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Abstract

We develop a global measure of college quality based on the earnings of each college's graduates around the world. We use a new database that details earnings and alma maters for a large number of natives and migrants, who are key to our identification strategy. We find that: i) college quality is an important determinant of earnings, as graduates of top colleges earn 57 percent more than graduates of typical colleges, ii) college quality is strongly correlated with development, as graduates from the richest countries earn 65 percent more than graduates of the poorest countries in the same labor market, and iii) college quality predicts innovation and entrepreneurship across countries and colleges. Last, we estimate average human capital for migrants by origin-destination pair. We show that developing countries lose more to brain drain and a small set of OECD countries gain more from global talent flows than traditional measures based on numbers of skilled migrants alone would suggest.

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

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1 Introduction

Internationally standardized achievement tests point to large cross-country differences in primary and secondary education quality.[1] These test scores are an essential building block for work demonstrating the importance of education quality for a country's income level and growth rate.[2] Existing testing programs do not extend to tertiary education, leaving us with little evidence on the extent of cross-country variation in college quality. This absence is notable given the growing evidence that college quality plays an important role in human capital formation and innovation within the United States.[3]

We address this gap by developing a measure of college quality that is meaningfully scaled and comparable across countries. Our approach builds on recent work that evaluates colleges within a country based on their graduates' earnings. We implement a generalization of this approach that ranks colleges around the world on the same basis. Our measure provides new insights relative to the standard, proxy-based rankings of colleges. For example, it ranks the quality of the very top colleges in developing countries much higher. Nonetheless, the covariance between average college quality and gross domestic product (GDP) per worker is positive and large, indicating that college quality is an important contributor to cross-country human capital and income differences. We then show that college quality is closely related to the global supply of top talent by linking it to measures of entrepreneurs and innovators across countries and across colleges within a country.

Our analysis utilizes the proprietary database of the website Glassdoor.[4] The website collects information on job and pay from users in return for providing comparisons to their peers. Many users also upload their resumes, which provide detailed educational histories. The database includes a sample of earnings for 1.4 million workers who obtained a Bachelor's degree from 2,872 different colleges in 48 countries. Many countries in our sample produce similar earnings data for graduates who are employed domestically, such as the "College Scorecard" released by the U.S. Department of Education. We

[1] Most prominently, the OECD's PISA exams are administered to 15 year-olds, while the U.S. Department of Education's TIMSS exams are administered to students in grades 4 and 8.

[2] See Hanushek and Woessmann (2011), Schoellman (2012), and Cubas et al. (2016).

[3] We use the word college throughout for institutions that offer accredited, four-year tertiary education. See Card and Krueger (1992) and Heckman et al. (1996) on cross-state variation in education quality in the United States. Bell et al. (2019) shows that invention in the United States is concentrated among graduates of a narrow set of colleges; Biasi and Ma (2020) show these colleges are high-quality, as measured by their propensity to teach frontier rather than out-of-date knowledge.

[4] This database has also been used to explore the drivers of variable pay (Sockin and Sockin, 2019a), the use of variable pay to reduce firm-level volatility (Sockin and Sockin, 2021), and the pass-through of firm-specific shocks to worker compensation (Gadgil and Sockin, 2020). This paper is the first to explore differences between colleges.

show that in this case our ranking agrees closely with this existing information both in terms of the level of earnings and the rank correlation across colleges.

These rankings cannot be compared across countries without further work. The challenge goes beyond the usual problem with currencies and exchange rates. More fundamentally, the earnings of Oxford and Indian Institute of Technology (IIT) graduates reflect the human capital of graduates as well as the influence of the very different countries where they work. We want to isolate the former. The key to making progress on this issue is that the Glassdoor database includes a large sample of workers who report earnings for multiple countries. These migrants provide information that makes it possible to adjust for the effect of country and construct an internationally comparable measure of college quality.

Our approach can be understood using a hypothetical worker who graduates from an IIT, works in India, and subsequently migrates to and works in the United Kingdom. The worker's post-migration earnings are informative about how her human capital compares to that of Oxford graduates within a common country. This particular worker is generally not the average IIT graduate. However, we can compare the migrant's pre-migration earnings to those of other IIT graduates within India to measure where the migrant fits in the overall earnings distribution and adjust for selection. An alternative way to understand this approach is that the change in earnings at migration informs us about the importance of country of work for earnings of college workers, as in Hendricks and Schoellman (2018).[5] We then apply this estimated country effect to all graduates to put them on a common footing. Our implementation builds on this intuition, using the data provided by migrants among a large set of countries.

Our estimates show that alma mater matters. As a first approach, we estimate the earnings gain from attending top colleges based on the rankings of the Center for World University Rankings (CWUR), one of the more widely used proxy-based rankings. We find that graduates of their top-20 colleges earn 57 percent more than graduates of unranked colleges. That figure is in line with standard estimates on the total earnings premium for attending college in the United States.[6] Alternatively, we construct our own ranking based solely on earnings. Our ranking is positively correlated with existing global and within-country rankings (correlation coefficients 0.38 and 0.61). However, it gives new insights along several dimensions. For example, selective liberal arts colleges perform much better in our rankings than in existing ones. There are also many more

[5]We follow also a large literature that uses 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; Rossi, 2020).

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

colleges from developing countries at the top of our rankings, particularly those that focus on science and technical education. The most striking example is that four of the top ten colleges in our rankings are different branches of the IITs, which rank in the 500–1000 range in CWUR rankings. Those low rankings seem inconsistent with the high salaries their graduates command throughout the world.

We aggregate our findings to the country level and study their importance for growth and development. The quality of a nation's colleges in various percentile bins is strongly correlated with development, with the estimated elasticity centered on 0.2. This finding seems to hold equally well for top and median colleges, suggesting that college quality is uniformly lower in poorer countries. To put these figures into perspective, graduates of our richest countries' colleges would be expected to earn about 65 percent more in the same labor market compared with graduates of the poorest countries' colleges.

The quality of a nation's colleges is particularly important for the supply of top talent responsible for much of entrepreneurship and innovation. We link our measures of college quality to data on where chief executive officers (CEOs) of S&P 500 firms, Nobel laureates, and patent holders receive their undergraduate degrees. We show that college quality is a robust predictor of each for both Americans and non-Americans. The relationship holds at the country level, even if we also control for Gross Domestic Product (GDP) per worker. It holds at the college level, even if we control for country fixed effects. These findings reinforce the view that college quality is an important determinant of a nation's ability to develop leading firms and undertake innovation.

We also use our data to provide new evidence on brain drain and global talent flows. The existing literature documents that less developed countries lose skilled workers (brain drain) and that they mostly migrate to a small subset of OECD countries (global talent flows). We add to this body of work by providing new evidence on the average human capital per emigrant and per immigrant for each country in our database. We document that less developed countries lose more from brain drain because their emigrants are also significantly positively selected on average human capital. We also find that global talent flows are more concentrated than what is implied by traditional quantity-based measures because only a subset of developed countries attract skilled migrants with average human capital that exceeds that of natives.

The remainder of the paper is organized as follows. Section 2 details our empirical approach, while section 3 overviews the Glassdoor data that make it feasible. Section 4 gives our main results, while section 5 provides details on sensitivity. Section 6 presents our results for global talent flows. Finally, section 7 provides a brief conclusion.

2 Methodology

In this section we present the methodology that allows us to build an internationally comparable, earnings-based measure of college quality. Our baseline analysis builds on three assumptions that are widely used in the literature that draws inferences about cross-country human capital differences from the experiences of migrants. First, we assume the marginal product of labor is log-separable with respect to the effects of country, college quality, and worker's ability.[7] Second, we assume that labor markets are perfectly competitive, which implies that wages are equal to the marginal product of labor. Third, we assume that a worker supplies the same human capital in any country where he or she might work. This assumption rules out both difficulty among migrants in transferring their skills to their new country or migrants having (and sorting along) country-specific skills. We investigate the sensitivity of our analysis to departures from these assumptions in Section 5.

Under these assumptions, the wage of worker i who earned her bachelor's degree from college j in country c and is employed in country c' is given by

$$\log(w_{i,j,c,c'}) = z_{c'} + q_j + \varepsilon_{i,j,c,c'}. \tag{1}$$

Here, $z_{c'}$ is the effect of country of work (e.g., total factor productivity), q_j is the quality of college j, and $\varepsilon_{i,j,c,c'}$ is the ability of worker i.

We normalize $\mathbb{E}[\varepsilon_{i,j,c,c}] \equiv 0$, which implies that q_j is the average human capital of graduates from college j. We think of this measure as the relevant information for potential employers, which might use alma mater to draw inference about an applicant's skills. As we show in Section 4, this measure is also a strong predictor of innovation and entrepreneurship. Our measure of quality is distinct from the college's value added, which may be the more relevant measure of quality for students or policymakers. As we discuss below, our data do not allow us to pursue this interesting avenue.

Migrants play an essential role in our identification by allowing us to estimate and adjust for the effect of country $z_{c'}$. While non-migrants are not selected, migrants may be. In our baseline analysis, we assume that selection is the same for migrants from any college j in c who are employed in c'. This assumption implies that we have to control for average selection $\bar{\varepsilon}_{c,c'}$ for each origin-destination pair (c, c'). This is the fourth assumption of our benchmark approach that we investigate further in Section 5.

[7] Hendricks and Schoellman (2018) show that a Cobb-Douglas aggregate production function and perfect substitution among workers with different levels of human capital is one way to satisfy this assumption.

2.1 Identification

We illustrate the sources of variation in the data that allow us to compare college quality across countries. In doing so, we highlight the minimal set of observations needed to address the threats to identification that arise both from cross-country differences in productivity that are unrelated to human capital and selection into migration.

Consider, for simplicity, the case of two countries, c and c', and three groups of workers: stayers in c denoted by S_c, movers from c to c' denoted by $M_{c,c'}$, and stayers in c' denoted by $S_{c'}$. Let $\bar{w}_{y,c}$ be the average earnings of workers in group $y = \{S_c, M_{c,c'}, S_{c'}\}$ and country c. Under specification (1), we can express average earnings as

$$
\begin{aligned}
\bar{w}_{j,S_c,c} &= q_j + z_c \\
\bar{w}_{j,M_{c,c'},c} &= q_j + z_c + \bar{\varepsilon}_{c,c'} \\
\bar{w}_{j,M_{c,c'},c'} &= q_j + z_{c'} + \bar{\varepsilon}_{c,c'} \\
\bar{w}_{j',S_{c'},c'} &= q_{j'} + z_{c'},
\end{aligned}
\tag{2}
$$

where j and j' denote colleges in country c and c', respectively. In what follows, we omit the indices j and j' from the expressions for average wages since we consider one college per country. We are interested in estimating the difference in (log-)quality $q_j - q_{j'}$. Combining the equalities from equation (2), it is easy to show that

$$
q_j - q_{j'} = (\bar{w}_{S_c,c} - \bar{w}_{S_{c'},c'}) - (\bar{w}_{M_{c,c'},c} - \bar{w}_{M_{c,c'},c'}). \tag{3}
$$

That is, the quality gap between schools j and j' is given by the difference in wage between stayers in those countries, $\bar{w}_{S_c,c} - \bar{w}_{S_{c'},c'}$, net of the wage change experienced by movers from country c to c', $\bar{w}_{M_{c,c'},c} - \bar{w}_{M_{c,c'},c'}$.

