Return Migration and Human Capital Flows*

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Abstract

We bring to bear a novel dataset covering the employment history of about 450 million individuals from 180 countries to study return migration and the impact of skilled international migration on human capital stocks across countries. Return migration is a common phenomenon, with 38% of skilled migrants returning to their origin countries within 10 years. Return migration is significantly correlated with industry growth in the origin and destination countries, and is asymmetrically exposed to negative firm employment growth. Using an AKM-style model, we identify worker and country-firm fixed effects, as well as the returns to experience and education by location and current workplace. For workers in emerging economies, the returns to a year of experience in the United States are 59-204% higher than a year of experience in the origin country. Migrants to advanced economies are positively selected on ability relative to stayers, while within this migrant population, returnees exhibit lower ability. Simulations suggest that eliminating skilled international migration would have highly heterogeneous effects across countries, adjusting total (average) human capital stocks within a range of -60% to 40% (-3% to 4%).

Keywords: Migration, return migration, development

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1 Introduction

There are large flows of human capital across countries. According to the United Nations, by 2020 the number of international migrants reached 281 million, equal to approximately 3.6% of the world's population (McAuliffe and Triandafyllidou 2022). It is estimated that more than 5% of the skilled labor force has migrated at least once. Existing survey evidence further suggests that return migration is a common phenomenon, with a significant fraction of international migrants returning to their origin (home) countries within 5 years (Hagan and Wassink 2020). The extent of skilled human capital flows has raised concerns surrounding brain drain in a number of countries experiencing significant outflows of skilled human capital. On the other hand, countries that receive significant skilled migrant flows may receive benefits in the form of greater innovation and increased economic growth (Bernstein et al. 2022). Ultimately, the costs and benefits of international mobility depend on a variety of factors, including the raw migration and *return migration* patterns, the selection of individuals by skill into migration, the extent of human capital accumulation by skilled workers in different countries, and potential knowledge spillovers (Saxenian et al. 2002, Kerr 2008, and Prato 2022).

Despite the policy interest surrounding these questions, research into them has been stymied by lack of data that tracks skilled labor across countries, provides detailed information on pre and post migration occupational histories, and has global coverage. This paper fills this gap by introducing a novel dataset tracking the global employment histories of approximately 450 million skilled workers from 180 countries. This dataset provides detailed information on the educational history of skilled workers, the location and firm where they worked, their occupational title, and the wage they received. Leveraging this powerful data, we document basic facts regarding the phenomenon of return migration, study potential determinants of the return migration decision, use a development accounting framework to study the differential returns to experience across countries, examine the selection of individuals into migration and return migration by skill, and finally quantify the impact of international migration on cross-sectional skilled human capital stocks across countries using counterfactual analyses. For some of our analysis, we further supplement this data with raw global salary postings data from Glassdoor.

We first show that skilled labor is highly mobile across countries. Using hazard analysis, we estimate that 3.4% (4.4%) of skilled workers migrate to a different country within five (ten) years. There is significant international heterogeneity in the propensity of skilled workers to migrate, with India experiencing twice the global average, and countries such as the United States and China experiencing fewer outflows of skilled labor than the global average. Approximately 23% of skilled international migration is for education, with this propensity being larger for migrants from emerging market economies and for migrants to advanced economies.

Return migration is a significant phenomenon and demonstrates a concave relationship with time. Approximately 10% of international skilled migrants return to their origin country within the first year. Within five years 33% of migrants return to their origin countries, and 38% return within ten years. As with out-migration, there is substantial heterogeneity across countries in return migration rates. On average, advanced economies such as the United States and high-income countries in the European Union experience higher return migration rates than other countries. Furthermore, emerging market economies tend to have lower return rates, although this is not uniformly true. Countries such as Chile, Brazil, and Indonesia have relatively high return rates compared to the global average. India, which has large skilled migrant outflows, experiences relatively little return migration.

Having documented basic facts regarding the extent of return migration, we subsequently examine the correlates of bilateral migration flows and the return migration decision. We first show that a simple gravity model controlling for GDP per capita, the population of individuals with tertiary education in the origin (home) and destination (host) country, the distance between the two countries, and a dummy variable for a common language can explain approximately 80% of bilateral skilled migrant flows. Outflows are larger in lower income per capita countries and are targeted towards higher income per capita countries. Bilateral migrant flows, that is outflows from an origin country to the destination country, are also larger when the two countries share a common language. Smaller population countries also tend to experience greater outflows. Distance reduces migrant flows, but the effect is relatively smaller than in the trade literature.

Turning to return migration, we find that A 10% increase in the origin country's income per capita is associated with a 4% higher likelihood of return migration within 10 years, while 10% higher income per capita in the destination country is associated with 1% lower probability of return. Controlling for origin country outflows, distance has little impact on return migration rates. Migrants to countries with a common official language are 15% more likely to return to their origin country, consistent with workers being more mobile between labor markets with a common cultural bearing.

Turning to more granular analyses, we further show that return migration is sensitive to industry growth in the origin country and destination country. A one standard deviation increase in origin country industry growth leads to 2.3% increase in the return rate of migrants, while a one standard deviation increase in destination country industry growth leads to a 7.4% decline in the rate of return migration. Return migration is also sensitive to industry growth in "adjacent" industries to the migrant's industry, as measured by bilateral job-to-job transition flows. Finally, return migration is asymmetrically exposed to employment growth at migrant's firm, with employment declines having a more substantial impact on return migration rates than positive employment shocks.

One potential benefit of international migration for the origin country is that migrants may accumulate disproportionately more human capital abroad than they otherwise would have by remaining, and a fraction of this acquired human capital may be transferred back to the origin country through return migration. This raises the question of whether the returns to experience *in the origin country* depend on where that experience was acquired. To answer this question, we develop a neoclassical development accounting framework. A country's output production function combines total factor productivity (TFP), physical capital, and human capital. An individual's human capital is a function of an individual fixed effect, their educational and occupational history, and random shocks. In particular, the effect of a worker's experience on her human capital depends on both where the experience was acquired and where the worker is currently employed. Using this specification for human capital in the firm's profit maximization first-order condition leads to an extension of the standard Abowd, Kramarz, and Margolis (Abowd et al. (1999)) (AKM hereafter) equation for wages allowing for the endogenous accumulation of human capital over time through learning-by-doing.

We estimate this augmented AKM style equation using our global employment history data and salary data provided by Revelio and Glassdoor. Returns to job experience in the United States are highest for experience that is accrued in the United States, relative to experience acquired in other advanced economies or emerging market economies. We additionally find that advanced economy and especially US experience is at a significant premium in emerging market economies, generating significantly higher returns than own-market experience. In specifications with country by year and individual fixed effects, but without firm fixed effects, an additional year of US experience, for an individual with 10 total years of experience, generates approximately 62%-212% higher returns than an additional year of own market experience, depending on the exact specification and salary data used.

These effects could be driven by return migrants sorting into higher wage firms or by return migrants occupying higher wage, more senior positions. To control for the former, we re-estimate the equation including firm fixed effects. We continue to find a positive premium to US experience in emerging market economies, An additional year of US experience, for an individual with 10 years of total experience, generates approximately 59%-204% higher returns than an additional year of own market experience.

To address endogeneity concerns that migration or return migration could be correlated with persistent, idiosyncratic shocks to the human capital of the worker, we take a twofold approach. To assess the robustness of our findings, we first employ a matching estimator in which for each return migrant, we match to workers in the same origin country of the same educational cohort who attended the same school, work at the same firm and role, have the same levels of job experience, and earn similar wages before migration. We find that our results are robust to this specification, pre-trends are negligible, and, moreover, that treatment heterogeneity is consistent with intuition. The wage gap between return migrants and the matched control group is larger for those migrants who had more years of experience in the United States. As an additional test, within this matched sample, we restrict to those workers who return migrate following layoffs at the firm they worked for in the destination country, which provides a plausibly exogenous shock to the incentives of workers to return. The results are highly stable to this specification and heterogeneity again conforms with intuition.

We next use our development accounting empirical framework to study who selects into migration and return migration, which speaks to one of the primary debates surrounding international migration flows. That is, does international migration create a brain drain from some countries, and does return migration act as a mitigating force? Using the individual fixed effects recovered from our AKM regressions, we show that migrants from emerging market economies have 6% higher (intrinsic) human capital than non-migrants[1]. Within the migrant population, return migrants are negatively selected on human capital but are still positively selected relative to non-migrants. Returnees from the US to Emerging Markets and non-returnee migrants of Emerging Markets to the US demonstrate 6.3% and 16.5%

[1]Migrants from Emerging Markets to the US, other Advanced Economies and other Emerging Market Economies exhibit, on average, 12.9% and 6.2% and 2.8% higher worker ability compared to non-migrants, respectively.

higher worker ability, respectively, in comparison to non-migrants of Emerging Markets.

We finally use our reduced-form estimates and counterfactual analysis to assess the quantitative impact of skilled international migration on skilled human capital stocks across countries. In our primary counterfactual specification, we shut down international migrant flows completely. This shuts down the potential brain drain. However, countries also will not benefit from migrant inflows. Finally, since return migration is shut down, a fraction of workers may accumulate less human capital than they otherwise would have through experience abroad.

We find that international skilled migrant flows have sizable and heterogeneous effects across countries. Relative to the baseline, shutting down such flows adjusts per capita human capital stocks within a range of -3% to 4%. The biggest winners include Ireland, Lebanon, and Jordan, countries that experience significant outflows of disproportionately skilled labor, while the biggest losers include Qatar and the UAE. The United States suffers a modest decline in its per capita human capital stock, reflecting the benefits the United States receives from brain drain in the rest of the world. Total human capital stocks adjust within a range of -60 to 40 percent. The largest percent increases occur in Belarus, Jordan, Lebanon, and Costa Rica, while the largest losses occur in Qatar, the UAE, Luxembourg, Kuwait, and Oman, reflecting the large migrant populations in those countries.

The remainder of this paper is organized as follows: Section 2 provides a literature review, detailing our contributions. In Section 3, we present an overview of our unique dataset. Section 4 documents the patterns observed in migration and return migration. Section 5 explores the correlations between migration/return migration and origin and destination country characteristics, industry specifics, and firm attributes. Section 6 focuses on measuring human capital dynamics in migration through a development accounting framework. We estimate returns to experience using matching estimators and analyze the effects of mass layoff shocks on migrants. Section 7 presents counterfactual analyses to ascertain the impact of migration and return migration on the skilled human capital of countries. Finally, in Section 8, we provide our concluding remarks.

2 Literature Review

This paper contributes to an extensive literature on various aspects of the migration of skilled human capital.

First, we contribute to the literature on the measurement of global talent flows across countries (Kerr et al. 2016 and Kerr et al. 2017), and in particular to the discussion on brain drain (Bhagwati and Rodriguez 1975, Beine et al. 2001, and Docquier and Rapoport 2012) vs. brain gain and brain circulation (Mayr and Peri 2009 and Saxenian 2005). A primary challenge in this literature is the lack of appropriate data. For instance, most studies on brain drain lack data on the place of education, relying instead on the place of birth. However, some patterns of human capital flows can change significantly if one considers migration patterns based on the place of education (Özden and Phillips 2015). More importantly, net benefits from skilled labor migration depend not only on emigration rates but also on the return rates of migrants. However, most studies on return migration either focus on a specific country (e.g., Singh and Krishna 2015 and Bucheli and Fontenla 2022) or rely on individual countries' census data, which does not track individuals across countries. Thus, additional assumptions on mortality rate, onward migration, and outmigration rates are required to calculate return migration (Chen et al. 2022 and Bossavie and Özden 2023). Our data, which tracks both educational attainments and work history of individuals across different countries, significantly improves previous measures of outmigration and return migration.

Net benefits from migration also depend on the degree of selection of outmigrants and returnees (Wahba 2015, Ambrosini et al. 2015, Dustmann and Görlach 2016, Akee and Jones 2019 and Adda et al. 2022), as well as the transferability of human capital across countries

(Abramitzky et al. 2019, Wahba 2015 and Reinhold and Thom 2013).[2] Again, most studies in this literature, with the exception of Martellini et al. (2023), rely on information from a specific country and lack data on individuals' income in both the origin and destination countries. Our detailed individual-level data allow us to go beyond focusing on a specific country and enable us to control for significantly more observable factors. Indeed, we find that the degree of selection of migrants and returnees varies significantly as a function of the origin and destination countries, and therefore one should be cautious in generalizing findings based on a specific country. Moreover, our data allows us to compare return migrants with non-migrants who attended the same universities, worked for the same companies, and had similar years of experience and education in the pre-period, which is a significant improvement in terms of controlling for selection between migrants and non-migrants. Furthermore, our layoff research design helps us to control for selection in return migration. Martellini et al. (2023) use Glassdoor data to measure the global distribution of college graduates, as well as the selection and transferability of human capital across countries. The fact that our data has significantly higher coverage across space and time enables us to investigate return migrations (and their economic and social determinants) in addition to migration patterns. Moreover, we estimate the transferability of experience across different countries.

The results in our paper are similar to the findings in the literature on economic and social determinants of migration within countries (Blanchard and Katz 1992, Bartik 1993, Kennan and Walker 2011, Koşar et al. 2022 and Howard and Shao 2023), and the costs of migration (Bayer and Juessen 2012, Bartik 2018 and Porcher 2020). Our results on the selection of skills in migration patterns across different countries and the higher rate of return to experience in more advanced countries resemble the findings in Roca and Puga (2017) and Card et al. (2023) for the movement of individuals within Spain and the US.[3]

[2] In this paper, we abstract from the dynamic impact of immigration on skill acquisition before migration. See Khanna and Morales 2023 for an analysis of how US immigration policy induced more high-skilled Indian workers to choose majors related to the IT industry.

[3] Our findings regarding the significance of economic factors and salaries at the destination in influencing migration decisions also relate to studies examining the impact of taxation on migration patterns (Kleven

Finally, our paper relates to the literature on human capital accounting (Klenow and Rodriguez-Clare 1997, Caselli 2005, Jones 2014, Hendricks and Schoellman 2018 and Martellini et al. 2023). Compared to this literature, our main advantage is in accounting for the impact of return migration on total human capital. Return migration accounts for a large share of immigration flows to developing countries. Moreover, our results confirm that return migrants from advanced economies accumulate valuable human capital which influences our estimates of the impact of migration on human capital accumulation. Our main finding here is that there is significant heterogeneity in the net benefits from migration. However, these net benefits are not significantly correlated with cross-country variations in income per capita.

3 Data

Our research primarily uses data from Revelio Labs, which gathers information from public LinkedIn profiles and other sources. LinkedIn, launched in 2003, is a widely used online platform for professional networking with over 700 million users worldwide. On LinkedIn, users create profiles that list their educational and employment histories, including the universities they've attended, their fields and degrees, their employers, job titles, and the dates they held these positions. Revelio Labs provides access to publicly available information from over 450 million LinkedIn accounts from 180 countries as of early 2023. For simplicity, we refer to this data as *"professional profiles"*.

The presence of professional profiles on LinkedIn varies greatly by occupation, location, and time. Individuals with a college education and those in white-collar jobs are more likely to have a LinkedIn profile compared to those without higher education or in blue-collar positions. Therefore, we consider LinkedIn a more representative platform for college-educated individuals and white-collar professions.

et al. (2014), Kleven et al. (2020) and Muñoz (2020)

To assess coverage disparities across countries, we define "country coverage" as the ratio of professional profiles in a specific country to the total number of college-educated individuals there, using ILO data. The coverage rate across different countries is summarized in Table A1 and Figure A1. Developed countries, like the US, often have a coverage rate of over 80%. Yet, countries such as Japan and South Korea have coverage rates below 5%, possibly due to alternative platforms and language barriers. Developing countries typically show lower coverage rates, but some, including Argentina, Chile, and South Africa, have rates close to global averages. India, with its significant labor force, has a coverage rate of about 40%, which, despite being lower, represents a considerable portion of its skilled workforce.

Country coverage has been increasing. Figure A2 shows the coverage index over time, normalized to 100% for 2022, with coverage in 2000, 2010, and 2015 at about 26, 62, and 87% respectively. For analyses like out-migration rates, we focus on recent years with stable coverage to avoid bias from earlier fluctuations. The figure is derived from panel data of education and job experience start and end dates in LinkedIn profiles, showing occupation and location annually. We count users with education or job entries per year, noting that this method differs from when users join LinkedIn; they can add their entire history upon joining.

To analyze international flow rates, we use a weighting system influenced by country coverage levels. We recognize that people who move abroad are likelier to maintain a professional profile, especially when moving from a country with lower to higher coverage. We hypothesize that relocating to a country with better coverage increases the chances of an individual creating and updating their profile, including their time in their home country. Therefore, we calculate the weight for individual i based on this premise.

$$w_i = \frac{1}{\max\limits_{j(i)}(\text{coverage}_{ij})} \tag{1}$$

Here, $j(i)$ represents the countries where individual i has worked or studied. For example, if two individuals, i and i', are from a country with a 20% coverage rate, but i also has experience in a country with 100% coverage, while i' does not, their weights would be 1 and 5, respectively. See Table A1 for detailed country coverage rates.

We clean the location data in user profiles because about 50% of the job positions reported do not include a country. To fill this gap, we examine the companies listed in profiles and the countries associated with them (reported by users). If a company is predominantly linked to a specific country (over 90% of associations), we infer all its employees with a missing country in their profile work in that country, identifying the location for about half of the jobs with missing data. For education records, which typically lack country details, we use the location data listed in job positions, assuming the institutions are located where their personnel report working. This method helps us determine the country for approximately 65% of education records, utilizing the link between universities and the job locations of their associated staff.

In addition to our main dataset sourced from publicly available profiles, we utilize supplementary imputed wage data provided by Revelio Labs. This supplementary dataset offers salary information for individual job positions, estimated using an imputation process primarily reliant on job titles categorized into 1500 distinct categories, geographic locations, and companies. According to documentation provided by Revelio Labs, the imputation process relies on a regression-based model extensively trained on a vast dataset comprising over 200 million salaries gathered from global job postings, including data from LinkedIn, job posting aggregators, and publicly available labor certification applications (LCAs) specifically within the United States.

Initially, the wages for each job category are estimated for the US. Subsequently, adjustments are made for other countries in two main ways: Firstly, country averages are adjusted based on the Purchasing Power Parity (PPP) in each respective country. Secondly, the distribution of wages within each country is estimated by comparing the wages for a specific job category in that country to the wages for the same category in the US. Moreover, to accommodate temporal variations, the model incorporates country-level inflation rates, enabling it to estimate changes in salary levels over time.

In addition to the imputed wages provided by Revelio, we also bring to bear country-firm-position level wages using raw global salary data from Glassdoor. This data provides exact wage data at the firm level. While using such data restricts our sample sizes and does not control for within position variation in wages due to seniority, it allows us to run wage regressions without relying on the Revelio imputation procedure. Appendix Table C2 compares the summary statistics of observable characteristics of individual profiles covered in the Glassdoor data with those not covered. This confirms that the distribution of individual characteristics between the two sets is relatively similar and has significant overlap. Appendix Table C3 further compares the differences in observable characteristics between these two sets after controlling for country fixed effects. The main finding is that those individuals with wage data from Glassdoor are generally slightly younger and slightly more educated.

We conduct multiple data validity checks, including comparing the number of professional profiles across countries with the International Labour Organization's (ILO) figures for the college-educated workforce as discussed earlier in this section. Our assessment of the professional profiles dataset involves a wide range of evaluations, done in two stages: first, by comparing it to U.S. data, and second, by comparing it to international measures.

For U.S. comparisons, we match the inflow of college-educated individuals to U.S. data from the Current Population Survey (CPS) from 2018 to 2022, as seen in Figure A3. The data closely matches the 45-degree line, indicating reliability. Additionally, we compare the number of international students in the U.S. with data from the Institute of International Education (IIE), shown in Figure A4. This comparison also shows a strong alignment, further validating our data.

In comparing our data with international measures, we also use sources like the Database on Immigrants in OECD and non-OECD Countries (DIOC) to validate our figures on the stock of college-educated migrants (see Figure A5 and Table A2 in the Appendix). This comparison reveals a close match with DIOC data. Overall, our validity checks show that our dataset accurately reflects trends seen in independent data sources, providing strong evidence of its reliability.

4 Migration and Return Migration Patterns

This section outlines the international mobility of skilled workers, focusing on international migration patterns and, notably, return migrations by countries of origin and destination.

Figure 1 illustrates the cumulative hazard ratio of out-migration for the global average and select countries. This depiction is based on the analysis of individuals within a country at the onset (year 0) and their subsequent tracking in subsequent years ($t = 1, 2, ..., 10$). The y-axis represents the percentage of individuals observed in another country by year t. We have applied the weights defined in Equation 1 to derive these insights. The figure reveals that, on average, 3.4% (4.4%) of skilled laborers migrate within 5 (10) years.

The figure shows a non-linear and concave out-migration pattern over time, aligning with Howard and Shao (2023). This pattern can be explained by two factors. First, the decreasing probability of migrating in year t, assuming no migration by year t-1, indicates that as time goes on, many mobile individuals have already moved, leaving behind those less likely to migrate. Second, individuals who migrated between year 1 and year t-1 might return to their home country, being counted again in year t, which adds to the observed non-linear pattern.

