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Cross-country disparities in skill premium and skill acquisition

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Abstract

Skilled individuals are rewarded more in poor than in rich countries. Why aren't more individuals acquiring skills in poor countries? We document that the unemployment rate of the skilled net of that of the unskilled decreases with a country's level of development. Using a matching model of occupational choice and skill acquisition, we quantify the role of barriers to enter entrepreneurship for these unemployment rates, skill premium and acquisition. The cross-country correlation between skill premium and acquisition decreases by 45% when each country's gap to the US in the entrepreneurship barrier is decreased enough to even the unemployment differential.

KEYWORDS
entrepreneurship barrier, skill acquisition, unemployment

JEL CLASSIFICATION
O11, J31, J24, E24

1 | INTRODUCTION

Cross-country data on wages and schooling indicate that although poor countries have a higher skill premium than rich countries, skill acquisition is substantially lower in poor countries. A 1% increase in output per capita is associated with a 0.54 percentage-point *decrease* in the ratio of tertiary- and secondary-educated average wages relative to primary-educated average wages ("skill premium", panel (a) of Figure 1) and with an *increase* of 0.16% points in the fraction of men with secondary and tertiary schooling ("skill acquisition", panel (b) of Figure 1).[1] If skilled individuals are rewarded more in poor countries, why aren't more individuals acquiring skills in these countries?

In this paper, we argue that disparities in the unemployment rates by skill level are quantitatively important for generating the cross-country pattern of skill premium and acquisition. Using the World Development Indicator dataset provided by the World Bank, we compile the unemployment rates of skilled and unskilled men in a sample of 52 countries over the period 2000–2010. Panel (c) of Figure 1 plots the unemployment rate of the skilled net of that of the

Abbreviations: GDP, Gross Domestic Product; GEM, Global Entrepreneurship Monitor; GNI, Gross National Product; ILO, International Labour Organization; IPUMS, Integrated Public Use Microdata Series; OECD, Organisation for Economic Co-operation and Development; UN, United Nations; US, United States; WDI, World Development Indicator.

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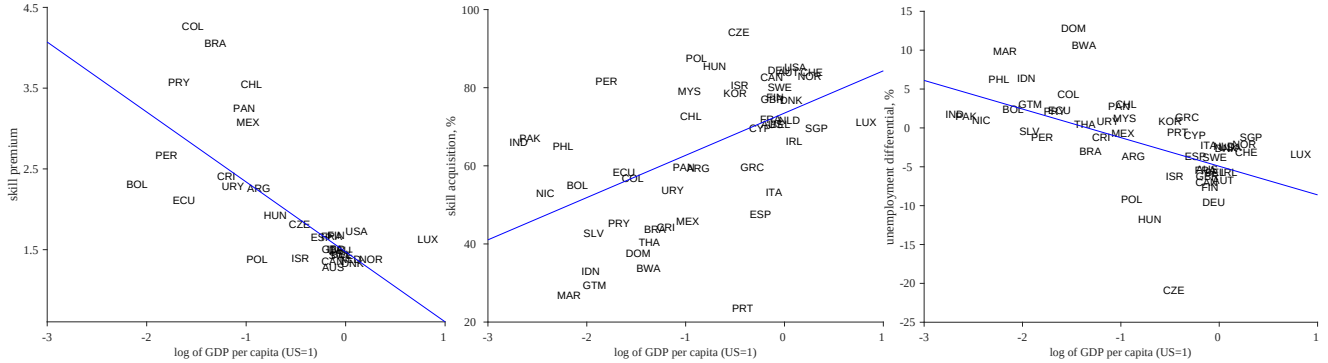

(a) skill premium **(b)** fraction of skilled individuals **(c)** unemployment differential

FIGURE 1 Skill premium, acquisition, and unemployment differential across countries. For each country, the skill premium is computed as the ratio of secondary and tertiary-educated wages relative to primary-educated wages. Data are measured between year 1992 and year 1998. Skill acquisition is computed as fraction of tertiary-educated and secondary-educated men. The unemployment differential is computed as the unemployment rate of tertiary-educated and secondary-educated men minus that of primary-educated men. Data are measured between year 2000 and year 2010 and calculated as average during these years. GDP per capita in constant 2017 international $. *Source*: Fernández et al. (2005) and the World Bank

unskilled ("unemployment differential") and shows a negative association with output per capita. That is, skilled individuals consistently face a higher risk of unemployment than unskilled individuals in poor countries compared to rich countries. Taking into account this unemployment risk closes the disparities in measured rewards to skill acquisition between rich and poor countries, and may therefore rationalize the negative cross-country association between skill premium and acquisition. Suggestive to this conjecture, a regression of skill acquisition on the skill premium shows that the resulting negative coefficient decreases, in absolute value, when controlling for the unemployment differential.[2]

We investigate the quantitative role of unemployment by skill level in reconciling a lower skill acquisition and a higher skill premium in poor compared to rich countries. To do so, we quantify a matching model of occupational choice and skill acquisition where unemployment rates by skill level, skill acquisition, and skill premium arise as equilibrium outcomes of exogenous barriers to enter entrepreneurship, barriers to acquire schooling, and skill-productivity profiles. We include a barrier to enter entrepreneurship as a determinant of the unemployment rates (see, e.g., Fonseca et al., 2001).[3] Through the lenses of our model we infer a higher barrier to enter entrepreneurship in poor countries and find that a decrease in cross-country disparities in such barrier that is enough to even the unemployment differential accounts for 45% of the cross-country negative correlation between skill premium and acquisition.

In our model, ex-ante identical individuals face barriers to improve their skill and/or to become an entrepreneur. We refer to these barriers as schooling and entrepreneurship barriers, respectively, and model them as monetary costs. Workers and entrepreneurs randomly and anonymously match in the labor market to produce output (a match productivity) in relation to both their skills. Given match productivities, schooling and entrepreneurship barriers determine the relative supplies of skilled and unskilled workers and entrepreneurs. We show that the entrepreneurship barrier influences the unemployment rate differential and ultimately the fraction of skilled individuals in relation to the shape of the skill-match productivity profile and the extent of risk aversion. Under risk neutrality and a structure of match productivities that is log supermodular in worker's skill, a higher entrepreneurship barrier increases the unemployment rate differential. The fraction of skilled workers decreases and that of skilled entrepreneurs increases and, overall, the fraction of skilled individuals decreases.[4]

We use our model to assess the role of the entrepreneurship barrier for skill premium and acquisition across countries. To do so, we first calibrate our model. We allow countries to differ by their schooling barrier, entrepreneurship barrier, match productivities, and number of jobs created by each entrepreneur. We measure the last parameter directly in the data and calibrate the remaining parameters so that the model implied fraction of skilled individuals, unemployment rates of skilled and unskilled individuals, fraction of skilled entrepreneurs, and skill premium are as close as possible to replicating these same moments observed in each country in our sample. We calibrate a higher entrepreneurship barrier for poor countries compared to rich countries, consistently with measurable components of this barrier, such as regulatory costs of entry to business (Djankov et al., 2002) and how conducive to business operations the regulatory environment is (the World Bank). The cross-country correlation between the calibrated entrepreneurship barrier and the logarithm of output per capita is −0.239.

We then run a counterfactual exercise where we progressively reduce each country's gap in the entrepreneurship barrier to the US by 10%–50%. We find the entrepreneurship barrier explains between 21% (for a 10% reduction in the gap) and 45% (for a 33% reduction in the gap) of the cross-country correlation between skill premium and acquisition. The channel through which the entrepreneurship barrier affects skill acquisition is via the unemployment differential: a decreased entrepreneurship barrier decreases the unemployment rate of skilled individuals net of that of unskilled individuals and so boosts the returns to acquiring skill. We find that a 33% decrease in each country's gap to the US in the entrepreneurship barrier closes the gap in the unemployment differential and decreases the cross-country correlation between skill premium and acquisition by 45%.[5]

Various studies on the skill premium highlight the key role of skill-biased technical change for the rise of the skill premium in both rich (see, among others, Acemoglu, 2002, Goldin & Katz, 2008, and Krusell et al., 2000) and poor countries (Burstein et al., 2013; Caselli & Coleman, 2006). In addition, La Porta and Shleifer (2014) highlight that firms run by skilled entrepreneurs exhibit higher productivity and become more prominent as a country develops. Consistently with these studies, we calibrate lower productivities of matches where at least one party between the worker and the entrepreneur is skilled in poor countries compared to rich countries. We also find that the skill premium is most responsive to a decrease of the gaps to the US in the match productivity when both parties are skilled.

