The Global Distribution of College Graduate Quality

Paolo Martellini

University of Wisconsin–Madison

Todd Schoellman

Federal Reserve Bank Minneapolis

Jason Sockin

US Treasury

We measure college graduate quality—the average human capital of a college's graduates—for graduates from 2,800 colleges in 48 countries. Graduates of colleges in the richest countries have 50% more human capital than graduates of colleges in the poorest countries. Migration reinforces these differences: emigrants from poorer countries are highly positively selected on human capital. Finally, we show that these stocks and flows matter for growth and development by showing that college graduate quality predicts the share of a college's students who become inventors, engage in entrepreneurship, and become top executives both within and across countries.

I. Introduction

A growing body of work shows that a nation's college-educated workforce plays a critical role in fostering its growth and development. For example,

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analysis of the backgrounds of inventors in the United States reveals that most attended college when they were young and that one-third attended a small set of the nation's best colleges (Akcigit, Grigsby, and Nicholas 2017; Bell et al. 2019).[1] Similarly, entrepreneurs and chief executive officers (CEOs) of leading firms in the United States are disproportionately college educated, with top colleges again overrepresented among the latter (Levine and Rubinstein 2017; Flynn and Quinn 2010). Results like these affect migration policy: the United Kingdom recently introduced a High Potential Individual visa program that would offer an easy pathway for migration for graduates of the world's top colleges, with a stated aim of allowing the United Kingdom to "grow as a leading international hub for innovation, creativity and entrepreneurship."[2]

These findings suggest that cross-country variation in the college-educated workforce may contribute to differences in outcomes that are crucial for growth, such as innovation and entrepreneurship. Existing data show clearly that countries differ widely in the quantity of college-educated workers. These differences start with large cross-country variation in college enrollment and graduation rates (Barro and Lee 2013). Migration redistributes college-educated workers among countries, particularly from poorer to richer ones (Docquier and Rapoport 2012; Kerr et al. 2016). That said, we currently have no internationally comparable, economically scaled measures of the quality of college graduates or college-educated migrants that span a large number of countries.[3]

In this paper, we propose and implement a measure of the average human capital of graduates from colleges around the world, which we call

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[1] Bell et al. (2019) shows that for only 86 colleges do more than 1% of attendees file patents. Combined, these colleges account for one-third of all US-born inventors.

[2] Program details and policy rationale can be found at https://www.gov.uk/government/news/points-based-system-welcomes-high-skilled-graduates-to-uk.

[3] The most well-developed assessment measures and compares knowledge and learning among computer science and electrical engineering students in four countries (Loyalka et al. 2019, 2021). By contrast, several major international testing programs evaluate the quality of primary and secondary school (most notably, the Programme for International Student Assessment). Scores from these programs have been an essential building block for work demonstrating the importance of education quality for a country's income level and growth rate (Hanushek and Woessmann 2011; Schoellman 2012; Cubas, Ravikumar, and Ventura 2016).

college graduate quality. It is a gross measure of human capital at graduation, not the value added of the college itself, and may be thought of as the object of interest for employers or migration policy makers but not potential students. We find that college graduate quality varies substantially within and across countries, particularly between developing and developed countries. We show that existing measures of global talent flows—which are based on only the number of college-educated migrants—understate the impact of migration on human capital supply because they ignore how migrants are also selected on average human capital. Finally, we show that college graduate quality differences are important for development accounting and predict a number of outcomes of interest, including the number or share of a college's graduates who engage in innovation (patenting and winning Nobel Prizes), become entrepreneurs (found new businesses), or ascend to executive positions.

We start by estimating college graduate quality. Our approach builds on the fact that under standard assumptions, the average human capital of a college's graduates is proportional to their average earnings. This approach makes it straightforward to compare college graduate quality within a country, but the average earnings for graduates of colleges in different countries reflect both human capital differences and the differential effect of countries through, for example, aggregate productivity. We use data on the earnings of migrants who work in multiple countries to estimate the effect of country as well as skill portability and selection on comparative advantage on earnings.[4] We then adjust workers' earnings so that they capture what each worker would earn in a common labor market. We take the average of these adjusted earnings by alma mater as our measure of college graduate quality.

Our approach requires data with two features. First, we need to be able to link a worker's earnings with where they went to college, ideally for a large number of colleges worldwide. Second, we need information on the pre- and postmigration earnings of migrants, ideally among a large set of countries. Our implementation uses the proprietary database of the website Glassdoor, which contains a wealth of both types of information.[5] Glassdoor is a popular web platform that collects earnings and résumés (with details on education) from workers in return for providing them with information, notably about how workers' earnings compare

[4] Here we build on a larger literature that uses the experiences of migrants to disentangle the importance of human capital from place-based effects, such as physical capital intensity, total factor productivity, or the skill bias of technology (Hendricks 2002; Schoellman 2012, 2016; Okoye 2016; Hendricks and Schoellman 2018, 2023; De Philippis and Rossi 2021; Ek 2022; Rossi 2022).

[5] A small set of previous papers has used the Glassdoor database on workers' earnings from the United States to study variable pay, the pass-through of firm-level shocks to worker compensation, the importance of firms' nonwage amenities, and the effects of employer collusion (Sockin and Sockin 2019, 2021; Gadgil and Sockin 2020; Gibson 2021; Sockin 2022).

with their peers'. Glassdoor provides us with a large global sample consisting of 2.2 million workers who obtained a bachelor's degree from 2,873 different colleges in 48 countries. It also contains data on thousands of workers who report earnings before and after migrating among a large set of countries.

Our estimates reveal large differences in college graduate quality across colleges and countries. As a first approach, we estimate the difference in earnings for graduates of top colleges. Our estimate is based on the rankings of the Center for World University Rankings (CWUR), one of the more widely used proxy-based rankings. We find that graduates of their global top 20 colleges earn 60% more than graduates of unranked colleges in the same labor market. That figure is as large as standard estimates of the total earnings premium for attending college in the United States.[6] We aggregate our findings to the country level and find that college graduate quality is strongly correlated with development, with an estimated elasticity centered on 0.21. To put this figure into perspective, it implies that college graduates from the country at the 95th percentile of the income distribution in our sample earn 52% more than college graduates from the country at the 5th percentile.

The human capital of a nation's college-educated workforce depends not only on graduates of its colleges but also on the human capital of its emigrants and immigrants. As noted above, the existing literature focuses on flows in the number or share of college-educated workers. We document new and complementary facts on the average human capital per migrant, building again on the large number of migrants in the Glassdoor database who are educated in one country but work in another. Our main finding is that brain drain from developing countries is more extensive than previously thought; not only do they lose a higher share of their college-educated workers, but also individuals who leave have 50% more human capital than nonmigrants, reflecting mostly selection on earnings ability, not college of graduation. We also show that there is substantial heterogeneity among rich countries in terms of the average human capital of their immigrants; for the United States or the United Kingdom, they have more human capital than graduates of domestic colleges, but for other countries, such as Japan or Korea, they have much less.

Finally, we assess whether college graduate quality is also correlated with outcomes of interest, such as entrepreneurship or innovation in the global context. We collect data from Glassdoor (using the history of jobs that workers list on their résumés) and external data sources (e.g., data on where patent holders or Nobel laureates attended college).

[6] The ratio of median earnings in 2019 for workers with a bachelor's degree to those of workers with a high school degree was 1.59 (National Center for Education Statistics 2020, table 502.30).

We estimate the correlation between college graduate quality and the number or share of such workers for each college. Our preferred specifications include country fixed effects so that our results are identified off of within-country cross-college variation in college graduate quality. We find college graduate quality to be positively and statistically significantly correlated with all outcomes we consider. Further, the estimated effects are economically large. For example, 1 standard deviation greater college graduate quality is associated with a near doubling of the share of graduates who become inventors, 0.1 more Nobel laureates, and almost 1 percentage point more entrepreneurs among a college's graduates.

Our paper is most closely related to two literatures. The first is the literature that documents cross-country variation in management quality, firm dynamics, and patenting and innovation.[7] Existing work documents a number of potential causes for these differences, including competitiveness of markets, regulation, and taxation (Bloom and Van Reenen 2007; Guner, Ventura, and Xu 2008; Garicano, Lelarge, and Van Reenen 2016; Akcigit et al. 2022). We add to this literature by providing suggestive evidence that college graduate quality may also play a role in explaining why poor countries have fewer executives, entrepreneurs, and innovators. The second is a literature that documents the importance of immigration for the same factors, particularly entrepreneurship and innovation.[8] Our main contribution to this literature is to show that many of these patterns can be understood as stemming from a combination of two forces: an important role for college graduate quality and strong selection of migrants, particularly into the United States, the most widely studied country in this literature.

Our work is also related to the literature that seeks to disentangle the value added of a college, selection of who attends which college, and the complementarity between the two.[9] Given the nature of the Glassdoor database, it is beyond the scope of this research project to attempt such a decomposition. Most existing work suggests that both selection and college value added play a role in determining student earnings.[10] This interpretation implies that policies that improve college quality could help close the gaps we measure.

[7] See Bloom et al. (2014) and Hjort, Malmberg, and Schoellman (2021) for the quality and price of management across countries; Hsieh and Klenow (2014) for firm growth rates across countries; and Dutta et al. (2021) for differences in innovativeness and patenting.

[8] Kerr (2020) provides an excellent overview of this large literature. See also Hunt and Gauthier-Loiselle (2010), Moser, Voena, and Waldinger (2014), Moser and San (2020), and Prato (2021) on innovation or Kerr and Kerr (2020) and Azoulay et al. (2022) on entrepreneurship.

[9] See, e.g., Dale and Krueger (2002), Hoekstra (2009), Dillon and Smith (2017), and Mountjoy and Hickman (2021).

[10] This view is also consistent with recent work by Biasi and Ma (2020) showing that more selective colleges teach more up-to-date information to their students.

The remainder of the paper is organized as follows. Section II details our empirical approach. Section III describes the Glassdoor database and validates key aspects of it against available external benchmarks. Section IV presents our estimates of college graduate quality and the human capital of migrants. Section V describes the implications of these findings for development accounting and the global distribution of entrepreneurs, innovators, and executives. Section VI provides a sensitivity analysis. Finally, section VII provides a brief conclusion.

II. Methodology

In this section, we present the methodology that allows us to estimate the average human capital of a college's graduates as well as the average human capital of a nation's emigrants and immigrants. In each case, our methodology constructs average human capital as average earnings adjusted to a common labor market. We emphasize the key assumptions and their role in the methodology. We also describe briefly what aspects of the data can be used to explore the sensitivity of our results to relaxing these assumptions. We reserve the full sensitivity analysis to section VI.

We start with the simplest case, which involves measuring college graduate quality for colleges in a single country using data on nonmigrants. Let $w_{i,j,t}$ denote the logarithm of earnings for college graduate i who received their bachelor's degree from college j and at time t is employed in the same country $b(j)$ where j is located. In the following, we use simply b when doing so runs no risk of confusion. We express log earnings as the sum of three components:

$$w_{i,j,t} = z_b + h_{i,j} + \eta_{i,j,t}. \tag{1}$$

Here z_b is the logarithm of the skill price—the price per unit of college-educated labor—in country b. It reflects the marginal product of college-educated labor in production, which in turn depends on the country's total factor productivity, capital-output ratio, relative supply of college-educated labor, and skill bias of technology (Hendricks and Schoellman 2023). It can also capture noncompetitive labor markets through a markdown in wages as long as the markdown does not systematically vary across colleges. The term $h_{i,j}$ is the logarithm of the worker's human capital, which depends on the worker i and the college j they attended. Finally, $\eta_{i,j,t}$ captures other idiosyncratic determinants of earnings, such as search frictions or luck.

For our empirical implementation, we decompose $h_{i,j}$ into two terms,

$$w_{i,j,t} = z_b + q_j + \varepsilon_i + \eta_{i,j,t}, \tag{2}$$

where q_j is defined as the average human capital of j's graduates, $q_j \equiv \mathbb{E}_j[h_{i,j}]$, and $\varepsilon_i \equiv h_{i,j} - \mathbb{E}_j[h_{i,j}]$ is the worker's idiosyncratic human capital

relative to other graduates of j. We impose the following identifying assumption.

ASSUMPTION 1. Within any given country, the idiosyncratic residuals have mean 0 conditional on college and individual: $\mathbb{E}(\eta_{i,j,t}|q_j, \varepsilon_i) = 0$.

