned} V_j(z) = \max_{c_j, e_j} \quad & \log(c_j) \\ s.t. \qquad & c_j = I_j(h_j; \boldsymbol{\omega}) - e_j, \\ & h_j = z e_j^{\theta}, \quad \theta > 0 \end{aligned}$$

where all common parameters and functions play the same role as before. Occupation-specific income $I_j(h_j; \boldsymbol{\omega})$ is now simply a worker type's wage rate $\omega(h_w)$, or managerial income. To see how the latter is determined, let x and y index the different types of workers and managers (as defined by the different levels of h_w and h_m, respectively). Taking worker-type wages $\omega(x)$ as given, managers solve:

$$\Pi_m(y; x, \boldsymbol{\omega}) = \max_{l(x)} \int_x \Big(\left[\alpha_m h_m(y)^p + (1-\alpha_m) h_w(x)^p\right]^{1/p} l(x)^{\alpha} - l(x)\omega(x) \Big)\, dx,$$

where $\alpha \in (0, 1)$ governs the share of income accruing to labor (and the managerial input), α_m determines the share of manager productivity in production, and p determines the complementarity between worker and manager productivity. Equilibrium in this economy is subject to the same market clearing conditions as in the benchmark, in particular, labor markets for every worker type (as given by their human capital) need to clear.

To calibrate the model, we keep the same externally calibrated parameters for years of education and for the complementarity in the production function. We keep the same targets wherever possible. We are dropping two parameters related to the own-account sector that and one related to the cost of technology adoption since those features of the model are no longer present in this version. We now calibrate α jointly with the remaining parameters. All parameter values and targets are shown in Table 6.

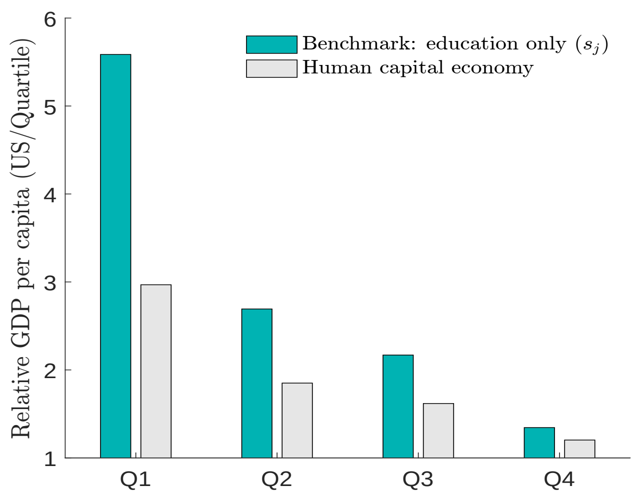
The experiment now simply consists of varying the average years of schooling to match the ones observed in each of the quartiles of the income distribution. The results in Figure 12 show that reducing schooling to match the data in the poorest quartile decreases output by a factor of 2.9 only, compared to a factor of 5.6 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.

Table 6: Calibration (human capital economy)

Parameters	Targets matched
$s = 0.806$	Average Years of schooling: 12.9
$\alpha_m = 0.636$	Estimated by Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018)
$p = -0.208$	Estimated by Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018)
$\alpha = 0.715$	Share of salaried workers: 86.5%
$\lambda = 0.777$	Std. dev. of log employment: 1.3
$\phi = 0.891$	Mincer return (modern sector): 8.9%
$\sigma = 0.922$	Variance of log-earnings: 0.46
$\theta = 0.072$	Education spending: 6.6% of GDP

