Does Alma Mater Matter? A Global Look at University Quality*

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Abstract

We propose a new measure of college quality that has an economically significant scale and is comparable within and among countries. It is based on the earnings of a college's graduates and exploits the fact that graduates of top universities are increasingly internationally mobile and so work in common labor markets, facilitating comparison. We implement it using rich data from Glassdoor, a website that has collected resume and earnings data from more than a million workers worldwide. College quality is important for earnings: graduates of top colleges earn 50 percent more than graduates of typical colleges, which is roughly two-thirds the average college earnings premium. Our ranking of colleges is correlated with typical, proxy-based rankings, but it ranks liberal arts colleges and top science and engineering schools in developing countries much higher. When aggregated to the country level, we find that college quality is strongly correlated with development. College quality is a particularly important determinant of the supply of the most talented workers who become entrepreneurs and innovators.

JEL: O15, O11, J3, J6.
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1 Introduction

Internationally standardized achievement tests point to large cross-country differences in primary and secondary education quality.[1] Test scores from these programs 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 or importance 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 propose and implement a generalization of this approach that ranks colleges around the world on the same basis. We relate this ranking to the available alternatives, which are based on weighted averages of proxies for quality, such as scientific publications of faculty or employment rates of graduates. We evaluate both the mean and distribution of university quality and the importance of college quality for understanding cross-country differences in human capital.

Our approach utilizes heavily a novel source of data, which is the database of the website Glassdoor.[4] Glassdoor users register and provide information about their current job (employer, location, job title, and salary) in return for information on how their earnings compare to those of similar workers. A large share of users also upload a resume that typically includes standard information such as education and work history. We have access to a snapshot of the entire database as of January 1, 2021. We focus on workers for which we have college and earnings information, which yields a basic sample of 1.1 million workers who obtain a Bachelor's degree from 2,175 different universities in 40 countries.

These data allow us to measure average earnings of graduates from a large number

[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] 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 universities; Biasi and Ma (2020) show these universities are high-quality, as measured by their propensity to teach frontier rather than out-of-date knowledge.

[4] This proprietary database has also been used to explore the drivers of variable pay (Sockin and Sockin (2019a)), the contribution of variable pay to gender gaps in earnings and job representation (Sockin and Sockin (2019b)), and the pass-through of firm-specific shocks to worker compensation (Gadgil and Sockin (2020)). This paper is the first to explore university-specific outcomes.

of colleges around the world. If we restrict our attention to graduates who attend college and work in the same country, we obtain separate rankings for each country. Many countries in our sample produce similar data, such as the College Scorecard data in the United States. We 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 Ivy League and Indian Institute of Technology (IIT) graduates reflect the human capital of graduates and 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 Glassdoor includes a sample of workers who report earnings in multiple countries, including some who provide resumes. These workers provide information that makes it possible to 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 States. The worker's post-migration earnings are informative about how his or her human capital compares to that of Ivy League 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 for earnings of college workers, as in Hendricks and Schoellman (2018).[5] We then apply this estimated country effect to the average graduate (or 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 Center for World University Rankings (CWUR) rankings, one of the more widely used proxy-based rankings. We find that graduates of their top-20 universities earn 50 percent more than graduates of unranked universities. That figure is roughly two-thirds of the average earnings gain from attending any college. Alternatively, we construct our own ranking based solely on earnings. Our ranking is positively correlated with existing global and within-country rankings (correlation coefficients 0.37 and 0.61). However, it gives new insights answers along several dimensions. For example, selective liberal arts colleges perform much better in

[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).

our rankings than in existing ones. There are also many more 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 three 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. We estimate the quality of each country's universities in percentile bins, such as the top 5 percent, to control for cross-country differences in the number of universities. Once we do this, we find that there is a strong and consistent relationship between university quality and development, with the estimated elasticity around 0.18. This finding applies equally to the top and bottom of the quality distribution, suggesting that college quality is uniformly lower in poorer countries. To put these figures into perspective, they imply that graduates of our poorest countries' colleges would be expected to earn about 60 percent less in the same labor market as compared to graduates of the richest countries' colleges.

Our findings are particularly useful for quantifying which universities and countries produce leading graduates that become global entrepreneurs and innovators. We link our measures of college quality to data on where chief executive officers (CEOs) of S&P 500 firms, Nobel Prize winners, and patent holders receive their undergraduate degrees. We show that college quality is a robust predictor of each of these measures for Americans and non-Americans, at the country or university level. We explore controlling for GDP per capita in the cross-country results and find that college quality has an economically and statistically significant effect, while development does not. These findings reinforce the importance of high-quality college for producing top talent.

The richness of the Glassdoor data allows us explore the heterogeneity and robustness of these results along a number of dimensions. We clean and standardize a number of other characteristics from resumes. With these, we show that there is a substantial return to higher college grade point average (GPA) around the world, suggesting that our findings reflect at least in part human capital rather than simply signaling on where the degree was acquired. We explore the difference in earnings and estimated quality by broad subject of study and by employer. Finally, we use the subset of students who attend graduate school to control for the graduate university and to provide some preliminary estimates for the quality of graduate schools.

In addition to the work discussed so far, our paper is related to two additional literatures. The first is the role of migration for redirecting top talent across countries (Kerr et al., 2016). Migration plays a particularly important and well-documented role for innovation.[6] Our findings use existing flows to compare college quality across countries. They are also useful for quantifying the size of the global stock of talent, which turns out to be concentrated in a small set of countries. Second, some of our results on quality heterogeneity touch on the literature on the effects of college major or graduate school choice (see Altonji et al. (2016) for an overview). Our work differs in that we are the first we know of to consider these factors in an international context.

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. Section 5 discusses heterogeneity, while section 6 provides details on robustness. Finally, section 7 provides a brief conclusion.

2 Methodology

We are interested in comparing the quality of colleges around the world, as measured by the labor market compensation of their graduates. Since most college graduates work in the same country in which they studied, our first key challenge consists in separately identifying differences in workers' productivity that are due to the quality of their education from those that are due to the characteristics of the labor market in which work. For example, comparing a Oxford graduate who works in the UK with an Indian Institute of Technology (IIT) graduate who works in India would conflate differences in quality between Oxford and IIT with TFP differences between the UK and India. To overcome this challenge, we exploit the presence of migrants in our dataset, which allows us to difference out heterogeneity in labor market characteristics across countries. Following up with our previous example, we purge cross-country TFP differences from wage observations by comparing an Oxford with an IIT graduate, both working in the same country (e.g. the United States).

While it addresses our first identification challenge, the use of migrants' labor market outcomes introduces a second threat to identification. If migrants are not representative of the population of their home country, a comparison between migrants, both working in the same country, would not identify differences in college quality as long as the degree of selection into migration varies systematically across countries.[7]. In other words, the quality of IIT would be overstated, compared to that of Oxford, in so far as graduates from IIT who work in the United States are more positively selected than graduates from

[6]See Hunt and Gauthier-Loiselle (2010), Moser et al. (2014), Akcigit et al. (2017), or Moser and San (2020).

[7]In Section 6, we check the robustness of our results to allowing for selection into migration to vary by university within the same country

Oxford. To address this issue, we measure selection into migration by comparing the wage of migrants with that of stayers, while they both work in their home country. In our example, we compare the wage of two IIT graduates (one of which is also observed in the United States) while they both work in India, and apply the analogous comparison to Oxford graduates. After correcting for selection, differences in wages between IIT and Oxford graduates in the United States identify the *average* gap in college quality between IIT and Oxford. Once we are able to compare (a subset of) universities located in different countries (e.g. India and the UK), we exploit wage heterogeneity in the domestic markets to obtain a global ranking of universities, including those whose graduates we do not observe in any foreign country.

2.1 Implementation

In this section, we introduce the main regression we use to generate a worldwide consistent measure of college quality. We do so by combining the variation discussed in the previous section with three additional assumptions: perfectly competitive markets; log-separability of wages with respect to TFP, quality of human capital, and unobserved individual ability; perfect transferability of human capital across countries.

Let wage of worker i from school j in country c who works in country c' be given by

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

Let $M_{c,c'}$ be the set of movers from country c to c' and S_c the set of stayers. We want to estimate the country-specific productivity, z_c, for all c, the school-specific quality, q_j, for all j, and the extent of selection of movers from country c to country c', $\mathbb{E}[\varepsilon_{i,j,c,c'}|i \in M_{c,c'}] - \mathbb{E}[\varepsilon_{i,j,c,c'}|i \in S_c]$, for all pairs (c, c'). Our main regression is

$$log(w_{i,j,c,c'}) = z_{c'} + q_j + s_{c,c'} + \tilde{\varepsilon}_{i,j,c,c'} \tag{2}$$

where

$$s_{c,c'} = \mathbb{1}\{i \text{ is a mover from } c \text{ to } c'\}, \tag{3}$$

and $\tilde{\varepsilon}_{i,j,c,c'} \sim F$, for some distribution F with mean equal to 0.

2.2 Identification

We illustrate the sources of variation in the data that allow us to rank colleges located in different countries. In doing so, we highlight the minimal set of observations that are necessary in order to address the identification threats 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 group of workers: stayers in c, movers from c to c', stayers in c'. Let $\bar{w}_{y,c}$ be the average wage of workers in group $y = \{S_c, M_{c,c'}, S_{c'}\}$, and country c. Under specification (2), we can express average wages as

$$\begin{aligned} \bar{w}_{S_c,c} =& q_j + z_c \\ \bar{w}_{M_{c,c'},c} =& q_j + z_c + s_{c,c'} \\ \bar{w}_{M_{c,c'},c'} =& q_j + z_{c'} + s_{c,c'} \\ \bar{w}_{S_{c'},c'} =& q_{j'} + z_{c'}, \end{aligned} \tag{4}$$

where j and j' denote given universities in country c and c', respectively. We omit the indices j and j' from the LHS since we consider one university per country. We are interested in estimating the difference in (log-)quality $q_j - q_{j'}$. Combining the expressions in (4) it is easy to show that

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

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

$$(q_j - q_{j'}) + (z_c - z_{c'}) = (\bar{w}_{S_c,c} - \bar{w}_{S_{c'},c'}). \tag{6}$$

Absent movers, it is not possible to distinguish the cross-country wage gap that is attributable to differences in school quality from other country-specific determinants of productivity, z. 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

$$(q_j - q_{j'}) + s_{c,c'} = (\bar{w}_{M_{c,c'},c} - \bar{w}_{S_{c'},c'}) - (\bar{w}_{M_{c,c'},c} - \bar{w}_{M_{c,c'},c'}). \tag{7}$$

Equation (7) shows that we cannot infer differences in the *average* human capital of college graduates across countries without using stayers in both countries, unless under the assumption that movers were representative of the population of college graduates itself, i.e. $\bar{w}_{S_c,c} = \bar{w}_{M_{c,c'},c}$.

