Return Migration and Human Capital Flows[*]

Naser Amanzadeh[†] Amir Kermani[‡] Timothy McQuade[§]

March 21, 2024

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 59-212% 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
JEL Codes: F22, J61, O15

[*]We thank seminar participants at UC Berkeley Macro-Lunch, CKGSB, and West Coast Trade Workshop 2024. We are particularly grateful to Mathilde Muñoz, Emi Nakamura, Andrés Rodríguez-Clare and Benjamin Schoefer. This work was supported by the Fisher Center for Real Estate and Urban Economics and the Clausen Center at UC Berkeley. All remaining errors are ours.
[†]UC Berkeley, Haas School of Business, amanzadeh@berkeley.edu
[‡]UC Berkeley, Haas School of Business, kermani@berkeley.edu
[§]UC Berkeley, Haas School of Business, tmcquade@berkeley.edu

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 supplement this data with raw global salary postings data from Glassdoor.

We first show that skilled labor is highly mobile across the 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, while emerging market economies tend to have lower return rates, 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. Destination, country income per capita and a common language are important drivers of migrant flows, whereas origin country income per capita is not associated with a higher out-migration rate. 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 the origin country's income per capita is a much more important driver of return flows than the destination country's income per capita. This difference in the impact of origin country income per capita on out-migration and return migration explains the disparity in the literature on the extent of brain drain based on flows vs. stock of migrants. 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.

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 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 remarkably 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% and 12% higher worker ability, respectively, in comparison to non-migrants of Emerging Markets.

[1]Migrants from Emerging Markets to the US and other Advanced Economies exhibit, on average, 11% and 10% higher worker ability compared to non-migrants, respectively but, migrants to other emerging market economies are not significantly different than stayer.

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). Again, most studies in this literature, except 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.[1]

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

[1] 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 et al. (2014), Kleven et al. (2020) and Muñoz (2020)

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 relies mainly on data from Revelio Labs which obtains data from the public LinkedIn profiles and some other sources. LinkedIn is a popular internet-based platform that facilitates professional networking. Since its launch in 2003, it has amassed a user base of over 700 million worldwide. Users create profiles on the platform detailing their education and employment history, including information on the universities they attended, the fields and degrees they studied, and the companies they worked for, along with their job titles and dates (year and month). Through Revelio Labs, we can access all publicly available individual-level information for over 450 million public accounts on LinkedIn by early 2023[1].

The coverage of professional profiles varies significantly based on occupation, location, and time. Notably, individuals with a college education are more likely to have a professional profile compared to those without higher education. Similarly, white-collar positions exhibit a higher likelihood of representation on LinkedIn in contrast to blue-collar roles. Essentially, we assume that LinkedIn is a representative platform for college-educated individuals and white-collar jobs.

[1]From here, we simply use *professional profiles* to refer to this data.

To evaluate disparities in coverage across countries, we define "country coverage" as the ratio of professional profiles in a specific country to the count of college-educated individuals in that country, based on ILO data. Table A1 and Figure A1 in the Appendix A provide an overview of this coverage rate across countries. Typically, developed nations, such as the US, exhibit a coverage rate of more than 80%. However, exceptions exist in countries like Japan and South Korea, where the convergence is below 5%. This divergence may be influenced by factors such as alternative platforms and language barriers. Developing countries generally display lower coverage rates, although some, like Argentina, Chile, and South Africa, approach global coverage rates. India, significant in terms of labor force dynamics, maintains a coverage rate of around 40%, which, although lower, still represents a substantial proportion of the country's skilled labor force.

Country coverage is increasing over time as well. Figure A2 depicts the country coverage index over time for the world average and selected countries. The coverage is normalized for each line to be 100% in the year 2022. The country coverage in the years 2000, 2010, and 2015 averages approximately 26, 62, and 87% of that in the year 2022, respectively. When investigating cross-sections at a specific point in time, such as analyzing the percentage of country out-migrations, it's common practice to limit our sample to the most recent years where the coverage remains stable. This approach helps mitigate potential biases that could arise due to fluctuations or expansions in coverage over earlier periods. To generate this figure, we construct panel data based on the start and end dates of education and job experience reported in professional profiles, displaying the occupation (education or job) and location of each individual for each year. Then, we count the total number of users with education or job entries for a particular year. It is important to note that this methodology differs from the time individuals join LinkedIn. People may join LinkedIn at different times, but upon joining, they can report their entire education and job histories.

To derive some of the findings presented in this paper, particularly international flow rates, we utilize a weighting system based on country coverages. We acknowledge that individuals who relocate may have a greater likelihood of having a professional profile compared to those who remain in a country, particularly if they move from a nation with low coverage to one with higher coverage. We assume that if an individual relocates to a country with higher coverage, they are more inclined to create and update their profile, even for the years spent in their origin country. Consequently, we define the weight for individual i as follows:

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

where $j(i)$ denotes the countries where the individual i has experience[1]. For instance, consider two individuals i and i' from a country with a coverage rate of 20%. Suppose individual i has experience in another country with a 100% coverage rate, while individual i' only resides in the first country. In this scenario, individuals i and i' will have weights equal to 1 and 5, respectively.

We also perform some data cleaning on location (country) data. While reporting a position (job experience), users can provide a location for the position. However, this field is not mandatory, resulting in missing raw country data reported by users for approximately 50% of the positions. To address this gap, we endeavor to utilize the comprehensive data available within professional profiles to identify missing locations whenever possible. Our approach involves analyzing the names of companies and the countries that users have associated with those companies. We calculate the distribution of countries linked to each company. Subsequently, if a specific country constitutes more than 90% of the associations for a given company, we assume that all individuals working for that company reside in that country. This methodology aids in identifying the country for approximately 50% of the missing country data in position records. In terms of education records, users typically do not report the country. However, leveraging information from firm locations, we determine

[1] See Table A1 in the Appendix A for the country coverages.

the country of educational institutions, too. This determination is possible because each university typically has personnel associated with it, providing the location for those positions. Using this method, we were able to determine the location of approximately 65% of education records.

In addition to our primary 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 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 within the context of the US. Subsequently, adjustments are made for other countries. There are two main adjustments made for other countries: 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 posted 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.

We perform a variety of data validity checks. Alongside comparing the number of professional profiles across countries with the ILO college-educated labor force (as discussed earlier in this section), we have rigorously conducted numerous validity assessments on our professional profiles dataset, encompassing a diverse range of evaluations. We perform these validity checks in two parts: First, comparisons with data from the United States, and second, comparisons with international measures.

For the comparisons in the US, we cross-reference inflow figures of college-educated people to the United States with data from the Current Population Survey (CPS) from 2018 to 2022 (Figure A3 in the Appendix A)[1]. Measures are generally around the 45-degree line confirming data reliability. Another example includes examining the stock of international students in the US by comparing it with data from the Institute of International Education (IIE) (Figure A4 in the Appendix A). The comparison reveals a close alignment, with the measures closely following the 45-degree line.