To gain intuition into why all three sets of workers are necessary for our analysis, consider two alternative scenarios in which information on either movers from or stayers in country c were missing. In the first scenario, we would obtain

$$
(q_j - q_{j'}) + (z_c - z_{c'}) = (\bar{w}_{S_c,c} - \bar{w}_{S_{c'},c'}). \tag{4}
$$

Absent movers, it would not be possible to distinguish the cross-country earnings gap that is attributable to differences in school quality from other country-specific determinants of productivity. In the second scenario, if we replaced the missing observation from stayers in country c, $\bar{w}_{S_c,c}$, with that of movers from the same country, $\bar{w}_{M_{c,c'},c}$, we could only recover

$$(q_j - q_{j'}) + \bar{\varepsilon}_{c,c'} = (\bar{w}_{M_{c,c'},c} - \bar{w}_{S_{c'},c'}) - (\bar{w}_{M_{c,c'},c} - \bar{w}_{M_{c,c'},c'}). \tag{5}$$

Equation (5) shows that we cannot infer differences in the *average* human capital of college graduates across countries without using stayers in both countries, except under the assumption that movers are representative of the college graduate population, i.e. $\bar{w}_{S_c,c} = \bar{w}_{M_{c,c'},c}$ or $\bar{\varepsilon}_{c,c'} = 0$. As shown in section 6, this assumption is strongly rejected by the data.

2.2 Estimation Procedure

In practice, the structure of the Glassdoor database leads us to use a two-step estimation process for extracting our three coefficient vectors of interest: i) the earnings premium specific to country of work $z_{c'}$, ii) the selection in unobserved quality among graduates who migrate for work $\bar{\varepsilon}_{c,c'}$, and iii) school quality q_j. The first step uses workers who report earnings in more than one country. On this sample, we estimate

$$\log(w_{i,t,c'}) = z_{c'} + \lambda_i + \beta X_{it} + \varepsilon_{i,t,c'}. \tag{6}$$

where λ_i are worker fixed effects and X_{it} includes a quadratic in years of experience and year fixed effects. Intuitively, this equation estimates how much earnings grow at migration (after adjusting for time and changes in work experience) and assigns this gain 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 $\bar{\varepsilon}_{c,c'}$ and q_j are jointly estimated from the larger sample of workers who provide information on where they attained their bachelor's degree and at least one earnings report. On this sample, we estimate

$$\log(w_{i,j,c,c'}) - z_{c'} = q_j + \gamma X_{it} + \bar{\varepsilon}_{c,c'} + \eta_{i,j,c,c'}, \tag{7}$$

where X_{it} includes a quadratic in years of experience along with major of study and year fixed effects, and $\eta_{i,j,c,c'} = \varepsilon_{i,j,c,c'} - \bar{\varepsilon}_{c,c'}$ is a mean-zero residual. We now turn to the dataset that makes implementing this two-step procedure possible.

3 Data

The primary data source for our work comes from the online platform Glassdoor, where workers can 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 pay report, gain access to the reviews and pay reports submitted (anonymously) by others. Users provide Glassdoor with a wealth of information. First, users are asked when registering to provide a resume, which 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 in order to receive new or updated comparisons. Consequently, our earnings data consist of employee-employer matches with a rich set of worker observables.

We have access to the full database on earnings spanning the years 2006–2020. Later years contribute disproportionately to the sample as Glassdoor has become more widely used over time. We impose several sample restrictions throughout to ensure comparability and limit measurement error. First, we restrict our attention to only full-time employees to avoid imputing hours worked. Second, we annualize labor earnings, assuming that full-time hourly workers are employed two thousand hours per year and full-time monthly workers are employed twelve 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.[8] Last, we exclude workers for whom the currency of earnings does not match their country of employment's predominant currency, and winsorize the top and bottom 0.1% of earnings to limit the influence of any outliers.

As detailed in Section 2.2, we follow a two-step estimation process. 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 migrants (emigrants or immigrants) to or from the ten countries with the most migrants in Glassdoor to be included in our sample. 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 73,000 workers migrating among 55 countries around the world; see appendix table A1 for details. As discussed in Section 2, we would also be interested in constructing a value-added measure of college quality, if possible. How-

[8] 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% of salaried workers in Glassdoor abroad (table A-5 of Sockin and Sockin (2019b)) report earning variable income, Sockin and Sockin (2019a) estimate that variable pay accounts for 4–7% of employee labor income.

ever, the nature of the Glassdoor database is such that very few workers submit earnings reports from before and after they graduate college, rendering this estimation infeasible.[9]

The second step uses earnings net of the effect of country to estimate college quality. This step requires joint evidence 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. Resumes typically contain data on educational attainment; around one-half of resumes contain information regarding college and degree that we can use after cleaning. We keep information for the colleges where the respondent received their bachelor's degree and their most advanced post-bachelor's degree, if one is present. We clean and standardize information on the college name, the degree attained, major, and grade point average. Our benchmark sample includes workers who report their alma mater and for whom we know or can infer with a high probability that the degree in question was a bachelor's degree. See Appendix C for further details.

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. Our sample for the second stage consists of 1.4 million workers with data on undergraduate alma mater and earnings from 2,872 colleges in 48 different countries, with 1,318 colleges residing outside of the United States. We are able to capture global college quality because our sample has sufficient coverage of graduates from universities outside the United States: 372,000 workers who received their bachelor's degree outside the United States, 65% of which are then 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 2000 colleges, which provides a natural comparison for our earnings-based rankings. Each college included in the list is also assigned a national ranking, which we use to compare top colleges between countries. To adjust earnings by inflation and purchasing power parity (PPP), we obtain purchasing PPP-adjusted exchange rates from World Bank (2020). To analyze the import of country-specific income, we obtain PPP-adjusted GDP per worker from World Bank (2020). To adjust for the number of colleges per country we use the data provided by World Higher Education Database (World Higher Education Database, 2021).

[9] Alternatively, we could estimate pre-collegiate earnings, as in Belfield et al. (2018). Glassdoor also has limited information for doing so.

Table 1: Summary of Global College Coverage

Country	Abb.	GDP per worker ($)	Colleges		Graduates	
			Overall	Top 5%	Domestically	Abroad
Bangladesh	BGD	9,661	16	1	524	1,100
Pakistan	PAK	13,299	30	4	1,748	2,596
India	IND	15,722	289	24	130,078	49,841
Nigeria	NGA	17,724	31	4	1,272	2,333
Philippines	PHL	18,031	75	2	5,058	4,591
Indonesia	IDN	21,670	16	1	1,015	377
China	CHN	22,977	133	46	1,257	12,832
Thailand	THA	28,898	11	4	546	414
Colombia	COL	29,103	11	5	134	608
Brazil	BRA	33,645	41	21	3,542	1,358
Egypt	EGY	38,698	24	2	3,178	2,290
South Africa	ZAF	44,370	13	2	1,217	1,415
Mexico	MEX	45,198	24	8	1,173	1,300
Iran	IRN	45,915	15	10	221	1,994
Bulgaria	BGR	46,839	5	1	162	207
Chile	CHL	52,647	2	2	36	100
Malaysia	MYS	53,222	29	4	3,042	956
Russia	RUS	53,319	9	4	240	591
Argentina	ARG	56,252	6	1	259	305
Romania	ROU	56,288	10	3	551	683
Poland	POL	62,843	12	9	354	418
Hungary	HUN	64,450	10	1	534	341
Portugal	PRT	70,406	7	4	272	236
Turkey	TUR	74,854	25	8	2,229	1,942
South Korea	KOR	75,170	25	9	432	1,472
Czech Republic	CZE	75,376	3	2	77	89
Japan	JPN	77,951	6	5	130	248
New Zealand	NZL	78,314	7	1	641	1,059
Greece	GRC	82,353	14	1	796	882
Israel	ISR	86,447	18	1	2,489	1,078
United Arab Emirates	ARE	89,182	2	0	102	82
United Kingdom	GBR	90,885	131	12	34,281	14,184
Canada	CAN	91,897	80	7	26,405	7,263
Spain	ESP	94,672	28	5	1,003	1,436
Australia	AUS	95,166	35	4	4,300	7,019
Germany	DEU	102,505	7	4	125	171
Sweden	SWE	102,530	3	1	67	157
France	FRA	105,775	11	1	185	403
Netherlands	NLD	105,986	17	3	537	513
Italy	ITA	109,284	34	4	1,516	2,174
Hong Kong	HKG	110,352	9	0	1,817	551
Denmark	DNK	111,352	4	1	83	215
Belgium	BEL	119,767	6	2	130	210
United States	USA	123,239	1,554	92	1,029,946	14,969
Switzerland	CHE	123,657	1	0	27	32
Saudi Arabia	SAU	124,616	4	2	205	77
Singapore	SGP	151,616	9	0	5,122	493
Ireland	IRL	153,923	20	2	2,451	1,557
Total	48		2,872	330	1,271,509	145,162
Total excluding USA	47		1,318	238	241,563	130,193

Notes: Table lists the 48 countries for which we can estimate college quality for at least one college. Each row gives country name and abbreviation, GDP per worker (annual average from 2010–2020, from World Bank (2020), number of colleges for which we can estimate quality, and the number of graduates from those colleges employed domestically and abroad.

3.1 Sample Validation

All of our results rest on analysis of the Glassdoor database. This naturally raises the question of whether our sample is representative of the underlying population. Karabarbounis and Pinto (2019) show that Glassdoor wage data broadly match first and second moments of the earnings distribution by industry and by region in the United States using data from the Quarterly Census for Employment and Wages and the Panel Study of Income Dynamics. Sockin and Sockin (2019b) find correlations of about 0.9 and 0.8 for the first and second moments of total income between industry and three-digit standard occupation category occupations in the United States using the American Community Survey. We add to this evidence by comparing mean earnings by college between Glassdoor and representative samples from select countries.

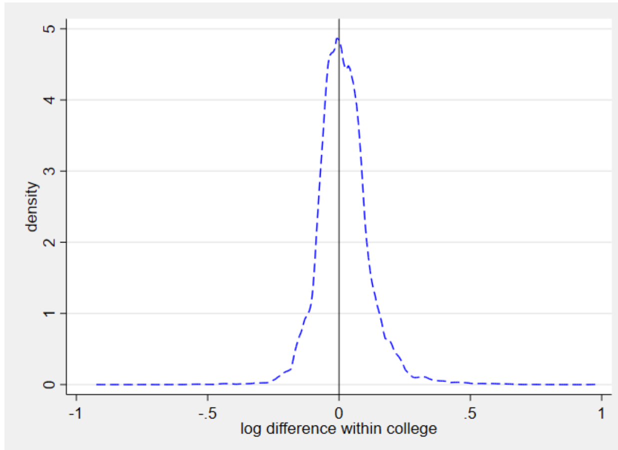
We start with the United States. The United States Department of Education publishes a "College Scorecard" that uses tax data from the United States Treasury to provide "median earnings of graduates working and not enrolled 1 [2] year[s] after completing highest credential." The median earnings data is 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 resumes. We match these observations to the College Scorecard data by college, degree, major, and years since graduation, which captures 78,000 workers in Glassdoor from 1,429 colleges.

The difference in log earnings between Glassdoor and the College Scorecard data provides a measure of selection at the college, degree, major, and cohort level. We aggregate this measure of selection to the college level (using the Glassdoor sample as weights) and plot the density of college-level selection in Figure 1. The distribution is symmetric, centered on zero, and has small tails. This indicates that Glassdoor provides an unbiased sample of earnings by college in the United States.

Our goal is to measure college quality using earnings of graduates around the world. An important concern is that Glassdoor may be less representative in other countries where the platform has a smaller presence. To provide evidence on this concern, we repeat the same selection exercise using nine other countries for which we have been able to find representative data on earnings by college. The details for each country are laid out in Appendix B.