Figure 12: Comparison to human capital economy

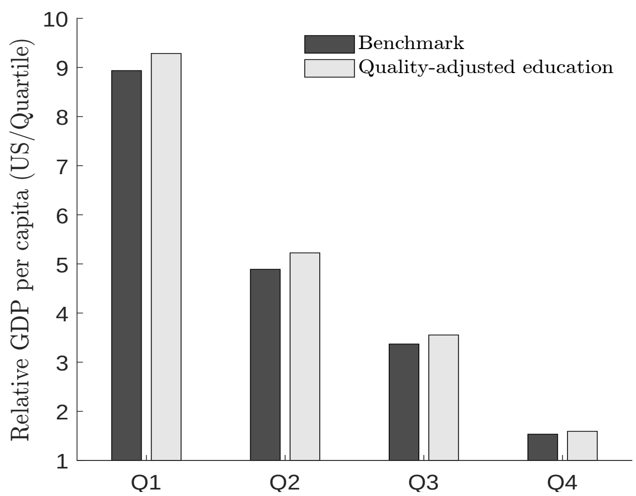


5.4 Adjusting for education quality

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 the World Bank uses in computing its Human Capital Index.[26] These test scores adjustment factors are country-specific and are shown in Table 10 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. The larger differences in adjusted schooling between the U.S. 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 slightly smaller than before (0.35 versus 0.4 in our unadjusted benchmark). The large income factor differences we found are robust to this adjustment. In fact, they are a little larger, if anything, as Figure 13 shows. We conclude that accounting for education quality reinforces our findings, and further helps to highlight the fact that in our model, education differences can be substantially amplified with relatively small differences in barriers to adoption across countries.

Figure 13: Adjusting for education quality



Moreover, this experiment also highlights the importance of the human capital-occupational choice nexus for the size of the barriers needed to rationalize cross-country income differences in our model. The larger human capital differences implied by the education-adjusted data result in larger amplification with *smaller* barriers (while targeting the same shares of own-account workers). Because lower human capital leads more individuals to select into more unproductive occupations, barriers to more productive occupations need not be so high in order to generate the same income differences, compared to models where human capital and occupational choice are unconnected.

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

[26]See World Bank (2020b).

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 typically associated with limited opportunities for technological adoption.

We use microdata to 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 93% 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 explaining 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 the literature (see e.g., 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.

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. Countries with a generic category for self-employment are not useful for our analysis as they do not allow us to distinguish between traditional and modern forms of entrepreneurship.[27] 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 7 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 shows that we have a good number of developing and poor economies in our data.

Table 7: Aggregate Summary Statistics

Region	No. Countries	Education Years	Share of Wage/Salary Workers
Africa	16	5.1	0.41
Asia	11	7.5	0.50
Europe	8	11.2	0.77
Latin America	15	7.3	0.55
USA/Canada	2	12.9	0.85

Source: Authors' estimations using IPUMS-International data.

Table 8 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 quantitative application of the model for cross-country comparisons.

[27] A particular case is the United States, which reports data for self-employment based on incorporated and unincorporated status. 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 8: Summary Statistics by Country

Country	GDP pc	N_o	N_w	N_m	Educ. Yrs	Tech Lag
CHE	1.20	0.08	0.79	0.13	13	9.6
IRL	1.10	0.12	0.76	0.13	12	19.1
USA	1.00	0.07	0.86	0.06	13	0.0
CAN	0.87	0.05	0.84	0.11	13	4.5
ITA	0.82	0.10	0.74	0.16	11	20.5
FRA	0.81	0.06	0.85	0.10	12	15.6
ESP	0.71	0.07	0.82	0.11	11	24.0
PRT	0.59	0.06	0.80	0.14	9	27.3
GRC	0.57	0.19	0.66	0.15	11	27.7
POL	0.44	0.18	0.73	0.08	11	36.4
MYS	0.39	0.26	0.65	0.09	7	29.9
CHL	0.39	0.13	0.76	0.11	9	36.4
URY	0.39	0.24	0.60	0.15	8	44.9
PAN	0.38	0.32	0.64	0.04	9	41.6
TUR	0.34	0.33	0.60	0.07	8	43.3
MEX	0.34	0.20	0.74	0.06	10	39.7
MUS	0.31	0.14	0.79	0.07	8	35.3
CRI	0.30	0.25	0.62	0.13	8	37.2
BRA	0.28	0.23	0.68	0.08	8	40.2
THA	0.27	0.53	0.40	0.07	6	42.2
BWA	0.25	0.13	0.81	0.06	8	46.1
IRN	0.22	0.49	0.42	0.09	8	48.4
PRY	0.20	0.49	0.42	0.09	6	46.1
EGY	0.20	0.04	0.89	0.06	7	48.7
ECU	0.19	0.32	0.61	0.07	8	43.0
PER	0.19	0.42	0.51	0.06	10	43.9
MNG	0.17	0.52	0.44	0.04	10	41.1
GTM	0.16	0.39	0.46	0.15	5	39.5
JOR	0.16	0.10	0.81	0.09	11	34.0
IDN	0.15	0.53	0.40	0.07	8	49.3
SLV	0.14	0.30	0.61	0.09	6	36.8
BOL	0.13	0.48	0.43	0.09	9	33.3
MAR	0.12	0.41	0.52	0.07	4	44.9
PHL	0.11	0.30	0.59	0.11	9	43.9
NIC	0.10	0.44	0.52	0.04	5	39.0
HND	0.09	0.45	0.46	0.09	4	42.8
IND	0.08	0.37	0.53	0.10	7	49.9
GHA	0.08	0.59	0.32	0.09	7	47.7
CMR	0.07	0.66	0.32	0.03	6	46.1
SDN	0.07	0.36	0.45	0.19	4	51.8
KHM	0.06	0.71	0.27	0.02	5	38.8
SEN	0.06	0.66	0.23	0.11	3	47.3
HTI	0.05	0.81	0.16	0.04	4	53.0
NPL	0.05	0.61	0.35	0.05	5	41.9
ZMB	0.05	0.57	0.39	0.03	8	45.4
BEN	0.05	0.78	0.15	0.07	4	51.3
GIN	0.04	0.89	0.08	0.03	2	46.0
TZA	0.04	0.75	0.19	0.06	6	52.8
LSO	0.04	0.31	0.68	0.02	5	45.8
MLI	0.04	0.63	0.35	0.02	1	56.4
TGO	0.03	0.76	0.19	0.05	5	48.6
RWA	0.03	0.73	0.26	0.01	4	60.4