As a comparison with international measures, we compare our data with various international measures, too. For instance, using the Database on Immigrants in OECD and non-OECD Countries (DIOC), we attempt to validate the stock of migrants with a college degree in our data (Figure A5 and Table A2 in the Appendix A). In summary, the outcomes of our validity checks provide compelling evidence that our dataset effectively mirrors the fundamental data patterns observed in independent data sources.

4 Migration and Return Migration Patterns

In this section, we document measures of skilled worker international mobility, which includes international migration patterns and more importantly, return migrations by countries of origin and destination.

Figure 1 illustrates the cumulative hazard ratio of out-migration for the global average

[1]For detailed insights into figure preparation, refer to the notes on Figure A3

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've 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.

Moreover, there is a non-linear and concave pattern of out-migration over time, as depicted in the figure and consistent with Howard and Shao (2023), which can be explained in two primary ways. First, the declining likelihood of migration in year t, given no migration until year t-1, suggests that as time progresses, a larger fraction of mobile individuals have already migrated, leaving a higher proportion of non-mobile individuals behind. Second, some individuals who migrated from year 1 to year t-1 may return to their country of origin, leading to their observation in year t, thus contributing to the non-linear pattern observed.

Additionally, Figure 1 and with more details, Figure 2, underscore the heterogeneous nature of out-migration rates across different countries. Skilled labor from the United States and Germany displays slightly less and more mobility, respectively, compared to the global average. However, the out-migration rate for skilled labor from India is approximately twice the world average. Conversely, Chinese skilled labor demonstrates a significantly lower out-migration rate (one-fourth of the average), highlighting a substantial difference compared to the global trend. 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[1].

Figure B1 illustrates the share of out-migrations attributed to education by the origin country, with the remaining portion, by definition, corresponding to job purposes. On average approximately 23% of migrants leave their origin countries seeking educational opportunities. However, this percentage exhibits significant variation, ranging from around 10% for countries like Australia, Russia, and Japan to roughly 50% for nations such as China,

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

Colombia, and Iran.

Providing further insight, Figure B2 delves deeper into this data, offering the breakdown across different categories of origin and destination countries. It reveals that the share of out-migration for education differs for the different categories of the origin and destination countries. Generally, the tendency for out-migration due to education is higher when the origin country is an Emerging Market Economy or when the destination is an Advanced Economy (including the US). Around 30% of total out-migrations are attributed to individuals seeking job opportunities in multinational corporations[1], while the remaining 50% migrate to local companies. Within the subset of migrants entering multinational corporations, it is observed that 11.5% of them transition to the same multinational corporation in the host country as they were employed in their origin country. This trend of remaining within the same multinational corporation in a different country is notably more prevalent among migrants moving among Advanced Economies (including US).

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. Additionally, we define the origin country of each individual as the initial country where that individual first appears in our data, either for educational pursuits or job experiences. Figure 3 illustrates the return migration trends of migrants over time, considering both the global average and select countries. Within this figure, year 0 represents the initial year of migration (entry into the host country), and the migrants are tracked for 10 years to ascertain the percentage returning to their origin country after t years. On average, approximately 10% of migrants return to their origin country within the first year, indicating short-term visits. Over 5 (10) years, a notable share, around 33% (38%), of migrants return to their origin countries, signifying a substantial proportion of return migration. Additionally, within the same 10-year period, approximately 12% of migrants opt to migrate from the first host country to a third country,

[1] We define multinational corporations as companies represented in our data with a minimum of 250 employees, where at least 10% of the total workforce is distributed across countries other than the primary country of operation.

while around 50% of them choose to remain in the initial host country[1]. In essence, within a decade of migration, approximately 50% of migrants depart from the destination country, and conditional on leaving, approximately 75% of them eventually return to their origin country.

Figure 3 also exhibits a concave pattern, which could stem from two main factors. First, individuals who returned from year 1 to t-1 might re-migrate from their origin country. Additionally, as time progresses, there might be a selective process among migrants in terms of not returning. This could be due to the likelihood that a portion of individuals who initially intended to return have already done so, while those who remain are less inclined or not interested in returning to their origin country despite the elapsed time.

Figure 3 and, in more detail, Figure 4, reveal substantial heterogeneity among countries in terms of return migration. Typically, Advanced Economies like the US and various EU countries exhibit higher return rates, but interestingly, there are some Emerging Market Economies with notably elevated return rates, such as Chile, Argentina, and Indonesia. While Indians demonstrate a high outflow rate, their return rate is relatively low. Conversely, the return rate of Chinese migrants in the long run appears to be comparable to the world average, despite a very low outflow rate. [2].

Figure B4 displays the distribution of returnees among education, multinational corporations, and local companies categorized by their origin and destination countries. Notably, around 10% of returnees opt to return to their origin country for educational pursuits, while the overwhelming majority, around 90%, return for employment opportunities. Approximately 35% of all returnees rejoin the workforce through multinational corporations. Notably, there is a higher proportion of returnees opting for education when returning to the US (roughly 15%), while the percentage of returnees joining multinational corporations

[1]Refer to Figure B3 in the Appendix B for a similar plot, illustrating the percentage of migrants departing from the host country. This includes individuals returning to their origin country and those choosing to migrate to a third country.

[2]In Section 5, we shed light on the determinants influencing return migration.

is relatively lower for those coming back to the US (around 31%).

Among individuals who migrated for educational purposes (being in education during the initial year of their migration) and subsequently returned to their origin countries, on average, 25% promptly returned upon completing their education (as depicted in Figure B5, which provides a country-wise breakdown of this trend). Additionally, Figures B6 and B7 showcase the average years of education and job experience accumulated abroad before their return. On average, returnees acquire 0.9 years of education and 2.2 years of job experience before returning to their origin countries.

It's important to note that these numbers represent the average education and job experience for all returnees, regardless of whether they have any education or not. Approximately 68% of all returnees do not have any education accumulated abroad, while about 27% return without any job experience. Only 5% of the returnees possess both education and job experience acquired abroad. If we narrow our focus to returnees with at least some education accumulated abroad, the average years of education would be 2.8 years. Similarly, for returnees with some job experience, the average years of job experience accumulated abroad would be 3 years.