2.3 Estimation Procedure

We follow 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 $s_{c,c'}$, and iii) school quality q_j. The first step capitalizes on workers whom we observe with wage reports in more than one country. The number of workers satisfying this condition for each country is presented in the latter two columns of Table 1. On this sample, we estimate

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

where X_{it} includes a quadratic in years of experience and year fixed effects. With the vector of country-specific premia $z_{c'}$ in hand, we turn to the second step in which $s_{c,c'}$ and q_j are jointly estimated off the sample of Bachelor's degree earners for whom we observe at least one earnings reports. The number of workers satisfying this condition for each country is presented in Columns 5–6 of Table 1. On this sample, we estimate

$$\log(w_{i,j,c,c'}) - z_{c'} = q_j + s_{c,c'} + \gamma X_{it} + \varepsilon_{i,j,c,c'}, \tag{9}$$

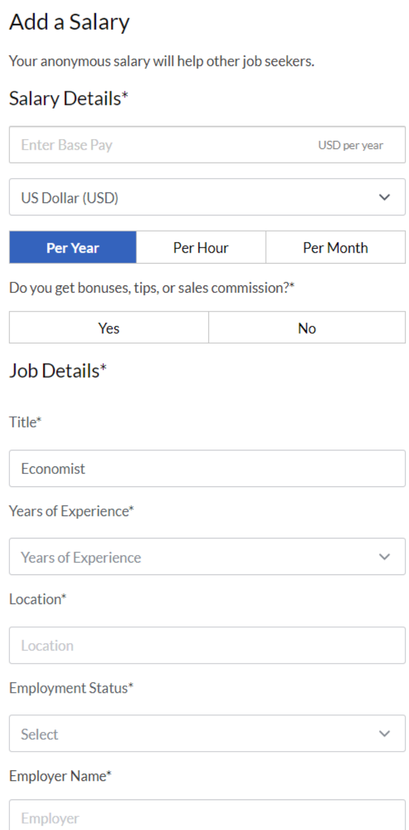
where X_{it} includes a quadratic in years of experience along with major of study and year fixed effects.

3 Data

The primary data source for our work comes from the online labor market platform Glassdoor, where workers can review their employers, document their earnings, and search for jobs. Individuals are incentivized to contribute to the nexus of available 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. Each respondent can submit multiple earnings reports, but is limited to providing at most one report corresponding to a given firm-year. When a user decides to volunteer their earnings on Glassdoor, the survey she is presented is shown in Figure 1. In completing the survey, a respondent provides the following information:

her base earnings, the currency denomination of her earnings, the frequency with which her earnings are received, whether she receives performance-based earnings, her job title, her years of experience, her location of employment, her employment status, and her employer. Consequently, our earnings data consist of employee-employer matches with a rich set of worker observables.

Figure 1: Earnings Report Survey for Glassdoor



Notes: The image above is a screenshot from March 2021 of a blank survey for submitting an earnings report for an Economist. An asterisk signals that an entry is required for the corresponding category. We do not have details on how the presentation of the survey has changed over time, but incorporate year fixed effects in our analysis to account for any such changes to the survey that may have occurred over time.

To ensure comparability and limit measurement error, we impose a handful of sample restrictions. First, we restrict our attention to only full-time employees to forgo having to impute hours for other workers (including part-time, temporary, or seasonal workers). Next, we annualize labor earnings, assuming that full-time hourly workers work 2000 hours per year and full-time monthly employees work 12 months per year. Then, we consider only base income, which necessarily excludes any performance-based earnings from cash bonuses, stock bonuses, profit sharing, or sales commissions, as well as income from tips/gratuities or overtime.[8] Last, we exclude any pay reports whose currency of

[8]Our concern here is measurement error, as bonuses are reported imprecisely for workers paid on an

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 potential outliers. The data span from 2006–2019, with later years contributing disproportionately to the sample as Glassdoor became an increasingly prevalent website over time.

Users are also asked to submit their resumes when creating a profile on the website, which some do. Resumes are the source of our information about collegiate history. For each university attended, the worker can provide information on the degree attained, the program of study, overall grade point average, the starting date, and the graduation date. We focus on information for up to two universities per respondent. Most of our analysis concerns bachelors degree and the corresponding characteristics. We also keep track of additional college exposure (post-bachelors degree, if present; pre-bachelors degree, if not) and corresponding characteristics. Our benchmark sample includes workers who report a bachelor's degree and focuses on where they received the degree. We also include a small number of respondents who only report data for one university but do not list the degree; our results are robust to excluding this latter degree; see Appendix B.

Given the free response nature of workers' resumes, we devote substantial effort to cleanign and harmonizing university information. For degrees and majors, we take a fully supervised approach, textually matching keywords into categories, the details of which are presented in Appendix B. For degrees, we consider the following seven categories: Bachelor's, Associate's, Master's, Postgraduate, MBA, JD, and PhD. For majors, we consider eleven categories that extend the "Major Field Categories" delineated by the National Survey of Student Engagement (NSSE): arts and humanities, biological sciences, business, communications, education, engineering, health services, physical sciences, social sciences, social services, and technology. All majors that do no 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.

Finally, we standardize university names. For U.S. institutions, we match entries against a list of all four-year universities and their subsequent abbreviations or pseudonyms available through the Integrated Postsecondary Education Data System (IPEDS).[9] For non-U.S. institutions, we first rely on lists of universities made available through uniRank and the Center for World University Rankings (CWUR). We then manually add

hourly or monthly basis. While more than one-third of U.S. workers in the United States (Lemieux et al. (2009); Sockin and Sockin (2019a)) and 22%–55% of salaried workers in Glassdoor abroad (Table A-5 of Sockin and Sockin (2019b)) report earning performance-based income, Sockin and Sockin (2019a) estimate that performance pay accounts for 4–7% of employee labor income.

[9]We rely primarily on the string matching algorithm *fuzzymatch* available through Python to match resume entries with the external university 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.

universities that are not included on either of these two lists yet have appreciable coverage on Glassdoor. Our final sample of 2,175 universities covers 40 different nations and is comprised of 1.1 million workers employed in the same country in which they earned their bachelor's and 110,000 workers who migrated to a different country for employment (Table 1).

In addition to Glassdoor, we rely upon a handful of other datasets. From the CWUR, we obtain a global ranking of the top 2000 universities, which provides a natural comparison for our earnings-based rankings. Each university included in the list is also assigned a national ranking, which we use to compare the top universities between countries. To adjust earnings by inflation and purchasing power parity, we obtain PPP-adjusted exchange rates from World Bank (2018). To analyze the import of country-specific income, we obtain GDP per worker from World Bank (2018).

3.1 Sample Selection

In using income data from a proprietary source, naturally the question arises of external validity. Karabarbounis and Pinto (2019) show that Glassdoor wage data broadly matches first and second moments of the earnings distribution between industries and regions using data from the Quarterly Census for Employment and Wages (QCEW) and the Panel Study of Income Dynamics (PSID). 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 (SOC) occupations using the American Community Survey (ACS). We add to this evidence by studying how representative college graduates in Glassdoor are of select countries' undergraduate populations more broadly.

We start with the United States. The United States Department of Education publishes a "College Scorecard" which contains myriad details regarding U.S. institutions related to aspects such as degrees awarded, student loan disbursement, and labor market experience for recent graduates. Using individual tax records from the United States Treasury, the scorecard includes "median earnings of graduates working and not enrolled 1 [2] year[s] after completing highest credential." This offers two cohorts for comparison with Glassdoor, graduates employed one or two years after graduation. The median earnings data is disaggregated by university, degree attained and major of study. This affords a close comparison between college graduates in our sample and the median graduate by school-degree-major-cohort, limiting our attention to earnings following Bachelor's degrees.

In the Glassdoor resume data, a sub-sample of college graduates report the date of completion specific to a university and degree (and major). Earnings in our sample are

Table 1: Summary of Global University Coverage

Country	Abbreviation	GDP per Worker ($)	Universities	University graduates employed		Workers with multiple earnings reports	
				Domestically	Abroad	Migrating in	Migrating out
Bangladesh	BGD	9,421	7	270	783	36	5
Pakistan	PAK	13,163	16	1007	1941	121	28
India	IND	15,425	230	108230	42303	7312	1961
Philippines	PHL	17,802	44	3552	3642	166	49
Nigeria	NGA	17,886	15	786	1523	49	9
Indonesia	IDN	21,467	6	507	226	45	14
China	CHN	22,313	71	915	9544	436	151
Thailand	THA	28,640	4	302	268	41	52
Colombia	COL	29,014	4	81	320	77	20
Brazil	BRA	33,529	25	2548	924	1674	529
Egypt	EGY	37,829	14	2310	1787	151	45
South Africa	ZAF	44,409	8	830	1047	151	45
Mexico	MEX	45,382	10	745	840	373	199
Bulgaria	BGR	46,515	2	79	92	54	19
Russia	RUS	53,020	4	118	289	401	70
Malaysia	MYS	53,028	21	2117	664	301	152
Romania	ROU	55,488	7	408	516	171	65
Argentina	ARG	56,637	2	143	168	151	92
Poland	POL	62,408	3	104	128	258	191
Hungary	HUN	64,358	6	362	212	179	77
Portugal	PRT	70,656	1	50	29	272	194
Turkey	TUR	73,827	18	1688	1461	191	40
South Korea	KOR	74,822	9	225	843	122	57
New Zealand	NZL	77,256	6	516	862	221	220
Japan	JPN	77,848	4	99	221	236	144
Greece	GRC	84,453	8	564	602	169	43
Israel	ISR	86,383	10	1829	855	305	101
United Arab Emirates	ARE	89,365	1	81	52	338	360
United Kingdom	GBR	91,975	118	26980	11666	3142	3477
Canada	CAN	92,165	63	22051	6360	2461	2677
Spain	ESP	95,424	14	569	868	685	514
Australia	AUS	95,564	31	3495	5797	909	986
Netherlands	NLD	106,741	5	307	161	483	667
Denmark	DNK	109,324	1	26	72	86	89
Hong Kong	HKG	109,769	6	1182	441	237	287
Italy	ITA	110,462	20	957	1422	550	222
United States	USA	122,615	1440	922693	12505	6024	14153
Saudi Arabia	SAU	125,452	3	146	59	89	56
Ireland	IRL	148,689	15	1921	1224	750	879
Singapore	SGP	150,396	4	4065	416	812	1057
Total	40		2276	1114858	113133	30229	29996
Total excluding USA	39		836	192165	100628	24205	15843