Given this assumption and a dataset that links workers' earnings to the college from which they graduated, our approach is straightforward: we estimate q_j by regressing log earnings on college fixed effects. This approach is closely related to existing measures that build on average or median earnings of colleges' graduates, such as the College Scorecard in the United States. The interpretation of these coefficients requires two further comments. First, q_j is by construction a measure of the average human capital of college j's graduates and not the human capital value added imparted by college j. We use the term college graduate quality to reflect this fact. Second, we are measuring average human capital as average earnings. As the orthogonality condition makes clear, factors that are correlated with earnings by college will necessarily be captured in our estimates of q_j. For example, if graduates of different colleges vary systematically in their networks, information on relevant job opportunities, or signals they can provide their employers, this will be captured in college graduate quality.

However, this methodology does not allow comparisons of college graduate quality for colleges in different countries. Intuitively, it is not possible to identify whether cross-country gaps in pay reflect gaps in average college graduate quality, q_j, or in the skill price, z_b. We now explain how migrants can help us estimate and correct for differences in z_b, which then allows us to estimate q_j for multiple countries simultaneously.

A. *Migrants and College Graduate Quality*

We pose the following general formulation for the wage of migrant workers who graduate from college j in country b and work in country c:

$$w_{i,j,c,t} = z_c + h_{i,j,c} + \eta_{i,j,c,t}.$$

Notice that both human capital and the idiosyncratic residual are now allowed to vary by country of work c. To illustrate our approach, it is convenient to start by imposing the following simplifying assumption.

ASSUMPTION 2. (i) Human capital is fully portable: $h_{i,j,c} = h_{i,j}$ for all countries c. (ii) There is no selection into migration based on unobserved idiosyncratic country-specific factors: $\mathbb{E}(\eta_{i,j,c,t'}|z_b, z_c) = \mathbb{E}(\eta_{i,j,b,t}|z_b, z_c)$ for all country pairs (b, c).

This assumption implies that a migrant's change in earnings upon moving from country b to country c is given by

$$w_{i,j,c,t'} - w_{i,j,b,t} = z_c - z_b + \eta_{i,j,c,t'} - \eta_{i,j,b,t}, \tag{3}$$

where $\mathbb{E}(\eta_{i,j,c,t'} - \eta_{i,j,b,t}|z_b, z_c) = 0$. Equation (3) illustrates how a migrant's change in earnings reveals the change in the skill price between their origin and destination countries. One could then apply this insight by estimating a regression with worker and country fixed effects on a sample of workers who report earnings in multiple countries (Hendricks and Schoellman 2018). The country fixed effects would provide an estimate of z. We could then compare colleges across countries by taking data on the earnings of nonmigrants and repeating the estimation introduced in the previous section using each worker's *country-adjusted* earnings, $w_{i,j,t} - \hat{z}_{b(j)}$.

In the estimation procedure we implement, we go further and allow for the possibility that human capital might not be perfectly portable across countries and that workers might select the country they migrate to on the basis of unobserved idiosyncratic country-specific factors. We relax assumption 2 as follows.

ASSUMPTION 3. (i) Human capital takes the form $h_{i,j,c} = h_{i,j} + \tau^h_{b,c}$ for all country pairs (b, c). (ii) Selection into migration satisfies $\mathbb{E}(\eta_{i,j,c,t'}|z_b, z_c) = \mathbb{E}(\eta_{i,j,b,t}|z_b, z_c) + \tau^\eta_{b,c}$ for all country pairs (b, c).

Under assumption 3, the wage change upon migration is given by

$$w_{i,j,c,t'} - w_{i,j,b,t} = z_c - z_b + \tau^h_{b,c} + \tau^\eta_{b,c} + \tilde{\eta}_{i,j,c,t'} - \tilde{\eta}_{i,j,b,t}, \tag{4}$$

where $\tilde{\eta}_{i,j,c,t'} \equiv \eta_{i,j,c,t'} - \tau^\eta_{b,c}$ is such that $\mathbb{E}(\tilde{\eta}_{i,j,c,t'} - \tilde{\eta}_{i,j,b,t}|z_b, z_c) = 0$.[11] This specification implies that the earnings changes of migrants reflect not only the change in skill price between their origin and destination but also the effects of skill portability and selection into migration.

Assumption 3 introduces two distinct effects that likely push in opposite directions. First, it captures the possibility that a migrant's human capital may not be fully portable across countries (Chiswick and Miller 2009). For example, they may lack information on jobs that use their skills; alternatively, they may not receive the full value of their skills if they face language barriers, licensure, or discrimination in the labor market. This force implies that $\tau^h < 0$ is the natural case. Second, a worker's human capital or earnings in a country may include an idiosyncratic country-specific component (McKenzie, Stillman, and Gibson 2010). For example, a worker's bundle of skills may be more suitable for some countries than others. Alternatively, their networks and the quality of job opportunities that they can access may vary by country. These forces generate a notion of comparative advantage as in Roy (1951), which implies that the earnings of migrants may be affected by *selection on comparative advantage*, which implies that $\tau^\eta > 0$ is the natural case. In the end, the overall sign of $\tau^h + \tau^\eta$ is ambiguous.

[11] Throughout the analysis, we impose the normalization $\tau^h_{b,b} = \tau^\eta_{b,b} = 0$. It is also immediate to see that assumption 2 is a special case of assumption 3 in which $\tau^h_{b,c} = \tau^\eta_{b,c} = 0$.

An important advantage of our dataset relative to earlier work is that we have information on workers who migrate among a large set of countries. This gives us scope to estimate the importance of skill portability and selection on comparative advantage using techniques from the trade and technology transfer literatures (Alviarez, Cravino, and Ramondo 2023). We parameterize the joint effect of skill portability and selection as follows:

$$\tau^{h}_{b,c} + \tau^{\eta}_{b,c} = \begin{cases} d_c + \beta|y_c - y_b| & \text{if } c \neq b, \\ 0 & \text{if } c = b. \end{cases} \tag{5}$$

Here d_c is a destination fixed effect. It captures the idea that countries have very different migration policies and institutions that may affect the ability of workers to transfer their skills or identify good matches. It can also capture a differential wage markdown for migrants to c. We use y_c to denote average gross domestic product (GDP) per worker of country c, so the term $\beta|y_c - y_b|$ captures the idea that it may be more difficult to transfer skills between countries at very different income levels.

Previous work on the earnings changes of migrants has generally used data on migrants to a single country—for example, the United States (Hendricks and Schoellman 2018). Combining equations (4) and (5), we can express this earnings change for a college graduate who migrates to the United States as

$$w_{i,j,\mathrm{US},t'} - w_{i,j,b,t} = z_{\mathrm{US}} - z_b + d_{\mathrm{US}} + \beta|y_{\mathrm{US}} - y_b| + \tilde{\eta}_{i,j,\mathrm{US},t'} - \tilde{\eta}_{i,j,b,t}. \tag{6}$$

With only data on migration flows into the United States, it is not possible to estimate all the parameters in equation (6). Skill prices z can be estimated only by imposing the stricter assumption 2 behind equation (3). For example, note that all migrants to the United States have in common the term $z_{\mathrm{US}} + d_{\mathrm{US}}$, which implies that low average earnings among migrants could equally well be rationalized by a low skill price in the United States or by large skill losses for migrants to the United States. Previous work has generally proceeded using two approaches. First, if one is willing to assume $\beta = 0$, then it is possible to estimate z_b for all countries other than the United States by taking the difference in average earnings changes between migrants from b and from b'. Intuitively, the relative changes upon migration are unaffected by factors specific to the United States. Second, one can use ancillary information—for example, about the type of visa or pre- and postmigration occupations or employers—to provide external evidence on skill portability and selection.

Having data on earnings for workers migrating among many countries allows us to estimate directly the importance of skill portability and selection on comparative advantage. To understand this, we return to the previous example and maintain the assumption that $\beta = 0$. By observing

relative earnings changes for migrants from both the United States and country b into a third country b', we can estimate $z_{US} - z_b$. Combined with the information gained from earnings changes of migrants to the United States, this is sufficient to identify all z (up to a normalizing constant). With this estimate of z_c, it is then possible to identify d_c for all countries using equation (6). In words, d_c is estimated as the average difference between the earnings change of migrants to c and what one would expect on the basis of the difference in skill prices. Finally, we relax the assumption $\beta = 0$. Intuitively, given data on bilateral flows among a sufficient number of countries, β is identified from the covariance between GDP per worker and earnings changes at migration net of differences in skill prices.

Our implementation relies on a two-step procedure. In the first step, we use the earnings changes of migrants to estimate the influence of country on earnings. As the discussion around equations (3) and (4) makes clear, our specification addresses the main threats to identification originating from human capital portability and selection into migration. Further concerns might involve transitory wage effects for new migrants, which we are able to control for using time between pre- and postmigration observations, or imperfect substitution between some subgroups of workers, which requires the estimation of skill prices that vary by subgroup and country. We explore these and other concerns in the sensitivity analysis.[12]

In the second step, we return to the sample of nonmigrants, construct country-adjusted earnings by correcting for $\hat{z}_b$, and estimate college graduate quality using college fixed effects as in equation (2). The main threat to identification in this stage is that the average earnings of a college's graduates may not capture their average human capital. Our approach allows for noncompetitive labor markets through a country-specific markdown in wages. We explore controlling for a number of possible factors that might generate deviations between earnings and human capital, such as an important role for firm or local labor market effects, in the sensitivity analysis. We refer the reader to appendix A (apps. A–E are available online) for a description of our exact specifications in both steps, which includes additional controls for demographics and time fixed effects, and to section VI for the sensitivity analysis.

B. Human Capital of Migrants

A final and complementary goal of our analysis is to quantify the human capital of college-educated migrants, who play an important role in the overall stock of college graduate quality by country. Doing so is straightforward given our approach. We can construct the human capital for

[12] We also explore alternative implementations, like allowing $\tau_{b,c}$ to depend on the country of education or bilateral gravity terms capturing the distance between b and c.

migrants by adjusting their raw earnings for the effect of country as well as the estimated effect of skill portability and selection, $h_{i,j} = w_{i,j,c,t} - \hat{z}_c - \hat{\tau}^h_{b,c} - \hat{\tau}^\eta_{b,c}$. Using this, we measure the selection of emigrants as the average human capital of emigrants from c relative to the average human capital of nonmigrants in c, and we measure the selection of immigrants as the average human capital of immigrants to c relative to the average human capital of nonmigrants in c.

We can relate our migration findings to our college graduate quality findings by using the fact that $h_{i,j} = q_j + \varepsilon_i$. Selection of emigrants can be decomposed into selection on college graduate quality (differences in the average q_j of migrants and nonmigrants) and selection on earnings ability (differences in the average ε_i of migrants and nonmigrants). For immigrants, we can further decompose selection on college graduate quality into the portion accounted for by country of origin (having attended college in a country with comparatively low or high average college graduate quality) and the effect of college graduate quality conditional on country (having attended the best or worst college within the country of origin).

To summarize, we have proposed a procedure that allows us to estimate college graduate quality for colleges around the world and for countries as a whole, accounting for the effects of immigration and emigration. The method also produces estimates of the skill price for each country and the importance of skill portability and selection into migration for migrants' earnings. Although the method is conceptually simple, it requires particular data: we need to be able to connect earnings to alma mater for college graduates for a set of colleges around the world. We also need information on pre- and postmigration earnings for a large sample of migrants moving among countries. We now describe the database that contains this information and allows us to implement this approach.

III. Data

A. Datasets

The primary data source for our work comes from the online platform Glassdoor, which allows workers to review their employers, compare their earnings with their peers', and search for jobs. Individuals are incentivized to contribute information through a "give-to-get" policy, whereby those who contribute to the website via an employer review or earnings report gain access to the reviews and earnings submitted (anonymously) by others. Users provide Glassdoor with a wealth of information. First, when registering, users are asked to provide a résumé; about one-quarter do. Second, users provide information on their earnings (base pay, variable pay, currency, and periodicity) and the detailed nature of their work

(employment status, job title, location, and firm). Some users provide this information for multiple years, multiple jobs, and multiple countries. Repeated reporting has been encouraged for workers who want updated comparisons with their peers and is now required for workers who have not contributed a review or pay report within the past year. Consequently, our earnings data consist of employer-employee matches with a rich set of worker observables.

We have access to the full earnings database from 2006 through the first half of 2022. Later years contribute disproportionately to the sample because Glassdoor has become more widely used over time.[13] We impose several sample restrictions to ensure comparability and limit measurement error. First, we restrict our attention to full-time employees. Second, we annualize labor earnings, assuming that full-time hourly workers are employed 2,000 hours per year and full-time monthly workers are employed 12 months per year. We focus on base income, which excludes any variable earnings from cash bonuses, stock bonuses, profit sharing, sales commissions, tips, gratuities, or overtime.[14] To account for possible misreporting, we exclude workers if their currency of earnings does not match their country of employment's predominant currency. Finally, to limit the influence of outliers, we exclude workers whose earnings are less than 10% or more than 10 times the GDP per worker of their country of work.