Our paper relates to the literature in macroeconomics and development addressing disparities in skill acquisition and skill premium across countries. Of particular relevance of our paper, Erosa et al. (2010), Cordoba and Ripoll (2013) and Restuccia and Vandenbroucke (2014), consider the role of productivity, credit frictions, access to public education, fertility, and life expectancy. We focus on the role of the entrepreneurship barrier, via its determination of the unemployment differential, for skill premium and acquisition. Reduced form evidence shows that the significantly negative association between skill acquisition and the unemployment differential is robust to including controls for proxies of channels considered in previous studies, for which we can find cross-country evidence.[6]

Finally, Cuadras-Morat and Mateos-Planas (2006) also simultaneously study the unemployment differential, skill premium, and acquisition. Similarly to our findings, they highlight the importance of barriers and skill-biased technical change for the determination of these labor market variables. Differently, they consider the US between 1970 and 1990, while we consider a cross-section of countries. Feng et al. (2021) and Poschke (2019) also document cross-country patterns of the unemployment rates by skill level, using household data. The patterns we document are consistent with the ones in these studies. Differently, our objective is not that of investigating the determinants of unemployment across countries. In our study, the unemployment rate gives a measure of the extent to which an individual's skill is used in the labor market and therefore determines the link between skill acquisition and premium. We use the entrepreneurship barrier to calibrate the model to the unemployment differential in the data, so to analyze its role for the cross-country covariation in skill premium and acquisition. The calibrated barrier encompasses, in reduced form, different forces driving the unemployment differential.

The rest of the paper is organized as follows. Section 2 outlines the model. Section 3 calibrates the model and details the results of the quantitative experiment. Section 4 concludes.

2 | MODEL

We consider a matching model of occupational choice and skill acquisition. There is a continuum of individuals of measure one. Individuals are ex-ante identical and live for one period.[7] They are endowed with y_0 units of goods and one unit of time. Individuals take two decisions simultaneously: a skill acquisition decision as to whether to pay a monetary cost (schooling barrier) and gain skills and an occupational decision as to whether to pay a monetary cost (entrepreneurship barrier) and run a business. If a schooling cost is incurred, the individual gains the status of "skilled", s, otherwise he remains "unskilled", u. If an entrepreneurship barrier is incurred, the individual acquires the status of "entrepreneur", f, otherwise he remains a "worker", w. Entrepreneurs manage firms and create a set number n of jobs per firm. Workers occupy jobs. The skill acquisition and occupational decisions give rise to a set of four individual types: (i) skilled entrepreneur (of mass p_{sf}), (ii) skilled worker (of mass p_{sw}), (iii) unskilled entrepreneur (of mass p_{uf}), and (iv) unskilled worker (of mass p_{uw}).

All individuals enter the labor market: each entrepreneur posts n of job openings and each worker looks for one job. Workers and jobs are matched randomly and anonymously. Define S_n to be the mass of workers and jobs – that is, $S_n \equiv n(p_{sf} + p_{uf}) + p_{sw} + p_{uw} = np_f + p_w$ for $p_f = p_{sf} + p_{uf}$ and $p_w = p_{sw} + p_{uw}$. A worker is matched to a job posted by a skilled entrepreneur with probability $\tilde{p}_{sf} = np_{sf}/S_n$ and with a job posted by an unskilled entrepreneur with probability

$\tilde{p}_{uf} = np_{uf}/S_n$. With the complementary probability $1 - \tilde{p}_{sf} - \tilde{p}_{uf}$ the worker remains unemployed. Analogously, a job is matched with a skilled worker with probability $\tilde{p}_{sw} = p_{sw}/S_n$ and with an unskilled worker with probability $\tilde{p}_{uw} = p_{uw}/S_n$. With probability $1 - \tilde{p}_{sw} - \tilde{p}_{uw}$ the job remains vacant and the entrepreneur runs a non-employee firm (own-account work). Those workers who are not matched with a job are deemed unemployed since their labor is unused. Entrepreneurs are always engaged since their labor is used up to open and manage the firm.[8]

After matching in the labor market, production takes place. A job posted by an entrepreneur with skill status $i \in \{sf, uf\}$ matched with a worker with skill status $j \in \{sw, uw\}$ produces non-negative output $y_{ij} \in \{y_{uu}, y_{su}, y_{us}, y_{ss}\}$. A firm's output is split between the worker and the entrepreneur: the latter pays the former a wage, w_{ij}, determined via Nash bargaining.

We now turn to the expected payoff of the individuals of all four types from various matches. Let $\Phi(\cdot)$ be an increasing and concave utility function with the standard regularity conditions. An entrepreneur's value of a matched job is represented by the following matrix:

	Job posted by an entrepreneur who is:	
Matched with:	**Unskilled**	**Skilled**
Unskilled worker	$J_{uu} = \Phi(y_{uu} - w_{uu} + y_0 - c)$	$J_{su} = \Phi(y_{su} - w_{su} + y_0 - c - sc)$
Skilled worker	$J_{us} = \Phi(y_{us} - w_{us} + y_0 - c)$	$J_{ss} = \Phi(y_{ss} - w_{ss} + y_0 - c - sc)$
Unmatched (own-account work)	$V_u = \Phi(y_0 - c)$	$V_s = \Phi(y_0 - c - sc)$

The terms c and sc indicate the entrepreneurship barrier and the schooling barrier, respectively. The value of a job posting for an entrepreneur of type $i \in \{u, s\}$ is:

$$J_i = \tilde{p}_{sw}J_{is} + \tilde{p}_{uw}J_{iu} + \left(1 - \tilde{p}_{sw} - \tilde{p}_{uw}\right)V_i.$$

The expected utility of filling n jobs independently by the entrepreneur is nJ_i. Note that the entrepreneurship barrier and the schooling barrier are monetary costs paid by the entrepreneur for each job posting – that is, an unskilled entrepreneur pays a cost of c to post a job and a skilled entrepreneur pays a cost of $c + sc$. This reflects, in monetary terms, that managing more jobs requires more time, resources, and skill. For example, an entrepreneur may incur costs of health insurance for each worker and various overhead costs.

A worker's value of matching with a job is represented by the following matrix:

	Worker:	
Matched with:	**Unskilled**	**Skilled**
Job posted by an unskilled entrepreneur	$E_{uu} = \Phi(w_{uu} + y_0)$	$E_{us} = \Phi(w_{us} + y_0 - sc)$
Job posted by a skilled entrepreneur	$E_{su} = \Phi(w_{su} + y_0)$	$E_{ss} = \Phi(w_{ss} + y_0 - sc)$
Unmatched (unemployed)	$U_u = \Phi(y_0)$	$U_s = \Phi(y_0 - sc)$

The value of a job posting for a worker of type $j \in \{u, s\}$ is:

$$W_j = \tilde{p}_{sf}E_{sj} + \tilde{p}_{uf}E_{uj} + \left(1 - \tilde{p}_{sf} - \tilde{p}_{uf}\right)U_j.$$

The total surplus of a match, $J_{ij} + E_{ij} - V_i - U_j$, is divided between the worker and the entrepreneur. We assume the wages, $\mathbf{w} = \{w_{uu}, w_{su}, w_{us}, w_{uu}\}$, are determined via Nash bargaining between the worker and the entrepreneur for each job (Mortensen & Pissarides, 1999):

$$w_{ij} = \arg\max\left[\left(J_{ij} - V_i\right)^{\theta}\left(E_{ij} - U_j\right)^{1-\theta}\right],$$

where $\theta \in [0, 1]$ is a parameter that measures the entrepreneur's bargaining power.

Equilibrium. In equilibrium, each individual optimally chooses its skill acquisition and occupation to maximize his expected utility, given the distribution of choices of other individuals. Define a probability distribution of individual types in the set of probability distributions $\mathcal{P}$ as $\mathbf{p} \equiv \{p_{uf}, p_{sf}, p_{sw}, p_{uw}\}$. An equilibrium is a vector $\{\mathbf{p}, \mathbf{w}\}$, such that each individual chooses the best response option as follows:

1. Choose to be a skilled entrepreneur (sf) if $nJ_s \geq \max(nJ_u, W_s, W_u)$,
2. Choose to be an skilled worker (sw) if $W_s \geq \max(nJ_u, nJ_s, W_u)$,
3. Choose to be an unskilled entrepreneur (uf) if $nJ_u \geq \max(W_s, nJ_s, W_u)$,
4. Choose to be a unskilled worker (uw) if $W_u \geq \max(W_s, nJ_s, nJ_u)$.

In an interior equilibrium, with a non-degenerate probability distribution of individual types, individuals have no incentives to deviate from their chosen option if the following value matching condition holds:

$$nJ_s = nJ_u = W_s = W_u.$$

The equilibrium distribution of skill acquisition and occupational choices $\mathbf{p}$ is a fixed point within the set of probability distributions $\mathcal{P}$. Since individuals are non-atomistic, only individuals with zero measure can deviate in equilibrium. Note that the game is symmetric and therefore by Mas-Colell (1984) (Theorem 2) the equilibrium exists.

Discussion. The focus of our paper is on the determinants of skill acquisition, skill premium and unemployment rates by skill level. In the following, we consider the response of these three variables to changes in the entrepreneurship barrier.