Figure 1, and with more details Figure 2, highlight the variation in out-migration rates among countries. Skilled workers from the US have slightly lower mobility, while those from Germany are more mobile than the global average. Indian skilled workers migrate at twice the global rate, while Chinese skilled workers migrate at only a quarter of this rate, showing significant differences from the global pattern. Interestingly, it appears that there isn't a clear pattern indicating a direct correlation between the level of out-migration and a country's development status[4].

Figure B1 shows the proportion of out-migrations for education from each origin country, with the rest being for job reasons. On average, about 23% of migrants leave their home countries for education. Yet, this percentage varies widely, from about 10% in countries like Australia, Russia, and Japan to around 50% in China, Colombia, and Iran.

Providing further insight, Figure B2 provides a detailed breakdown of out-migration by origin and destination country categories. It shows that out-migration for education is more common *from* Emerging Market Economies or *to* Advanced Economies (including the US). Approximately 30% of all out-migrations are for jobs in multinational corporations. [5] The rest, 50%, migrate to local companies. Within the group moving to multinationals, 11.5% transfer to the same company in the host country. This trend is especially common among migrants between Advanced Economies.

Subsequently, we examine the patterns of return migration. In this paper, return migration refers to the return of a migrant to their country of origin. The origin country is where individuals first appear in our data, either for education or work. Figure 3 shows the trends of migrants returning over time, globally and for specific countries. Year 0 is the migration year (entry into the host country), and tracking continues for 10 years to see the return rate. Initially, about 10% return within a year, likely for short visits. At 5 and 10 years, about 33% and 38% have returned, showing that a large and significant portion of migrants do return to their origin countries. Additionally, within 10 years, 12% move to a third country, while 50% stay in the first host country. Thus, 50% leave the destination within a decade,

[4] We explore the correlations between bilateral out-migrations and country-specific characteristics in more detail in Section 5.

[5] We define multinational corporations as companies with at least 250 employees in our data and at least 10% of the workforce in countries outside the main country of operation.

and of those, 75% return to their origin. [6].

Figure 3 shows a concave pattern of return migration that could result from two main factors. First, individuals who returned early might re-migrate from their origin country. Second, over time, a selection process occurs among migrants, where those intending to return have already done so, leaving behind those less inclined or uninterested in returning, regardless of the time passed.

Figures 3 and 4 show significant variations in return migration rates across countries. Advanced Economies, including the US and EU countries, generally have higher return rates. However, some Emerging Market Economies like Chile, Argentina, and Indonesia also show high return rates. While India has a high out-migration rate, its return migration rate is relatively low. In contrast, the long-term return rate for Chinese migrants aligns with the global average, despite their low out-migration rate[7].

Figure B4 shows where returnees go in terms of education, multinational corporations, and local companies, based on their origin and destination countries. About 10% return for education, while 90% come back for jobs. Around 35% of all returnees find employment in multinational corporations. Notably, a higher share of returnees (about 15%) pursue education when returning to the US, and a slightly smaller percentage (31%) rejoin multinational corporations in the US.

Figure B5 shows that, on average, 25% of those who migrated for education return to their home countries immediately after completing their studies. Additionally, Figures B6 and B7 indicate that returnees typically gain 0.9 years of education and 2.2 years of job experience abroad before going back to their origin countries.

These figures reflect the average education and job experience of all returnees, including those without any education or job experience gained abroad. About 68% of returnees have

[6]See Figure B3 for a graph showing the percentage of migrants leaving their host country, including those returning to their origin country and those moving to a third country.

[7]In Section 5, we explore the factors that influence return migration.

no education from abroad, and around 27% come back without any job experience. Only 5% have both education and job experience from overseas. Focusing on those with some education abroad, the average education is 2.8 years, and for those with job experience, job experience averages 3 years.

5 Determinants of Outflows and Return Migrations

Having documented basic quantitative facts regarding the extent of out-migration and return migration, we turn now to an analysis of the factors correlated with bilateral outflows and return migration between countries. In particular, we follow the international trade literature and estimate the following gravity regression:

$$M_{od} = exp\Big[\beta_1 log(y_o) + \beta_2 log(y_d) + \beta_3 log(dist_{od}) + \beta_4 Lang_{od} + X_o\Gamma_o + X_d\Gamma_d\Big]\epsilon_{od} \qquad (2)$$

Where M_{od} represents the number of migrants from the origin country o to the destination country d. y_o and y_d are the PPP-adjusted per capita incomes of the origin and destination countries, respectively, in 2022. $dist_{od}$ is the logarithmic distance between these countries, and $Lang_{od}$ is a dummy variable indicating if they share an official language. We include other origin and destination country characteristics, such as the number of professional profiles, adjusted for coverage. To address concerns about the direct impact of our data coverage on the measured bilateral flows, we also control for the coverage of LinkedIn data in both the origin and destination countries. To handle zero bilateral flows between many country pairs, we use Poisson Pseudo Maximum Likelihood (PPML) for estimation, following Silva and Tenreyro (2006) and Correia et al. (2020).

The results in Table 1 column (1) show that even a simple gravity model that only controls for GDP per capita and the population of individuals with tertiary education of the origin and destination country, the distance between the two countries and the dummy for a common official language can explain a large fraction of bilateral flows between the countries and has an R-squared of 80%. Countries with lower income per capita have larger outflows of skilled workers, while countries with higher income per capita attract higher flows of skilled human capital. The negative impact of distance on bilateral flows is smaller than its impact in the trade literature, suggesting travel costs don't increase linearly with distance. The estimated coefficients on the population of the origin and destination countries suggest that skilled workers from smaller countries are relatively more likely to relocate internationally. This result is similar to the results on the relationship between country size and bilateral trade (see Silva and Tenreyro 2006). A common official language significantly boosts skilled labor migration between countries by about fourfold. Column (2) shows these findings hold even when controlling for origin country fixed effects. Moreover, controlling for country fixed effects increases the R-squared of the regression by only 3%.[8]

We next study the association between return migration and aggregate country characteristics. In particular, we now run a regression similar to Equation 2 except that the left-hand side is the logarithm of the number of return migrants from country d to their country of origin o. We also control for the logarithm of the number of migrants from country o to country d on the right-hand side. Results in column (3) show that migrants from higher GDP per capita countries have significantly higher return rates, and the effect is larger than the negative impact destination country GDP per capita has on return rates. Controlling for outflows, distance affects return migrations less than outflows. Migrants to countries sharing an official language are 15% more likely to return, suggesting greater mobility between markets with a common language, possibly due to a higher proportion of these migrants initially intending temporary stays. Finally, and not surprisingly, the estimated elasticity on outflows is close to one, suggesting that the return migration rate does not vary significantly with the size of outflows.

[8]In Appendix Table C1 we restricted the data to bilateral flows between countries with LinkedIn coverage above 25% and find similar results.

Moving from aggregate factors that are associated with bilateral flows to more disaggregate factors, we construct a 25% representative sample of skilled migrants in our data and run the following regression:

$$R_{m(odi)t} = \beta_1 g_{oit} + \beta_2 g_{dit} + \delta_{ot} + \delta_{dt} + \delta_{it} + \varepsilon_{mt} \tag{3}$$

Where $R_{m(odi)t}$ is a dummy variable indicating if migrant m, currently in destination country d and working in industry i, returns to origin country o at time $t+1$; it's 100 if they return and zero otherwise. g_{oit} and g_{dit} are the employment growth of industry i in the origin country and the current destination country of individual m. These growth rates are based on changes in the user numbers in our data from $t-3$ to t. In order to account for any aggregate country level or worldwide industry level variation, Equation 3 also includes origin and destination time fixed effects as well as industry time fixed effects.

Table 2 suggests that higher employment growth in a migrant's current industry in their origin country is associated with a significantly higher probability of return migration. For example, a one standard deviation increase in industry growth in the country of origin is associated with an approximately 2.3% increase in the return rate of migrants, as shown in column (1). Conversely, we find that destination country industry growth reduces the rate of return migration, with a one standard deviation increase lowering the rate of return by approximately 7.4.%. We find that migrants who have been in their destination country for fewer than 5 years are more sensitive to origin and destination country industry growth as illustrated in columns (2) and (3).

In column (4) of Table 2, we additionally explore the extent to which return migration is sensitive to growth in "adjacent" industries. Using the Revelio data, we construct the matrix of bilateral job-to-job transition flows between industries. We then construct adjacent industry growth as a weighted average, with the weights determined by the propensity of workers to switch from their current industry to the specified one. Column (4) shows that return migration decreases in response to the destination country's adjacent industry growth and increases in response to the origin country's adjacent industry growth. Return migration continues to be sensitive to own industry growth.

Finally, we estimate the following regression to investigate the sensitivity of return migration to own firm employment growth:

$$R_{m(odif)t} = \beta_1 g_{ft} \times (g_{ft} < 0) + \beta_2 g_{ft} \times (g_{ft} \geq 0) + \delta_{oit} + \delta_{dit} + \varepsilon_{mt} \quad (4)$$

Where g_{ft} represents the employment growth of the firm where individual m is currently employed. We allow the employment growth of the worker's firm to have an asymmetric impact on the return migration of individuals. Additionally, we control for the origin country by industry by year and destination country by industry by year fixed effects.

Table 3 presents the estimation results of Equation 4. Column (1) shows that positive firm employment growth decreases return migration, while negative firm employment growth increases return migration. Migrants are more affected by negative employment shocks than positive ones. Specifically, a standard deviation decrease in firm employment boosts return migration by 9.6%, whereas a similar increase lowers it by 3.5%. Columns (2) and (3) examine these patterns according to the length of time migrants have spent in the destination country. Similar to the findings in Table 2, workers with smaller tenures in the destination country appear more sensitive to firm growth, both negative and positive, than migrants with longer tenures. Column (4) shows that migrants in multinational companies without a branch in the origin country are less likely to return on average, while those migrants at firms with branches in the origin country are more likely to return home. Finally, column (5) shows that return migration is more sensitive to negative firm employment growth when the firm has a branch in the origin country. These results will provide useful as a source of identification in later analyses.[9]

[9] In Appendix Table C4, we examine the relationship between industry and firm growth and the probability of

6 Human Capital Dynamics in Migration

We next introduce a formal development accounting framework to measure the extent of human capital accumulation acquired by skilled migrants abroad and the extent to which those skills are transferable to the origin country through return migration. These estimates will allow us to quantify the role migration and return migration play in accounting for the skilled human capital stocks across countries.

6.1 Development Accounting Framework

Following the literature, we assume that the aggregate production function in country j is neoclassical, given by:

$$Y_{jt} = K_{jt}^{\alpha} \left(A_{jt} H_{jt}\right)^{1-\alpha}, \tag{5}$$

where Y_{jt} is the total output, K_{jt} is the total physical capital stock, H_{jt} is the human capital stock, and A_{jt} is total factor productivity (TFP). The total human capital stock reflects the aggregation of the human capital h_{ijt} of individual workers i in country j, i.e. $H_{jt} = L_{jt} \int h_i dF_{jt}(h_i)$ where L_{jt} is the total number of workers in country j at time t. Following Klenow and Rodriguez-Clare (1997), Hsieh and Klenow (2010), and Hendricks and Schoellman (2018), we rewrite the aggregate production function in per capita terms as:

$$y_{jt} = A_{jt} \left(\frac{K_{jt}}{Y_{jt}}\right)^{\frac{\alpha}{1-\alpha}} h_{jt} = z_{jt} h_{jt}, \tag{6}$$

where $y_{jt} = Y_{jt}/L_{jt}$ is per capita output, $h_{jt} = H_{jt}/L_{jt}$ is the per capita human capital stock and $z_{jt} = A_{jt} \left(K_{jt}/Y_{jt}\right)^{\alpha/(1-\alpha)}$ combines the country's TFP and the capital-output ratio.

leaving the destination country. Compared to the results in Table 2 and Table 3, the coefficients for leaving are approximately 50% larger, suggesting that the majority of those who leave the destination country due to economic opportunity shocks return to their country of origin.

We assume that the human capital h_{ij} of an individual worker i in country j is given by:

$$\log\left(h_{ijt}\right) = \xi_i + \sum_{j'} \beta_{jj'} E_{ij't} + \gamma_j E_{it}^2 + \varepsilon_{it}. \tag{7}$$

Here $E_{ij'}$ is the years of experience of worker i in country j', E_{it} is the total years of experience of worker i, ξ_i is a worker fixed effect, and ε_{it} is a worker-specific shock. In this way, we allow for a worker's human capital to accumulate over time as the worker gains experience. Moreover, we allow for the impact of experience to depend flexibly on both the country where the experience was acquired and also the country where the worker is currently employed. Specifically, through this specification we are able to study the effects of migrants' experience abroad on their human capital stocks and, furthermore, the extent to which that experience increases their human capital stocks in their origin countries.

Taking logs of the firm's profit maximization first-order condition (FOC) and combining them with the human capital accumulation equation gives an equilibrium determination of wages:

$$\log\left(w_{ijt}\right) = \log\left(\left(1-\alpha\right) z_{jt}\right) + \xi_i + \sum_{j'} \beta_{jj'} E_{ij't} + \gamma_j E_{it}^2 + \varepsilon_{it}. \tag{8}$$

Here individual wages are a function of a location-time fixed effect $\log\left(\left(1-\alpha\right) z_{jt}\right)$, the individual time-invariant worker fixed effect ξ_i, the accumulation of human capital reflecting the worker's experience history $\sum_{j'} \beta_{jj'(i)} E_{ij't}$, and an idiosyncratic worker-specific shock ε_{it}. This equation is thus an extension of the standard Abowd, Kramarz, and Margolis (AKM) framework allowing for the endogenous accumulation of human capital over time through learning-by-doing.

6.2 Empirical Estimates of Returns to Experience

In our baseline empirical implementation of equation (8), we group countries into the United States (US), advanced economies (AE), and emerging markets (EM) according to the International Monetary Fund's (IMF) classification. Our baseline results are in Figure 5, using both the Revelio Labs wage data and the Glassdoor wage data. The figure shows that returns to experience are highest when that experience is acquired in the United States. This gap between the returns to US experience and own-market experience is particularly pronounced in emerging markets. We also find the gap to be quantitatively larger using the Revelio Labs wage data than the Glassdoor wage data, which we will discuss further below.

Table 4 describes these results in greater detail. Column (1) estimates the results using the Glassdoor wage data without individual fixed effects. An additional year of own-market experience, for an individual with 10 years of total experience, increased own-market wages by 1.57%, 1.70%, and 3.16% for the United States, advanced economies, and emerging markets respectively. An additional year of US experience increases advanced economy wages by 1.70%+0.91%=2.61%, a percentage increase of 53.5% relative to own-market returns, and increases emerging market wages by 3.16%+2.70=5.86%, a percentage increase of 85.4% relative to own-market returns. A concern here, however, is that since the specification does not control for individual fixed effects, the results could be driven by endogenous selection into migration by unobservable skill.

Column (2) estimates the model including individual fixed effects using the Glassdoor data. The baseline own-market returns to experience are similar between columns (1) and (2). An additional year of own-market experience, for an individual with 10 years of total experience, increases own-market wages by 1.20%, 1.28%, and 2.20% for the United States, advanced economies, and emerging markets respectively. Column (2) also shows an economically and statistically significant positive incremental effect of US experience over own-market experience in emerging market economies, though the magnitudes are smaller than in column (1), consistent with endogenous selection into migration on skill. Specifically, an additional year of US increases emerging market wages by 3.57%, a percentage increase of 62.27% relative to own-market returns. Column (2) also shows that experience in other advanced economies and emerging markets is less valuable to US wages than US experience, though the effect for advanced economies is statistically insignificant.

The results in column (2) indicating a positive wage premium to US experience in emerging market economies could be driven by return migrants sorting into higher wage firms or by return migrants occupying higher wage, more senior positions. To control for the first effect, column (3) estimates the model including both individual fixed effects and firm fixed effects. We continue to find a positive premium to US experience in emerging market economies, indicating that the results are not being driven solely by return migrants sorting into higher paying firms. Specifically, an additional year of US experience, for an individual with 10 years of total experience, increases emerging market wages by 2.85%, an increase of 59.15% relative to the own-market return of 1.79%[10].

Columns (4)-(6) repeat the analysis using Revelio Labs wage data instead of Glassdoor data. Column (4) estimates the model without individual fixed effects, column (5) includes individual fixed effects, and column (6) includes both individual and firm fixed effects. As was indicated by Figure B7, the results are qualitatively similar, although the magnitude of the incremental effect of US experience on advanced economy and emerging market wages is larger. As shown in column (5), an additional year of US experience, for an individual with 10 years total experience, increases advanced economy wages by 0.89%, a percentage increase of 81.4% relative to own-market returns, and increases emerging market wages by 1.82%, a percentage increase of 195.7% relative to own-market returns.[11] When firm fixed effects are included, in column (6), an additional year of US experience increases advanced economy wages by 0.88% and emerging market wages by 1.84%, percentages increases of 84.8% and 204% relative to own market returns[12]. It should be noted that there are seniority differences

[10] Refer to panel (a) in Figure B7 for a graphical illustration of the numbers in column (3).

[11] One can compare our results on the impact of own-market experience on wages with the impact of experience on wages of college graduates across different countries in Lagakos et al. 2018. While our results based on the Revelio Lab wages suggest that the return to own-market experience is higher for the US, the results based on Glassdoor data suggest that the return to experience can be relatively higher in some emerging markets. The latter is consistent with the patterns in Hjort et al. 2022.

[12] Refer to panel (b) in Figure B7 for a graphical illustration of the numbers in column (6).

within a position which our Glassdoor wage imputation does not account for, but that are adjusted for in the Revelio Labs wage data. This suggests that the returns to experience may be somewhat attenuated in the Glassdoor data. Our matching procedure below will attempt to correct for such attenuation.

6.3 Identification Concerns and Interpretation

A potential threat to a causal interpretation of the results above is if either outmigration or return migration decisions are correlated with shocks to earning potential in the origin country. For example, if emerging market workers are more likely to find employment in the United States or advanced economies following a positive shock to their human capital then this could bias our results upwards. Similarly, if migrants return to their origin countries following positive human capital shocks, this too could bias our results upwards. In the subsequent section, we address these concerns using a detailed matching procedure to stayers (i.e. non-migrants) in the origin country, as well as exploiting shocks in the destination country which induce return migration, but are plausibly uncorrelated with shocks to human capital at the individual level.

Conditional on such concerns being addressed, it is also worthwhile to comment on the interpretation of the return to experience estimates. In the basic development accounting framework we laid out in Section 6.1, we assumed that the returns $\beta_{jj'}$ to experience acquired in country j', while currently working in country j, depended only on the bilateral pair j and j'. This implicitly models such returns as being uniform across individuals. In practice, there could be individual level heterogeneity in such returns, which we would denote as $\beta_{ijj'}$. That is, some individuals might be idiosyncratically more successful at acquiring transferable human capital while working abroad. The issue then is, to the extent that individuals understand such features about themselves, those who migrate and subsequently return migrate might at least partially select on such features, consistent with the logic of

Roy (1951).

Thus, letting $D_{ijj'} = 1$ denote the event that individual i migrates to country j' and then return migrates to country j, our procedure actually estimates the quantity $E\left[\beta_{ijj'}|D_{ijj'} = 1\right]$, which will not necessarily equal the average treatment if $Cov(\beta_{ijj'}, D_{ijj'}) \neq 0$.. On the one hand, from the perspective of development accounting and for the purposes of the counterfactuals we run, this is not an issue. Indeed, from the perspective of development accounting, this is exactly the quantity one wishes to measure, i.e. the incremental accumulation of human capital relative to staying in the origin country *of those who actually migrate and return migrate.* If, however, one wanted to perform a policy counterfactual evaluating the impact of sending an average (marginal) emerging market worker abroad, or incentivizing the average (marginal) migrant to return home, then the object of interest would be the average (marginal) treatment effect, which may differ from our estimates.

6.4 Matching Estimates and Firm Layoffs

As noted in the previous subsection, the key endogeneity threat to a causal identification of the returns to experience, and to AKM style designs more generally, is that moves, either migration or return migration, could be correlated with persistent, idiosyncratic shocks to the human capital of the worker. To confront these issues and assess the robustness of our results, we use both a matching strategy and a strategy that exploits plausibly exogenous shocks at the worker level that induce return migration. We focus on emerging market migrants since it is there that the results are most stark and, moreover, is the setting that is likely of the greatest policy interest. To start, for each emerging market migrant, we *exactly* match to other origin country workers based on the firm and position (150 categories) at the time of migration, and years of job experience and education in different rank universities. This is, for each emerging market migrant we find workers in the same country of the same cohort who work at the same firm and the same position, have the same levels of education and experience of the migrant. We then compare the wages of the migrant worker to his matched control group in the year the migrant returns to the origin country.

The results of this matching procedure using Glassdoor data are reported in Panel A of Table 5. We find results economically consistent with our baseline AKM specification. Relative to the matched control group, the wages of emerging market return migrants from the United States are 7.63% higher in the origin country in the year of return. Consistent with the effects being cumulative, they are stronger for those migrants who spent at least 5 years in the United States. For those return migrants, origin country wages are 14.4% higher in the year of return than the matched control group. We also conduct an event study in which we restrict the sample to individuals with at least 5 years of experience in the US for whom we observe their salary at least three years before the migration and at least three years after their return migration. The results in Panel A of Figure 8 confirm that the difference in wages between return migrants and their matched sample upon their return is not driven by any differential pre-trends.