5 Determinants of Outflows and Return Migrations

We start our analysis by studying the correlates of bilateral outflows and return migration between countries. In particular, we follow the international trade literature and estimate the following gravity regression:

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

Where M_{od} is the number of migrants from country of origin o in destination country d. y_o and y_d are the PPP-adjusted per capita income of origin and destination countries in the year 2022. $dist_{od}$ is the logarithm of the distance between the origin and destination countries, and $Lang_{od}$ is a dummy variable equal to one if the two countries have the same official language. We also control for other characteristics of the origin and destination countries like the number of professional profiles after adjusting for the coverage. We estimate Equation 2 using Poisson Pseudo Maximum Likelihood (PPML) to account for zero bilateral flows between many country pairs (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%. Interestingly, and consistent with patterns in Figure 1, we found that countries' outflows are not necessarily correlated with their income per capita. However, countries with higher income per capita attract a higher number of skilled human capital. We find that the negative impact of distance on bilateral flows is smaller than its impact in the trade literature, which is consistent with individuals' cost of travel not scaling up linearly with distance. The estimated coefficients on the population of the origin and destination countries suggest that skilled workers in smaller countries are relatively more likely to relocate internationally. This result is similar to the results on the relationship between countries' size and bilateral trade (see Silva and Tenreyro 2006). We also find that everything else equal, bilateral migration of skilled labor between countries is about four times larger if the two countries have a common official language. The results in column(2) suggest that these results are largely unchanged if we control for origin country fixed effects. Moreover, controlling for country fixed effects increases the R-squared of the regression by only 3%.

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. While we did not find a significant correlation between outflows and the origin country's GDP per capita, the results in column (3) suggest that migrants from countries with higher GDP per capita have significantly higher rates of return to their origin country. We also find that controlling for outflows, distance has a relatively small impact on return migrations. Interestingly, migrants to countries with a common official language are 15% more likely to return to their origin country. This is consistent with workers being more mobile between labor markets with a common official language. This may also reflect the fact that migrants from countries with a common language consist of a higher share of migrants with temporary migration intention in the first place. 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.

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 on:

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

Where $R_{m(odi)t}$ is a dummy that is equal to 100 if the migrant m who currently resides in country d, works in industry i returns to her country of origin o at time $t+1$ and is equal to 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. All growth rates are calculated based on changes in the number of users 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.

The results in Table 2 suggest that the employment growth of the current industry of an individual 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 appear more sensitive to origin and destination country industry growth than migrants with longer destination country tenures, 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 adjacent industry growth and increases in response to the origin country 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:

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

Where g_{ft} is the employment growth of the current employer of individual m. 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 appear to be more sensitive to negative shocks to firm employment than positive shocks. Specifically, a one standard deviation decline in firm employment increases return migration by 9.6%, while a one standard deviation increase in firm employment reduces return migration 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 migrate on average, while those migrants at firms with branches in the origin country are more likely to return migrate. 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.

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 per capita physical capital stock.

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

1.47%, 1.66%, and 2.94% for the United States, advanced economies, and emerging markets respectively. An additional year of US experience increases advanced economy wages by 1.66%+1.11%=2.77%, a percentage increase of 66.71% relative to own-market returns, and increases emerging market wages by 6.52%, a percentage increase of 121.77% 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.[1] 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

[1] Refer to panel (a) in Figure B7 for a graphical illustration of the numbers in this paragraph.

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%.

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)[1], an additional year of US experience, for an individual with 10 years total experience, increases advanced economy wages by 1.82%, a percentage increase of 82.46% relative to own-market returns, and increases emerging market wages by 2.57%, a percentage increase of 212% relative to own-market returns. When firm fixed effects are included, in column (6), an additional year of US experience increases advanced economy wages by 1.82% and emerging market wages by 2.74%, precentages increases of 84.8% and 204% relative to own market returns. It should be noted that there are seniority differences 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 Matching Estimates and Firm Layoffs

The key endogeneity threat to the results above, and to AKM style designs more generally, is that moves, either migration or return migration, are correlated with persistent, idiosyncratic shocks to the human capital of the worker. 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

[1] Refer to panel (b) in Figure B7 for a graphical illustration of the numbers in this paragraph.

return to their origin countries following positive human capital shocks, this too could bias our results upwards.

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 last school attended before migration (conditional on availability), the firm and position (150 categories) at the time of migration, years of education in different rank universities, years of job experience, and start year of Bachelor's degree, all at the time of migration. 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 7.79% 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 11.6% 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 10.2% 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 15.6% 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 these 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[1]. The results are reported in the last two columns of Tables 5 for the Glassdoor wage data and Revelio wage data respectively. We see that results are robust to this specification and, in fact, become even stronger. Using the Glassdoor wage data, return migrant wages are 7.92% 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, the results are again stronger, with origin country wages 13.1% higher than the matched control group. In the Revelio Labs data, return migrant wages are 11.2% 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 19.8% higher than the matched control group.

That the results grow even stronger when restring to workers impacted by firm layoffs

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

suggests that return migration may be negatively selected on contemporaneous shocks to human capital. We will further explore selection on skill into migration and return migration in Section 6.5. Finally, one might argue that firm layoffs do not force all of the foreign workers to return to their origin countries, and thus those who do not return migrate may still be selected. However, it is most likely those migrants with poor outside job opportunities in the US, and thus lower levels of contemporaneous human capital at the time of the layoffs, who will be induced to return to their origin countries. In this way, the estimates we recover from our layoffs analysis should provide a lower bound on the returns to US experience in emerging markets.

6.4 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 B6 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 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 Figure B6. 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.

6.5 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[1].

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[2].

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 even milder in the US. Focusing on individuals from emerging market economies, approximately 28.5% (11.6%) of those in the highest ventile of abilities migrate to other countries (US), compared to around 16-19% (2-4%) for ventiles 1-17. Similar patterns are observed

[1]Migrants from Emerging Markets to the US, Advanced Economies, and other Emerging Markets display, on average, 15%, 5.5%, and 2.3% higher worker ability compared to non-migrants, respectively.

[2]Returnees from the US to emerging markets and non-returnee migrants of emerging markets to the US demonstrate 9% and 18% higher worker ability, respectively, in comparison to non-migrants of emerging markets.

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.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Abramitzky, R., Boustan, L., and Eriksson, K. (2019). To the new world and back again: Return migrants in the age of mass migration. *ILR Review*, 72(2):300–322.

Adda, J., Dustmann, C., and Görlach, J.-S. (2022). The dynamics of return migration, human capital accumulation, and wage assimilation. *The Review of Economic Studies*, 89(6):2841–2871.

Akee, R. and Jones, M. R. (2019). Immigrants' earnings growth and return migration from the us: Examining their determinants using linked survey and administrative data. Technical report, National Bureau of Economic Research.

Ambrosini, J. W., Mayr, K., Peri, G., and Radu, D. (2015). The selection of migrants and returnees in romania: Evidence and long-run implications. *Economics of Transition*, 23(4):753–793.

Bartik, A. W. (2018). Moving costs and worker adjustment to changes in labor demand: Evidence from longitudinal census data. *Manuscript, University of Illinois at Urbana-Champaign*.