We start by defining skill acquisition, skill premium and unemployment rates by skill level in the context of our model. Skill acquisition is given by the fraction of skilled individuals. As the population has total measure of one, the proportion of skilled individuals, p_s, is the sum of skilled workers and skilled entrepreneurs:

$$p_s = p_{sw} + p_{sf}. \tag{1}$$

We compute the skill premium as the average wages of employed skilled individuals relative to that of employed unskilled individuals:

$$skp = \frac{E_s}{E_u}, \tag{2}$$

where

$$E_s = \frac{n(y_{ss} - w_{ss})\tilde{p}_{sw}p_{sf} + n(y_{su} - w_{su})\tilde{p}_{uw}p_{sf} + w_{us}\tilde{p}_{uf}p_{sw} + w_{ss}\tilde{p}_{sf}p_{sw}}{p_{sw}\tilde{p}_f + p_{sf}}, \tag{3}$$

$$E_u = \frac{n(y_{us} - w_{us})\tilde{p}_{sw}p_{uf} + n(y_{uu} - w_{uu})\tilde{p}_{uw}p_{uf} + w_{uu}\tilde{p}_{uf}p_{uw} + w_{su}\tilde{p}_{sf}p_{uw}}{p_{uw}\tilde{p}_f + p_{uf}}. \tag{4}$$

The numerator of the first (second) equation is the weighted sum of the wages of (un-) skilled individuals, where the weights are the relevant match probabilities. The denominator of the same equation is the proportion of employed (un-) skilled individuals. The wage of a worker is his take-home wage paid by the entrepreneur, while the wage of an entrepreneur is the firm's profit flow, $n(y - w)$. Last, the unemployment rate of (un) skilled individuals, u_s (u_u), is the proportion of skilled workers that are not matched with a firm out of all (un) skilled individuals:

$$u_s = \frac{p_{sw}\left(1 - \tilde{p}_{uf} - \tilde{p}_{sf}\right)}{p_s}, \tag{5}$$

$$u_u = \frac{p_{uw}\left(1 - \tilde{p}_{uf} - \tilde{p}_{sf}\right)}{p_u}. \tag{6}$$

Recall that entrepreneurs are always employed in our model as they spend their time managing and opening the firm, independently of whether workers are hired or not.

Next, for illustration, we study response of the endogenous moments of interest in Equations (1)–(6) with respect to the entrepreneurship barrier. To do so, we solve for the interior equilibrium of our model under risk neutrality (a linear utility function), an entrepreneur's share in bargaining equal to $\theta = 50\%$ (as in the quantitative exercise), and $n = 1$. The assumption of risk neutrality allows us to solve for the equilibrium in closed form. Equilibrium wages are linear in output: $w_{ij} = (1 - \theta)y_{ij}$. We report the equilibrium probabilities, p, in Appendix A2 to simplify the technical details of the derivation.

Proposition 1 *Assume risk neutrality, $n = 1$, a share bargaining parameter $\theta = 0.5$, and skill productivities that are log-supermodular in worker's skill,*[9] *i.e.:*

$$\log(y_{ss}) - \log(y_{su}) > \log(y_{su}) - \log(y_{us}) > \log(y_{us}) - \log(y_{uu}) > 0. \tag{7}$$

Then,

1. *For any value of c and sc,*

$$\frac{\partial p_s}{\partial c} < 0.$$

2. *In the in the neighborhood of $c = 0$ and $sc = 0$,*

$$\left.\frac{\partial skp}{\partial c}\right|_{c=0,sc=0} > 0.$$

3. *Further assume that y_{ss} is high enough, such that $y_{ss} > \frac{(y_{su}+y_{us})^2 - 4y_{su}y_{uu}}{y_{us}-y_{uu}}$. Then, in the neighborhood of $c = 0$ and $sc = 0$,*

$$\left.\frac{\partial u_s - u_u}{\partial c}\right|_{c=0,sc=0} > 0.$$

Proof. see Appendix A2.

The response of the proportion of skilled individuals to a change in the entrepreneurship barrier, c, is:

$$\begin{aligned}\frac{\partial p_s}{\partial c} &= \underbrace{\frac{y_{uu}-y_{su}}{y_{ss}y_{uu}-y_{su}y_{us}}}_{\frac{\partial p_{sw}}{\partial c}} + \underbrace{\frac{y_{us}-y_{uu}}{y_{ss}y_{uu}-y_{su}y_{us}}}_{\frac{\partial p_{sf}}{\partial c}}, \\ &= \frac{y_{us}-y_{su}}{y_{ss}y_{uu}-y_{su}y_{us}}.\end{aligned}$$

The first term in the above equation shows the response of workers, $\frac{\partial p_{sw}}{\partial c}$, whereas the second term shows the response of entrepreneurs, $\frac{\partial p_{sf}}{\partial c}$. Two things are important to notice. First, the log supermodularity assumption, a form of strategic complementarity, implies that the denominator of the above equation is positive and so the fraction of skilled workers decreases with the entrepreneurship barrier while that of entrepreneurs increases. The assumption of $y_{su} > y_{us}$ is plausible because an unskilled worker could receive proper training and infrastructure

when he is associated with a skilled firm. This assumption also implies that the fraction of the skilled among entrepreneurs increases with an increasing entrepreneurship barrier, while the overall fraction of entrepreneurs decreases (see Appendix A2). Second, the overall change in the fraction of skilled individuals with the entrepreneurship barrier depends on the relative sizes of the responses of workers and entrepreneurs as determined by the productivities of their intermediate matches (*su* and *us*). These productivities shape the returns to skill acquisition under risk neutrality. The match productivity pair for a worker goes from (y_{uu}, y_{su}) to (y_{us}, y_{ss}) when he becomes skilled, whereas that of an entrepreneur goes from (y_{uu}, y_{us}) to (y_{su}, y_{ss}). When y_{su} is greater than y_{us}, workers respond more strongly than entrepreneurs to a change in the entrepreneurship barrier. Therefore, the overall fraction fo skilled individuals decreases.

Proposition 1 implies that our model can generate a negative correlation between the fraction of skilled individuals and both the unemployment rate differential and the skill premium, in a world where countries only differ by their entrepreneurship barrier. Indeed, in the neighborhood of $c = 0$ and $sc = 0$:

$$\frac{\partial p_s}{\partial c} \Big/ \frac{\partial u_s - u_u}{\partial c} < 0, \quad \frac{\partial p_s}{\partial c} \Big/ \frac{\partial skp}{\partial c} < 0.$$

This result holds under the further assumption of a high enough value for the match productivity of skilled workers and entrepreneurs, y_{ss}. A high enough value for y_{ss} also assures that as the entrepreneurship barrier rises, the unemployment rates of both skilled and unskilled individuals rise (see Appendix A2).

3 | ENTREPRENEURSHIP BARRIER FOR SKILL PREMIUM AND ACQUISITION

We run a quantitative experiment with the objective of understanding the main forces that drive the negative cross-country correlation between skill premium and acquisition. Our quantitative strategy consists of two steps. First, we calibrate cross-country disparities in schooling barrier, entrepreneurship barrier, and match productivities to cross-country disparities in skill acquisition, skill premium, and unemployment. Then, we measure the importance of the entrepreneurship barrier for skill premium and acquisition via counterfactual exercises in which we progressively decrease the cross-country disparities in the entrepreneurship barrier.

Data. We construct a dataset of skill acquisition by entrepreneurial status, unemployment rates by skill, skill premium, and average number of employees per entrepreneur. We collect data on skill acquisition and unemployment by skill level from the World Bank's World Development Indicators (WDI) dataset. We focus on male individuals and define an individual as skilled if he holds either secondary or tertiary education. In the WDI dataset, an individual is defined unemployed in accordance with the UN system of national accounts if he is without work or has been seeking work in a recent past period and is currently available for work. This definition implies that self-employed individuals (including non-employee entrepreneurs) are considered as employed, consistently with our model.[10] The unemployment data provided in the WDI dataset are part of the International Labour Organization (ILO) estimates and are suitable to our study as they are "harmonized to ensure comparability across countries and over time by accounting for differences in data source, scope of coverage, methodology, and other country-specific factors".[11] We compute the relevant statistics as country averages over the period 2000–2010, based on country-specific data availability.

We measure the skill premium from wages of individuals with more than a high-school education relative to those of individuals with less than a high-school education. We use the data in Fernández et al. (2005), between 1992 and 1998.[12] These data cover an earlier period than that covered by the remaining data in our dataset. At the same time, they also offer the largest cross-country coverage, for the skill premium. An alternative is to compute the skill-premium from cross-country micro-data compiled by IPUMS (2020). Using these data, Rossi (2019) documents the skill premium for 12 countries over the 2000–2010 period. For 8 of those 12 countries we also have data on the unemployment rate by skill level. Hence, our quantitative exercise would only cover 8 countries if we were to use these micro-data for the skill premium.[13] Instead, we choose to use the data in Fernández et al. (2005) and report that the correlation in the skill-premium computed using these data and the one computed using the data in Rossi (2019) is 0.858 (*p*-value 0.006), for the countries in our sample that overlap.