The first two columns of Panel B of Table 5 replicate this analysis using the Revelio Labs wage data. Using this data, the wages of emerging market return migrants from the United States are 9.11% higher in the origin country in the year of return. For those migrants who spend more than 5 years in the United States, wages are 13.1% higher than their matched counterparts in the year of return. Panel B of Figure 8 shows an analogous event study using the Revelio Labs wage data and once again shows no evidence of differential pre-trends. Note that the results are now more quantitatively similar between the Glassdoor wage data and Revelio Labs wage data. This suggests that the tight matching procedure we employ addresses some of the attenuation concerns present in the Glassdoor data.

Finally, using the matched samples, we exploit plausibly exogenous shocks at the worker level that induce return migration to address concerns that the endogenous return migration decision may be correlated with contemporaneous shocks to worker human capital. In particular, within the matched sample, we restrict the analysis to those workers who return migrate following layoffs at the US firm they work for, defined as a firm that has an annual decline of 10% or greater in its workforce[13]. The results are reported in the last two columns of Panel B, Table 5 for the Revelio wage data. The sample becomes too small using the Glassdoor data. We see that results are robust to this specification and, in fact, become even stronger for migrants with greater than 5 years in the destination country. In the Revelio Labs data, return migrant wages are 8.64% higher in the origin country following firm layoffs relative to the matched control group. For those return migrants who have at least 5 years of experience in the United States, origin country wages are 17.4% higher than the matched control group.

6.5 Returns to Education

In this subsection, we briefly use our regression results to consider the returns to education, by regressing our recovered individual fixed effects on the quality of education the worker received. In particular, we group schools into the global top 50, the 51-200 globally ranked schools, the 201-1000 globally ranked schools, and all others. We note that this exercise does not provide causal evidence, since more intrinsically skilled workers may obtain an education from higher ranked schools. However, we think the correlation patters are interesting in their own right and, moreover, provide a useful validation check on the data.

Panel A of Figure 6 reports these results using Glassdoor salary data, while Panel B uses the Revelio salary data. The results are broadly consistent across the two datasets. Across all regions, there is monotonic relationship between the quality of the school attended and individual wages. In emerging markets, according to the Glassdoor data the return to an additional year of education in a top 1-50 ranked school is approximately twice as large as the return to an additional year of education outside the top 1000 schools. The return is

[13]Table 2 and Figure B8 demonstrate a significant increase in return migration among migrants whose firms witnessed a workforce decline of 10% or more.

approximately 4.5 times larger in the Revelio data.

In the United States, the returns to education are similar to the returns in emerging markets, as shown in the bottom panels of Figure 6. The estimated returns to education are lower in advanced economies and there is less spread in the returns between higher ranked and lower ranked schools. However, as noted above, these results should be interpreted cautiosly. There may be less sorting of students into differentially ranked schools based on intrinsic skill in advanced economies relative to the United States and emerging markets.

6.6 Selection into Migration and Return Migration

To quantify the effects of migration and return migration on cross-sectional country human capital stocks, in addition to understanding the human capital returns to experience abroad, it is also important to understand who selects into migration and return migration. This question speaks to one of the primary debates surrounding international migration flows; that is, does international migration create brain drain from some countries and, to what extent does return migration act as a mitigating force.

To answer this question, we use the individual fixed effects recovered from the estimation of equation (8) and then study the distribution of these worker effects by the decision to remain in the origin country, the decision to migrate, and the decision to return migrate. We focus here on the migrants from emerging markets, although our counterfactual analysis in the subsequent section will use the fixed effects recovered for all individuals in our data.

Figure 7, panel A and C, show the distribution of individual fixed effects for workers in emerging markets who stay in the origin country, emigrate to another emerging market economy, emigrate to an advanced economy other than the United States, and emigrate to the United States, using Glassdoor data and Revelio data respectively. We first see that across all destination locations, migrants have higher estimated levels of human capital than non-migrants. Migrants to advanced economies other than the United States have slightly higher levels of human capital than migrants to other emerging market economies. However, there is a sharp discrepancy between migrants to the United States and other emerging market workers. Migrants to the United States have substantially higher levels of human capital than both non-migrants and migrants to locations other than the United States[14].

Figure 7, panel B and D, shows the distribution of individual fixed effects for emerging market migrants in the United States who stay in the United States and the distribution of those who return migrate to their origin counties, relative to the distribution of fixed effects for emerging market workers who remain in their origin countries, again using Glassdoor Data and Revelio data respectively. The evidence here is a bit more mixed. According to the Revelio data, in panel D, we see that return migrants are negatively selected on human capital relative to those migrants who stay in the United States. In the Glassdoor data, however, return migrants appear to have a slightly thicker right tail. However, in both datasets, return migrants are still positively selected on human capital relative to non-migrants[15].

In Figure B10, using the Revelio data, we categorize the original populations of the United States, advanced economies, and emerging markets into 20 ventiles using their individual fixed effects. For each ventile, we determine the proportion of individuals migrating to the US, advanced economies, and emerging markets. Panels a, b, and c illustrate the migration shares for people originally from the US, AE, and EM, respectively. The figure reveals that individuals with higher ability exhibit a greater likelihood of migration, evidenced by a substantial increase in the probability of migration for the highest ability groups. This pattern is more pronounced in emerging markets, less significant in advanced economies, and

[14] Migrants from Emerging Markets to the US, Advanced Economies, and other Emerging Markets display, on average, 12.9%, 6.2%, and 2.8% higher worker ability compared to non-migrants, respectively, according to Revelio data (panel C of Figure 7).

[15] Returnees from the US to emerging markets and non-returnee migrants of emerging markets to the US demonstrate 6.3% and 16.5% higher worker ability, respectively, in comparison to non-migrants of emerging markets using Revelio Lab data (Panel D in Figure 7).

even milder in the US. Focusing on individuals from emerging market economies, approximately 14.3% (5.5%) of those in the highest ventile of abilities migrate to other countries (US), compared to around 6-10% (1-3%) for ventiles 1-17. Similar patterns are observed for individuals from advanced economies, with a higher share migrating to other advanced economies.

7 Impact of Migration and Return Migration on Skilled Human Capital Stocks

We finally use our estimates from the previous section to quantify the impact of migration and return migration on total and per capita skilled human capital stocks. To do so, we construct counterfactual estimates in which we shut down various aspects of international migration flows.

We first construct a counterfactual in which we shut down all skilled migrant flows across countries (except for education). This has three effects. First, it shuts down potential brain drain, since migrants with disproportionately more human capital stock than the typical worker now stay in the country rather than leave. On the flip side, countries now do not benefit from skilled migrants *into* the country. Finally, for emerging markets especially, since there is no more return migration from the United States and other advanced economies, a portion of their workers accumulate less human capital than they otherwise would.

The cumulative result of these channels on the per capita human capital stock and total human capital across countries is shown in Figure 9. As Figure 9 panel A shows, relative to baseline, the effects of shutting down skilled migration on per capita human capital stocks is sizable and heterogeneous across countries. Countries that see the largest percent increases in per capita human capital include Nicaragua, Ireland, Lebanon, and Jordan, reflecting significant levels of brain drain, while those who see the largest percent declines in per capita human capital include Angola, Mauritius, and Haiti. The United States sees a small decline in its per capita human capital, reflecting the fact that it benefits from brain drain in the rest of the world.

Figure 9 panel B shows the impact of migration on total human capital stocks, which incorporates the effects of brain drain and human capital accumulation, but also total migrant flows. The biggest percent increases in total human capital stocks occur in Jordan, Lebanon, and Costa Rica, reflecting the large migrant outflows of skilled labor from those countries. The biggest losers include Kuwait, the UAE, and Qatar, reflecting the large populations of migrant workers in those countries. Indeed, shutting down skilled migrant flows is estimated to reduce total human capital stocks in those countries on the order of 45%-60%.

While it is clear that skilled migration has large and heterogeneous effects on human capital stocks across countries, this heterogeneity is not particularly correlated with GDP or GDP per capita. Thus, while skilled migrant flows has substantial impact on the cross-sectional dispersion of human capital across countries, it by itself does not fully account for explain income differences across countries.

In Figure B11, we report the results of an alternative counterfactual in which we allow for out-migration and return migration but shut down the in-migration of skilled foreign workers. As Figure B11 panel A shows, the biggest winners in terms of per capita human capital include Kuwait, Australia, Ireland, and Japan, although the effects are modest and less than 1 percent. Indeed, the distribution is highly skewed. Countries such as Mauritius, Mozambique, Yemen, and Haiti suffer large per capita losses on the order of 5-8 percent when skilled in-migration is shut down. The United States also suffers, with the per capita human capital stock falling by approximately 1 percent, again reflecting the highly skilled human capital that migrates to the US.

Finally, Figure B11 panel B shows the impact of shutting down skilled in-migration from foreign countries on total human capital stocks. Qatar, Luxembourg, United Arab Emirates, and Kuwait suffer large losses on the order of 60 to 80 percent from such a world. The United States and other advanced economies also suffer significant reductions in their total human capital stocks, equal to approximately 10 percent for the United States and 15 percent for other advanced economies.

8 Conclusion

In this paper, we leverage a novel dataset detailing the employment records of approximately 450 million individuals across 180 countries to explore return migration and the influence of skilled international migration on the worldwide distribution of skilled human capital stocks. Return migration proves a prevalent trend, as 38% of skilled migrants return to their origin countries within a decade. The phenomenon of return migration correlates significantly with income similarity, cultural proximity, and industry growth in the migrants' origin countries.

We then employ a development accounting framework to formalize AKM-style model for worker wages, and account for worker and country fixed effects, to examine the returns to experience and education based on where that experience was acquired and the country the worker currently works in. In emerging economies, a year of experience in the United States increases wages by 59%-212% more than a year of experience in the origin country. We further find that migrants to advanced economies are positively selected for ability compared to non-migrants, yet among them, returnees demonstrate lower ability. Counterfactual simulations indicate that abolishing skilled international migration would yield diverse impacts, ranging from a -60% to 40% adjustment in total skilled human capital stocks across countries, and a -3% to 4% adjustment in per capita skilled human capital stocks.

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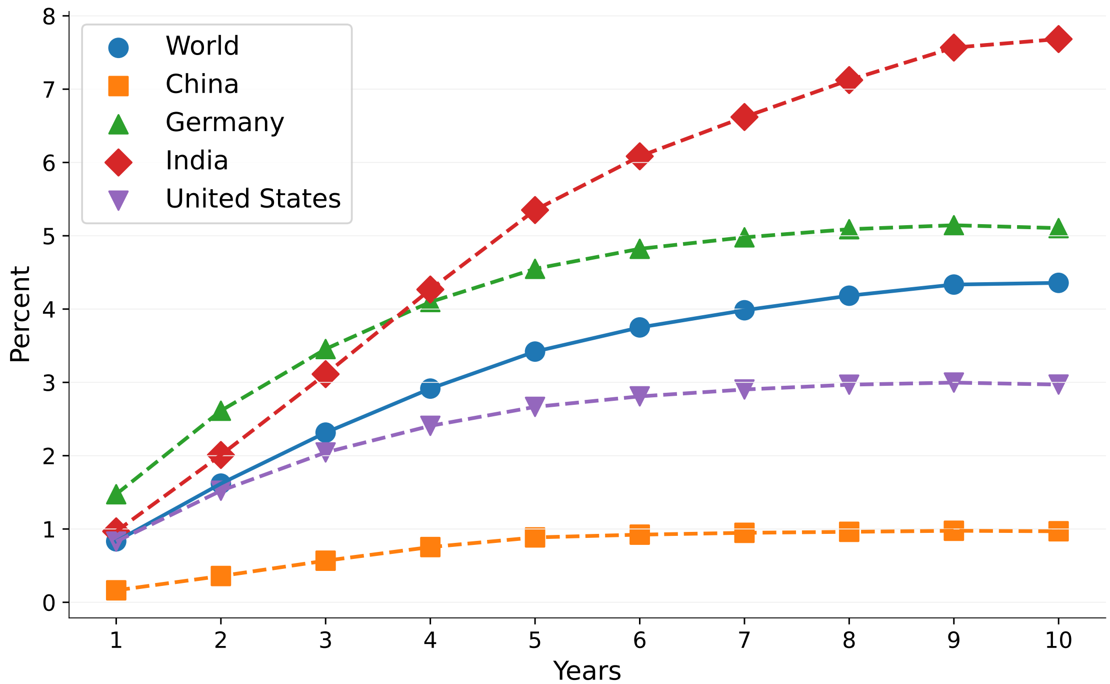
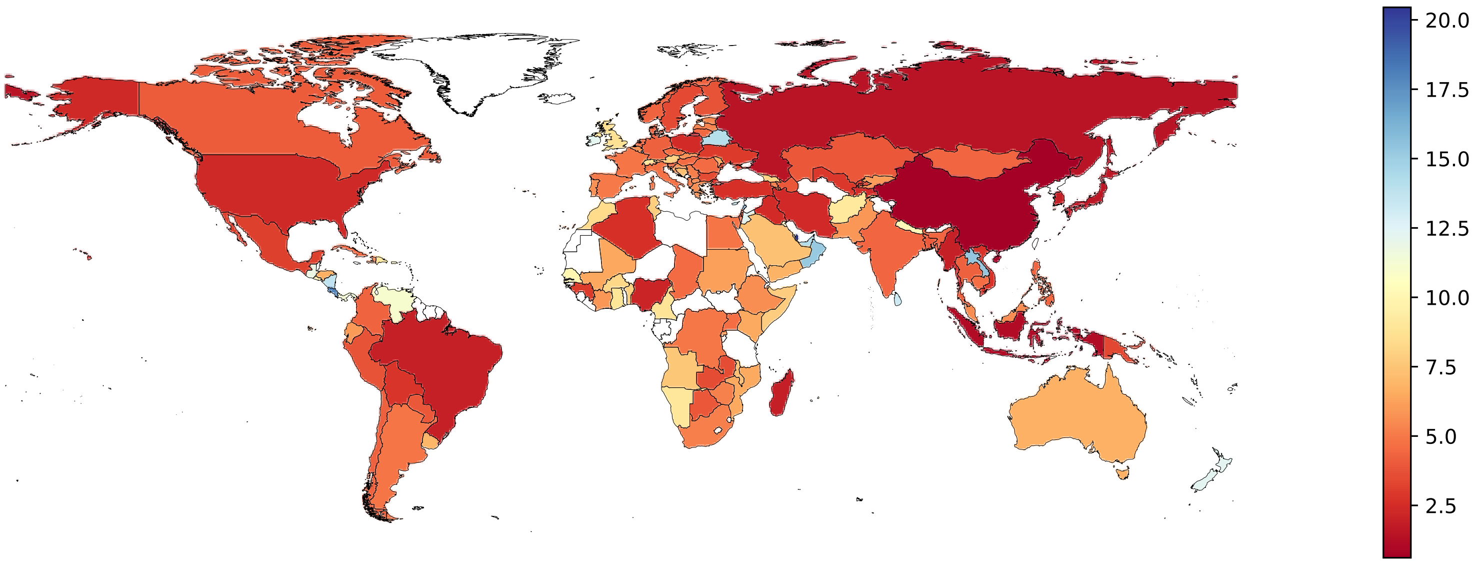
Figure 1: Hazard Ratio of Outflows



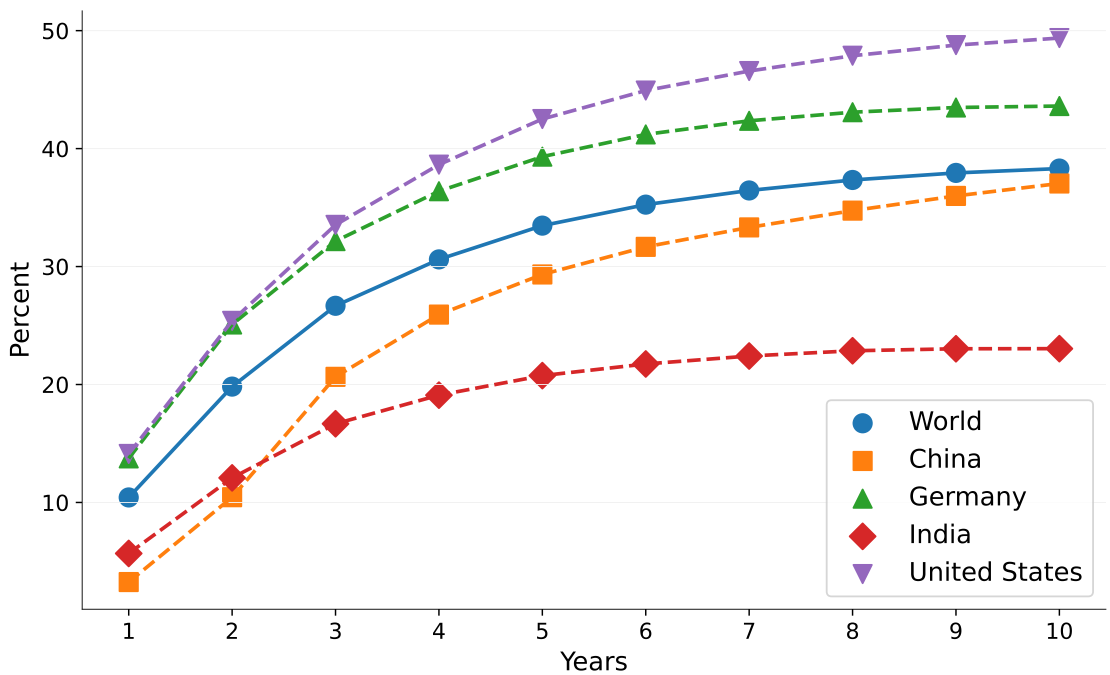
Notes: This figure shows the out-migration rate observed over 10 years. In this analysis, we begin by examining the total population within a country having the same origin country (i.e., the country they initially appeared in the data) at time 0. Subsequently, for each time (t=1, 2,..., 10), the out-migration rate is computed as the proportion of individuals who, by that year, have been observed in the data and residing in another country. A similar approach is adopted for the global analysis (labeled world), yet considering the entire world population. This involves calculating the weighted average of country-level out-migration rates, where the weights are determined by the proportion of each country's population from the total world population in our dataset. The individual weights are based on the formulation specified in Equation 1. We utilized data spanning from 2010 to 2022 to generate this figure for a selected group of 134 ILO members, each with more than 100,000 college-educated individuals, along with China and Saudi Arabia included in the analysis. For further details on this dataset, refer to Appendix A. A comprehensive list of these 136 countries can be found in Table A1.

Figure 2: Map Displaying Outflows After 5 Years by Country



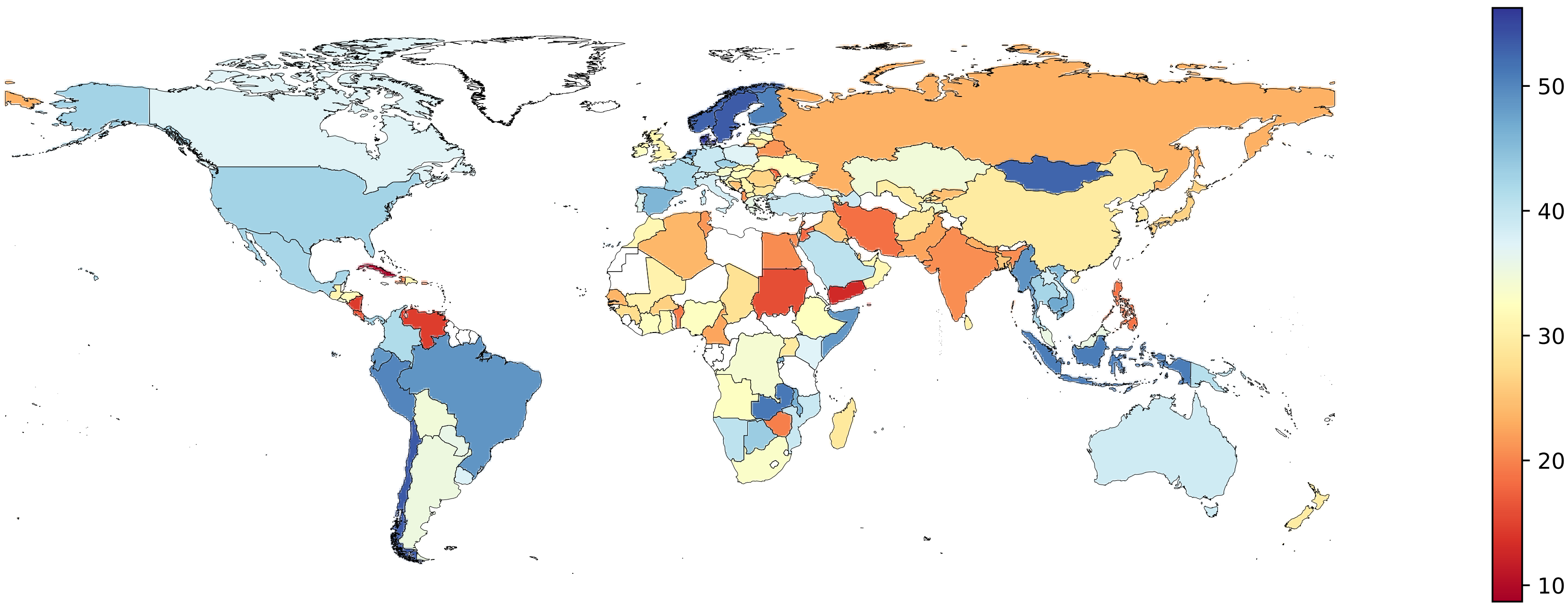
Notes: Refer to the notes on Figure 1. The content presented here mirrors Figure 1; however, we specifically focus on capturing the out-migration rate snapshot for year 5 and visually display it on a map for each country.