Bartik, T. J. (1993). Who benefits from local job growth: migrants or the original residents? *Regional studies*, 27(4):297–311.

Bayer, C. and Juessen, F. (2012). On the dynamics of interstate migration: Migration costs and self-selection. *Review of Economic Dynamics*, 15(3):377–401.

Beine, M., Docquier, F., and Rapoport, H. (2001). Brain drain and economic growth: theory and evidence. *Journal of development economics*, 64(1):275–289.

Bernstein, S., Diamond, R., Jiranaphawiboon, A., McQuade, T., and Pousada, B. (2022). The contribution of high-skilled immigrants to innovation in the united states. Technical report, National Bureau of Economic Research.

Bhagwati, J. and Rodriguez, C. (1975). Welfare-theoretical analyses of the brain drain. *Journal of development Economics*, 2(3):195–221.

Blanchard, O. and Katz, L. F. (1992). Regional evolutions. washington dc. *Brookings Institute*.

Bossavie, L. and Özden, Ç. (2023). Impacts of temporary migration on development in origin countries. *The World Bank Research Observer*, page lkad003.

Bucheli, J. R. and Fontenla, M. (2022). The impact of return migration on economic development. *Review of Economics and Statistics*, pages 1–45.

Card, D., Rothstein, J., and Yi, M. (2023). Location, location, location. Technical report, National Bureau of Economic Research.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth*, 1:679–741.

Chen, C., Bernard, A., Rylee, R., and Abel, G. (2022). Brain circulation: The educational profile of return migrants. *Population Research and Policy Review*, 41(1):387–399.

Correia, S., Guimarães, P., and Zylkin, T. (2020). Fast poisson estimation with high-dimensional fixed effects. *The Stata Journal*, 20(1):95–115.

Docquier, F. and Rapoport, H. (2012). Globalization, brain drain, and development. *Journal of economic literature*, 50(3):681–730.

Dustmann, C. and Görlach, J.-S. (2016). The economics of temporary migrations. *Journal of Economic Literature*, 54(1):98–136.

Hagan, J. M. and Wassink, J. (2020). Return migration around the world: An integrated agenda for future research. *Annual Review of Sociology*, 46:533–552.

Hendricks, L. and Schoellman, T. (2018). Human capital and development accounting: New evidence from wage gains at migration. *The Quarterly Journal of Economics*, 133(2):665–700.

Howard, G. and Shao, H. (2023). The dynamics of internal migration: A new fact and its implications.

Hsieh, C.-T. and Klenow, P. J. (2010). Development accounting. *American Economic Journal: Macroeconomics*, 2(1):207–223.

Jones, B. F. (2014). The human capital stock: a generalized approach. *American Economic Review*, 104(11):3752–3777.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Kerr, S. P., Kerr, W., Özden, Ç., and Parsons, C. (2016). Global talent flows. *Journal of Economic Perspectives*, 30(4):83–106.

Kerr, S. P., Kerr, W., Özden, Ç., and Parsons, C. (2017). High-skilled migration and agglomeration. *Annual Review of Economics*, 9:201–234.

Kerr, W. R. (2008). Ethnic scientific communities and international technology diffusion. *The Review of Economics and Statistics*, 90(3):518–537.

Klenow, P. J. and Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER macroeconomics annual*, 12:73–103.

Kleven, H., Landais, C., Munoz, M., and Stantcheva, S. (2020). Taxation and migration: Evidence and policy implications. *Journal of Economic Perspectives*, 34(2):119–142.

Kleven, H. J., Landais, C., Saez, E., and Schultz, E. (2014). Migration and wage effects of taxing top earners: Evidence from the foreigners' tax scheme in denmark. *The Quarterly Journal of Economics*, 129(1):333–378.

Koşar, G., Ransom, T., and Van der Klaauw, W. (2022). Understanding migration aversion using elicited counterfactual choice probabilities. *Journal of Econometrics*, 231(1):123–147.

Martellini, P., Schoellman, T., and Sockin, J. (2023). The global distribution of college graduate quality. *Journal of Political Economy*.

Mayr, K. and Peri, G. (2009). Brain drain and brain return: theory and application to eastern-western europe. *The BE Journal of Economic Analysis & Policy*, 9(1).

McAuliffe, M. and Triandafyllidou, A. (2022). World migration report 2022. Technical report, International Organization for Migration (IOM), Geneva.

Muñoz, M. (2020). Do european top earners react to labour taxation through migration.

Özden, Ç. and Phillips, D. (2015). What really is brain drain? location of birth, education and migration dynamics of african doctors. *Work. Pap*, 4.

Porcher, C. (2020). Migration with costly information. *Unpublished Manuscript*, 1(3).

Prato, M. (2022). The global race for talent: Brain drain, knowledge transfer, and growth. *Knowledge Transfer, and Growth (November 28, 2022)*.

Reinhold, S. and Thom, K. (2013). Migration experience and earnings in the mexican labor market. *Journal of Human Resources*, 48(3):768–820.

Roca, J. D. L. and Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1):106–142.

Saxenian, A. (2005). From brain drain to brain circulation: Transnational communities and regional upgrading in india and china. *Studies in comparative international development*, 40:35–61.

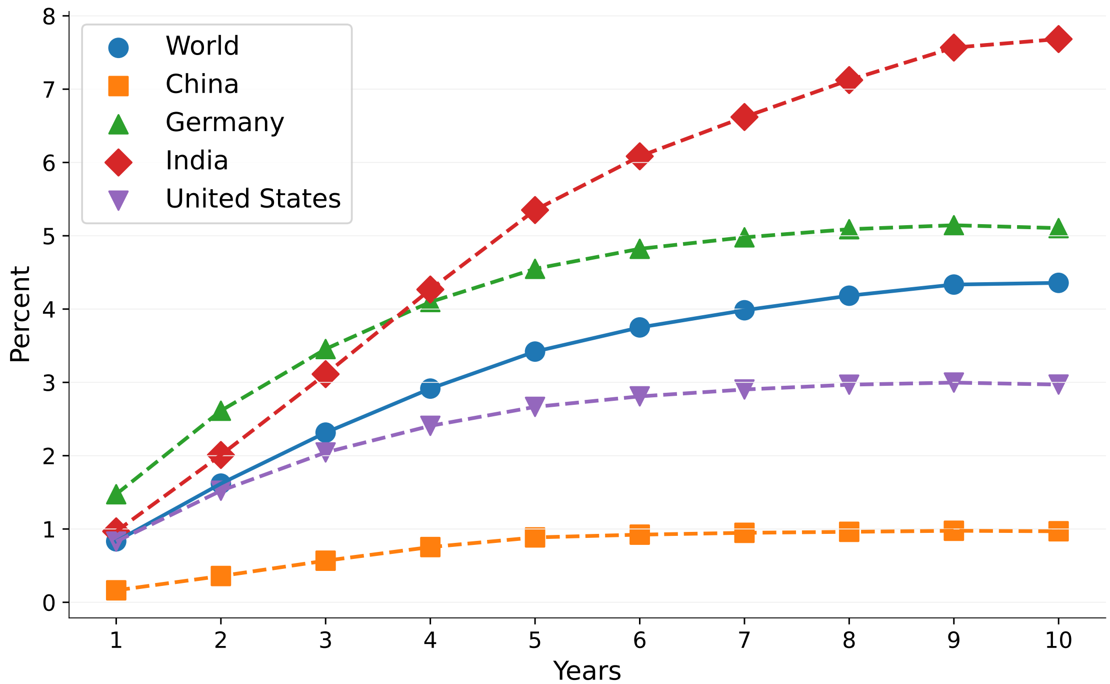
Saxenian, A., Motoyama, Y., and Quan, X. (2002). *Local and global networks of immigrant professionals in Silicon Valley*. Public Policy Instit. of CA.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Singh, J. and Krishna, V. V. (2015). Trends in brain drain, gain and circulation: Indian experience of knowledge workers. *Science, Technology and Society*, 20(3):300–321.