Notes: N_j refer to employment shares 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 for at least 5 of the major technologies considered. GDP per capita is expressed relative to the US.

A.2 Industries technology ranking

The following table presents the ranking of industries based on usage of modern technologies.

Table 9: Technology Use Ranking by Industry in the United States

Industry	Technology use intensity	Rank
Financial services and insurance	47	1
Health and social work	40	2
Business services and real estate	40	3
Education	38	4
Manufacturing	35	5
Electricity, gas, water and waste management	34	6
Transportation, storage, and communications	31	7
Other services	26	8
Wholesale and retail trade	25	9
Construction	22	10
Mining and extraction	21	11
Hotels and restaurants	20	12
Agriculture, fishing, and forestry	18	13

Notes: Industries are classified according to IPUMS International. Technology use intensity represents the percentage of firms that use modern technologies based on ABS 2019 data. See main text for details.

A.3 Education quality adjustment

Table 10 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 13 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 10: Quality-adjusted years of schooling

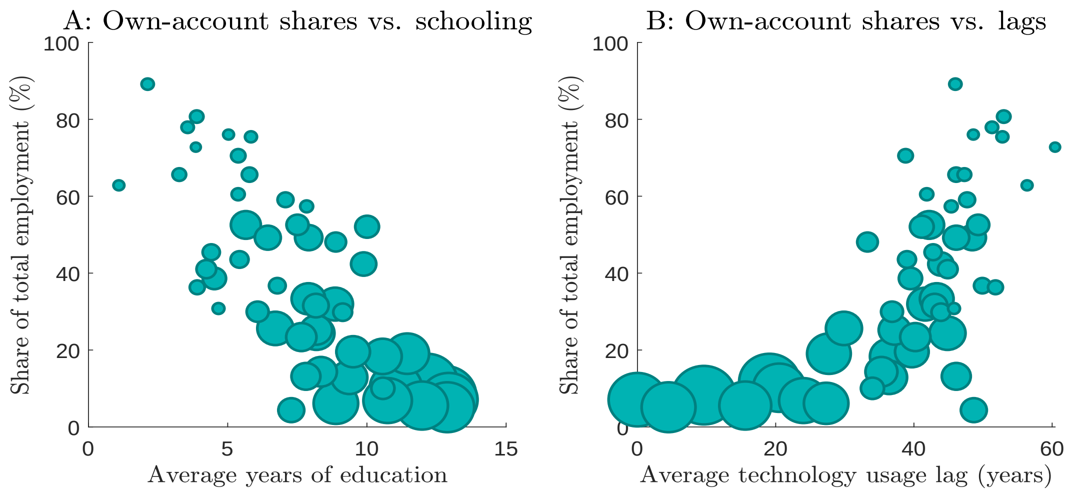
	Raw	Adjusted	Adjustment factor
USA	12.93	10.61	0.82
4th quartile	10.75	7.63	0.71
3rd quartile	7.97	5.10	0.64
2nd quartile	6.95	4.17	0.60
1st quartile	4.29	2.53	0.59

Notes: Data from Patrinos and Angrist (2018) and authors' calculations.