Figure 3: Hazard Ratio of Return Migration by Country of Origin



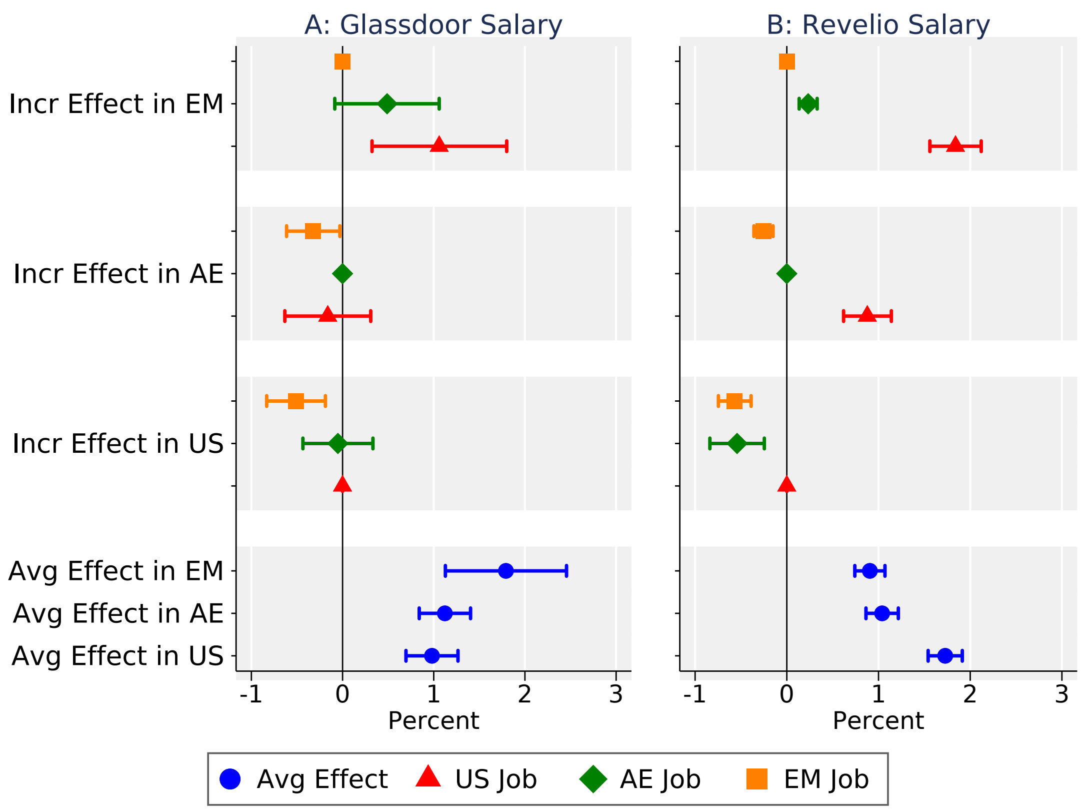
Notes: This figure tracks the return migration of migrants over a decade, starting from their origin country—the country where an individual first appeared in our dataset (either through education or job records). Migrants are followed from the first year they entered their destination country (time 0) across the subsequent 10 years (t=1 to t=10), monitoring those who return to their origin country during this period. For the global analysis (labeled "World"), we calculate the weighted average of country-level return migration rates. These weights are calculated based on the proportion of migrants from each country relative to the total world migrants in our dataset. The weight calculation for individuals is specified in Equation 1. The data includes migrants who moved in 2000 or later and focuses on a group of 134 ILO member countries, each with over 100,000 college-educated individuals, plus China and Saudi Arabia.

Figure 4: Map Illustrating Return Rates After 5 Years by Country of Origin



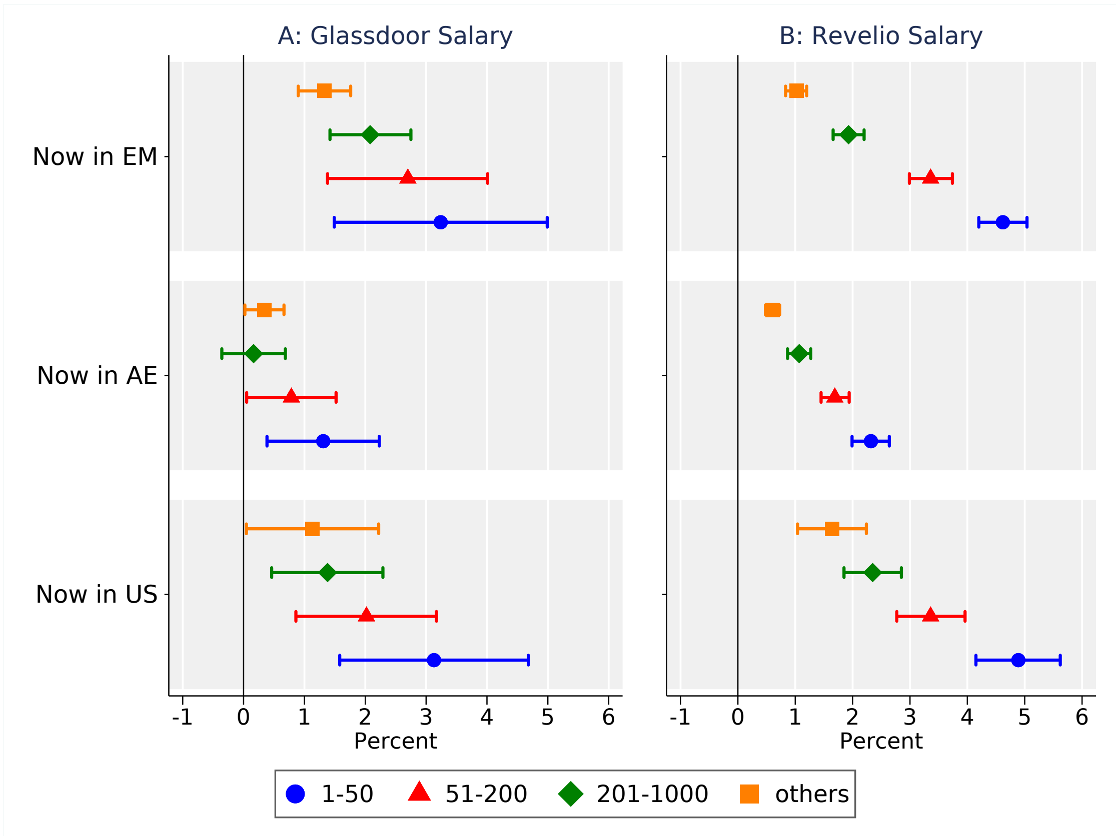
Notes: Refer to the notes on Figure 3. This content mirrors Figure 3; however, our specific focus here is to capture the return migration rate snapshot for year 5 and present it visually on a map for each country of origin.

Figure 5: Return to Job Experience and its Transferability



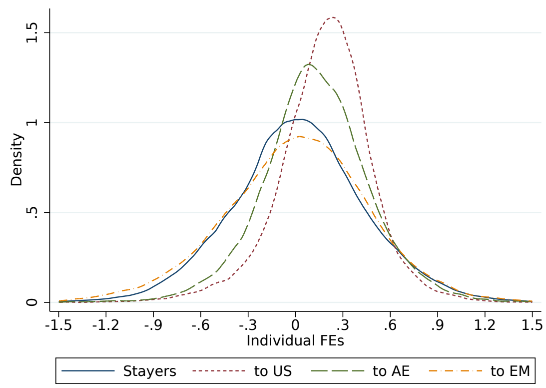
Notes: This figure shows the coefficients ($\beta_{jj'}$) and their standard errors for Equation 8, which includes country-by-year, individual and firm fixed effects (columns 3 and 6 in Table 4). The dependent variables are the logarithm of salary estimated using Glassdoor salary data and the logarithm of salary imputed by Revelio Labs in panels A and B, respectively. The average effect demonstrates the elasticity of salary in response to an additional year of total experience for an individual with 10 years of total job experience, represented as "$a + 2 \times b \times 10$", where a and b denote the coefficients for total experience and total experience^2, respectively. The graph also includes incremental effects of job experience in different regions and job categories. To estimate this equation, we initially restrict our sample to individuals who have reported a bachelor's degree at some point (although the results remain robust even after relaxing this criterion, as shown in Table C5). To efficiently handle the data size, we employ a 25% completely random sample and focus on the years 2010-2022 (note that the results are consistent across different sample sizes). We categorize years of job experience into three groups based on countries: United States (US), Advanced Economies (AE), and Emerging Market Economies (EM) observed until each respective year. Our salary data is imputed for each position, irrespective of its duration, with only the final year of each position retained as an observation. Consequently, education years are excluded from this analysis as they do not directly correspond to an associated salary. The standard errors are clustered at the individual level, and 95% confidence intervals are displayed for each coefficient.

Figure 6: Returns to Education

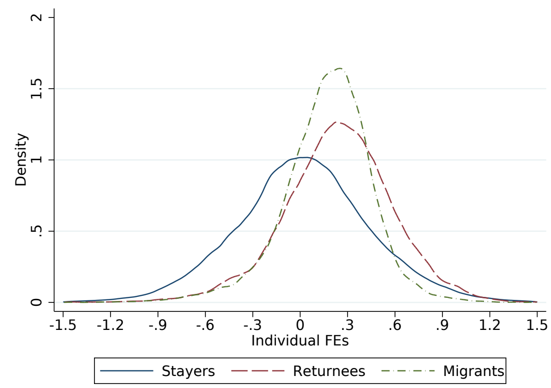


Notes: This figure illustrates the coefficients from regressions of individual fixed effects on years of education across various educational categories: top 50 schools, schools ranked 51-200, schools ranked 201-1000, and all other schools. In panels A and B, we use individual fixed effects estimated from columns (3) and (6) in Table 4, respectively. These regressions also have country-by-year and firm fixed effects. Standard errors are clustered at the individual level, and 95% confidence intervals are displayed for each coefficient. The same coefficients are also presented in Table C6 but in tabular format.

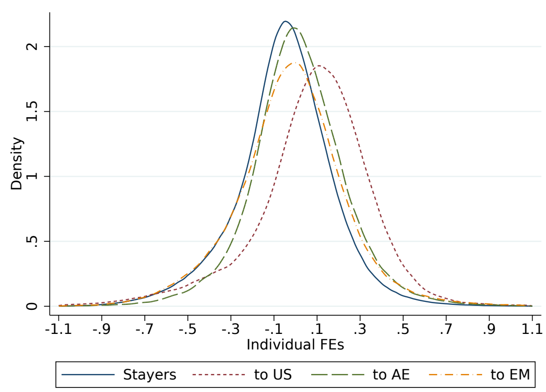
Figure 7: Selection of Outflows from Emerging Markets and Returnees



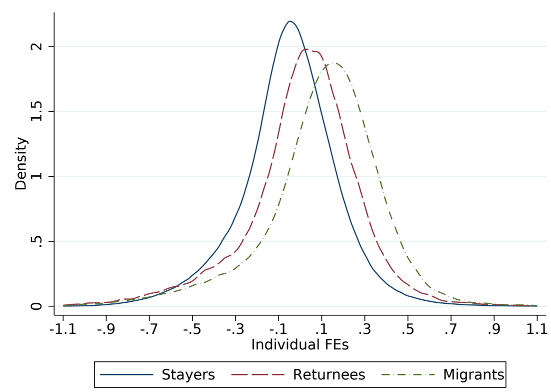
(a) Outflows - Glassdoor



(b) Return Migrations - Glassdoor



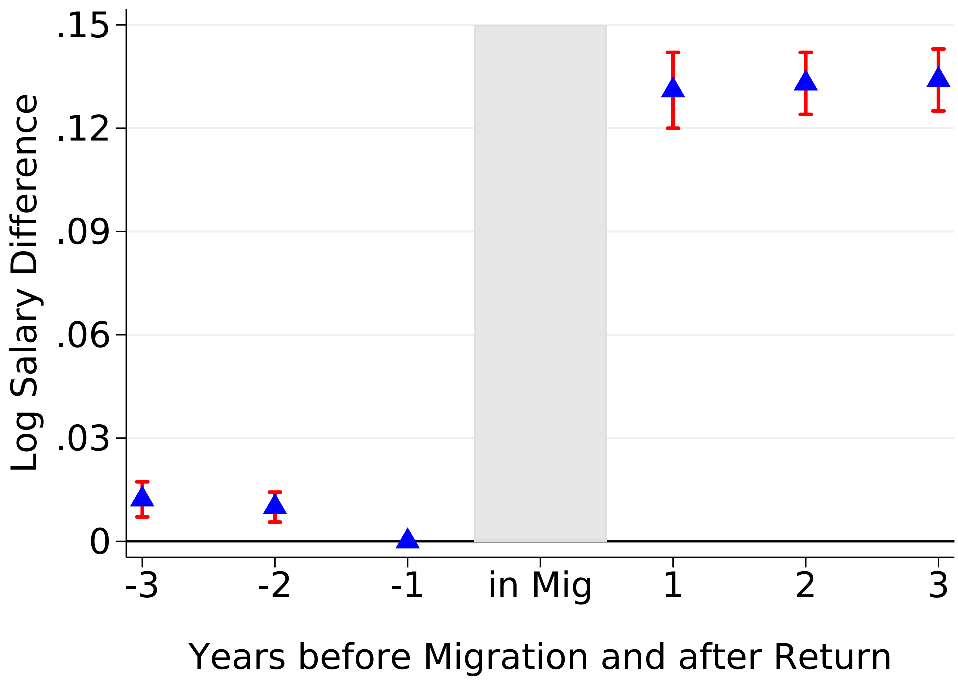
(c) Outflows - Revelio



(d) Return Migration - Revelio

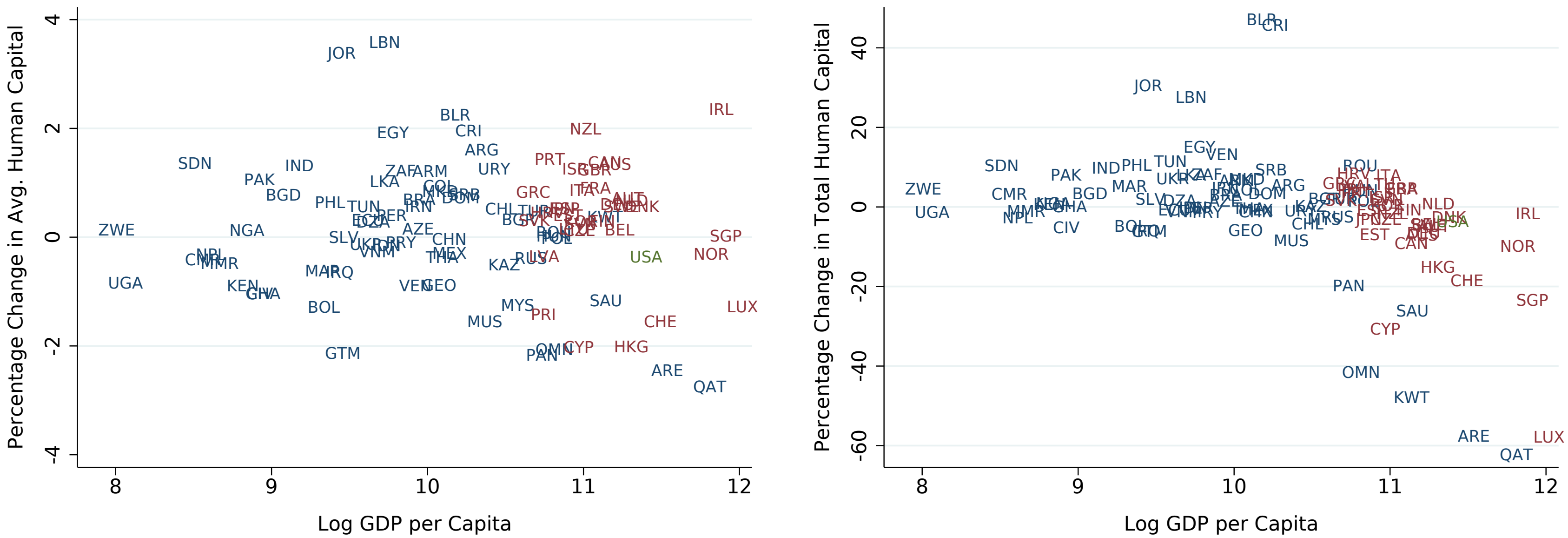
Notes: Refer to the notes in Figure 5 and Table 4. Panels (a) and (c) show the distribution of estimated individual fixed effects (for individuals working in firms with at least 10 workers), as calculated in Equation 8, across four categories: 1) Individuals who consistently remain in their original Emerging Market (EM) country (Stayers); 2) Outflows from EM countries to the United States (to US); 3) Outflows from EM countries to Advanced Economies (to AE); and 4) Outflows from EM countries to other EM countries (to EM). On the other hand, panels (b) and (d) show the distribution of estimated individual fixed effects across three categories: 1) Individuals who consistently remain in their original Emerging Market (EM) country (Stayers); 2) Individuals who migrate from EM to the US and subsequently return to their EM country (Returnees); and 3) Individuals who migrate from Emerging Markets to the US but do not return and continue to reside in the US (Migrants). In panels (a) and (b), we utilize the individual fixed effects estimated from column (3) in Table 4, while in panels (c) and (d), we use the individual fixed effects estimated from column (6) of the same table.

Figure 8: Event Study of Migration from EM to US and Return - At least 5 Years in US



Notes: Refer to the notes on Table 5. In this figure, we implement the matching procedure outlined in section 6.4 and the corresponding notes from Table 5. However, our analysis now expands to compare the treatment and control groups across a wider temporal range: specifically, from 3 years prior to migration (years -3 to -1) to 3 years following the return to the origin country (years 1 to 3). Similar to Table 5, our matching process is based on the year (-1), the year before migration. We keep all observations within the treatment and control groups if they have salary data available for the entire 3 years pre-migration and 3 years post-return, while also meeting the criteria of having resided in the United States for at least 5 years (similar to Column (2) in Table 5, panel A). The shaded area in the figure represents the years of migration (US). Standard errors are clustered at the origin country level, and 95% confidence intervals are displayed in the figure. Each point illustrates the difference in the logarithm of salary between each treatment and control group, which is by definition zero at year (-1). Figure B9 in the appendix presents similar results, but on all returnees regardless of the duration of their stay in the United States.

Figure 9: Counterfactual: Migration Shut Down and Human Capital Change



(a) Average Changes

(b) Total Changes

Notes: This figure in panels (a) and (b) presents the average and total changes in human capital resulting from a counterfactual analysis that assumes the shutting down of all flows among countries, except for education, respectively. When simulating the shutdown of flows, we replace all job experiences abroad with job experiences gained in the individual's origin country. By utilizing the coefficients and individual fixed effects estimated in Equation 8 and in column (6) of Table 4, we compute the counterfactual human capital for each individual and subsequently aggregate these values to find the averages for each country. To find the total changes, we aggregate the entire human capital stock for each country, using the weights derived from Equation 1 to determine these aggregations. The colors red, blue, and green correspond to Emerging Market Economies (EM), Advanced Economies (AE), and the United States (US), respectively.