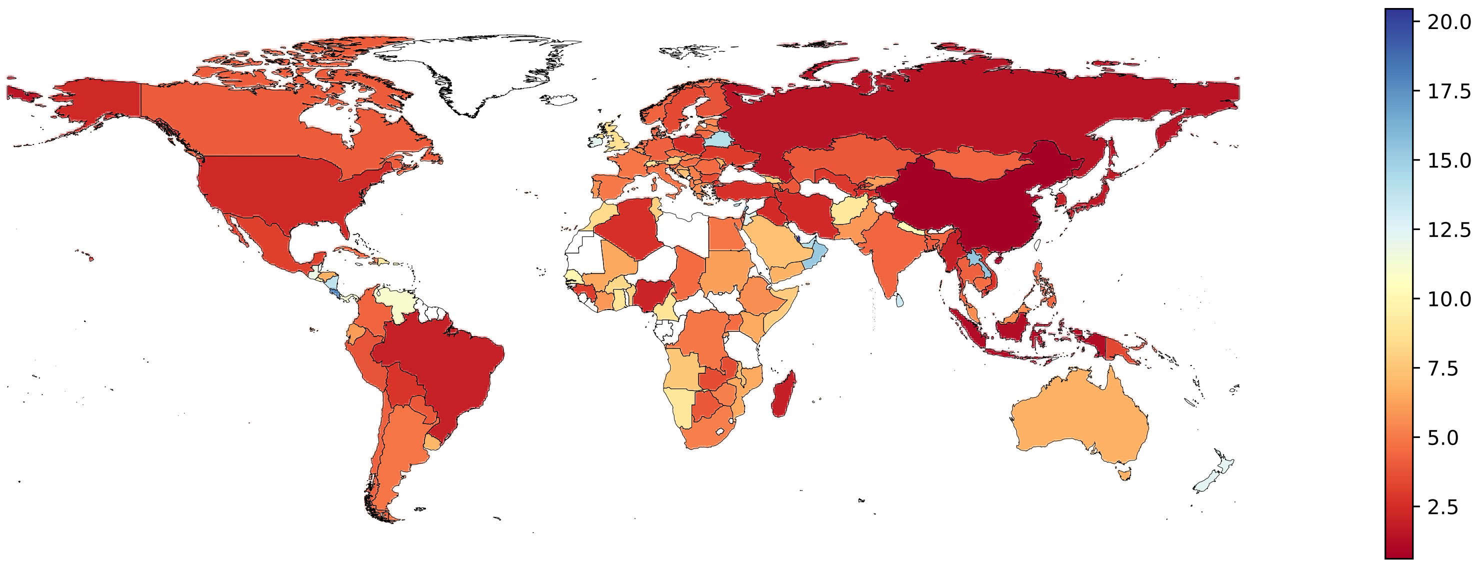
Wahba, J. (2015). Selection, selection, selection: the impact of return migration. *Journal of Population Economics*, 28:535–563.

Figure 1: Hazard Ratio of Outflows



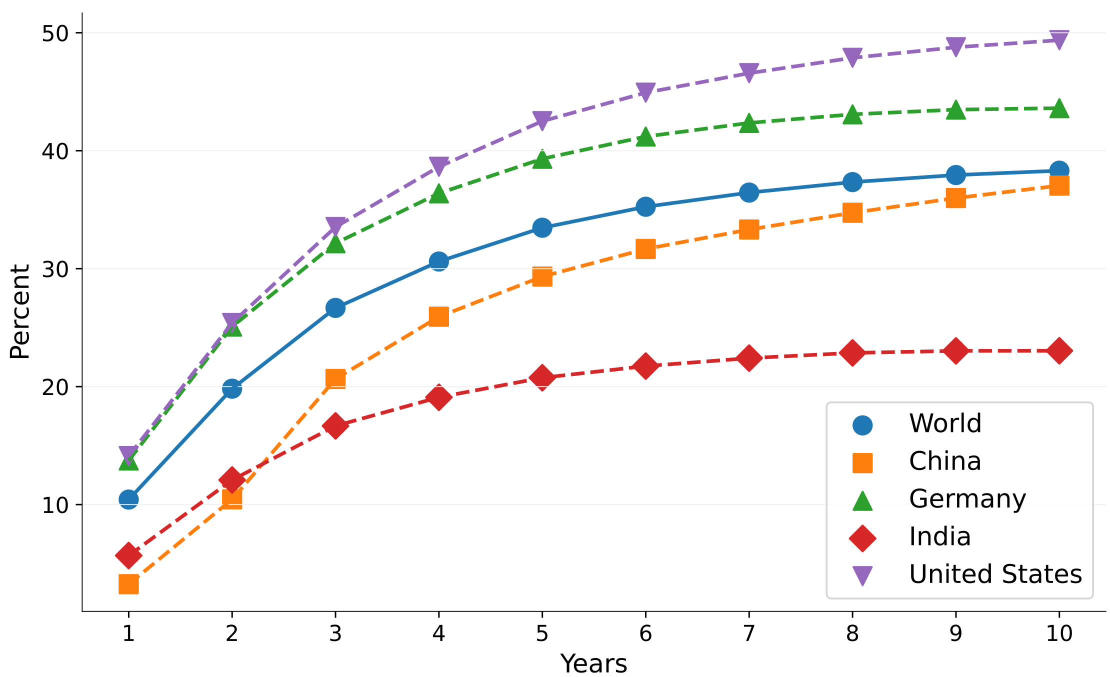
Notes: This figure illustrates the out-migration rate observed over 10 years. In this analysis, we begin by examining the total population within a country having the same origin country (i.e., the country they initially appeared in the data) at time 0. Subsequently, for each time (t=1, 2,..., 10), the 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