As detailed in section II, we estimate college graduate quality using a two-step estimation procedure. The Glassdoor database provides a unique wealth of data for each step. The first step utilizes the sample of college graduates who provide earnings reports for more than one country. There are 12 countries in our sample that each receive more than 1% of all immigrants.[15] We restrict the sample to migrants to and from countries that have at least 25 emigrants to one of these 11 countries to ensure that our sample is sufficiently interconnected and that the country effects are estimated with sufficient precision. The resulting sample includes 13,942 workers migrating among 48 countries around the world. This sample is large relative to previous work and, importantly for our approach, includes migrants among a much larger set of countries; previous papers have focused only on migrants to or from a single country

[13] We have performed all analysis in this paper using only data from before COVID-19 (i.e., before 2020). Our main results are quantitatively very similar, although we cover fewer colleges and fewer countries because Glassdoor has expanded rapidly since then.

[14] Our concern here is measurement error, as variable pay is reported imprecisely for workers paid on an hourly or monthly basis. While more than one-third of US workers (Lemieux, Macleod, and Parent 2009) and 20%–40% of salaried workers in Glassdoor abroad (Sockin and Sockin 2019) report earning variable income, Sockin and Sockin (2021) estimate that variable pay accounts for roughly 6% of labor earnings in Glassdoor.

[15] In descending order of share of immigrants: United States, Canada, United Kingdom, Germany, India, Singapore, Ireland, Australia, Netherlands, Spain, France, and Sweden.

(McKenzie, Stillman, and Gibson 2010; Clemens 2013; Hendricks and Schoellman 2018).

The second step uses earnings net of the effect of country to estimate college graduate quality. This step requires joint information on a worker's earnings and where they received their bachelor's degree. Here we use the one-quarter of workers who submit résumés when creating a profile on Glassdoor. We clean and standardize information on college name, the degree attained, major, and grade point average for all workers who report receiving a bachelor's degree; see appendix D for further details. Around one-half of résumés contain usable college information. Our baseline results connect graduates' earnings to the college where they received their bachelor's degree. We also keep the same information for the most advanced postbachelor's degree for each worker, if one is reported. We use this information to explore the effect of advanced degrees on earnings and our estimates of college (undergraduate) quality in section VI.B.

For the second step, we restrict attention to colleges with at least 25 nonmigrant graduates with an earnings report in Glassdoor. This restriction ensures that the college effects are estimated with sufficient precision. Again, Glassdoor presents us with a uniquely large and global sample of workers with data on earnings and alma mater: we observe 2.0 million nonmigrant graduates from 2,873 colleges in 48 different countries. We are able to capture global college graduate quality because our sample has sufficient coverage outside the United States: 470,000 nonmigrant graduates from 1,265 colleges. See table 1 for details of this sample.

Finally, we estimate the human capital of emigrants and immigrants. We measure migration as when someone graduates college in one country and works in another. We do not know birthplace or nativity status, so we cannot disentangle whether the individual studied in the country of their birth and migrated for work, studied abroad and return migrated to their country of birth to work, or experienced an even more complicated migration history. Whereas the first step of our two-step estimation procedure requires information on migrants' earnings in multiple countries, in the second step we can also measure the human capital of migrants who report earnings in a single country. The Glassdoor database provides 200,000 such observations, allowing us to quantify selection for a large sample.

In addition to Glassdoor, we rely on a handful of other datasets. From the CWUR, we obtain a global ranking of the top 2,000 colleges—a natural comparison for our earnings-based measure. We adjust all earnings for inflation and purchasing power parity (PPP) using the PPP-adjusted exchange rates from the World Development Indicators (World Bank 2022). We analyze the relationship between college graduate quality and

development using PPP-adjusted GDP per worker from the same source.[16] We adjust for the number of colleges by country in some exercises using data provided by the World Higher Education Database (2021).

B. Sample Validation

As we emphasized in section III.A, the Glassdoor database is ideal for our research design because it combines a large sample of migrants with earnings reported in more than one country with a large sample of workers with data on alma mater and earnings. These are exactly the features needed to implement our two-step procedure and recover estimates of college graduate quality for a large number of colleges and countries around the world. However, the Glassdoor database is a convenience sample, which implies that the results are not necessarily representative. This fact motivates us to validate our sample against external benchmarks before proceeding to our analysis.

Previous research has used the Glassdoor database primarily to study earnings patterns within the United States. This research documents that the mean and variance of earnings by industry, region, and occupation are highly correlated (coefficients of 0.8–0.9) with the same statistics in representative datasets, including the Quarterly Census of Employment and Wages, the American Community Survey, and the Panel Study of Income Dynamics (Karabarbounis and Pinto 2018; Sockin and Sockin 2019). This work provides reassurance that the data capture key features of the US labor market. Sockin (2022) also uses the panel dimension of the Glassdoor database. He shows that workers' second and subsequent earnings reports are 5%–10% higher than observable characteristics would lead one to expect. This finding suggests that workers with multiple earnings reports may be positively selected on earnings. We explore the sensitivity of our results to corrections for this type of selection in section VI.

Our research utilizes primarily two additional features of the database that previous work has not: the earnings changes at migration for migrants and the average earnings by college for workers around the world. We focus on validating these moments against external sources that provide comparable data.

We first compare our results for the earnings change at migration with those of other sources. A small previous literature estimates similar results for migrants to or from a single country. Hendricks and Schoellman (2018) study migrants from poorer countries to the United States using the New Immigrant Survey, a representative sample of adult immigrants

[16] Data from 2022 are not yet available; we use 2021 GDP per worker and PPP exchange rates for the first half of 2022.

TABLE 1
Summary of Global College Coverage

Country	Abbreviation	GDP per Worker ($)	Colleges		Top Colleges		Graduates	
			Exists	In Sample	Exists	In Sample	Domestically	Abroad
Bangladesh	BGD	11,847	120	16	6	1	1,240	1,609
Pakistan	PAK	15,402	155	34	7	4	4,365	4,508
India	IND	16,717	809	324	40	24	229,431	83,471
Nigeria	NGA	17,667	126	32	6	4	3,596	5,050
Philippines	PHL	18,688	1,332	82	66	2	11,360	6,957
China	CHN	24,021	1,060	17	53	14	582	7,936
Thailand	THA	29,199	146	13	7	6	1,285	718
Colombia	COL	29,652	255	3	12	2	176	550
Sri Lanka	LKA	31,124	26	6	1	1	495	580
Brazil	BRA	34,702	1,043	80	52	29	38,395	3,563
Egypt	EGY	40,546	55	24	2	2	6,450	3,854
Mexico	MEX	45,817	1,642	23	82	10	2,400	1,854
South Africa	ZAF	49,487	49	15	2	2	3,000	2,564
Malaysia	MYS	53,589	81	33	4	4	7,218	1,735
Russia	RUS	53,748	709	8	35	4	431	696
Iran	IRN	54,360	263	3	13	3	152	1,906
Chile	CHL	55,277	60	1	3	1	42	98
Argentina	ARG	56,596	116	7	5	1	616	604
Romania	ROU	58,126	76	9	3	3	1,005	1,124
Poland	POL	64,492	349	14	17	9	820	820
Hungary	HUN	64,926	39	11	1	1	1,074	602
Portugal	PRT	70,388	89	8	4	4	586	471
South Korea	KOR	75,315	248	8	12	6	377	1,452
Czech Republic	CZE	76,115	45	5	2	2	177	185
Turkey	TUR	76,338	172	29	8	8	4,435	3,880
New Zealand	NZL	77,746	29	7	1	1	1,165	1,728

Japan	JPN	78,979	765	5	38	3	232	369
Greece	GRC	82,280	26	15	1	1	1,549	1,624
Israel	ISR	87,249	58	20	2	1	5,247	1,819
United Kingdom	GBR	91,426	248	134	12	12	66,877	23,941
Canada	CAN	91,938	142	85	7	7	46,606	10,713
Spain	ESP	93,892	112	26	5	5	2,005	2,445
United Arab Emirates	ARE	93,910	53	3	2	0	206	165
Australia	AUS	95,421	94	33	4	4	7,730	11,092
Germany	DEU	102,270	359	10	17	4	366	273
Sweden	SWE	103,142	44	5	2	1	207	320
France	FRA	105,250	400	9	20	1	435	493
Netherlands	NLD	105,262	70	19	3	3	1,177	970
Italy	ITA	109,005	99	35	4	4	3,253	4,018
Hong Kong	HKG	110,565	14	9	0	0	3,424	1,133
Denmark	DNK	111,583	33	4	1	1	171	342
Belgium	BEL	119,738	63	6	3	3	290	188
Saudi Arabia	SAU	122,508	72	4	3	2	362	118
Qatar	QAT	122,825	4	1	0	0	25	27
Switzerland	CHE	124,241	33	3	1	0	128	105
United States	USA	124,587	2,117	1,608	105	95	1,482,894	24,042
Singapore	SGP	154,262	9	7	0	0	8,343	731
Ireland	IRL	160,814	49	20	2	2	5,048	2,753
Total: 48			13,958	2,873	676	297	1,957,448	226,196
Total excluding United States: 47			11,841	1,265	571	202	474,554	202,154

NOTE.—The table lists the 48 countries for which we can estimate college graduate quality for at least one college. Each row gives the country name and abbreviation, GDP per worker (2010–21 annual average) from World Bank (2022), number of colleges in existence and number represented in our sample for colleges overall and top colleges, and number of graduates from those colleges employed domestically and abroad.

granted lawful permanent residence in the United States between May and November of 2003. They find that the log wage change at migration for college-educated migrants is around 0.37 of the total difference in log GDP per worker between pre- and postmigration country of work. Clemens (2013) uses the H-1B lottery to estimate the causal effect of migration to the United States on the earnings of Indian software workers, who are all college graduates. He finds a higher estimate of 0.62–0.63. McKenzie, Stillman, and Gibson (2010) and Gibson et al. (2018) also use a lottery to provide experimental estimates of the effect of migrating from Tonga to New Zealand on wages. They do not report results separately for college graduates, but the corresponding estimate for all migrants in their work is 0.48.

We construct similar moments for the Glassdoor database. Table 2 shows the results. Column 1 shows that if we use the whole sample, we find that the mean and median log earnings change is about one-half of the difference in log GDP per worker, in line with the overall consensus in the literature. Column 2 constructs the most similar possible sample to Hendricks and Schoellman (2018), focusing on migrants into the United States from countries with GDP per worker less than one-fourth of the United States. For this sample, we find a higher figure than in the overall sample or in previous work, about 0.57–0.60 as compared with 0.37. Column 3 focuses on Indian migrants to the United States; while we do not know each worker's visa status, this is the closest counterpart we observe to the sample of Clemens (2013). We see that most migrants from poor countries to the United States in Glassdoor come from India and that the earnings gains for this group is similar to what Clemens (2013) estimates, 0.60–0.62 versus 0.62–0.63. We do not have enough Tongan migrants to New Zealand to compare our results with those of McKenzie, Stillman, and Gibson (2010).

Second, we compare our estimates of the average earnings by college with those of sources that provide similar data for countries in our

TABLE 2
Validation: Earnings Change at Migration

log(Earnings Change at Migration)/log (GDP per Worker Difference)	All Migrants (1)	Migrants into United States: From Poor Countries (2)	Migrants into United States: From India (3)
Mean	.518	.577	.604
Median	.488	.599	.621
Total migrants	12,210	3,158	2,749

Note.—The table shows the mean and median of the log change in earnings relative to the log difference in GDP per worker for the listed samples of migrants. All samples are restricted to migrants moving between countries with absolute change in log GDP per worker of at least 0.25.

sample. One prominent example is the US Department of Education's College Scorecard, which uses tax data from the US Treasury to provide "median earnings of graduates working and not enrolled 1 [2] year[s] after completing highest credential." The median earnings data are disaggregated by college, degree attained, and major of study. We limit attention in Glassdoor to recipients of bachelor's degrees from US colleges who report earnings 1 or 2 years after the graduation dates reported on their résumés. We match these observations to the College Scorecard data by college, major, and years since graduation. We are able to match 134,000 workers from 1,484 colleges in the Glassdoor database on this basis.

The difference in log earnings between Glassdoor and the College Scorecard data provides a measure of selection into the Glassdoor sample at the college, major, and cohort level. We aggregate this measure of selection to the college level (weighting by the number of workers of each type in the Glassdoor sample) and plot the density of college-level selection in figure 1. The distribution is symmetric, centered near zero, and has small tails. This indicates that Glassdoor provides an unbiased sample of earnings by college in the United States.