Lastly, we compile data on the skill distribution of entrepreneurs and on the average number of employees per entrepreneur from the Adult Population Survey administered by the Global Entrepreneurship Monitor (GEM), in 2010.

The survey is designed to obtain harmonized data across countries and is therefore suitable to our study.[14] In our statistics, we consider established business only – that is, those businesses that are operating since more than 3.5 years.

Our sample includes 32 countries at different stages of development: Argentina, Australia, Belgium, Bolivia, Brazil, Great Britain, Canada, Chile, Colombia, Costa Rica, Check Republic, Denmark, Ecuador, Finland, France, Germany, Hungary, Israel, Italy, Luxembourg, Mexico, Netherlands, Norway, Panama, Paraguay, Peru, Poland, Spain, Sweden, Uruguay, United States, Venezuela. These are the countries for which we observe skill acquisition, skill premium, and unemployment rates by skill.[15] For some of the countries in our sample, we don't observe the distribution of entrepreneurs by skill and/or the number of employees per firm. We impute these data using GDP per capita as a predictor. The poorest country in our sample is Bolivia, with a per-capita GDP of 11.0% that in the US, and 9.6% that of Norway, the richest county in our sample.[16]

3.1 | Parameterization

We assume countries differ from one another on four dimensions: (i) entrepreneurship barrier, c, (ii) schooling barrier, sc, (iii) productivity of worker-firm match by skill, y_{ss}, y_{su}, and y_{us}, (iv) number of jobs created by each entrepreneur, n. We calibrate the first three sources of cross-country heterogeneity within the model, given a set of parameters that we set without solving the model, and measure the latter source directly from the data.

The parameters that we set without solving the model are reported in Table 1, together with the assigned values. In particular, we normalize the number of jobs per entrepreneur in the US to 1, $n_{US} = 1$, and set n_j in all other countries to the ratio of the number of employees per entrepreneur in the country relative to the US. We set the entrepreneur's share in bargaining, θ, to 50%. We assume individual preferences are represented by a logarithmic utility function, $\gamma = 1$. The curvature of the utility function measures the willingness of an individual to endure variability in his consumption stream: the higher the γ, the less variability the individual wants in his consumption stream. The microeconomics literature suggests that γ must be approximately equal to 1 (see, among others, the early works of Arrow, 1971, Kydland & Prescott, 1982, and Kehoe, 1983). Last, we normalize y_0 to 1 and y_{uu} to 0.

We calibrate cross-country heterogeneity by targeting the following statistics, for each country:

1. Fraction of skilled individuals: number of secondary- and tertiary-educated men divided by number of primary educated men,
2. Skill premium: ratio of tertiary- and secondary-educated wages relative to primary-educated wages,
3. Unemployment rate of unskilled individuals: number of secondary- and tertiary-educated unemployed male workers divided by number of secondary- and tertiary-educated men,
4. Unemployment rate of skilled individuals: number of primary-educated unemployed male workers divided by number of primary-educated men,
5. Fraction of skilled entrepreneurs: fraction of individuals with at least a high-school education among male individuals owning an established business in the labor force.

In our sample of 32 countries, the fraction of skilled individuals is positively correlated with the logarithm of GDP per capita, at 0.507, while the skill premium is negatively correlated, at −0.716. The unemployment rate of skilled individuals is negatively correlated with the logarithm of GDP per capita, at −0.427, while the unemployment rate of unskilled individuals does not significantly vary with development. Lastly, the fraction of skilled entrepreneurs is positively correlated with the logarithm of GDP per capita, at 0.308.

TABLE 1 Calibration: parameters chosen without solving the model

Parameter	Symbol	Value
Number of employees per entrepreneur	n_j	Data
Workers' share in bargaining	θ	0.5
Curvature of the utility function	γ	1
Initial endowment	y_0	1
Unskill-unskill match productivity	y_{uu}	0

Even though the parameter values are chosen simultaneously to match the data targets, each parameter has a first-order effect on some targets. The entrepreneurship barrier in a country, c, is important for matching the unemployment rate by skill in that country. The comparative statics of our model under the risk neutrality assumption reported in the preceding section show that the unemployment rate differential responds to changes in the entrepreneurship barrier (see Section 2). The average of the match productivities for which at least one party is skilled, y, is key to match the data on the skill premium. Then, given a value for y and c, the schooling barrier in a country, sc, and the dispersion of match productivities, $\{y_{ss}, y_{su}, y_{us}\}$, are parameterized so that the model implied skill distribution and average unemployment rate is as close as possible to replicating the these statistics in the data for that country.

Outcome. The values of the calibrated parameters are shown in Figure 2 and summarized in Table 2, reporting the cross-country correlations with the logarithm of observed GDP per capita. The calibrated entrepreneurship barrier tends to be lower in richer countries: the correlation between the calibrated c and the logarithm of observed GDP per capita is −0.239 (p-value: 0.187, Table 2, first row). This finding is supported by anecdotal evidence on measurable components of this barrier. The World Bank complies data on an index of how conducive to business operations the regulatory environment in a country is as well as on the cost of business startup procedures as a fraction of GNI per capita. The former correlates positively with GDP per capita (0.778, for the countries in our sample), while the latter correlates negatively (−0.239, for the countries in our sample). Further, Djankov et al. (2002) show that regulatory costs of entry to business are higher in poorer countries than in richer countries.

Second, the calibrated schooling barrier decreases with development. The correlation between the calibrated sc and the observed logarithm of GDP per capita is −0.351 (p-value: 0.049, Table 2, second row). On the one hand, direct schooling costs (such as fees and tuitions) represents a higher fraction of family income for individuals in poorer countries, on average, and so much so to make schooling unaffordable more frequently (see, e.g., Lee & Barro, 2001). This evidence is suggestive of a schooling barrier that decreases with development. On the other hand, indirect

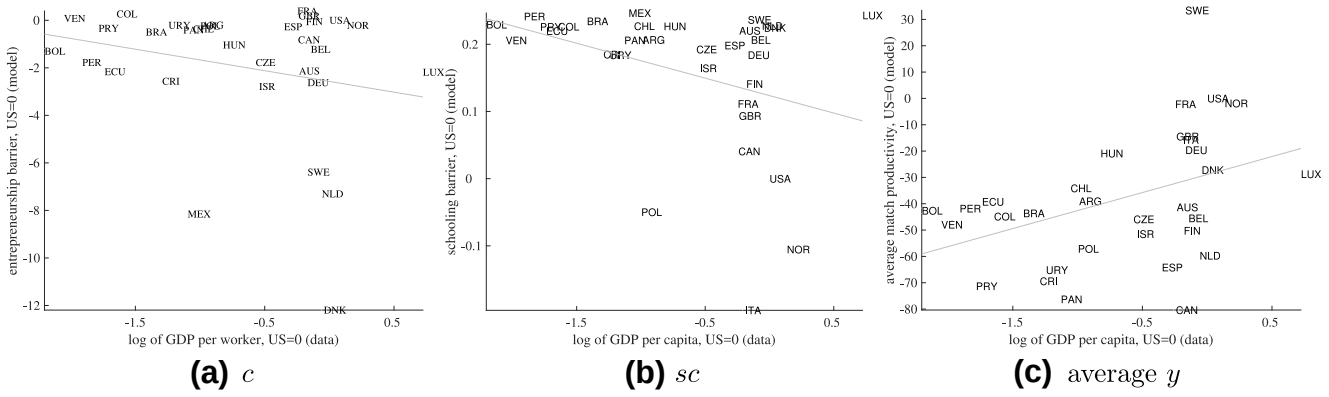

FIGURE 2 Calibration: entrepreneurship barrier c, schooling barrier sc, and average match productivity y. For clarity, figures disregard outliers: Italy for the entrepreneurship barrier and Mexico for the match productivity. *Source*: The World Bank for cross-country data on GDP per capita and own computations

TABLE 2 Calibration: statistics on calibrated parameters

Correlations of and:	Observed log(GDP per capita)
Entrepreneurship barrier, c	−0.239 (0.187)
Schooling barrier, sc	−0.351 (0.049)
Match productivity y_{ss}	−0.029 (0.873)
Match productivity y_{su}	0.538 (0.000)
Match productivity y_{us}	0.005 (0.978)
Average match productivity, y	0.372 (0.036)

Note: p-values are in parenthesis.

Source: The World Bank for cross-country data on GDP per capita and own computations.

schooling costs (such as foregone wages) are a sizable component of the schooling cost of higher education, and these costs tend to increase with development. For example, for individuals born between 1920 and 1980 in the US, foregone wages while attending college are, on average, at least twice as high as college fees and tuitions; and the wages of low-skill individuals increase development.[17] This evidence is suggestive of a schooling barriers. That increases with development. In our calibration, the first effects prevails.

