FEDERAL RESERVE BANK OF MINNEAPOLIS | Research Division

WORKING PAPER
No. 791

The Global Distribution of College Graduate Quality

March 2022

Paolo Martellini
University of Wisconsin-Madison

Todd Schoellman
Federal Reserve Bank of Minneapolis

Jason Sockin
University of Pennsylvania

DOI: https://doi.org/10.21034/wp.791
Keywords: College quality; Human capital; Entrepreneurship; Innovation; Development; Migration
JEL classification: O15, O11, J3, J6

The Global Distribution of College Graduate Quality*

Paolo Martellini† Todd Schoellman‡ Jason Sockin§

March 2022

Abstract

We measure *college graduate quality* — the average human capital of a college's graduates — using the average earnings of the college's graduates adjusted to a common labor market. Our implementation uses the database of the website Glassdoor, which has the necessary information on earnings and education for non-migrants and migrants who graduate from roughly 3,300 colleges in 66 countries. Graduates of colleges in the richest countries have 50 percent more human capital than graduates of colleges in the poorest countries. Migration reinforces these differences. Poorer countries do not just lose a higher share of their skilled workers; their emigrants 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.

JEL: O15, O11, J3, J6.
Keywords: College quality, human capital, entrepreneurship, innovation, development, migration.

*We thank audiences at the Human Capital Conference at the St. Louis Fed, the IZA Economics of Education Workshop, the IZA Workshop on Matching Workers and Jobs Online, the University of Pennsylvania, ESADE, Williams College, Colby College, and the University of Connecticut for comments and feedback. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

†University of Wisconsin-Madison. E-mail: martellini@wisc.edu
‡Federal Reserve Bank of Minneapolis. E-mail: todd.schoellman@gmail.com
§University of Pennsylvania. Email: jsockin@sas.upenn.edu

1 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, an analysis into 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 *et al.*, 2017; Bell *et al.*, 2019).[1] Similarly, entrepreneurs and chief executive officers of leading firms in the United States are also disproportionately college-educated, with top colleges again overrepresented among the latter (Levine & Rubinstein, 2017; Flynn & Quinn, 2010). Finally, a recent development accounting literature that allows for imperfect substitution between workers with different education levels finds that the quality of college-educated workers, and not just the average human capital level, is important in accounting for cross-country income differences (Jones, 2014; Hendricks & Schoellman, forthcoming).

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 & Lee, 2013). Migration redistributes college-educated workers among countries, particularly from poorer to richer ones (Docquier & Rapoport, 2012; Kerr *et al.*, 2016). However, 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.[2]

In this paper, we propose and implement such a measure, which we call *college graduate quality*. This measure reflects the average earnings of a college's graduates, adjusted to a common labor market, and is equal to the average human capital of a college's graduates under standard assumptions, in which case it is both internationally comparable and economically scaled. We find that college graduate quality varies substantially within and across countries, particularly between poor and rich countries. We show that existing measures of global talent flows – which are based only on the number of college-educated migrants – understate the impact of migration on human capital supply because they

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

[2] By contrast, several major international testing programs evaluate the 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 & Woessmann, 2011; Schoellman, 2012; Cubas *et al.*, 2016).

miss that migrants are also selected on college graduate quality. Finally, we show that college graduate quality predicts a number of outcomes of interest, including the number or share of a college's students who engage in innovation (patenting and winning Nobel Prizes), become entrepreneurs (found new businesses), or ascend to executive positions.

Our analysis uses the proprietary database of the website Glassdoor.[3] Glassdoor collects resumes and information on earnings from workers in return for the services it provides, which include informing workers about how their earnings and employers compare with those of their peers. Two features of the database are central to our analysis. First, our data allow us to connect workers' alma maters to their earnings for a large, global sample consisting of 2 million workers who obtained a Bachelor's degree from 3,368 different colleges in 66 countries. This feature allows us to construct average earnings of graduates from colleges around the world. It extends existing information that uses a similar measure to compare colleges within a single country – the College Scorecard released by the U.S. Department of Education is one example.

Direct comparisons of average earnings for colleges in different countries conflate differences in average human capital with the differential effect of countries, through, for example, aggregate productivity. Conceptually, we would like to observe graduates of all colleges in a common labor market so that we could isolate differences in average human capital. We overcome this challenge by using the second central feature of the Glassdoor database, which is that it contains data on pre- and post-migration earnings for tens of thousands of college-educated migrants. We use the change in earnings at migration to estimate the effect of each country on earnings.[4] We then adjust each worker's earnings so that they capture what the worker would earn in a common labor market. In addition, the difference between what an average worker would earn if she migrated and what actual migrants do earn provides us with an estimate of the extent of selection among migrants.

Our estimates reveal large differences in college graduate quality across colleges and countries. As a first approach, we estimate the earnings gain from attending 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

[3] A small set of previous papers has used Glassdoor data from the United States to study variable pay, the pass-through of firm-level shocks to worker compensation, the importance of firms' non-wage amenities, and the effects of employer collusion (Sockin & Sockin, 2019b, 2021; Gadgil & Sockin, 2020; Sockin, 2022; Gibson, 2021). As far as we know, this paper is the first to utilize educational data or data from outside the United States.

[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 capital intensity, total factor productivity, or the skill bias of technology (Hendricks, 2002; Schoellman, 2012, 2016; Okoye, 2016; Hendricks & Schoellman, 2018, forthcoming; De Philippis & Rossi, 2021; Rossi, 2022).

their global top-20 colleges earn 60 percent 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.[5] 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 0.22. To put this figure into perspective, note that it implies that college graduates from a typical rich country would earn 50 percent more than college graduates from a typical poor country in the same labor market.

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 poor countries is more extensive than previously thought; not only do they lose a higher share of their college-educated workers, but those who leave have 50 percent higher human capital than non-migrants. 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 natives, but for other countries, such as Japan or Korea, they have much less.

Finally, we assess whether differences in college graduate quality and global talent flows are important contributors to entrepreneurship and innovation. We collect data from Glassdoor (using jobs workers list on their resumes) and external data sources (for example, data on where patent holders or Nobel laureates attended college). We estimate the effect of college graduate quality on 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 a positive and statistically significant predictor of all outcomes we consider. Further, the estimated effects are economically large. For example, a one standard deviation rise in college graduate quality is associated with a near doubling of the share of graduates who become inventors, 0.1 more Nobel laureates, and 1 percentage point (pp) 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.[6] Existing work documents a number of potential causes for these differences,

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

[6]See Bloom *et al.* (2014) and Hjort *et al.* (2021) for the quality and price of management across countries;

including competitiveness of markets, regulation, and taxation (Bloom & Van Reenen, 2007; Guner *et al.*, 2008; Garicano *et al.*, 2016; Akcigit *et al.*, 2022). We add to this literature by showing that college graduate quality plays an important 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.[7] Our main contribution to this literature is to show that many of these patterns can be understood as resulting 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.

Throughout, we focus on measuring the average human capital of a college's graduates. We demonstrate that average human capital varies widely across colleges and countries and that it is a strong predictor for a number of outcomes of interest. This approach distinguishes us from a literature that instead seeks to disentangle the value added of a college, selection of who attends the college, and the complementarity between the two.[8] 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.[9] This interpretation implies that policies that improve college quality would raise the human capital of graduates, thereby increasing the share of the population who become inventors, engage in entrepreneurship, or become executives.

The remainder of the paper is organized as follows. Section 2 details our empirical approach. Section 3 describes the Glassdoor data and validates key aspects of them against available external benchmarks. Section 4 presents our estimates of college graduate quality and the human capital of migrants. Section 5 shows the relationship between college graduate quality and outcomes of interest, such as being an entrepreneur, executive, or innovator. Section 6 provides a sensitivity analysis. Finally, Section 7 provides a brief conclusion.

Hsieh & Klenow (2014) for firm growth rates across countries; and Dutta *et al.* (2021) for differences in innovativeness and patenting.

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

[8] See, for example, Dale & Krueger (2002), Hoekstra (2009), Dillon & Smith (2017), and Mountjoy & Hickman (2021).

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

2 Methodology

In this section, we present the methodology that allows us to build an internationally comparable measure of college graduate quality. Let $w_{i,j,c}$ denote the logarithm of earnings for worker i who received her bachelor's degree from college j and is now employed in country c. Our baseline analysis uses a standard log-separable earnings equation:

$$\begin{aligned} w_{i,j,c} &= z_c + h_{i,j} \\ &= z_c + q_j + \varepsilon_i. \end{aligned} \tag{1}$$

Here, z_c is the effect of country of work (e.g., total factor productivity) and $h_{i,j}$ is the worker's human capital. The second line decomposes the human capital into a term common to all graduates of college j, q_j, and a term capturing ability specific to the worker, ε_i.

Most of our results rely on comparisons of average earnings for groups of workers. Average earnings are given by

$$\bar{w}_{j,c} = z_c + q_j + \bar{\varepsilon}_{j,c}, \tag{2}$$

where the over-bar denotes the average for the corresponding group. Importantly, we allow the average ability of college j graduates to vary according to where they work c. For example, if we denote by $b(j)$, or simply b, the country where college j is located, then we allow that the average ability of domestic graduates from a given college, $\bar{\varepsilon}_{j,b}$ differs from the average ability of its graduates who work abroad, $\bar{\varepsilon}_{j,c}$, for $c \neq b$.

This type of earnings equation provides a consistent measure of human capital given several assumptions that have important implications in our context. We discuss these assumptions and their implications in this section; we explore relaxing these assumptions in the sensitivity analysis of Section 6.[10] First, each country is assumed to be endowed with a Cobb-Douglas production function that uses capital and labor, with labor of different types treated as perfect substitutes. This assumption rules out any role for relative scarcity of different types of labor. Second, workers are assumed to supply the same human capital everywhere, including in foreign countries. This assumption rules out difficulty among migrants in demonstrating or transferring their skills to new countries. It also rules out selection on unobserved comparative advantage or idiosyncratic worker-country match quality. Third, labor markets are assumed to be competitive, so that workers are paid their marginal product. This assumption rules out, for example,

[10] See also Bils & Klenow (2000) or Hendricks & Schoellman (2018) for further discussion.

discrimination or labor market power.

2.1 Identification

We now discuss the measurement and identification of college graduate quality. We start by normalizing $\bar{\varepsilon}_{i,b(j)} = 0$ for all colleges j. This step is a normalization because it implies that college graduate quality q_j is equal to the average human capital of college j's locally employed graduates (those employed in $b(j)$); ε_i then captures variation in a worker's human capital relative to that of the average locally employed graduate. As discussed in the Introduction, college graduate quality is thus a gross measure (average human capital of college j graduates) rather than a net measure (value added by college j). This measure is useful when comparing the human capital of college graduates across countries to, for example, understand the importance of that human capital for growth and development. On the other hand, a value added measure would be more relevant for students who are evaluating where to attend college, for example, or for researchers who are evaluating the role of college separately from that of primary and secondary school.

Under this normalization, we can infer the relative quality of two colleges in the same country b using the relative earnings of their locally employed graduates:

$$\bar{w}_{j,b} - \bar{w}_{j',b} = q_j - q_{j'}.$$

While country of work matters for earnings, these graduates all work in the same country, and so relative earnings are proportional to relative human capital. This framework thus provides support for the common practice of ranking colleges within the same country according to the average earnings of their graduates, which is used by the College Scorecard in the United States.

This approach, however, cannot be used to compare college graduate quality for colleges in different countries – for example, college j in b and college j' in $b' \neq b$. Using the average earnings of locally employed graduates for each college confounds college graduate quality with other country-specific determinants of productivity, z_c:

$$\bar{w}_{j,b} - \bar{w}_{j',b'} = z_b - z_{b'} + q_j - q_{j'}. \tag{3}$$

Conceptually, we would like to know what graduates of j' would earn in country b rather than b'. Our approach uses the experiences of migrants to inform this counterfactual. Specifically, the average change in earnings for migrants who work in the same countries b and b' is informative about what non-migrants in b' would earn if they worked instead in b. Formally, the change in wages of migrants from b' to b is given by

$$w_{i,\hat{j}',b'} - w_{i,\hat{j}',b} = z_{b'} - z_b. \tag{4}$$

We use the notation $\hat{j}'$ to emphasize that the college of this migrant can be different from either of the colleges we wish to compare. Combining equations (3) and (4) yields an estimate of relative college graduate quality, $q_j - q_{j'}$, for all pairs of colleges located in countries that are connected by migration flows in our data. More generally, the earnings changes of migrants who work in more than one country are informative about the relative productivity of the countries involved.

As emphasized by Hendricks & Schoellman (2018), compared to the prior literature that compares wages of non-migrants and migrants within a common country, the earnings change approach has two strengths. First, it is less likely to be contaminated by selection. Returning to the above example, suppose instead that we compare non-migrants from j in b to migrants from j' now working in b. The earnings difference is given by

$$\bar{w}_{j,b} - \bar{w}_{j',b} = q_j - q_{j'} - \bar{\varepsilon}_{j',b}. \tag{5}$$

This approach recovers the difference in college graduate quality only under the strong assumption that migrants of a given college are not selected. This assumption contradicts substantial evidence from the economics of immigration literature, as well as our own results in Section 4.3. By contrast, our approach relies on the weaker assumption that migrants not be selected on the gains to migration. Our data allow us to measure the extent of selection on gains to migration by comparing the change in earnings of migrants from c to c' with the change of migrants from c' to c. As we show in Section 6, these changes are nearly equal in magnitude and of opposite sign, suggesting that selection on gains to migration is small or counterbalanced by other forces.

Second, the earnings change approach allows us to quantify the extent of selection of migrants. Hendricks & Schoellman (2018) previously studied the selection of immigrants to the United States by comparing their pre-migration earnings to GDP per worker in the corresponding country. We extend this work in two ways. First, we have data on flows in both directions among a large set of countries, rather than flows into a single country. Second, we can directly compare the pre-migration earnings of emigrants with the earnings of non-migrants, rather than using proxies such as GDP per worker. These two ingredients allow us to provide an improved measure of the selection of emigrants and immigrants for a large set of countries, which is a critical ingredient for our new evidence on brain drain and global talent flows in Section 4.3.

2.2 Estimation Procedure

In practice, the structure of the Glassdoor database leads us to use a two-step estimation process. The first step uses workers who report earnings in more than one country. On this sample, we estimate

$$w_{i,t,c} = z_c + \lambda_i + \beta X_{i,t} + \eta_{i,t}, \tag{6}$$

where w is again the log of earnings, λ_i is worker fixed effects and $X_{i,t}$ includes a quadratic in years of experience and year fixed effects. Intuitively, this equation estimates by how much earnings change at migration (after adjusting for time and changes in work experience) and assigns this change to the effect of country, z_c.

With the vector of country-specific premia z_c in hand, we turn to the second step, in which q_j is estimated from the larger sample of workers who provide information on where they obtained their bachelor's degree and at least one earnings report. On this sample, we estimate

$$w_{i,j,t,c} - z_c = q_j + \gamma X_{i,t} + s_{j,c} + \eta_{i,t}, \tag{7}$$

where X_{it} includes a quadratic in years of experience along with major of study and year fixed effects, $s_{j,c}$ is a dummy that is equal to 1 if the wage observation pertains to a graduate from college j who works in country c, and $\mathbb{E}[\eta_{i,t}] = 0$. The above-mentioned normalization of the value of q_j as the average quality of locally employed college graduates amounts to imposing $s_{j,b(j)} = 0$.

For our baseline approach, we also assume that average selection is common across colleges j among all migrants from $b(j)$ to c, $s_{j,c} = s_{b(j),c}$. Under this assumption, the relative earnings of migrants are informative about q_j. Intuitively, if Oxford and Cambridge graduates working in the United States are equally selected, then their relative earnings are informative about relative college graduate quality. Again, in Section 6, we explore the results that arise when we relax this assumption and allow for heterogeneous selection into migration across colleges within the same country. We now turn to the database that makes implementing this two-step procedure possible.

3 Data

The primary data source for our work comes from the online platform Glassdoor, which allows workers to review their employers, document their earnings, 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 resume; 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 employee-employer matches with a rich set of worker observables.

We have access to the full earnings database spanning the years 2006–2021. Later years contribute disproportionately to the sample, because Glassdoor has become more widely used over time.[11] We impose several sample restrictions throughout 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.[12] 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 percent or more than 10 times the GDP per worker of their country of work.

As detailed in Section 2.2, we follow a two-step estimation process. The Glassdoor database provides a unique wealth of data for each step. The first step utilizes the sample of workers who provide earnings reports for more than one country. We require that a country be connected through at least 25 emigrants to one of the 11 countries that each account for at least 2.5 percent of all immigrants in the Glassdoor sample.[13] This restriction ensures that countries in our sample are sufficiently connected through migration and that the country effects are estimated with sufficient precision. The resulting sample includes 76,000 workers migrating among 76 countries around the world; see Figure A1 for countries and the estimates for z_c. This sample of migrants is more than an order of

[11] We have performed all analysis in this paper using only data from before COVID (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.

[12] 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 U.S. workers (Lemieux *et al.*, 2009) and 22–55 percent of salaried workers in Glassdoor abroad (Sockin & Sockin, 2019b) report earning variable income, Sockin & Sockin (2019a) estimate that variable pay accounts for 4–7 percent of labor earnings.

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

magnitude larger than previous work and also includes migrants among a much larger set of countries; previous papers have focused on migrants to or from a single country (McKenzie *et al.*, 2010; Gibson *et al.*, 2018; Hendricks & 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 degree. Here we use the one-quarter of workers who submit resumes 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 C for further details. Around one-half of resumes contain usable college information after cleaning. 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 post-bachelor'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 (undergraduate) college quality in Section 6.