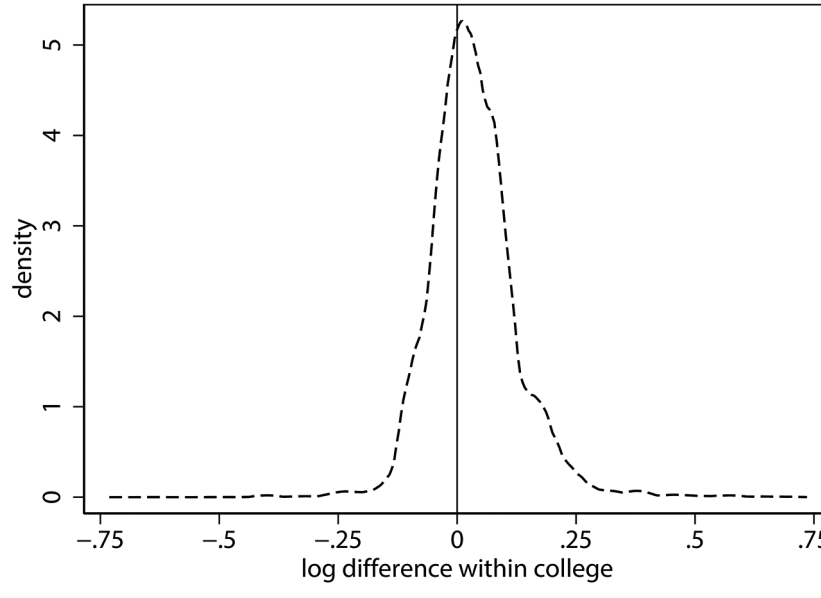

FIG. 1.—Sample selection into Glassdoor for US graduates. The figure shows the distribution across colleges of the difference between mean log earnings in Glassdoor and mean log earnings in the US Department of Education's College Scorecard database.

We conduct a similar analysis for as many of the countries in our database as possible. We give preference to representative government-sponsored data sources when they are available. For countries that lack such sources, we use a wide variety of other data sources, including surveys run by colleges themselves and convenience samples derived from local data sources, such as job websites. We have identified suitable data sources for 16 other countries; details on the source, the data, and how we construct comparable moments in Glassdoor are available in appendix C. We intentionally avoid using other sources that collect data on earnings for colleges around the world. These sources are likely to be very similar to Glassdoor in the sense that they are based in English-speaking countries and ask workers to self-report earnings via web platforms. We are concerned that they may have a similar sample selection as Glassdoor and hence may not provide a useful validation exercise.[17]

Table 3 summarizes some of the key moments from the comparison exercises for the United States and these 16 other countries. For each country, it shows the PPP-adjusted GDP per worker, the number of colleges and graduates in Glassdoor that we match to the external data source, and the resulting estimates of selection. Because many of our results specifically concern top colleges in each country, we also present the difference in earnings between Glassdoor and the external data for top and nontop colleges in each country (see sec. IV.B for a definition of top colleges). Glassdoor appears to capture a positively selected sample for some countries, such as Nigeria, Poland, or Italy. However, the extent of selection is not correlated with development. In section VI, we show that our results are almost unchanged if we implement a correction for the degree of selection into Glassdoor for these 17 countries. With these validation results in hand, we turn to using the sample to estimate college graduate quality.

IV. College Graduate Quality and Development

This section presents our main results. We focus on the distribution of college graduate quality by college and the implications of migration for the global distribution of college graduate quality. Our two-step procedure also produces estimates of the skill price by country as well as the implications of skill portability and selection on comparative advantage for the earnings of migrants. Since these are not our main results of interest, we

[17] For example, Emolument (https://www.emolument.com/) and Payscale (https://www.payscale.com/) provide average self-reported earnings or salaries for graduates of a large number of colleges around the world, but they are based in the United States and the United Kingdom, respectively.

TABLE 3
COMPARISON OF GLASSDOOR DATA ON EARNINGS BY COLLEGE WITH EXTERNAL SOURCES

Country	GDP per Worker ($)	Colleges		Graduates		Average Selection Estimate		
		Overall	Top Colleges	Overall	Top Colleges	Overall	Top Colleges	Nontop Colleges
India	16,717	32	10	657	228	−.08	−.15	−.04
Nigeria	17,667	18	4	946	371	.43	.41	.45
Philippines	18,688	13	1	2,963	518	−.05	.00	−.06
China	24,021	70	34	298	170	.10	.15	.02
Colombia	29,652	15	3	51	16	.22	.41	.14
South Africa	49,487	13	2	333	101	.19	.00	.27
Poland	64,492	19	10	810	527	.31	.36	.22
South Korea	75,315	27	6	185	113	.05	.03	.09
New Zealand	77,746	7	1	730	290	−.03	.00	−.04
Japan	78,979	20	13	63	46	.02	.04	−.06
United Kingdom	91,426	119	12	8,382	1,056	.03	−.09	.04
Australia	95,421	39	4	1,039	245	.00	.03	−.01
Netherlands	105,262	12	3	89	29	−.09	−.04	−.11
Italy	109,005	31	3	94	37	.35	.27	.41
United States	124,587	1,484	96	133,525	37,915	.03	.02	.04
Singapore	154,262	5	0	530	0	−.10	. . .	−.10
Ireland	160,814	16	2	727	169	−.02	−.03	−.01

NOTE.—The table summarizes the average selection into Glassdoor data for 17 countries for which external data for comparison are available. For details regarding the external data used for each nation and a summary of how comparison samples in Glassdoor are constructed, see app. C.

describe them briefly here and reserve a more complete discussion of the results with accompanying figures and tables to appendix B.1.

Our estimates of skill prices are closely related to log GDP per worker (correlation of 0.60). Consistent with Hendricks and Schoellman (2018), skill prices vary much less than GDP per worker. Our baseline estimates of the joint effect of skill portability and selection on comparative advantage point to heterogeneity across destinations in their effect on earnings, d_c. For example, the estimate for the United States is 0.13, suggesting selection on gains to migration that outweigh skill nonportability and raise earnings by about 14%. At the other end of the range, the estimate for Canada is –0.11, suggesting that skill nonportability is the dominant effect and that it lowers earnings by about 12%. Overall, the estimates are clustered around zero. The estimated effect of moving to a country with a different income level, β, is also small and statistically insignificant. We also explore several other specifications of $\tau_{b,c}$. Our estimates of z_c are highly correlated across specifications.

After adjusting for the effects of country of work, skill portability, and selection on comparative advantage, we arrive at estimates of the average human capital of each college, migrant, and country. We now turn to these main results.

A. *College Graduate Quality and College Rankings*

We start by comparing our estimates of college graduate quality with the widely used CWUR ranking. This comparison serves two functions. First, it allows us to check whether our estimates of college graduate quality align with independent rankings of colleges around the world. Second, we can use our estimates to provide an economically meaningful scale to college rankings. This is useful for understanding how much more human capital graduates of highly ranked colleges have.

For this comparison, we estimate the average graduate quality for colleges in various ranking bins (e.g., 1–20, 21–50, etc.) compared with that for unranked (outside the global top 2,000) colleges. The estimated college graduate quality within each bin and their respective standard errors are shown in table 4. We also include the number of colleges in each bin; recall that we include only colleges for which we have at least 25 graduates who report earnings in the Glassdoor database.

Table 4 shows two main results. First, college graduate quality is highly correlated with external college rankings. The estimated college graduate quality increases smoothly with ranking bin. This result is a reassuring check on our methodology. Second, our results can be used to provide a quantitatively meaningful scale to what are otherwise ordinal rankings. We find substantial gaps in college graduate quality between colleges of different ranks. Graduates of colleges ranked 1,001–2,000 have quality 11 log points higher than that of graduates of unranked colleges, meaning that they would be expected to earn 12% more in the same labor market. The gap in quality grows to 34 log points for colleges ranked 51–100 and reaches a substantial 47 log points (60%) for graduates of colleges ranked in the top 20. To put these numbers into perspective, we note that the college earnings premium in 2019 for the United States was 59% (see n. 6 for details and source). That is, the earnings difference between attending a college ranked in the global top 20 instead of outside the global top 2,000 is as large in magnitude as the earnings difference in the United States between college and high school graduates.

We build on these results in three ways that we describe briefly here, with details in the appendix. First, we show that these (country-adjusted) earnings differences are fairly stable over the life cycle (table B3). This finding suggests that our results do not reflect prestige effects, which would fade over time with employer learning (Bordón and Braga 2020). Second, we show that the entire distribution of human capital (country-adjusted earnings) is shifted to the right for higher-ranked colleges but that there is substantial overlap between colleges at different rankings groups, even when comparing colleges ranked in the top 20 with unranked colleges (fig. B4). Third, we construct our own global ranking of colleges on the basis of their estimated graduate quality (table B4 displays the

TABLE 4
College Graduate Quality and CWUR World Ranking

	World Ranking						
	1–20	21–50	51–100	101–250	251–500	501–1,000	1,001–2,000
College graduate quality	.472***	.341***	.343***	.266***	.201***	.161***	.106***
	(.022)	(.024)	(.020)	(.011)	(.011)	(.013)	(.012)
Observations	19	22	38	103	154	221	317

Note.—The table displays our measure of (log) college graduate quality q_j as a function of various ranking groups from the CWUR. Omitted category is unranked (below 2,000). Standard errors are in parentheses. N = number of colleges in our sample within each bin.

*** Significant at the 1% level.

top 100; the full ranking is available online). Given that the sample size for some colleges is small, we focus on broad trends of which types of colleges are estimated to have high graduate quality rather than on specific colleges.

First, we estimate high graduate quality for many of the expected colleges: most of the Ivy League as well as a number of renowned colleges outside the United States are ranked in the top 100. Second, among US colleges, selective liberal arts colleges and military academies have high estimated graduate quality—they are ranked much more highly than on standard rankings. Third, foreign colleges with a technical orientation rank much more highly in college graduate quality. The most notable example is the dominance of the Indian Institutes of Technology at the top of our earnings-based ranking as well as Technion, Technical University of Munich, or Moscow Institute of Physics and Technology. While these colleges are ranked outside the top 100 according to the CWUR, we argue that these rankings are not commensurate with the earnings their graduates command around the globe.

Although interesting, this ranking concerns only 100 of the 2,873 colleges for which we can estimate graduate quality. Our next results focus on the overall distribution of college graduate quality by country.

B. College Graduate Quality and Cross-Country Income Differences

In this section, we show that college graduate quality is highly correlated with GDP per worker. We also compare the distribution of college graduate quality across countries and find that many (but not all) developing countries have no colleges equivalent to even the median college in developed countries. This evidence shows that cross-country differences in the stock of skilled labor are larger than the typical estimates based on the share of college graduates in the workforce.

When comparing colleges across countries, it is important to keep in mind that we estimate college graduate quality only for colleges with at least 25 graduates in Glassdoor. We cover roughly three-quarters of colleges for the United States (table 1) but a lower share for most other countries. Further, our sample is more likely to contain top colleges. For example, table 4 shows that the share of colleges in our data declines with CWUR world ranking: we have 95% of the top 20 colleges, 69% of colleges ranked 101–250, and 32% of colleges ranked 1,001–2,000. Given this, we focus on comparing top colleges across countries and try to understand how the top colleges of other countries fit into the distribution of college graduate quality in the United States.

Our preferred metric for comparing top colleges is the top 5% of colleges in each country, which we compute for countries that have at least

20 colleges (table 1, col. 3). We use data on the total number of colleges from World Higher Education Database (2021) to measure how many colleges constitute the top 5% for each country. We use the CWUR rankings to identify which colleges to include in the top 5% for each country. For example, World Higher Education Database (2021) reports that Chile has 60 colleges, so the top 5% comprises three colleges; CWUR tells us that the top three colleges for Chile are Pontifical Catholic University of Chile, University of Chile, and University of Concepción. The CWUR ranks only 2,000 colleges worldwide. If there are not enough colleges from a country ranked in the top 2,000, we take the average quality of the colleges that are ranked. For example, if Chile had only two ranked colleges, we would take the average of the two. This leads us to overstate the college graduate quality of these countries, which in practice are developing countries. Altogether, our approach is conservative for measuring the extent of college graduate quality differences between developed and developing countries.

As a comparison, we also study a simple absolute ranking that takes the five best colleges for countries with at least five colleges. Again, for some developing countries, there are not enough ranked colleges to round out the top five. For these countries, we focus on however many colleges are ranked.