Table 1: Bilateral Flows and Country Characteristics

	Log Outflows		Log Returns	
	(1)	(2)	(3)	(4)
Log Origin GDP Per Capita	-0.240***		0.385***	0.362***
	(0.0871)		(0.0531)	(0.0540)
Log Destination GDP Per Capita	0.620***	0.627***	-0.119***	
	(0.101)	(0.101)	(0.0416)	
Log Distance	-0.612***	-0.673***	-0.00475	-0.0317
	(0.0690)	(0.0939)	(0.0345)	(0.0420)
Common Official Language	1.277***	1.323***	0.126***	0.137**
	(0.152)	(0.172)	(0.0467)	(0.0610)
Log Origin ILO Count	0.881***		0.0707***	0.0892***
	(0.0349)		(0.0190)	(0.0241)
Log Destination ILO Count	0.745***	0.760***	0.0851***	
	(0.0276)	(0.0319)	(0.0243)	
Origin Coverage	0.938***		0.189*	0.223**
	(0.202)		(0.100)	(0.0961)
Destination Coverage	0.499**	0.524**	0.305*	
	(0.234)	(0.228)	(0.178)	
Log Outflow			0.944***	0.925***
			(0.0284)	(0.0288)
Observations	13447	13447	11514	11514
R-Squared	0.814	0.837	0.964	0.970
Origin FE		Y		
Destination FE				Y

Notes: Table illustrates the outcomes of regression Equation 2. In columns (1, 2) the dependent variable is the logarithm of bilateral flows between two countries, while columns (3, 4) denote the logarithm of the number of return migrations between pairs of countries. Bilateral flows from country "o" to country "d" are characterized as the weighted total number of individuals who are presently in country o but are located in country d in the following year. Individual weights are derived from Equation 1. To derive the annual flows for each pair of countries, we first compute the flows for each year from 2014 to 2018 (before the COVID-19 pandemic) and then average these values across the 5 years. Regarding the determination of return numbers between countries o and d, we accumulate the total count of migrants originating from country o and residing in country d who eventually return to their country of origin within 10 years. These return figures encompass all migrants who migrated from the year 2000 onward. All standard errors are two-way clustered based on the country of origin and destination and are reported in parenthesis below the coefficients. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Industry Growth and Return Migration

	All (1)	Mig < 5 (2)	Mig ≥ 5 (3)	Mig < 5 (4)
Origin Same Industry Growth	2.279***	4.182***	0.649**	4.013***
	(0.557)	(1.063)	(0.291)	(1.028)
Destination Same Industry Growth	-7.390***	-9.354***	-2.431***	-9.490***
	(1.535)	(1.811)	(0.835)	(1.724)
Origin Adjacent Industries Growth				6.509***
				(2.470)
Destination Adjacent Industries Growth				-7.354**
				(3.341)
Constant	5.402***	8.847***	2.112***	8.894***
	(0.0258)	(0.0246)	(0.0144)	(0.313)
Observations	23001013	10948138	12052711	10883198
R-Squared	0.0475	0.0352	0.0132	0.0352
Origin by Year FE	Y	Y	Y	Y
Destination by Year FE	Y	Y	Y	Y
Industry by Year FE	Y	Y	Y	Y
Years from First Migration FE	Y	Y	Y	Y
Years from Last Migration FE	Y	Y	Y	Y

Notes: This table presents the estimation of Equation 3. Here, we construct an individual-level panel of migrants employed (excluding those in education) in their destination country and define a return dummy as 100 if they return to their origin country the following year, and 0 otherwise. We utilize three-digit North American Industry Classification System (NAICS) industry codes for each firm to identify the industry in which the migrant works. The industry growth is calculated as the average growth ($\log(1 + \text{growth})$) of the industry over the last three years. Column (1) includes all migrants, but in columns (2) and (3), we run regressions separately on subsamples of migrants who have been in the destination country for less than 5 years and at least 5 years, respectively. In column (4), we also add the weighted growth of the adjacent industries for each industry. Weights are derived from the transition matrix of domestic workers for each county among different industries. All analyses presented in this table are based on data collected from 2010 onwards. Standard errors are two-way clustered based on the country of origin and destination and reported in parentheses below the coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Firm Growth and Return Migration

	All	Mig < 5	Mig ≥ 5	Mig < 5	Mig < 5
	(1)	(2)	(3)	(4)	(5)
Firm Growth $\times$ Negative	-9.619***	-15.97***	-4.853***	-14.94***	-10.85***
	(1.085)	(2.064)	(0.674)	(1.615)	(1.053)
Firm Growth $\times$ Positive	-3.487***	-5.270***	-1.320***	-4.803***	-4.478***
	(0.256)	(0.375)	(0.129)	(0.384)	(0.402)
Multinational Company				-0.727***	-0.730***
				(0.148)	(0.139)
Branch in Origin Country				3.182***	2.943***
				(0.318)	(0.316)
Branch in Origin Country $\times$ Firm Growth $\times$ Negative					-9.182***
					(1.535)
Branch in Origin Country $\times$ Firm Growth $\times$ Positive					-0.670
					(0.548)
Observations	19257124	8799480	10505939	8747738	8747738
R-Squared	0.0639	0.0360	0.0121	0.0674	0.0676
Years from First Migration FE	Y	Y	Y	Y	Y
Years from Last Migration FE	Y	Y	Y	Y	Y
Origin by Industry by Year FE	Y	Y	Y	Y	Y
Destination by Industry by Year FE	Y	Y	Y	Y	Y

Notes: This table presents the estimation of Equation 4. Here, we construct an individual-level panel of migrants employed (excluding those in education) in their destination country and define a return dummy as 100 if they return to their origin country the following year and 0 otherwise. The firm growth is calculated as the average growth ($\log(1 + \text{growth})$) of the firm employees from this year to the next year. We restrict the sample to firms with a median number of employees greater than 50 after 2010. We allow the slope to vary for positive and negative growth in firm employees. The "Multinational Company" dummy equals 1 if the migrant is now working in a multinational company, and "Branch in the Origin Country" equals 1 if the current multinational company has a branch in the migrant's origin country. All analyses presented in this table are based on data collected from 2010 onwards. Standard errors are two-way clustered based on the country of origin and destination and reported in parentheses below the coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Returns to Job Experience

	Glassdoor			Revelio		
	(1)	(2)	(3)	(4)	(5)	(6)
Incremental Effect:						
Exp in US × Now in AE	0.00908***	0.00115	-0.00162	0.0120***	0.00887***	0.00878***
	(0.00302)	(0.00240)	(0.00240)	(0.000706)	(0.00144)	(0.00132)
Exp in US × Now in EM	0.0270***	0.0137***	0.0106***	0.0225***	0.0182***	0.0184***
	(0.00516)	(0.00316)	(0.00377)	(0.00161)	(0.00157)	(0.00143)
Exp in AE × Now in US	0.0145***	-0.00137	-0.000507	0.0128***	-0.00465***	-0.00542***
	(0.00263)	(0.00178)	(0.00196)	(0.00105)	(0.00159)	(0.00151)
Exp in AE × Now in EM	0.0165***	0.00429	0.00489*	0.0141***	0.00220***	0.00233***
	(0.00540)	(0.00292)	(0.00293)	(0.000747)	(0.000556)	(0.000499)
Exp in EM × Now in US	0.0177***	-0.00379**	-0.00510***	0.00344*	-0.00504***	-0.00568***
	(0.00431)	(0.00164)	(0.00164)	(0.00193)	(0.000986)	(0.000910)
Exp in EM × Now in AE	0.00463**	-0.00338	-0.00322**	-0.00783***	-0.00256***	-0.00255***
	(0.00197)	(0.00232)	(0.00149)	(0.000694)	(0.000524)	(0.000533)
Own-Market Effect:						
Total Exp × Now in US	0.0276***	0.0238***	0.0170***	0.0366***	0.0371***	0.0349***
	(0.00331)	(0.00191)	(0.00172)	(0.00175)	(0.00137)	(0.00135)
Total Exp × Now in AE	0.0284***	0.0236***	0.0181***	0.0257***	0.0266***	0.0255***
	(0.00244)	(0.00222)	(0.00172)	(0.000962)	(0.00121)	(0.00123)
Total Exp × Now in EM	0.0584***	0.0508***	0.0319***	0.0244***	0.0234***	0.0225***
	(0.00753)	(0.00575)	(0.00611)	(0.00107)	(0.00122)	(0.00124)
Total Exp^2 × Now in US	-0.000595***	-0.000590***	-0.000359***	-0.000761***	-0.000945***	-0.000881***
	(0.0000752)	(0.0000354)	(0.0000277)	(0.0000415)	(0.0000334)	(0.0000312)
Total Exp^2 × Now in AE	-0.000569***	-0.000538***	-0.000342***	-0.000497***	-0.000784***	-0.000757***
	(0.0000532)	(0.0000337)	(0.0000360)	(0.0000257)	(0.0000266)	(0.0000266)
Total Exp^2 × Now in EM	-0.00134***	-0.00144***	-0.000699***	-0.000438***	-0.000705***	-0.000674***
	(0.000238)	(0.000162)	(0.000170)	(0.0000351)	(0.0000277)	(0.0000279)
Observations	4181469	4181469	4181469	22960532	22960532	22960532
R-Squared	0.831	0.924	0.938	0.818	0.897	0.905
Country by Year FE	Y	Y	Y	Y	Y	Y
Individual FE		Y	Y		Y	Y
Firm FE			Y			Y

Notes: Refer to the notes on Figure B7. This table presents the coefficients ($\beta_{jj'}$) for Equation 8. The dependent variable in columns (1-3) and (4-6) is the logarithm of Glassdoor salary and Revelio Lab imputed salary data, respectively. The sample used for this analysis comprises a 25% completely random sample of individuals who have reported holding a bachelor's degree at some point and includes years following their last education year (graduation). In columns (3) and (6), we further restrict the sample to individuals for whom we can estimate their Glassdoor salary for at least 75% of their positions. The standard errors, clustered at the individual level, are reported in parentheses below the coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Differences in Salaries: Matched Treatment and Controls Pre-Migration to US and Post-Return to EM

	Entire Sample		Mass Layoff	
	Total	Mig. Years ≥ 5	Total	Mig. Years ≥ 5
	(1)	(2)	(3)	(4)
Panel A: Glassdoor Salary				
Treatment $\times$ Post	0.0763***	0.144***		
	(0.0112)	(0.0113)		
Observations	18802	4721		
R-Squared	0.922	0.837		
Panel B: Revelio Salary				
Treatment $\times$ Post	0.0911***	0.131***	0.0864***	0.174***
	(0.00611)	(0.00803)	(0.0128)	(0.0353)
Observations	195492	40218	5753	924
R-Squared	0.709	0.694	0.710	0.782

Notes: This table presents the regression results of a matching regression that matches the treatment group (comprising individuals migrating from Emerging Markets to the US and subsequently returning to their origin country) to control individuals who never migrate. The matching process focuses solely on the characteristics observed in the year just before migration. We restrict the sample to individuals who were employed the year before migration. The characteristics used for matching include the country of origin, years of job experience, the firm, and role (150 categories) of employment at the time of migration. Additionally, we match based on the years of education categorized into different university ranks (as illustrated in Figure 6) (In Table C7 we do not match on education records). The dependent variable in panels (a) and (b) is the logarithm of Glassdoor salary and Revelio salary, respectively. Here we use observations from the year before migration and the first year after return. All columns control for the matched group (each treatment individual and their matched control individual) by time fixed effects and also treatment by time fixed effects. Column (1) represents the entire sample, while column (2) focuses on a subsample of returnees with at least 5 years of experience in the US. Columns (3) and (4) mirror columns (1) and (2), respectively, but specifically consider a subsample of migrants who experienced a mass layoff in their firm just before returning. We define a mass layoff as a reduction in the total number of employees by more than 10% within a single year, specifically for firms with a minimum of 50 employees, which corresponds to the median number observed from 2010 to 2022. All standard errors are clustered at the country of origin level and are reported in parentheses below the coefficients. *** p<0.01, ** p<0.05, * p<0.1.

A Data Appendix

In this appendix, we aim to provide further insights into our professional profiles dataset and explain the data cleaning processes we implemented. Additionally, we discuss the validity checks performed on the dataset to ensure its accuracy and reliability.

We use data from the International Labor Organization (ILO) on the number of college-educated individuals across 186 member countries. Notably, China and Saudi Arabia, which are not ILO members, are included separately. We added data for these countries from independent sources, totaling 240 million in China and 6 million in Saudi Arabia. Countries with fewer than 100,000 college-educated individuals are excluded from our analysis. Thus, our primary focus is on the remaining 134 ILO members and the two additional countries, each with at least 100,000 college-educated individuals.

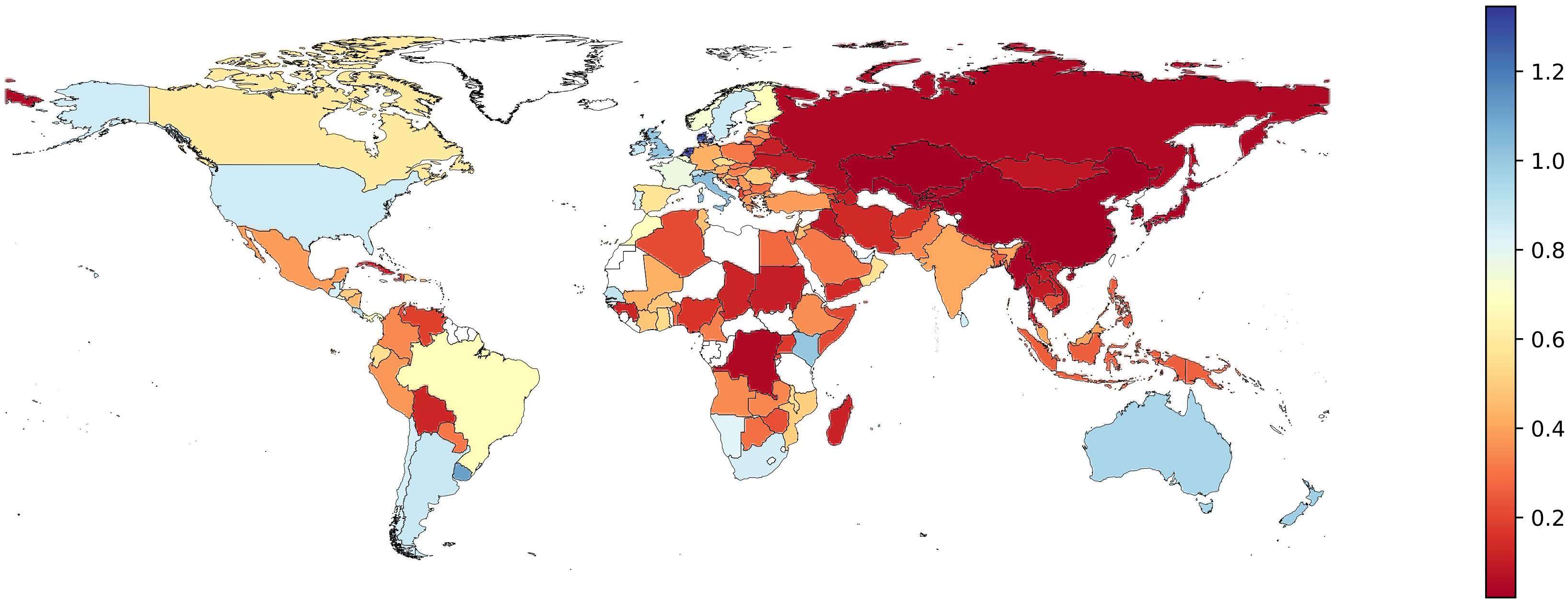
We also use the International Monetary Fund's classifications of Advanced Economies (AE) and Emerging Market and Developing Economies (EM) in our analyses (International Monetary Fund 2023). In the paper, we use "EM" to abbreviate Emerging Market and Developing Economies. We categorize the United States separately because of its significant presence in our dataset. Table A1 shows the number of college-educated individuals from the ILO, professional profiles, and whether the 136 selected countries are classified as AE or EM. Figure A1 also shows the ratio of professional profiles in our dataset to the ILO's counts of college-educated individuals.

Table A1: Country Coverage and Weight Distribution

Part 1								Part 2								Part 3							
N (1)	Country (2)	Cat. (3)	Link (4)	ILO (5)	ILO Yr (6)	Covrg (7)	W (8)	N (1)	Country (2)	Cat. (3)	Link (4)	ILO (5)	ILO Yr (6)	Covrg (7)	W (8)	N (1)	Country (2)	Cat. (3)	Link (4)	ILO (5)	ILO Yr (6)	Covrg (7)	W (8)
1	United States	US	70851	82699	2022	0.86	1.17	47	Finland	AE	770	1144	2021	0.67	1.49	93	Azerbaijan	EM	151	1476	2021	0.10	9.77
2	India	EM	24097	59555	2020	0.40	2.47	48	Morocco	EM	770	1131	2021	0.68	1.47	94	Ethiopia	EM	150	427	2013	0.35	2.83
3	Brazil	EM	16528	24692	2021	0.67	1.49	49	Israel	AE	765	1580	2021	0.48	2.07	95	Myanmar	EM	150	4379	2020	0.03	29.05
4	United Kingdom	AE	15110	15083	2019	1	1	50	Vietnam	EM	759	7774	2021	0.10	10.24	96	Cyprus	AE	145	225	2021	0.65	1.55
5	France	AE	10118	13245	2021	0.76	1.31	51	Austria	AE	743	1672	2021	0.44	2.25	97	Slovenia	AE	143	438	2021	0.33	3.05
6	Canada	AE	8451	14232	2022	0.59	1.68	52	South Korea	AE	740	15887	2022	0.05	21.44	98	Honduras	EM	138	277	2019	0.50	2.01
7	Italy	AE	5930	5779	2021	1.03	0.97	53	Hong Kong	AE	734	1259	2021	0.58	1.71	99	Georgia	EM	135	650	2020	0.21	4.80
8	Australia	AE	5840	6107	2020	0.96	1.05	54	Ecuador	EM	700	1273	2021	0.55	1.82	100	Latvia	AE	134	381	2021	0.35	2.84
9	Spain	AE	5715	10071	2021	0.57	1.76	55	Greece	AE	654	1731	2021	0.38	2.64	101	Cambodia	EM	128	561	2019	0.23	4.38
10	Germany	AE	5706	13370	2021	0.43	2.34	56	Thailand	EM	652	6697	2021	0.10	10.26	102	Estonia	AE	125	289	2021	0.43	2.31
11	China	EM	5553	240000	2022	0.02	43.21	57	Hungary	EM	491	1485	2021	0.33	3.02	103	Nicaragua	EM	123	275	2014	0.45	2.23
12	Netherlands	AE	5248	3901	2021	1.35	0.74	58	Algeria	EM	489	2293	2017	0.21	4.68	104	Sudan	EM	113	1080	2011	0.11	9.50
13	Indonesia	EM	4466	17582	2022	0.25	3.94	59	Ghana	EM	455	845	2017	0.54	1.86	105	Mozambique	EM	106	210	2015	0.51	1.98
14	Mexico	EM	4402	11488	2021	0.38	2.61	60	Costa Rica	EM	453	502	2021	0.90	1.11	106	Albania	EM	102	564	2019	0.18	5.50
15	Turkey	EM	3529	9142	2021	0.39	2.59	61	Sri Lanka	EM	450	529	2020	0.85	1.18	107	Mauritius	EM	102	110	2020	0.92	1.08
16	South Africa	EM	3142	3705	2021	0.85	1.18	62	Qatar	EM	425	558	2021	0.76	1.31	108	Botswana	EM	95	328	2020	0.29	3.45
17	Argentina	EM	2896	3319	2021	0.87	1.15	63	Tunisia	EM	418	900	2017	0.46	2.15	109	Armenia	EM	88	463	2021	0.19	5.23
18	Philippines	EM	2595	10471	2018	0.25	4.03	64	Lebanon	EM	356	600	2019	0.59	1.68	110	DR Congo	EM	87	1715	2020	0.05	19.61
19	Colombia	EM	2489	7247	2021	0.34	2.91	65	Serbia	EM	333	872	2021	0.38	2.61	111	Afghanistan	EM	86	506	2021	0.17	5.87
20	U.A. Emirates	EM	2408	2915	2021	0.83	1.21	66	Jordan	EM	332	715	2021	0.47	2.15	112	Namibia	EM	83	102	2018	0.81	1.24
21	Sweden	AE	2121	2462	2021	0.86	1.16	67	Dominican Rep.	EM	323	664	2021	0.49	2.05	113	Bosnia and Herz.	EM	80	284	2021	0.28	3.56
22	Pakistan	EM	2035	6136	2021	0.33	3.01	68	Bulgaria	EM	311	1062	2021	0.29	3.41	114	Macedonia	EM	79	519	2021	0.31	3.27
23	Poland	EM	1968	6304	2021	0.31	3.20	69	Guatemala	EM	301	358	2019	0.84	1.19	115	Cuba	EM	76	793	2010	0.10	10.40
24	Russia	EM	1944	38060	2021	0.05	19.58	70	Uruguay	EM	289	260	2019	1.11	0.90	116	Rwanda	EM	64	327	2021	0.20	5.09
25	Nigeria	EM	1889	11833	2019	0.16	6.26	71	Kuwait	EM	275	530	2016	0.52	1.93	117	Burkina Faso	EM	62	130	2018	0.48	2.08
26	Saudi Arabia	EM	1870	6000	2020	0.31	3.21	72	Slovakia	AE	247	801	2021	0.31	3.23	118	Papua New Guinea	EM	62	240	2010	0.26	3.84
27	Chile	EM	1869	2220	2021	0.84	1.19	73	Croatia	AE	244	513	2021	0.48	2.10	119	Mali	EM	62	145	2020	0.43	2.34
28	Switzerland	AE	1860	2094	2021	0.89	1.13	74	Puerto Rico	AE	243	587	2015	0.42	2.41	120	Madagascar	EM	61	540	2015	0.11	8.73
29	Belgium	AE	1853	2570	2021	0.72	1.39	75	Panama	EM	235	344	2021	0.68	1.46	121	Malawi	EM	61	112	2020	0.55	1.83
30	Malaysia	EM	1811	4497	2020	0.40	2.48	76	Oman	EM	230	411	2021	0.56	1.79	122	Uzbekistan	EM	59	2681	2020	0.02	44.92
31	Egypt	EM	1685	6113	2021	0.28	3.63	77	Nepal	EM	228	751	2017	0.30	3.29	123	Palestine	EM	57	404	2021	0.14	7.02
32	Denmark	AE	1561	1203	2021	1.30	0.77	78	Ivory Coast	EM	227	473	2019	0.48	2.08	124	Benin	EM	53	189	2018	0.28	3.53
33	Peru	EM	1541	4149	2021	0.37	2.69	79	Lithuania	AE	221	695	2021	0.32	3.14	125	Haiti	EM	53	388	2012	0.14	7.26
34	Portugal	AE	1400	1741	2021	0.80	1.24	80	Uganda	EM	213	1235	2021	0.17	5.78	126	Yemen	EM	52	383	2014	0.14	7.37
35	Singapore	AE	1370	1464	2021	0.94	1.07	81	Zimbabwe	EM	207	953	2021	0.22	4.58	127	Moldova	EM	51	279	2021	0.19	5.40
36	Ireland	AE	1142	1307	2021	0.87	1.14	82	Iraq	EM	200	2477	2021	0.08	12.34	128	Mongolia	EM	43	515	2021	0.08	11.96
37	Bangladesh	EM	1061	4108	2017	0.26	3.87	83	Bolivia	EM	186	1470	2021	0.13	7.89	129	Guinea	EM	41	338	2019	0.12	8.21
38	New Zealand	AE	1054	1074	2020	0.98	1.02	84	Luxembourg	AE	185	168	2021	1.10	0.91	130	Somalia	EM	36	174	2019	0.21	4.82
39	Norway	AE	966	1333	2021	0.72	1.38	85	Kazakhstan	EM	183	7486	2020	0.02	40.90	131	Kosovo	EM	35	147	2021	0.24	4.15
40	Japan	AE	964	33210	2020	0.03	34.42	86	Cameroon	EM	180	548	2014	0.33	3.04	132	Macao	AE	33	134	2016	0.25	3.96
41	Venezuela	EM	954	5035	2017	0.19	5.28	87	Belarus	EM	179	1714	2021	0.10	9.58	133	Kyrgyzstan	EM	26	566	2018	0.05	21.77
42	Iran	EM	945	7205	2020	0.13	7.62	88	Senegal	EM	166	186	2019	0.89	1.12	134	Laos	EM	25	257	2017	0.10	10.05
43	Romania	EM	932	1842	2021	0.51	1.98	89	Zambia	EM	161	479	2021	0.34	2.96	135	Chad	EM	16	134	2018	0.12	8.22
44	Ukraine	EM	886	9494	2021	0.09	10.71	90	El Salvador	EM	161	224	2021	0.72	1.39	136	Tajikistan	EM	12	581	2016	0.02	48.37
45	Kenya	EM	869	867	2019	1	1	91	Angola	EM	153	438	2021	0.35	2.86								
46	Czech Republic	AE	782	1437	2021	0.54	1.84	92	Paraguay	EM	152	494	2017	0.31	3.24								