For the second step, we restrict attention to colleges with at least 25 workers with earnings reports 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 million workers from 3,368 colleges in 66 different countries. We are able to capture global college graduate quality because our sample has sufficient coverage outside the United States: 650,000 workers who received their bachelor's degrees from 1,749 colleges outside of the United States, 68 percent of whom are employed in their country of study. See Table 1 for details of this sample.

In addition to Glassdoor, we rely upon 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, 2021). We analyze the relationship between college graduate quality and development using PPP-adjusted GDP per worker from the World Development Indicators (World Bank, 2021).[14] We adjust for the number of colleges by country in some exercises by using the data provided by the World Higher Education Database (World Higher Education Database, 2021).

[14] Data from 2021 are not yet available. For 2021, we use 2020 GDP per worker. We generate 2021 PPP exchange rates by adjusting the 2020 PPP exchange rates for inflation using data from International Monetary Fund (2021).

Table 1: Summary of Global College Coverage

Country	Abb.	GDP per worker ($)	Colleges		Top Colleges		Graduates	
			Exists	In Sample	Exists	In Sample	Domestically	Abroad
Kenya	KEN	9,194	51	17	2	1	1,693	565
Bangladesh	BGD	9,869	120	22	6	1	1,148	1,887
Vietnam	VNM	11,338	172	11	8	1	233	496
Pakistan	PAK	13,419	155	40	7	4	3,952	4,284
India	IND	15,990	809	328	40	24	208,334	75,060
Nigeria	NGA	17,738	126	49	6	4	3,348	4,674
Philippines	PHL	18,234	1,332	105	66	2	10,693	6,851
Indonesia	IDN	21,874	1,258	22	62	1	2,531	573
Jamaica	JAM	21,929	14	3	0	0	128	756
Peru	PER	22,201	98	6	4	1	118	442
China	CHN	23,584	1,060	161	53	46	1,686	19,259
Ukraine	UKR	27,908	298	5	14	1	41	310
Thailand	THA	29,121	146	16	7	7	1,190	679
Colombia	COL	29,381	255	17	12	5	319	1,086
Sri Lanka	LKA	29,965	26	7	1	1	443	534
Brazil	BRA	33,731	1,043	81	52	30	34,802	3,058
Dominican Republic	DOM	37,164	38	6	1	0	70	778
Egypt	EGY	39,328	55	27	2	2	5,777	3,613
Serbia	SRB	43,725	15	2	0	0	62	304
South Africa	ZAF	44,330	49	15	2	2	2,651	2,264
Costa Rica	CRI	44,366	55	3	2	1	163	199
Mexico	MEX	45,168	1,642	30	82	11	2,291	2,041
Iran	IRN	45,730	263	31	13	10	606	3,872
Bulgaria	BGR	47,154	50	5	2	1	317	325
Chile	CHL	52,987	60	2	3	2	58	147
Malaysia	MYS	53,477	81	34	4	3	6,171	1,622
Russia	RUS	53,631	709	22	35	10	517	1,260
Argentina	ARG	55,947	116	9	5	3	429	603
Romania	ROU	56,978	76	13	3	3	986	1,123
Cyprus	CYP	58,306	36	2	1	1	51	70
Latvia	LVA	58,510	26	1	1	1	55	78
Poland	POL	63,386	349	16	17	9	763	770
Hungary	HUN	64,641	39	12	1	1	965	606
Croatia	HRV	65,997	38	2	1	1	76	185
Estonia	EST	66,217	10	3	0	0	151	108
Lithuania	LTU	68,185	18	4	0	0	174	314
Portugal	PRT	70,275	89	10	4	4	556	464
South Korea	KOR	75,596	248	31	12	9	616	2,296
Czech Republic	CZE	75,634	45	5	2	2	162	176
Turkey	TUR	75,728	172	32	8	8	4,069	3,430
Japan	JPN	77,951	765	19	38	8	230	730
New Zealand	NZL	78,396	29	7	1	1	1,038	1,592
Bahrain	BHR	79,883	13	1	0	0	32	21
Greece	GRC	81,623	26	17	1	1	1,411	1,533
Malta	MLT	85,957	3	1	0	0	31	77
Israel	ISR	86,703	58	21	2	1	4,758	1,688
United Arab Emirates	ARE	89,182	53	4	2	0	168	158
United Kingdom	GBR	90,309	248	139	12	12	59,698	22,378
Canada	CAN	92,078	142	86	7	7	41,744	10,101
Spain	ESP	94,202	112	36	5	5	1,877	2,552
Australia	AUS	95,526	94	35	4	4	7,012	10,467
Finland	FIN	102,210	34	3	1	1	80	79
Germany	DEU	102,472	359	15	17	6	393	422
Sweden	SWE	102,705	44	9	2	1	230	436
France	FRA	105,557	400	24	20	7	537	1,033
Netherlands	NLD	105,904	70	20	3	3	1,058	914
Italy	ITA	108,666	99	41	4	4	2,930	3,855
Austria	AUT	108,866	70	3	3	1	66	112
Hong Kong	HKG	110,901	14	9	0	0	3,073	958
Denmark	DNK	111,602	33	6	1	1	184	383
Belgium	BEL	119,441	63	9	3	3	308	336
Switzerland	CHE	123,794	33	5	1	0	152	120
United States	USA	123,872	2,117	1,619	105	95	1,376,466	22,126
Saudi Arabia	SAU	123,902	72	4	3	2	335	112
Singapore	SGP	152,399	9	7	0	0	7,608	686
Ireland	IRL	157,066	49	21	2	2	4,431	2,490
Total	66		16,251	3,368	778	378	1,814,245	232,521
Total excluding USA	65		14,134	1,749	673	283	437,779	210,395

Notes: Table lists the 66 countries for which we can estimate college graduate quality for at least one college. Each row gives country name and abbreviation, GDP per worker (annual average from 2010–2021) from World Bank (2021), number of colleges in existence and the number represented in our sample for colleges overall and top colleges, and the number of graduates from those colleges employed domestically and abroad.

3.1 Sample Validation

As we emphasized in the last section, 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 (coefficient 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 & Pinto, 2018; Sockin & Sockin, 2019b). This work provides reassurance that the data capture key features of the U.S. labor market. Sockin & Sockin (2021) also uses the panel dimension of the Glassdoor database. He shows that workers' second and subsequent earnings reports are 5–10 percent 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 selection in Section 6.

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 & Schoellman (2018) study migrants from poorer countries to the United States using the New Immigrant Survey, a representative sample of adult immigrants granted lawful permanent residence in the United States between May and November of 2003. For college-educated immigrants,they find that the log-wage change at migration is around 0.37 of the total difference in log GDP per worker between pre- and post-migration country of work. This figure is in line with the same statistic constructed in other studies. For example, McKenzie *et al.* (2010) and Gibson *et al.* (2018) provide similar estimates on wage gains from an experimental setting using migrants who won a lottery to move from Tonga to New Zealand; their corresponding estimate is 0.48.

Table 2: Validation: Earnings Change at Migration

$\frac{\text{log(earnings change at migration)}}{\text{log(GDP p.w. difference)}}$	All migrants	Migrants into U.S.	Migrants into U.S. from poor countries
Mean	0.493	0.773	0.493
Median	0.437	0.605	0.503
Total migrants	56,653	21,296	10,297

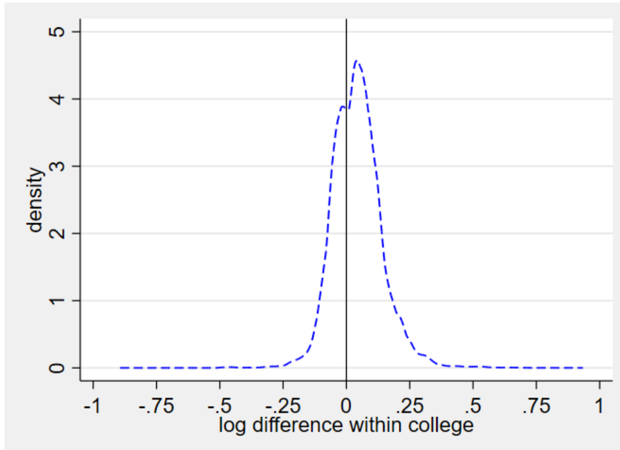
Notes: Table shows mean and median of the log change in earnings relative to the log difference in GDP per worker for the listed samples of migrants. All samples restricted to migrants moving between countries with absolute change in log GDP p.w. of at least 0.25.

We construct the same moment for the Glassdoor database. Table 2 shows the results. The three columns show the results if we use the whole sample, if we focus on migrants into the United States, and if we focus specifically on migrants into the United States from countries with GDP per worker less than one-fourth that of the United States, as in Hendricks & Schoellman (2018). The first row shows the mean of the statistic across migrants, which ranges from 0.49 to 0.77 across the three samples. The second row shows the median, which is less affected by outliers. Here, we find the wage change at migration is 0.44–0.61 of the gap in GDP per worker. These findings show that the change in log earnings at migration relative to the gap in log GDP per worker is similar to or perhaps slightly larger than estimates in previous work in the literature.

Second, we compare our estimates of the average earnings by college to those of sources that provide similar data for countries in our sample. One prominent example is the U.S. Department of Education's 'College Scorecard", which uses tax data from the U.S. 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 U.S. colleges who report earnings one or two years after the graduation dates reported on their resumes. We match these observations to the College Scorecard data by college, major, and years since graduation. We are able to match 135,000 workers from 1,482 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

Figure 1: Sample Selection into Glassdoor for U.S. Graduates



Notes: Figure shows the distribution across colleges of the difference between mean log earnings in Glassdoor and mean log earnings in the Department of Education's College Scorecard database.

the United States.

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 B. We intentionally avoid using other data sources that collect data on earnings for colleges around the world. These data 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 similar sample selection as Glassdoor and hence may not provide a useful validation exercise.[15]

Table 3 summarizes some of the key moments from the comparison exercises for 17 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 non-top colleges in each country (see Section 4.2 for a definition of "top colleges"). Glassdoor appears to capture a positively selected sample for

[15]For example, the websites https://www.emolument.com/ and 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: Overall	Colleges: Top Colleges	Graduates: Overall	Graduates: Top Colleges	Average selection estimate: Overall	Average selection estimate: Top Colleges	Average selection estimate: Non-Top Colleges
India	15,990	33	10	624	220	-0.10	-0.21	-0.05
Nigeria	17,738	18	4	785	300	0.39	0.36	0.41
Philippines	18,234	13	1	2684	467	-0.06	-0.02	-0.07
China	23,584	70	34	287	162	0.08	0.14	0.02
Colombia	29,381	15	3	52	14	0.14	0.44	0.03
South Africa	44,330	13	2	319	96	0.20	0.01	0.29
Poland	63,386	19	10	727	475	0.31	0.36	0.21
South Korea	75,596	28	6	177	107	0.07	0.03	0.12
Japan	77,951	19	13	51	38	-0.02	0.00	-0.09
New Zealand	78,396	7	1	658	255	-0.02	0.01	-0.04
United Kingdom	90,309	119	12	7304	919	0.01	-0.09	0.03
Australia	95,526	38	4	969	231	-0.01	0.02	-0.02
Netherlands	105,904	12	3	81	24	-0.11	-0.09	-0.12
Italy	108,666	29	3	89	36	0.34	0.25	0.40
United States	123,872	1482	96	135437	38901	0.04	0.04	0.04
Singapore	152,399	4	0	502	0	-0.10	–	-0.10
Ireland	157,066	16	2	1456	371	-0.08	-0.13	-0.07

Notes: Table above 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, the level of aggregation for each comparison group, and a summary of how comparison samples in Glassdoor are constructed, see Appendix B.

some countries, such as Nigeria, Poland, or Italy. However, the extent of selection is not correlated with development. In Section 6, we show that our results do not meaningfully change 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.

4 College Graduate Quality and Development

This section presents our estimates of college graduate quality. We provide an overview of the estimates and how they compare with external rankings of college quality in Section 4.1. We then study the relationship between college graduate quality and development. We show that college graduates employed in richer countries have higher average human capital, for two reasons. First, in Section 4.2, we show that colleges in richer countries have consistently higher graduate quality. Second, in Section 4.3, we show that migration – in particular, brain drain out of developing countries – magnifies these differences.

4.1 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 top colleges have compared with graduates of non-top colleges.

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 in brackets 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 percent more in the same labor market. The gap in quality grows to 36 log points for colleges ranked 51–100 and reaches a substantial 47 log points (60 percent) for graduates of the colleges ranked in the top 20. To put this last number into perspective, we note that the college earnings premium in 2019 for the United States was 59 percent (see footnote 5 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 attending and not attending college.

Figure A2 shows the raw distribution of human capital (equivalently, earnings net of country-specific productivity z_c) for selected CWUR ranking bins. There is substantial variation in the distribution of human capital within each bin and substantial overlap in the distribution of human capital between colleges in different bins. Being in a higher ranking bin corresponds to a rightward shift of the entire human capital distribution.

Alternatively, we can construct our own global ranking based on each college's estimated graduate quality. Table 5 shows the top 100 colleges according to our ranking

Table 4: College Graduate Quality and CWUR World Ranking

	World ranking						
	1–20	21–50	51–100	101–250	251–500	501–1000	1001–2000
College graduate quality	0.470***	0.371***	0.356***	0.288***	0.216***	0.166***	0.114***
	(0.026)	(0.017)	(0.020)	(0.011)	(0.009)	(0.011)	(0.011)
	[19]	[24]	[39]	[119]	[195]	[302]	[420]

Notes: Table displays our measure of (log) college graduate quality q_j as a function of various ranking groups from the Center for World University Rankings. Omitted category is "unranked" (below 2,000). Standard errors are in parentheses and number of colleges in our sample within each bin in brackets.

and, for each, presents the estimate for graduate quality and the number of graduates represented in our sample. The sample size for some colleges is small, so we focus on broad trends for the types of colleges that are highly ranked rather than the ranking of any individual college. The ranking includes many expected groups of colleges. For example, it features most of the Ivy League colleges, several of the world's top technical colleges (e.g., California Institute of Technology, Technical University of Munich, Technion – Israel Institute of Technology), renowned colleges outside the United States (e.g., Australian National University, École Polytechnique, LSE), and two of the top U.S. public colleges (University of Michigan and University of California, Berkeley).

However, the ranking also reveals some surprises. We highlight three. First, selective liberal arts colleges perform much better in our ranking than in the CWUR ranking (e.g., Cooper Union, Williams, Claremont McKenna). Second, the U.S. armed forces academies place particularly high in our ranking, with three appearing in the top 100. Third, our ranking more heavily emphasizes colleges with a technical orientation from around the world, even after controlling for major of study. The most notable example is the dominance of the Indian Institutes of Technology at the top of our earnings-based ranking. For some of the institutes, these high rankings may reflect small sample sizes, but we observe hundreds of highly paid graduates from many of these institutions. 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, the ranking in Table 5 uses data from only 100 of our 3,368 total colleges. For those interested, the ranking for every college in our sample is available in an online appendix. Our next results focus on the overall distribution of college graduate quality by country.