Lastly, on average, richer countries calibrate higher productivities of matches where at least one of the two parties is skilled (the correlation with the logarithm of observed GDP per capita is 0.372, see Table 2, row 6). In particular, a strong association of the match productivity with the logarithm of observed GDP per capita is for matches where the entrepreneur is skilled and the worker is unskilled (correlation of 0.538, see Table 2, row 5). In our framework, cross-country disparities in match productivities originate from cross-country disparities in the bias toward skill of the production technology as well as in individuals' productivities. In particular, a stronger bias toward skill in the production technology and a higher productivity of skilled individuals relative to that of unskilled individuals, due for example, to higher schooling quality, feeds into the model via higher mach productivities for matches where at least one of the two parties between the worker and the firm is skilled.[18] The calibrated cross-country pattern of our match productivities are therefore consistent with Caselli and Coleman (2006) who, for a cross-section of 52 countries in the late 1980s, find that the bias toward skill of the production technology increases with a country's output per capita and with the development literature documenting a higher quality of the educational system in richer countries (see, among others, Caselli, 2005).

The model's performance on targets is shown in Table 3, which reports the correlations between the logarithm of observed GDP per capita and targeted moments, for both the data and the simulated model. The model-generated fraction of skilled individuals and the skill premium show a correlation with the logarithm of observed GDP per capita of 0.476 and −0.703, respectively. These correlations are close to those observed in the data which are of 0.501 and −0.667, respectively. The model, consistently with the data, generates a negative correlation between the logarithm of observed GDP per capita and the unemployment rate of skilled individuals and a positive, non-significant, correlation between the unemployment rate of unskilled individuals and the logarithm of observed GDP per capita. Lastly, the correlation between the fraction of entrepreneurs who are skilled and the logarithm of observed GDP per capita is 0.224 in the data and a higher 0.586 in the model.[19]

After calibration, the model-generated skill premium is negatively correlated with the fraction of skilled individuals, as in the data (Table 3, row 6). The unemployment differential in the model correlates at −0.603 with the logarithm of observed GDP per capita, which is consistent but, in absolute value, higher than the correlation measured in the data (Table 3, row 7). Lastly, Table 3, row 8, reports the model-performance on the cross-country correlation between the logarithm of observed GDP per capita and the entrepreneurship rate – that is, the fraction of entrepreneurs in the economy. The model generates a negative correlation, of −0.330. The lower entrepreneurship barrier in richer countries

TABLE 3 Calibration: model fit

Correlations	Data	Model
Targets:		
Log GDP and skilled individuals	0.501 (0.004)	0.476 (0.006)
Log GDP and skill premium	−0.667 (0.000)	−0.703 (0.000)
Log GDP and skilled unemployment	−0.469 (0.007)	−0.443 (0.011)
Log GDP and unskilled unemployment	0.227 (0.212)	0.305 (0.090)
Log GDP and skilled entrepreneurs	0.224 (0.218)	0.586 (0.000)
Implied Targets:		
Skilled individuals and skill premium	−0.519 (0.002)	−0.423 (0.016)
Log GDP and unemployment differential	−0.469 (0.007)	−0.603 (0.000)
Non Targets:		
Log GDP and entrepreneurship rate	−0.391 (0.072)	−0.330 (0.065)

Note: In parenthesis are *p*-values.

Source: The World Bank, Fernández et al. (2005) and own computations.

pushes up the entrepreneurship rate, while the higher number of jobs posted by each entrepreneur pushes the rate down. We compute the same correlation in the data using Poschke (2018)'s computations based on the GEM dataset and find −0.391.[20] The alignment of the model to the data on this non-targeted moment shows the merits of our quantitative analysis.

To summarize, Figure 3 plots the model fit on skill premium and acquisition along with the particular channel this paper focuses on – that is, the unemployment differential. In poor countries, individuals tend to face low match productivities for skilled matches, higher entrepreneurship barrier, and higher schooling barrier, all of which decrease the returns to skill acquisition. Countries in the bottom-quarter of the income distribution have an average entrepreneurship barrier which is 1.5 as high as that of countries in the top-quarter of the income distribution, and an average schooling barrier that is 7% higher. The average match productivity for countries in the bottom-quarter of the income distribution is about 89% that of countries in the top-quarter of the income distribution, mostly because of differences in the match productivity of unskilled entrepreneurs and skilled workers.

3.2 | Counterfactual exercises

How much of the cross-country variation in skill premium and acquisition is explained by the entrepreneurship barrier? In this section, we answer this question via counterfactual exercises on the paramterized model. We then further explore the role of the schooling barrier and of the match productivities.

Entrepreneurship barrier. We conduct counterfactual exercises where we progressively attenuate each country's gap to the US in the entrepreneurship barrier by 10%–50%. For each counterfactual experiment, Table 4 reports the cross-country correlation with the observed logarithm of GDP per capita and three moments: (i) the fraction of skilled individuals, (ii) the skill premium, and (iii) the unemployment differential. In addition, the same table also reports the correlation between skill acquisition and premium.

The entrepreneurship barrier explains between 21% (0.334/0.423–1) and 44% (0.238/0.423–1) of the cross-country correlation between skill premium and acquisition. When each country's gap to the US in the entrepreneurship barrier is reduced by 10%, this correlation reduces from a significant −0.423 to a significant −0.334 (Table 4, row 4, column "$x = 10\%$"), whereas when the entrepreneurship barrier is reduced by 50%, the correlation reduces to a non-significant −0.238.

The channel via which the entrepreneurship barrier influences skill acquisition is the unemployment differential. This differential is one of the determinants of the returns to skill acquisition. Table 4, row 3, shows that cross-country differences in the entrepreneurship barrier shape the evolution of the unemployment differential along the development spectrum. A 33% reduction in each country's gap to the US in the entrepreneurship barrier accounts for the entire cross-country correlation between the logarithm of observed GDP per capita and the unemployment differential – that is, this correlation goes from −0.603 in the baseline to −0.009 in the counterfactual experiment. In this experiment, the cross-country correlation between skill-premium and acquisition decreases from −0.423 to −0.234. Hence, we conclude

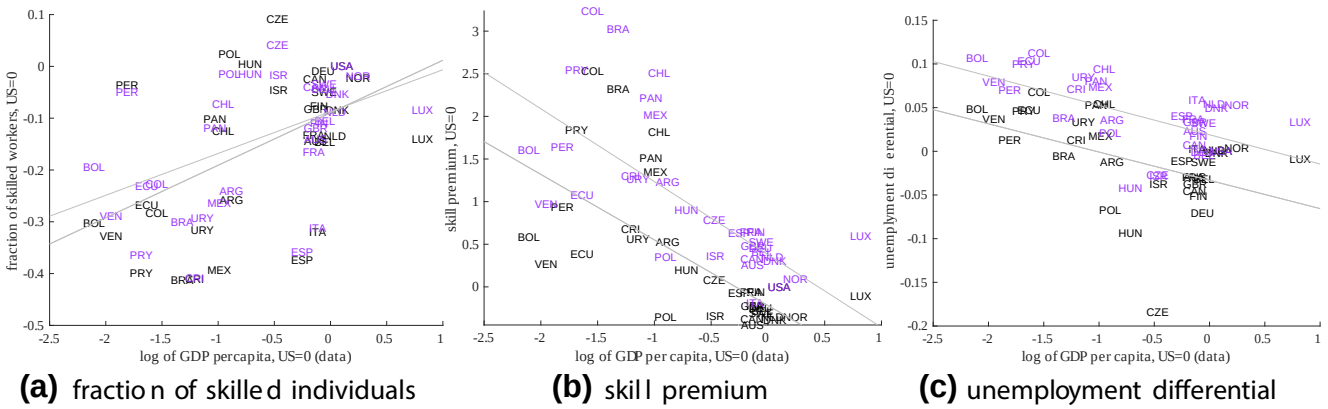

FIGURE 3 Calibration: performance overview. Darker entries are data, lighter entires are model. *Source*: The World Bank, Fernández et al. (2005) and own computations

TABLE 4 The role of the entrepreneurship barrier

			Without x% variation in the entrepreneurship barrier			
	Data	**Model**	$x = 10$	$x = 25$	$x = 33$	$x = 50$
GDP & skilled individuals	0.501	0.476	0.466	0.450	0.543	0.530
	0.004	0.006	0.007	0.010	0.001	0.002
GDP & skill premium	−0.667	−0.703	−0.694	−0.695	−0.571	−0.579
	0.000	0.000	0.000	0.000	0.001	0.001
GDP & unemp. diff.	−0.469	−0.603	−0.588	−0.585	−0.009	0.012
	0.007	0.000	0.000	0.000	0.960	0.947
Skilled individuals & premium	−0.519	−0.423	−0.334	−0.317	−0.234	−0.238
	0.002	0.016	0.061	0.077	0.198	0.189

Note: The table reports the correlation between the logarithm of observed GDP per capita and moments in the data, in the calibrated model, and in each counterfacual experiments. The experiments are explained in the text.

Source: The World Bank, Fernández et al. (2005) and own computations.

that a closure in each country's gap to the US in the entrepreneurship barrier of a magnitude that closes the gap in the unemployment differential accounts for 45% of the cross-country correlation between skill premium and acquisition.