Table 2 summarizes some of the key results of these exercises for all ten countries. For each country it shows their PPP GDP per worker, the number of colleges and graduates in Glassdoor that we match to representative data sources, and the resulting estimates of selection. Overall selection varies by country and appears correlated with development,

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



Notes: Figure captures 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.

consistent with the hypothesis that Glassdoor users are a more selected segment of the college graduate workforce in developing countries. Our main result in this paper is that college quality is lower in developing countries as measured by earnings in Glassdoor. If workers who participate in Glassdoor are more selected in developing countries, this only works to strengthen the result. We also compare selection for the top five percent of colleges versus other colleges within each country, where the top five percent are based on CWUR rankings for each country. The degree of selection is similar for most countries and there is no clear pattern with respect to development. With these results in hand, we now turn to using the sample to estimate college quality.

Table 2: Sample Selection into Glassdoor for Select Nations

	GDP per	Colleges		Graduates		Average selection estimate ($\hat{\omega}_j$)		
Country	worker ($)	Overall	Top 5%	Overall	Top 5%	Overall	Top 5%	Other 95%
India	15,722	31	10	400	163	-0.09	-0.13	-0.06
China	22,977	3	–	155	–	0.71	–	–
Colombia	29,103	11	2	25	6	0.11	0.09	0.11
Poland	62,843	19	10	394	263	0.28	0.33	0.19
New Zealand	78,314	7	1	398	160	-0.01	0.02	-0.03
United Kingdom	90,885	116	12	4070	534	0.03	-0.11	0.05
Australia	95,166	36	4	565	153	-0.01	0.01	-0.02
Italy	109,284	28	3	67	25	0.31	0.35	0.28
United States	123,239	1429	95	77939	20818	0.02	0.00	0.03
Singapore	151,616	4	0	340	0	-0.15	–	-0.15

Notes: Table above summarizes the average selection into Glassdoor data for ten 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 Section B of the Internet Appendix.

4 Main Results

The two-step estimation procedure outlined in Section 2 along with the Glassdoor data described in Section 3 allow us to estimate the earnings premium for 48 countries and college quality for 2,872 colleges. Appendix table A1 shows the estimated country effect, $z_{c'}$, which generally lines up with, but varies much less than, GDP per worker. This result is similar to the finding in Hendricks and Schoellman (2018). In this section, we highlight our first main results of interest: the estimates of college quality and their importance for entrepreneurship and innovation.

4.1 Measuring College Quality

We start by using our estimates of college quality to provide an economically significant scale to the widely-used CWUR rankings. To do so, we estimate the average quality for colleges in various ranking bins (e.g., 1–20, 21–50, etc.) as compared to unranked (outside the global top 2000) colleges. The results are shown in table 3, along with standard errors and the number of colleges in each ranking bin included in our sample. Our analysis excludes colleges that have fewer than twenty-five graduates who report earnings in Glassdoor. There is a statistically and economically significant premium for graduating from a highly-ranked college. The premium grows from 12 log points for colleges ranked 1001–2000, to 33 log points for colleges ranked 51–100, and reaches a substantial 45 log points (57 percent) for colleges ranked in the top twenty. To put this last number into perspective, we note that the college earnings premium is 59 percent in the United States in 2019 (see footnote 6 for details and source). That is, the earnings difference between attending a college ranked in the global top twenty instead of outside the global top 2000 is nearly as large as the earnings difference between attending college or not in the United States.

Table 3: College Premia and CWUR World Ranking

	World ranking						
	1–20	21–50	51–100	101–250	251–500	501–1000	1001–2000
College quality	0.452***	0.359***	0.329***	0.267***	0.197***	0.163***	0.118***
	(0.045)	(0.041)	(0.033)	(0.019)	(0.015)	(0.012)	(0.011)
	[19]	[23]	[36]	[104]	[174]	[276]	[335]

Notes: Table displays our measure of (log) college quality q_j as a function of various ranking groups from the Center for World University Rankings. Omitted category is unranked (below 2000). Standard errors are in parentheses and number of colleges in our sample within each bin in brackets.

Alternatively, we can construct our own global ranking based on the estimated quality of each college. The top 100 colleges are shown in table 4. We focus on broad trends rather than the ranking of any particular school, which may be affected by noise in estimated college quality. 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), 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 two. First, selective liberal arts colleges do much better in our ranking than in the CWUR ranking. Fourteen of the top one hundred colleges are U.S. liberal arts colleges.[10] Second, our ranking emphasizes much more colleges with a technical orientation from around the world. The most notable example is the dominance of the Indian Institutes of Technology at the top of the rankings. While these colleges are typically ranked in the 500–1000 range in CWUR, we argue that these rankings are not commensurate with the earnings their graduates command around the globe.

One potential concern with these and subsequent results is that they may reflect signaling and university prestige rather than human capital. The fact that our ranking diverges from standard ones provides one piece of evidence against this hypothesis. As a second piece of evidence, we estimate the return to standard normalized GPA within each college. We find a large return to GPA for migrants and non-migrants, in the United States and around the world. See table A2 for details. We view this return as further evidence that employers pay for human capital rather than prestige.

Although interesting, the ranking in table 4 uses data from only 100 of our 2,872 total colleges. Our next results focus on the overall distribution of college quality by country and its contribution to cross-country human capital and income differences.

4.2 College Quality and Cross-Country Human Capital Differences

In this section we show that college quality is systematically related to GDP per worker. This finding implies that the common practice of focusing on the share of a nation's workforce that has graduated college understates cross-country differences in the supply of skilled labor.

The Glassdoor data have better coverage of graduates from top colleges. Given this, we start by focusing on the quality of top colleges by country and how it correlates with development. We consider two notions of top colleges: either the average quality of a

[10] They are Amherst, Barnard, Claremont McKenna, Colgate, Cooper Union, Harvey Mudd, Haverford, Middlebury, Pomona, Swarthmore, US Air Force Academy, Washington and Lee, Wesleyan, and Williams.

Table 4: Top 100 Colleges By Estimated Quality

				College quality						College quality	
Rank	College	Country	World ranking	Graduates	q_j	Rank	College	Country	World ranking	Graduates	q_j
1	Indian Institute of Information Technology Allahabad	IND	.	55	0.46	51	Université Paris-Dauphine	FRA	885	26	0.26
2	University of Pennsylvania	USA	9	600	0.43	52	Swarthmore College	USA	815	288	0.26
3	Keio University	JPN	86	64	0.42	53	Indian Institute of Technology, BHU	IND	1519	116	0.26
4	Indian Institute of Technology Kanpur	IND	830	173	0.38	54	The American University of Paris	FRA	.	84	0.26
5	Indian Institute of Technology Delhi	IND	548	145	0.38	55	Babson College	USA	940	597	0.26
6	Sophia University	JPN	1837	77	0.38	56	Technische Universität Darmstadt	DEU	476	25	0.26
7	Harvard University	USA	1	325	0.37	57	Queensland University of Technology	AUS	390	390	0.25
8	Indian Institute of Technology Kharagpur	IND	674	266	0.36	58	United States Air Force Academy	USA	.	473	0.25
9	Emory University	USA	90	203	0.35	59	Western Sydney University	AUS	516	321	0.25
10	Indian Institute of Technology Guwahati	IND	969	154	0.34	60	Australian Catholic University	AUS	1176	57	0.25
11	Indian Institute of Technology Bombay	IND	587	136	0.34	61	Middlebury College	USA	1947	443	0.25
12	Indian Institute of Technology Roorkee	IND	788	218	0.33	62	Tokyo University of Science	JPN	654	27	0.25
13	California Institute of Technology	USA	11	220	0.33	63	Santa Clara University	USA	1125	1509	0.25
14	Columbia University in the City of New York	USA	6	451	0.33	64	Cornell University	USA	14	334	0.25
15	Waseda University	JPN	168	92	0.33	65	Rice University	USA	109	661	0.25
16	United States Naval Academy	USA	1220	985	0.32	66	United States Merchant Marine Academy	USA	.	94	0.25
17	Cooper Union for the Advancement of Science and Art	USA	.	122	0.32	67	Vanderbilt University	USA	46	56	0.25
18	Williams College	USA	1295	335	0.32	68	Sciences Po	FRA	618	38	0.24
19	The University of Tokyo	JPN	13	41	0.32	69	Technion – Israel Institute of Technology	ISR	111	413	0.24
20	The Interdisciplinary Center	ISR	.	26	0.31	70	The Business School	GBR	.	85	0.24
21	University of Canberra	AUS	1087	108	0.31	71	École Polytechnique de Montréal	CAN	.	27	0.24
22	The University of Sydney	AUS	100	584	0.31	72	Macquarie University	AUS	371	444	0.24
23	Brown University	USA	45	963	0.31	73	Amherst College	USA	458	314	0.24
24	University of Chicago	USA	10	113	0.31	74	Flinders University	AUS	509	45	0.24
25	Indraprastha Institute of Information Technology	IND	.	26	0.31	75	The University of Queensland	AUS	115	449	0.24
26	Carnegie Mellon University	USA	84	1576	0.31	76	Washington and Lee University	USA	1356	233	0.24
27	Dartmouth College	USA	49	965	0.31	77	Hadassah Academic College	ISR	.	27	0.24
28	Universität Hamburg	DEU	176	35	0.31	78	University of Notre Dame	USA	140	1833	0.24
29	Netaji Subhas University of Technology	IND	.	250	0.31	79	University of Tasmania	AUS	408	105	0.23
30	University of Michigan-Ann Arbor	USA	17	354	0.30	80	University of California-Berkeley	USA	8	8856	0.23
31	Southern Cross University	AUS	1409	88	0.30	81	Colgate University	USA	856	678	0.23
32	The University of Melbourne	AUS	64	601	0.30	82	Monash University	AUS	102	1018	0.23
33	Claremont McKenna College	USA	1036	301	0.30	83	Stevens Institute of Technology	USA	1027	551	0.23
34	Harvey Mudd College	USA	.	184	0.30	84	Barnard College	USA	.	389	0.23
35	St. Louis College of Pharmacy	USA	.	42	0.30	85	Haverford College	USA	1155	220	0.23
36	Copenhagen Business School	DNK	1098	82	0.30	86	Rose-Hulman Institute of Technology	USA	.	466	0.23
37	Australian National University	AUS	108	206	0.29	87	University of Waterloo	CAN	179	1906	0.23
38	Washington University in St Louis	USA	41	72	0.29	88	Yeshiva University	USA	229	246	0.22
39	Technical University of Munich	DEU	76	41	0.29	89	The London School of Economics and Political Science	GBR	293	367	0.22
40	Yale University	USA	12	58	0.28	90	Freie Universität Berlin	DEU	71	43	0.22
41	United States Military Academy	USA	1009	991	0.28	91	Wesleyan University	USA	707	637	0.22
42	Cranfield University	GBR	804	26	0.28	92	Dhirubhai Ambani Institute of Information and Communication Technology	IND	.	116	0.22
43	Georgetown University	USA	203	111	0.28	93	College of the Holy Cross	USA	893	500	0.22
44	Tufts University	USA	94	1244	0.28	94	Pomona College	USA	1054	336	0.22
45	The University of New South Wales	AUS	113	666	0.28	95	La Trobe University	AUS	529	210	0.22
46	Charles Sturt University	AUS	1025	137	0.28	96	Massachusetts Maritime Academy	USA	.	134	0.22
47	University of Technology Sydney	AUS	463	329	0.27	97	Yonsei University	KOR	161	241	0.21
48	Samuel Merritt University	USA	.	49	0.27	98	Lehigh University	USA	449	1226	0.21
49	Kyoto University	JPN	21	26	0.27	99	Indian Institute of Technology Madras	IND	600	154	0.21
50	University of Copenhagen	DNK	39	44	0.26	100	Griffith University	AUS	379	237	0.21

Notes: Table displays the one-hundred schools with the highest estimated quality ranking in descending order, along with the country where it is located, its place in the the Center for World University Rankings, the number of students in our sample, and the estimated quality. School quality is normalized relative to The University of Texas at Austin.