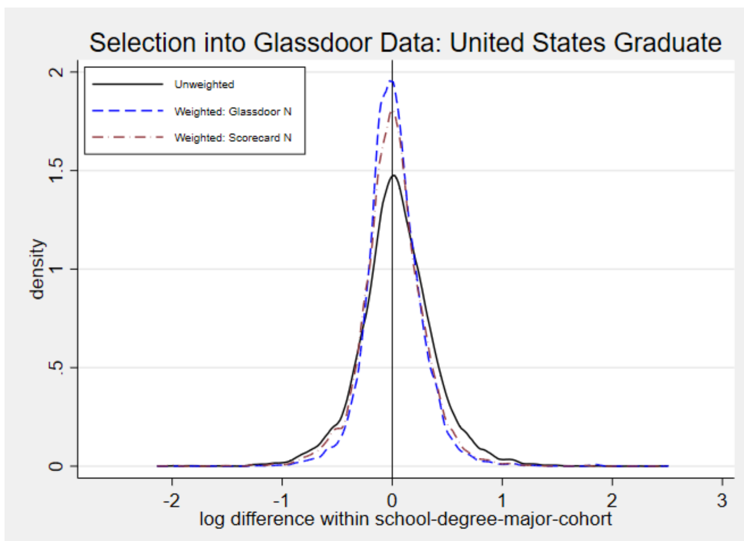
Notes: The table above lists the number of universities, number of domestic graduates, and number of graduates working abroad according to the country of study for attaining a bachelor's degree, as well as the number of migrants for which two wages are observed in the data for the country. Log GDP per worker reflects the annual average from 2010–2019. Sample of countries restricted to those which have at least 25 migrants in the Glassdoor data who migrate from the country of schooling to the top ten most frequent country destinations. Sample further restricted to country of study-country of work pairs with at least 25 (domestic-worker, abroad-worker) pairs where both workers studied at the same university. Sample then further restricted to universities with at least 50 graduates.

reported annually, so taking the difference between the year of earnings and the year of graduation affords a measure of time since completion. Graduates who report earnings one or two years after completion provide natural comparisons with the two cohorts detailed above. There are 11,930 school-bachelors-major-cohort groupings for comparison, represented by 62,650 workers in the Glassdoor sample. We calculate for each school j, major m, and cohort c,

$$\bar{w}^{Glassdoor}_{j,bachelors,m,c} - \bar{w}^{Scorecard}_{j,bachelors,m,c}.$$

If there is an issue with selection into the Glassdoor sample, this distribution will either have non-zero mean or a non-normal distribution. As evidenced in Figure 2, the distribution of these log differences is neither. We conclude that our earnings data is representative of U.S. college graduates.

Figure 2: Sample Selection into Glassdoor for U.S. Graduates



Notes: The figure above captures the degree to which U.S. college graduates in Glassdoor are representative of U.S. graduates more broadly. The figure above is a (weighted) probability density function of the log difference between the average log wage for a college graduate in Glassdoor for a given school-degree-major-cohort compared with the corresponding estimate from the same grouping according to the Department of Education's College Scorecard. For groupings, we consider only bachelor's degrees and eleven possible majors. There are 11,930 groupings represented in Glassdoor, corresponding to 62,650 graduates.

While we find little evidence of selection into the Glassdoor sample for U.S. graduates, our analysis rests on a reliable comparison across countries. With this in mind, we repeat a similar exercise for nine other countries in our database for which we have been able to find representative data on earnings by university. The details for each nation are laid out in Appendix A. The main results are summarized in Table 2. For wealthier nations such as Australia, New Zealand, and the United Kingdom, we see Glassdoor is fairly representative of these graduates more broadly. For less developed countries, workers in Glassdor appear to be positively selected.

Table 2: Sample Selection into Glassdoor for Select Nations

Country of Schooling	GDP per Worker ($)	Comparison groups	Number of graduates	Weighted average selection estimate	Coefficient of 1/CWUR national rank on degree of selection	
					unweighted	weighted by sample size
India	15,425	57	350	-0.12	-0.533 (0.768)	-0.295 (0.572)
China	22,313	3	86	0.62	–	–
Colombia	29,014	10	21	0.24	-0.174 (0.549)	-0.197 (0.480)
Poland	62,408	83	301	0.28	0.122 (0.132)	0.317*** (0.100)
New Zealand	77,256	35	332	-0.01	0.001 (0.056)	0.069* (0.028)
United Kingdom	91,975	114	3178	0.04	-0.554*** (0.133)	-0.520*** (0.110)
Australia	95,564	35	448	0.01	0.042 (0.152)	0.033 (0.064)
Italy	110,462	26	54	0.29	0.221 (0.538)	0.199 (0.254)
United States	122,615	11935	63386	0.01	-0.023 (0.195)	-0.234 (0.218)
Singapore	150,396	62	281	-0.14	0.256 (0.234)	0.097 (0.121)

Notes: The 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 A of the Online Only Appendix

Our main result in this paper is that college quality is lower in developing countries as measured by earnings in Glassdoor. If workers in Glassdoor are more positively selected, this only strengthens the result. Thus, the results that follow are likely to be lower bounds on the extent of cross-country heterogeneity in college quality.

4 Main Results

Our empirical analysis delivers three main results. First, we relate our measure of college quality to the widely used CWUR ranking. This exercise provides a quantification of the heterogeneity in labor market returns along the worldwide college quality distribution. Second, we aggregate our measure of college quality at the country level and explore the implication of our estimates for the extent of human capital variation across countries with different levels of GDP per worker. Finally, we explore the relationship between the quality of a country's top universities and its supply of globally important entrepreneurs and innovators.

4.1 Measuring College Quality

We start by estimating the earnings premium to attending a highly ranked college in the CWUR ranking. This exercise provides an economically significant scale to the ranking. The results are shown in Table 3. The coefficients measure the log-earnings premium associated with graduating from a school with the corresponding ranking, as compared to the omitted category of attending an unranked university. There is a statistically and economically significant premium for graduating from a highly ranked university. The premium grows from 11 log points for schools ranked 1001–2000, 30 log points for schools ranked 51–100, and reaches a substantial 41 log points (51 percent) for schools ranked in the top 20. To put these numbers into perspective, the median college premium in the United States—i.e. the difference in median earnings between college and high school graduates—is equal to 65%. That is, the earning difference between attending a top 20 college instead of one of the more 20000 unranked colleges is about 2/3 of the earning difference between attending or not a college in the United States.

Our data on workers' alma mater and labor market outcomes allows us to go one step further and create our own earnings-based ranking of colleges around the world. The results are presented in Table 4. Our list of Top 100 colleges is dominated by US institutions, and to a lesser extent by schools from other Anglo-Saxon countries like Australia, Canada and the UK. Perhaps more surprisingly, the very top positions of our ranking see a significant representation of different Indian Institute of Technology, which are ranked in the 500–1000 range in CWUR. Similarly, within the United States, our Top 100 disproportionately features selective liberal art colleges compared with traditional rankings dominated by the Ivy League and other research-centered institutions.

Table 3: University Premia and CWUR World Ranking

	World ranking overall	World ranking research performance
World rank: 1–20	0.417***	0.400***
	(0.045)	(0.045)
World rank: 21–50	0.315***	0.289***
	(0.040)	(0.036)
World rank: 51–100	0.311***	0.287***
	(0.032)	(0.035)
World rank: 101–250	0.244***	0.220***
	(0.019)	(0.019)
World rank: 251–500	0.184***	0.192***
	(0.015)	(0.016)
World rank: 501–1000	0.158***	0.144***
	(0.013)	(0.013)
World rank: 1001–2000	0.115***	0.097***
	(0.012)	(0.012)
N: Rank 1–20	15	15
N: Rank 21–50	19	24
N: Rank 51–100	30	26
N: Rank 101–250	88	93
N: Rank 251–500	143	135
N: Rank 501–1000	197	194
N: Rank 1001–2000	261	236
N: Total	2276	2276
Adjusted R^2	0.21	0.19

Notes: The table above displays the relation between our ranking of university quality q_j (in log points) and rankings of university quality according to the Center for World University Rankings, which globally ranks the top 2000 universities overall and by research performance. The reference group is comprised of universities that are unranked according to CWUR. Sample of universities restricted to those with at least 50 graduates in our sample.