In figure 2, we plot the relative and absolute measures of college graduate quality by country against PPP GDP per worker. The key insight from these plots is that richer countries have higher college graduate quality. Again, the effect is economically and quantitatively significant. The 95–5 ratio of GDP per worker in our sample is a factor of 7.5 (United States–India). Multiplying this difference by the estimated trend line shown in the figures suggests that top universities in richer countries have college

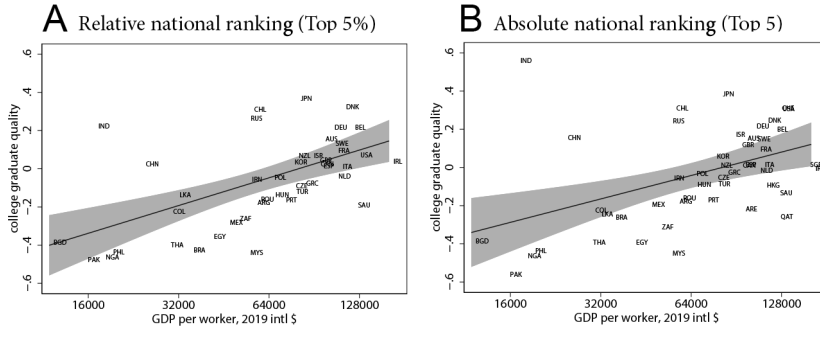

FIG. 2.—College graduate quality of top colleges and development. The figure plots the average estimated college graduate quality among the top 5% (*A*) or top 5 (*B*) of a country's colleges (on the basis of CWUR) against PPP GDP per worker from World Bank (2022) in log scale.

graduate quality 52% higher than that of top universities in poorer countries. The overall relationship is similar whether we use the top 5% of colleges (relative ranking, fig. 2*A*) or the top 5 colleges (absolute ranking, fig. 2*B*). The top 5 ranking shows a pronounced size advantage, which benefits large nations with many colleges (e.g., India, China, and the United States). With this in mind, we focus on relative national rankings for the remainder of the paper.

The relationship between college graduate quality and GDP per worker is not sensitive to the choice of threshold for identifying top colleges. Table 5 shows the estimated elasticity of college graduate quality with respect to development for alternative specifications of top colleges. When focusing on the top 5% of colleges, we estimate an elasticity of 0.21. If we consider a more restrictive sampling of only the top 2%, a wider bandwidth including the top 25%, or all colleges in our sample, very similar results prevail.

These findings relate to an existing literature that estimates cross-country differences in education quality, which is generally assumed to be common across education levels. Our estimated elasticity for college graduate quality is slightly larger than what is typically estimated for education quality. For example, the corresponding elasticity implied by Schoellman (2012) is 0.19; Erosa, Koreshkova, and Restuccia (2010) report a preferred range of results that correspond to an elasticity of 0.18–0.19. We interpret these findings as saying that variation in human capital per college-educated worker is of a similar magnitude as variation in human capital per worker at other education levels. Our results allow us to add to this literature by providing evidence on the distribution of college graduate quality, which we turn to now. We also use the data to provide new evidence on the role of majors and advanced degrees in section VI.

We start our analysis of the distribution of college graduate quality by plotting the standard deviation of college graduate quality across colleges within each country against that country's PPP GDP per worker. As described

TABLE 5
TOP PERCENT COLLEGES WITHIN COUNTRIES AND GDP PER WORKER

	Top 2%	Top 5%	Top 10%	Top 25%	All
Log(GDP per worker)	.191***	.209***	.221***	.198***	.242***
	(.058)	(.045)	(.043)	(.043)	(.044)
Countries	32	43	46	48	48
Adjusted R^2	.24	.33	.36	.30	.39
Corr(GDP per worker, college graduate quality)	.29	.35	.45	.41	.50

NOTE.—The table displays the estimated coefficient from regressing the average graduate quality of a country's colleges in the respective group on the log of PPP GDP per worker from World Bank (2022). See text for description of the construction of percentile bins.
*** Significant at the 1% level.

above, our database has better coverage of top colleges, particularly in developing countries. This leads us to expect that we probably underestimate dispersion in all countries but more so in developing countries. As figure 3 shows, we nonetheless find a strong negative relationship between dispersion and development. This finding is consistent with broader recent evidence showing that developing countries also have more dispersion of revenue-based total factor productivity across plants (Hsieh and Klenow 2009), management quality across firms (Bloom and Van Reenen 2010), and student-teacher ratios across schools (Walter 2020).

Another useful way to visualize these results is to show how the distribution of college graduate quality for other countries compares with the distribution of the United States. Given our discussion above, we think of the distribution for the United States as being reasonably complete and that for other countries as overrepresenting the country's top colleges. We focus on three groups of countries. The first group consists of three developed countries for which we capture a large number and share of colleges: Canada, Ireland, and the United Kingdom. The second group consists of two developing economies that are outliers in terms of college graduate quality for their development level in figure 2: China and India. The third consists

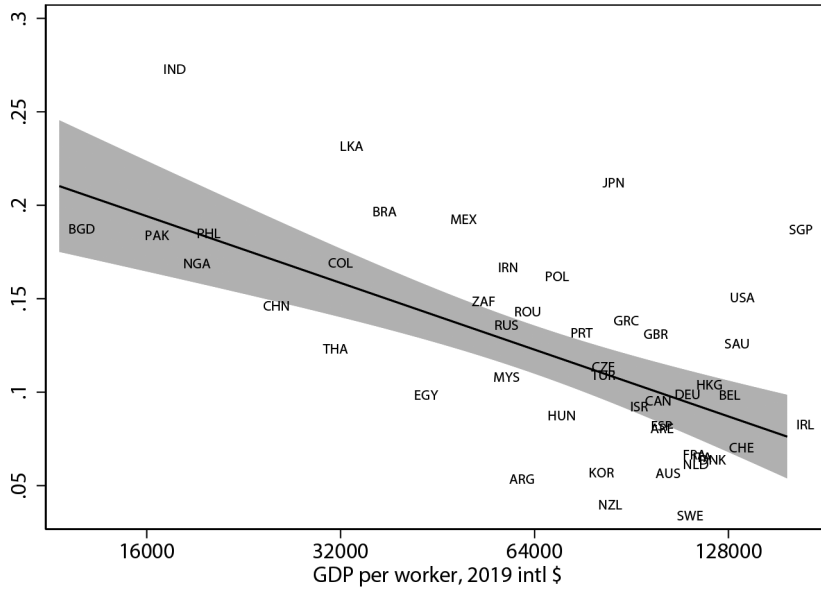

FIG. 3.—Within-country dispersion in college graduate quality and development. The figure plots the standard deviation in estimated college graduate quality of a country's colleges against PPP GDP per worker from World Bank (2022) in log scale.

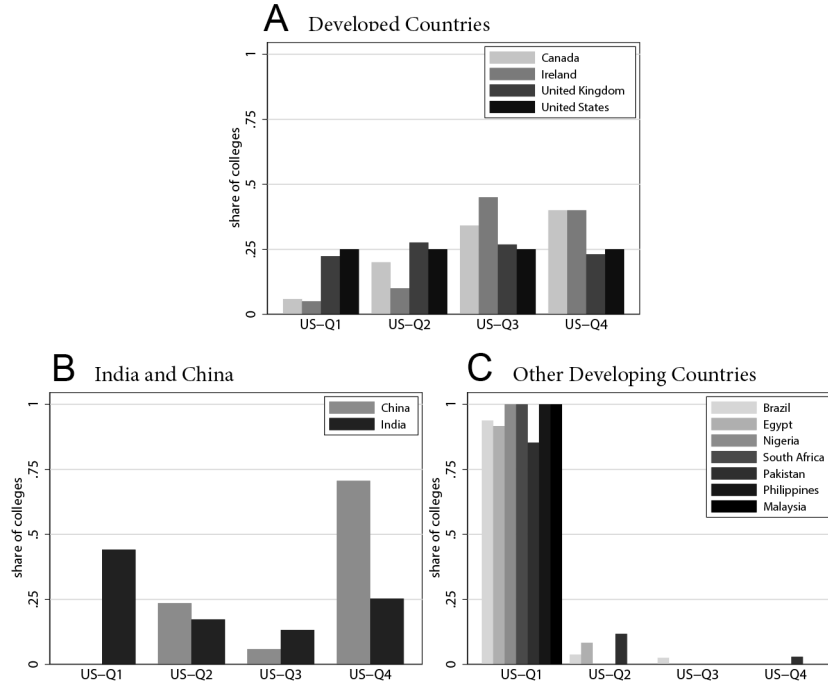

FIG. 4.—Comparison of distribution of college graduate quality. The figure plots for each country the share of colleges that have estimated graduate quality that falls in the first quartile of the US college graduate quality distribution (or below), the second quartile, the third quartile, or the fourth quartile (or above).

of developing countries that are not outliers and for which we have either a large number or share of colleges: Brazil, Egypt, Nigeria, South Africa, Pakistan, Philippines, and Malaysia. Figure 4 plots a histogram showing the fraction of each country's colleges in our database with college graduate quality in the first through fourth quartiles of the US distribution.[18]

Figure 4*A* shows the results for the first group. Not surprisingly, the distribution for these countries is similar to that of the United States. Each distribution shows a higher mass of colleges above the US median, but again this may reflect selection in terms of which colleges are captured in Glassdoor. Figure 4*B* shows the results for India and China. The main finding is that the top Chinese and Indian colleges appear to have college graduate quality comparable to American colleges, with many colleges scoring above the US median and even in the top quartile of the US distribution. Figure 4*C* shows the same results for the other developing countries

[18] A few colleges have estimated graduate quality outside the US range; we group these with the first or fourth quartile as appropriate.

with reasonably broad coverage in Glassdoor. Here, the pattern is very different: the vast majority of colleges from Brazil, Egypt, Nigeria, South Africa, Pakistan, Philippines, and Malaysia have college graduate quality comparable to the lowest quartile of American colleges. Four of the seven countries have no college with estimated graduate quality above the first quartile of the US distribution, and only two of the seven have a college with graduate quality above the US median. These findings point to large differences in the entire distribution of the quality of skilled labor across countries.

C. *Selection of Migrants*

The human capital of a nation's college-educated workforce depends not only on graduates of its colleges but also on the human capital of its emigrants and immigrants. In this section, we complement our findings on college graduate quality with new results on the average human capital of college-educated emigrants and immigrants by country. Specifically, for each country c, we estimate the log difference in average human capital for emigrants from c as compared with nonmigrants and for immigrants to c relative to nonmigrants. Figure 5 plots these measures of selection against GDP per worker.

Figure 5*A* shows the implications for brain drain. The average selection of emigrants is negatively correlated with development. Not only do developing countries lose a larger share of their college graduates to emigration, but also those emigrants are strongly positively selected on their human capital. For a number of countries, the average emigrant has 40 log points (50%) more human capital than the average nonmigrant. By

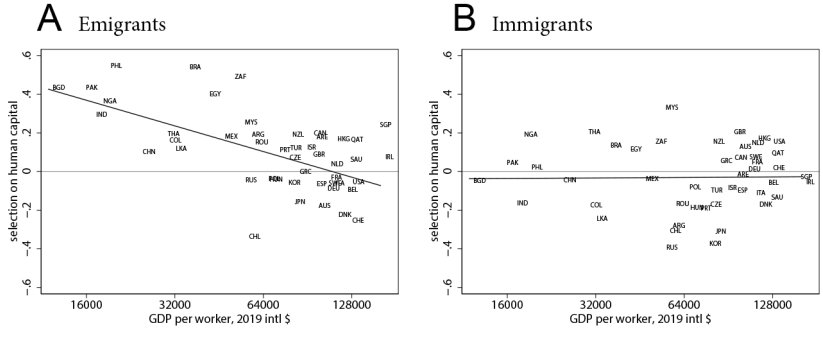

FIG. 5.—Average selection of migrants by country. The figure plots against PPP GDP per worker (in log scale) the average selection of each country's emigrants (*A*) and each country's immigrants (*B*), measured as the log difference between the average human capital of that respective group and the average human capital of the country's nonmigrants. Data on GDP per worker are from World Bank (2022).

contrast, emigrants from developed countries are on average hardly selected at all. This finding indicates that the proximate effect of brain drain on developing countries is stronger than what has been found in the literature focusing solely on the number of college-educated migrants.