Table 5: Top 100 Colleges By Estimated Graduate Quality

			World	College graduate quality					World	College graduate quality	
Rank	College	Country	ranking	Graduates	q_j	Rank	College	Country	ranking	Graduates	q_j
1	Indian Institute of Technology Ropar	IND	.	33	0.69	51	The University of Sydney	AUS	100	945	0.29
2	International Institute of Information Technology, Hyderabad	IND	.	30	0.58	52	Technical University of Denmark	DNK	213	32	0.28
3	Keio University	JPN	86	86	0.45	53	The University of Melbourne	AUS	64	974	0.28
4	Indian Institute of Information Technology Allahabad	IND	.	70	0.44	54	University of Michigan-Ann Arbor	USA	17	438	0.27
5	Indian Institute of Technology Delhi	IND	548	217	0.44	55	École Polytechnique	FRA	32	75	0.27
6	Aoyama Gakuin University	JPN	1525	31	0.43	56	Université Paris-Dauphine	FRA	885	41	0.27
7	Franklin W Olin College of Engineering	USA	.	47	0.43	57	Nanzan University	JPN	.	31	0.27
8	Indian Institute of Technology Guwahati	IND	969	228	0.43	58	International School of Management	DEU	.	25	0.27
9	The University of Tokyo	JPN	13	60	0.42	59	University of Canberra	AUS	1087	157	0.27
10	University of Pennsylvania	USA	9	728	0.41	60	The Interdisciplinary Center	ISR	.	31	0.26
11	University of Basel	CHE	106	29	0.39	61	Stanford University	USA	3	42	0.26
12	Indian Institute of Technology Kharagpur	IND	674	383	0.39	62	Washington University in St Louis	USA	41	101	0.26
13	Indian Institute of Technology Roorkee	IND	788	320	0.39	63	National Institute of Technology, Kurukshetra	IND	.	111	0.26
14	Sophia University	JPN	1837	105	0.36	64	United States Military Academy	USA	1009	1318	0.26
15	Samuel Merritt University	USA	.	97	0.35	65	The University of New South Wales	AUS	113	1082	0.26
16	Emory University	USA	90	238	0.35	66	Yale University	USA	12	115	0.26
17	Indian Statistical Institute	IND	.	28	0.35	67	University of Chicago	USA	10	194	0.26
18	Indian Institute of Technology Patna	IND	.	31	0.35	68	University of Maryland Baltimore	USA	253	26	0.26
19	Indian Institute of Technology Kanpur	IND	830	268	0.35	69	Tufts University	USA	94	1650	0.26
20	Chuo University	JPN	899	25	0.34	70	Nihon University	JPN	825	26	0.26
21	Netaji Subhas University of Technology	IND	.	378	0.34	71	Universität Hamburg	DEU	176	51	0.25
22	Indraprastha Institute of Information Technology	IND	.	55	0.34	72	Cornell University	USA	14	469	0.25
23	Kyoto University	JPN	21	30	0.34	73	University of Southern Denmark	DNK	352	36	0.25
24	Karlsruhe Institute of Technology	DEU	232	25	0.33	74	Princeton University	USA	7	51	0.25
25	Indian Institute of Technology, BHU	IND	1519	174	0.33	75	Tokyo University of Foreign Studies	JPN	.	28	0.24
26	Harvard University	USA	1	414	0.33	76	Kansai Gaidai University	JPN	.	27	0.24
27	Indian Institute of Technology Madras	IND	600	212	0.32	77	Technion Israel Institute of Technology	ISR	111	644	0.24
28	Harvey Mudd College	USA	.	252	0.32	78	École Polytechnique Fédérale de Lausanne	CHE	79	37	0.24
29	St. Louis College of Pharmacy	USA	.	47	0.32	79	Swarthmore College	USA	815	397	0.24
30	Columbia University in the City of New York	USA	6	595	0.32	80	University of Regensburg	DEU	364	29	0.24
31	Stockholm School of Economics	SWE	384	32	0.32	81	The Business School	GBR	.	122	0.24
32	Technical University of Munich	DEU	76	71	0.31	82	Queensland University of Technology	AUS	390	583	0.24
33	IPAG Business School	FRA	.	26	0.31	83	University of Lausanne	CHE	181	26	0.23
34	United States Naval Academy	USA	1220	1232	0.31	84	Babson College	USA	940	766	0.23
35	California Institute of Technology	USA	11	283	0.31	85	The London School of Economics and Political Science	GBR	293	614	0.23
36	Indian Institute of Technology Bombay	IND	587	174	0.30	86	Charles Sturt University	AUS	1025	207	0.23
37	Tokyo University of Science	JPN	654	27	0.30	87	Meiji University	JPN	1637	32	0.23
38	Cooper Union for the Advancement of Science and Art	USA	.	171	0.30	88	University of California-Berkeley	USA	8	10977	0.23
39	Roseman University of Health Sciences	USA	.	29	0.30	89	Santa Clara University	USA	1125	1989	0.23
40	Australian National University	AUS	108	285	0.30	90	United States Air Force Academy	USA	.	800	0.23
41	SUNY Downstate Medical Center	USA	603	35	0.30	91	Technische Universität Darmstadt	DEU	476	41	0.23
42	Carnegie Mellon University	USA	84	2139	0.30	92	Rice University	USA	109	931	0.23
43	Osaka University	JPN	80	30	0.30	93	Motilal Nehru National Institute of Technology Allahabad	IND	.	428	0.23
44	Brown University	USA	45	1292	0.29	94	ESSEC Business School	FRA	1206	63	0.23
45	Doshisha University	JPN	1231	25	0.29	95	Amherst College	USA	458	449	0.23
46	Williams College	USA	1295	473	0.29	96	Middlebury College	USA	1947	640	0.23
47	Georgetown University	USA	203	139	0.29	97	University of Technology Sydney	AUS	463	554	0.22
48	Claremont McKenna College	USA	1036	403	0.29	98	University of Waterloo	CAN	179	2907	0.22
49	Dartmouth College	USA	49	1347	0.29	99	Copenhagen Business School	DNK	1098	138	0.22
50	Waseda University	JPN	168	139	0.29	100	Haverford College	USA	1155	286	0.22

Notes: Table displays the one hundred colleges with the highest estimated graduate quality ranking in descending order, along with, for each college, the country where it is located, its place in the Center for World University Rankings, the number of graduates from the college in our sample, and the college's estimated graduate quality. College graduate quality is normalized relative to The University of Texas at Austin.

4.2 College Graduate Quality and Cross-Country Income Differences

In this section, we show that college graduate quality is related to GDP per worker. This finding implies that the common practice of equating each country's supply of skilled labor with the share of workers who have graduated college understates cross-country differences in such supply.

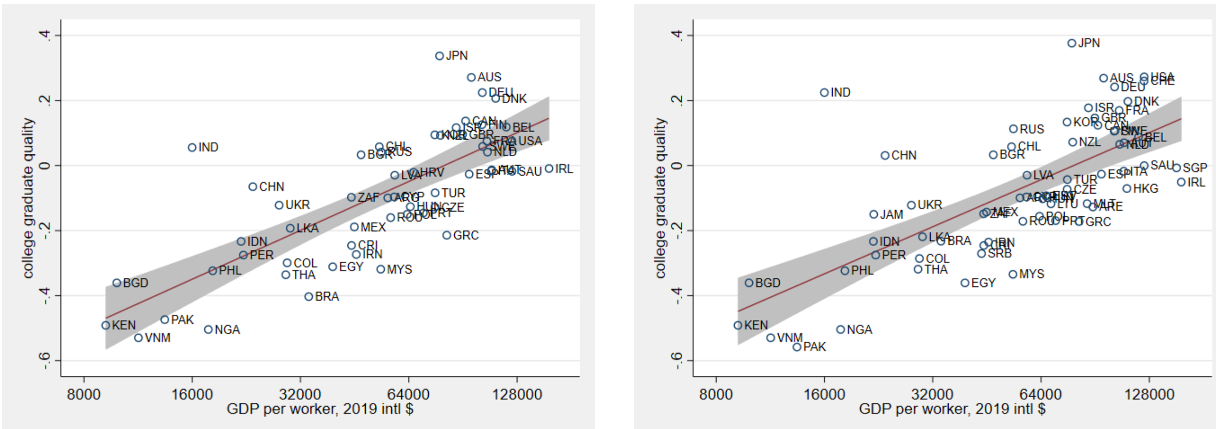
The Glassdoor database has more extensive coverage of graduates from top colleges. Given this, we start by comparing the college graduate quality among top colleges across countries. Our preferred measure for top colleges is the top 5 percent of colleges in each country, which we compute for countries with at least 20 colleges. We use the CWUR's nation-specific rankings to order colleges from the top and incorporate data on the total number of colleges from the World Higher Education Database (2021) to determine percent rankings. For example, the latter source tells us that Chile has 60 colleges, so the top 5 percent comprises three colleges; the former source tells us that these colleges 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 colleges to round out the top five. For these countries, we focus on however many colleges are ranked.

In Figure 2, the relative and absolute measures of college graduate quality by country are plotted against PPP GDP per worker. The key insight from these plots is that greater GDP per worker is associated with higher college graduate quality. Again, the effect is economically and quantitatively significant. The 90-10 ratio of GDP per worker in our sample is a factor of 6.7 (Belgium–Nigeria). Multiplying this difference by the estimated trend line shown in the figures suggests that top universities in the richer countries have college graduate quality 51 percent higher than that of top universities in poorer countries. The overall relationship is similar whether we use the top 5 percent of colleges (relative ranking, Figure 2a) or the top five colleges (absolute ranking, Figure 2b). The top five 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.

Figure 2: College Graduate Quality of Top Colleges and Development

(a) Relative national ranking (Top 5%) (b) Absolute national ranking (Top 5)



Notes: Figures plot the average estimated college graduate quality among the top 5 percent (left panel) or top five (right panel) of a country's colleges (based on Center for World University Rankings) against PPP GDP per worker from World Bank (2021) in log scale.

The relationship between college graduate quality and GDP per worker is not sensitive to the choice of threshold for identifying top colleges. Table 6 shows the estimated elasticity of college graduate quality with respect to development for alternative specifications of top colleges. When focusing on the top 5 percent of colleges, we estimate an elasticity of 0.22. If we consider a more restrictive sampling of only the top 2 percent, a wider bandwidth including the top 25 percent, or all colleges in our sample, very similar results prevail.

Table 6: Top Percent Colleges within Countries and GDP per worker

	Top 2%	Top 5%	Top 10%	Top 25%	All
Log(gdppw)	0.227***	0.217***	0.218***	0.211***	0.226***
	(0.035)	(0.026)	(0.024)	(0.023)	(0.026)
Countries	40	55	62	63	66
Adjusted R^2	0.52	0.57	0.57	0.56	0.54
Corr(gdppw,college graduate quality)	0.61	0.61	0.66	0.65	0.57

Notes: Table displays 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 (2021). See text for description of the construction of percentile bins.

These results relate to an existing literature that quantifies the extent of cross-country differences in education quality. Our main contribution is to bring to bear new evidence that measures separately the human capital of college graduates. Existing evidence either relates to primary and secondary school quality or mixes measures of education quality across primary, secondary, and tertiary schooling. For example, Cubas *et al.* (2016) calibrate their model to replicate data from the age-15 score distribution from 2009 PISA data. These estimates thus capture secondary school quality. Erosa *et al.* (2010) and Manuelli & Seshadri (2014) model educational expenditures as a source of education quality. They calibrate their models to fit data on educational expenditures for primary through tertiary schooling in the United States. Their results thus cover a mixture of education quality across educational levels.

Our second contribution to this literature is to provide new evidence on the global distribution of college quality. We estimate the entire distribution of college graduate quality by country and conclude that this distribution is shifted right in richer countries. We also explore whether developing countries have a comparative advantage in particular subjects by separately estimating college graduate quality for STEM fields, business/social science fields, and other fields. We find that STEM graduates consistently earn more than business/social science graduates, who in turn earn more than graduates of other fields. However, the magnitude of this effect appears fairly common across countries (see Figure A3).

4.3 Selection of Migrants

The human capital of a country's college-educated workforce depends on its own college graduates, but it is also affected by migration. We complement our analysis of college graduate quality by country with an analysis of selection in terms of human capital of college-educated migrants for each country. The existing literature documents that developing countries typically lose a larger share of college-educated workers to migration, a phenomenon referred to as "brain drain" (Docquier & Rapoport, 2012).[16] The literature also documents that college-educated workers disproportionately flow to a small set of OECD countries, particularly the United States, the United Kingdom, Australia, and Canada (Kerr *et al.*, 2016). Our contribution is to use the Glassdoor database to estimate how selected emigrants and immigrants are for each country in terms of their human capital.

All of our results pertain to migrants in the Glassdoor database. A limitation of our analysis is that we are not aware of any representative data sources that cover earnings by alma mater for migrants, so we cannot validate or adjust these earnings as we do for non-migrants (see Section 6). We view our results as a first attempt to quantify the patterns

[16] Recent work has also shown that these flows are to some extent offset by the fact that migration increases the incentive to acquire human capital in the first place as well as by return migration. Our data do not allow us to quantify these dynamic effects.

of human capital among skilled migrants using a novel source of data. We also note that we measure brain drain and global talent flows as cases in which workers graduate from college in one country and then work 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.

Our approach builds on the regression outlined in Section 2. Within Glassdoor we focus on workers who attend college in country b and report earnings in country $c \neq b$. Their average human capital is given by

$$\bar{h}_{j,c} = q_j + \bar{\varepsilon}_{b(j),c} = \bar{w}_{j,c} - z_c. \tag{8}$$

The first equality captures that average human capital of migrants depends on both college graduate quality and selection. The second equality shows how we construct average human capital of migrants, which is again to use country-adjusted earnings. We use this equation as the basis for the study of the human capital of emigrants and immigrants.

We measure the selection of country b emigrants, EM_b, as the average human capital of graduates from all colleges j in country b, which we denote by $j \in b$, who emigrate to all possible destinations $c \neq b$, relative to the average human capital of non-migrants who are employed in b, $\bar{h}_b = \bar{q}_b$:

$$\begin{aligned} EM_b &= \sum_{j \in b} \sum_{c \neq b} \ell_{j,c} \bar{h}_{j,c} - \bar{h}_b \\ &= \underbrace{\sum_{j \in b} \sum_{c \neq b} \ell_{j,c} \left[q_j - \bar{q}_b \right]}_{\text{selection on college graduate quality}} + \underbrace{\sum_{j \in b} \sum_{c \neq b} \ell_{j,c} \bar{\varepsilon}_{b(j),c}}_{\text{selection on ability}}. \end{aligned} \tag{9}$$

The first line captures the total effect, with $\ell_{j,c}$ denoting the share of country b's emigrants in the Glassdoor database who graduate from j and move to c. The second line uses equation (8) to decompose the total effect into two components: the selection on college graduate quality (relative to country b average, denoted by $\bar{q}_b$) and selection on ability (human capital conditional on alma mater).

We follow a similar approach to measure and decompose the selection of immigrants, meaning the average human capital of immigrants to a country relative to the average human capital of its non-migrant workers:

$$IM_c = \sum_{b \neq c} \sum_{j \in b} \omega_{j,c} \bar{h}_{j,c} - \bar{h}_c \tag{10}$$
$$= \underbrace{\sum_{b \neq c} \sum_{j \in b} \omega_{j,c} \left[\bar{q}_b - \bar{q}_c\right]}_{\text{selection on country}} + \underbrace{\sum_{b \neq c} \sum_{j \in b} \omega_{j,c} \left[q_j - \bar{q}_b\right]}_{\text{selection on college graduate quality} \mid \text{country}} + \underbrace{\sum_{b \neq c} \sum_{j \in b} \omega_{j,c} \bar{\varepsilon}_{b(j),c}}_{\text{selection on ability}}.$$

The first line again captures the average human capital of immigrants to country c relative to the average human capital of domestic workers who attended college in c, $\bar{h}_c$. Here $\omega_{j,c}$ denotes the share of immigrants to country c who graduate from college j in country b in the Glassdoor database. The second line uses equation (8) to decompose the total effect into three pieces, which capture selection in terms of the country of origin (measured using average college graduate quality), selection in terms of college graduate quality conditional on country, and selection on ability.

The full results of these two decompositions in terms of EM_b and IM_c, along with each of the five sub-components for each country, are available in Table A2. Here we focus on two main results. First, Figure 3 plots the average selection of each country's emigrants and immigrants against GDP per worker. Selection is measured as the average human capital of each group relative to the average human capital of that country's non-migrants. All measures here are captured as log-differences, so zero corresponds to the case in which migrants and non-migrants have the same average human capital.

Figure 3a shows the implications for brain drain. The average selection of emigrants is negatively correlated with development. Not only do less developed countries lose a larger share of their skilled workers to emigration, but those emigrants are strongly positively selected on their human capital. For a number of countries, the average emigrant has 40 log points (50 percent) more human capital than the average non-migrant. By contrast, emigrants from developed countries are on average hardly selected at all. This finding indicates that the proximate effect of brain drain on less developed countries is stronger than what has been found in the literature focusing solely on the number of college-educated migrants.

Figure 3b shows the implications for global talent flows. For most countries, the average human capital of immigrants is close to that of non-migrants. 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 rich 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

Figure 3: Average Selection of Migrants by Country

(a) Emigrants

(b) Immigrants

Notes: Figures plot against PPP GDP per worker (in log scale) the average selection of each country's emigrants, measured as the log-difference between the average human capital of that group and the average human capital of the country's non-migrants. GDP data from World Bank (2021); selection measured constructed using Glassdoor data and equations (9) and (10).

of the world's college-educated immigrants but also immigrants whose average human capital exceeds that of natives by a significant amount. We also find evidence that other countries attract talented immigrants by this metric, including Malaysia, Hong Kong, and Ireland. On the other hand, a handful of rich countries attract immigrants whose average human capital is more than 20 percent lower than that of natives, including South Korea, Argentina, and Japan.

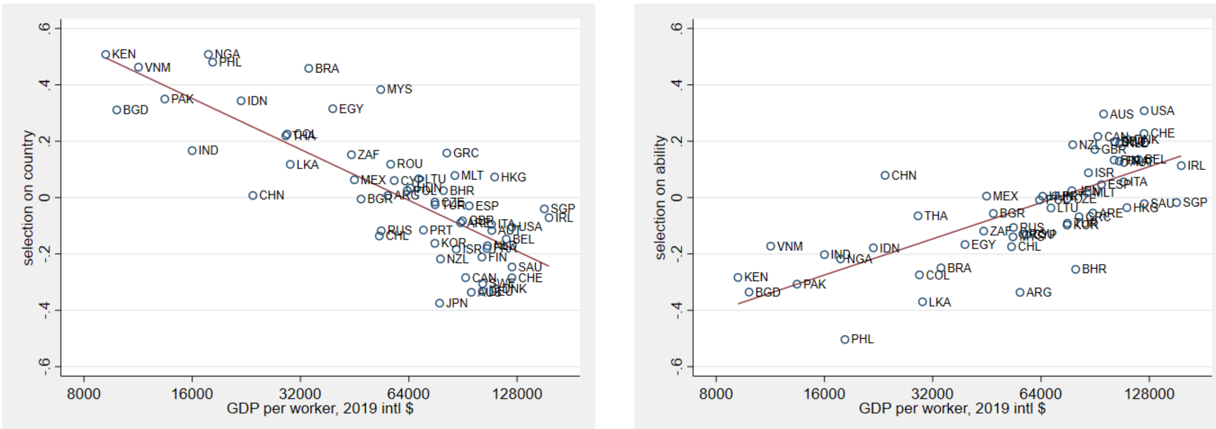
We decompose our measures of selection using equations (9) and (10). In each case, we find that selection in terms of alma mater conditional on country accounts for a negligible share of our findings (see Table A2). It follows that the selection of emigrants is entirely due to selection on ability. The selection of immigrants is more nuanced. In Figure 4, we plot the two remaining terms – selection on country and selection on ability – against GDP per worker.

Figure 4a plots the selection on country (measured as average college graduate quality) against GDP per worker. There is a strong negative correlation between the two. This is intuitive: less developed countries find it easier to attract immigrants from countries with higher average college graduate quality than their own. Figure 4b plots the selection on ability against GDP per worker. This figure shows a strong positive correlation. Put differently, less developed 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 4 also helps explain why there is so much heterogeneity in terms of selection

Figure 4: Decomposing Selection of Immigrants

(a) Selection on Country (b) Selection on Ability



Notes: Figures plot selection on ability and selection on country computed as in equation (10) against PPP GDP per worker from World Bank (2021) in log scale.

of immigrants among developed countries. Consider two examples. First, we find that Japan and Denmark have roughly similar levels of selection of immigrants in terms of country (-0.37 and -0.32). However, Denmark's immigrants are much more selected on ability (0.21 versus 0.02), which leads to large differences in overall selection. Second, we find that the United States and Australia have roughly similar levels of selection in terms of ability (0.31 and 0.30). However, immigrants to the United States are much more selected on country (-0.10 versus -0.34), which explains a large gap in total selection of their immigrants.