Table 4: Top 100 Universities By Estimated Quality

Rank	University of Schooling	Country	World Ranking	University Premia N	University Premia Estimate	Rank	University of Schooling	Country	World Ranking	University Premia N	University Premia Estimate
1	Keio University	JPN	86	62	0.45	51	Copenhagen Business School	DNK	1098	57	0.26
2	University of Pennsylvania	USA	9	552	0.44	52	Technion Israel Institute of Technology	ISR	111	342	0.26
3	St. Louis College of Pharmacy	USA	.	94	0.44	53	Middlebury College	USA	1947	389	0.26
4	Indian Institute of Technology Delhi	IND	548	123	0.42	54	The Business School	GBR	.	71	0.26
5	Sophia University	JPN	1837	71	0.41	55	Macquarie University	AUS	371	372	0.25
6	Indian Institute of Technology Bombay	IND	587	118	0.38	56	Santa Clara University	USA	1125	1365	0.25
7	Indian Institute of Technology Kanpur	IND	830	143	0.37	57	Rice University	USA	109	580	0.25
8	Harvard University	USA	1	295	0.35	58	The University of Western Australia	AUS	126	253	0.25
9	Waseda University	JPN	168	84	0.35	59	Cornell University	USA	14	292	0.24
10	Emory University	USA	90	184	0.35	60	Barnard College	USA	.	358	0.24
11	Indian Institute of Technology Guwahati	IND	969	130	0.35	61	La Trobe University	AUS	529	173	0.24
12	Indian Institute of Technology Kharagpur	IND	674	219	0.34	62	Rose-Hulman Institute of Technology	USA	.	401	0.24
13	Indian Institute of Technology Roorkee	IND	788	193	0.33	63	University of Notre Dame	USA	140	1641	0.24
14	Williams College	USA	1295	300	0.33	64	Yonsei University	KOR	161	214	0.24
15	The University of Sydney	AUS	100	502	0.33	65	Stevens Institute of Technology	USA	1027	490	0.23
16	United States Naval Academy	USA	1220	892	0.33	66	Washington and Lee University	USA	1356	211	0.23
17	University of Canberra	AUS	1087	90	0.32	67	Instituto TecnolÃ³gico AutonÃ³mo de MÃ©xico	MEX	.	75	0.23
18	The University of Melbourne	AUS	64	503	0.32	68	Amherst College	USA	458	284	0.23
19	Columbia University in the City of New York	USA	6	406	0.32	69	University of Waterloo	CAN	179	1661	0.23
20	Australian National University	AUS	108	175	0.32	70	Pomona College	USA	1054	293	0.23
21	Southern Cross University	AUS	1409	68	0.31	71	University of California-Berkeley	USA	8	8199	0.23
22	California Institute of Technology	USA	11	191	0.31	72	Wesleyan University	USA	707	572	0.23
23	University of Michigan-Ann Arbor	USA	17	301	0.31	73	Colgate University	USA	856	602	0.23
24	Brown University	USA	45	888	0.31	74	Yeshiva University	USA	229	227	0.23
25	Dartmouth College	USA	49	865	0.31	75	Tel Aviv University	ISR	143	678	0.23
26	University of Technology Sydney	AUS	463	259	0.31	76	Massachusetts Maritime Academy	USA	.	118	0.23
27	Carnegie Mellon University	USA	84	1419	0.30	77	Sogang University	KOR	904	68	0.22
28	Charles Sturt University	AUS	1025	108	0.30	78	Haverford College	USA	1155	195	0.22
29	Cooper Union for the Advancement of Science and Art	USA	.	105	0.30	79	The London School of Economics and Political Science	GBR	293	293	0.22
30	The University of New South Wales	AUS	113	548	0.30	80	Lehigh University	USA	449	1100	0.22
31	Netaji Subhas University of Technology	IND	.	215	0.30	81	Griffith University	AUS	379	202	0.22
32	Washington University in St Louis	USA	41	67	0.30	82	College of the Holy Cross	USA	893	445	0.22
33	United States Military Academy	USA	1009	887	0.30	83	Holon Institute of Technology	ISR	.	98	0.21
34	Claremont McKenna College	USA	1036	275	0.30	84	Deakin University	AUS	402	232	0.21
35	Harvey Mudd College	USA	.	168	0.29	85	Curtin University	AUS	360	461	0.21
36	Queensland University of Technology	AUS	390	331	0.29	86	Xidian University	CHN	604	82	0.21
37	University of Tasmania	AUS	408	87	0.29	87	Worcester Polytechnic Institute	USA	1032	948	0.21
38	Georgetown University	USA	203	96	0.28	88	University of Virginia-Main Campus	USA	53	2524	0.21
39	Indian Institute of Technology Madras	IND	600	139	0.28	89	Rensselaer Polytechnic Institute	USA	436	1388	0.21
40	Tufts University	USA	94	1126	0.28	90	Bucknell University	USA	819	737	0.21
41	United States Merchant Marine Academy	USA	.	81	0.28	91	Edith Cowan University	AUS	1076	133	0.21
42	Indian Institute of Technology, BHU	IND	1519	99	0.27	92	California State University Maritime Academy	USA	.	51	0.21
43	Kansai Gaidai University	JPN	.	51	0.27	93	United States Coast Guard Academy	USA	.	70	0.21
44	University of Chicago	USA	10	86	0.27	94	Bond University	AUS	1624	89	0.20
45	Babson College	USA	940	556	0.27	95	University of Sherbrooke	CAN	541	87	0.20
46	Western Sydney University	AUS	516	271	0.27	96	Lafayette College	USA	.	496	0.20
47	The University of Queensland	AUS	115	383	0.26	97	Colorado School of Mines	USA	433	600	0.20
48	Swarthmore College	USA	815	261	0.26	98	Colby College	USA	1991	317	0.20
49	Monash University	AUS	102	855	0.26	99	Korea University	KOR	178	159	0.20
50	United States Air Force Academy	USA	.	414	0.26	100	Boston College	USA	428	1722	0.20

Notes: The table above displays the top 100 schools ranked in descending order according to their quality q_j. Sample of countries restricted to those which have at least 25 migrants in the Glassdoor data who migrate from the country of schooling to the top ten most frequent country destinations. Sample further restricted to country of study-country of work pairs with at least 25 (domestic-worker, abroad-worker) pairs where both workers studied at the same university. Sample then further restricted to universities with at least 50 graduates, for which 2175 satisfy these criteria.

4.2 College Quality and Cross-Country Human Capital Differences

Our first set of results suggest that college quality is highly heterogeneous. In this section we show that college quality is systematically related to development. This finding implies that the common practice of focusing on the share of a nation's workforce that has graduated college may understate cross-country differences in the share of skilled workers.

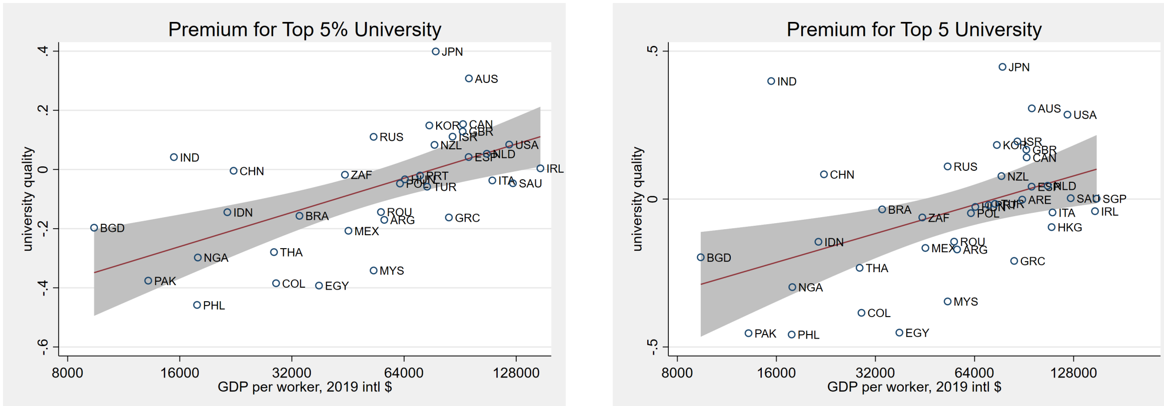
The Glassdoor data have better coverage of top universities, which are more likely to produce workers who migrate. Given this, we explore the quality of top universities by country and how it correlates with development. We consider two notions of top universities: either the top 5 percent of a country's universities or its top 5 universities, each measured using the nation-specific CWUR rankings. The resulting estimate of college quality is plotted against GDP per worker in Figure 3.

The key insight from this plot is that higher GDP per worker is associated with a better college quality. Again, the effect is economically and quantitatively significant. For example, the average graduate from a top 10 percent Australian university has a college quality 45 log points higher than the average graduate from a top 10 percent Bangladeshi university, indicating that they earn nearly 60 percent more in the same labor market. The result is similar when we focus on the top 5 universities (left panel) or the top 5 percent universities (right panel), although the relative ranking offers a more precise estimate relationship because it better accounts for overall country size.

We explore how this result changes as we vary the set of colleges we include by repeating our regression at different points of the within country college quality distribution (Table 5). The estimates are consistently large and fairly stable. For example, the elasticity of the quality of the top 2 percent of colleges and bottom 75 percent of colleges are nearly the same, at 0.164 and 0.160. These findings indicate that poorer countries are characterized by a leftward shift of the entire distribution of college quality.

The findings in this section complement previous work that estimated the returns to schooling of foreign-educated workers or the wage gains at migration by school group (Schoellman, 2012; Hendricks and Schoellman, 2018). Relative to this literature, our analysis presents two main differences. On the one hand, our sample is limited in that it excludes workers whose highest degree is high school or less. This implies that we have little to say about the quality of pre-college education or the relative quality of different stages of education. Moreover, while each country's top colleges are likely to be well-represented in our dataset, we might not be observing graduates from lower ranked colleges, especially in developing countries. On the other hand, the data include a large sample of college graduates and is the first we are aware of to include information on

Figure 3: Returns to Nations' Top Universities



(a) Relative national ranking

(b) Absolute national ranking

Notes: The figures above display the relationship between top university quality and income per worker. Top 5 distinction is drawn directly from the CWUR's nation-specific rankings. Top 5% distinction is calculated using the same nation-specific ranking, but adjusting for how many total universities are in each country. Each dot represents the average q_j among all universities that fall in the Top 5 (left panel) or Top 5% (right panel) for a given country.

the specific college people attended. This means that our work is the first to explicitly estimate quality by college and to allow for heterogeneous education quality within a country.

Table 5: Top Percent Universities within Countries and GDPPW

	Top 2%	Top 3–5%	Top 5–10%	Top 10–25%	Other
Log(gdppw)	0.164***	0.153***	0.215***	0.124	0.160***
	(0.053)	(0.046)	(0.054)	(0.088)	(0.041)
N	27	23	24	21	33
Adjusted R^2	0.25	0.31	0.39	0.05	0.31

Notes: The table above displays the relationship between university quality and income per worker across universities of differing rank. Determining the percent ranking for each university is drawn directly from the CWUR's nation-specific rankings. Other category includes universities ranked outside the top 25%, as well as unranked universities according to the CWUR. Each county of study enters the regression once, represented by the average q_j among all universities that fall within the ranking partition.