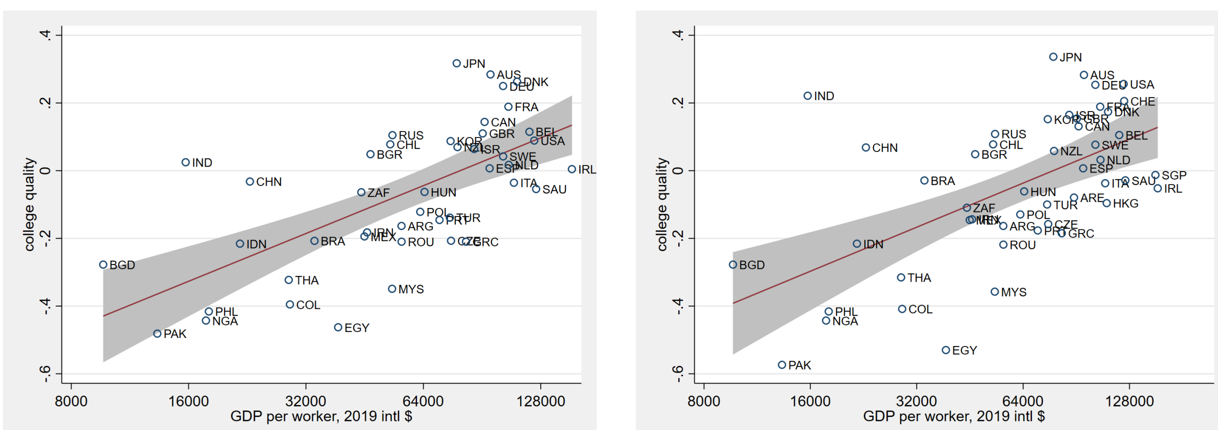
nation's top five colleges, or the average quality of its top five percent of colleges. Top colleges are based on nation-specific CWUR rankings, which include only colleges ranked in the global top 2000. To convert absolute rankings to percent rankings, we normalize by the total number of colleges by country from World Higher Education Database (2021). We exclude countries with fewer than twenty total colleges when calculating the top five percent. The resulting estimates of top college quality are plotted against PPP GDP per worker in Figure 2.

The key insight from this plot is that higher GDP per worker is associated with better college quality. Again, the effect is economically and quantitatively significant. The regression line indicates that top universities in the richest countries have college quality about 50 log points higher than top universities in the poorest countries, indicating that graduates from rich nations' top universities earn 65 percent more in the same labor market. The overall trend relationship is similar whether we use the top five percent of colleges (Figure 2a) or the top five colleges (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 percent rankings for the remainder of the paper.

Figure 2: Returns to Nations' Top Colleges

(a) Relative national ranking (Top 5%)

(b) Absolute national ranking (Top 5)



Notes: Figures plot the average estimated quality among the top five 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 (2020) in log scale.

This first finding is quantitatively consistent with the broader literature on cross-country differences in human capital. For example, Schoellman (2012) estimates overall education quality by country using Census data for the United States. His findings imply an elasticity of overall education quality with respect to development of 0.19. The slope of the regression line in Figure 2a corresponds to an elasticity of 0.20, a strikingly similar number.

An advantage of our work relative to Schoellman (2012) is that we estimate the quality of specific colleges rather than assuming that each country has a single education quality. We utilize this fact to estimate for the first time how the distribution of college quality varies with development. To do so, we split each country's colleges into various percentile ranges based on CWUR rankings and regress their quality against log GDP per worker. The resulting elasticity of college quality with respect to development for each bin is shown in table 5. The estimates are consistently large and quite stable. For example, the elasticity of the quality of the top two percent, top five percent, and top twenty-five percent are all around 0.20. The elasticity of the quality of unranked colleges is only modestly smaller, at 0.169.

These results suggest that the entire distribution of college quality is shifted left in developing countries. At first glance, these results may appear inconsistent with the result from the previous subsection that developing countries possess some of the world's top colleges. The key to reconciling the two results is to note that large developing countries have a handful of world-class colleges but also have other colleges at the top of their national rankings that do not score nearly so well and drag down the average. For example, India has 812 colleges; the top five percent for India consists of 41 colleges, mixing the IITs with other, less-renowned colleges.

We also explore whether developing countries have a comparative advantage in particular subjects by estimating separately college quality for STEM fields, business/social science fields, and other fields. We find that STEM graduates systematically 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 A1).

In summary, developing countries seem to have uniformly worse college quality, which accounts for about one-fifth of cross-country income differences. Alternatively, college quality accounts for about one-third of cross-country differences in human capital per

Table 5: Top Percent Colleges within Countries and GDP per worker

	Top 2%	Top 3–5%	Top 5%	Top 5–10%	Top 10–25%	Top 25%	Unranked
Log(gdppw)	0.217^{***}	0.209^{***}	0.204^{***}	0.242^{***}	0.207^{**}	0.202^{***}	0.169^{***}
	(0.046)	(0.047)	(0.036)	(0.049)	(0.080)	(0.033)	(0.037)
N	35	33	44	34	27	48	36
Adjusted R^2	0.39	0.37	0.42	0.41	0.18	0.43	0.37

Notes: Table displays estimated coefficient from regressing the average quality of a country's colleges in the respective group on the log of PPP GDP per worker from World Bank (2020). Percentile bins based on based on Center for World University Rankings. N is number of countries.

worker, given the finding that the elasticity of human capital with respect to GDP per worker is 0.6 (Hendricks and Schoellman, 2018). Finally, these findings are consistent with recent work that finds that developing countries appear to be scarce in the quality as well as the quantity of skilled workers (Jones, 2014; Okoye, 2016; Rossi, 2020; Hendricks and Schoellman, 2021).

4.3 College Quality and Top Talent

Our measure of college quality captures the earnings of each college's graduates by construction. In this section we show that it also captures the ability of the college to produce talented graduates who become entrepreneurs or innovators. We measure entrepreneurs as CEOs of S&P 500 firms and innovators as Nobel Laureates (in Physics, Chemistry, Medicine, and Economics) or holders of patents. All patenting data are derived from patents granted by the U.S. Patent and Trademark Office and S&P firms are American, so we analyze the results separately for American and non-American colleges.

We start with the relationship between college quality and entrepreneurship or innovation among U.S. colleges. Bell et al. (2019) provide data on the share of students at each college who are granted patents, the number of patents by college, and the number of citations to patents by college. Data cover colleges with more than ten patents granted among students in the 1980–1984 birth cohorts; see their paper for further details. Details on other outcomes are available in Appendix D.

We merge these measures of the number of innovators and entrepreneurs graduating from each college with our measure of college quality. We regress the share of student inventors, the log of (one plus) the number of patents or citations, the number of Nobel laureates, and the number of CEOs on college quality. We use a censored regression specification and report marginal effects for the number of Nobel laureates and CEOs to account for the fact that there are a substantial number of zeros in the data. The results are shown in table 6. College quality is a statistically significant predictor of each outcome, as shown in the first row. We also report the mean of each outcome and the standard deviation of college quality in the United States to give a sense of magnitudes. The implied economic significance is large. For example, a one standard deviation increase in college quality corresponds to 50 percent more patents, 0.15 more Nobel laureates, and 0.3 more CEOs of S&P500 companies.[11]

We now turn to results for non-American colleges. We start with results at the country level. They allow us to address whether countries with high-quality colleges have more

[11] Calculated as $\exp(3.008 \times 0.15) = 1.57$, $0.991 \times 0.15 = 0.15$, and $1.994 \times 0.15 = 0.30$, respectively.

Table 6: College Quality and Notable Achievements, U.S. Colleges Only

	Share student inventors	Log patents+1	Log cites+1	Nobel prizes	S&P500 CEOs
College quality	0.050***	3.008***	2.774***	0.991***	1.994***
	(0.006)	(0.655)	(0.411)	(0.148)	(0.128)
Mean outcome	0.011	4.188	3.928	0.088	0.259
Std. dev. college quality	0.15	0.15	0.15	0.15	0.15
N	326	326	326	1554	3108

Notes: Table relates our measure of college quality to notable achievements across U.S. colleges. The former three dependent variables and the set of colleges for which such data are available are from Bell et al. (2019). Estimates for the former three dependent variables from standard OLS, while estimates for Nobel prizes and S&P500 CEOs reflect marginal effects from Tobit specifications. For S&P500 CEOs, data for 2005 and 2020 are stacked into a single regression that includes a dummy variable for 2005 observation. For further details on the latter two dependent variables, see Appendix D.

entrepreneurs and innovators. An obvious confounding factor is that countries with high-quality colleges tend to be richer, so we control for GDP per worker throughout. We use the same outcomes as for Americans, except that we now rely on total U.S. patents filed by foreign nationals by country from the U.S. Patent and Trademark Office rather than patents by college (which are not available for non-American colleges). We divide outcomes by the population of the country to make results more comparable. We again use a censored regression specification for the number of Nobel laureates and CEOs.

Table 7: Top College Quality and Notable Achievements Across Countries

	Patents per million persons		Nobel prizes per million persons		S&P500 CEOs per million persons	
Log(gdppw)	642.551***	176.233	0.104***	0.047	0.038***	0.026**
	(195.660)	(236.217)	(0.032)	(0.033)	(0.011)	(0.012)
Top 5% college quality		2288.935***		0.284***		0.066*
		(757.945)		(0.099)		(0.038)

Notes: Table relates top college quality to notable achievements looking across forty-three countries and excluding the United States. Top 5% college quality reflects the average across our measure of college quality for the top 5% of colleges in each country according to CWUR national rankings. Estimates for patents from standard OLS, while estimates for Nobel prizes and S&P500 CEOs reflect marginal effects from Tobit specifications. For S&P500 CEOs, data for 2005 and 2020 are stacked into a single regression that includes a dummy variable for 2005 observation. For further detail regarding each of the dependent variables, see Appendix D.

We first regress each outcome against GDP per worker. As shown in table 7, we verify positive and statistically significant correlations for all three outcomes. We then regress each outcome against GDP per worker and the average quality of the nation's top five percent of colleges. College quality is a statistically significant predictor of patents and Nobel laureates. For these outcomes it also greatly reduces the magnitude and eliminates the significance of GDP per worker. For CEOs the results are more mixed: the point estimate has the right sign and is economically large, but it is only marginally statistically significant and reduces the estimated effect of GDP per worker by a smaller amount. This result is consistent with the view that technical, codifiable, knowledge is more directly linked to education quality, compared with managerial ability.

While patenting data are only available at a country level, we also know the number of CEOs and Nobel laureates for each foreign college. For our final analysis we estimate the relationship between college quality and these two measures at the college level. This analysis gives us a larger sample size. It also allows us to sidestep the usual concern that it is challenging to control for all plausible confounding factors in cross-country regressions. To highlight this, we conduct the analysis using country fixed effects. The results are shown in table 8.