These findings are also relevant for the literature that uses the experiences of migrants to disentangle the importance of human capital from place-based effects, such as capital intensity, total factor productivity, or the skill bias of technology. An important question for this literature is how migrants are selected and whether this selection biases the inferences being drawn (Hendricks & Schoellman, 2018). We contribute two important, novel findings for this literature. First, migrants do not appear to be strongly selected on what college they graduate from conditional on country. This provides the first evidence that the experiences of migrants are informative about the average college, rather than just a selected subset. Second, both the sign and magnitude of selection on ability among immigrants varies widely by country. Our finding of strong positive selection among immigrants to the United States is consistent with much of the literature. However, the selection for most other countries is weaker and, in some cases, negative.

5 College Graduate Quality, Innovation, and Entrepreneurship

The previous section documents that poorer countries have colleges with lower graduate quality. In addition, a positively selected set of their graduates subsequently emigrates. A country with a lower college graduate quality workforce can expect its workers to be less productive and to earn less, by construction. 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 D. The first source is the Glassdoor database itself. From this database, we use the job titles that workers provide on their resumes. We count as entrepreneurs any workers who include the term "founder" or "co-founder" in a job title. We count as executives any worker whose job title 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.

Table 7 presents the results. The first two columns show results for entrepreneurship, while the last two concern executive positions. As discussed above, we include country fixed effects; we also separate results for U.S. and non-U.S. colleges to explore whether our results are U.S. specific. We find a positive, statistically significant effect in all four cases. Further, these effects are economically large. For example, a one standard deviation rise in college graduate quality is associated with 1.0 percentage points more entrepreneurs and 0.5 percentage points more executives outside the United States —

Table 7: College Graduate Quality and Occupation: Glassdoor Database

	Share entrepreneurs		Share c-suite	
	U.S. colleges	Non-U.S. colleges	U.S. colleges	Non-U.S. colleges
College graduate quality	0.075***	0.053***	0.047***	0.024***
	(0.003)	(0.004)	(0.003)	(0.004)
Country FE		✓		✓
Mean outcome	0.024	0.024	0.033	0.020
Std. dev. college graduate quality	0.13	0.19	0.13	0.19
N	192179	88731	192179	88731

Notes: Table relates our measure of college graduate quality to whether workers ever engage in entrepreneurship or become C-suite executives after graduating from U.S. and non-U.S. universities. Estimates reflect marginal effects from logit specifications. A worker is considered an entrepreneur if there is a job title on her resume that includes the term "founder." A worker is considered C-suite if there is a job title on her resume 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.

sizable effects relative to baseline shares of 2.4 and 2.0 percent, respectively.

Our second source of data is patent records from the United States 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 detail the share of students who are granted patents as well as the share of students who are among the top 5 percent most-cited inventors in their cohort for U.S. colleges with more than 10 patents granted among students in the 1980–1984 birth cohorts; see their paper for further details. Second, using data provided by the United States 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 its residents filed in the United States per capita; see Appendix D for details.

Table 8 shows the results for the United States. Both outcomes are positive and statistically significant. Again, the results are also economically large. Even focusing on the colleges with at least 10 inventors, a one standard deviation rise in college graduate quality is associated with a 0.8 percentage point increase in the share of students who are inventors, when the mean rate is just 1 percent. The cross-country results, shown in Table A1, are consistent. 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

Table 8: College Graduate Quality and Innovation: Patent Records

	Share inventors	Share inventors in top 5% of citations
College graduate quality	0.052***	0.003***
	(0.005)	(0.001)
Mean outcome	0.0098	0.0006
Std. dev. college graduate quality	0.15	0.15
N	364	364

Notes: Table relates our measure of college quality to notable achievements related to innovation across U.S. colleges using OLS 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.

is positive and statistically significant, while that for GDP per worker becomes small, has an inconsistent sign, and is not statistically significant.

Finally, some outcomes are uncommon enough that we can use web searches to recover the alma mater of all people who achieve them. We focus here on Nobel laureates and CEOs of Standard & Poor 500 index firms as of 2020. We regress the number of Nobel laureates and S&P 500 CEOs on college graduate quality with 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 9.

Table 9: College Graduate Quality and Notable Achievements

	Number of Nobel laureates		Number of CEOs of S&P 500 firms	
	U.S. colleges	Non-U.S. colleges	U.S. colleges	Non-U.S. colleges
College graduate quality	0.918***	0.315***	1.825***	0.175***
	(0.138)	(0.078)	(0.159)	(0.041)
Country FE		✓		✓
Mean outcome	0.084	0.057	0.243	0.034
Std. dev. college graduate quality	0.15	0.27	0.15	0.27
N	1619	1749	1619	1749

Notes: Table relates our measure of college quality to notable achievements, specifically becoming a Nobel laureate or CEO of an S&P 500 company in 2020 after graduating from U.S. and non-U.S. universities. Estimates reflect marginal effects from tobit specifications. For further details regarding the two dependent variables, see Appendix D.

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 both graduates of U.S. and non-U.S. colleges and is statistically significant in all cases. The magnitudes are smaller for non-U.S. colleges, possibly reflecting that these outcomes are overall less common for non-U.S. colleges, as shown in the row mean outcomes. Again, the economic magnitudes are large. A college outside the United States with one standard deviation higher graduate quality has 0.09 more Nobel laureates and 0.05 more CEOs, whereas the sample average for these outcomes is only 0.06 and 0.03, respectively.

Altogether, these results show that a college's graduate quality is strongly correlated with the share or number of its graduates who engage in innovation, found firms, or become executives. When combined with the large cross-country differences in college graduate quality that we document in Section 4, this finding implies that we can explain a substantial share of cross-country differences in the share of the population that engages in these activities, which are important for growth and development. For example, we found in Section 4 that top colleges in richer countries have graduate quality 51 percent higher than that of top colleges in poorer countries. Multiplying that difference by the coefficients estimated in this section implies that richer countries would be expected to have 2.1 percentage points more entrepreneurs, 2.1 percentage points more inventors, and 0.13 more Nobel laureates among their college graduates, solely because of their higher levels of human capital.[17]

6 Sensitivity

In this section, we investigate the sensitivity of our results to relaxing the assumptions we make and the details of our implementation process. We focus throughout on our main result for the elasticity of college graduate quality with respect to development. We estimate the elasticity separately for the top 5 percent of colleges and all other colleges to highlight any possible impact on the distribution of quality. All results are presented in Table 10. For example, the first row shows that the baseline estimate for these two groups of colleges is 0.217 and 0.227, respectively. Below each estimate we include the standard errors in parentheses and the number of countries included in the corresponding regression in brackets.

The standard errors reported in parentheses are the conventional ones from the regression of college graduate quality on GDP per worker. Since college graduate quality is itself estimated in a two-step procedure, one possible concern is that these standard errors significantly understate the degree of uncertainty around our point estimates. We

[17] These figures were computed by multiplying $\log(1.51) = 0.41$ by the estimated coefficients for non-U.S. colleges for entrepreneurs (0.053), for U.S. colleges for inventors (0.052), and for non-U.S. colleges for Nobel laureates (0.315).

use a bootstrapping exercise to help gauge the importance of this issue.

For each of 1,000 simulations, we sample with replacement 75,586 migrants from the first-stage sample who report earnings in more than one country and 2,046,766 workers 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 non-top colleges on GDP per worker. Figure A4 shows the distribution of point estimates for the elasticity of college graduate quality across the 1,000 simulations, along with bars indicating the 95 percent confidence interval. The main result is that the bootstrapping exercise suggests a nearly identical confidence interval. For example, the conventional standard errors imply that the 95 percent confidence interval for the estimate among top colleges is [0.192, 0.242], whereas the bootstrapped 95 percent confidence interval is actually just slightly narrower at [0.198,0.236].

As we note in Section 2, the log-linear earnings equation that underlies our baseline approach recovers human capital under several strong assumptions. We relax each of these in turn. First, we relax the log-separable earnings equation by allowing an interaction between worker human capital and country productivity in the earnings equation. The results, shown in Table A3, strongly support a negative coefficient on this interaction, implying that workers with higher human capital face a smaller earnings premium in higher z_c (richer) countries. This finding is consistent with models that allow imperfect substitution between workers with different skill levels. In these models, skilled workers are relatively abundant in richer countries, and so they earn a lower wage; recent work has provided additional evidence consistent with such frameworks (Jones, 2014; Okoye, 2016; Rossi, 2022; Hendricks & Schoellman, forthcoming).[18] As row 2 of Table 10 shows, allowing for this effect changes our estimated elasticity little.

Allowing workers of different types to be imperfect substitutes also affects our first-stage estimation that leverages migrants with earnings observations in more than one country. With imperfect substitution, a worker's earnings depend on the type of human capital k that they supply and the corresponding price of that human capital in the country where they work $p_{k,c'}$:

$$w_{i,j,k,c} = z_c + p_{k,c} + h_{i,j,k}.$$

The earnings change at migration now captures the change in $z_c + p_{k,c}$. This is exactly what we want to net off in the second stage, as long as we are careful to use comparable workers in the first and second stages. Following this logic, we explore limiting the

[18] We also explore specifications that allow for higher-order interactions and find similar results.

Table 10: Sensitivity Analysis: College Graduate Quality and Development

Alternative specification	Top Colleges	Non-Top Colleges
1. Baseline	0.217***	0.227***
	(0.026)	(0.026)
	[55]	[64]
2. Allow college quality-country effect (2nd step)	0.196***	0.195***
	(0.025)	(0.026)
	[55]	[64]
3. Use only college-educated migrants (1st step)	0.207***	0.242***
	(0.039)	(0.040)
	[38]	[42]
4. Use only migrants who are firm-stayers (1st step)	0.306***	0.366***
	(0.063)	(0.062)
	[40]	[43]
5. Use only migrants who retain the same job title (1st step)	0.186***	0.250***
	(0.048)	(0.045)
	[40]	[44]
6. Account for skill loss in migration (1st step)	0.219***	0.229***
	(0.026)	(0.026)
	[55]	[64]
7. Account for skill loss over time in migration (1st step)	0.220***	0.230***
	(0.026)	(0.026)
	[55]	[64]
8. Include job title fixed effects	0.183***	0.191***
	(0.021)	(0.021)
	[55]	[64]
9. Include firm fixed effects	0.198***	0.213***
	(0.023)	(0.023)
	[55]	[64]
10. College-specific selection (2nd step)	0.205***	0.221***
	(0.032)	(0.026)
	[51]	[58]
11. Sample selection correction	0.233*	0.265**
	(0.110)	(0.095)
	[16]	[17]
12. Use only earnings reports outside the United States	0.202***	0.224***
	(0.032)	(0.027)
	[48]	[56]
13. Minimum N=50 observations	0.211***	0.210***
	(0.034)	(0.029)
	[44]	[47]
14. Country-specific return to experience (2nd step)	0.347***	0.353***
	(0.033)	(0.031)
	[55]	[64]
15. At most an undergraduate degree (2nd step)	0.225***	0.219***
	(0.033)	(0.027)
	[51]	[61]
16. Jointly estimate undergraduate and graduate quality (2nd step)	0.222***	0.228***
	(0.027)	(0.028)
	[55]	[64]

Notes: Table displays estimated coefficient from regressing the average quality of a country's top 5 percent and other colleges on the log of PPP GDP per worker from World Bank (2021). Rows correspond to various sensitivity checks in terms of sample restrictions or changes in the estimation procedure. See text for details.

sample in the first stage to college-educated workers, consistent with our second-stage sample restriction. As shown in row 3 of Table 10, the results are similar.

Our second assumption is that workers supply the same human capital in any country where they work. This assumption implies that the earnings change of a migrant reveals exactly the difference in z_c between the two countries. There are two potential concerns. The first is that human capital might not perfectly transfer for migrants. In this case, gains in earnings would tend to understate cross-country differences in z_c. The second is that workers may have country-specific abilities or skills, and migrants may be selected in part on comparative advantage for their destination country. In this case. gains in earnings would tend to overstate cross-country differences in z_c.

We provide two approaches to thinking about the sensitivity of our results to this assumption. The first approach focuses specifically on the possibility that migrants might have difficulty transferring their skills. Specifically, we re-estimate our first-stage regression using the subset of migrants who work for the same firm or who have the same job title before and after migration. We have in mind that these migrants are less likely to have experienced difficulty in transferring their skills. The results are shown in rows 4 and 5. Since we use a subset of migrants, we are able to estimate z_c for only a subset of countries and so our sample (shown in brackets) is smaller. However, the estimated cross-country differences in college graduate quality are unchanged or even larger.

Our second approach is more general. A strength of the Glassdoor database is that it includes observations of workers who move in both directions between many pairs of countries. This fact allows us to implement an expanded first-stage regression of the form

$$w_{i,t,c} = z_c + \lambda_i + d_{\mathcal{S}} + \beta X_{i,t} + \eta_{i,t}, \tag{11}$$

where $d_{\mathcal{S}}$ is a dummy variable that takes the value of zero if a given earnings report is pre-migration and one if a given earnings report is post-migration. Intuitively, a negative estimated coefficient for this dummy captures the case in which workers earn less than expected after migration, consistent with skill loss; a positive estimated coefficient captures the case in which workers earn more than expected after migration, consistent with selection on gains to migration. Note that to be identified, this regression requires data on migrants moving in both directions between a pair of countries.

We implement this regression using the Glassdoor database; the full results are reported in Table A4. We find a small, positive earnings effect for the post-migration earnings dummy. For the baseline regression, the effect is about 7.0 percent. We also explore controlling for a quadratic in the time between first (pre-migration) and second (post-migration) earnings reports as a proxy for time since migration (which we do not observe). In this case, we find a smaller effect of 3.3 percent. These findings suggest that the impact of skill transferability and selection based on country-specific comparative advantage is either small or roughly balanced. As shown in rows 6 and 7 of Table 10, incorporating these adjustments in the first stage makes little difference to our main results.

Our third assumption is that labor markets are competitive, which allows us to map earnings differentials (which we observe) into human capital differentials. Many forms of non-competitive labor markets manifest as occupation 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 controlling for fixed effects for each. Rows 8 and 9 show that doing so changes little the elasticity of college graduate quality with respect to GDP per worker.

In addition to these assumptions, our results also rest on a number of implementation details. In our baseline approach we assume that the degree of selection is common across colleges for all migrants from b to c. We can relax this assumption by allowing selection to vary at the college-destination pair level instead of origin-destination. In this case, emigrants cannot be used to help estimate college graduate quality in the second stage. Intuitively, the earnings of Oxford graduates in the United States cannot contribute to the estimation of Oxford's graduate quality if selection of Oxford graduates to the United States is a free variable. Row 10 shows the results are still similar, although again we lose some countries from the sample.

We also explore correcting our sample for selection into Glassdoor. We restrict our attention to the 16 countries for which we were able to to estimate college graduate quality of top colleges and find external benchmarks of earnings by college (Section 3.1). Figure A5 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 11.

Glassdoor is based in the United States, and so earnings observations from the United States are overrepresented in Glassdoor. Row 12 shows the results are very similar if we conduct the entire analysis while excluding workers' earnings from the United States. Our baseline analysis considers only countries and colleges that have a minimum of 25 migrants and workers, respectively, in our sample. Row 13 shows that the results are also similar if we raise the sampling threshold to 50 in each case.

Further, while most of our paper assumes that the returns to experience are common across countries, Lagakos *et al.* (2018) show that they consistently vary with development. Row 14 includes our estimated elasticities when we allow returns to experience to vary by country of work. In this case, we find larger cross-country differences in college graduate quality.

We also assess whether college graduate quality interacts with experience, drawing on the fact that the Glassdoor database includes workers at different points in their careers. We re-estimate the relationship between college graduate quality and CWUR rankings separately for workers with different experience levels. The results are shown in Table A5. The main finding is that the effect of attending a highly ranked college on country-adjusted earnings is just as large for experienced workers (10 or more years since graduation) as it is for new workers (zero to two years since graduation). For example, college graduate quality for the global top 20 universities is estimated to be 0.413 among the former group and 0.439 among the latter. The durable value of attending a top college is consistent with the interpretation that college graduate quality reflects human capital rather than a signal to employers.[19]

To summarize, our baseline analysis rests on three assumptions as well as a number of practical choices. In this section, we use the richness of the Glassdoor data to relax these assumptions and investigate alternative choices. As shown in Table 10, we consistently find that college graduate quality varies substantially and is strongly correlated with development. Among top colleges, the range of plausible elasticities stretches from 0.18–0.35; with two exceptions, the range is actually much tighter, 0.18–0.23.

6.1 Advanced Degrees

Our results so far have related college graduate quality to where each worker received her bachelor's degree. We now delve into the importance of advanced (graduate) degrees for measured college graduate quality across countries. This analysis has two components. First, advanced degrees are a possible confounding force when estimating college graduate quality. Altonji *et al.* (2016) find that roughly 38 percent of 24-year-olds in the United States with a bachelor's degree have a master's degree as well. Within our sample, about 24 percent of graduates from colleges outside the United States 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 this may artificially inflate our measure of college graduate quality. With this in mind, we explore the sensitivity of our results to accounting for advanced degrees. Second, we use this opportunity to provide some preliminary results on the relationship between advanced degrees and earnings.