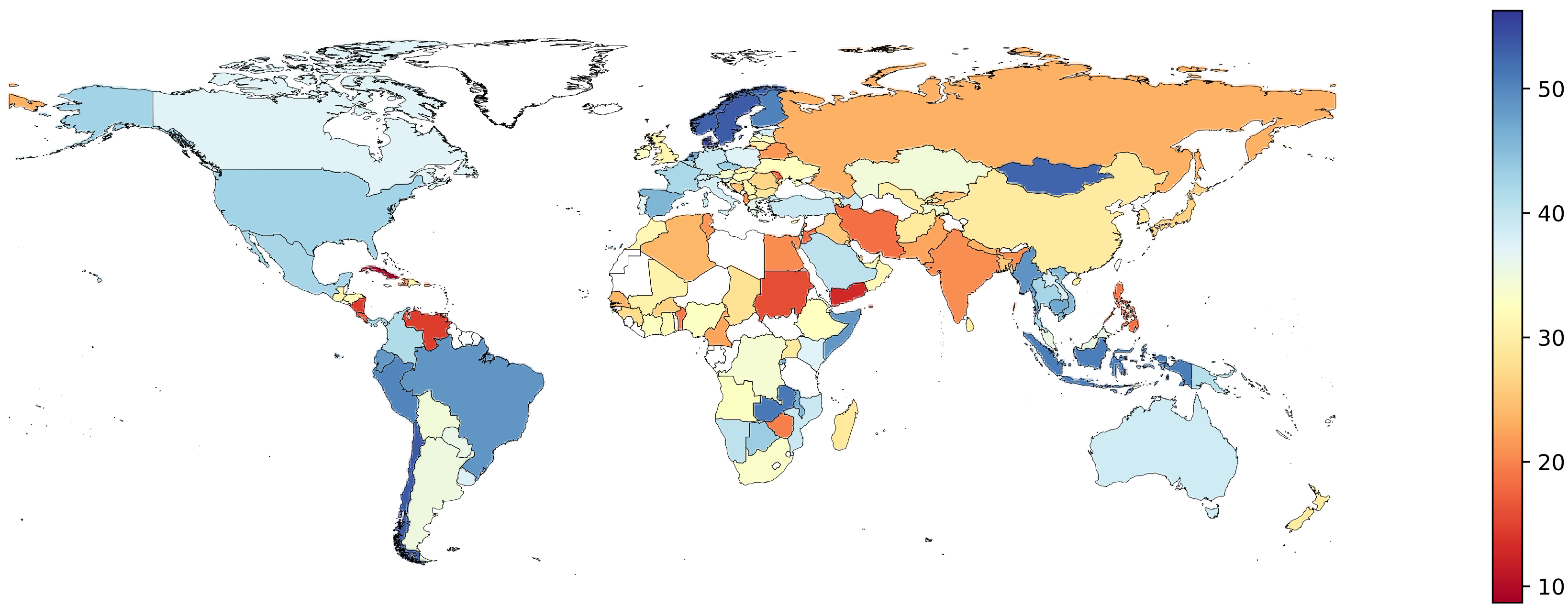
Notes: Refer to the notes on Figure 1. The content presented here mirrors Figure 1; however, we specifically focus on capturing the out-migration rate snapshot for year 5 and visually display it on a map for each country.

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



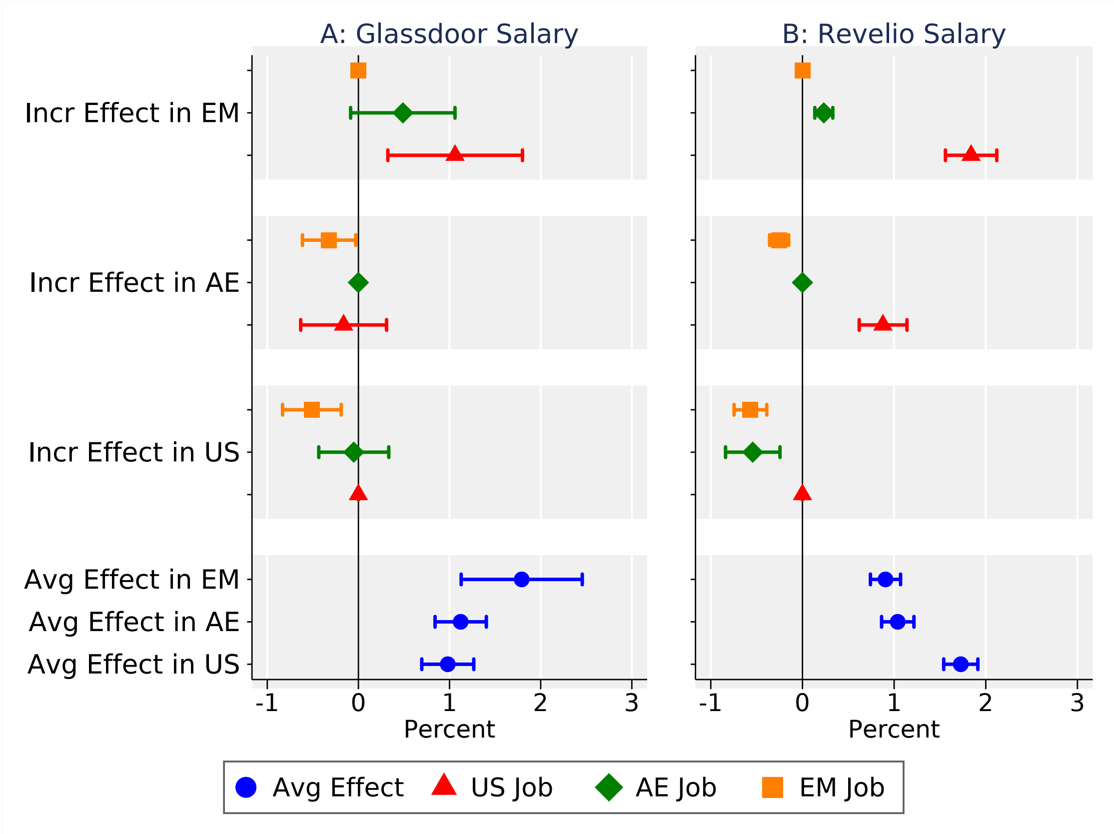
Notes: This figure showcases the return migration of migrants over a decade based on their origin country. We define the origin country as the initial country where an individual first appeared in our dataset (first education or job record). To create this figure, we track migrants, designating the first year of entry into the destination country as time 0. Subsequently, we follow migrants in years t=1, 2, ..., 10 and determine the proportion of individuals observed back in their origin country during those years. For the global analysis (labeled "World"), we compute 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 adheres to the formulation specified in Equation 1. This figure is derived from data encompassing all migrants who migrated in 2000 or later, specifically focusing on a selected group of 134 ILO members, each hosting more than 100,000 college-educated individuals. Additionally, China and Saudi Arabia are included in this analysis.