A.4 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 14 we show the fraction of own-account employment against average schooling attainment across countries. 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 14: The importance of occupational choices



Panel B of Figure 14 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 11: Own-account Employment and Technology Usage Lag

	All	Internet	PCs	Electricity	Aviation-Cargo	Tractors	Cellphones
Own-account (%)	0.363	0.150	0.198	0.676	0.462	0.386	0.159
	(0.0661)	(0.0173)	(0.0344)	(0.104)	(0.0935)	(0.0881)	(0.0157)
Observations	52	49	48	51	40	52	52

Notes: Robust standard errors are in parenthesis. Employment shares are estimated with IPUMS-International data and technology usage lags are obtained from Comin, Hobijn, and Rovito (2008).

In Table 11, we confirm the strength and statistical significance of this relationship by running simple cross-country regressions of technology usage lags on own-account employment shares. The positive correlation between both variables is weaker for digital age technologies, such as the Internet, but still meaningful (and always statistically significant). In Table 12 we do a similar estimation using educational attainment instead of own-account employment. The results confirm the negative correlation between education and technology usage lags across countries.

Table 12: Education and Technology Usage Lags

	All	Internet	PCs	Electricity	Aviation-Cargo	Tractors	Cellphones
Average Education	-3.414	-1.161	-1.744	-6.406	-3.811	-3.865	-1.270
	(0.478)	(0.111)	(0.261)	(0.725)	(0.613)	(0.778)	(0.109)
Observations	52	49	48	51	40	52	52

Notes: Robust standard errors are in parenthesis. Educational attainment is estimated with IPUMS-International data and technology usage lags are obtained from Comin, Hobijn, and Rovito (2008).

A.5 Sensitivity analysis

In this section we conduct various exercises related to sensitivity analysis.

A.5.1 Elasticity of targets with respect to parameters

We start by asking how sensitive are the moments we use to calibrate the model to each of the model's parameters. Table 13 shows the elasticities of the various targets (along the columns) with respect to the parameters (in rows) at our benchmark calibration, where all targets are exactly matched.

Table 13: Sensitivity Matrix

	% workers	% managers	E to GDP	Mincer (all)	Mincer (trad.)	SD(log. empl.)	VAR(earnings)
η	-0.260	4.287	-1.340	-1.158	-0.002	-0.409	-2.964
σ	0.296	-1.650	-0.416	-0.082	-0.002	0.212	2.048
ψ	-0.139	-0.073	-0.027	-0.085	-0.002	-0.024	-0.004
θ	0.024	-0.301	0.978	0.001	0.022	-0.020	0.129
ϕ	-0.030	-0.029	0.048	1.014	1.014	-0.010	0.002
λ	-0.205	0.489	-0.022	-0.045	-0.002	0.508	0.061
ρ	0.059	0.004	0.012	0.054	1.038	0.003	0.045

Notes: Values are elasticities (in percentage) from target (column) with respect to parameter (row).

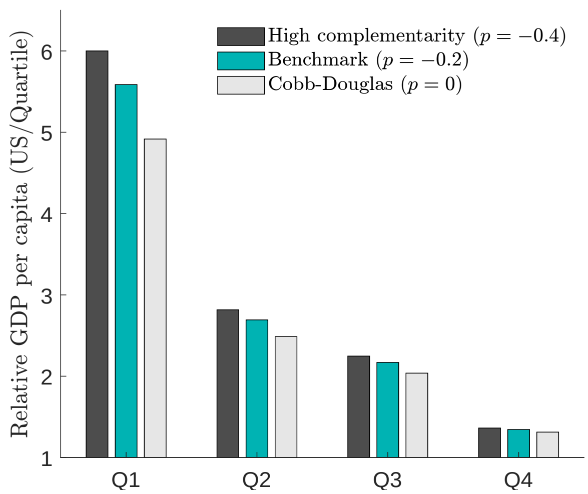
The targets we picked are all sensitive to the model's parameters. Setting a (admittedly arbitrary) threshold at an absolute elasticity of 0.25%, all targets respond above this threshold to at least two parameters. Conversely, all but two parameters have effects above this threshold for at least two targets. The exceptions are ψ and ρ that control the traditional sector production, because this is a fairly small sector in the US benchmark so the effect on macro targets is necessarily relatively smaller. Note that these parameters result in a an elasticity above the threshold for the share of traditional sector workers.