[19] As additional supporting evidence, we show in Table A6 that there are robust and positive returns to GPA for migrants and non-migrants, inside and outside the United States.

Our baseline approach estimates college graduate quality without accounting for any possible advanced degrees. We consider two alternatives for the second step of our estimation procedure to explore the sensitivity of these results. First, we estimate college graduate quality using only workers who have no advanced degrees. As shown in row 15 of Table 10, doing so does little to change our results. Second, we estimate the earnings effect of bachelor's degrees $q_{j,u}$ and advanced degrees $q_{j,g}$ separately for each college j, assigning graduates with at most a bachelor's degree to a single "unavailable" group for graduate school. The regression specification for the second step is then

$$w_{i,j_u,j_g,t,c} - z_c = \gamma X_{i,t} + q_{j_u} + q_{j_g} + s_{b(j_u),c} + s_{b(j_g),c} + \eta_{i,t}, \tag{12}$$

where $X_{i,t}$ includes a quadratic in years of experience along with undergraduate major of study, graduate degree (postgraduate, master's, JD, MBA, or PhD) interacted with graduate major, and year fixed effects. We assume that selection has two additive components capturing the average selection of migrants with undergraduate degrees from a college in $b(j_u)$ working in c and the average selection of migrants with graduate degrees from a college in $b(j_g)$ working in c. As shown in row 16 of Table 10, this assumption again does little to change the estimated relationship between college (undergraduate) quality and GDP per worker.

The estimates from equation (12) also allow us to compare the estimated effect of bachelor's and advanced degrees on earnings. The college-by-college rankings can be somewhat imprecise for advanced degrees because we have smaller samples of advanced degree recipients for most colleges. Thus, in Table 11 we compare the estimated earnings premia for bachelor's and advanced degrees from colleges in various bins according to the CWUR world rankings.

Table 11: College Premia and CWUR World Ranking, Undergraduate and Graduate

	World ranking						
	1–20	21–50	51–100	101–250	251–500	501–1000	1001–2000
Undergraduate quality	0.461***	0.375***	0.358***	0.288***	0.217***	0.168***	0.113***
	(0.047)	(0.042)	(0.033)	(0.019)	(0.015)	(0.012)	(0.011)
	[19]	[24]	[39]	[119]	[195]	[302]	[420]
Graduate quality	0.195***	0.072***	0.068***	0.029***	0.029***	0.028***	0.030***
	(0.026)	(0.022)	(0.018)	(0.012)	(0.011)	(0.010)	(0.009)
	[19]	[25]	[38]	[101]	[117]	[141]	[200]

Notes: Table displays our measure of (log) college quality q_j separately for undegraduate and graduate degrees as a function of various ranking groups from the Center for World University Rankings. Omitted category is unranked (below 2,000). There are 3,368 colleges for undergraduate quality and 1,432 for graduate quality. Standard errors are in parentheses and number of colleges in our sample within each bin in brackets.

There are two main findings of note. First, the estimated value of college undergraduate quality is similar to our baseline findings in Table 4. Second, the return to advanced degrees is lower and non-linear. Advanced degrees from colleges ranked anywhere between 101–2,000 pay a modest premium of around 3 percent over advanced degrees from unranked colleges. From there the premium jumps to 6–8 percent for colleges ranked between 21–100 and 22 percent for colleges in the top 20. The return enjoyed by workers with advanced degrees from a top 20 college is consistent with the 20–25 percent estimate for top 25 MBA programs from Arcidiacono *et al.* (2008).

7 Conclusions

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 allows us to connect workers' alma maters to their earnings for a large, global sample consisting of 2 million workers who obtained a Bachelor's degree from 3,368 different colleges in 66 countries. Second, it contains data on pre- and post-migration earnings for tens of thousands of college-educated migrants, which provide the information needed to adjust earnings to a common labor market.

We find that college graduate quality varies substantially among colleges and on average between poor and rich countries. These gaps are further magnified by migration. In particular, brain drain from poor countries is more extensive than what the previous literature has documented. Not only do poorer countries lose a higher share of their college-educated workers, but those who leave have 50 percent more human capital than non-migrants. 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? Attempts to disentangle these questions require either data about pre-college characteristics or quasi-random variation in college attendance choices, both of which we lack. We believe this to be an interesting avenue for future research.

References

AKCIGIT, UFUK, GRIGSBY, JOHN, & NICHOLAS, TOM. 2017. *The Rise of American Ingenuity: Innovation and Inventors of the Golden Age*. Mimeo, University of Chicago.

AKCIGIT, UFUK, GRIGSBY, JOHN, NICHOLAS, TOM, & STANTCHEVA, STEFANIE. 2022. Taxation and Innovation in the Twentieth Century. *Quarterly Journal of Economics*, **137**(1), 329–385.

ALTONJI, JOSEPH G., ARCIDIACANO, PETER, & MAUREL, ARNAUD. 2016. The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects. *Chap. 7, pages 305–396 of:* HANUSHEK, ERIC A., MACHIN, STEPHEN, & WOESSMANN, LUDGER (eds), *Handbook of the Economics of Education*, vol. 5. Elsevier.

ARCIDIACONO, PETER, COOLEY, JANE, & HUSSEY, ANDREW. 2008. The Economic Returns to an MBA. *International Economic Review*, **49**(3), 873–899.

AZOULAY, PIERRE, JONES, BENJAMIN F., KIM, J. DANIEL, & MIRANDA, JAVIER. 2022. Immigration and Entrepreneurship in the United States. *American Economic Review: Insights*, **4**(1), 71–88.

BARRO, ROBERT J., & LEE, JONG WHA. 2013. A New Data Set of Educational Attainment in the World, 1950–2010. *Journal of Development Economics*, **104**, 184–198.

BELFIELD, CHRIS, BRITTON, JACK, BUSCHA, FRANZ, DEARDEN, LORRAINE, DICKSON, MATT, VAN DER ERVE, LAURA, SIBIETA, LUKE, VIGNOLES, ANNA, WALKER, IAN, & ZHU, YU. 2018 (November). *The Impact of Undergraduate Degrees on Early-Career Earnings*. Tech. rept. Institute for Fiscal Studies.

BELL, ALEX, CHETTY, RAJ, JARAVEL, XAVIER, PETKOVA, NEVIANA, & VAN REENEN, JOHN. 2019. Who Becomes an Inventor in America? The Importance of Exposure to Innovation. *Quarterly Journal of Economics*, **134**(2), 647–713.

BIASI, BARBARA, & MA, SONG. 2020. *The Education-Innovation Gap*. Mimeo, Yale School of Management.

BILS, MARK, & KLENOW, PETER J. 2000. Does Schooling Cause Growth? *American Economic Review*, **90**(5), 1160–1183.

BLOOM, NICHOLAS, & VAN REENEN, JOHN. 2007. Measuring and Explaining Management Practices across Firms and Countries. *Quarterly Journal of Economics*, **122**(4), 1351–1408.

BLOOM, NICHOLAS, LEMOS, RENATA, SADUN, RAFFAELLA, SCUR, DANIELA, & VAN REENEN, JOHN. 2014. The New Empirical Economics of Management. *Journal of the European Economic Association*, **12**(4), 835–876.

CUBAS, GERMAN, RAVIKUMAR, B., & VENTURA, GUSTAVO. 2016. Talent, Labor Quality, and Economic Development. *Review of Economic Dynamics*, **21**, 160–181.

DALE, STACY BERG, & KRUEGER, ALAN B. 2002. Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables. *Quarterly Journal of Economics*, **117**(4), 1491–1527.

DE PHILIPPIS, MARTA, & ROSSI, FEDERICO. 2021. Parents, Schools and Human Capital Differences across Countries. *Journal of the European Economic Association*, **19**(2), 1364–1406.

DILLON, ELEANOR WISKE, & SMITH, JEFFREY A. 2017. Determinants of the Match between Student Ability and College Quality. *Journal of Labor Economics*, **35**(1), 45–66.

DOCQUIER, FRÉDÉRIC, & RAPOPORT, HILLEL. 2012. Globalization, Brain Drain, and Development. *Journal of Economic Literature*, **50**(3), 681–730.

DUTTA, SOUMITRA, LANVIN, BRUNO, RIVERA LEÓN, LORENA, & WUNSCH-VINCENT, SACHA (eds). 2021. *Global Innovation Index 2021: Tracking Innovation through the COVID-19 Crisis*. Geneva: World Intellectual Property Organization.

ENTREPRENEUR PHILIPPINES, & JOBSTREET.COM PHILIPPINES. 2017. *Which Schools Produce the Highest-Paid Employees According to JobStreet Data?* Available online at https://asksonnie.info/schools-highest-paid/. Accessed November 17, 2021.

EROSA, ANDRÉS, KORESHKOVA, TATYANA, & RESTUCCIA, DIEGO. 2010. How Important Is Human Capital? A Quantitative Theory Assessment of World Income Inequality. *Review of Economic Studies*, **77**(4), 1421–1449.

FLYNN, PATRICIA M., & QUINN, MICHAEL A. 2010. Economics: Good Choice of Major for Future CEOs. *American Economist*, **55**(1), 58–72.

GADGIL, SALIL, & SOCKIN, JASON. 2020. *Caught in the Act: How Corporate Scandals Hurt Employees*. Mimeo, UCLA Anderson School of Management and University of Pennsylvania.

GARICANO, LUIS, LELARGE, CLAIRE, & VAN REENEN, JOHN. 2016. Firm Size Distortions and the Productivity Distribution: Evidence from France. *American Economic Review*, **106**(11), 3439–3479.

GIBSON, JOHN, MCKENZIE, DAVID, ROHORUA, HALAHINGANO, & STILLMAN, STEVEN. 2018. The Long-Term Impacts of International Migration: Evidence from a Lottery. *World Bank Economic Review*, **32**(1), 127–147.

GIBSON, MATTHEW. 2021. *Employer Market Power in Silicon Valley*. Mimeo, Williams College.

GUNER, NEZIH, VENTURA, GUSTAVO, & XU, YI. 2008. Macroeconomic Implications of Size-Dependent Policies. *Review of Economic Dynamics*, **11**(4), 721–744.

HANUSHEK, ERIC A., & WOESSMANN, LUDGER. 2011. The Economics of International Differences in Educational Achievement. *Chap. 2, pages 89–200 of:* HANUSHEK, ERIC A., MACHIN, STEPHEN, & WOESSMANN, LUDGER (eds), *Handbook of the Economics of Education*, vol. 3. Elsevier.

HENDRICKS, LUTZ. 2002. How Important Is Human Capital for Development? Evidence from Immigrant Earnings. *American Economic Review*, **92**(1), 198–219.

HENDRICKS, LUTZ, & SCHOELLMAN, TODD. 2018. Human Capital and Development Accounting: New Evidence from Wage Gains at Migration. *Quarterly Journal of Economics*, **133**(2), 665–700.

HENDRICKS, LUTZ, & SCHOELLMAN, TODD. forthcoming. Skilled Labor Productivity and Cross-Country Income Differences. *American Economic Journal: Macroeconomics*.

HJORT, JONAS, MALMBERG, HANNES, & SCHOELLMAN, TODD. 2021. *The Missing Middle Managers: Labor Costs, Firm Structure, and Development*. Mimeo, Federal Reserve Bank of Minneapolis.

HOEKSTRA, MARK. 2009. The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach. *Review of Economics and Statistics*, **91**(4), 717–724.

HSIEH, CHANG-TAI, & KLENOW, PETER J. 2014. The Life Cycle of Plants in India and Mexico. *Quarterly Journal of Economics*, **129**(3), 1035–1084.

HUNT, JENNIFER, & GAUTHIER-LOISELLE, MARJOLAINE. 2010. How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics*, **2**(2), 31–56.

INTERNATIONAL MONETARY FUND. 2021. *World Economic Outlook*. Washington, DC: International Monetary Fund.

JONES, BENJAMIN F. 2014. The Human Capital Stock: A Generalized Approach. *American Economic Review*, **104**(11), 3752–3777.

KARABARBOUNIS, MARIOS, & PINTO, SANTIAGO. 2018. What Can We Learn from Online Wage Postings? Evidence from Glassdoor. *Economic Quarterly*, **104**(4), 173–189.

KERR, SARI PEKKALA, & KERR, WILLIAM. 2020. Immigrant Entrepreneurship in America: Evidence from the Survey of Business Owners 2007 & 2012. *Research Policy*, **49**(3).

KERR, SARI PEKKALA, KERR, WILLIAM, ÖZDEN, ÇAĞLAR, & PARSONS, CHRISTOPHER. 2016. Global Talent Flows. *Journal of Economic Perspectives*, **30**(4), 83–106.

KERR, WILLIAM. 2020. *Global Talent and U.S. Immigration Policy*. Working paper, Harvard Business School.

LAGAKOS, DAVID, MOLL, BENJAMIN, PORZIO, TOMMASO, QIAN, NANCY, & SCHOELLMAN, TODD. 2018. Life Cycle Wage Growth across Countries. *Journal of Political Economy*, **126**(2), 797–849.

LEMIEUX, THOMAS, MACLEOD, W. BENTLEY, & PARENT, DANIEL. 2009. Performance Pay and Wage Inequality. *Quarterly Journal of Economics*, **124**(1), 1–49.

LEVINE, ROSS, & RUBINSTEIN, YONA. 2017. Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More? *Quarterly Journal of Economics*, **132**(2), 963–1018.

MANUELLI, RODOLFO E., & SESHADRI, ANANTH. 2014. Human Capital and the Wealth of Nations. *American Economic Review*, **104**(9), 2736–2762.

MCKENZIE, DAVID, STILLMAN, STEVEN, & GIBSON, JOHN. 2010. How Important is Selection? Experimental vs. Non-experimental Measures of the Income Gains from Migration. *Journal of the European Economic Association*, **8**(4), 913–945.

METTL. 2018. *Campus Hiring: Salary & Employment Report 2018*. Available online at https://mettl.com/en/content/research/Campus-report/.

MOSER, PETRA, & SAN, SHMUEL. 2020. *Immigration, Science and Invention. Lessons from the Quota Acts*. Mimeo, New York University.

MOSER, PETRA, VOENA, ALESSANDRA, & WALDINGER, FABIAN. 2014. German Jewish Émigrés and US Invention. *American Economic Review*, **104**(10), 3222–3255.

MOUNTJOY, JACK, & HICKMAN, BRENT R. 2021. *The Returns to College(s): Relative Value-Added and Match Effects in Higher Education*. NBER Working Paper 29276.

MYBROADBAND. 2016. *South African Universities Whose Students Get the Highest Starting Salaries*. Available online at https://mybroadband.co.za/news/business/169817-south-african-universities-whose-students-get-the-highest-starting-salaries.html. Accessed November 17, 2021.

NATIONAL CENTER FOR EDUCATION STATISTICS. 2020. *Digest of Educational Statistics*. Washington, D.C.: U.S. Department of Health, Education, and Welfare, Office of Education.

OKOYE, DOZIE. 2016. Appropriate Technology and Income Differences. *International Economic Review*, **57**(3), 955–996.

PRATO, MARTA. 2021. *The Global Race for Talent: Brain Drain, Knowledge Transfer, and Economic Growth*. Mimeo, University of Chicago.

QUALITY INDICATORS FOR LEARNING AND TEACHING, SOCIAL RESEARCH CENTRE. 2019a (January). *2018 Graduate Outcomes Survey: National Report*. Available online at https://www.qilt.edu.au/qilt-surveys/graduate-employment.

QUALITY INDICATORS FOR LEARNING AND TEACHING, SOCIAL RESEARCH CENTRE. 2019b (October). *2019 Graduate Outcomes Survey: National Report*. Available online at https://www.qilt.edu.au/qilt-surveys/graduate-employment.

QUALITY INDICATORS FOR LEARNING AND TEACHING, SOCIAL RESEARCH CENTRE. 2020 (November). *2020 Graduate Outcomes Survey: National Report*. Available online at https://www.qilt.edu.au/qilt-surveys/graduate-employment.

ROSSI, FEDERICO. 2022. The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation. *American Economic Review*, **112**(1), 235–266.

SCHOELLMAN, TODD. 2012. Education Quality and Development Accounting. *Review of Economic Studies*, **79**(1), 388–417.

SCHOELLMAN, TODD. 2016. Early Childhood Human Capital and Development. *American Economic Journal: Macroeconomics*, **8**(3), 145–174.

SOCKIN, JASON. 2022. *Show Me the Amenity: Are Higher-Paying Firms Better All Around?* Mimeo, University of Pennsylvania.

Sockin, Jason, & Sockin, Michael. 2019a. *Job Characteristics, Employee Demographics, and the Cross-Section of Performance Pay*. Mimeo, University of Pennsylvania.

Sockin, Jason, & Sockin, Michael. 2019b. *A Pay Scale of Their Own: Gender Differences in Variable Pay*. Mimeo, University of Pennsylvania.

Sockin, Jason, & Sockin, Michael. 2021. *Performance Pay and Risk Sharing between Firms and Workers*. Mimeo, University of Pennsylvania.

Stanley, Brian, Pigott, Victor, & Harvey, Valerie. 2021 (June). *An Analysis of Graduate Earnings across Higher Education Institutions, Graduation Cohorts: 2010–2017*. Tech. rept. Higher Education Authority.

Stutern. 2018. *The Nigerian Graduate Report 2018*. Available online at https://www.jobberman.com/blog/stutern-nigerian-graduate-report/.