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



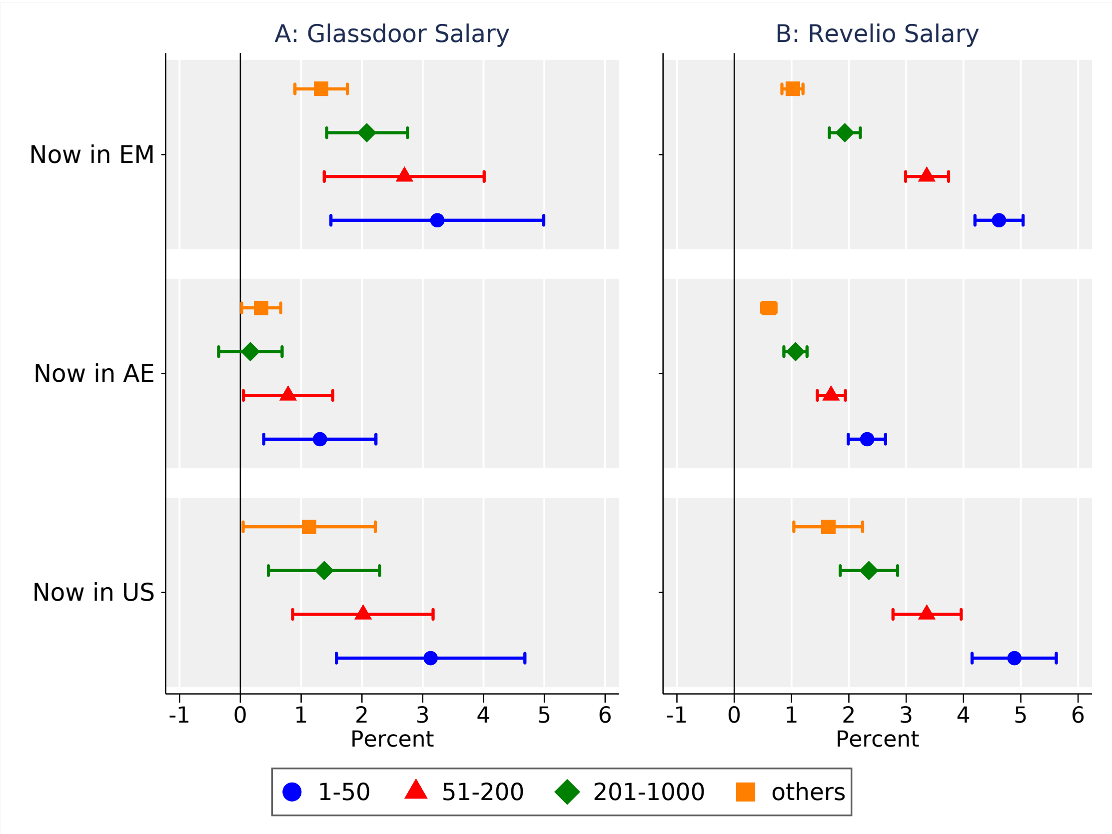
Notes: Refer to the notes on Figure 3. This content mirrors Figure 3; however, our specific focus here is to capture the return migration rate snapshot for year 5 and present it visually on a map for each country of origin.

Figure 5: Return to Job Experience and its Transferability



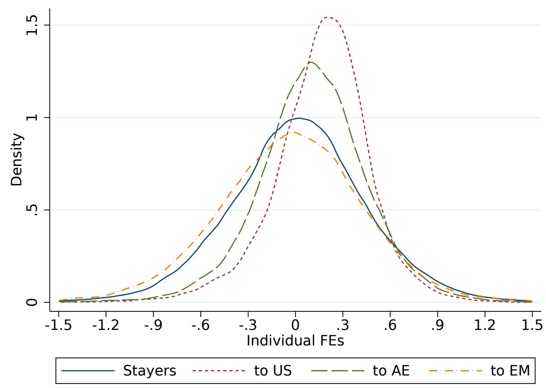
Notes: This figure depicts the coefficients ($\beta_{jj'}$) alongside their corresponding standard errors for Equation 8, which incorporates country-by-year and individual fixed effects (columns 3 and 5 in Table 4). The dependent variables are the logarithm of salary estimated using Glassdoor salary 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 remaining points represent the incremental effects of job experience accumulated in various regions, considering different current category combinations. 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 C2). 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 depicted for each coefficient.

Figure 6: Returns to Education

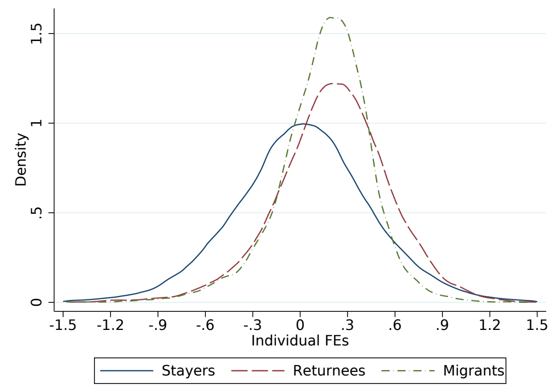


Notes: This figure presents the coefficients obtained from regressing the individual fixed effects on years of education across different education categories: top 50 schools, 51-200 ranked schools, 201-1000 ranked schools, and all others. Various current category combinations are considered in this analysis. In panels A and B, we utilize individual fixed effects estimated from columns (3) and (5) in Table 4, respectively. These regressions also incorporate country-by-year fixed effects. Standard errors are clustered at the individual level, and 95% confidence intervals are depicted for each coefficient.