Table 8: College Quality and Notable Achievements, Non-U.S. Colleges

	Nobel prizes		S&P500 CEOs in 2020	
College quality	0.411***	0.376***	0.166***	0.223***
	(0.089)	(0.103)	(0.043)	(0.054)
Country FE		✓		✓
Mean outcome	0.07	0.07	0.04	0.04
Std. dev. college quality	0.27	0.27	0.27	0.27
N	1318	1318	1318	1318

Notes: Table relates our measure of college quality to notable achievements across colleges outside the United States. Estimates reflect marginal effects from Tobit specifications. For further details regarding the two dependent variables, see Appendix D.

This table shows that foreign graduates from higher-quality colleges are more likely to win Nobel prizes or become CEOs in the United States. Further, this relationship is similar if not *stronger* when we control for country fixed effects. Again, the economic magnitudes are large. A college outside the United States that is one standard deviation higher in our measure of quality has 0.1 more Nobel laureates and 0.06 more CEOs, when the sample average for the outcomes are only 0.07 and 0.04. Put together, these results suggest that high-quality colleges are disproportionately responsible for producing the highly talented workers who become innovators and entrepreneurs. They further emphasize the importance of the heterogeneity in top college quality by country that we document in Figure 2.

5 Sensitivity

In this section we investigate the sensitivity of our results to relaxing the assumptions we made and details of our implementation. We focus throughout on our main result for the elasticity of college quality with respect to development. We estimate the elasticity separately for the top five percent of colleges and all other colleges to highlight any possible impact on the distribution of quality. All results are presented in table 9. For example, the first row shows that the baseline estimate for these two groups of colleges is 0.204 and 0.237, respectively.

We start by relaxing the four assumptions that underlie our approach as outlined in Section 2. The first 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 take the form of 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. The second and third rows show that doing so changes the elasticity of college quality with respect to GDP per worker very little.

The second assumption is that earnings are log-separable between country effects and human capital, which in turn is decomposed into college quality and worker ability. We relax this assumption by allowing for an interaction between college quality and the country effect in the earnings equation. The estimated coefficient on this interaction term is negative and statistically significant (see Table A3), suggesting that graduates from better colleges earn a smaller earnings premium in higher $z_{c'}$ (richer) countries. This 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, 2020; Hendricks and Schoellman, 2021).[12] As the fourth row shows, allowing for this effect changes our estimated relationship elasticity very little.

Allowing workers of different types to be imperfect substitutes introduces relative prices into the earnings equation. These relative prices would also appear in the earnings equation for the first stage of our estimation procedure. In this case we use the earnings change of migrants to estimate the change in $z_{c'} + p_{\iota,c'}$, where $p_{\iota,c'}$ is the price of type ι labor in c'. We can then net off the effect of country effect and relative price in the second stage, as long as the types of workers used in the first and second stage are suitably

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

Table 9: Sensitivity Analysis: Elasticity of College Quality with Respect to Development

Alternative specification	Top 5%	Other 95%
1. Baseline	0.204***	0.237***
	(0.036)	(0.036)
	[44]	[47]
2. Include job title fixed effects	0.193***	0.228***
	(0.031)	(0.030)
	[44]	[47]
3. Include firm fixed effects	0.269***	0.296***
	(0.039)	(0.036)
	[44]	[47]
4. Allow college quality-country effect (2nd step)	0.184***	0.209***
	(0.036)	(0.036)
	[44]	[47]
5. Use only college-educated migrants (1st step)	0.150**	0.201***
	(0.068)	(0.069)
	[24]	[27]
6. Account for skill loss in migration (1st step)	0.213***	0.247***
	(0.036)	(0.036)
	[44]	[47]
7. Account for skill loss over time in migration (1st step)	0.216***	0.250***
	(0.036)	(0.036)
	[44]	[47]
8. College-specific selection (2nd step)	0.182***	0.231***
	(0.042)	(0.035)
	[40]	[43]
9. Minimum N=50 observations	0.193***	0.228***
	(0.047)	(0.048)
	[33]	[36]
10. Country-specific return to experience (2nd step)	0.308***	0.334***
	(0.043)	(0.044)
	[44]	[47]
11. At most an undergraduate degree (2nd step)	0.202***	0.248***
	(0.038)	(0.036)
	[44]	[47]
12. Jointly estimate undergraduate and graduate quality (2nd step)	0.209***	0.253***
	(0.037)	(0.037)
	[44]	[47]

Notes: Table displays estimated coefficient from regressing the average quality of a country's top five percent and other colleges on the log of PPP GDP per worker from World Bank (2020). Rows correspond to various sensitivity checks in terms of sample restrictions or changes in the estimation procedure. See text for details.

matched. Following this idea, we explore limiting the sample in the first stage to college educated workers, consistent with our second stage sample restriction. As shown in the fifth row, the elasticities are slightly smaller and the standard errors larger because we can include fewer countries in this case.

The third assumption is that workers supply the same human capital in any country where they might work. Under perfect substitution between worker types, 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 that 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 $z_{c'}$.

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

$$\log(w_{i,t,c'}) = z_{c'} + \lambda_i + d_{\mathcal{S}} + \beta X_{it} + \varepsilon_{i,t,c'}. \tag{8}$$

where $d_{\mathcal{S}}$ is a dummy variable for the post-migration earnings observation for a given worker. Intuitively, we expect the estimated coefficient for this dummy to be negative if workers lose part of their human capital at migration; positive if migrants are selected based on comparative advantage in skills or abilities; and zero if neither operates or they cancel. Note this regression requires data on migrants moving in both directions to be identified; ours is the first paper we know to have such data.

We estimate small, positive coefficients (see table A4). For the baseline regression, the effect is under 10 percent. We also explore controlling for 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 almost no effect for the post-migration earnings. These findings suggest that the impact of skill transferability and selection based on country-specific comparative advantage are either small or roughly balanced. As shown in the sixth and seventh row of table 9, incorporating these adjustments in the first stage makes little difference to our main results.

Our fourth assumption is that selection of migrants is common across colleges within a country pair. We can relax this by allowing it to vary at the college-destination pair level instead of origin-destination. In this case, emigrants cannot be used to help estimate college quality in the second stage. Intuitively, the earnings of Oxford graduates in the United States cannot contribute to the estimation of Oxford's college quality if selection of Oxford graduates to the United States is a free variable. The eighth row of table 9 shows the results are still similar, although again we lose some countries from the sample.

In addition to these four assumptions, our results also rest on a number of implementation details. The next two rows of table 9 consider the sensitivity of our results to several of these details. Our baseline analysis focuses on countries and colleges that have at least a minimum of 25 migrants and workers, respectively, in our sample. The ninth shows that the results are similar if we raise the threshold to 50 in each case. Finally, most of our paper assumes that the returns to experience are common across countries. Lagakos et al. (2018) show that they vary systematically with development. The tenth row of table 9 shows our estimated elasticities when we allow returns to experience to vary by country. We find much larger cross-country differences in college quality in this case.

To summarize, our baseline analysis rests on four 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 9, we consistently find that college quality varies substantially and is strongly correlated with development. Among top colleges, the range of plausible elasticities stretches from 0.15–0.30; among the remainder, from 0.20–0.33.

5.1 Graduate School Quality

Finally, we delve into the importance of graduate school education for measured college quality across countries. This analysis has two components. First, we can think of graduate school as a possible confounding force when estimating undergraduate college quality. While about 40% of 24-year olds in the United States in 2013 held a bachelor's degree, roughly 15% of 24-year olds held a Master's degree; and nearly 1.1% of 28-year olds held a PhD (Altonji et al. (2016)). Within our sample, 24% of graduates from colleges outside the United States hold a graduate degree. To the extent that obtaining a graduate education is correlated with undergraduate college quality, if holding a graduate degree commands a large earnings premium, then not accounting for graduate school may artificially inflate the return to undergraduate degrees from top universities. With this in mind, we explore the sensitivity of our results to accounting for graduate education. Second, we use this opportunity to provide some preliminary results on the heterogeneity in graduate school quality around the world.

Our baseline approach estimates (undergraduate) college quality without accounting for any possible graduate school. We consider two alternatives for the second step of our estimation to explore the sensitivity of these results. First, we estimate college quality using only workers that have no graduate education. As shown in row 11 of table 9 this does little to change our results. Second, we estimate jointly the returns to undergraduate quality q_{j_u} and graduate quality q_{j_g} for each school j, assigning graduates with at most a bachelor's degree to a single "unavailable" grouping for graduate school. The regression specification for the second step is then:

$$\log(w_{i,j_u,j_g,c_u,c_j,c'}) - z_{c'} = \gamma X_{it} + q_{j_u} + q_{j_g} + \bar{\varepsilon}_{c_u,c'} + \bar{\varepsilon}_{c_g,c'} + \eta_{i,j_u,j_g,c_u,c_j,c'}. \tag{9}$$

where X_{it} 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 allow for workers who pursue a graduate degree in country c_g yet work in a different country c' to have an average degree of selection $\bar{\varepsilon}_{c_g,c'}$. As shown in row 12 of table 9, this again does little to change the estimated relationship between (undergraduate) college quality and GDP per worker.

The estimates from equation (9) also allow us to compare the importance of undergraduate and graduate education for earnings. The college-by-college rankings can be somewhat imprecise for graduate earnings because we have smaller samples of graduate degree recipients for most colleges. Instead, in table 10 we compare the estimated earnings premia for undergraduate and graduate degrees from colleges in various bins according to the CWUR world rankings.

Table 10: 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	0.443***	0.356***	0.331***	0.269***	0.202***	0.164***	0.116***
	(0.046)	(0.042)	(0.034)	(0.020)	(0.016)	(0.013)	(0.012)
	[19]	[23]	[36]	[104]	[173]	[270]	[329]
Graduate quality	0.211***	0.093***	0.060***	0.031***	0.036***	0.049***	0.037***
	(0.024)	(0.022)	(0.018)	(0.012)	(0.012)	(0.010)	(0.009)
	[19]	[23]	[35]	[88]	[90]	[120]	[171]

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 2000). There are 2,857 colleges for undergraduate quality and 1,169 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 undergraduate quality is similar to our baseline findings (table 3). Second, the return to graduate degrees is lower and somewhat nonmonotone. Graduate degrees in schools ranked anywhere between 101–2000 pay a modest premium over graduate degrees from unranked colleges, in the range of 3–5 percent. The premium rises substantially from there, to 6–10 percent for schools ranked between 21–100 and more than 20 percent for schools in the top 20. The return enjoyed by workers with a graduate degree from a top 20 college is consistent with the 20–25% estimate for top 25 MBA programs from Arcidiacono et al. (2008).

6 Global Talent Flows

For our final main result we consider what the Glassdoor database reveals about global talent flows, meaning the cross-country flows of college-educated workers. The existing literature provides important facts about these flows. First, the brain drain literature documents that developing countries lose the most skilled emigrants, particularly as a share of their total stock of skilled workers (Docquier and Rapoport, 2012). Second, a literature on global talent flows documents that a small set of OECD countries (particularly the United States, United Kingdom, Australia, and Canada) receive an outsized share of the world's skilled immigrants. The Glassdoor database allows us to add to each of these literatures by estimating additionally the average human capital per college-educated (skilled) immigrant and emigrant for each country. Thus, for example, we can quantify whether the human capital of a country's skilled emigrants are above- or below-average relative to the country's skilled non-migrants.