Figure 5*B* shows the implications for immigration. For most countries, the average human capital of immigrants is close to that of nonmigrants. Further, the gap between the two is only weakly correlated with development. The more striking feature is the substantial heterogeneity in terms of the selection of immigrants among developed countries. These results reinforce the findings from the global talent flows literature (Kerr et al. 2016). The United States and United Kingdom attract not only a disproportionate share of the world's college-educated immigrants but also immigrants whose average human capital exceeds that of local graduates by a significant amount. We also find evidence that other countries attract talented immigrants by this metric, including Australia, Hong Kong, and the Netherlands. On the other hand, a handful of developed countries attract immigrants whose average human capital is more than 20% lower than that of local graduates, including South Korea, Denmark, and Japan.

These findings have important implications for our understanding of migration patterns. In figure 6, we plot the net gain of college graduate labor by country, defined as the effect of immigration minus emigration relative to the country's current college-educated labor force. The gray bars capture the gain computed using number of migrants as reported in the Database on Immigrants in OECD and Non-OECD Countries (DIOC-E).[19] The black bars capture the gain computed using both the number and the human capital of migrants. Consistent with the discussion above, the loss in many developing countries is even larger once we adjust for human capital differences. For example, the loss of college-educated labor is 4 percentage points larger for Argentina and 12 percentage points larger for South Africa. Among developed countries, Australia stands out as having the largest positive revision, gaining 6 percentage points more after adjusting for human capital differences. The United States and United Kingdom also experience positive revisions, gaining 3 and 4 percentage points more, respectively, when the human capital of migrants is considered. Table B5 provides results separately for net immigration and net emigration by country, including net emigration results for some countries absent from figure 6 because data on immigration are not available for them.

We decompose the selection of migrants into selection on college graduate quality, q_j, and selection on idiosyncratic ability, ε_i; full results are available in table B6. For emigration, we find that our results are essentially entirely explained by selection on idiosyncratic earnings ability. For

[19] https://www.oecd.org/els/mig/dioc.htm.

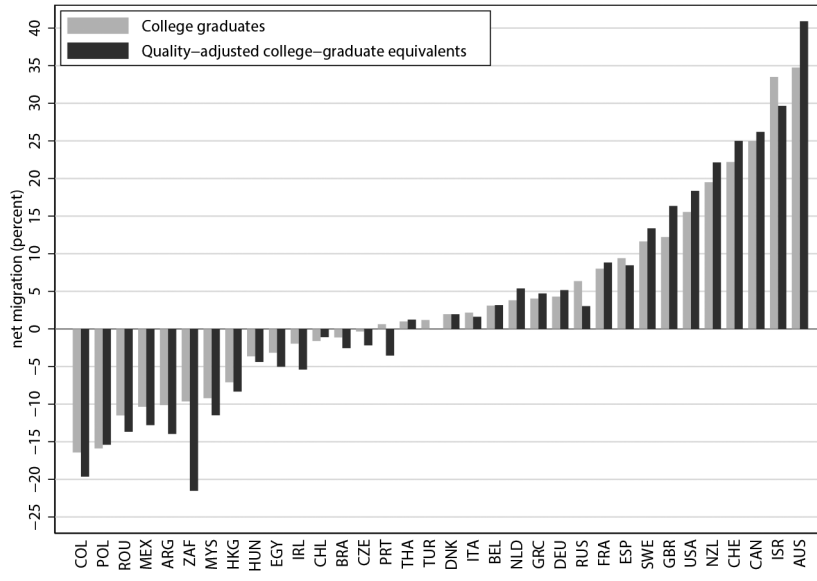

FIG. 6.—Net migration of college graduates, accounting for human capital. The figure plots the net contribution of migration to each country's college-educated labor force. Gray bars (college graduates) measure the labor force as number of workers; black bars (quality-adjusted college graduate equivalents) measure it as units of human capital. Contribution is (immigration − emigration)/(current labor force). Data on number of emigrants, immigrants, and college graduates are from the DIOC-E; data on human capital per worker are authors' estimates from Glassdoor data.

immigration, we find a more nuanced result. Selection on college graduate quality conditional on country plays a minor role. However, there are large and offsetting trends in the role of selection on country and selection on idiosyncratic earnings ability, which we focus on in figure 7.

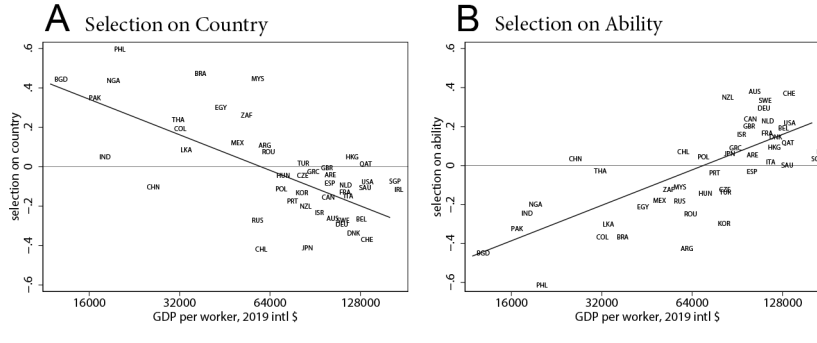

FIG. 7.—Decomposing selection of immigrants. The figure plots selection on country (average college graduate quality of sending countries; *A*) and selection on ability (idiosyncratic earnings; *B*) against PPP GDP per worker from World Bank (2022) in log scale.

Figure 7*A* plots the selection on country (measured as average college graduate quality of the country where each immigrant was educated) against GDP per worker. There is a strong negative correlation between the two. This is intuitive: developing countries find it easier to attract immigrants from countries with higher average college graduate quality than their own. Figure 7*B* plots the selection on ability against GDP per worker. This figure shows a strong positive correlation. Put differently, developing countries draw immigrants of below-average ability from richer countries with higher college graduate quality. Developed countries draw immigrants of above-average ability from poorer countries with lower college graduate quality.

Figure 7 also helps explain why there is such a high degree of heterogeneity in terms of selection of immigrants among developed countries. Consider two examples. First, we find that Switzerland and Japan have roughly similar levels of selection of immigrants in terms of country (–0.37 and –0.41, respectively). However, Switzerland's immigrants are more selected on ability than Japan's (0.37 vs. 0.06, respectively), which leads to large differences in overall selection. Second, we find that the United States and Denmark have similar levels of selection in terms of ability (0.22 and 0.15, respectively). However, immigrants to the United States are much more selected on country (–0.08 vs. –0.34), which explains a large gap in total selection of their immigrants. Our finding of strong positive selection among immigrants to the United States is consistent with much of the literature. However, we provide novel evidence suggesting that such strong selection does not generalize even to other developed countries.

V. Implications of College Graduate Quality Differences

Section IV documents the existence of large differences in college graduate quality around the world and particularly between developing and developed countries. Graduates of colleges in developed countries have much higher average human capital than those in developing countries; many developing countries have no colleges with graduate quality above the first quartile of the US distribution. These differences are then magnified by migration, particularly by the fact that the set of graduates who emigrate from developing countries tend to be strongly positively selected. The goal of this section is to consider the implications of these findings for growth and development.

A. Development Accounting

We start by revisiting the implications of our findings for development accounting, which seeks to understand the role of physical capital, human

capital, and total factor productivity in accounting for cross-country income differences. Our findings, particularly those in table 5, point to an important role for cross-country variation in the average human capital of college-educated workers by country. However, this is by itself just one component of a nation's overall human capital, which is also affected, for example, by the school attainment of the population, experience, and health.

Our results can best be understood in comparison to Hendricks and Schoellman (2018). They estimate the wage changes of cross-country migrants, which they show capture the changes in country-specific factors, such as physical capital and total factor productivity. Once these factors are accounted for, then cross-country differences in the stock of human capital are captured as a residual. The advantage of this approach is that it allows them—and us—to estimate human capital stocks without specifying and estimating all the separate components of human capital. As we described in section II.A, the first step of our approach is closely related to their work, except that we use the fact that we have data on bilateral migration flows among a large number of countries to estimate country-specific factors while simultaneously controlling for the effects of skill portability and selection on comparative advantage for migrants.

We follow Hendricks and Schoellman (2018) by estimating the average change in skill prices relative to the average change in GDP per worker for immigrants to the United States from countries with GDP per worker less than one-fourth the United States. We find a ratio of 0.33, which is very similar to their estimated ratio of 0.37. This suggests that our findings point to a similar role for country-specific factors and human capital.[20]

We arrive at this result in a different way. We start with a larger relative wage gain than Hendricks and Schoellman (2018), 0.58 versus 0.37, as we show in table 2. Our novel estimates of skill portability and selection on comparative advantage include a large destination effect for the United States that offsets this wage gain. While similar results are not available for Hendricks and Schoellman (2018), one plausible interpretation of these differences is that the sample of immigrants from developing countries to the United States in Glassdoor is more strongly positively selected on comparative advantage for working in the United States. To this point, we note that a large majority of migrants in question were educated in

[20] These results are also consistent with the emerging consensus that much of cross-country differences in the relative productivity of skilled labor are attributable to skill bias of technology, which in turn is consistent with a larger cross-country or long-run elasticity of substitution between skilled and unskilled labor. However, our evidence speaks to only skilled labor. See Okoye (2016), Rossi (2022), and Hendricks and Schoellman (2023) for a complete argument on the measurement and decomposition of skilled labor productivity and Bils, Kaymak, and Wu (2022) and Hendricks and Schoellman (2023) on the elasticity of substitution.

India (table 2) and work in the US technology sector—a natural candidate for sorting on comparative advantage. If we reestimate the first step while excluding these workers, we find a smaller relative wage gain for migrants to the United States (39% of the GDP per worker gap) and a smaller US-specific destination effect (0.026 instead of 0.133). However, the estimates of z_c from this exercise are highly correlated with our benchmark (0.97).

It is also useful to think about how our benchmark estimate—that college graduate quality varies 20% as much as GDP per worker—fits with the finding of Hendricks and Schoellman (2018) that human capital in total accounts for 60% of cross-country income differences. Existing work in this literature points to a large role for educational attainment (years of schooling) and experience (life cycle human capital accumulation) that are distinct from our estimates of college graduate quality (Hall and Jones 1999; Lagakos et al. 2018a, 2018b). If we convert estimates of these standard effects to the same accounting metric, we find that they already account for 40% of cross-country income differences. Incorporating our estimate of college graduate quality then gets us close to an estimate that is consistent with the finding of Hendricks and Schoellman (2018). For example, if non–college graduate quality varies by as much as college graduate quality, we could simply add our benchmark estimate of 20% to arrive at a total estimate of 60% for the combined effect of school attainment, experience, and education quality. Details and data sources for these calculations are available in appendix B.2.

These results speak to a direct effect of college graduate quality on labor productivity. In section V.B, we provide evidence on additional mechanisms through which college graduate quality might matter for growth and development.

B. Innovation and Entrepreneurship

In this section, we document that college graduate quality also matters for the share or number of workers who engage in specific activities that are important contributors to growth and development. We provide new results showing that colleges with higher graduate quality also have a larger share of graduates who become entrepreneurs, innovators, or executives. Thus, college graduate quality may play an important role in explaining the large cross-country differences in business formation and business growth rates, patenting and innovation, or the quality of management at large firms.

Our approach is to collect data on how many graduates of a set of colleges subsequently become entrepreneurs, innovators, or executives. We merge this data with our estimates of college graduate quality and regress the number or share of each college's graduates engaging in these activities on our estimate of college graduate quality. We use country fixed effects

throughout so that our identifying variation is across colleges within a country rather than across countries.

We use three different sources of data on the share of a college's graduates who become entrepreneurs, innovators, or executives. Details on data sources and relevant measures are available in appendix E. The first source is the Glassdoor database itself. From this database, we use the job titles that workers provide on their résumés. We count as entrepreneurs any workers who list a current or previous job title on their résumé that includes the term "founder" or "cofounder." We count as executives any workers who list a current or previous job title on their résumé that includes the words "chief" and "officer" or any of the common three-letter C–O abbreviations, such as CEO and CFO. We then regress the share of each college's graduates who have ever held the corresponding occupations on their alma mater's college graduate quality. Mechanically, the earnings of workers who are currently entrepreneurs or executives affect estimated college graduate quality, but the share of such workers is sufficiently low (0.3%) that this effect is small.