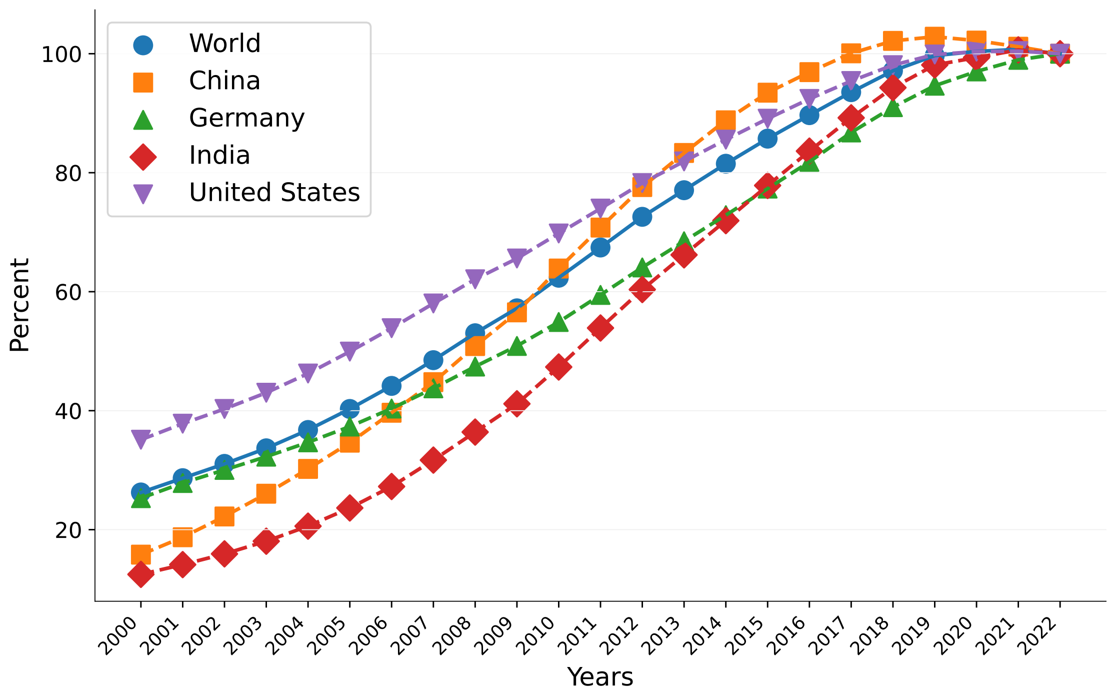
Notes: The table has three sections and lists the following for each country: order (1), country name (2), IMF country category (3), professional profile counts (4), ILO college-educated counts (5), data year from ILO (6), country coverage (7), and country weight (8). The ILO counts reflect the number of college-educated individuals per country based on International Labor Organization data. The professional profile count includes users within the country from two years before to two years after the ILO data year. Columns (4, 5) show values in units of 1,000 individuals. Country coverage is calculated by dividing the professional profile count by the ILO counts, and country weights are the inverse of this ratio. The table includes 134 ILO member countries with over 100,000 college-educated individuals, plus China and Saudi Arabia, where we estimate 240 million and 6 million college-educated individuals, respectively.

Figure A1: Rate of Professional Profile to ILO College Educated Counts



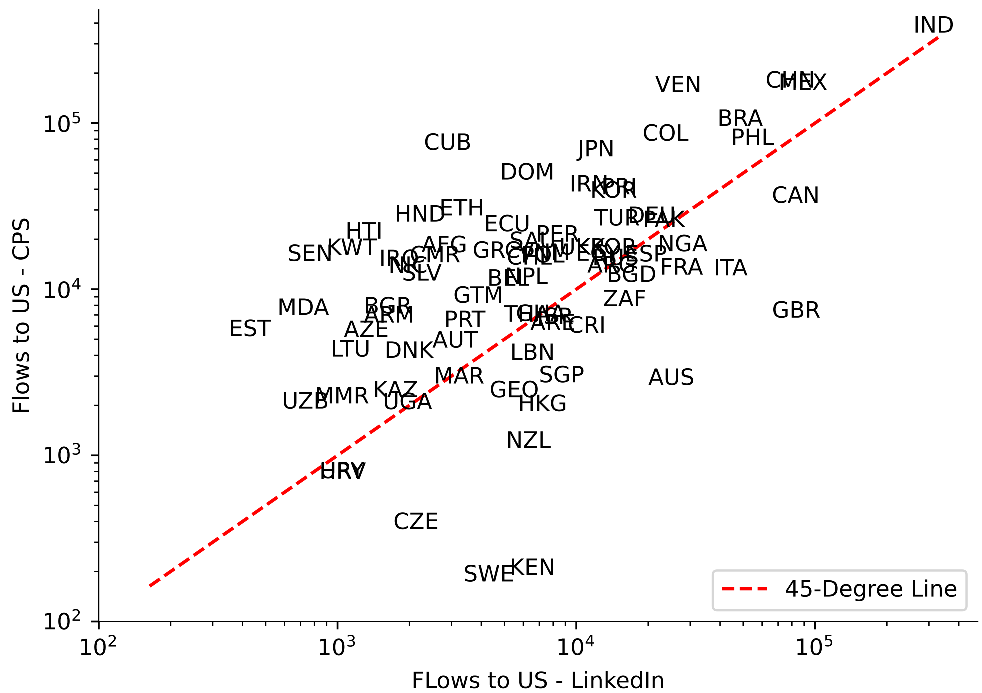
Notes: Refer to the notes on Table A1. This map illustrates the country coverage (Column (7) in Table A1) for the selected 136 countries.

Figure A2: Professional Profiles Coverage Over Time



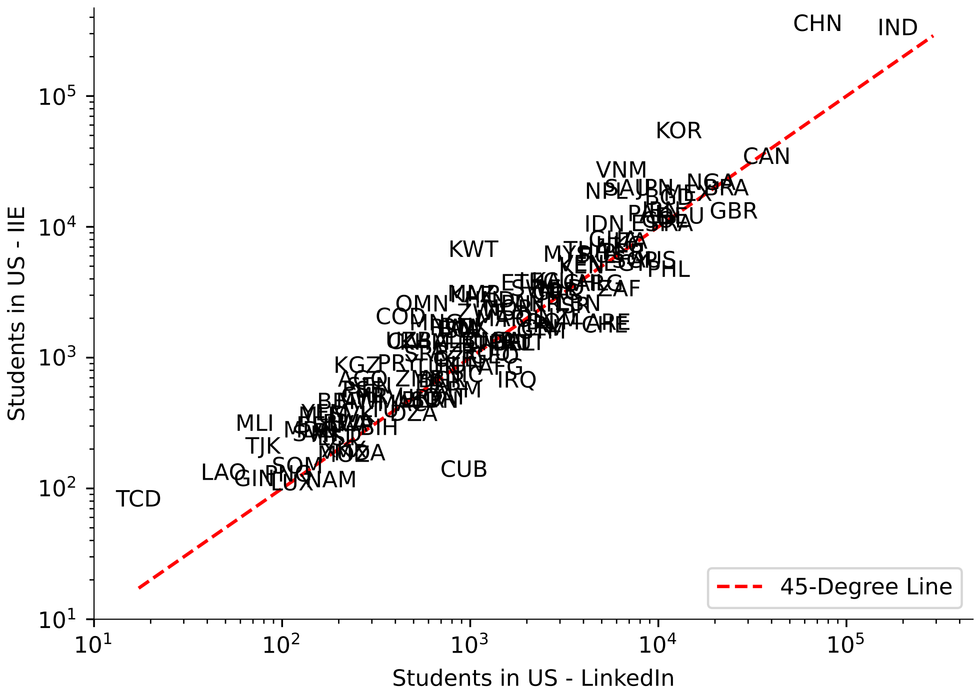
Notes: The figure shows the professional profile coverage over time for the world average and selected countries. To calculate the country coverage trend, we standardize the country coverage in the year 2022 (the final year in our dataset) to 100. Subsequently, we divide the count of professional profiles in our data for each country in each year by the count of users in 2022 to determine the country coverage across the years. This calculation utilizes individual weights as defined in Equation 1. The "World" average represents the aggregated weighted averages of all users, irrespective of their country.

Figure A3: Inflows to the United States: Professional Profiles vs. Current Population Survey (CPS)



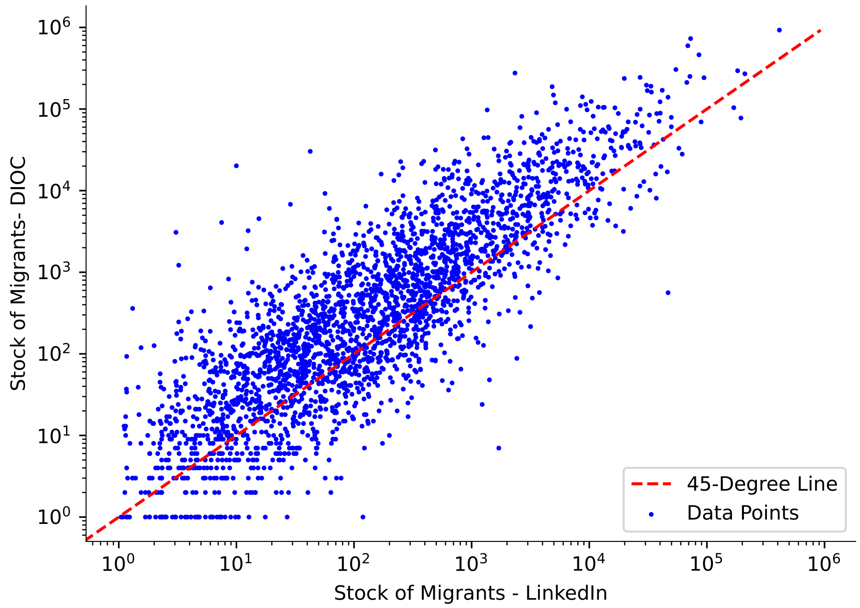
Notes: This figure compares the inflows to the United States in our professional profiles data versus the inflows of people with a college degree in the Current Population Survey (CPS) 2022 data. The CPS 2022 data specifically represents individuals residing in the US in 2022. Similarly, we restrict our professional profile sample to individuals residing in the US in 2022. The sample is further narrowed down to those who entered the US in the last 5 years, covering the period from 2018 to 2022. The countries included in the analysis are limited to a subsample of selected countries outlined in Table A1, which are also present in the CPS data. Additionally, we focus on countries with non-missing values for the inflows of college-educated individuals from 2018 to 2022, resulting in a total of 79 countries for analysis. Individual weights are applied for the professional profile measurement, noting that 77% of them share the same weight, corresponding to the weight of the United States at Table A1.

Figure A4: International Students in the United States: Professional Profiles vs. IIE



Notes: This figure illustrates the count of international students in the United States in 2022, comparing our data with the **Institute of International Education (IIE)** data. The analysis involves 133 countries, a subset of the 136 countries listed in Table A1 that can be merged with the IIE dataset. Individual weights are applied for the professional profiles measurement, noting that 84% of them share the same weight, corresponding to the weight of the United States at Table A1.

Figure A5: Stock of Migrants in OECD Countries: Professional Profiles vs. DIOC



Notes: This figure illustrates the count of college-educated employed migrants in OECD countries in the year 2011, comparing our data with the **Database on Immigrants in OECD and non-OECD Countries (DIOC)** data. Each dot represents a pair of countries of origin (OECD and non-OECD) and destination (OECD). The choice of 2011 as the reference year is due to its status as the last year with available bilateral stock measures of migrants in the DIOC dataset. The analysis encompasses college-educated employed migrants in 36 OECD countries originating from 112 selected OECD and non-OECD countries, which constitutes a subset of the 136 countries listed in Table A1 that can be merged with the DIOC dataset. Individual weights derived from Table A1 are applied to the professional profiles measurement.

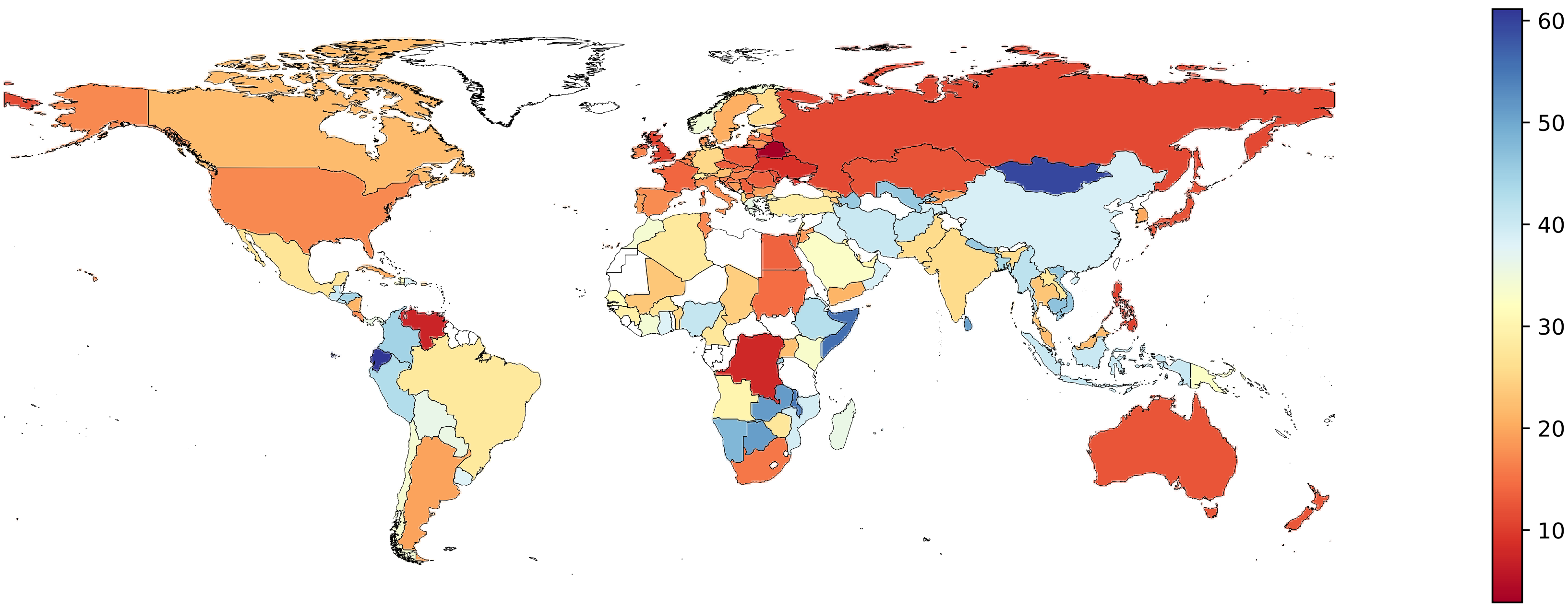
Table A2: Regression of Log Stock of Migrants in DIOC Data on Professional Profiles

	(1)	(2)
Log Migrant Stock in LinkedIn	0.962***	0.956***
	(22.37)	(23.92)
Constant	0.991***	1.019***
	(3.76)	(5.26)
Observations	2776	2776
R-squared	0.724	0.892
Origin FE		Y
Destination FE		Y

Notes: Refer to the notes on Figure A5. In this table, the dependent variable is the logarithm of the stock of college-educated employed migrants in the DIOC data, while the main independent variable is a similar measure derived from our LinkedIn dataset. Standard errors, indicated in parentheses, are two-way clustered at the country of origin and destination levels.

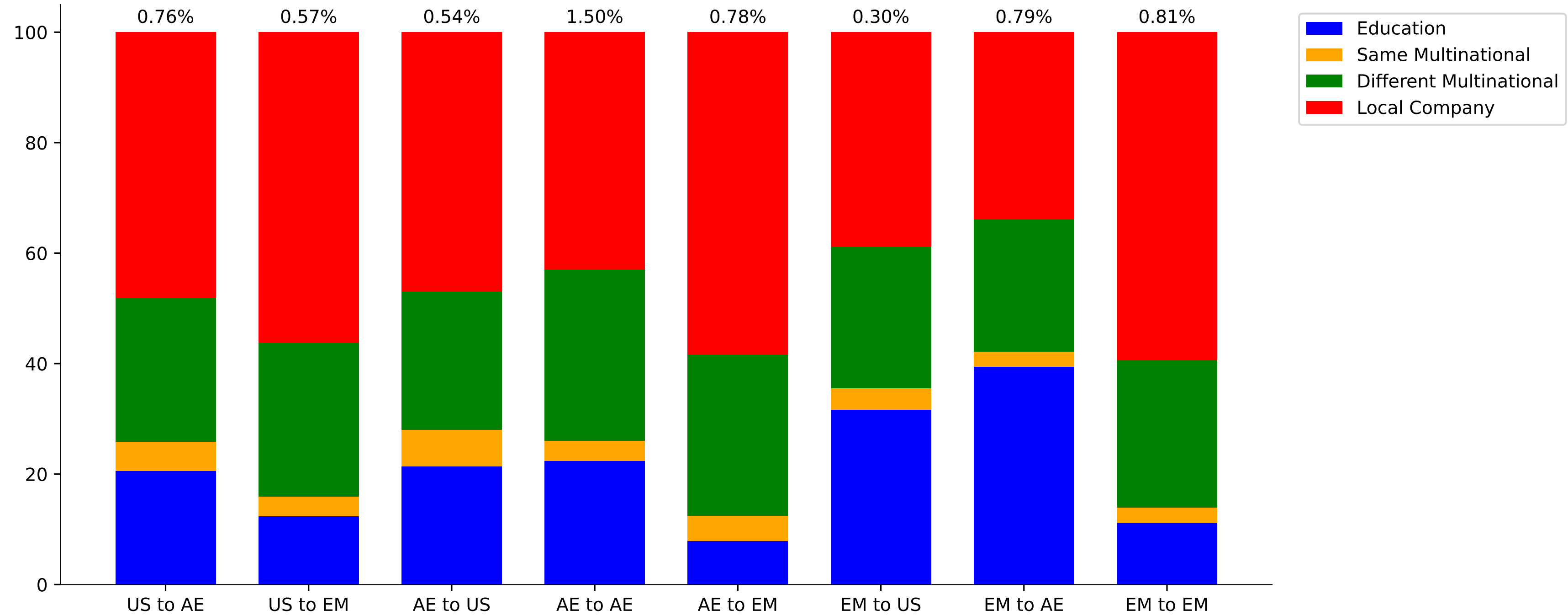
B Appendix Figures

Figure B1: Share of Out-Migration for Education



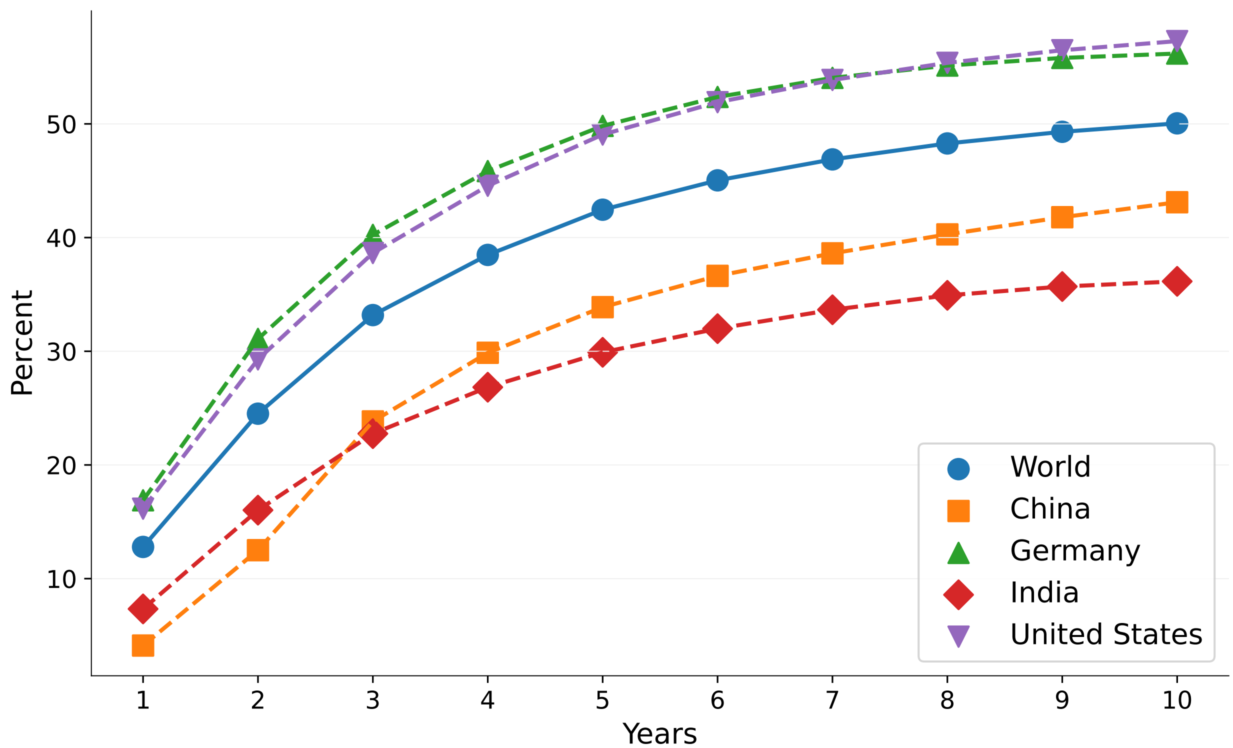
Notes: Refer to the notes in Figures 1 and 2. This figure illustrates the proportion of the total outflows after 5 years that are in education in the destination country.