We emphasize at the outset two limitations of our analysis. First, our results are derived from college-educated migrants in Glassdoor. Studying only college-educated workers is reasonable given our focus on global talent flows. However, our results may miss labor markets where Glassdoor is less common. Second, we measure migration and global talent flows using workers who attend 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 has an even more complicated migration history. Each of these movements is still a form of global talent flow and disentangling the relative importance of different types of flows is an interesting avenue for future work.

Our approach builds on the regression outlined in Section 2. Within Glassdoor we focus on workers who attend college in country c and report earnings in a (different) country c'. If we net off the effect associated with their country of work, we have an estimate of the average human capital of these migrants,

$$\bar{w}_{j,c,c'} - z_{c'} = q_j + \bar{\varepsilon}_{c,c'}, \tag{10}$$

where the right hand side consists of college quality and selection of migrants. We use this equation as the basis for the study of the human capital of emigrants and immigrants.

Our measure of the average human capital of emigrants from country c, EM_c, is the human capital of graduates from all colleges j in country c who migrate to all possible destinations c', relative to the average human capital of college graduates in c, $\bar{q}_c$:

$$
\begin{aligned}
EM_c &= \sum_{j \in c} \sum_{c' \neq c} \ell_{j,c,c'} \left[\bar{w}_{j,c,c'} - z_{c'} \right] - \bar{q}_c \\
&= \underbrace{\sum_{j \in c} \sum_{c' \neq c} \ell_{j,c,c'} \left[q_j - \bar{q}_c \right]}_{\text{selection on college quality}} + \underbrace{\sum_{j \in c} \sum_{c' \neq c} \ell_{j,c,c'} \bar{\varepsilon}_{c,c'}}_{\text{selection on ability}} .
\end{aligned}
\tag{11}
$$

The first line captures the total effect, with $\ell_{j,c,c'}$ denoting the share of country c's emigrants that graduate from j and move to c' in the Glassdoor database. We normalize by country c average human capital to focus on whether emigration raises or lowers the country's average human capital.[13] The second line uses equation (10) to decompose the total effect into two pieces: the selection on college quality (relative to country c average, denoted by $\bar{q}_c$) and selection on ability (human capital conditional on alma mater).

We follow a similar approach to measure and decompose the average human capital of immigrants,

$$
\begin{aligned}
IM_{c'} &= \sum_{c \neq c'} \sum_{j \in c} \omega_{j,c,c'} \left[\bar{w}_{j,c,c'} - z_{c'} - \bar{q}_{c'} \right] \\
&= \underbrace{\sum_{c \neq c'} \sum_{j \in c} \omega_{j,c,c'} \left[q_j - \bar{q}_c \right]}_{\text{selection on college quality} \mid \text{country}} + \underbrace{\sum_{c \neq c'} \sum_{j \in c} \omega_{j,c,c'} \left[\bar{q}_c - \bar{q}_{c'} \right]}_{\text{selection on country}} + \underbrace{\sum_{c \neq c'} \sum_{j \in c} \omega_{j,c,c'} \bar{\varepsilon}_{c,c'}}_{\text{selection on ability}}
\end{aligned}
\tag{12}
$$

The first line again captures the total human capital of immigrants to country c' relative to domestic workers, $\bar{q}_{c'}$. Here $\omega_{j,c,c'}$ denotes the share of immigrants to country c' that graduate from college j in country c in the Glassdoor database. The second line uses equation (10) to decompose the total effect into three pieces, which capture selection on college quality within country c; selection on average college quality of the country $\bar{q}_c$; and selection on ability (human capital conditional on alma mater).

The full results of this decomposition in terms of EM_c, $IM_{c'}$, and each of the five subcomponents for each country are available in Table A5. Here we focus on two main results. First, figure 3 plots the average human capital per migrant against GDP per worker separately for emigrants and immigrants. This figure summarizes our contribution to the literatures on brain drain and global talent flows, which is to estimate how the human capital of skilled migrants compares to skilled non-migrants for a large number of sending and receiving countries.

[13] Note that we construct the average quality of c using only non-migrants. Outside of disaster zones like Italy only a small share of the country emigrates, so this is generally innocuous.

Figure [3a](#) shows the implications for brain drain. The average human capital per emigrant (relative to non-migrants) is strongly negatively correlated with GDP per worker. The main implication is that 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 five countries the average emigrant has 50 percent (40 log points) more human capital than the average non-migrant. By contrast, emigrants from developed countries are on average only weakly positively selected and for several developed countries emigrants have below-average human capital. This finding indicates that the proximate effect of brain drain on less developed countries is even stronger than what the literature estimates.

Figure 3: Average Human Capital per Migrant

(a) Emigrants (b) Immigrants

Notes: Figures plot the average human capital for each country's emigrants and immigrants constructed using equations (11) and (12), respectively, against PPP GDP per worker from World Bank (2020) in log scale.

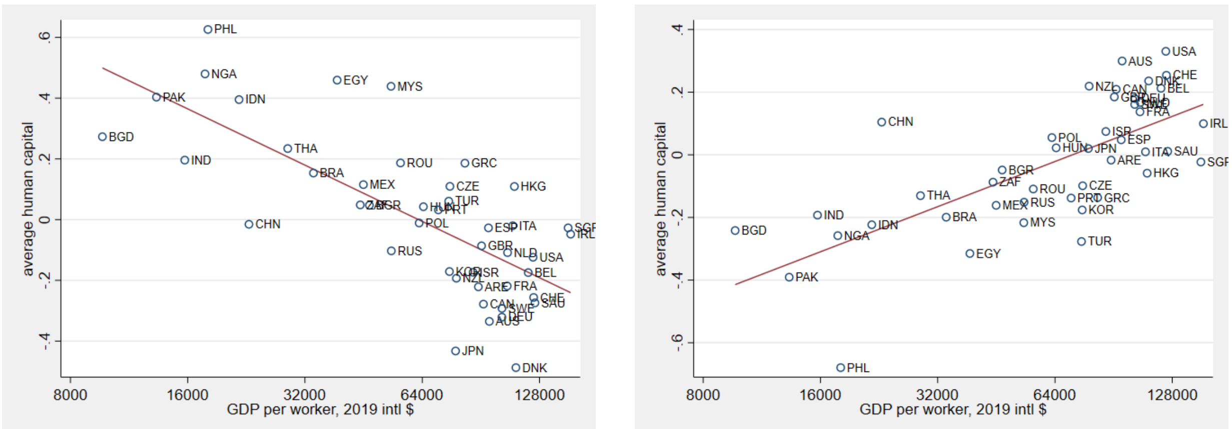
Figure 3b shows the implications for global talent flows. Kerr et al. (2016) show that most skilled migrants flow to developed countries, so we focus on these countries. The main finding in this figure is that there is substantial heterogeneity among developed countries in terms of the average human capital per skilled immigrant as compared to skilled natives. Not only do the United States and United Kingdom attract a disproportionate share of the world's skilled immigrants, but they also attract immigrants whose average human capital exceeds that of natives by a significant amount. 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 Denmark, South Korea, and Japan.

We decompose our measures of average human capital per migrant using equations (11) and (12). In each case, the term that captures selection on college quality accounts for a negligible share of our findings (see table A5). It follows that variation in the average human capital per emigrant is due entirely to selection on ability. The variation in human capital per immigrant is more nuanced. In figure 4 we plot the two remaining terms against GDP per worker.

Figure 4: Decomposing Average Human Capital per Immigrant

(a) Selection on Country

(b) Selection on Ability



Notes: Figures plot selection on ability and selection on country computed as in equation (12) against PPP GDP per worker from World Bank (2020) in log scale.

Figure 4a shows that there is a strong negative correlation between selection on country and development. This is intuitive: less developed countries find it easier to attract immigrants from countries with higher average college quality than their own. On the other hand, figure 4b shows that there is a strong positive correlation between selection on ability and development that largely offsets this effect (as shown in Figure 3b). Put differently, less developed countries draw immigrants of below-average ability from countries with higher college quality, while developed countries draw immigrants of above-average ability from countries with lower college quality.

Figure 4 also helps understand the heterogeneity of average human capital per immigrant among rich countries. We find that each component explains a portion of our results. For example, the high average human capital per immigrant for Singapore is attributable mostly to selection on country of origin, while for the United States it is attributable mostly to selection on ability. On the other end of the spectrum, the low average human capital per immigrant for Japan is attributable almost entirely to selection on country, while for South Korea it is attributable in equal measure to selection on country and ability.

7 Conclusions

In this paper we propose a new approach to measuring college quality across countries. The approach uses earnings data and uses the information provided by migrants who work in multiple countries to disentangle the role of country versus college quality. We implement it using rich data from Glassdoor, a website that has collected resume and earnings data from millions of workers worldwide. We arrive at four main findings. First, college quality matters: graduates of top global colleges earn 57 percent more than those of typical colleges in a common labor market. Second, college quality is strongly correlated with development: graduates of colleges in rich countries earn 65 percent more in the same labor market as compared to graduates of colleges in poor countries. This shift affects the entire distribution of college quality. Third, college quality is a strong predictor of the number of innovators and entrepreneurs within and between countries. Fourth, we measure the average human capital of each country's emigrants and immigrants and show that accounting for human capital amplifies existing findings in the brain drain and global talent flows literature.

Our ranking of colleges around the world is constructed using the average earnings of graduates. 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 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. Indeed, this topic remains unsettled even within the United States (Dale and Krueger, 2002; Hoekstra, 2009). Nonetheless, it would be an interesting avenue for future research.

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Appendix

A Further Results

Table A1: Estimated Premium to Working in Each Country

Rank	Country of work	Migrants	$z_{c'}$	Rank	Country of work	Migrants	$z_{c'}$
1	Saudi Arabia	173	0.49	29	France	1730	-0.04
2	South Africa	231	0.35	30	New Zealand	525	-0.05
3	United Arab Emirates	721	0.31	31	Belgium	559	-0.06
4	Singapore	2026	0.27	32	Slovakia	77	-0.07
5	Thailand	111	0.25	33	Japan	385	-0.07
6	Colombia	121	0.23	34	Israel	448	-0.07
7	Qatar	103	0.22	35	Finland	204	-0.07
8	United States	20756	0.19	36	Australia	2127	-0.08
9	Switzerland	1100	0.17	37	Hungary	282	-0.09
10	Germany	2654	0.17	38	Canada	5302	-0.09
11	Hong Kong	592	0.14	39	Italy	865	-0.12
12	Denmark	197	0.14	40	Sweden	492	-0.12
13	Turkey	293	0.12	41	Argentina	282	-0.13
14	Ireland	1815	0.08	42	China	655	-0.14
15	Netherlands	1383	0.06	43	Philippines	254	-0.15
16	Luxembourg	326	0.05	44	Indonesia	86	-0.19
17	Chile	79	0.05	45	Egypt	228	-0.19
18	Austria	274	0.04	46	Cyprus	57	-0.22
19	United Kingdom	7464	0.04	47	Romania	261	-0.23
20	South Korea	192	0.03	48	Portugal	627	-0.26
21	Poland	510	0.02	49	Brazil	2577	-0.26
22	Czech Republic	330	0.02	50	Nigeria	82	-0.33
23	Spain	1412	0.01	51	Greece	249	-0.33
24	Malaysia	503	0.01	52	India	10005	-0.38
25	Russia	535	-0.02	53	Pakistan	162	-0.42
26	Norway	118	-0.02	54	Bangladesh	54	-0.48
27	Mexico	640	-0.03	55	Iran	36	-0.55
28	Bulgaria	80	-0.03		Total	73350	

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 wages in multiple countries. Countries are listed in descending order according to $z_{c'}$. Sample of countries restricted to those which have at least 25 workers who migrate to the top ten most frequent destinations.