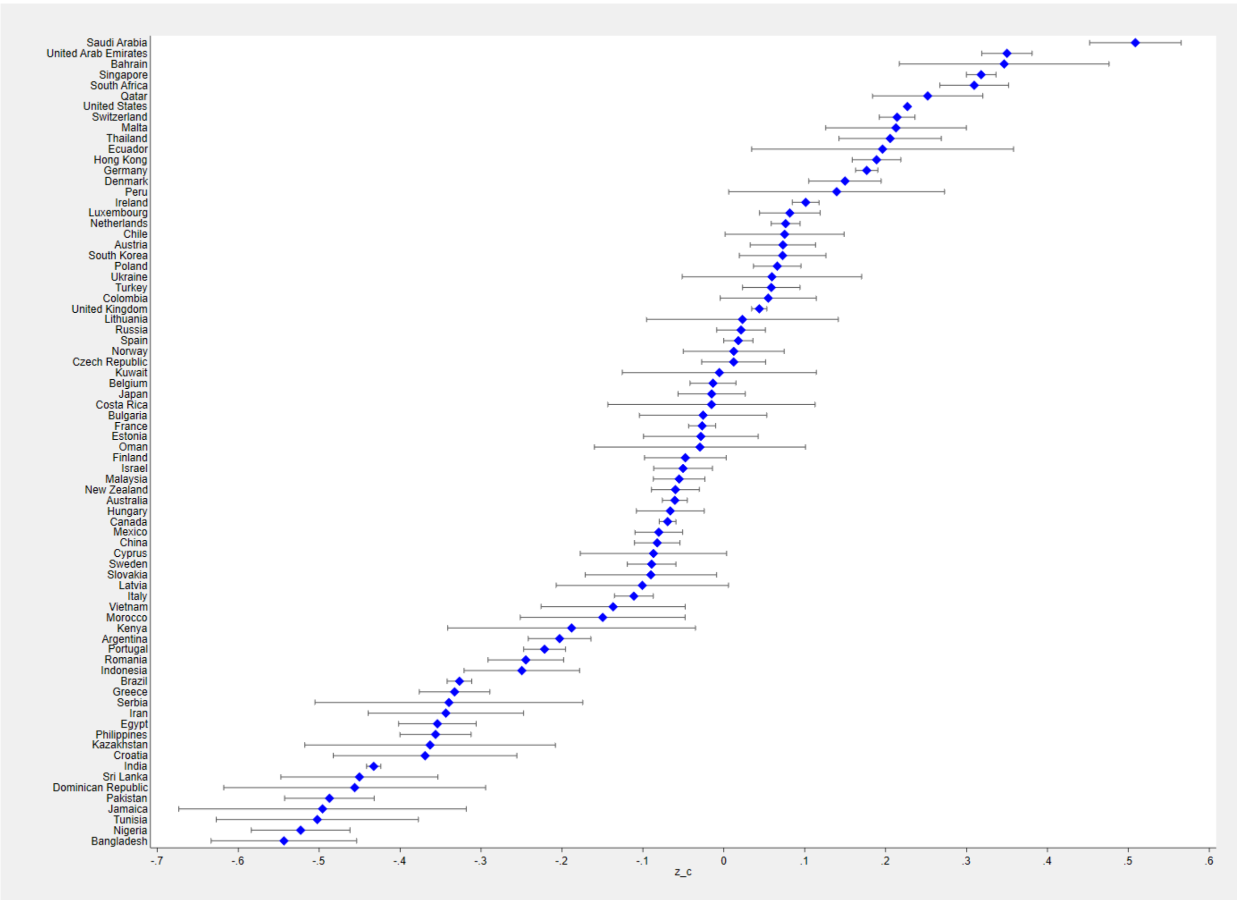
World Bank. 2021. *World Development Indicators*. Washington, DC: World Bank.

World Higher Education Database. 2021. *World Higher Education Database*. http://www.whed.net/home.php. Accessed online 1/26/2021.

Appendix

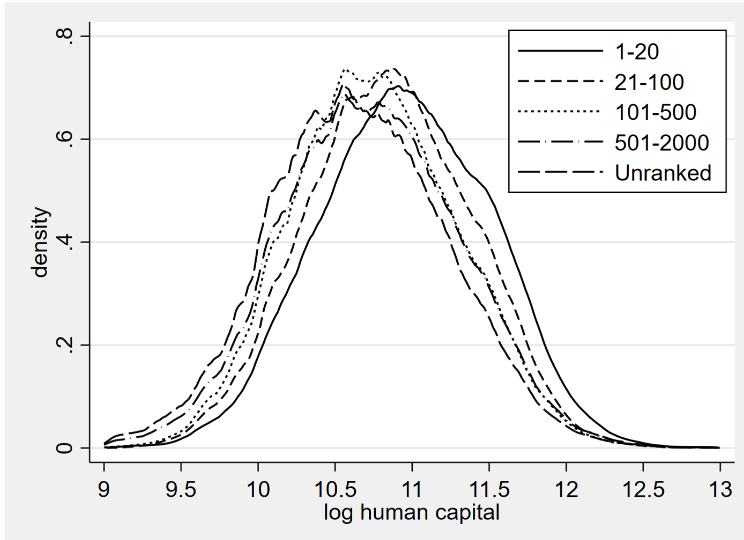
A Further Results

Figure A1: Estimated Premium to Working in Each Country



Notes: The table above displays the labor market premium from working in country c' obtained in the first estimation step ($z_{c'}$), which is estimated using migrants with earnings in multiple countries. Countries are listed in descending order according to $z_{c'}$. Sample of countries countries restricted to those that have at least 25 workers who migrate to or from the 11 countries that account for at least 2.5 percent of all migrants in the Glassdoor sample. There are 75,586 migrants in total.

Figure A2: Distribution of Country-Adjusted Earnings by CWUR Rankings Bin

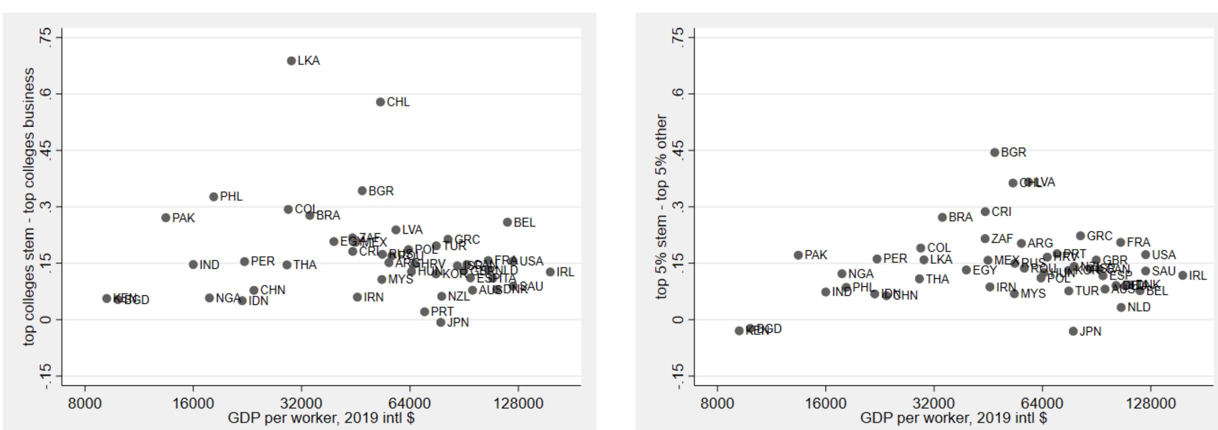


Notes: Figure plots the distribution of log human capital (earnings adjusted by z_c) for colleges binned by world ranking in the CWUR.

Figure A3: College Graduate Quality for Top Colleges, by Country and Major

(a) STEM vs. business majors

(b) STEM vs. other majors

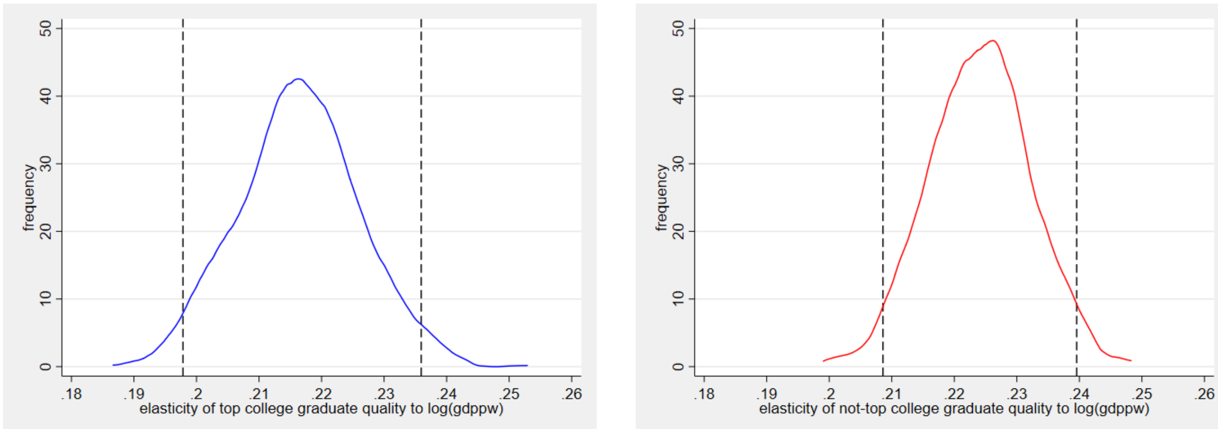


Notes: Figures display the difference in the estimated college graduate quality for STEM (science, engineering, and other technical fields) graduates relative to that of business and social science graduates (left) or STEM graduates relative to graduates of other fields (right) against PPP GDP per worker from World Bank (2021).

Figure A4: Elasticity of College Graduate Quality to Log GDPPW, Bootstrapped Samples

(a) Top Colleges

(b) Non-Top Colleges

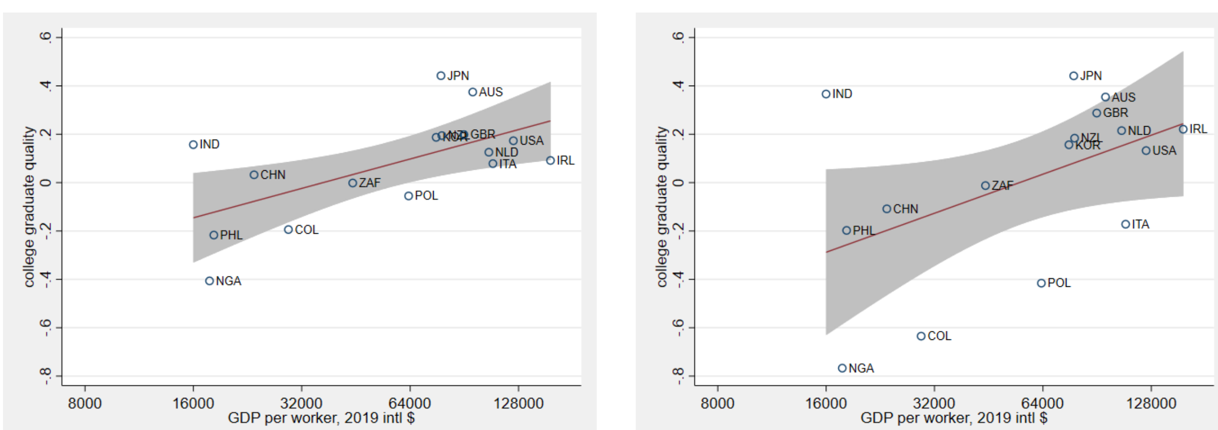


Notes: Figures plot the distribution of estimated coefficients from regressing the average quality of a country's top colleges (panel a) and non-top colleges (panel b) on the log of PPP GDP per worker from World Bank (2021) for 1,000 bootstrapped samples where for each sample, the set of migrants used in the first step is sampled with replacement, and the set of graduates' earnings used in the second step is sampled with replacement. Dashed vertical lines indicate the 2.5th and 97.5th percentiles.

Figure A5: College Graduate Quality and Development, Selection into Glassdoor Sample

(a) Without selection adjustment

(b) With selection adjustment



Notes: Figures plot the average estimated quality among the top 5 percent of colleges for the 16 nations for which we estimate an average degree of selection into the sample (Table 3: Column 8) against PPP GDP per worker from World Bank (2021) in log scale. Selection adjustment entails subtracting off the selection estimate from log earnings for the 16 countries in between steps one and two of the estimation strategy.

Table A1: College Graduate Quality and Innovation: Patents Filed in U.S. per Capita

		Incorporating college graduate quality			
		Top 2%	Top 5%	Top 10%	Top 25%
Log(gdppw)	0.638***	0.049	0.041	-0.070	-0.024
	(0.142)	(0.197)	(0.214)	(0.194)	(0.188)
College graduate quality		1.901***	2.660***	3.248***	3.200***
		(0.629)	(0.744)	(0.674)	(0.668)
Mean patents per thousands of persons	0.502	0.381	0.501	0.507	0.524
N	65	39	54	61	62
R^2	0.24	0.37	0.39	0.46	0.46

Notes: Table relates college graduate quality for a country's top colleges to utility patents filed in the United States granted to foreign nationals of each country per thousands of persons. The United States is excluded from each specification.

Table A2: Decomposition of Emigration and Immigration Effects

Country	GDP per worker ($)	Emigration: Selection on college graduate quality	Emigration: Selection on ability	Immigration: Selection on college graduate quality	Immigration: Selection on country	Immigration: Selection on ability
Kenya	9,194	0.01	0.43	-0.01	0.51	-0.28
Bangladesh	9,869	0.03	0.29	-0.06	0.31	-0.34
Vietnam	11,338	-0.01	0.42	0.00	0.46	-0.17
Pakistan	13,419	0.00	0.39	0.00	0.35	-0.31
India	15,990	0.00	0.36	0.03	0.17	-0.20
Nigeria	17,738	0.01	0.50	-0.05	0.51	-0.22
Philippines	18,234	0.03	0.36	0.03	0.48	-0.50
Indonesia	21,874	0.01	0.32	0.03	0.34	-0.18
Jamaica	21,929	0.00	0.08	.	.	.
Peru	22,201	0.00	0.26	.	.	.
China	23,584	0.00	0.21	0.03	0.01	0.08
Ukraine	27,908	0.00	0.12	.	.	.
Thailand	29,121	0.00	0.21	0.01	0.22	-0.07
Colombia	29,381	0.00	0.24	0.02	0.23	-0.27
Sri Lanka	29,965	-0.02	0.06	-0.03	0.12	-0.37
Brazil	33,731	0.10	0.41	0.03	0.46	-0.25
Dominican Republic	37,164	0.01	-0.08	.	.	.
Egypt	39,328	0.00	0.28	0.02	0.32	-0.17
Serbia	43,725	0.00	0.25	.	.	.
South Africa	44,330	0.00	0.33	0.00	0.15	-0.12
Costa Rica	44,366	0.00	0.20	.	.	.
Mexico	45,168	0.01	0.15	0.01	0.06	0.01
Iran	45,730	0.00	0.22	.	.	.
Bulgaria	47,154	0.01	0.03	-0.01	-0.01	-0.06
Chile	52,987	0.00	0.00	0.07	-0.14	-0.17
Malaysia	53,477	0.02	0.16	-0.01	0.38	-0.14
Russia	53,631	0.01	-0.06	0.05	-0.12	-0.11
Argentina	55,947	0.00	0.14	0.02	0.01	-0.34
Romania	56,978	0.00	0.12	0.01	0.12	-0.13
Cyprus	58,306	0.00	0.03	0.01	0.06	-0.13
Latvia	58,510	0.00	-0.04	.	.	.
Poland	63,386	-0.01	0.09	-0.01	0.02	-0.01
Hungary	64,641	0.00	0.03	-0.01	0.03	0.00
Croatia	65,997	0.00	-0.04	.	.	.
Estonia	66,217	0.01	0.13	.	.	.
Lithuania	68,185	0.00	0.04	0.01	0.07	-0.04
Portugal	70,275	-0.02	0.19	0.03	-0.12	0.01
South Korea	75,596	0.00	-0.01	0.06	-0.16	-0.10
Czech Republic	75,634	0.01	0.10	0.00	-0.02	0.00
Turkey	75,728	0.00	0.14	0.04	-0.03	-0.09
Japan	77,951	-0.01	-0.14	0.05	-0.37	0.02
New Zealand	78,396	0.00	0.10	0.00	-0.22	0.19
Bahrain	79,883	.	.	-0.03	0.02	-0.25
Greece	81,623	0.00	0.21	-0.01	0.16	-0.07
Malta	85,957	0.00	0.14	0.00	0.08	0.02
Israel	86,703	0.01	0.04	-0.01	-0.18	0.09
United Arab Emirates	89,182	0.01	0.12	-0.02	-0.09	-0.05
United Kingdom	90,309	0.00	0.04	0.01	-0.08	0.17
Canada	92,078	0.00	0.08	-0.01	-0.28	0.22
Spain	94,202	0.00	0.06	0.02	-0.03	0.05
Australia	95,526	-0.01	-0.18	0.02	-0.34	0.30
Finland	102,210	0.01	0.14	0.01	-0.21	0.13
Germany	102,472	0.00	-0.06	0.01	-0.33	0.20
Sweden	102,705	0.01	-0.01	0.01	-0.31	0.20
France	105,557	0.01	-0.04	0.01	-0.18	0.13
Netherlands	105,904	0.00	0.09	0.01	-0.17	0.19
Italy	108,666	-0.01	0.04	0.02	-0.10	0.06
Austria	108,866	-0.02	0.10	0.00	-0.12	0.12
Hong Kong	110,901	0.01	0.20	0.03	0.07	-0.04
Denmark	111,602	0.00	0.02	0.02	-0.32	0.21
Belgium	119,441	-0.01	0.05	0.02	-0.15	0.14
Switzerland	123,794	-0.01	-0.05	0.02	-0.28	0.23
United States	123,872	0.03	-0.01	0.01	-0.10	0.31
Saudi Arabia	123,902	0.00	-0.01	-0.03	-0.25	-0.02
Singapore	152,399	0.02	0.22	0.00	-0.04	-0.02
Ireland	157,066	0.01	0.13	0.00	-0.07	0.11

Notes: Table shows for each country GDP per worker from World Bank (2021) and the decomposition of the average human capital lost per emigrant and gained per immigrant from equations (9) and (10).