Table 6 presents the results. Columns 1 and 2 show results for entrepreneurship, while columns 3 and 4 concern executive positions. As discussed above, we include country fixed effects; we also separate results for colleges in the United States to see whether our results are driven by this country. We find a positive statistically significant effect in all four cases. Further, these effects are economically large. For example, a 1 standard deviation rise in college graduate quality is associated with 0.8 percentage points more entrepreneurs and 0.3 percentage points more executives

TABLE 6
College Graduate Quality and Occupation: Glassdoor Database

	Share Entrepreneurs		Share C-Suite	
	US Colleges (1)	Non-US Colleges (2)	US Colleges (3)	Non-US Colleges (4)
College graduate quality	.072***	.041***	.044***	.017***
	(.003)	(.005)	(.004)	(.004)
Country fixed effects		Yes		Yes
Mean outcome	.024	.023	.034	.020
SD college graduate quality	.13	.20	.13	.20
Observations	212,985	91,567	212,985	91,567

Note.—The table relates our measure of college graduate quality to whether workers ever engage in entrepreneurship or become chief-level (C-suite) executives after graduating from US and non-US universities. Estimates reflect marginal effects from logit specifications. A worker is considered an entrepreneur if there is a job title on their résumé that includes the term "founder." A worker is considered C-suite if there is a job title on their résumé that includes both "chief" and "officer" or includes any of the following: "CEO," "CFO," "CIO," "COO," "CMO," or "CTO." Sample is restricted to workers born between 1960 and 1995 and includes year of birth fixed effects. Standard errors (in parentheses) are clustered by college.

*** Significant at the 1% level.

outside the United States—sizable effects relative to baseline shares of 2.3% and 2.0%, respectively.

Our second source of data is patent records from the US Patent and Trademark Office. Unfortunately, there are no data on patents by alma mater for graduates of foreign colleges. Instead, we employ two empirical strategies. First, we estimate the relationship between college graduate quality and patenting by college within the United States. We use data from Bell et al. (2019), who provide the share of students who are granted patents as well as the share of students who are among the top 5% most-cited inventors in their cohort for US colleges with more than 10 patents granted among students in the 1980–84 birth cohorts; see their paper for further details. Second, using data provided by the US Patent and Trademark Office, we estimate the cross-country relationship between college graduate quality among a country's top colleges and the number of patents per capita its residents have filed in the United States; see appendix E for details.

Table 7 shows the results for the United States. Both of the coefficients of interest are positive and statistically significant. Again, the results are also economically large. Even focusing on the colleges with at least 10 inventors, a 1 standard deviation rise in college graduate quality is associated with a 0.9 percentage point increase in the share of students who are inventors, when the mean rate is just 1%. The cross-country results, shown in table B7, are consistent with the US findings. If we regress the rate at which a country's residents patent in the United States on the country's GDP per worker, we find a positive and statistically significant estimate. However, if we also include the country's college graduate quality, the latter soaks up the entirety of the effect: the estimated effect for college graduate quality is positive and statistically significant, while that for GDP per worker becomes small, has an inconsistent sign, and is not statistically significant.

TABLE 7
College Graduate Quality and Innovation: Patent Records

	Share Inventors	Share Inventors in Top 5% of Citations
College graduate quality	.061***	.004***
	(.005)	(.001)
Mean outcome	.0099	.0006
SD college graduate quality	.15	.15
Observations	362	362

Note.—The table relates our measure of college quality to notable achievements related to innovation across US colleges using ordinary least squares estimation. The two dependent variables are from Bell et al. (2019). Their data cover only colleges with a minimum number of inventors. For observations in their data that incorporate multiple colleges, we weight colleges according to their respective shares of the estimation sample. Units are in percentage points.

*** Significant at the 1% level.

TABLE 8
COLLEGE GRADUATE QUALITY AND NOTABLE ACHIEVEMENTS

	NUMBER OF NOBEL LAUREATES		NUMBER OF CEOS OF S&P 500 FIRMS	
	US Colleges	Non-US Colleges	US Colleges	Non-US Colleges
College graduate quality	.862***	.290***	1.810***	.190***
	(.129)	(.082)	(.153)	(.046)
Country fixed effects		Yes		Yes
Mean outcome	.085	.070	.248	.042
SD college graduate quality	.15	.30	.15	.30
Observations	1,608	1,265	1,608	1,265

NOTE.—The table relates our measure of college quality to notable achievements, specifically the number of S&P 500 CEOs as of 2020 or Nobel laureates who won prizes over the years 1990–2020. Estimates reflect marginal effects from tobit specifications. For further details regarding the two dependent variables, see app. E.

*** Significant at the 1% level.

Finally, some outcomes are uncommon enough that we can use web searches to recover the alma mater of each person who achieves them. We focus on CEOs of Standard and Poor's (S&P) 500 index firms as of 2020 and Nobel laureates who won prizes in the years 1990–2020. We regress the number of Nobel laureates and S&P 500 CEOs on college graduate quality while including country fixed effects. We use a tobit specification because these outcomes are sufficiently uncommon that there is substantial censoring. The results are shown in table 8.

This table shows that colleges with higher graduate quality are more likely to have Nobel prize winners and CEOs among their graduates. This finding applies for graduates of both US and non-US colleges and is statistically significant in all cases. The magnitudes are smaller for non-US colleges, possibly reflecting that these outcomes are overall less common for non-US colleges, as shown in the row of mean outcomes. Again, the economic magnitudes are large. A college outside the United States with 1 standard deviation higher graduate quality has 0.09 more Nobel laureates and 0.06 more CEOs, whereas the sample average for these outcomes is only 0.07 and 0.04, respectively.

VI. Sensitivity

In this section, we investigate the sensitivity of our results in two main directions. First, we explore whether our results are sensitive to relaxing the assumptions that underlie our methodology or the details of the implementation. Second, we use the Glassdoor database to provide new evidence on the relative earnings for workers with different majors or advanced degrees around the globe and to assess whether the conclusions we have drawn so far are altered by considering these additional factors.

We start with the broad sensitivity analysis. We focus on how relaxing assumptions or making plausible alternative implementation choices changes the elasticity of college graduate quality for the top 5% of colleges and other colleges with respect to development. We also show how college graduate quality estimates q_j and skill price estimates z_c are correlated with those in the baseline to give another metric of how answers differ. All results are presented in table 9. For example, row 1 shows that the baseline estimate for these two groups of colleges is 0.209 and 0.259, respectively. Finally, below each estimate we show the standard errors in parentheses and the number of countries included in the corresponding cross-country regression.

All of our estimates of college graduate quality derive from a two-step procedure, where we first use migrants to estimate z_c and then use nonmigrants to estimate q_j from country-adjusted earnings $w_{i,j,c,t} - z_c$. Given this approach, noise or bias in our estimates of z_c affects our estimates of q_j. One concern related to this is that we have few migrants per country and that as a result our estimates of z_c may be imprecise. This concern is closely related to the incidental parameter problem that arises when estimating earnings as a function of worker and firm fixed effects—the underlying challenge there is that most samples include few job switchers per firm (Abowd, Kramarz, and Margolis 1999; Bonhomme, Lamadon, and Manresa 2019). Bonhomme, Lamadon, and Manresa (2019) propose a method that uses *k*-means clustering algorithms to identify firms that are similar and can be grouped together, reducing the dimensionality of the problem. We pursue a related approach. Theory strongly suggests that "true" z_c should be closely related to GDP per worker because it reflects factors such as total factor productivity and capital-output ratios that are highly correlated with GDP per worker. We impose this relationship in a three-step procedure. First, we estimate z_c using migrants as before. Second, we project z_c on log GDP per worker and recover the fitted values $\hat{z}_c$. Third, we estimate q_j from country-adjusted earnings $w_{i,j,c,t} - \hat{z}_c$. The results, shown in row 2, suggest that this three-step procedure changes our estimates of z_c but does not much change our estimate of how college graduate quality varies with development.

A second concern with our two-step procedure is that the traditional standard errors we report here and elsewhere may understate the degree of uncertainty around our point estimates. We use a bootstrapping exercise to help gauge the importance of this issue. For each of 500 simulations, we sample with replacement 13,942 migrants from the first-stage sample who report earnings in more than one country and 2 million nonmigrants from the second-stage sample who report earnings and alma mater, so that the sample sizes for each stage are the same as those in the baseline. After using the samples to estimate z_c and then q_j, we regress college graduate quality for top colleges and nontop colleges on GDP

per worker. Figure B5 shows the distribution of point estimates for the elasticity of college graduate quality across the 500 simulations along with bars indicating 95% confidence intervals. The main result is that the bootstrapping exercise suggests a smaller confidence interval. For example, the conventional standard errors imply that the 95% confidence interval for the estimates among top colleges is 0.118–0.300, whereas the bootstrapped 95% confidence interval is 0.198–0.243.

Our benchmark approach builds on the assumption that earnings are proportional to human capital, although it does allow for a common wage markdown for natives and another for migrants. A potential concern is that this is not sufficient to capture the effects of discrimination or monopsony power in labor markets (Manning 2021; Sokolova and Sorensen 2021). Ek (2022) estimates the labor productivity of migrants to Sweden by country of birth and shows that they align closely with earnings. His results speak against a large role for discrimination, at least for Sweden. Another approach is to control for observable factors that might help capture variation in wage markdowns, such as occupational premia (e.g., occupational licensing) or firm premia (e.g., a premium to working for large or multinational firms). Because the Glassdoor database includes information on occupation and firm, we can explore the effect of including fixed effects for each throughout. Rows 3 and 4 show that controlling for these fixed effects does not much change the elasticity of college graduate quality with respect to GDP per worker.

Another concern is that our estimates of college graduate quality might be affected by differences in compensation across local labor markets, for example, due to differences in labor market competition or productivity. Such differences might be particularly important since college graduates tend to concentrate in the local labor markets where their colleges are located (Conzelmann et al. 2022). Glassdoor data include predefined local labor markets that roughly correspond to metropolitan regions.[21] We include fixed effects for local labor markets in our second step. The results, shown in row 5, are essentially the same as the baseline.

Our baseline approach to the issue of skill portability and selection on comparative advantage estimates their joint effect as a function of the destination fixed effects and the gap in GDP per worker between origin and destination country. We explore several other specifications and find broadly similar estimates of z_o, which implies that our estimates of q_j are also similar (table B1). A related concern is that these issues might apply particularly to new migrants. Although we do not observe when migrants move, we do observe what years they worked their pre- and postmigration jobs. We focus on migrants with at least a 4-year gap between the two, as they are more likely to have moved and had time to acclimate to their new

[21] Table B9 gives the number of local labor markets that we cover per country.

TABLE 9
Sensitivity Analysis: College Graduate Quality and Development

	Elasticity of College Graduate Quality with GDP per Worker		Correlation with Baseline	
	Top Colleges	Nontop Colleges	College Graduate Quality	Skill Prices
1. Baseline	.209***	.259***	1.00	1.00
	(.045)	(.039)		
Observations	43	46		
2. Projection on GDP per worker	.181***	.256***	.89	.60
	(.060)	(.050)		
Observations	43	46		
3. Include job title fixed effects	.162***	.214***	.87	.98
	(.034)	(.028)		
Observations	43	46		
4. Include firm fixed effects	.201***	.236***	.90	.97
	(.034)	(.031)		
Observations	43	46		
5. Include metropolitan area fixed effects	.208***	.257***	.93	1.00
	(.045)	(.039)		
Observations	43	46		
6. Only migrations with 4+ years between observations	.191***	.228***	.99	.98
	(.062)	(.055)		
Observations	27	30		
7. Sample selection correction	.213**	.284***	.96	.89
	(.079)	(.086)		
Observations	16	17		
8. Include college graduates employed abroad	.141***	.174***	.97	1.00
	(.033)	(.034)		
Observations	43	46		
9. Exclude United States	.174***	.233***	.96	.98
	(.044)	(.038)		
Observations	39	42		

10. Minimum number = 50 observations	.192***	.246***	1.00	1.00
	(.056)	(.050)		
Observations	32	32		
11. Include variable-based compensation	.206***	.256***	1.00	1.00
	(.047)	(.041)		
Observations	43	46		
12. Alternative sample truncation	.198***	.245***	.99	.99
	(.044)	(.038)		
Observations	43	46		
13. Include job number fixed effects	.204***	.253***	1.00	1.00
	(.045)	(.039)		
Observations	43	46		
14. Include major of study fixed effects	.213***	.268***	.97	.99
	(.045)	(.043)		
Observations	39	44		
15. At most undergraduate degree	.170***	.249***	.98	.99
	(.054)	(.049)		
Observations	35	37		
16. Jointly estimate undergraduate and graduate quality	.223***	.266***	.99	1.00
	(.051)	(.040)		
Observations	43	46		

NOTE.—The table displays the estimated coefficient from regressing the average quality of a country's top 5% and other colleges on the log of PPP GDP per worker from World Bank (2022). Rows correspond to various sensitivity checks in terms of sample restrictions or changes in the estimation procedure. See text for details. N = number of countries included in corresponding cross-country regression.

** Significant at the 5% level.

*** Significant at the 1% level.

country in the intervening period. As we show in row 6, this reduces the estimate of the elasticity slightly to 0.191.