A.5.2 Complementarity between worker and manager productivity

Recall that our estimate for p is not calibrated to match a target, and was instead obtained from Abowd, Kramarz, Pérez-Duarte, and Schmutte (2018), who estimate it directly from US data described in Section 4. It is therefore important to understand how sensitive the cross-country income dispersion we obtain is to this parameter. In order to do this we consider two alternative values for p, one above and one below what we use in our benchmark calibration ($p = -0.208$). For a production function with more substitutability, we consider the standard Cobb-Douglas ($p = 0$), and for one with stronger complementarity we use $p = -0.4$. In both cases we recalibrate all the other parameters to continue to hit the same targets. Figure 15 compares the amplification we get under the three different calibrations when we only change education.[28]

While it is not the case that skill complementarity in production is necessary to obtain a substantial amount of income dispersion – as the Cobb-Douglas case shows – it does generate much more amplification (for a given level of human capital). Models of cross-country income dispersion that fail to feature this channel therefore risk underestimating income differences. Moreover, complementarity in skills gets amplified by the fact that more productive units, in terms of human capital, also operate with better technologies, and the extent to which they do depends crucially on the parameter η, which we now turn to.

Figure 15: Sensitivity to p



A.5.3 Convexity of adoption costs

In section 3 we used equation 5 to argue that η, the parameter governing the convexity of the cost of adoption impacts an important amplification channel: given human capital complementarity in production $f(x, y)$, the smaller η is, the more productive technology a manager will adopt. Here, we confirm that this channel is quantitatively important for cross-country income differences.

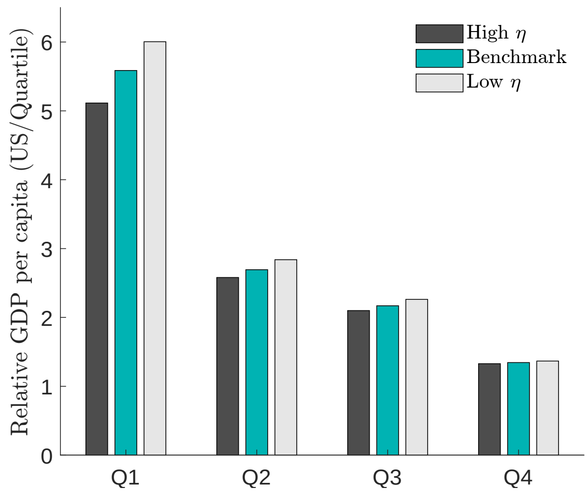
Unlike what is the case for p, the value of η is chosen to match (joint) targets. As we experiment with values 10 percent above and below our benchmark value of $\eta = 1.5$, we opted for keeping all the same targets, resulting in an over-identified system.[29] Note, from Table 13 that all but one of the targets is highly sensitive to η, especially the share of modern managers. We think the value of η is pinned down credibly by our calibration strategy. Our goal in this exercise is simply to ascertain how important this channel is in driving cross-country income differences.

As Figure 16 shows, this channel is rather important, and quantitatively similar to skill complementarity.

[28]Had we changed barriers at the same time, the calibrated values for τ that would match the share of traditional workers in each specification would be different, which would confound the pure effect of changing p.

[29]In practice, all targets are exactly matched, except for the standard deviation of log employment and the variance of log earnings, which are within 10 percent of their target values.