Figure B2: Outflow to Education and Multinational Companies



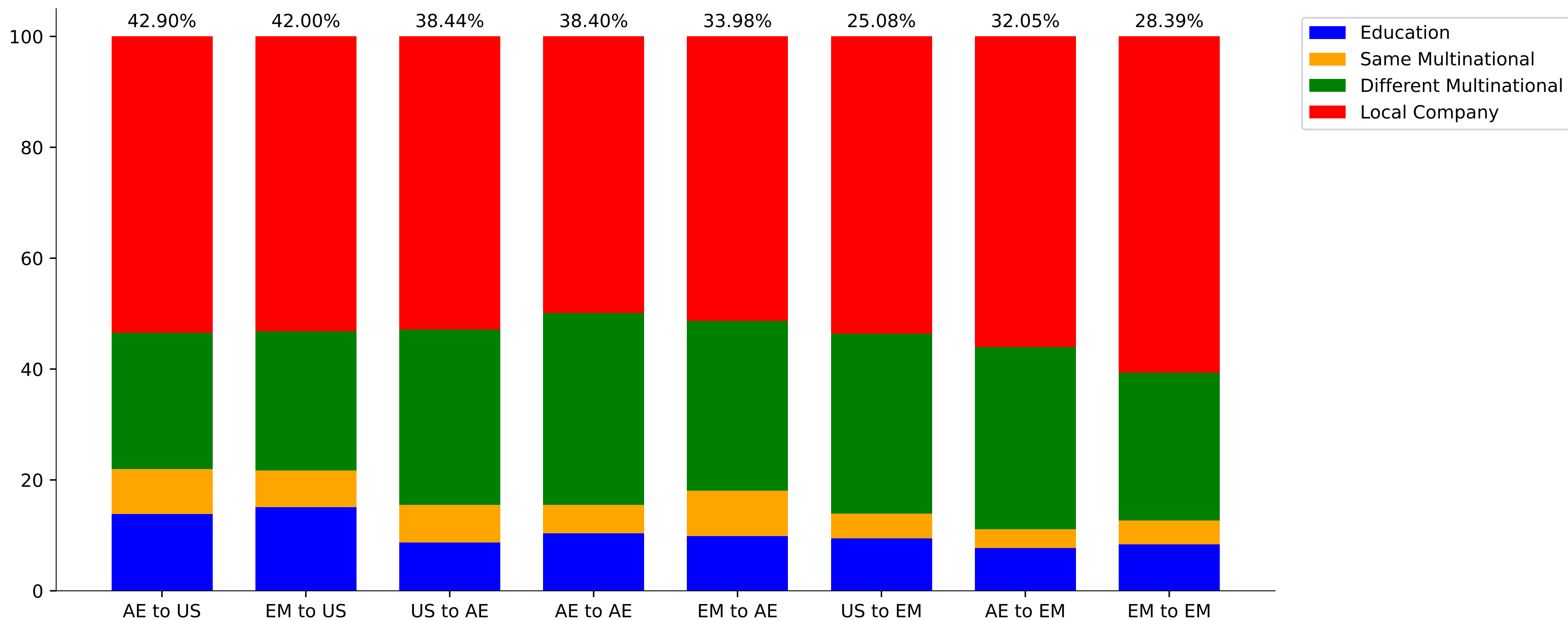
Notes: See notes on Figure 1. This figure shows the distribution of outflows across various origin and destination country categories. The numerical values displayed on the bars represent the outflow rate after 5 years. The color divisions within the bars signify the total outflows categorized into education and job-related migrations. Within the job category, the divisions represent the migrations across three different types: within the same multinational corporation, across different multinational corporations, and within local companies. For our categorization, multinational corporations are defined as companies within our dataset that have a minimum workforce of 250 employees, with at least 10% of their employees located in countries other than their primary operational country. Migrants who work in the same multinational corporation before and after migration are classified under the "same multinational corporation" category. All those who work in a multinational company in the destination country but not the same as the origin country are classified as "different multinational corporations". Migrants employed in non-multinational corporations in the destination country fall under the "local companies" category.

Figure B3: Re-migration of Migrants from the Host Country by Origin Country



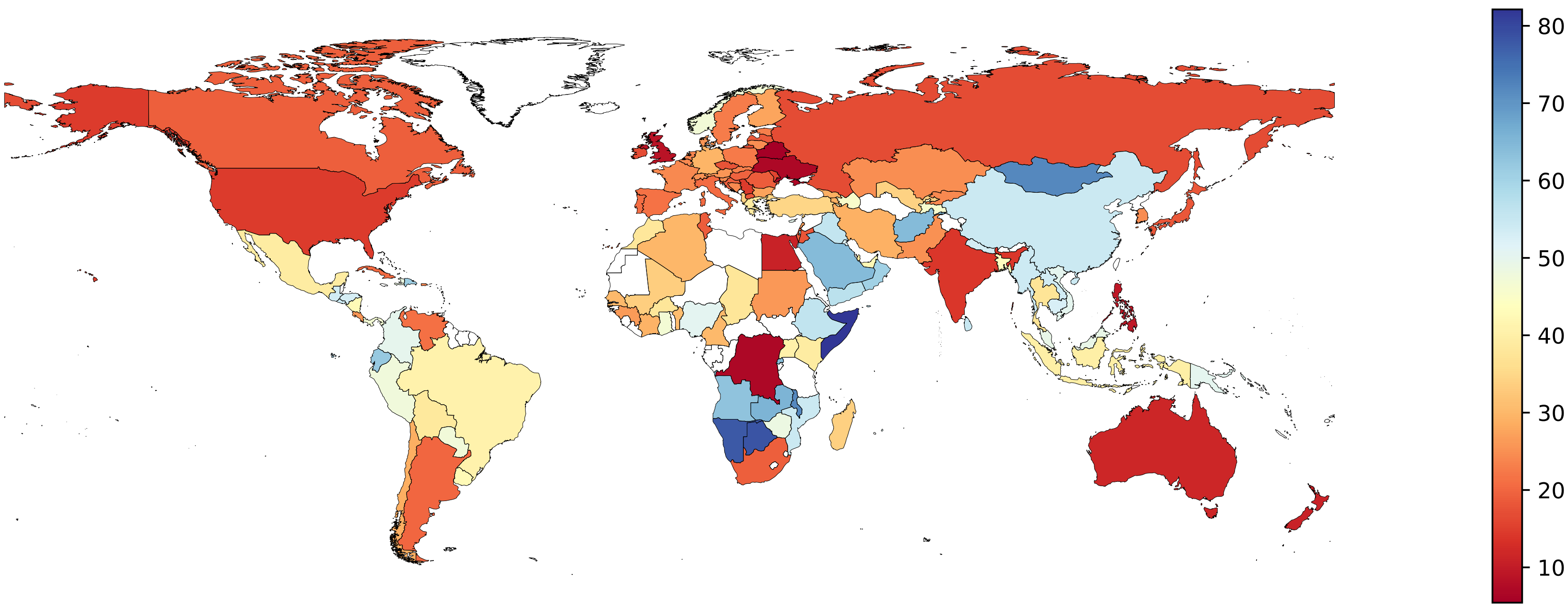
Notes: See notes on Figure 3. This figure is similar to Figure 3, but it now encompasses migrants who depart the destination country to a third country (not solely returning to the origin country). In essence, this figure depicts the percentage of migrants who leave the destination country, either returning to their origin country or moving to a third country.

Figure B4: Return Migration to Education and Multinational Companies



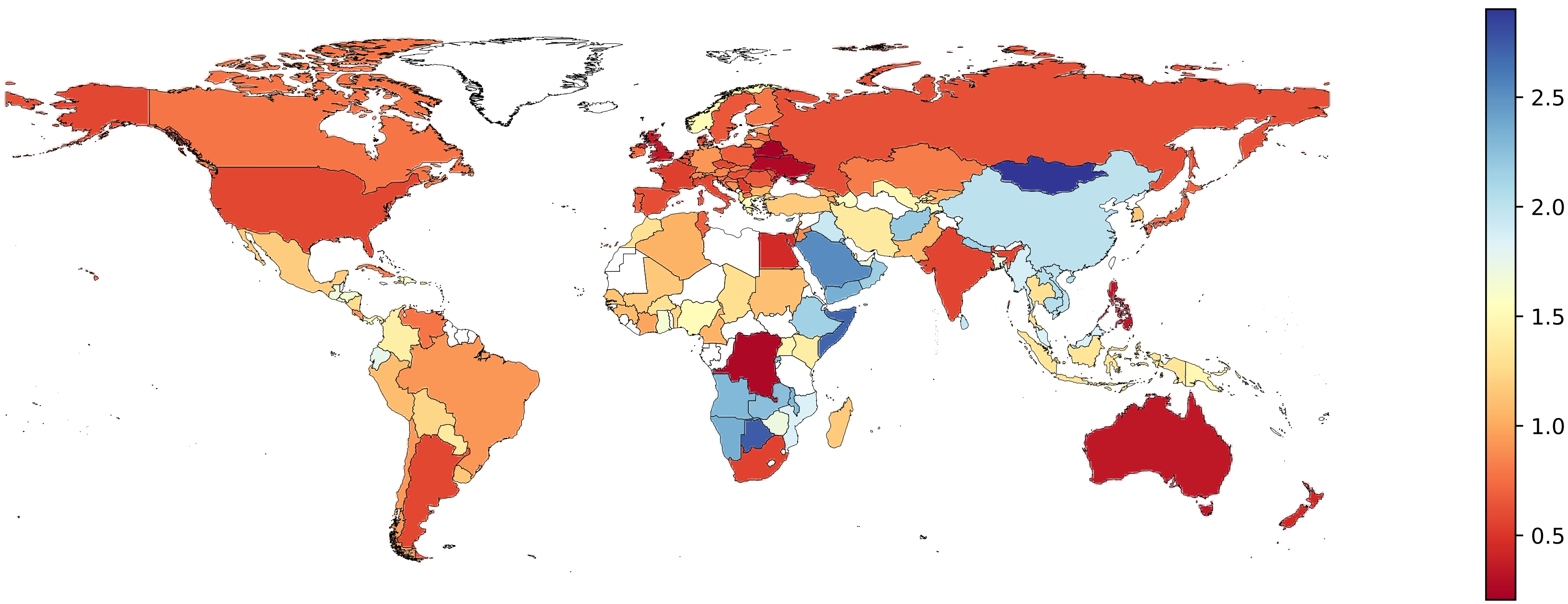
Notes: See the notes on Figure 3. This figure illustrates the distribution of returns across various origin and destination country categories. The numerical values displayed on the bars represent the return rate after 5 years of migration. The color divisions within the bars represent the total returns categorized into education and job-related aspects upon return to the origin country. Within the job category, the divisions signify the return across three distinct types: within the same multinational corporation, across different multinational corporations, and within local companies. In our categorization, multinational corporations are defined as companies in our dataset with a minimum workforce of 250 employees, where at least 10% of employees are situated in countries other than the primary operational country. Returnees who resume work in the same multinational corporation before return (in the destination country) and after return (in the origin country) are classified under the "same multinational corporation" category. Those who work in a multinational company after return but not in the same one as when they were migrants are categorized as "different multinational corporations". Returnees employed in non-multinational corporations in the origin country are classified as "local companies".

Figure B5: Percentage of Returnees Immediately After Graduation



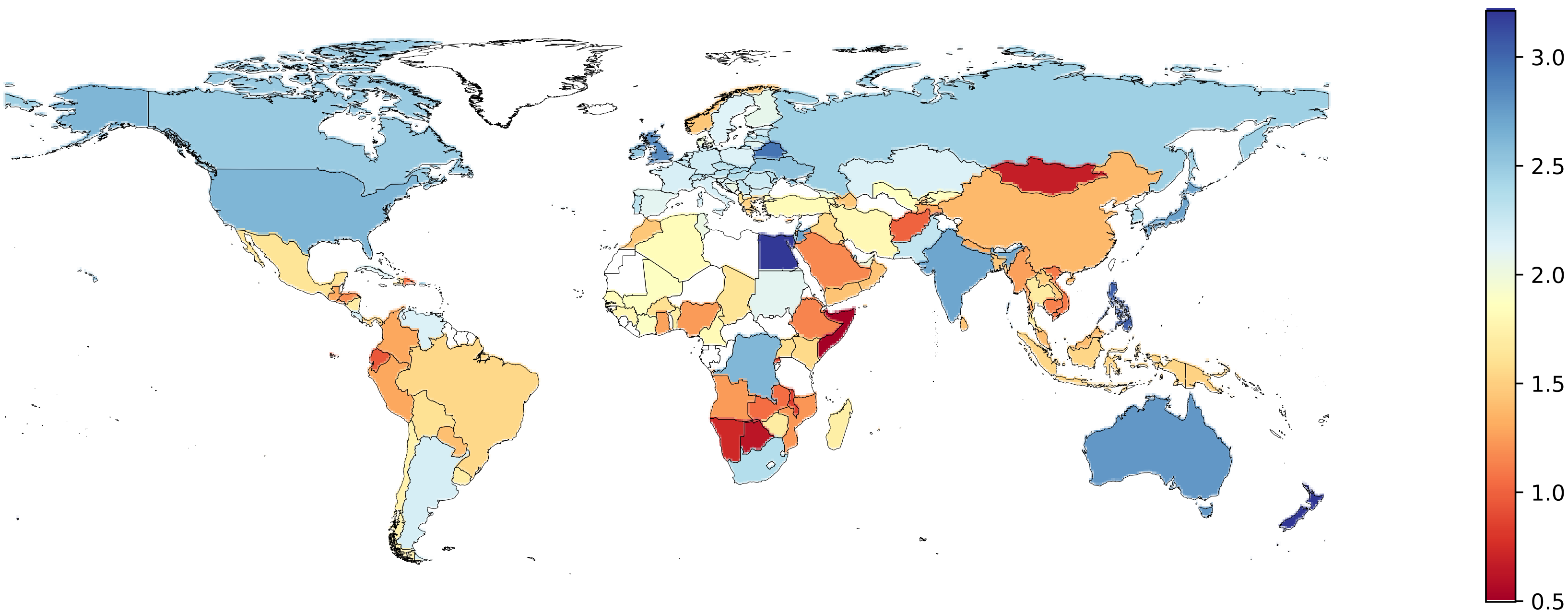
Notes: See notes on Figure 3. This figure presents the percentage of education migrants who promptly return to their origin country immediately after graduating without accumulating any job experience abroad. This percentage is derived from the subset of education migrants, defined as individuals engaged in educational pursuits in the destination country during the first year of migration.

Figure B6: Average Accumulated Education Years Abroad Before Return



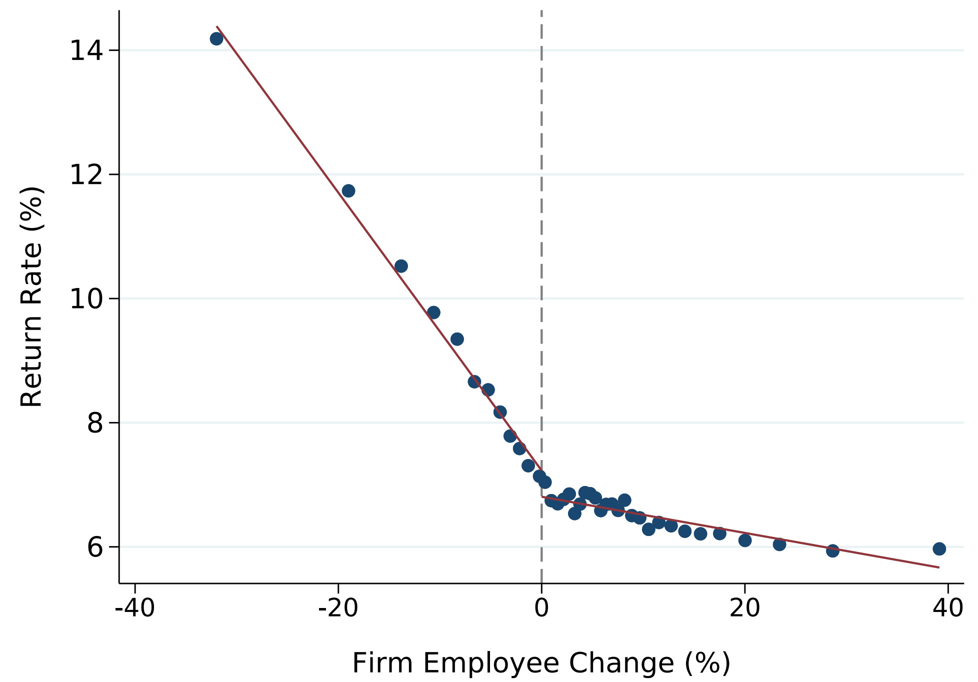
Notes: See notes on Figure 3. This figure illustrates the total number of education years accumulated abroad by returnees before their return to their origin country. The average is calculated across all returnees, not solely those who migrated for education.

Figure B7: Average Accumulated Job Experience Abroad Before Return



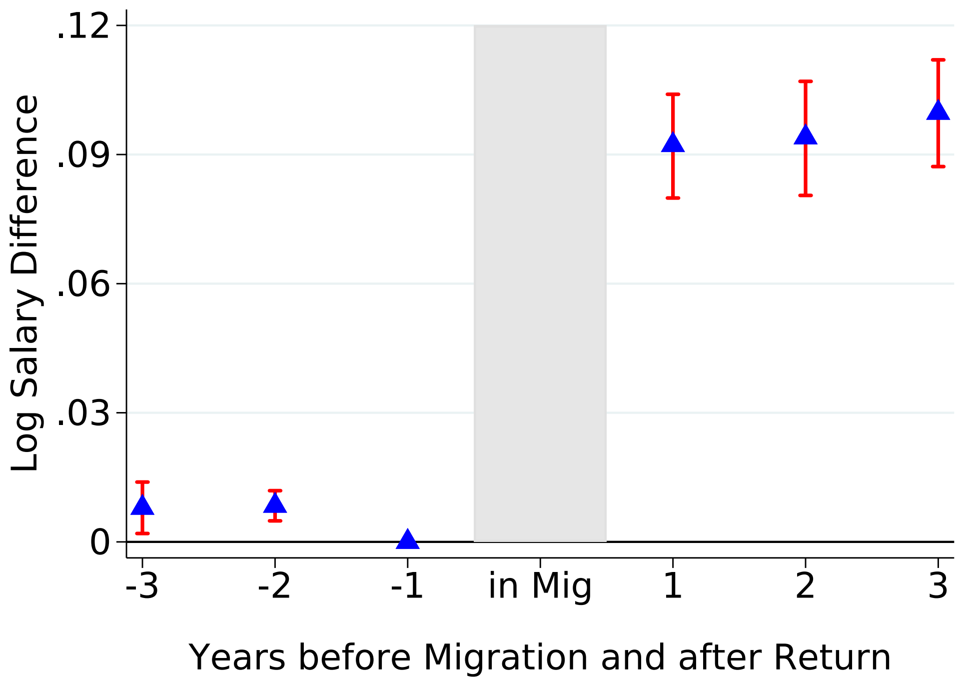
Notes: See notes on Figure 3. This figure depicts the total number of job experience years accumulated abroad by returnees before their return to their origin country. The average is calculated across all returnees and specifically includes those who migrated for education and returned after graduation.