Lastly, Table 4 shows non-linearities in the effects that the entrepreneurship barrier has on, separately, the skill premium and skill acquisition. For small changes in the entrepreneurship barrier – that is, for a closure in the gap by 10% or 25% – the cross-country correlation between skill acquisition and development reduces while that between skill premium and development remains unchanged. Instead for more sizable changes in the entrepreneurship barrier – that is, for a closure in the gap by 33% or 50% – the cross-country correlation between skill acquisition and development increases while that between skill premium and development reduces (in absolute terms). This result reveals that the entrepreneurship barrier primarily influences the cross-country correlation between skill premium and acquisition by shaping the covariation in skill acquisition for small changes in the entrepreneurship barrier, and by shaping the covariation in skill premium for more sizable changes in the entrepreneurship barrier. Relatedly, the response of the unemployment differential to changes in the entrepreneurship barrier is also non-linear as it is much stronger for a closures that are higher than 25%.[21]

Other forces at play. We now turn to analyze the contribution of the match productivities and the cost of schooling for the returns to acquiring skill and so the cross country correlation between skill premium and acquisition. We quantify the contribution of these other exogenous forces via five counterfactual experiments in which we attenuate cross-country heterogeneity in schooling barrier and match productivities. In particular, in each counterfactual experiment we decrease of 10% each country's gap to the US values of, respectively, the schooling barrier and each of the match productivities for which at least one of the two parties is skilled. In addition, we run an experiment in which we decrease the gap to the US for all match productivities at once. A 10% attenuation in the gap is chosen to assure that the model solves in all the exercises for most countries (27 out of 32 countries). The outcomes of each of the experiments for the correlation with the logarithm of observed GDP per capita and skill acquisition, skill premium, and unemployment differential are reported in Table 5, along with comparative statistics for the baseline model and the data.[22]

We find that the skill premium is most responsive to a decrease of the countries' gaps to the US in the cost of schooling and in the match productivity when both parties are skilled, out of all counterfactual experiments. The correlation between the logarithm of observed GDP per capita and the skill premium decreases, in absolute value, from −0.720 in the baseline to, respectively, −0.707 and −0.697 in the two counterfactual experiments. As a consequence, the schooling barrier and match productivity for which both parties are skilled are important drivers of the negative cross-country correlation between skill premium and acquisition. The correlation between the fraction of skilled individuals and the skill premium drops by 23% when the gap in the schooling barrier decreases of 10% and by 10% when the gap in this specific match productivity decreases of 10% – that is, the correlation goes from −0.396 to −0.304 and −0.357.

The match productivities where the worker is skilled are important drivers of the positive cross-country correlation in skill acquisition. The correlation between the logarithm of observed GDP per capita and the fraction of skilled individuals drops by 20% when the gap in each of these two match productivities is reduced by 10% – that is, the correlation goes from 0.440 in the baseline to, respectively, 0.357 and 0.352 in the counterfactual experiments. This makes

TABLE 5 Other forces at play

			With 10% reduction in the gap to the US in:				
	Data	**Model**	***sc***	y_{ss}	y_{su}	y_{us}	***y***
GDP & skilled individuals	0.415	0.440	0.527	0.357	0.629	0.352	0.619
	0.031	0.022	0.005	0.067	0.000	0.072	0.001
GDP & skill premium	−0.703	−0.720	−0.707	−0.697	−0.710	−0.716	−0.727
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GDP & unemp. diff.	−0.409	−0.550	−0.635	−0.528	−0.740	−0.637	−0.716
	0.034	0.003	0.000	0.005	0.000	0.000	0.000
Skilled individuals & premium	−0.433	−0.396	−0.304	−0.357	−0.577	−0.357	−0.530
	0.024	0.041	0.123	0.068	0.002	0.068	0.004

Note: The table reports the correlation between the logarithm of observed GDP per capita and moments in the data, in the calibrated model, and in each counterfactual experiments. The experiments are explained in the text.

Source: The World Bank, Fernández et al. (2005) and own computations.

the match productivity match when the firm is skilled and the worker is unskilled an additional quantitatively relevant driver of the negative cross-country correlation between skill premium and acquisition. Lastly, note that the schooling barrier exerts a small role on the cross-country differences in skill acquisition. This is because the calibrated schooling barrier for the subsample of countries considered in the exercise shows only a weak negative correlation with the logarithm of observed GDP per capita (−0.084, *p*-value: 0.676) in comparison to the stronger positive correlation of the match productivity when both parties as skilled (0.397, *p*-value: 0.040).

Lastly, turning to the unemployment differential, Table 5 shows that the measured gap in the schooling barrier and match productivities go toward increasing, in absolute value, the negative cross-country correlation between the logarithm of observed GDP per capita and the unemployment differential. For example, such correlation goes from −0.550 in the baseline to −0.716 where the match productivities are equalized across countries. This result speaks to the role of the entrepreneurship barrier in our model as a determinant of the unemployment differential in the data and, through it, as one of the drivers of the negative cross-country correlation between skill premium and acquisition.

4 | CONCLUSION

In this paper, we study the role of the entrepreneurship barrier for the cross-country patterns of skill premium and acquisition. In a cross section of countries, a 1% increase in output per capita is associated with an increase of 0.16 percentage-point in the fraction of skilled individuals and with a 0.54 percentage-point decrease in the skill premium. In light of cross-country evidence of a negative correlation between the unemployment differential and output per capita, we argue that the entrepreneurship barrier, as a determinant of the unemployment rate, can reconcile a higher skill premium and a lower skill acquisition in poor countries compared to rich countries.

We develop a simple model of occupational choice and skill acquisition and use it to assess the quantitative significance of differences in the entrepreneurship barrier along with differences in the schooling barrier and in the skill-productivity profile in explaining skill acquisition and skill premium across countries. We calibrate a higher entrepreneurship barrier for poorer countries and find that disparities in such barrier account for about half of the cross-country correlation between skill premium and acquisition. The significant response of skill acquisition to changes in the entrepreneurship barrier is indicative of the potential role of policies and other trends affecting the entrepreneurship barrier. To inform on this angle, identifying the sources of cross-country differences in the entrepreneurship barrier is a central step.

Lastly, various studies report micro-evidence on convex returns to schooling in schooling attainment, and especially so in developing countries (see Banerjee & Duflo, 2011, for a review). We believe that investigating the feedback between such convexities and the unemployment differential is a promising avenue for future research.

DATA AVAILABILITY STATEMENT

The data we used are publicly available.

ENDNOTES

[1] Many in the literature report cross-country patterns in skill premium and acquisition similar to ours (see, among others, Caselli, 2005, and Cordoba & Ripoll, 2013).

[2] The coefficient on the skill premium decreases, in absolute value, from −0.091 (*p*-value 0.027) to −0.0455 (*p*-value 0.028) when we control for the difference in the unemployment rates of skilled and unskilled individuals. Details in Appendix A1.

[3] Fonseca et al. (2001) report a negative correlation between startup entrepreneurship barriers, a measurable component of entrepreneurship barriers, and employment levels across major OECD economies and show that, in a standard equilibrium search framework with endogenous occupational choice, startup entrepreneurship barriers and employment are monotonically related.

[4] Our model is close to that in Fonseca et al. (2001), which endogenizes sorting between entrepreneurs and workers through heterogeneity in entrepreneurial ability that does affect the output of a match. Differently, we endogenize the skill acquisition decision, which induces heterogeneity on both workers and entrepreneurs and allows us to describe the equilibrium effects of costs related to the acquisition of skills.

[5] The entrepreneurship barrier, as a determinant of the economic environment in which firms operate, has been found relevant in explaining various cross-country economic outcomes. The seminal paper of Hall and Jones (1999) shows that countries with good social infrastructures have high human capital and output per capita. Studies on cross-country market regulations include, among others, Bertrand and Kramarz (2002), Botero et al. (2004) and Fang and Rogerson (2011).

[6] As controls, we consider the skill premium, the fertility rate, private and government expenditures on education, and output per capita. The coefficient on the unemployment differential decreases, in absolute value, from −2.17 (0.337) to −1.5 (0.479), when including the controls. Further details are in Appendix A1.

[7] The equilibrium described in our static model can be thought of as the steady state equilibrium of a dynamic extension of our model, with entry and exit into unemployment, on the lines of Fonseca et al. (2001). Details in the Online Appendix.

[8] Note that because jobs are fungible, filled and vacant jobs can be assigned randomly to entrepreneurs, in equilibrium. For example, a unit-mass entrepreneur posting two jobs and filling one is equivalent to 50% of entrepreneurs in the unit mass posting two jobs with both jobs remaining vacant (own-account work) and the remaining 50% of entrepreneurs posting two jobs and filling both.

[9] The assumption of log supermodularity implies that the skill acquisition decisions of workers and entrepreneurs reinforce one another (see Athey, 2002).