Our next three sensitivity analyses address possible concerns that Glassdoor is not a representative sample. In the baseline analysis, we use only nonmigrants to estimate q_j. We have compared the earnings of nonmigrants in Glassdoor with those in external datasets for 17 countries (sec. III.B). Our first check is to restrict attention to these 17 countries and correct for the degree of selection that we found for each country, separately for top and nontop colleges. Figure B6 shows the relationship between college graduate quality and development without any selection adjustment and with a selection adjustment for each country taken from table 3. The estimated relationship is almost unchanged, as we confirm in row 7.

Second, we can explore incorporating migrants when estimating q_j. Conceptually, we would like to estimate q_j using a random sample of graduates of each college j. That sample should include migrants, particularly given the evidence that migrants from developing countries are often substantially positively selected. On the other hand, a disproportionate share of graduates from developing countries in Glassdoor are migrants. For example, table 1 shows that for many developing countries, more than half of the graduates in our sample are observed abroad. Including these workers puts a disproportionate weight on positively selected migrants. Consistent with this intuition, row 8 shows that including migrants when estimating q_j raises the college graduate quality of developing countries and flattens the relationship between college graduate quality and development. We have explored specifications where we reweight nonmigrants and migrants to match the share of each country's college-educated labor force that emigrates from the DIOC-E database; doing so yields results closer to the larger baseline elasticity for the smaller set of countries for which weights are available.

Third, Glassdoor is based in the United States, with the consequence that migrants to and workers in the United States are overrepresented. We explore reimplementing the two-step procedure while excluding all earnings observations from the United States. Doing so implies that migrants to and from the United States do not help identify z_c or $\tau_{b,c}$ in the first step and that we have no estimates of q_j for American colleges in the second step. Row 9 shows that the resulting elasticity of college graduate quality falls slightly to 0.174.

Our remaining sensitivity analyses deal with details of how we implement our two-step procedure. Our baseline analysis considers only countries and colleges that have a minimum of 25 migrants and workers, respectively, in our sample. Row 10 shows that the results are also similar if we raise the sampling threshold to 50 in each case.

For our baseline results, we focus on base pay and drop workers who make less than 10% or more than 10 times the GDP per worker of the country where

they work. Row 11 shows that the results are essentially the same if we include variable pay for workers who report it, while row 12 shows that the results are also similar if we instead exclude the bottom 1% and top 1% of earners.

Sockin (2022) finds that workers who submit multiple earnings reports in Glassdoor tend to have higher earnings growth than is suggested by panel data on random samples of workers. This finding is consistent with the idea that workers who submit multiple earnings reports are positively selected on earnings growth or job changes. We estimate and control for fixed effects for whether a given earnings report is the first, second, and so on for a given worker. Row 13 shows that the results are essentially unchanged.

To summarize, we investigate here a number of corrections, alternative subsamples, and alternative specifications. Throughout, we find that the elasticity of college graduate quality with respect to development is positive and statistically significant. Among top colleges, the range of plausible elasticities stretches from 0.14 to 0.22 (closer to the upper end in most cases), which indicates that our results are not sensitive to these corrections or alternatives. We now turn to the role of majors and advanced degrees for our findings.

A. Relative Earnings by Majors

It is well known that there are large differences in earnings across majors in the United States (Altonji, Kahn, and Speer 2016). In this section, we show that the same thing holds for the 48 countries in our sample. Broadly, STEM (science, technology, engineering, and math) majors pay more than non-STEM majors. We assess whether allowing or controlling for this changes our results.

About three-fourths of respondents with bachelor's degrees provide usable information about their major on their résumé. We group the raw textual responses into 11 broad major categories: arts and humanities, biological sciences, business, communication, education, engineering, health services, physical sciences, social service, social sciences, and technology. See appendix D for further details.

We use this information to conduct three exercises. First, we reestimate college graduate quality while including college major fixed effects. We find earnings gaps of as much as 20 log points between majors. Technology and engineering majors earn the most, whereas social services and arts and humanities majors earn the least (table B2). This exercise also provides a natural avenue for us to investigate the importance of composition effects since it yields alternative estimates of q_j that control for differences in average earnings by major. We find that this adjustment has a negligible effect on our main findings. For example, the variance of q_j is hardly changed,

and the relationship between college graduate quality and development is essentially the same (row 14 of table 9).

Using major fixed effects imposes that the earnings gap between majors is constant across colleges and countries. For our second exercise, we relax this assumption. We aggregate majors into STEM (biological sciences, engineering, physical sciences, and technology) and non-STEM (all other) groups. We then estimate college graduate quality for each college major group with at least 25 workers in Glassdoor. We do two things with these estimates. First, we construct the STEM earnings premium for each country. To do so, we focus on each country's top 5% of colleges, construct the average $q_{j,\text{STEM}}$ and $q_{j,\text{non–STEM}}$ among these colleges, and take the difference between the two. The resulting earnings premium averages 15 log points and is uncorrelated with development (fig. B2). This finding suggests that on the whole, colleges in developing countries do not have a comparative advantage or disadvantage in producing STEM versus non-STEM graduates.

However, our estimates of $q_{j,\text{STEM}}$ and $q_{j,\text{non–STEM}}$ yield important insights for our implied ranking of top colleges. Returning to table B4, in the last four columns we show the estimated graduate quality and ranking separately for STEM and non-STEM graduates of each college. The table makes clear that a college's overall ranking is closely aligned with its STEM ranking but only loosely related to its non-STEM ranking. Indeed, many of the top colleges have too few non-STEM graduates to even estimate a non-STEM graduate quality. Thus, the high rankings in particular of the Indian Institutes of Technology reflect both high earnings among their STEM graduates (compared with STEM graduates from other colleges) and an absence of non-STEM graduates. As another example of the importance of major composition, the University of Pennsylvania ranks second in non-STEM graduate quality and sixteenth in STEM but twentieth overall.

Third, we explore whether there are cross-country differences in the scarcity of STEM skills. By scarcity, we have in mind that STEM and non-STEM skills might be imperfect substitutes in production and that the relative supply of STEM to non-STEM skills might vary by country. We can test for this by estimating a price per unit of STEM labor $z_{c,\text{STEM}}$ and a price per unit of non-STEM labor $z_{c,\text{non–STEM}}$ using the earnings changes at migration for graduates with STEM and non-STEM majors. When we estimate this more general specification, we find that the values of $z_{c,\text{STEM}}$ and $z_{c,\text{non–STEM}}$ are similar for most countries (fig. B3), which weighs against an important role for scarcity effects.

Overall, we conclude that there are large differences in earnings across majors around the world. Broadly, graduates with STEM majors earn more in most countries. We do not find that developing countries have a comparative advantage in producing STEM or non-STEM graduates, and we do not find that developing countries are relatively abundant in STEM

or non-STEM skills. Because of this, our main conclusions about the relationship between college graduate quality and development remain unchanged. However, these findings do provide new insights about why colleges that focus mostly or exclusively on STEM subjects have high estimated graduate quality.

B. Advanced Degrees

Our results so far have related college graduate quality to where each worker received their bachelor's degree. We now delve into the importance of advanced (graduate) degrees for measured college graduate quality across countries. As with majors, we use our data to quantify the global importance of advanced degrees and to investigate whether accounting for advanced degrees substantially alters our main conclusions. Altonji, Arcidiacano, and Maurel (2016) find that roughly 38% of 24-year-olds in the United States with a bachelor's degree have a master's degree as well. Within our sample, about 18% of graduates have an advanced degree. If obtaining an advanced degree is correlated with college graduate quality and advanced degrees have an independent effect on earnings, then not accounting for advanced degrees may artificially inflate our measure of college graduate quality.

We consider two approaches to controlling for the effect of advanced degrees. First, we estimate college graduate quality using only workers who have no advanced degrees. As shown in row 15 of table 9, doing so lowers the resulting elasticity of college graduate quality slightly to 0.17.

Second, we include workers with advanced degrees but allow human capital and earnings to depend separately on where a worker received their bachelor's degree and where they received their advanced degree, if they have one. Specifically, we let $h_{i,j_u,j_g} = q_{j_u} + q_{j_g} + \varepsilon_i$, where j_u is the college where the worker received their bachelor's degree and j_g is the college where they received their advanced degree, with "no degree" being one option for j_g. The term q_{j_u} captures the mean country-adjusted earnings or human capital among graduates from j_u without an advanced degree, while q_{j_g} captures the average gap in earnings between workers with an advanced degree from j_g and workers with a degree from the same undergraduate institution but no advanced degree. As before, these estimates do not reflect the value added of an advanced degree because even after we condition on undergraduate alma mater j_u, the set of workers who continue to graduate school may be selected on earnings ability. Row 16 of table 9 shows that this approach does little to change the estimated relationship between college (under)graduate quality and development.

We can also use this latter approach to provide preliminary evidence on the worldwide earnings gap for workers with advanced degrees. We have small samples of advanced degree recipients for most colleges, so

TABLE 10
COLLEGE PREMIA AND CWUR WORLD RANKING: GRADUATE DEGREES

	WORLD RANKING							
	1–20	21–50	51–100	101–250	251–500	501–1,000	1,001–2,000	Unranked
Graduate quality	.285***	.175***	.157***	.105***	.100***	.137***	.107***	.051***
	(.017)	(.013)	(.011)	(.010)	(.009)	(.009)	(.008)	(.004)
Observations	18	22	34	79	100	133	184	774

NOTE.—The table displays our measure of (log) college quality q_{j_c} for graduate degrees as a function of ranking groups from the CWUR. There are 1,344 colleges, and the omitted category is no graduate degree. Standard errors are in parentheses. N = number of colleges in our sample within each bin. Colleges are weighted by their sample sizes.
*** Significant at the 1% level.

we again aggregate colleges into bins on the basis of their CWUR world rankings, as we previously did in table 4. We then estimate q_{j_u} and q_{j_c} by rankings bin. For undergraduate degrees, we treat unranked as the omitted category; for advanced degrees, we treat no advanced degree as the omitted category. Table 10 shows the novel results for advanced degrees; results for bachelor's degrees are similar to the baseline.

The earnings gap between workers with advanced degrees and those without such degrees is a very nonlinear function of college rank. Workers with advanced degrees from colleges ranked in the global top 20 earn 33% more than workers without an advanced degree, a gap even larger than the 20%–25% estimate for the top 25 MBA programs from Arcidiacono, Cooley, and Hussey (2008). On the other hand, workers with advanced degrees from colleges ranked anywhere from 100 to 2,000 earn roughly 5% more than their peers from comparable undergraduate institutions who have an advanced degree from an unranked college and roughly 10% more than their peers without any advanced degree.

VII. Conclusion

In this paper, we propose a new approach to measure the average human capital of graduates from colleges around the world. Our measure of college graduate quality is the average earnings of a college's graduates, adjusted to a common labor market. We show how to implement this measure using the database of the website Glassdoor, which has two important features for our analysis. First, it contains data on pre- and post-migration earnings for thousands of college-educated migrants, which provides the information needed to adjust earnings to a common labor market. Second, it allows us to connect workers' alma maters to their earnings for a large global sample consisting of 2.2 million workers who obtained a bachelor's degree from 2,873 different colleges in 48 countries.

We find that college graduate quality varies substantially among colleges and on average between developing and developed countries. These gaps are further magnified by migration. Brain drain from developing countries is more extensive than what the previous literature based on raw college shares has documented. Not only do less developed countries lose a higher share of their college-educated workers, but also those who leave have 50% more human capital than nonmigrants. We also show that there is substantial heterogeneity among rich countries in terms of the average human capital of their immigrants. Finally, we show that college graduate quality matters for a number of outcomes of interest for growth and development. It is a strong and robust predictor of the propensity of a college's graduates to innovate, engage in entrepreneurship, or become executives.

Our findings are based on the average human capital of graduates by college, not the value added of the college itself. This approach implies that we cannot disentangle whether top colleges merely select the best students or provide high value added. This question is particularly relevant given our results for countries like India, which has low average quality but also some of the world's top colleges. Are the Indian Institutes of Technology the product of extreme selection among Indian students, world-class teaching, or both? Disentangling these questions requires a different approach. For example, it may be possible to build on the revealed preferences of college applicants and migrants to understand the value added of college and country (Avery et al. 2013; Lee, Lee, and Lin 2021). Alternatively, precollege information or exogenous shifters of college attendance choices may make it possible to separate the two. We believe this to be an interesting avenue for future research.

Data Availability

The primary data source for this paper is the proprietary database of the Glassdoor website. Researchers who acquire access to this database can find the remaining data and code to replicate our results in Martellini, Schoellman, and Sockin (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/BVDLMH.

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