Table A3: Interaction of College Graduate Quality and Country Effect

	(1)
College graduate quality x country premium	-0.923***
	(0.026)
Years of experience	0.082***
	(0.000)
Years of experience^2 / 100	-0.173***
	(0.001)
N	2037088
Adjusted R^2	0.36

Notes: Table reflects estimates from the second estimation step for specification 4 of Table 10. College graduate quality x country premium reflects the coefficient of $q_j \times z_{c'}$.

Table A4: Earnings Growth for Post-migration Earnings Report

	(1)	(2)
Post-migration report	0.070***	0.033***
	(0.005)	(0.008)
Post-migration report x years passed		0.010**
		(0.005)
Post-migration report x years passed^2		-0.004***
		(0.001)
Mean years passed	3.1	3.1
N	153162	153162
Adjusted R^2	0.62	0.62

Notes: Table shows earnings premium that migrants earn in the sample in their second earnings report after migrating between two countries, reflecting d_S from equation (11). Standard errors are clustered by country.

Table A5: Earnings Premium by CWUR Ranking, Partitioned by Years of Experience

		Years of experience		
	All	0–2	3–9	10+
World rank: 1–20	0.426***	0.439***	0.399***	0.413***
	(0.019)	(0.024)	(0.023)	(0.023)
World rank: 21–50	0.312***	0.319***	0.315***	0.274***
	(0.019)	(0.019)	(0.021)	(0.022)
World rank: 51–100	0.305***	0.322***	0.299***	0.269***
	(0.016)	(0.019)	(0.017)	(0.022)
World rank: 101–250	0.238***	0.250***	0.230***	0.207***
	(0.010)	(0.011)	(0.012)	(0.015)
World rank: 251–500	0.190***	0.192***	0.176***	0.192***
	(0.009)	(0.012)	(0.010)	(0.014)
World rank: 501–1000	0.149***	0.144***	0.145***	0.146***
	(0.010)	(0.013)	(0.011)	(0.012)
World rank: 1001–2000	0.110***	0.090***	0.116***	0.110***
	(0.009)	(0.011)	(0.009)	(0.012)
N	2037088	784681	813926	438463

Notes: Table displays college graduate quality estimated in the whole sample (column "All") or on subsamples with the specified years of experience. Omitted category in each case is global unranked colleges (outside the top 2,000). Each regression includes a quadratic in years of experience along with year, major, and country-of-study x country-of-work fixed effects. Observations are weighted so that each college receives equal weight. Standard errors are clustered by college.

Table A6: Earnings Differences by Grade Point Average

	U.S. Colleges		Non-U.S. Colleges	
	U.S. Worker	Non-U.S. Worker	U.S. Worker	Non-U.S. Worker
Standardized z-score for GPA	0.048***	0.052***	0.028***	0.053***
	(0.001)	(0.013)	(0.004)	(0.005)
Years of experience	0.065***	0.133***	0.053***	0.153***
	(0.001)	(0.008)	(0.003)	(0.004)
Years of experienceˆ2 / 100	-0.132***	-0.342***	-0.070***	-0.370***
	(0.003)	(0.044)	(0.017)	(0.015)
N	196071	2440	18304	61040
Adjusted R^2	0.27	0.36	0.23	0.36

Notes: Table displays return to GPA estimated from Mincer earnings regressions. Data come from the subset of Glassdoor users who provide grade point average (GPA) for their bachelor's degree on their resume. We clean and convert GPA to a common metric as described in Appendix C.5, then standard normalize within each college. Columns show returns separately for graduates from U.S. and non-U.S. colleges working in and outside the United States. Columns 2 and 4 include country-of-work fixed effects. Standard errors are clustered by college.

B Comparison with Representative Data Sources

Our primary data source for our analysis is the global database of Glassdoor. Our first main results are measures of college graduate quality built on comparing earnings of workers who attend different colleges or attend college in different countries in this global database. An important question is whether the set of workers who provide data to Glassdoor is selected and particularly whether it is selected differently across countries. As discussed in the text, we compare data on earnings by college in Glassdoor to external samples with the same information for as many countries as possible.[20] In this appendix, we provide the source and details of the data construction, country by country.

B.1 Australia

Our data for Australia come from the Graduate Outcomes Survey, which is sponsored by the Australian government's Department of Education, Skills, and Employment as part of the Quality Indicators for Learning and Teaching survey program. The Graduate Outcomes Survey is online and represents most of the country's colleges and other institutions of higher education. Graduates are solicited to fill out the survey roughly six to 12 months after graduation. Our data come from the 2018–2020 surveys, when 120,000–132,000 students representing 42–44 percent of graduates (across the three years) completed the survey (Quality Indicators for Learning and Teaching, Social Research Centre, 2019a,b, 2020).

Among other indicators, the survey collects and tabulates the median annual salary by college among graduates who are employed full-time. The 2018 survey collects this data for graduates of undergraduate and graduate programs during 2017, while the 2019 and 2020 surveys collect the data only for graduates of undergraduate programs during 2018 and 2019, respectively.

To compare this dataset with Glassdoor's, we calculate the PPP- and inflation-adjusted log median earnings for each college from this external data. Then, for Australian graduates employed in Australia, we restrict our attention to those who submit an earnings report the year of, the year after, or two years after they complete their bachelor's degree. We calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the Australian data and Glassdoor data college by college. Figure B1a shows the weighted probability density function (PDF) of the difference.

[20] Insight on additional data sources would be greatly welcome.

B.2 China

Our data for China come from the report produced by the company www.xinchou.cn ("xinchou" translates as "salary" in English). The company's main business is in the area of big data human resources services and salary analysis. It provides users with business services such as salary reporting, salary research, salary analysis, salary design, performance design, salary performance training, etc. The data include monthly earnings in 2018 for 99 colleges among the graduating cohorts of 2013, 2015, and 2017.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log mean earnings for each of the three graduating cohorts for each college from this external data. Then, for Chinese graduates employed in China, we restrict our attention to those who submit an earnings report one, three, or five years after graduating. We calculate the PPP- and inflation-adjusted log mean earnings among each cohort's graduates for each college. We then take the difference between the Chinese data and Glassdoor data fore each college and cohort. Figure B1b shows the weighted PDF of the difference.

B.3 Colombia

Our data for Colombia is derived from the Observatorio Laboral de Educación, which is a dataset constructed by the Ministry of Education that combines information on recent graduates, the college they attended, and their formal sector earnings from tax records. We access the data from the Vinculación Laboral de Recién Graduados.[21] The most recent data cover the average annual earnings of 2015 graduates during the 2016 year.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college from this external data. Then, for Colombian graduates employed in Colombia, we restrict our attention to those who submit an earnings report the year of, the year after, or two years after they complete their bachelor's degree. We calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the Colombian data and Glassdoor data by college. Figure B1c shows the weighted PDF of the difference.

B.4 India

Our data from India come from a report produced by consulting company Mettl (Mettl, 2018). They derive the data by surveying placement officers at a range of institutions about the typical salaries for new graduates in a given year (in this case, 2018). Given

[21] Available at http://bi.mineducacion.gov.co:8380/eportal/web/men-observatorio-laboral/tasa-de-cotizacion-por-ies. Accessed February 15, 2021.

this design, they focus on a narrow set of graduates with engineering and management degrees. This information is still useful for our purposes because these graduates are overrepresented in our database and these institutions are ranked among the highest in quality in our global ranking.

Engineering salaries are for graduates from undergraduate programs. Colleges are organized into groups, with top Indian Institutes of Technology and National Institutes of Technology representing two groups. Salaries are given for the whole as well as for four subgroups: computer science/information technology, electrical engineers, mechanical engineers, and civil engineers.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college from this external data. Then, for Indian graduates employed in India, we restrict our attention to those who submit an earnings report the year of or the year after they complete their bachelor's degree. We calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the Indian data and Glassdoor data by college. Figure B1d shows the weighted PDF of the difference.

B.5 Ireland

Our data from Ireland come from Stanley *et al.* (2021). Their results are derived from the Educational Longitudinal Database, an administrative dataset that links information on pre-college characteristics, college and program of attendance, and post-college earnings. They study the 2010–2017 college graduation cohorts over years 2011–2018. They adjust all earnings to real 2016 euros and estimate the average raw and adjusted weekly earnings by college. We focus on the exponential of estimated mean log earnings four years after graduation, where the regression includes college dummies (to capture earnings by college) and cohort dummies (to capture wage growth over time). All figures exclude the self-employed. Workers' earnings are attributed to their most recent degree.

For Irish graduates employed in Ireland in Glassdoor, we restrict attention to those who do not have a graduate degree and who submit an earnings report one to eight years after they complete their bachelor's degree. We adjust all earnings to 2016 dollars and divide by 52 to approximate weekly earnings. We estimate log weekly earnings as a function of college, graduation cohort, and year. We exponentiate mean residual log earnings by college. We then take the difference between the measure from Stanley *et al.* (2021) and Glassdoor by college. Figure B1e shows the weighted PDF of the difference.

B.6 Italy

Our data from Italy come from AlmaLaurea.[22] AlmaLaurea is a partnership between Italian colleges that jointly represent 90 percent of college graduates. AlmaLaurea conducts annual interviews with graduates from partner colleges and collects information about their post-degree labor market experience. Graduates report their net monthly income either one year after graduation (bachelor's degree) or one, three, and five years after graduation (master's degree).

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college from this external data, multiplying earnings by 125 percent to approximate pre-tax earnings. Then, for Italian graduates employed in Italy, we restrict our attention to those who submit an earnings report the year of or the year after they complete their bachelor's degree. For each college, we calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the Italian data and Glassdoor data college by college. Figure B1f shows the weighted PDF of the difference.

B.7 Japan

Our data from Japan come from Diamond Online.[23] Diamond Online is a Japanese journal that reported in an article earnings data from graduates who registed with the recruiting agency Openwork. The sample consisted of college graduates who registered between March 2018 and January 2021. It comprised 115,265 graduates spanning 206 universities. Graduates report their age and average annual income. Diamond Online reported the average annual income (in ten thousand yen) for graduates 25, 30, 35, 40, and 45 years of age at the top thirty universities (according to average earnings at age 30).

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college for each of the five ages from this external data. Then, for Japanese graduates employed in Japan, we restrict our attention to those who submit an earnings report at the ages of 24–26, 29–31, 34–36, 39–41, or 44–46. For each college, we calculate the PPP- and inflation-adjusted log median earnings among graduates for each college in each of the five age groups. We then take the difference between the Japanese data and Glassdoor data college by college. Figure B1g shows the weighted PDF of the difference.

[22] Data for 2009-2018 are available at `https://www.almalaurea.it`.

[23] Data are available at `https://diamond.jp/articles/-/264142?page=2`. We thank Akihisa Kato for helping to locate and translate the data.

B.8 The Netherlands

Our data for The Netherlands are based on the Monitor Wetenschappelijk Onderwijs (WO-Monitor) 2013, a survey of the 2013 graduating cohort 12–18 months after leaving college. The survey provides median gross monthly earnings. We access the results from a presentation prepared by one of the universities for public dissemination.[24]

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college from this external data. Then, for Dutch graduates employed in the Netherlands, we restrict our attention to those who submit an earnings report the year after or two years after they complete their bachelor's degree. We calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the Dutch data and Glassdoor data by college. Figure B1h shows the weighted PDF of the difference.

B.9 New Zealand

Our data from New Zealand draw on information provided by the Ministry of Education.[25] It uses the Integrated Data Infrastructure of Statistics New Zealand to calculate the median earnings of graduates by age range, degree level, field of study, and institution of study, taken from administrative tax data. Earnings are taxable earnings from wages and salary, paid parental leave, ACC compensation and self-employment during the years 2015–2018 (tax years 2016–2019). We use undergraduate earnings for those in the age group "less than 25 years old" one, three, five, seven, and nine years after, by college.

To compare this dataset with Glassdoor's, we calculate the PPP- and inflation-adjusted log median earnings for each cohort from each college in this external data. Then, for New Zealand graduates employed in New Zealand, we restrict our attention to those who submit an earnings report within nine years of completing their bachelor's degree. We assign those who submit a pay report the year of or the year following their graduation year to cohort 1, those who submit a report two or three years after to cohort 2, four or five years after to cohort 3, six or seven years to cohort 4, and eight or nine years to cohort 5. For each college and cohort, we then calculate the PPP- and inflation-adjusted log median earnings among these graduates, and aggregate to the college level. We then take the difference between the New Zealand data and Glassdoor data by college. Figure

[24] Available online at https://www.eur.nl/sites/corporate/files/Presentatie_WO_Monitor_2013.pdf. Accessed November 16, 2021.

[25] Data and description available at https://www.education.govt.nz/further-education/information-for-tertiary-students/employment-outcomes/, accessed February 15, 2021.

B1i shows the weighted PDF of the difference.

B.10 Nigeria

Our data from Nigeria come from a report produced by consulting company Stutern (Stutern, 2018). It recruited respondents via social media and email and conducted offline surveys in states with less widespread internet penetration. Stutern attracted more than 5,200 responses from graduates from the 2013–2018 cohorts. Among the information collected and reported is average annual salary among employed graduates from 20 universities.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log mean earnings for each college from this external data. Then, for Nigerian graduates employed in Nigeria, we restrict our attention to those who submit an earnings report within the first five years after graduation. We calculate the PPP- and inflation-adjusted log mean earnings among these graduates for each college. We then take the difference between the Nigerian data and Glassdoor data by college. Figure B1j shows the weighted PDF of the difference.

B.11 Philippines

Our data from Philippines come from a report produced by Entrepreneur Philippines & JobStreet.com Philippines (2017). The latter is an online jobs portal with data on job, earnings, and university for tens of thousands of workers in the country. They use this data to estimate average monthly earnings for new graduates and graduates with 1–5 years of experience from the 15 most common universities in the country.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log mean earnings for each college from this external data. Then, for Filipino graduates employed in the Philippines, we restrict our attention to those who submit an earnings report within the first five years after graduation. We calculate the PPP- and inflation-adjusted mean earnings for new graduates, meaning those that report earnings the same year as graduation, by college. We then repeat the same calculation for graduates reporting earnings between 1–5 years after graduation. We then take the difference between the Filipino data and Glassdoor data by college. Figure B1k shows the weighted PDF of the difference.

B.12 Poland

Our data from Poland draw on the Polish Graduate Tracking System commissioned by the Polish Ministry of Education and Science.[26] The underlying data on earnings draw on administrative tax data. The figures are gross monthly earnings for 2014–2018 graduates in year 2018, who have zero to one years of experience, one to two years of experience, and so on. We collect data for graduates from undergraduate (first-cycle) programs at all ranges of experience from the class of 2018.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log median earnings for each cohort from each college in this external data. Then, for Polish graduates employed in Poland, we restrict our attention to those who submit an earnings report within five years of completing their bachelor's degree. We assign those who submit a pay report the year of or the year following their graduation to cohort 1, those who submit a report one or two years after to cohort 2, two or three years after to cohort 3, three or four years to cohort 4, and four or five years to cohort 5. By construction, most graduates will belong to two cohorts. For each college and cohort, we then calculate the PPP- and inflation-adjusted log median earnings among these graduates. We then take the difference between the Polish data and Glassdoor data by college. Figure B11 shows the weighted PDF of the difference.

B.13 Singapore

Our data from Singapore draw on the Graduate Employment Survey conducted annually since 2013 by a varying set of universities in Singapore and provided by the Ministry of Education.[27] Graduates are surveyed approximately six months after graduation. The database provides gross mean and median monthly earnings by college and degree. We take the simple average of earnings across degrees to arrive at up to six earnings figures for each college, representing business, engineering, humanities/arts/sciences, education, computer science, and biological and physical sciences.

In Glassdoor, we restrict our attention to Singaporean graduates employed in Singapore from a handful of universities available in the Graduate Employment Survey, specifically Nanyang Technological University, National University of Singapore, and Singapore Institute of Management, each of which has earnings by major-cohort. Then, for Singaporean graduates employed in Singapore, we restrict our attention to those who submit

[26] Data and documentation available at https://ela.nauka.gov.pl/en, accessed February 15, 2021.

[27] Data for 2013–2018 available at https://data.gov.sg/dataset/graduate-employment-survey-ntu-nus-sit-smu-suss-sutd, accessed on February 15, 2021. Data for 2019–2020 were combed from various press releases from the Ministry of Education website.

an earnings report the year of or the year after they complete their bachelor's degree. For each college, we calculate the PPP- and inflation-adjusted log mean earnings among these graduates for each college-major-cohort, and aggregate to the college level. We then take the difference between the Singaporean data and Glassdoor data by college. Figure B1m shows the weighted PDF of the difference.

B.14 South Africa

Our data from South Africa come from a report produced by MyBroadband, a South African technology and business news website (MyBroadband, 2016). The site surveyed almost 6,000 South Africans about their alma mater, the year they started working, and annual starting salary. It restricted attention to graduates who started work in the 10 years prior, adjusted the starting salaries for inflation and wage growth, and then reported the average salary for 17 of the country's largest and leading universities.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log mean earnings for each college from this external data. Then, for South African graduates employed in South Africa, we restrict our attention to those who submit an earnings report within two years after graduation (corresponding to a starting salary). We calculate the PPP- and inflation-adjusted log mean earnings among these graduates for each college. We then take the difference between the South African data and Glassdoor data by college. Figure B1n shows the weighted PDF of the difference.

B.15 South Korea

Our data from South Korea come from the Korean Education and Employment Panel.[28] The dataset reflects a sample of about 6,000 students who have been surveyed annually since they were in middle school in 2004. Respondents are asked which college they attended and their labor income (in ten thousand South Korean won) in 2017. We consider workers who report annual or monthly earnings, and annualize monthly earnings assuming 12 months of work.