[10] As poorer countries have a higher fraction of their labor force in self-employment on family farms, the measurement of the unemployment rate may be affected by the fact that individuals may work only few hours in practice. Using household-level surveys, Feng et al. (2021) document the robustness of the negative co-variation of the unemployment differential with output per capita when focusing, separately, on rural and urban workers.

[11] Cross-country harmonization of unemployment data is intrinsically challenging as part of these data are imputed. Using household-level surveys, Feng et al. (2021) and Poschke (2019) build more comparable datasets on unemployment by skill and confirm our findings on the cross-country evolution of the unemployment differential with output per capita.

[12] Fernández et al. (2005) also provide comparable statistics to the wage ratio for lifetime income. We consider the former as it maps to the definition of the skill premium in our model. However, the covariation of the two measures with output per capita is comparable. A linear regression of the skill premium on the logarithm of GDP per capita estimates a coefficient of −0.09 for the wage ratio one of −0.12 for lifetime income ratio, in our sample of 32 countries.

[13] These countries are: Brazil, Canada, Israel, Mexico, Panama, Uruguay, the United States, and Venezuela.

[14] Because the survey provided by GEM is a household-level survey, it does not cover publicly listed firms with dispersed ownership. Poschke (2018) compares the cross-country covariation of the average number of employees per firm with output per capita using the GEM dataset and the Amadeus database collected by Bureau Van Dijk. He finds that such covariation is robust across the two datasets.

[15] Despite Slovakia satisfied the criteria to be included in the sample, we exclude it as its unemployment differential is an outlier. Slovakia measures an unemployment differential of −0.42, compared to a mean unemployment differential of −0.042 and the next closes of −0.21. In addition, for Venezuela we measure labor productivity differences to the US from differences in GDP per capita rather than from difference in PPP-adjusted GDP per capita, as we do for all other countries in the sample.

[16] In documenting motivating facts on the unemployment rates and skill acquisition in Section 1, we considered a larger sample, consisting on 52 countries. This sample includes all countries for which we have data on the unemployment differential and on the fraction of skilled individuals. Note that the statistics we report for this larger sample, also describe the smaller sample used in the quantitative exercise (Table A1 in the Online Appendix for the larger sample and Table 3, column *Data*, for the smaller sample).

[17] Using WDI data, we compute a correlation of 0.875 between logarithm of the average wage of low-skill individuals and the logarithm of GDP per capita, in a 191 sample of countries.

[18] Details on the mapping between the profile of match productivities and the bias toward skill of the production technology and individuals' productivities are in the Online Appendix.

[19] Note that high-school completion is an imperfect measure of skill acquisition when a significant fraction of the population in the sampled countries fall into one of the two categories. In that case, the measured cross-country correlation may be dampened. Figure 2 in the Online Appendix shows that this issue may be relevant for entrepreneurs.

[20] Poschke (2018)'s computations are available for 22 countries out of the 32 countries in our sample.

[21] In Appendix A2 we show that the response of the unemployment differential to the entrepreneurship barriers is non-linear in the match productivities, which are a component of GDP, even under risk neutrality.

[22] The countries for which the model does not solve across all five experiments are Bolivia, Brazil, Chile, Costa Rica, and Mexico.

[23] When we test the capability of these ease index and startup cost to predict the unemployment differential by regressing the unemployment differential on those two measures and an intercept, we find an adjusted R^2 of respectively, 0.21 and 0.08.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

A1 | Data

Motivating regressions. To provide suggestive evidence of our proposed mechanism, which operates via the unemployment differential, after taking into account some of the alternative explanations proposed in the literature, we estimate the following regression:

$$p_{sj} = \alpha_0 + \alpha_1 \left(u_{sj} - u_{uj}\right) + \alpha_3 \text{controls}_j + \epsilon_j,$$

where j indicates a country, p_s is the fraction of skilled individuals, $u_s - u_u$ is the unemployment differential (i.e., the unemployment rate of skilled individuals minus that of unskilled individuals) and ϵ_j is an error term, normally distributed, mean-zero, and i.i.d. across observations. The set of controls includes:

1. The skill premium (ratio of tertiary- and secondary-educated wages relative to primary-educated wages, source: Fernández et al., 2005);
2. The fertility rate (births per woman, source: the World Bank);
3. Government expenditure on education as a percentage of GDP (source: the World Bank);
4. Education expenditures as a fraction of the GNI (source: the World Bank);
5. The level of per-capita expenditures in points 3) and 4) computed by multiplying by GDP per capita in constant 2005 US dollars;
6. The logarithm of GDP per capita in constant 2017 international dollars (source: the World Bank).

All statistics are computed as averages between 2000 and 2010. The results are in Table A1. The effect of the unemployment differential on the fraction fo skilled individuals is significant across all specifications. The magnitude of the coefficient on the unemployment differential decreases, in absolute value, from −2.17 (0.336) to −1.5 (0.479). Importantly, note that in a specification that features the unemployment differential and the skill premium as regressors, the coefficient on the skill premium is −0.0455 (p-value 0.028). When instead we only consider the skill premium as regressor, the coefficient is −0.091 (p-value 0.027). This shows that including the unemployment differential attenuates the negative association between skill premium and acquisition across countries.

We further run additional specifications of the motivating regressions above that include measures of two components of the entrepreneurship barrier that are available in the WDI dataset: the index of how conducive to business operations the regulatory environment in a country is (ease index) and the cost of business startup procedures as a fraction of GNI per capita (startup cost). In particular, we run regressions (1) to (6) in Table A1 for the case where we additionally include one of these two measures and for the case where we include one of these two measures in alternative to the unemployment differential. Results are in Table A2 for the ease index and in Table A3 for the startup cost. We find that when we use the ease index, the coefficients on both the index and the unemployment differential are significant throughout all regressions. Instead, when we use the startup cost, the coefficient on the startup cost is not significant when included alongside the unemployment differential. In this case, despite the unemployment differential is significant on its own (Table A1), the startup cost loses significance when paired with additional controls. Lastly, the adjusted R^2 is significantly lower when measures of the entrepreneurship barrier are included instead of the unemployment differential. We take this evidence to indicate that, despite measurable components of the entrepreneurship barrier are correlated with the unemployment differential, there are other factors that determine the unemployment differential and therefore refrain from using such measures to parameterize the entrepreneurship barrier in our quantitative exercise.[23]

TABLE A1 Unemployment differential and skill acquisition

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment differential	−2.1666 (0.33652)	−1.9055 (0.42078)	−1.5058 (0.47859)	−1.6832 (0.59391)	−1.6630 (0.60446)	−1.7047 (0.62982)
Skill premium			−0.0455 (0.028113)	−0.0347 (0.034442)	−0.0293 (0.04243)	−0.0244 (0.045773)
Fertility rate				0.0239 (0.056292)	0.0468 (0.062632)	0.0533 (0.066848)
Public education expenditures, as a share of GDP				0.0440 (0.067649)		
Private education expenditure, as a share of GDP				−0.0342 (0.072712)		
Log of public education expenditure					0.2098 (0.26487)	0.2178 (0.2715)
Log of private education expenditure					−0.1802 (0.25567)	−0.2248 (0.2938)
Log of GDP per capita						0.0543 (0.16418)
intercept	0.6020 (0.019472)	0.6169 (0.025564)	0.7258 (0.071742)	0.5910 (0.19273)	0.2384 (0.65608)	0.0868 (0.81165)
Adjusted R^2	0.4423	0.3862	0.4176	0.3654	0.3609	0.3339
Number of countries	52	32	32	29	28	28

Note: The dependent variable of all the regressions is the fraction of skilled individuals in a country. Standard errors in parenthesis.

Source: The World Bank and Fernández et al. (2005).

TABLE A2 Unemployment differential and measurable entrepreneurship barriers (1)

	(1)	(2)	(3)	(4)	(5)	(6)
With unemployment diff.						
Unemployment differential	−1.806	−1.330	−1.177	−1.586	−1.593	−1.711
	0.371	0.427	0.463	0.544	0.548	0.556
	0.000	0.004	0.017	0.008	0.008	0.006
Ease index	0.392	0.542	0.486	0.630	0.981	1.109
	0.191	0.189	0.200	0.266	0.405	0.420
	0.046	0.008	0.022	0.027	0.025	0.016
Adjusted R^2	0.476	0.506	0.502	0.471	0.476	0.481
Without unemployment diff.						
Ease of doing business	0.835	0.817	0.635	0.689	1.043	1.103
	0.203	0.189	0.208	0.306	0.469	0.498
	0.000	0.000	0.005	0.034	0.037	0.038
Adjusted R^2	0.238	0.363	0.408	0.299	0.299	0.272

Note: The Table reports the regression results of the regression specifications (1) to (6) in Table A1, modified to include the ease index (*With unemployment diff.*) and to include the ease index instead of the unemployment differential (*Without unemployment diff.*). We report, in order, the estimated coefficient, the standard error, and the *p*-value. We omit the estimates of other coefficients for compactness.