4.3 College Quality and Top Talent

The presence of high-quality top colleges is particularly important for a nation's ability to produce talented workers who become entrepreneurs and innovators. We demonstrate this point by merging our estimates of college quality with measures of patenting, win-

Table 6: University Quality and Notable Achievements, U.S. Universities Only

	Share student inventors	Log patents+1	Log cites+1	Nobel prizes	S&P500 CEOs in 2005	S&P500 CEOs in 2020
University quality	0.049***	2.790***	2.674***	1.249***	2.229***	2.446***
	(0.006)	(0.669)	(0.417)	(0.117)	(0.166)	(0.150)
Mean outcome	0.010	4.156	3.903	0.086	0.266	0.259
Std. dev. university quality	0.15	0.15	0.15	0.15	0.15	0.15
N	320	320	320	1440	1440	1440
Adjusted R^2	0.18	0.05	0.11	0.07	0.11	0.16

Notes: First three dependent variables are from Bell et al. (2019).

ning Nobel prizes, and becoming a CEO of an S&P 500 firm. Patenting data is taken from the U.S. Patent and Trademark Office and 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 for 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 universities with more than ten patents granted among students in the 1980–1984 birth cohorts; see their paper for further detail. We add to this the number of Nobel prize-winners in Physics, Chemistry, Medicine, and Economics as well as the number of CEOs of S&P 500 companies who did their undergraduate studies at each institution. Details are available in Appendix C.

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. 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 university 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 university quality corresponds to ten percent more patents or a more than doubling in the probability of having an S&P500 CEO.

We now turn to results for non-American universities. We start with results at the level of the country. These allow us to address whether countries with high-quality universities have more entrepreneurs and innovators. An obvious confounding factor is that countries with high-quality universities tend to be richer, so we control for (log of) GDP per worker in all regressions. We use the same outcomes as for Americans, except that we now rely on

Table 7: Top University Quality and Notable Achievements

	Patents per 1000 persons		Nobel prizes		S&P500 CEOs in 2005		S&P500 CEOs in 2020	
Log(gdppw)	0.517**	0.090	2.591	-0.339	0.223	-0.390	0.139	-0.759
	(0.218)	(0.241)	(1.577)	(1.766)	(0.392)	(0.455)	(0.584)	(0.680)
Top 5% school quality		2.567***		17.616***		3.682**		5.400**
		(0.851)		(6.237)		(1.606)		(2.400)
N	34	34	34	34	34	34	34	34
R^2	0.15	0.34	0.08	0.27	0.01	0.15	0.00	0.14

Notes: Top 5% school quality reflects the average across universities in the top 5% according to CWUR national rankings. Regressions excludes the United States.

U.S. patents by foreign nationals by country from the U.S. Patent and Trademark Office rather than patents by university (which are not available). We divide patents by the population to adjust by country size.

The results are shown in Table 7. We first regress each outcome against GDP per worker. We verify positive correlations for all four outcomes, although the relationship is not statistically significant. We then regress each outcome against GDP per worker and the quality of the nation's top 5 percent of colleges. College quality is again a statistically and economically significant predictor, while GDP per worker is no longer statistically significant in any case and often has the wrong sign. We conclude that having top colleges is the dominant predictor of a nation's supply of innovators and entrepreneurs.

While patenting data is only available at a country level, the data on CEOs and Nobel laureates is available at a university level. For our final analysis we estimate the relationship between college quality and these two measures at the university level. This analysis gives us a larger sample size and mitigates the usual concerns associated with cross-country regressions. To highlight this, we explore conducting the analysis using country fixed effects. The results are shown in Table 8.

This table shows that foreign graduates from higher-quality colleges are more likely to win Nobel prizes or become CEOs. Further, this relationship is *stronger* when we control for country fixed effects. Again, the economic magnitudes are large. A college that is one standard deviation higher in our measure of quality is more than twice as likely to produce a Nobel laureate and nearly three times as likely to produce a top CEO as the average university in our sample. 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

Table 8: University-Specific Quality and Notable Achievements

	All countries		U.S. only	Excluding U.S.	
CEOs of S&P500 in 2020	1.037***	1.763***	2.445***	0.164***	0.379***
	(0.077)	(0.102)	(0.149)	(0.033)	(0.060)
Dependent variable mean	0.18	0.18	0.26	0.05	0.05
Adjusted R^2	0.07	0.12	0.16	0.03	0.06
Nobel prizes	0.661***	0.971***	1.249***	0.340***	0.407***
	(0.067)	(0.091)	(0.117)	(0.074)	(0.139)
Dependent variable mean	0.09	0.09	0.09	0.09	0.09
Adjusted R^2	0.04	0.05	0.07	0.02	0.04
Country FE		✓			✓
Universities	2276	2273	1440	836	833
Standard deviation q_j	0.19	0.19	0.15	0.25	0.25

Notes: Dependent variable is listed in first row of each panel.

the heterogeneity in top college quality by country that we document in Figure 3.

5 Heterogeneity of Results

In addition to the key information on alma mater, country, and earnings, the Glassdoor database includes information on a rich set of other characteristics for a subset of workers. In this section we use this data to understand the heterogeneity of our results along several dimensions of interest.

5.1 The Importance of GPA

One potential concern is that our findings reflect reputation rather than human capital, particularly for migrants. The fact that our ranking differs so much from standard ones is one piece of evidence against this hypothesis: some of the best schools according to our estimates do not belong to the set of worldwide renowned school that populate the top of traditional rankings. A second piece of evidence is that there are also substantial returns to grade point average (GPA), indicating that employers pay more workers who learned more in college.

To show this, we collect GPA data from resumes for all workers who provide it. Different countries and universities use different scales for reporting GPA. Further, some workers – particularly migrants – translate their GPA so that it is compatible with the standard norms in local labor markets. We clean GPA data so that it is reported consistently with local norms.[10] We then normalize reported GPA by university so that results are consistent across countries and universities.

We use this data in a standard Mincer regression, where we regress log-earnings on GPA, a quadratic in experience, and a host of controls, including university, major, and year fixed effects. We further break the sample into four subsamples, differentiating between U.S. and non-U.S. workers who graduated from U.S. or non-U.S. universities. The results, reported in Table 9, highlight that there is a substantial return to having a higher college GPA, even conditional on graduating from the same alma mater. Since we normalize GPA, the coefficients show that a one standard deviation increase in GPA is associated with 2–5 percent higher earnings. Further, the returns extend to foreign graduates; while the U.S. labor market puts a somewhat lower premium on foreign college GPA, other labor markets appear to value U.S. college GPA highly. We conclude from this there is heterogeneity in returns within a college and that this provides further evidence that the earnings premium of a college does not simply represent paying for the credential or signal.

5.2 Results by Subject

Our main results provide a single estimate of quality for each college. We document the ranking of colleges according to this estimate (Table 4). We also show that richer countries are characterized by a rightward shift in the distribution of college quality (Table 5). In this section we investigate heterogeneity in college quality by subject, to explore whether quality differences are general or whether rich and poor countries have different comparative advantages by subject.

To document this, we estimate separate education quality by university and subject. Doing so necessarily involves splitting our sample and thus reducing sample size per university. To mitigate this, we focus on a simple split of subjects into three broad groups of interest: STEM (science, engineering, and other technical fields); business and social science; and other. Further, while we estimate the quality by college, we aggregate results to the country level.

[10] For converting graduates' GPAs that have yet to be uniformized to the United States 4-point system, we rely on readily available mappings to foreign grading systems. For India, we rely on the university-specific and broad mapping available through Scholaro. For the United Kingdom, we use the system recommended by the The US-UK Fulbright Commission. And for the rest of the OECD nations in our sample, we use the mappings recommended by the OECD.

Table 9: Student Outcomes by Grade Point Average

	U.S. University		Non-U.S. University	
	U.S. Worker	Non-U.S. Worker	U.S. Worker	Non-U.S. Worker
Standardized z-score for GPA	0.053***	0.052***	0.024***	0.051***
	(0.002)	(0.017)	(0.006)	(0.006)
Years of experience	0.067***	0.135***	0.056***	0.160***
	(0.001)	(0.011)	(0.004)	(0.005)
Years of experience^2/100	-0.133***	-0.333***	-0.069***	-0.381***
	(0.004)	(0.053)	(0.019)	(0.026)
N	118191	1225	10218	30202
Adjusted R^2	0.25	0.36	0.22	0.35

Notes: The table above displays the additional returns that students who receive higher marks in their undergraduate studies earn in the labor market. Grade point average (GPA) is standardized within universities. U.S. University reflects students who received their Bachelor's in the United States, non-U.S. University those who received their Bachelor's elsewhere. U.S. Worker reflects students who work in the United States, non-U.S. Worker those who work elsewhere. Each regression includes university, major, and year fixed effects. Columns 6 and 8 additionally include country of employment fixed effects. Standard errors are clustered by university.

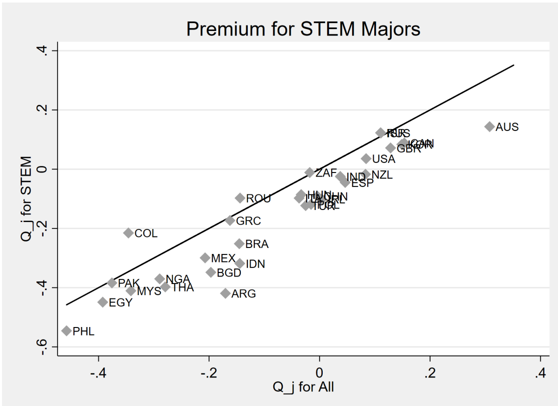
Figure 4 shows the resulting estimates of the quality of top ten percent of universities by country and broad field. The three panels show the three fields of STEM, business/social science, and other. In each case the field-specific quality is plotted against the overall estimate of quality obtained when we pool fields as in Section 4. Quality is normalized separately in each regression against a fixed university (UT-Austin, the most sampled college).

The figure shows two main results. First, deviations from the 45-degree line are indicative of comparative advantage, or field-specific college quality. Thus, we can see that Australia is better at business/social science and other fields than STEM, or that India has a comparative advantage in STEM. However, the second finding is that overall the results track the 45-degree line closely. This suggests that most differences in college quality are general: poor countries offer lower quality college roughly proportionally in these three broad fields.