Figure 16: Sensitivity to η



A.5.4 Occupation-specific taste shocks

Recall that λ represents the dispersion (scale) of the occupation-specific preference shock. Again, unlike what is the case for p, and just like what happens with η, the value of λ is chosen to match (joint) targets. As we experiment with values 10 percent above and below our benchmark value of $\lambda = 0.497$, we keep all the same calibration targets, resulting in an over-identified system. Nonetheless, all parameters except the standard deviation of log employment are matched exactly.[30]

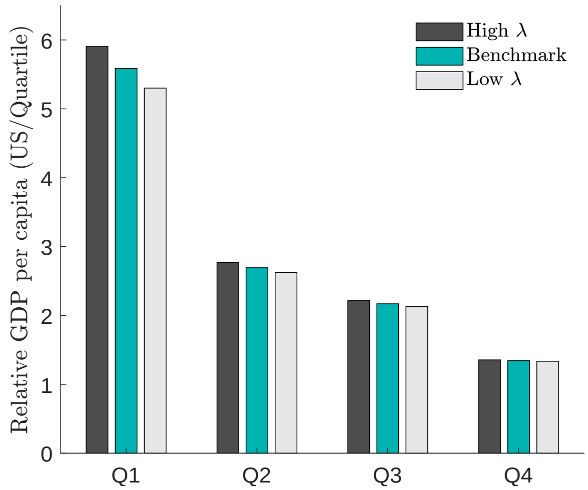
As λ increases and the dispersion of the occupation-specific preference shocks rises, the odds that an individual draws a shock that is large enough to bump them into an occupation that is not the most pecuniary attractive one increase. Raising λ blunts pecuniary motives and reduces the importance of human capital in occupational choice, bringing occupational shares, for each human capital type, closer together. As Table 13 shows, λ is "well-identified" by the moments we choose to target. Not only the two occupational shares, but also the standard deviation of log-employment are all sensitive to it.

As Figure 17 shows, income dispersion is not very sensitive to the choice of λ.[31] To the extent that it is, a higher λ increases income dispersion. Recall from our discussion in Section 4, that our calibration does a fairly reasonable job at capturing untargeted moments of the establishment distribution. It can deliver a large number of small establishments, but it falls short in generating a long enough right tail of the establishment size distribution. It fails to capture very large and very productive establishments. Everything else being the same, the more right-skewed the establishment distribution is in the US benchmark, the larger the dispersion will be, since these sort of establishments will be much smaller in less-educated, barrier-ridden, economies. Increasing λ, it turns out, makes for a more right-skewed distribution. Not because the larger establishments become larger or more productive, but because they constitute a larger share, one that is closer to the data. Therefore, we argue that our choice of targets and the resulting calibration strike a fair balance, were we to directly target the share of large establishments, the resulting amplification would be even larger.

[30]The target for the standard deviation of log employment is 1.3. We get 1.22 for the low λ and 1.39 for the high λ.

[31]As in the previous section, we only change education, and not barriers, because the calibrated values for τ that would match the share of traditional workers for each λ would be different, which would confound the pure effect of changing λ.

Figure 17: Sensitivity to λ



A.6 Profit maximization in modern production

Recall from equation (3) that the problem of a modern sector manager is:

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \max_{v(x),l(x)} \int_x \left(v(x) \left[\alpha_m h_m(y)^p + (1-\alpha_m) h_w(x)^p\right]^{1/p} l(x)^\alpha - l(x)\omega(x) - (1+\tau)\frac{v(x)^\eta}{\eta} \right) dx,$$

Letting $f(x,y) = \left[\alpha_m h_m(y)^p + (1-\alpha_m) h_w(x)^p\right]^{1/p}$, the F.O.C. w.r.t. $v(x)$ is:

$$f(x,y) l(x)^\alpha = (1+\tau) v(x)^{\eta-1},$$

and therefore,

$$v(x) = \left(\frac{f(x,y) l(x)^\alpha}{1+\tau} \right)^{\frac{1}{\eta-1}}. \tag{9}$$

Plugging this back into the objective:

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \max_{l(x)} \int_x \left(\left[\frac{(f(x,y)l(x)^\alpha)^\eta}{1+\tau} \right]^{\frac{1}{\eta-1}} - l(x)\omega(x) - \frac{1}{\eta} \left[\frac{(f(x,y)l(x)^\alpha)^\eta}{1+\tau} \right]^{\frac{1}{\eta-1}} \right) dx,$$

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \max_{l(x)} \int_x \left(\frac{\eta-1}{\eta} \left[\frac{(f(x,y)l(x)^\alpha)^\eta}{1+\tau} \right]^{\frac{1}{\eta-1}} - l(x)\omega(x) \right) dx,$$