Source: The World Bank and Fernández et al. (2005).

TABLE A3 Unemployment differential and measurable entrepreneurship barriers (2)

	(1)	(2)	(3)	(4)	(5)	(6)
With unemployment diff.						
Unemployment differential	−2.000	−1.612	−1.299	−1.597	−1.500	−1.533
	0.349	0.455	0.497	0.583	0.608	0.637
	0.000	0.001	0.014	0.012	0.022	0.026
Startup cost	−0.121	−0.146	−0.127	−0.289	−0.323	−0.319
	0.078	0.096	0.095	0.200	0.250	0.256
	0.129	0.138	0.195	0.163	0.209	0.227
Adjusted R^2	0.457	0.412	0.433	0.394	0.380	0.350
Without unemployment diff.						
Startup cost	−0.259	−0.291	−0.205	−0.344	−0.450	−0.453
	0.095	0.102	0.099	0.225	0.271	0.277
	0.000	0.000	0.005	0.034	0.037	0.038
Adjusted R^2	0.112	0.186	0.319	0.223	0.237	0.203

Note: The Table reports the regression results of the regression specifications (1) to (6) in Table A1, modified to include the startup cost (*With unemployment diff.*) and to include the startup cost instead of the unemployment differential (*Without unemployment diff.*). We report, in order, the estimated coefficient, the standard error, and the *p*-value. We omit the estimates of other coefficients for compactness.

Source: The World Bank and Fernández et al. (2005).

A2 | Derivations

Risk neutrality case. Under the risk neutrality assumption, $\theta = 0.5$, and $n = 1$, the equilibrium distribution of individuals by skill and occupation is described by the following four probabilities:

$$p_{sw} = \frac{cy_{ss}y_{su}y_{us} - cy_{ss}^2y_{su} + cy_{ss}y_{su}^2 - cy_{su}^2y_{us} + scy_{ss}y_{su}y_{us} - scy_{ss}y_{su}^2}{y_{ss}(y_{ss} - y_{su})(y_{ss}y_{uu} - y_{su}y_{us})} + \frac{2c + y_{ss}}{2y_{ss}}$$
$$+ \frac{4scy_{ss} - 2scy_{su} - 2scy_{us} + y_{ss}y_{su} + y_{ss}y_{us} - y_{ss}^2 - y_{su}y_{us}}{2(y_{ss} - y_{su})(y_{ss} - y_{su} - y_{us} + y_{uu})},$$
$$p_{uw} = \frac{-cy_{ss}y_{su} - cy_{ss}y_{us} + cy_{ss}^2 + cy_{su}y_{us} + scy_{ss}y_{su} - scy_{ss}y_{us}}{(y_{ss} - y_{su})(y_{ss}y_{uu} - y_{su}y_{us})}$$
$$+ \frac{-4scy_{ss} + 2scy_{su} + 2scy_{us} - y_{ss}y_{su} - y_{ss}y_{us} + y_{ss}^2 + y_{su}y_{us}}{2(y_{ss} - y_{su})(y_{ss} - y_{su} - y_{us} + y_{uu})},$$
$$p_{sf} = \frac{-cy_{ss}y_{su}y_{us} + cy_{ss}^2y_{us} - cy_{ss}y_{us}^2 + cy_{su}y_{us}^2 + scy_{ss}y_{su}y_{us} - scy_{ss}y_{us}^2}{y_{ss}(y_{ss} - y_{us})(y_{ss}y_{uu} - y_{su}y_{us})} - \frac{2c - y_{ss}}{2y_{ss}}$$
$$+ \frac{4scy_{ss} - 2scy_{su} - 2scy_{us} + y_{ss}y_{su} + y_{ss}y_{us} - y_{ss}^2 - y_{su}y_{us}}{2(y_{ss} - y_{us})(y_{ss} - y_{su} - y_{us} + y_{uu})},$$
$$p_{uf} = \frac{cy_{ss}y_{su} + cy_{ss}y_{us} - cy_{ss}^2 - cy_{su}y_{us} - scy_{ss}y_{su} + scy_{ss}y_{us}}{(y_{ss} - y_{us})(y_{ss}y_{uu} - y_{su}y_{us})}$$
$$+ \frac{-4scy_{ss} + 2scy_{su} + 2scy_{us} - y_{ss}y_{su} - y_{ss}y_{us} + y_{ss}^2 + y_{su}y_{us}}{2(y_{ss} - y_{us})(y_{ss} - y_{su} - y_{us} + y_{uu})}.$$

The comparative static of the fraction of entrepreneurs with respect to the entrepreneurship barrier is:

$$\frac{\partial p_f}{\partial c} = \frac{y_{us} - y_{su}}{y_{ss}y_{uu} - y_{su}y_{us}} < 0.$$

The comparative static of the fraction of the skilled among the entrepreneurs with respect to the entrepreneurship barrier is:

$$\frac{\partial\left(p_{sf}/p_f\right)}{\partial c} = -\frac{8sc(y_{su}y_{us} - y_{ss}y_{uu})}{(y_{su}(-2c + 2_{sc} + y_{us}) - 2(c + \mathrm{sc})y_{us} + y_{ss}(2c - y_{uu}) + 2cy_{uu})^2}.$$

The local comparative statics of the unemployment rates of skilled and unskilled individuals with respect to the entrepreneurship barrier, in the neighborhood of $c = 0$ and $sc = 0$, read:

$$\left.\frac{du_s}{dc}\right|_{c=0,sc=0} = \frac{(y_{su} - y_{uu})(y_{su} + 3y_{us} - 4y_{uu})(-y_{ss} + y_{su} + y_{us} - y_{uu})}{(y_{su} + y_{us} - 2y_{uu})^2(y_{su}y_{us} - y_{ss}y_{uu})},$$
$$\left.\frac{du_u}{dc}\right|_{c=0,sc=0} = \frac{(y_{ss} - y_{us})(4y_{ss} - 3y_{su} - y_{us})(y_{ss} - y_{su} - y_{us} + y_{uu})}{(-2y_{ss} + y_{su} + y_{us})^2(y_{ss}y_{uu} - y_{su}y_{us})},$$
$$\left.\frac{d(u_s - u_u)}{dc}\right|_{c=0,sc=0} = \frac{(y_{ss} - y_{su} - y_{us} + y_{uu})^2\left(4y_{ss}(y_{uu} - y_{us}) + (y_{su} + y_{us})^2 - 4y_{su}y_{uu}\right)}{(-2y_{ss} + y_{su} + y_{us})^2(y_{su} + y_{us} - 2y_{uu})^2}\frac{dp_s}{dc}.$$

The local comparative static of the skill premium with respect to the entrepreneurship barrier, in the neighborhood of $c = 0$ and $sc = 0$, reads:

$$\left.\frac{dE_s/E_u}{dc}\right|_{c=0,sc=0} = \frac{4(y_{su} + y_{us} - 2y_{uu})(y_{ss} - y_{su} - y_{us} + y_{uu})^2}{(-2y_{ss} + y_{su} + y_{us})(y_{su} + 2y_{us} - 3y_{uu})^2}\frac{dp_s}{dc}.$$

The local comparative static of the fraction of entrepreneurs with respect to the entrepreneurship barrier, in the neighborhood of $c = 0$ and $sc = 0$, reads:

$$\left.\frac{\partial p_f}{\partial c}\right|_{c=0,sc=0} = \frac{y_{ss} - y_{su} - y_{us} + y_{uu}}{y_{su}y_{us} - y_{ss}y_{uu}}.$$

Proof of Proposition 1. The assumption of log supermodularity in worker's skill implies that:

$$\begin{aligned}
&\log(y_{ss}) - \log(y_{su}) > \log(y_{us}) - \log(y_{uu}),\\
&\Rightarrow \frac{y_{ss}}{y_{su}} > \frac{y_{us}}{y_{uu}},\\
&\Rightarrow y_{ss}y_{uu} - y_{us}y_{su} > 0.
\end{aligned}$$

This assumption further implies:

$$y_{ss} > y_{su} > y_{us} > y_{uu}.$$

Therefore,

$$\frac{dp_s}{dc} < 0, \text{ and } \left.\frac{\partial skp}{\partial c}\right|_{c=0,sc=0} > 0.$$

The local comparative statics of the unemployment differential with respect to the entrepreneurship barrier, in the neighborhood of $c = 0$ and $sc = 0$, imply that:

$$\left.\frac{d(u_s - u_u)}{dc}\right|_{c=0,sc=0} > 0, \text{ if } 4y_{ss}(y_{uu} - y_{us}) + (y_{su} + y_{us})^2 - 4y_{su}y_{uu} < 0.$$

The above condition imposes a lower bound on $y_{ss} > \underline{y}_{ss}$, for $\underline{y}_{ss} = \frac{(y_{su}+y_{us})^2 - 4y_{su}y_{uu}}{y_{us} - y_{uu}}$. The log supermodularity assumption implies that $\underline{y}_{ss}$ is well define, $\underline{y}_{ss} < \infty$