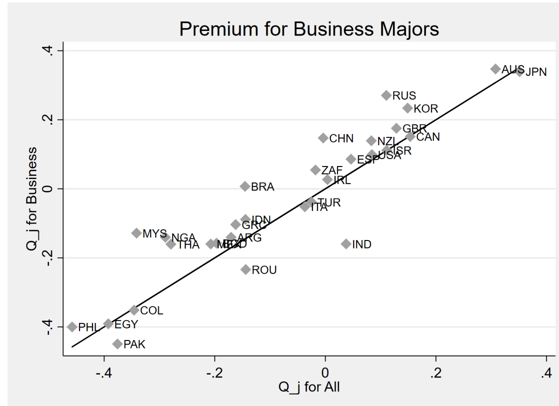
5.3 Effects of Graduate School

One concern with estimating undergraduate university quality for workers' alma maters using a snapshot of their earnings is that education does not necessarily terminate with a Bachelor's degree. 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

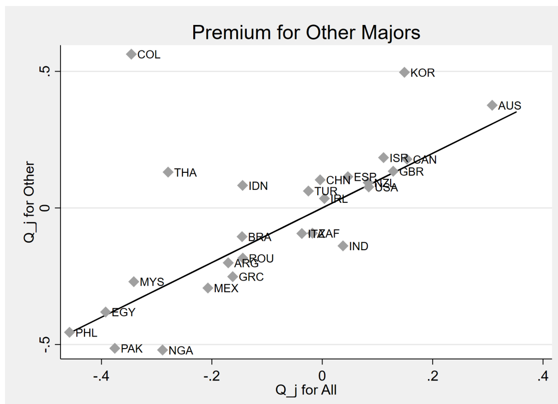
Figure 4: Returns to Nations' Top Universities by Major



(a) STEM



(b) Business/Social Science



(c) Other

Notes: The figures above display, for the average across top 10% universities, the relationship between our measure of university quality q_j and the estimates that would be obtained when considering only specific majors of study. Panel (a) captures STEM-related majors, panel (b) Business and Social Science majors, and panel (c) all other majors. For details on what programs of study fall within these three categories, see Section B.3 of the Online Only Appendix. Top 10% distinction is calculated using the same nation-specific ranking, but adjusting for how many total universities are in each country. Each dot represents the average q_j among all universities that fall in the Top 5% for a given country overall (x-axis) or for the given major of study (y-axis).

1.1% of 28-year olds held a PhD (Altonji et al. (2016)). Within our sample, 24% of college graduates from universities outside the United States earn a graduate degree. If workers earn outsized returns from attending graduate school, and graduates from higher quality undergraduate programs are more likely to attend (a higher quality) graduate school, then our estimates for school quality q_j, which are produced using one's undergraduate attendance, will be biased upwards for top universities. Given that we observe each worker's educational history, we can directly measure whether accounting for graduate school meaningfully alters our findings.

In particular, we closely examine whether our benchmark estimate for the elasticity of school quality to GDP per worker of 0.167—calculated irrespective of graduate school—fluctuates when attainment of post-Bachelor's degrees is considered. We consider four possible scenarios, the results of which are summarized in Columns 2–5 of Table 10. The first restricts the sample to workers with at most a bachelor's degree. The second controls for graduate school degrees using a simple dummy variable. The third estimates graduate school quality under the assumption that the quality of school j's graduate education is a fixed fraction α_g of the quality of the quality of its undergraduate education, where α_g is estimated. The fourth jointly estimates separate returns to undergraduate quality $q_{j,u}$ and graduate quality $q_{j,g}$, assigning graduates with at most a bachelor's degree to a single "unavailable" grouping for graduate school. The regression specification for the latter follows

$$\log(w_{i,j_u,j_g,c_u,c_j,c'}) = z_{c'} + q_{j_u} + q_{j_g} + s_{c_u,c'} + s_{c_g,c'} + \epsilon_{i,j_u,j_g,c_u,c_j,c'}. \tag{10}$$

Our primary focus is how these various specifications affect our estimates of the quality of undergraduate college quality. Table 10 gives a sense of this by showing the elasticity of quality among the top 5 percent of colleges with respect to GDP per worker. The first column shows the baseline estimate from ignoring graduate school is 0.167. The remaining columns show the result for the same elasticity when using the alternative approaches. The main finding is that the implied cross-country differences in college quality are large for all these specifications.

Table 10: School Premia for Top 5% Universities and GDP per Worker, Alternative Specifications Accounting for Graduate School

	Ignore graduate school	At most undergrad	Include graduate dummy	Undergrad + coef*graduate	Estimate simultaneously undergrad
Log(gdppw)	0.167***	0.168***	0.167***	0.233***	0.170***
	(0.039)	(0.043)	(0.039)	(0.059)	(0.042)
Variance of premia	0.0377	0.0398	0.0371	0.0718	0.0369
Covariance of premia with at most undergrad	0.0383	0.0398	0.0380	0.0513	0.0379
N	35	35	35	35	35
Adjusted R^2	0.34	0.30	0.34	0.30	0.31

Notes: The table above displays how sensitive the elasticity of school quality to GDP per worker is when graduate school attainment and quality is considered. We estimate four plausible specifications. Column 1 conveys the baseline specification in which graduate school is ignored. Column 2 restricts the sample to workers with at most a bachelor's degree. Column 3 incorporates a dummy variable for the worker earns a graduate degree. Column 4 takes the estimates from the baseline specification, estimates graduate school quality as a single slope parameter in undergraduate quality ($q_{j,g} = \alpha_g q_{j,u}$) and then relates the combination of undergraduate and graduate quality $(1+\alpha_g)q_{j,u}$ to GDP per worker. Column 5 jointly estimates separate returns to undergraduate quality $q_{j,u}$ and graduate quality $q_{j,g}$, assigning graduates with at most a bachelor's degree to a single "unavailable" grouping for graduate school.

The estimates from equation (10) 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. In Table 11 we compare the estimated earnings premium for undergraduate and graduate degrees for universities in various bins of the CWUR rankings.

Table 11: University Premia and CWUR World Ranking, Undergraduate vs. Graduate

	Undergraduate premia	Graduate premia
World rank: 1–20	0.393***	0.205***
	(0.044)	(0.021)
World rank: 21–50	0.303***	0.093***
	(0.040)	(0.020)
World rank: 51–100	0.308***	0.088***
	(0.032)	(0.016)
World rank: 101–250	0.244***	0.040***
	(0.019)	(0.012)
World rank: 251–500	0.180***	0.045***
	(0.015)	(0.011)
World rank: 501–1000	0.155***	0.045***
	(0.013)	(0.011)
World rank: 1001–2000	0.107***	0.035***
	(0.011)	(0.009)
N: Rank 1–20	15	17
N: Rank 21–50	19	20
N: Rank 51–100	30	29
N: Rank 101–250	88	59
N: Rank 251–500	143	70
N: Rank 501–1000	197	78
N: Rank 1001–2000	261	112
N: Total	2276	749
Adjusted R^2	0.21	0.16

Notes: The table above displays the relation between our ranking of undergraduate university quality $q_{j,u}$ and graduate university quality $q_{j,g}$ (in log points) and rankings of university quality according to the Center for World University Rankings, which globally ranks the top 2000 universities overall. We jointly estimate separate returns to undergraduate quality $q_{j,u}$ and graduate quality $q_{j,g}$, assigning graduates with at most a bachelor's degree to a single "unavailable" grouping for graduate school. The reference group is comprised of universities that are unranked according to CWUR. Sample of universities for which undergraduate or graduate quality restricted to those represented by at least 50 graduates in our sample.

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 nonlinear. Graduate degrees in schools ranked anywhere between 101–2000 all pay a modest earnings premium over graduate degrees from unranked universities, in the range of 3–5 percent. The premium rises substantially from there, to 9–10 percent for schools ranked between 21–100 and 20.5 percent for schools ranked in the top 20. This outsized return enjoyed by workers with a graduate degree from a top 20 university is consistent with the 20–25% estimate for top 25 MBA programs from Arcidiacono et al. (2008).

6 Robustness

Our simple model decomposes workers wages into a country component, a college component, unobservable ability (which is allowed to vary systematically between movers and stayers), and a set of controls including experience, major, and degree. In this section, we perform a number of robustness checks to verify that our main results are unaffected by reasonable departures from the main model specification. We focus on the correlation between average within country college quality and GDP per worker (Table 12). In our benchmark specification, such correlation is equal to 0.16 (panel A). We control for the possibility that our estimates of college quality are affected by differential representations of their graduates in certain types of jobs (panel B) or firms (panel C). We further restrict to sample we use for the estimation of country fixed effects (z_c) to coincide with the sample of workers for which we have college information, in order to mitigate the concern that migrants in this subsample are systematically different from the broader sample of migrants in Glassdoor (panel D). As documented in Lagakos et al. (2018), life-cycle wage profiles differ across countries, hence we control for country-specific experience profiles (panel E). Last, we entertain the hypothesis that selection into migration varies not only at the country of origin-country of destination level, but also by specific school (panel F). In all cases, modifying our baseline specification does not substantially alter our main results.

7 Conclusions

In this paper we propose and implement an approach to measure college quality consistently across countries. The approach uses earnings data and exploits the fact that graduates of top universities are increasingly internationally mobile and so move into common labor markets, facilitating comparison. 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 three main findings. First, graduates of top colleges earn roughly 50 percent more than those of typical colleges in a common labor market. Second, rankings of colleges based on earnings are correlated with more standard rankings, but systemati-

Table 12: Robustness Results: Alternative Specifications for Estimating Elasticity of School Quality with respect to Income per Worker

	Top 5%	Not-Top 5%
Panel A: Baseline specification	0.164***	0.192***
	(0.038)	(0.039)
	[35]	[39]
Panel B: Incorporate job title fixed effects	0.139***	0.167***
	(0.034)	(0.032)
	[35]	[39]
Panel C: Incorporate firm fixed effects	0.205***	0.227***
	(0.040)	(0.041)
	[35]	[39]
Panel D: Restrict migrants sample to college graduate sub-sample in first estimation step	0.131	0.192**
	(0.076)	(0.072)
	[21]	[25]
Panel E: Country-of-work-specific quadratic in experience in second estimation step	0.264***	0.276***
	(0.047)	(0.044)
	[35]	[39]
Panel F: Allow for university-specific selection $s_{j,c,c'}$ in second estimation step	0.147***	0.189***
	(0.042)	(0.038)
	[35]	[39]

Notes: The table above displays how sensitive the elasticity of school quality to GDP per worker is to the choice of sample or model specification. First estimation step refers to the process by which z_c is captured through observing migrants with wages in multiple countries. Second estimation step refers to the process by which q_j and $s_{c,c'}$ are jointly estimated, conditional on z_c from the first step. Sample of countries in each panel restricted to those which have at least 25 migrants who migrate from the country of schooling to the top ten most frequent country destinations and have earnings in both countries. Sample further restricted to country of study-country of work pairs with at least 25 (domestic-worker, abroad-worker) pairs where both workers studied at the same university. Sample then further restricted to universities with at least 50 graduates. Point estimates are presented, along with standard errors in parentheses and the number of countries included in the regression sample in brackets.

cally weight certain types of colleges, such as liberal arts schools and technical colleges in developing countries, higher. Third, we find that the entire distribution of college quality is shifted down in poorer countries.