To compare this dataset with Glassdoor's, we calculate the annualized PPP- and inflation-adjusted log mean earnings for each college from this external data by restricting the sample to college graduates, using representing sample weights, and calculating within graduation cohort up to 12 years after graduation. Then, for South Korean graduates employed in South Korea, we restrict our attention to those who submit an earnings report

[28]Data are available at `https://www.krivet.re.kr/ku/ha/kuCAFLs.jsp`. We thank Hoyoung Yoo for helping to locate and translate the data.

within 12 years of graduating. We calculate the PPP- and inflation-adjusted log mean earnings among each cohort's graduates for each college. We then take the difference between the South Korean data and Glassdoor data by college-cohort. Figure B1o shows the weighted PDF of the difference.

B.16 United Kingdom

Our data from the United Kingdom come from Belfield *et al.* (2018). They use the Longitudinal Educational Outcomes, an administrative dataset that links information on pre-college characteristics, college and program of attendance, and post-college earnings. The authors use this data to undertake a rich set of exercises. Their online data appendix includes information on outcomes by colleges.[29] We use the data in their Table 15, "Raw average earnings by HEI [higher education institution]," which focuses on the cohort of students who are 29 in the year 2015–2016 (the 2002 GCSE cohort). They report average earnings by gender and college in 2018 prices. We use the deflator to adjust prices back to 2015–2016 levels and take the simple average of earnings between the genders by college. Their earnings figures restrict attention to those who are in sustained employment and exclude self-employment, but include students who started and then dropped out from a college, who are 7.7 percent of all students who start college.

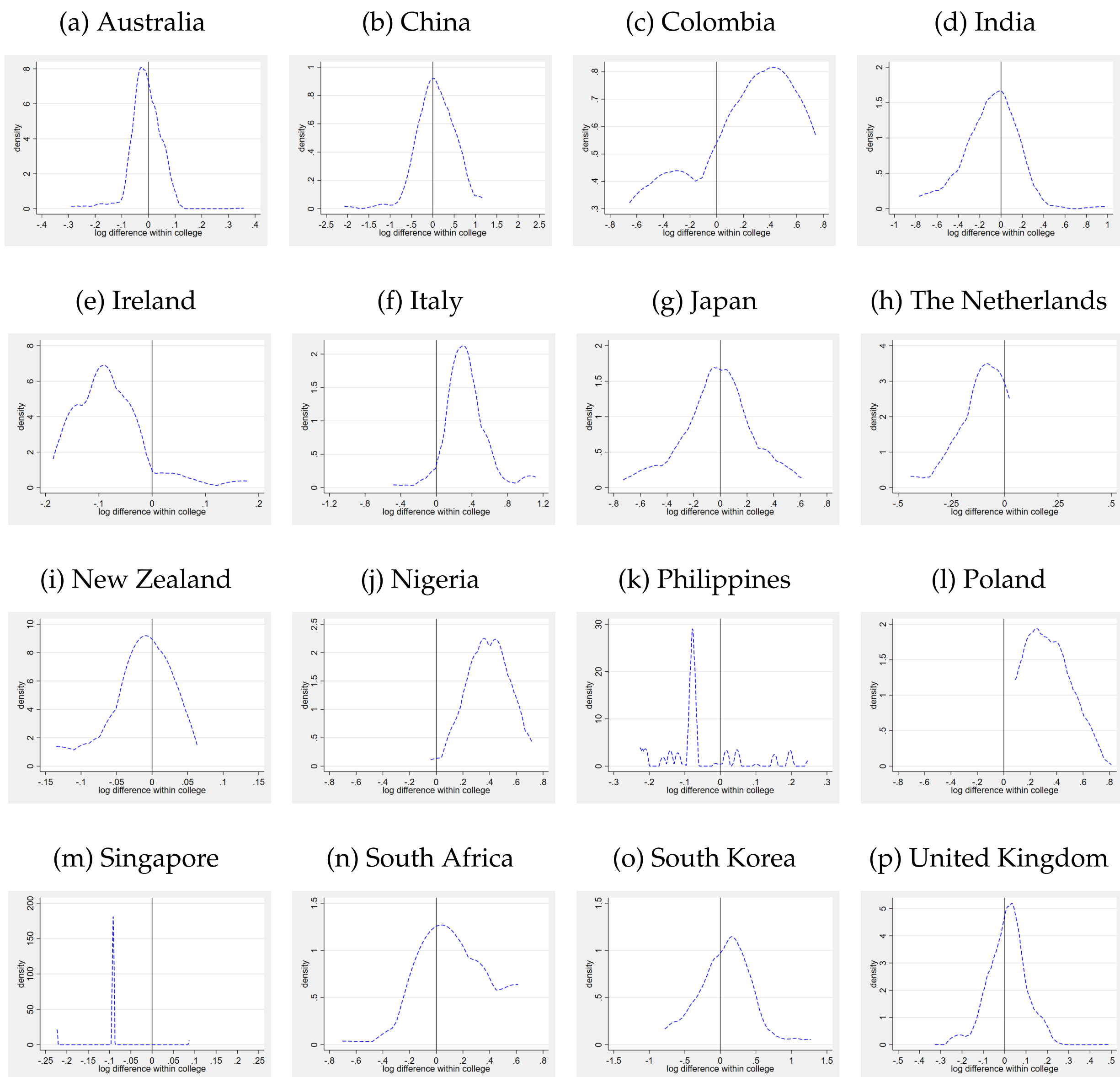
For U.K. graduates employed in the United Kingdom in Glassdoor, we restrict our attention to those who submit an earnings report six to eight years after they complete their bachelor's degree. For each university, we calculate the PPP- and inflation-adjusted log median earnings among these graduates for each college. We then take the difference between the measure from Belfield *et al.* (2018) and Glassdoor by college. Figure B1p shows the weighted PDF of the difference.

B.17 United States

Our data from the United States are from the U.S. Department of Education's College Scorecard database.[30] Figure 1 shows the weighted PDF of the difference in average wage by college between Glassdoor and the Scorecard.

[29] Available at `https://www.ifs.org.uk/publications/13731`, accessed February 15, 2021.
[30] Available at `https://collegescorecard.ed.gov/`, accessed 12/1/2020.

Figure B1: International Sample Selection into Glassdoor



Notes: Figures above capture the degree to which college graduates in Glassdoor are representative of each nation's graduates more broadly. The figures above are weighted probability density functions of the log difference between the median log wage for college graduates in Glassdoor for each university compared with the median log wage from external data. Sample sizes for each country are shown in Table 3.

C Data Details: Glassdoor Data

This section includes details of the Glassdoor data and sample selection. Given the free response nature of workers' resumes, we devote substantial effort to cleaning and harmonizing college information.

C.1 College Name

We start by standardizing college names. For U.S. institutions, we match entries against a list of all four-year colleges and their subsequent abbreviations or pseudonyms available through the Integrated Postsecondary Education Data System (IPEDS).[31] For non-U.S. colleges, we first rely on lists of colleges made available through uniRank and the Center for World University Rankings. We then manually add colleges that are not included on either of these two lists yet have appreciable coverage on Glassdoor.

C.2 Degree Assignment

For degrees, we take a fully supervised approach, textually matching keywords into categories. We consider seven categories: bachelor's, associate's, master's, postgraduate, MBA, JD, and PhD. For each college degree grouping, we match based on locating the keywords, or in the case of abbreviations, perfectly matching the phrases, listed below:

Bachelors: (ba), (bs), ab, b a, b com, b e, b ed, b eng, b s, b sc, b tech, ba, ba , baas, babs, baccalaureate, baccalauréat, bach, bacharel, bacharelado, bachelor, barch, bas, basc, bba, bbm, bbm, bbs, bca, bcom, bcom, bcom , bcomm, be, be in, bed, beng, bfa, bgs, bm, bms, bpharm, bs, bs , bs , bsa, bsba, bsc, bsc, bsc , bsc in, bscit, bscs, bse, bsee, bsme, bsn, bsw, btec, btec, btech, graduação, llb, mbbs.
Postgraduate: certificate of secondary education, graduate certificate, graduate diploma, higher secondary certificate, p g diploma, pg[a-z]*diploma, pgdm, post graduate, post graudation diploma, post[a-z]*diploma, postgraduate, professional diploma, pós graduação, pósgraduação.
Masters: llm, m a, m com, m ed, m eng, m s, m sc, m tech, ma, ma , ma in, masc, master, mca, mcom, mdiv, me, meng, mfa, mlis, mls, mm, mms, mpa, mph, mphil, mps, ms, ms , ms in, msa, msc, msc in, mse, msed, msee, msn, msw, mtech.
MBA: m b a, master[a-z]*business administration, mba.
JD: doctor[a-z]*jurisprudence, j d, jd, juris doctor.
PhD: doctor[a-z]*philosophy, doctoral, doctorate, ph d, phd.

C.3 Major Assignment

We also take a fully supervised approach to cleaning majors. We consider eleven categories that extend the "Major Field Categories" delineated by the National Survey of Student Engagement, available at *NSSE 8 Major Categories*, as well as the degree fields used by the American Community Survey, available at ACS DEGFIELD Codes. The resulting categories are arts and humanities, biological sciences, business, communications, education, engineering, health services, physical sciences, social sciences, social services,

[31] We rely primarily on the string matching algorithm *fuzzymatch*, available through Python, to match resume entries with the external college list, confirming whether each match is correct after it is made. We also exclude abbreviations for which the corresponding institution is not uniquely determined. For example, we exclude "MSU," since it can refer to Michigan State University or Montana State University.

and technology. All majors that do not fall within these eleven categories are assigned to an "other" category. Additionally, we include a "missing" category for workers who do not include a corresponding major with their degree. For each grouping, we match based on locating the keywords or, in the case of abbreviations, perfectly matching the phrases, listed below:

Arts and Humanities: Acting, Animation, Archaeology, Architect, Art, Bfa, Biblical, Chinese, Cinema, Classics, Clothing, Cultural, Dance, Design, Drama, English, Fashion, Film, French, German, History, Humanities, Illustration, Italian, Japan, Jornalismo, Journalism, Language, Liberal Studies, Linguistics, Literature, Mfa, Music, Painting, Philosophy, Photo, Playwrit, Religion, Religious, Rhetoric And Composition, Russian, Screenwrit, Sculpture, Spanish, Speech, Theater, Theatre, Theology, Vocal Performance, Writing.
Biological Sciences: Agricult, Agronomy, Animal, Animal Science, Atmospheric, Bacteriology, Biochem, Bioinform, Biological, Biology, Biomed, Biophysics, Bioscience, Biostatistics, Biotech, Botany, Ecology, Environment, Environmental Science, Food Science, Forestry, Genetics, Horticult, Life Science, Marine Science, Microbiology, Natural Resources, Natural Science, Neurobiology, Neuroscience, Physiology, Plant, Psychobiology, Sustainability, Zoology.
Business: Accountancy, Accounting, Actuarial, Administración De Empresas, Administração, Administração De Empresas, Advertising, BCom, Banking, Bba, Bcom, Bookkeeping, Buisness, Business, Ciências Contábeis, Commerce, Corporate, Customer Service, Employment Relations, Entrepreneur, Entreprenuer, Financ, Gestão, Hospitality, Hotel, Hr, Human Relations, Human Resource, Industrial, Insurance, Labor Relations, Leadership, Logistics, Logística, Manaerial, Management, Marketing, Mba, Merchandising, Mis, Operations, Organisation, Organization, Organizational Leadership, Publicidade E Propaganda, Real Estate, Sales And Distribution, Strategic, Strategy, Supply, Tax, Tourism.
Communication: Audio Production, Broadcast, Communication, Esl, Event Planning, Journalism, Media, Media, Multimedia, Public Relations, Publishing, Speech, Telecomm, Television, Translation, Video Production, Visual Effects.
Education: Child Development, Curriculum, Early Childhood, Education, Elementary, Teach.
Engineering: Aeronautic, Bioengineering, Ece, Ee, Eee, Electrical, Electronic, Engenharia, Engineer, Materials, Mech Eng, Mechanical, Mechatronics, Welding.
Health Service: Allied Health, Athletic Training, Audiology, Behavior Analysis, Bpharm, Bsn, Clinical, Cna, Dent, Dietetics, Emt, Enfermagem, Epidemiology, Exercise, Exercise Science, Health, Health Care, Health Sciences, Health Service, Health Studies, Health Technology, Health and Wellness, Healthcare, Hospital Administration, Human Development, Immun, Kinesiology, Laboratory, Lpn, Medic, Mental Health, Nurse, Nursing, Nutrition, Occupational, Optometry, Paramedic, Pediatrics, Personal Train, Pharmac, Phlebot, Physical Therapist, Physician, Physician Assistant, Physio, Pre-Health, Pre-Med, Pre-Vet, Premed, Public Health, Radiography, Radiologic, Radiology, Rehabilitation, Respiratory Care, Rn, Sports and Fitness, Therapy, Veterinar.
Physical Sciences: Analytics, Astronomy, Astrophysics, Chemistry, Computational, Earth Science, General Science, Geochemistry, Geological, Geology, Geophysics, Geoscience, Math, Meteorology, Physical Science, Physics, Quantitative, Química, Science, Statistics.
Social Service: Archival Science, Arquitetura E Urbanismo, Counseling, Criminal, Criminal Justice, Criminology, Direito, Fire Science, Forensic, Forensics, Homeland Security, Human Rights, Human Services, Jd, Juris Doctor, Jurisprudence, Justice, Law, Legal, Library, Military Science, Museum, Paralegal, Police, Public Administration, Public Affairs, Public Policy, Public Safety, Public Service, Regional Planning, Social Care, Social Service, Social Work, Socialwork, Urban Planning, Welfare.
Social Sciences: American, Anthropology, Asian Studies, Behavioral Science, Cognitive Science, Decision Science, Development Studies, Econom, Econôm, Ethnic Studies, European Studies, Family And Consumer Sciences, Foreign, Gender Studies, Geography, Global, Government, International, International Relations, Politic, Political Science, Psicologia, Psycholog, Psycolog, Relações Internacionais, Social Science, Social Work, Sociology, Urban Studies, Women's Studies.
Technology: BTech, Bca, Cis, Ciência Da Computação, CompSc, Computer, Computing, Cs, Cse, Cyber, Data, Informatics, Information, Informatique, Informática, It, It Program, It Security, MTech, Machine

Learning, Mca, Network, Sistemas De Informação, Software, System, Technology, Tecnologia, Tecnologia Da Informação, Web.

C.4 Sample Selection

As noted in the text, most of our sample consists of workers for whom we know the specific college where they completed their bachelor's degree. In order to increase our coverage of foreign colleges, we also explore including workers who attended only a single college but do not report the degree, under the hypothesis that this was likely a bachelor's degree.

To limit the possible impact of measurement error, we include only workers from colleges that meet two criteria. First, there must be at least 20 but fewer than 25 workers with bachelor's degrees from the institution in the data. Second, at least 90 percent of graduates from the college who do report a degree report bachelor's degrees.

Two alternative approaches would be either to conduct no imputation and use only workers for whom a bachelor's degree is clearly delineated in the resume, or to impute all workers with missing degrees as undergraduates. The correlation between our benchmark q_j and those obtained under the former is 1.000 (not surprising since the imputation involves only institutions that would have been excluded) between 3,323 institutions and under the latter is 0.980 between 3,368 institutions.

C.5 Grade Point Average

This section explains how we clean grade point average (GPA) to a common scheme. We confront three challenges. The first is that while the United States uses a scale that ranges from 0–4, other countries use different scales. The second is that migrants sometimes translate their GPA to the local context to provide potential employers more meaningful information. The third is that even within a country, colleges may have different GPA distributions, due, for example, to grade inflation.

We start by identifying which country's GPA scale a worker uses on her resume. For non-migrants, we assume it is the relevant country's GPA scale. For migrants it is generally clear from the context. For example, while U.S. GPA ranges from 0–4, India's two most commonly used scales range from 0–100 (with 30 as the cutoff for a passing grade) and 0–10 (with 4.0 as the cutoff for a passing grade). For cases in which it is not clear, we discard the observation.

We then translate each country's GPA scale to the U.S. scale, relying on available mappings. For India, we rely on the college-specific and broader mapping from Scholaro. For the United Kingdom, we use the rubric from the US-UK Fulbright Commission, and for the rest of the OECD, we use the rubric from the OECD. This step ensures that our results are consistent across countries.

Finally, we standard normalize reported GPA within each college. This step ensures that our results are consistent across colleges within a country.

D Data Details: Other Data Sources

This appendix contains details on the data sources for entrepreneurs and innovators. We collect the names of all Nobel Prize winners between 1990 and 2020 in the four main scientific categories (physics, chemistry, medicine, and economics).[32] We use Wikipedia to identify where each winner received her undergraduate degree. For some winners, the first degree was a master's degree (common particularly in Germany); we assign that university as the undergraduate degree.

We collect the names and colleges of CEOs of S&P 500 firms as of May 2021 from Wikipedia.[33] We identify where they received their undegraduate degree from information provided by Wikipedia, their LinkedIn profile, or from profiles provided on company websites.

We cannot link patents for non-Americans to specific inventors or universities. However, we can link them to countries. We use the U.S. Patent and Trademark Office database on patents granted by geographic location and year for the years 2010–2019.[34] We focus on utility patents granted to foreign nationals and sum across all years of the decade.

[32] https://en.wikipedia.org/wiki/List_of_Nobel_laureates, accessed online 5/7/2021.
[33] https://en.wikipedia.org/wiki/List_of_S%26P_500_companies, accessed 5/10/2021.
[34] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_stco.htm, accessed 5/5/2021.