Figure B8: Firm Employee Count Change and Return Migration



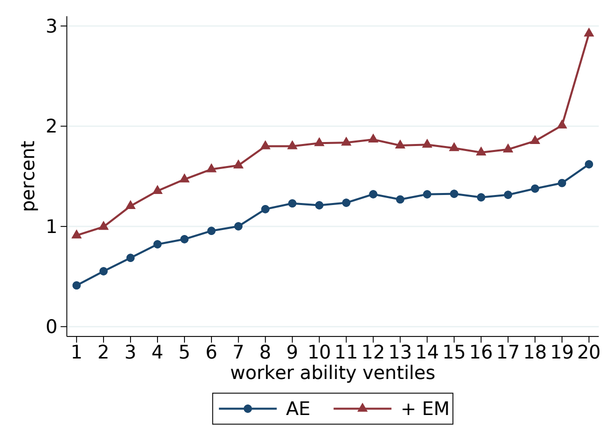
Notes: Figure displays a binscatter between the return migration of a migrant and the changes in the employee count of the firm where the migrant is currently employed. We establish an individual-level panel of migrants employed (excluding those in education) in their destination country and define a return dummy variable as 1 if they return to their origin country the following year, and 0 otherwise. The firm's employee growth is computed as the growth of the firm employees. Our sample is limited to firms with a median number of employees greater than 50 after 2010.

Figure B9: Event Study of Migration from EM to US and Return

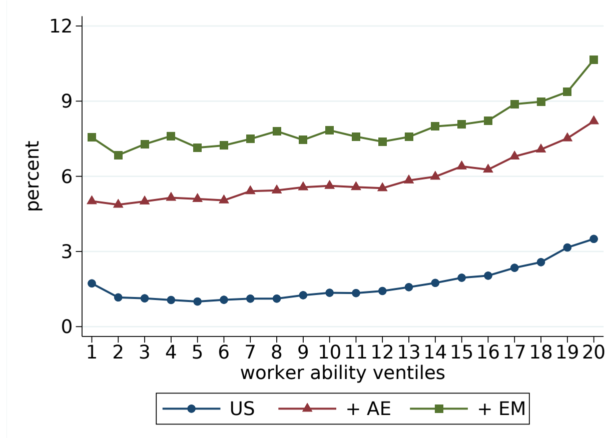


Notes: Refer to the notes on Table 5. In this figure, we apply the matching procedure detailed in section 6.4 and the associated notes from Table 5. However, our focus now extends to comparing the treatment and control groups over a broader temporal window: specifically, from 3 years before migration (years -3 to -1) to 3 years following the return to the origin country (years 1 to 3). Analogous to Table 5, our matching process centers on the year (-1) or the year just before migration. All observations within the treatment and control groups are kept if they have salary data for the full 3 years pre-migration and 3 years post-return, while also having resided in the United States for at least 5 years (mirroring Column (2) in Table 5, panel A). The shaded area denotes the years of migration (US). Standard errors are clustered at the origin country level and 95% confidence intervals are shown in the figure.

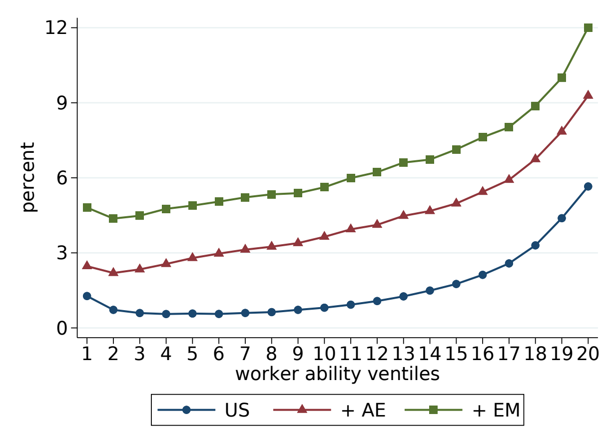
Figure B10: Share of Worker Ability Ventiles Across Different Regions in Year 2022



(a) United States



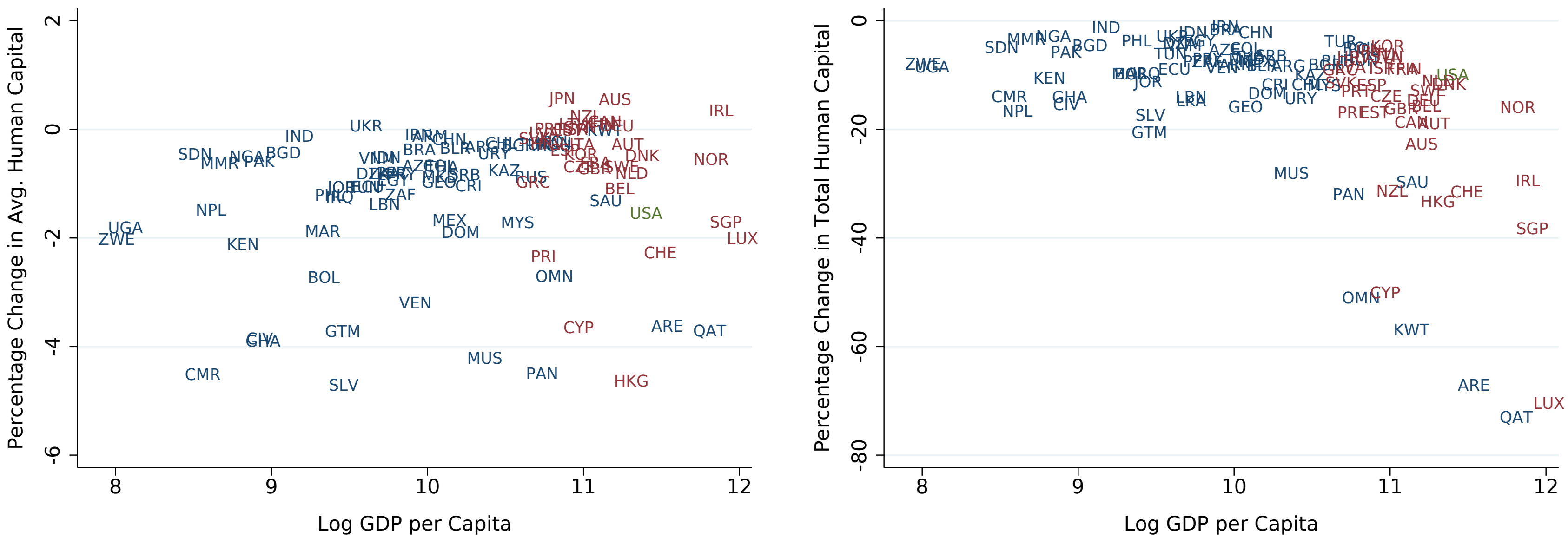
(b) Advanced Economies



(c) Emerging Market

Notes: Refer to the notes in Figure 5. We examine the stock of individuals in 2022 and categorize the populations originally from three major regions into 20 groups based on their individual fixed effects (worker mobility). We then calculate the migration share to the US, advanced economies (AE), and emerging markets (EM) for each group. Panels a, b, and c show the shares for people originally from the US, AE, and EM, respectively, with each line being the cumulative total of the previous lines. The ventiles, from 1 to 20, rank worker abilities from lowest to highest. The analysis only includes workers from firms with at least 10 employees.

Figure B11: Partial Counterfactual: Migrants Leaving and Human Capital Change



(a) Average Changes

(b) Total Changes

Notes: See notes on Figure 9. This figure presents an alternative (partial) counterfactual analysis similar to Figure 9. In this alternative scenario, we consider shutting down all in-migrations, assuming that all migrants in a particular country depart (with no return of the out-migrated individuals to their origin country).

C Appendix Tables

Table C1: Bilateral Flows and Country Characteristics - Minimum Coverage of 25%

	Log Outflows		Log Returns	
	(1)	(2)	(3)	(4)
Log Origin GDP Per Capita	-0.250***		0.415***	0.392***
	(0.0848)		(0.0509)	(0.0530)
Log Destination GDP Per Capita)	0.654***	0.658***	-0.165***	
	(0.111)	(0.113)	(0.0335)	
Log Distance	-0.550***	-0.597***	-0.0103	-0.0383
	(0.0718)	(0.0982)	(0.0343)	(0.0457)
Common Official Language	1.247***	1.307***	0.141***	0.164***
	(0.153)	(0.179)	(0.0429)	(0.0583)
Log Origin ILO Count	0.860***		0.0597***	0.0953***
	(0.0317)		(0.0218)	(0.0282)
Log Destination ILO Count	0.749***	0.763***	0.0807***	
	(0.0247)	(0.0298)	(0.0227)	
Origin Coverage	0.596***		0.0871	0.135
	(0.200)		(0.103)	(0.0976)
Destination Coverage	0.287	0.320	0.479***	
	(0.340)	(0.338)	(0.135)	
Log Outflow			0.950***	0.909***
			(0.0271)	(0.0317)
Observations	7760	7760	6949	6949
R-Squared	0.845	0.863	0.969	0.973
Origin FE		Y		
Destination FE				Y

Notes: See notes on Table 1. This table is identical to Table 1 but includes only the origin and destination countries with a minimum of 25% LinkedIn coverage. All standard errors are clustered by both the origin and destination countries and are presented in parentheses below the coefficients. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Glassdoor Data Sample Selection - Summary Statistics

	Glassdoor				Not in Glassdoor			
	Mean	SD	p10	p90	Mean	SD	p10	p90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: United States								
Education Years	6.82	2.52	5	10	6.60	2.39	5	10
Age	33.76	8.22	24	46	34.06	8.51	24	47
Revelio Salary (PPP USD)	84,211	39,039	42,774	128,299	82,329	38,338	41,221	125,799
Seniority Level (1 to 7)	2.76	1.43	1	5	2.85	1.53	1	5
Individual FE (Revelio)	0.06	0.31	-0.33	0.41	0.04	0.31	-0.36	0.40
Panel B: Advanced Economies								
Education Years	6.94	2.83	4	11	6.81	2.73	4	11
Age	32.67	7.50	24	44	33.14	7.80	24	45
Revelio Salary (PPP USD)	55,332	25,906	31,023	83,393	56,311	51,086	29,957	86,659
Seniority Level (1 to 7)	2.71	1.35	1	5	2.82	1.44	1	5
Individual FE (Revelio)	0.08	0.23	-0.20	0.35	0.08	0.24	-0.21	0.36
Panel C: Emerging Markets								
Education Years	6.48	2.70	4	10	6.57	2.59	4	10
Age	29.72	5.87	24	38	30.98	6.63	24	40
Revelio Salary (PPP USD)	14,686	12,103	7,760	24,304	19,439	20,774	7,757	38,792
Seniority Level (1 to 7)	2.53	1.14	1	4	2.61	1.33	1	5
Individual FE (Revelio)	-0.03	0.21	-0.26	0.21	-0.03	0.25	-0.34	0.25

Notes: The table presents summary statistics (mean, standard deviation, 10th and 90th percentiles) for Revelio data, comparing merged and unmerged datasets with Glassdoor salary information across four columns each. It examines a 50% random subsample of individuals with at least a bachelor's degree. The results are segmented into three panels for different regions: the US, Advanced Economies, and Emerging Market Economies. Age is calculated as the number of years since starting a bachelor's degree plus 18. Seniority levels, assigned by Revelio, range from 1 (most junior) to 7 (most senior). Revelio's individual fixed effects are based on estimates from Equation 8, with salaries from column 6 of Table 4 shown.

Table C3: Glassdoor Data Sample Selection - Regression

	Education (1)	Age (2)	Log Salary (3)	Seniority (4)	Individual FE (5)
Panel A: United States					
Glassdoor	0.234***	-0.159	0.0153	-0.0893***	0.0115*
	(0.0766)	(0.131)	(0.0130)	(0.0206)	(0.00602)
Constant	6.570***	33.94***	11.23***	2.844***	0.0504***
	(0.0936)	(0.244)	(0.0267)	(0.0506)	(0.0135)
Observations	8652931	8652931	8652931	8652931	8652931
R-Squared	0.00585	0.0760	0.0867	0.0146	0.00248
Panel B: Advanced Economies					
Glassdoor	0.198*	-0.364***	-0.0109*	-0.126***	-0.00358
	(0.116)	(0.108)	(0.00642)	(0.0325)	(0.00454)
Constant	6.770***	33.01***	10.85***	2.822***	0.0787***
	(0.0430)	(0.254)	(0.0104)	(0.0420)	(0.00307)
Observations	6308176	6308176	6308176	6308176	6308176
R-Squared	0.0509	0.0789	0.331	0.0195	0.0222
Panel C: Emerging Markets					
Glassdoor	-0.0441	-0.698***	-0.0255***	-0.108***	-0.0135***
	(0.0609)	(0.0499)	(0.00852)	(0.00865)	(0.00465)
Constant	6.566***	30.83***	9.578***	2.620***	-0.0231***
	(0.0265)	(0.141)	(0.00769)	(0.0213)	(0.00225)
Observations	8104044	8104044	8104044	8104044	8104044
R-Squared	0.0276	0.122	0.698	0.0272	0.0825
Country by Year Fixed Effects	Y	Y	Y	Y	Y

Notes: See notes on Table C2. The table displays the outcomes of five regression estimates per panel, with dependent variables including Education Years, Age, Log Revelio Salary, Seniority Level (ranging from 1 to 7), and Individual Fixed Effects (estimated in column 6 in Table 4). The main independent variable is a dummy variable named Glassdoor, assigned a value of 1 if the data merges with Glassdoor salary data and an alternative salary is found, and 0 otherwise. Country by Year fixed effects are included in all regressions. Standard errors are two-way clustered by country and 3-digit NAICS industry for panels B and C, and by industry alone for panel A, with values shown in parentheses below the coefficients. Significance levels are indicated by *** ($p<0.01$), ** ($p<0.05$), and * ($p<0.1$).

Table C4: Industry and Firm Growth and Leaving Destination Country

	All	Mig < 5	Mig ≥ 5	All	Mig < 5	Mig ≥ 5
	(1)	(2)	(3)	(4)	(5)	(6)
Origin Industry Growth	1.427**	2.765**	0.465	1.807***	3.415***	0.614
	(0.572)	(1.161)	(0.291)	(0.534)	(0.998)	(0.373)
Destination Industry Growth	-7.109***	-9.905***	-2.554***	-6.140***	-8.546***	-1.635
	(1.686)	(2.068)	(0.843)	(2.128)	(2.616)	(1.041)
Firm Employee Growth × Negative				-16.49***	-24.78***	-8.225***
				(1.792)	(2.173)	(1.001)
Firm Employee Growth × Positive				-5.436***	-7.858***	-2.038***
				(0.518)	(0.651)	(0.213)
Constant	8.590***	13.77***	3.790***	7.486***	12.31***	3.293***
	(0.0326)	(0.0370)	(0.0149)	(0.0789)	(0.0913)	(0.0547)
Observations	23001013	10948138	12052711	19294233	8794689	10499404
R-Squared	0.0606	0.0404	0.0187	0.0605	0.0452	0.0193
Origin by Year FE	Y	Y	Y	Y	Y	Y
Destination by Year FE	Y	Y	Y	Y	Y	Y
Industry by Year FE	Y	Y	Y	Y	Y	Y
Years from First Migration FE	Y	Y	Y	Y	Y	Y
Years from Last Migration FE	Y	Y	Y	Y	Y	Y

Notes: See notes on Table 2. This table presents similar estimations to Table 2, but the dependent variable is 100 if the migrant leaves the destination country (either returning to their origin country or moving to a third country) and 0 otherwise.

Table C5: Returns to Job Experience - All Individuals

	Glassdoor Salary				
Revelio Salary					
	(1)	(2)	(3)	(4)	(5)
Incremental Effect:					
Exp in US × Now in AE	0.00948***	0.00169***	0.00229***	0.00811***	0.0114***
	(0.00130)	(0.000639)	(0.000686)	(0.00111)	(0.00128)
Exp in US × Now in EM	0.0263***	0.00518***	0.00643***	0.0191***	0.0206***
	(0.00240)	(0.00167)	(0.00184)	(0.00148)	(0.00157)
Exp in AE × Now in US	0.0126***	-0.00174**	-0.00217***	-0.00417***	-0.00656***
	(0.00112)	(0.000681)	(0.000724)	(0.00111)	(0.00142)
Exp in AE × Now in EM	0.0248***	0.00594***	0.00657***	0.00428***	0.00432***
	(0.00190)	(0.00120)	(0.00132)	(0.000489)	(0.000724)
Exp in EM × Now in US	0.0106***	-0.00334***	-0.00403***	-0.00545***	-0.00390***
	(0.00191)	(0.000890)	(0.000956)	(0.000828)	(0.000913)
Exp in EM × Now in AE	0.00278***	-0.00512***	-0.00520***	-0.00242***	-0.00378***
	(0.000828)	(0.000570)	(0.000658)	(0.000439)	(0.000731)
Own-Market Effect:					
Total Exp × Now in US	0.0245***	0.0262***	0.0250***	0.0324***	0.0373***
	(0.00237)	(0.00119)	(0.00120)	(0.00121)	(0.00131)
Total Exp × Now in AE	0.0267***	0.0274***	0.0255***	0.0210***	0.0252***
	(0.00185)	(0.00103)	(0.00101)	(0.000894)	(0.00118)
Total Exp × Now in EM	0.0441***	0.0436***	0.0406***	0.0192***	0.0234***
	(0.00267)	(0.00201)	(0.00220)	(0.00102)	(0.00136)
Total Exp^2 × Now in US	-0.000500***	-0.000498***	-0.000483***	-0.000845***	-0.000894***
	(0.0000492)	(0.0000206)	(0.0000204)	(0.0000252)	(0.0000267)
Total Exp^2 × Now in AE	-0.000552***	-0.000471***	-0.000443***	-0.000628***	-0.000694***
	(0.0000390)	(0.0000166)	(0.0000156)	(0.0000182)	(0.0000207)
Total Exp^2 × Now in EM	-0.000988***	-0.000950***	-0.000906***	-0.000613***	-0.000691***
	(0.0000639)	(0.0000492)	(0.0000522)	(0.0000214)	(0.0000262)
Constant	-0.0455*	-0.0707***	-0.0295***	10.37***	10.45***
	(0.0242)	(0.00979)	(0.0101)	(0.00784)	(0.00973)
Observations	50417243	32393373	20901964	67585829	20038804
R-Squared	0.903	0.958	0.958	0.872	0.888
Country by Year FE	Y	Y	Y	Y	Y
Individual FE		Y	Y	Y	Y

Notes: See notes on Table 4. This table is identical to Table 4, but it includes all individuals in the analysis and is not restricted to those who have reported a bachelor's degree.

Table C6: Returns to education

	Glassdoor	Revelio
	(1)	(2)
Education in ranks 1-50 × Now in US	0.0313***	0.0489***
	(0.00790)	(0.00374)
Education in ranks 1-50 × Now in AE	0.0131***	0.0232***
	(0.00471)	(0.00167)
Education in ranks 1-50 × Now in EM	0.0324***	0.0462***
	(0.00892)	(0.00215)
Education in ranks 51-200 × Now in US	0.0202***	0.0336***
	(0.00590)	(0.00304)
Education in ranks 51-200 × Now in AE	0.00786**	0.0169***
	(0.00374)	(0.00127)
Education in ranks 51-200 × Now in EM	0.0270***	0.0336***
	(0.00671)	(0.00191)
Education in ranks 201-1000 × Now in US	0.0138***	0.0235***
	(0.00467)	(0.00255)
Education in ranks 201-1000 × Now in AE	0.00165	0.0107***
	(0.00266)	(0.00103)
Education in ranks 201-1000 × Now in EM	0.0208***	0.0193***
	(0.00338)	(0.00137)
Education in others × Now in US	0.0113**	0.0164***
	(0.00554)	(0.00306)
Education in others × Now in AE	0.00343**	0.00604***
	(0.00164)	(0.000636)
Education in others × Now in EM	0.0133***	0.0102***
	(0.00220)	(0.000949)
Constant	-0.0940***	-0.103***
	(0.0304)	(0.00917)
Observations	1238647	6461266
R-Squared	0.0487	0.0887

Notes: Refer to notes on Figure 6. This table shows the coefficients in Figure 6 but in a table format.

Table C7: Differences in Salaries: Matched Treatment and Controls Pre-Migration to US and Post-Return to EM - Matching only on job characteristics

	Entire Sample		Mass Layoff	
	Total	Mig. Years ≥ 5	Total	Mig. Years ≥ 5
	(1)	(2)	(3)	(4)
Panel A: Glassdoor Salary				
Treatment $\times$ Post	0.0901***	0.114***		
	(0.0128)	(0.0127)		
Observations	39531	10103		
R-Squared	0.928	0.854		
Panel B: Revelio Salary				
Treatment $\times$ Post	0.0968***	0.145***	0.0791***	0.125***
	(0.00559)	(0.00546)	(0.00835)	(0.0312)
Observations	394329	81124	10639	1698
R-Squared	0.743	0.740	0.702	0.714

Notes: See note on Table 5. The only difference here is that we do not match the education records. The characteristics used for matching include the country of origin, years of job experience, the firm, and role (150 categories) of employment at the time of migration.