We rank colleges based on the average earnings of their 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 a fascinating subject for future research.

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Appendix

A Country-Specific Earnings Premia

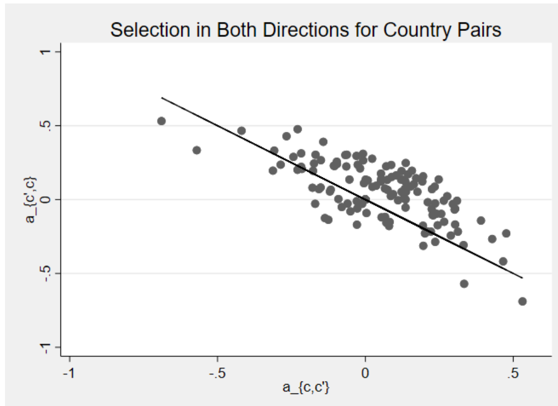
Table 13: Estimated Premium to Working in Each Country

Rank	Country of work	N	Wage premium	Rank	Country of work	N	Wage premium
1	Saudi Arabia	138	0.50	28	Norway	98	-0.05
2	South Africa	186	0.35	29	Bulgaria	66	-0.05
3	United Arab Emirates	642	0.30	30	New Zealand	407	-0.06
4	Singapore	1688	0.26	31	France	1404	-0.06
5	Qatar	91	0.25	32	Slovakia	68	-0.07
6	Thailand	86	0.21	33	Japan	354	-0.07
7	United States	17861	0.18	34	Israel	374	-0.08
8	Switzerland	903	0.17	35	Australia	1739	-0.08
9	Colombia	93	0.17	36	Finland	174	-0.09
10	Hong Kong	491	0.16	37	Canada	4352	-0.10
11	Germany	2031	0.16	38	Hungary	225	-0.10
12	Denmark	154	0.15	39	Italy	713	-0.10
13	Turkey	220	0.08	40	Argentina	223	-0.12
14	Ireland	1453	0.07	41	Sweden	351	-0.12
15	Netherlands	1058	0.07	42	Philippines	202	-0.13
16	Luxembourg	259	0.07	43	China	557	-0.19
17	Chile	64	0.07	44	Egypt	182	-0.22
18	United Kingdom	5869	0.04	45	Brazil	1959	-0.25
19	Austria	224	0.04	46	Indonesia	56	-0.25
20	Malaysia	413	0.01	47	Portugal	434	-0.26
21	South Korea	161	0.01	48	Romania	213	-0.27
22	Czech Republic	275	0.00	49	Greece	196	-0.35
23	Spain	1097	0.00	50	India	8479	-0.37
24	Poland	411	-0.01	51	Nigeria	57	-0.39
25	Mexico	522	-0.03	52	Pakistan	140	-0.43
26	Russia	443	-0.04	53	Bangladesh	40	-0.49
27	Belgium	457	-0.04				

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 country destinations.

B Selection Among Migrants

Figure 5: Selection Between Country Pairs (c, c') in Each Direction



Notes: The figure above plots for each pair of countries (c,c′) in our sample, selection estimate $s_{c,c'}$ for graduates who studied in country c but work in country c' against the selection estimate $s_{c',c}$ for graduates who studied in country c' but work in country c. Solid black line corresponds to a $--45°$ line.

Table 14: Selection Between Countries and Differences in Income

	Overall	STEM majors	Business majors	Other majors
log(gdppw c′) - log(gdppw c)	0.131***	0.117***	0.135***	0.132***
	(0.011)	(0.017)	(0.021)	(0.029)
Constant	0.040***	0.029	0.060***	0.065**
	(0.012)	(0.021)	(0.022)	(0.030)
N: (c,c′) pairs	253	112	90	55
Adjusted R^2	0.36	0.30	0.31	0.26

Notes: The table above relates the degree of selection in migrants who study in country c but are employed in country c' with the difference in GDP per worker between c and c'. Columns 2–4 reflect the same comparison, except when jointly estimating school quality q_j and selection $s_{c,c'}$, the samples are restricted to STEM majors, Business and Social Science majors, or Other majors, respectively.

Online Only Appendix

A 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 universities or attend university 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 university in Glassdoor to nationally representative samples for all countries for which we have identified such data.[11] Here we provide the data source and details of the data construction, country by country.

A.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 an online survey of graduates of the most of the country's universities and other institutions of higher education. Graduates are solicited to fill out the survey approximately 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).

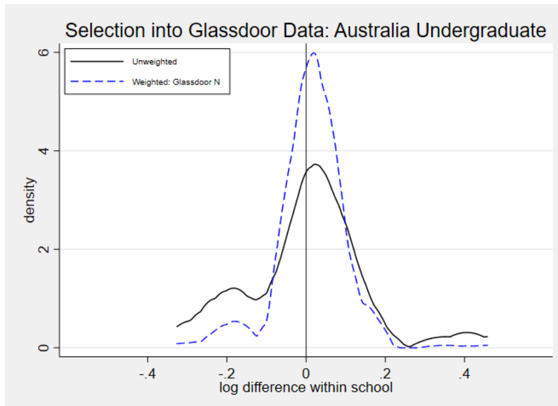
Among other indicators, the survey collects and tabulates the median annual salary by university among graduates who are employed full-time. The 2018 survey collects this data for graduates of undergraduate and graduate programs during 2017, while the 2019 and 2020 surveys collect the data only for graduates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

To compare with Glassdoor, we calculate the PPP- and inflation-adjusted log median earnings for each university 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 university. We then take the difference between the Australian data and Glassdoor data

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

university by university. Figure A1 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A1: Sample Selection into Glassdoor: Australia



Notes: The figure above captures the degree to which Australian college graduates in Glassdoor are representative of Australian 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 university compared with the median log wage from external data. There are 35 universities represented in the Glassdoor data, corresponding to 441 recent graduates.

A.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.[12] 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 university group. The groups consist of "985 Project", "211 Project" universities, and other universities. The "985 Project" group consists of the 39 most elite universities in China, including for example Tsinghua, Peking, and Shanghai Jiao Tong Universities. The "211 Project" group consists of a larger group of 112 universities; our salary figure applies to the universities that are in this group but not the 985 project group. Finally, the last group includes all other universities.

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 graduated between 2010 and 201 and submit an earnings report the year of or the year after they complete their bachelor's degree. We map university into the three categories using Wikipedia to identify which universities belong in each. We calculate the PPP- and

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

Table A1: Sample Selection into Glassdoor: China

University ranking	Median log wage: Chinese College Student Surveys	Median log wage: Glassdoor	Number of recent graduates
985	9.40	9.97	44
211 exc. 985	9.35	9.89	22
Neither	9.09	9.92	20

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 university 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.

inflation-adjusted log mean earnings for each of the three groups.Table A1 compares the results.

A.3 Colombia

Our data for Colombia is derived from the Observatorio Laboral de Educación, which is a dataset constructed by the Ministry of Education that combines information on recent graduates, the university they attended, and their formal sector earnings from tax records. We access the data from the Vinculación Laboral de Recién Graduados.[13] The most recent data cover the average annual earnings of 2015 graduates during the 2016 year.

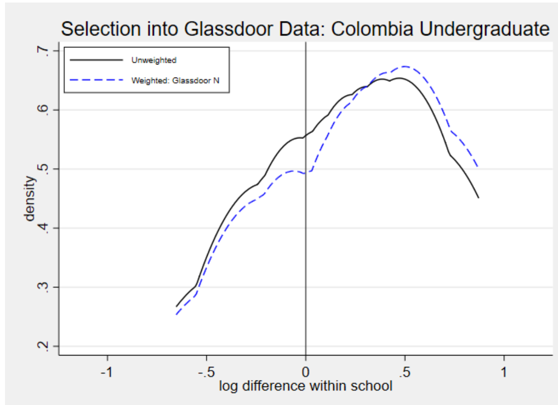
To compare with Glassdoor, we calculate the annualized PPP- and inflation-adjusted log median earnings for each university from this external data. Then, for Colombian graduates employed in Colombia, we restrict our attention to those who submit an earnings report the year of, the year after, or two years after they complete their bachelor's degree. We calculate the PPP- and inflation-adjusted log median earnings among these graduates for each university. We then take the difference between the Colombian data and Glassdoor data university by university. Figure A2 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

A.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

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

Figure A2: Sample Selection into Glassdoor: Colombia



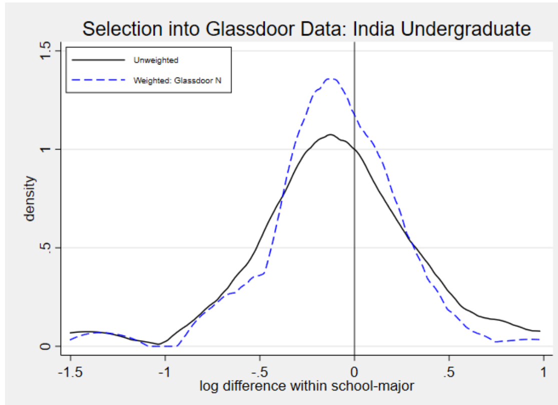
Notes: The figure above captures the degree to which Colombian college graduates in Glassdoor are representative of Colombian graduates more broadly. The figure above is a weighted probability density function of the log difference between the median log wage for college graduates in Glassdoor for each university compared with the median log wage from external data. There are 10 universities represented in the Glassdoor data, corresponding to 17 recent graduates.

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. Universities 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. Management salaries are for MBAs. Universities are again organized into groups, with the top Indian Institutes of Management again distinguished.