The F.O.C. w.r.t. $l(x)$ is:

$$\omega(x) = \alpha \left(\frac{[f(x,y)]^\eta}{1+\tau} \right)^{\frac{1}{\eta-1}} l(x)^{\frac{1+\eta(\alpha-1)}{\eta-1}}$$

Solving for $l(x)$:

$$l(x) = \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x,y)^{\eta}}{1+\tau}\right)^{\frac{1}{\eta(1-\alpha)-1}} \tag{10}$$

Plugging this back into the objective once more:

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \int_x \left(\frac{\eta-1}{\eta} \left(\frac{f(x,y)^{\eta}}{1+\tau} \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\alpha\eta(\eta-1)}{\eta(1-\alpha)-1}} \left(\frac{f(x,y)^{\eta}}{1+\tau}\right)^{\frac{\alpha\eta}{\eta(1-\alpha)-1}} \right)^{\frac{1}{\eta-1}} - \omega(x) \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x,y)^{\eta}}{1+\tau}\right)^{\frac{1}{\eta(1-\alpha)-1}} \right) dx.$$

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \int_x \left(\frac{\eta-1}{\eta} \left(\frac{f(x,y)^{\eta}}{1+\tau}\right)^{\frac{1}{\eta(1-\alpha)-1}} \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\alpha\eta}{\eta(1-\alpha)-1}} - \omega(x) \left(\frac{\alpha}{\omega(x)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x,y)^{\eta}}{1+\tau}\right)^{\frac{1}{\eta(1-\alpha)-1}} \right) dx.$$

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \int_x f(x,y)^{\frac{\eta}{\eta(1-\alpha)-1}} \left[\frac{1}{(1+\tau)\omega(x)^{\eta\alpha}}\right]^{\frac{1}{\eta(1-\alpha)-1}} \left[\left(\frac{\eta-1}{\eta}\right) \alpha^{\frac{\alpha\eta}{\eta(1-\alpha)-1}} - \alpha^{\frac{\eta-1}{\eta(1-\alpha)-1}} \right] dx.$$

Letting $C(\omega(x),\tau) = \left[\frac{1}{(1+\tau)\omega(x)^{\eta\alpha}}\right]^{\frac{1}{\eta(1-\alpha)-1}} \left[\left(\frac{\eta-1}{\eta}\right) \alpha^{\frac{\alpha\eta}{\eta(1-\alpha)-1}} - \alpha^{\frac{\eta-1}{\eta(1-\alpha)-1}} \right]$, this is

$$\Pi_m(y;x,\boldsymbol{\omega},\tau) = \int_x f(x,y)^{\frac{\eta}{\eta(1-\alpha)-1}} C(\omega(x),\tau) dx.$$

Proof of Proposition 1 part (ii). As a reminder, in the main text we defined the ratio of demand for workers of type x_1 to that for workers of type x_0 by any manager of type y, $R(y, x_1/x_0)$, as:

$$\frac{l^d(x_1,y)}{l^d(x_0,y)} = \left(\frac{w(x_0)}{w(x_1)}\right)^{\frac{\eta-1}{\eta(1-\alpha)-1}} \left(\frac{f(x_1,y)}{f(x_0,y)}\right)^{\frac{\eta}{\eta(1-\alpha)-1}}.$$

To show that $R(y, x_1/x_0)$ is increasing in type y whenever $h_w(x_1) > h_w(x_0)$ and $\eta(1-\alpha) > 1$, it is enough to show that the sectoral human captial ratio $f(x_1,y)/f(x_0,y)$ is increasing in y if and only if $\rho < 0$. Differentiating the ratio with respect to y, the condition for the derivative to be positive—when $h_w(x_1) > h_w(x_0)$—is:

$$\begin{aligned} & f_y(x_1,y)f(x_0,y) > f_y(x_0,y)f(x_1,y) \\ & \iff \frac{f_y(x_1,y)}{f_y(x_0,y)} > \frac{f(x_1,y)}{f(x_0,y)} \\ & \iff \left(\frac{f(x_1,y)}{f(x_0,y)}\right)^{1-\rho} > \frac{f(x_1,y)}{f(x_0,y)} > 1 \\ & \iff 1-\rho > 1 \quad \Rightarrow \quad \rho < 0 \end{aligned}$$

□

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