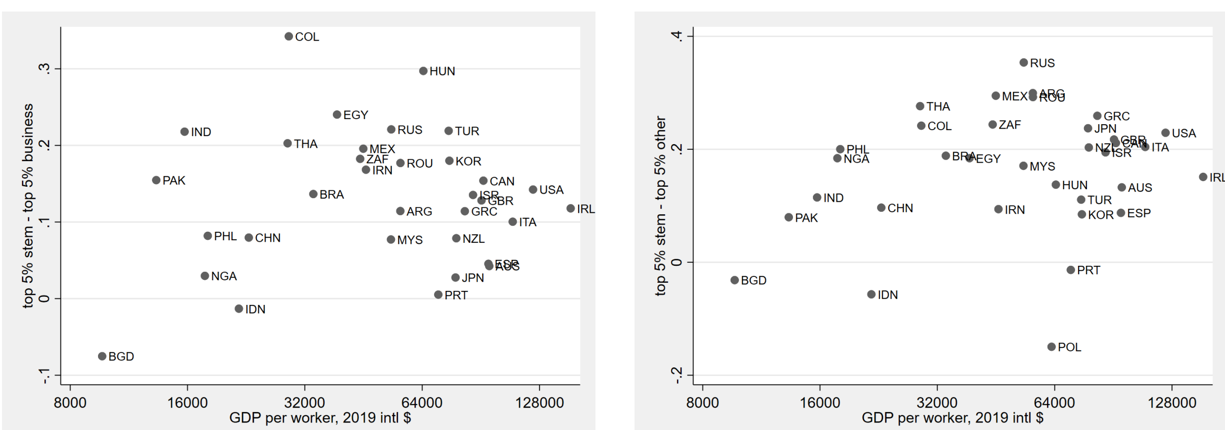
Table A2: Earnings Differences by Grade Point Average

	U.S. College		Non-U.S. College	
	U.S. Worker	Non-U.S. Worker	U.S. Worker	Non-U.S. Worker
Standardized z-score for GPA	0.052***	0.065***	0.025***	0.051***
	(0.002)	(0.017)	(0.005)	(0.006)
Years of experience	0.066***	0.136***	0.055***	0.157***
	(0.001)	(0.010)	(0.004)	(0.005)
Years of experience^2 / 100	-0.131***	-0.345***	-0.063***	-0.368***
	(0.003)	(0.048)	(0.019)	(0.024)
N	135782	1466	11964	36461
Adjusted R^2	0.25	0.34	0.22	0.35

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 the United States and outside the United States. Columns 2 and 4 include country-of-work fixed effects. Standard errors are clustered by college.

Figure A1: Returns to Nations' Top Colleges by Major

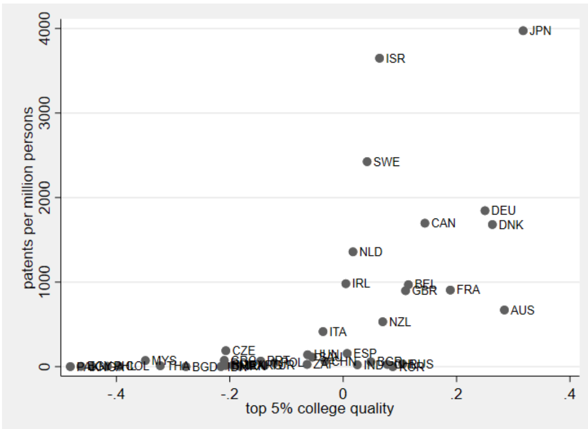
(a) Stem vs. business majors | (b) Stem vs. other majors



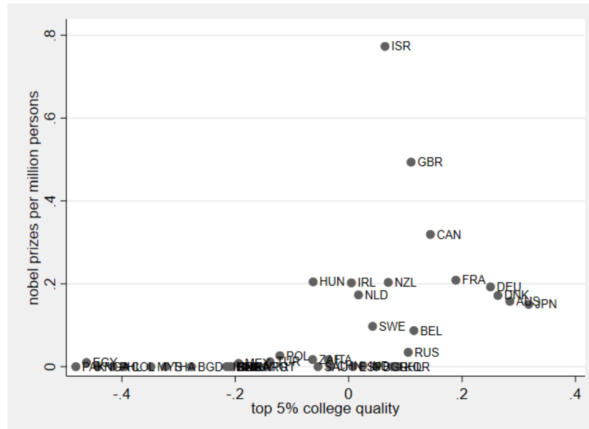
Notes: Figures display the difference in the estimated quality of college for STEM (science, engineering, and other technical fields) relative to business and social science fields (left) or STEM relative to other fields (right) against PPP GDP per worker from World Bank (2020).

Figure A2: Top College Quality and Accomplishments per Capita

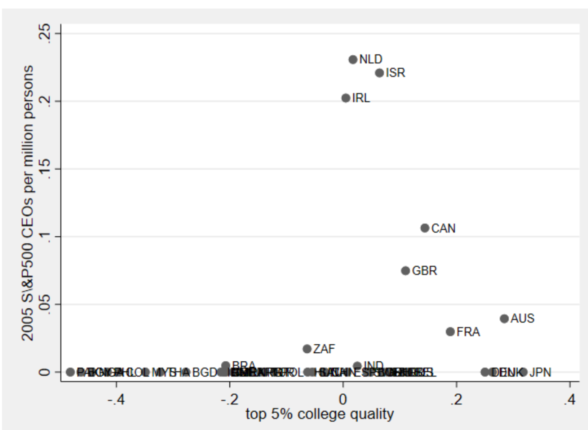
(a) Patents



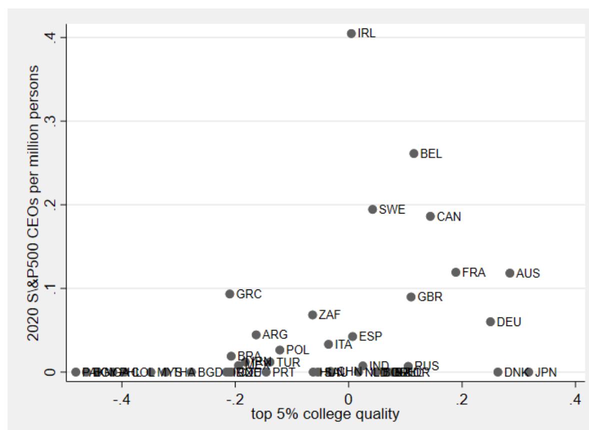
(b) Nobel prizes



(c) S&P500 CEOS in 2005



(d) S&P500 CEOS in 2020



Notes: Figures plot the relation between top college quality to notable achievements (patents, nobel prizes, and CEOs of S&P500 companies) looking across countries and excluding the United States. Top 5% college quality reflects the average across q_j for the top five percent of colleges in each country according to CWUR national rankings. For further detail regarding each of the dependent variables, see Appendix D.

Table A3: Allow College Quality-Country Effect in Estimating College Quality

	(1)
College quality x country premium	-1.064***
	(0.039)
Years of experience	0.082***
	(0.000)
Years of experience^2 / 100	-0.170***
	(0.001)
N	1410500
Adjusted R^2	0.36

Notes: Table reflects estimates from the second estimation step for specification 4 of Table 9. College quality x country premium reflects the coefficient of $q_j \times z_{c'}$.

Table A4: Wage Growth for Post-Migration Earnings Report

	(1)	(2)
Post-migration report	0.079***	0.025***
	(0.010)	(0.008)
Post-migration report x years passed		0.030***
		(0.007)
Post-migration report x years passed^2		-0.006***
		(0.001)
Mean years passed	2.9	2.9
N	66307	66307
Adjusted R^2	0.61	0.61

Notes: Table shows wage premium that migrants earn in the sample in their second earnings report after migrating between two countries, reflecting d_S from equation (8). Standard errors are clustered by country.

Table A5: Decomposition of Emigration and Immigration Effects

Country	GDP per worker ($)	Emigration: Selection on school quality	Emigration: Selection on ability	Immigration: Selection on school quality	Immigration: Selection on country	Immigration: Selection on ability
Bangladesh	9,661	0.03	0.18	-0.08	0.27	-0.24
Pakistan	13,299	-0.01	0.41	0.01	0.40	-0.39
India	15,722	0.00	0.41	0.03	0.20	-0.19
Nigeria	17,724	0.00	0.47	-0.05	0.48	-0.26
Philippines	18,031	0.02	0.49	0.04	0.63	-0.68
Indonesia	21,670	0.00	0.32	0.04	0.40	-0.22
China	22,977	0.00	0.16	0.03	-0.02	0.10
Thailand	28,898	0.00	0.26	0.01	0.23	-0.13
Colombia	29,103	0.00	0.34	.	.	.
Brazil	33,645	0.01	0.21	0.02	0.15	-0.20
Egypt	38,698	0.00	0.41	0.04	0.46	-0.32
South Africa	44,370	0.00	0.29	0.01	0.05	-0.09
Mexico	45,198	0.00	0.21	0.03	0.12	-0.16
Iran	45,915	0.00	0.11	.	.	.
Bulgaria	46,839	0.00	0.07	-0.04	0.05	-0.05
Chile	52,647	0.00	-0.03	.	.	.
Malaysia	53,222	0.02	0.19	-0.01	0.44	-0.22
Russia	53,319	0.00	0.10	0.04	-0.10	-0.15
Argentina	56,252	0.00	0.26	.	.	.
Romania	56,288	-0.01	0.17	0.00	0.19	-0.11
Poland	62,843	-0.01	0.04	-0.01	-0.01	0.05
Hungary	64,450	0.00	-0.03	0.01	0.04	0.02
Portugal	70,406	-0.04	0.26	0.01	0.03	-0.14
Turkey	74,854	0.00	0.17	0.06	0.06	-0.28
South Korea	75,170	0.00	0.00	0.06	-0.17	-0.18
Czech Republic	75,376	0.00	0.23	0.01	0.11	-0.10
Japan	77,951	0.00	-0.13	0.05	-0.43	0.02
New Zealand	78,314	0.00	0.14	0.00	-0.19	0.22
Greece	82,353	0.00	0.22	0.00	0.19	-0.14
Israel	86,447	0.00	0.08	-0.01	-0.17	0.07
United Arab Emirates	89,182	0.00	0.13	-0.01	-0.22	-0.02
United Kingdom	90,885	0.00	0.03	0.01	-0.09	0.18
Canada	91,897	0.00	0.10	-0.01	-0.28	0.21
Spain	94,672	0.00	0.05	0.02	-0.03	0.05
Australia	95,166	-0.01	-0.19	0.02	-0.34	0.30
Germany	102,505	-0.01	-0.13	0.00	-0.32	0.18
Sweden	102,530	0.01	0.04	0.00	-0.29	0.16
France	105,775	0.02	-0.07	0.01	-0.22	0.14
Netherlands	105,986	0.01	0.15	0.01	-0.11	0.17
Italy	109,284	-0.01	0.04	0.03	-0.02	0.01
Hong Kong	110,352	0.01	0.27	0.03	0.11	-0.06
Denmark	111,352	0.01	0.00	-0.01	-0.49	0.24
Belgium	119,767	-0.02	0.03	0.01	-0.17	0.21
United States	123,239	0.04	-0.05	0.01	-0.12	0.33
Switzerland	123,657	.	.	0.03	-0.26	0.25
Saudi Arabia	124,616	-0.01	0.09	-0.02	-0.27	0.01
Singapore	151,616	0.02	0.24	0.00	-0.03	-0.02
Ireland	153,923	0.01	0.15	-0.01	-0.05	0.10

Notes: Table shows for each country GDP per worker from World Bank (2020) and the decomposition of the average human capital lost per emigrant and gained per immigrant from equations (11) and (12).