To compare with Glassdoor, we calculate the PPP- and inflation-adjusted log median earnings for engineering and technology majors from each university available in this external data. For engineering majors, we use the average wage among electrical, mechanical, and civil engineers. For technology majors, we use the average for computer science/information technology. In Glassdoor, we restrict our attention to Indian graduates employed in India who majored in engineering or technology. We further 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 university, we calculate the PPP- and inflation-adjusted log mean earnings among engineering and technology graduates. We then take the difference between the Indian data and Glassdoor data university by university. Figure A3 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A3: Sample Selection into Glassdoor: India



Notes: The figure above captures the degree to which Indian college graduates in Glassdoor are representative of Indian 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 university-major compared with the median log wage for each grouping from external data. There are 54 university-majors represented in the Glassdoor data, corresponding to 343 graduates.

A.5 New Zealand

Our data from New Zealand draw on information provided by the Ministry of Education.[14] 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).

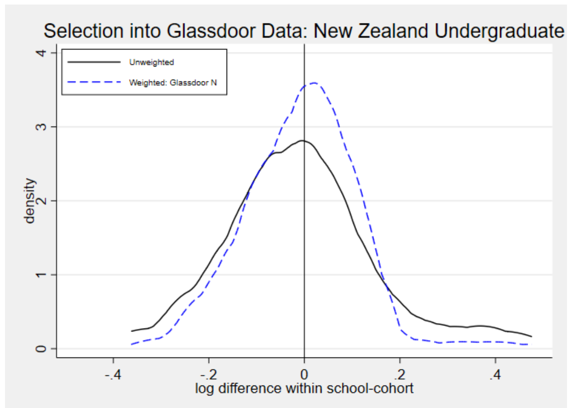
We use undergraduate earnings for those in the age group "less than 25 years old", 1, 3, 5, 7, and 9 years after graduation, by university. In addition to the overall median earnings, we take the median for workers with information technology, engineering, and management degrees. Finally, we use data on those with postgraduate earnings in the age group "25–39 years old" one year after graduation.

To compare with Glassdoor, we calculate the PPP- and inflation-adjusted log median earnings for each cohort from each university 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 university-cohort, we then calculate the PPP- and inflation-adjusted log median earnings among these graduates. We then take the difference between the New Zealand

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

data and Glassdoor data university by university. Figure A4 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A4: Sample Selection into Glassdoor: New Zealand



Notes: The figure above captures the degree to which New Zealand college graduates in Glassdoor are representative of New Zealand 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 university compared with the median log wage from external data. There are 35 university-cohorts represented in the Glassdoor data, corresponding to 332 graduates.

A.6 Poland

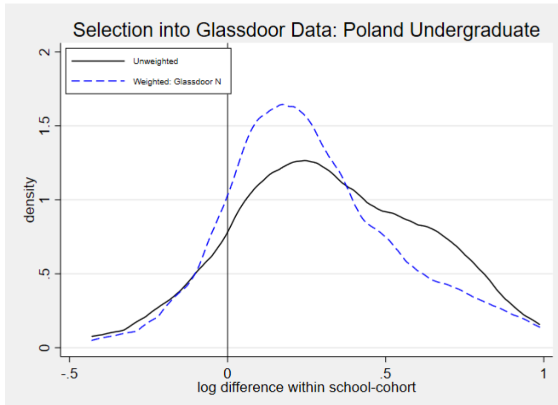
Our data from Poland draw on the Polish Graduate Tracking System commissioned by the Polish Ministry of Education and Science.[15] The underlying data on earnings draw on administrative tax data. The figures are gross monthly earnings for 2014–2018 graduates in year 2018, who have 0–1, 1–2, and so on years of experience. We collect data for graduates from undergraduate (first-cycle) programs at all ranges of experience and graduate (second-cycle) programs 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 university 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 university-cohort, we then calculate the PPP- and inflation-adjusted log median earnings among

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

these graduates. We then take the difference between the Polish data and Glassdoor data university by university. Figure A5 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A5: Sample Selection into Glassdoor: Poland



Notes: The figure above captures the degree to which Polish college graduates in Glassdoor are representative of Polish 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 university compared with the median log wage from external data. There are 83 university-cohorts represented in the Glassdoor data, corresponding to 301 graduates.

A.7 Singapore

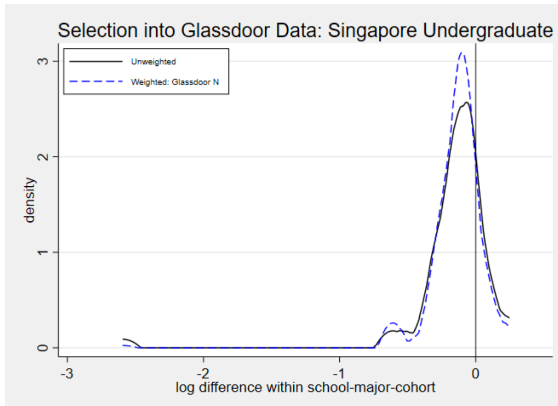
Our data from Singapore draw on the Graduate Employment Survey conducted annually since 2013 by a varying set of universities in Singapore and provided by the Ministry of Education.[16] Graduates are surveyed approximately six months after graduation. The database provides gross mean and median monthly earnings by university and degree. We take the simple average of earnings across degrees to arrive at up to six earnings figures for each university, representing: business, engineering, humanities/arts/sciences, education, computer science, and biological and physical sciences.

In Glassdoor, we restrict our attention to Singaporean graduates employed in Singapore from a handful of universities available in the Graduate Employment Survey, specifically Nanyang Technological University, National University of Singapore, and Singapore Institute of Management, each of which have earnings by major-cohort. We further 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 university, we calculate the PPP- and inflation-adjusted log mean earnings among these graduates for each university-major-cohort. We then take the difference between the Singaporean data and Glassdoor data

[16] Data for 2013–2018 are available online 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.

university by university-major-cohort. Figure A6 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A6: Sample Selection into Glassdoor: Singapore



Notes: The figure above captures the degree to which Singaporean college graduates in Glassdoor are representative of Singaporean 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 university-major-cohort compared with the median log wage for each grouping from external data. There are 62 university-major-cohorts represented in the Glassdoor data, corresponding to 281 graduates.

A.8 United Kingdom

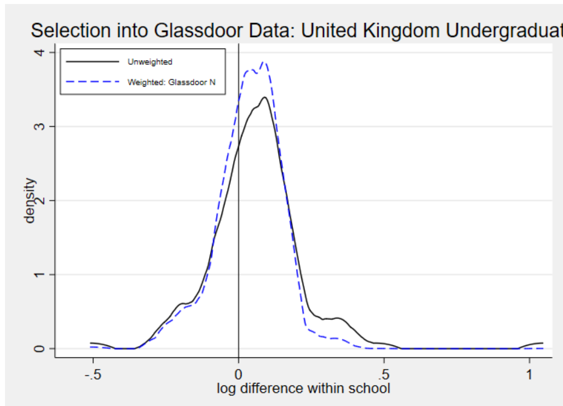
Our data from the United Kingdom come from Belfield et al. (2018). They use the Longitudinal Educational Outcomes, an administrative dataset that links information on pre-university characteristics, university and program of attendance, and post-university earnings. The authors use this data to undertake a rich set of exercises. Their online data appendix includes information on outcomes by universities.[17] 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 university 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 university. 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 university, which is 7.7 percent of all students who start university.

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

[17] Available online at https://www.ifs.org.uk/publications/13731, accessed February 15, 2021.

log median earnings among these graduates for each university. We then take the difference between this Glassdoor measure and the measure from Belfield et al. (2018) for each university. Figure A7 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

Figure A7: Sample Selection into Glassdoor: United Kingdom



Notes: The figure above captures the degree to which U.K. college graduates in Glassdoor are representative of U.K. 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 university compared with the median log wage from external data. There are 114 universities represented in the Glassdoor data, corresponding to 3178 graduates.

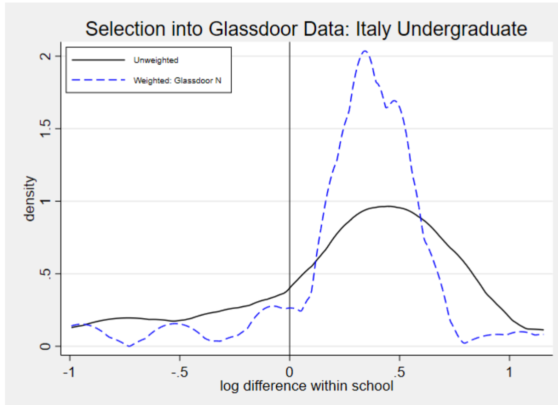
A.9 Italy

Our data from Italy come from AlmaLaurea.[18] AlmaLaurea is a partnership between Italian universities that jointly represent 90% of college graduates. AlmaLaurea conducts annual interviews with graduates from partner universities 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 university 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 university, we calculate the PPP- and inflation-adjusted log median earnings among these graduates for each university. We then take the difference between the Italian data and Glassdoor data university by university. Figure A8 shows the unweighted and weighted (by Glassdoor sample size per university) probability density function of the difference.

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

Figure A8: Sample Selection into Glassdoor: Italy



Notes: The figure above captures the degree to which Italian college graduates in Glassdoor are representative of Italian 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 university compared with the median log wage from external data. There are 26 universities represented in the Glassdoor data, corresponding to 54 recent graduates.

A.10 United States

Our data from the United States from the U.S. Department of Education's College Scorecard database.[19]

B Data Details: Glassdoor Data

This section includes details of the Glassdoor data and sample selection.

B.1 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 universities, 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 universities that meet two criteria. First, there must be at least 20 but fewer than 50 workers with bachelor's degrees from the institution in the data. Second, at least 90% of workers from the university 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

[19] Available online at `https://collegescorecard.ed.gov/`, accessed 12/1/2020.

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 2,173 institutions and under the latter is 0.977 between 2,274 institutions.

B.2 Degree Assignment

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.

B.3 Major Assignment

College major groupings follow the broad categories determined 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. 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 Data Details: Other Data Sources

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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.[20] 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.[21] We add to this by identifying the CEO of all S&P 500 firms as of May 2021 from Wikipedia.[22] 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.[23] We focus on utility patents granted to foreign nationals and sum across all years of the decade.

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

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

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

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