B Comparison to Representative Data Sources

Our primary data source for our analysis is the global database of Glassdoor. Our main results are measures of college 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 are selected and particularly are selected differently across countries. As discussed in the text, we compare data on earnings by college in Glassdoor to nationally representative samples for all countries for which we have identified such data.[14] Here we provide the source and details of the data construction, country by country.

B.1 Australia

Our data for Australia come from the Graduate Outcome Survey, which is sponsored by the Australian Government Department of Education and Training as part of the Quality Indicators for Learning and Teaching Survey program. The Graduate Outcome 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 twelve 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 with Glassdoor, 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. Panel a of figure B1 shows the weighted probability density function (pdf) of the difference.

[14] Tips on additional data sources would be greatly welcome.

Table B1: Sample Selection into Glassdoor: China

	Median log wage		
University ranking	Glassdoor	Chinese College Student Surveys	Graduates
985	10.03	9.40	70
211 excluding 985	10.06	9.35	44
985	9.92	9.09	41

Notes: The table above captures the degree to which Chinese college graduates in Glassdoor are representative of Chinese graduates more broadly. The figure above is a weighted probability density function of the log difference between the median log wage for college graduates in Glassdoor for each college ranking category compared with the median log wage from external data. There are three groupings represented in the Glassdoor data, corresponding to 86 recent graduates.

B.2 China

Our data for China are derived from the Chinese College Student Surveys. This data consists of an annual survey of students from a sample of Chinese colleges conducted by the China Data Center of Tsinghua University.[15] The survey asks respondents for the monthly survey of their best salary offer. While these data are not publicly available, Hong Song and Xican Xi of Fudan University graciously agreed to provide us with average value of this salary offer by year and college group. The groups consist of "985 Project" colleges, "211 Project" colleges, and other colleges. The "985 Project" group consists of the 39 most elite colleges in China, including for example Tsinghua, Peking, and Shanghai Jiao Tong Universities. The "211 Project" group consists of a larger group of 112 colleges; our salary figure applies to the colleges that are in this group but not the 985 project group. Finally, the last group includes all other colleges.

To compare with Glassdoor, we adjust these earnings for PPP and inflation differences. Then, for Chinese graduates employed in China, 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 map college into the three categories using Wikipedia to identify which colleges belong in each. We calculate the PPP- and inflation-adjusted log mean earnings for each of the three groups. Table B1 compares the results.

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

[15]This data has been previously used on research on the wage premium of elite colleges in China (Jia and Li, 2016).

graduates, the college they attended, and their formal sector earnings from tax records. We access the data from the Vinculación Laboral de Recién Graduados.[16] The most recent data cover the average annual earnings of 2015 graduates during the 2016 year.

To compare with Glassdoor, 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. Panel b of figure B1 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 that year (2018). Given 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 over-represented 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. Colleges are again organized into groups, with the top Indian Institutes of Management again distinguished.

To compare with Glassdoor, 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. Panel c of figure B1 shows the weighted pdf of the difference.

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

B.5 Italy

Our data from Italy come from AlmaLaurea.[17] AlmaLaurea is a partnership between Italian colleges that jointly represent 90% of college graduates. AlmaLaurea conducts annual interviews with graduates from partner colleges and collect information about their post-degree labor market experience. Relevant for our analysis, graduates report their net monthly income either 1 year after graduation (bachelor's degree) or 1, 3, and 5 years after graduation (master's degree).

To compare with Glassdoor, we calculate the annualized PPP- and inflation-adjusted log median earnings for each college from this external data, multiplying earnings by 125% 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. Panel d of figure B1 shows the weighted pdf of the difference.

B.6 New Zealand

Our data from New Zealand draw on information provided by the Ministry of Education.[18] They use 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", 1, 3, 5, 7, and 9 years after graduation, by college.

To compare with Glassdoor, 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 with the first 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-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

[17] Data for 2009-2018 is available at https://www.almalaurea.it

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

difference between the New Zealand data and Glassdoor data by college. Panel e of figure B1 shows the weighted pdf of the difference.

B.7 Poland

Our data from Poland draw on the Polish Graduate Tracking System commissioned by the Polish Ministry of Education and Science.[19] 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 0–1, 1–2, and so on years of experience. We collect data for graduates from undergraduate (first-cycle) programs at all ranges of experience from the class of 2018.

To compare with Glassdoor, 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 with the first 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 year 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-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. Panel f of figure B1 shows the weighted pdf of the difference.

B.8 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.[20] 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, specifi-

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

[20] 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.

cally Nanyang Technological University, National University of Singapore, and Singapore Institute of Management, each of which have earnings by major-cohort. Then, for Singaporean graduates employed in Singapore, 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 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. Panel g of figure B1 shows the weighted pdf of the difference.

B.9 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.[21] We use the data in table 15, "Raw average earnings by HEI [higher education institution]", which focuses on the cohort of students who are age 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, which is 7.7 percent of all students who start college.

In Glassdoor, among U.K. graduates employed in the United Kingdom, 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 this the measure from Belfield et al. (2018) and Glassdoor by college. Panel h of figure B1 shows the weighted pdf of the difference.

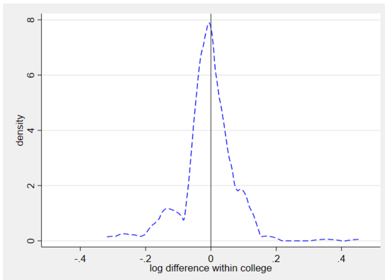
B.10 United States

Our data from the United States from the U.S. Department of Education's College Scorecard database.[22] Figure 1 shows the weighted pdf of the difference in average wage by college between Glassdoor and the Scorecard.

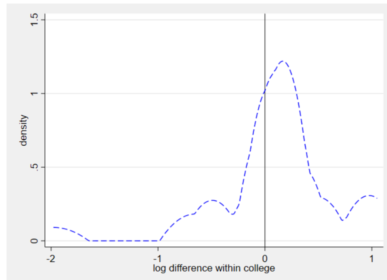
[21] Available at `https://www.ifs.org.uk/publications/13731`, accessed February 15, 2021.
[22] Available at `https://collegescorecard.ed.gov/`, accessed 12/1/2020.

Figure B1: International Sample Selection into Glassdoor

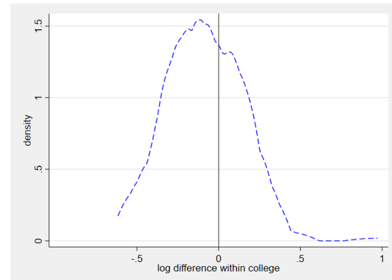
(a) Australia



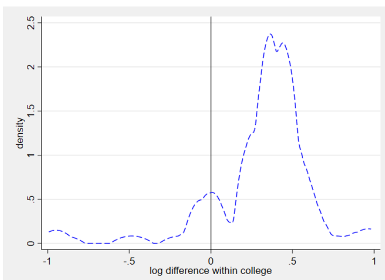
(b) Colombia



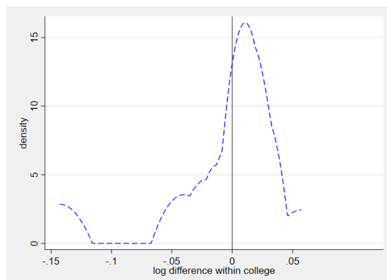
(c) India



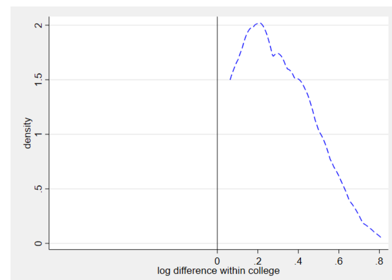
(d) Italy



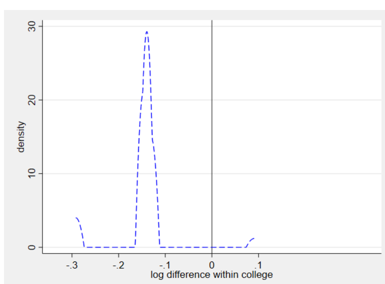
(e) New Zealand



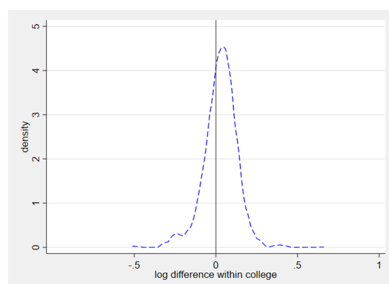
(f) Poland



(g) Singapore



(h) United Kingdom



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 detailed in table 2.

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).[23] 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, 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, 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.
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, and

[23] 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.

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, Journalism, Language, Liberal Studies, Linguistics, Literature, Mfa, Music, Painting, Philosophy, Photo, Playwrit, Religion, Religious, 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, Advertising, BCom, Banking, Bba, Bcom, Bookkeeping, Buisness, Business, Commerce, Corporate, Customer Service, Employment Relations, Entrepreneur, Entreprenuer, Financ, Hospitality, Hotel, Hr, Human Relations, Human Resource, Industrial, Insurance, Labor Relations, Leadership, Logistics, Manaerial, Management, Marketing, Mba, Merchandising, Mis, Operations, Organisation, Organization, Organizational Leadership, Real Estate, 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, Engineer, Materials, Mech Eng, Mechanical, Mechatronics, Welding.

Health Service: Allied Health, Athletic Training, Audiology, Behavior Analysis, Bpharm, Bsn, Clinical, Cna, Dent, Dietetics, Emt, 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, Science, Statistics.

Social Service: Archival Science, Counseling, Criminal, Criminal Justice, Criminology, 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, Ethnic Studies, European Studies, Family And Consumer Sciences, Foreign, Gender Studies, Geography, Global, Government, International, International Relations, Politic, Political Science, Psycholog, Psycolog, Social Science, Social Work, Sociology, Urban Studies, Women's Studies.

Technology: BTech, Bca, Cis, CompSc, Computer, Computing, Cs, Cse, Cyber, Data, Informatics, Information, It, It Program, It Security, MTech, Machine Learning, Mca, Network, Software, System, Technology, 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 only attended 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% 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 2,818 institutions and under the latter is 0.974 between 2,872 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, for example due to grade inflation.

We start by identifying which country's GPA scale each worker uses on their resume. For non-migrants we assume it is the relevant local country 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 where 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 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 in the four main scientific categories (Physics, Chemistry, Medicine, and Economics) between 1990 and 2020.[24] We use Wikipedia to identify where each winner received their 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 universities as of two dates. Howard (2010) reports the undergraduate institution for all such CEOs as of 2005.[25] The school names for foreign institutions are sufficient to identify the country but in some cases not the specific institution (e.g., the author pools Indian Institute of Technology into a single college). We add to this by identifying the CEO of all S&P 500 firms as of May 2021 from Wikipedia.[26] 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.[27] We focus on utility patents granted to foreign nationals and sum across all years of the decade.

[24] https://en.wikipedia.org/wiki/List_of_Nobel_laureates, accessed online 5/7/2021.

[25] This paper builds on a report by the consulting firm Spencer Stuart Research & Insight that can no longer be located.

[26] https://en.wikipedia.org/wiki/List_of_S%26P_500_companies, accessed 5/10/2021.

[27] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_stco.htm, accessed 5/5/2021.