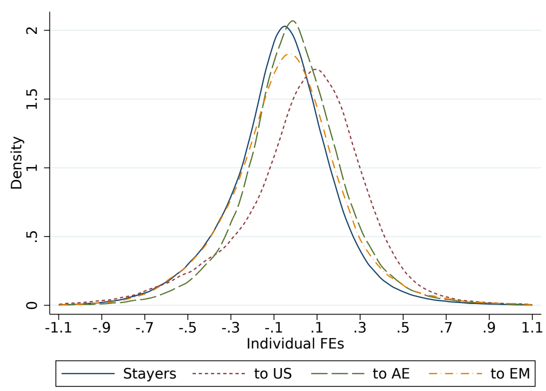
Figure 7: Selection of Outflows and Returnees



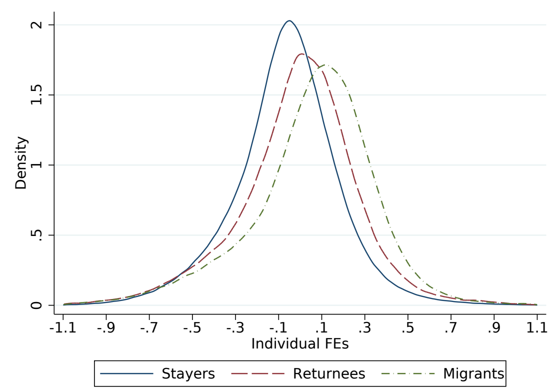
(a) Outflows - Glassdoor



(b) Return Migrations - Glassdoor



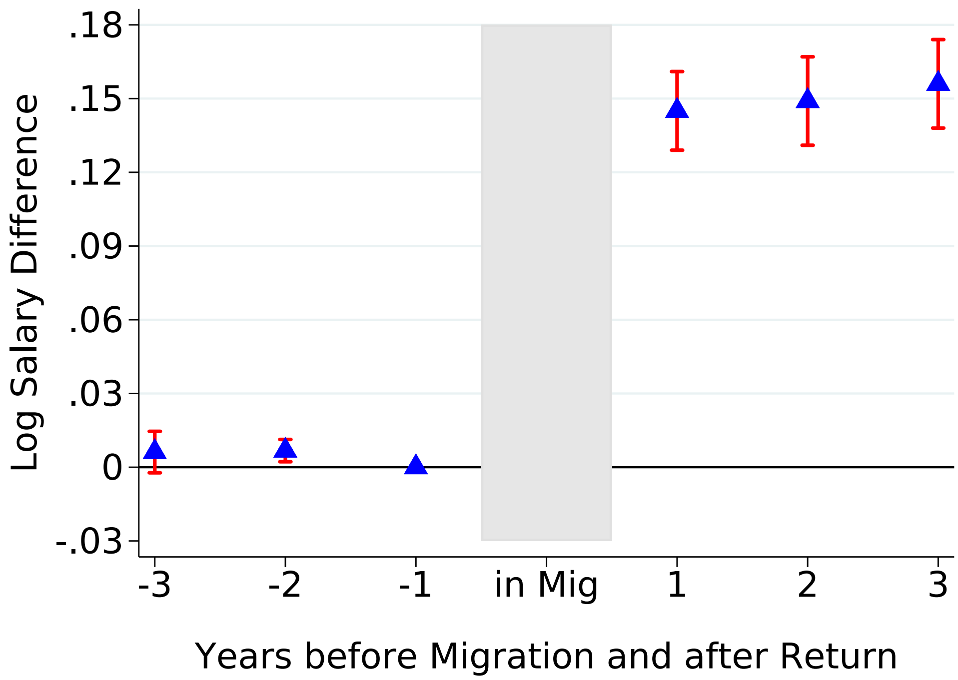
(c) Outflows - Revelio



(d) Return Migration - Revelio

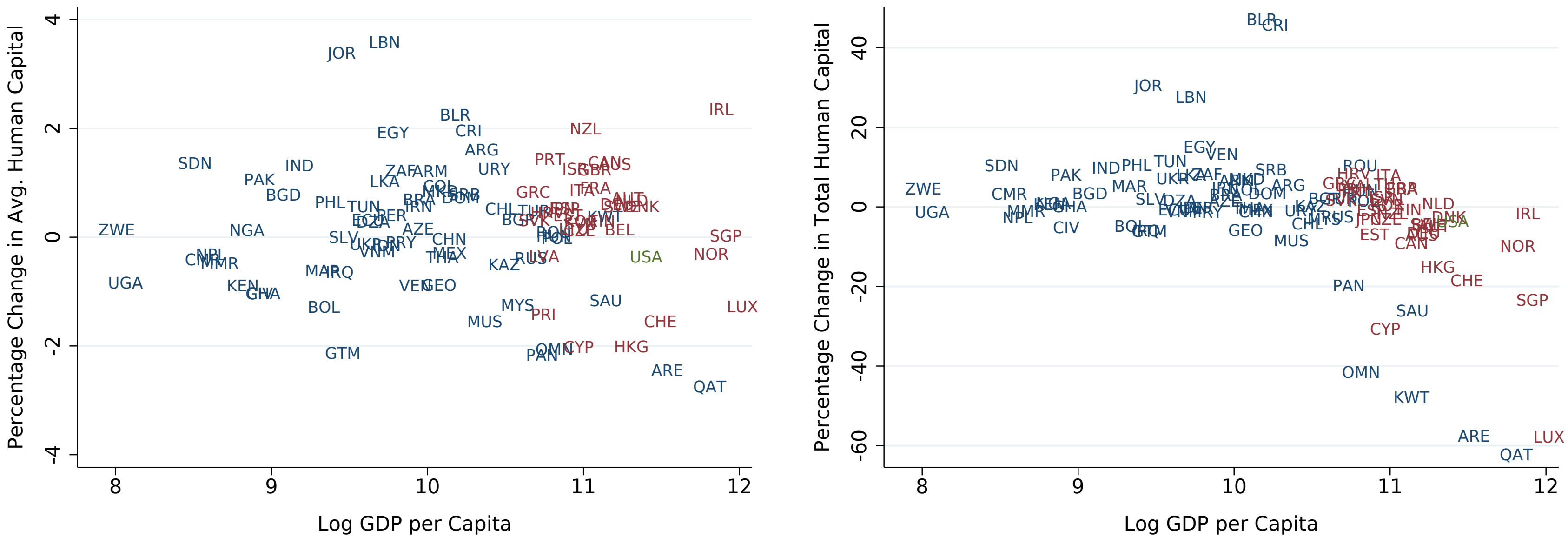
Notes: Refer to the notes on Figure 5 and Table 4. Panels (a) and (c) of this figure depict the distribution of estimated individual fixed effects, as calculated in Equation 8, across four distinct categories: 1) Individuals who consistently remain in their original Emerging Market (EM) country (Stayers); 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 distinct 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 (5) 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 6.3 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 revolves around the year (-1) or the year immediately before migration. We retain 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 as in the previous analysis, but this time focusing 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 (the country where they first appeared in the data). By utilizing the coefficients and individual fixed effects estimated in Equation 8 and in column (5) 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 obtain 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, in the visual representation.

Table 1: Bilateral Flows and Country Characteristics

	Log Outflows		Log Returns	
	(1)	(2)	(3)	(4)
Log Destination GDP Per Capita	0.735***	0.749***	-0.0614**	
	(0.0823)	(0.0829)	(0.0251)	
Log Origin GDP Per Capita	-0.0501		0.441***	0.412***
	(0.0937)		(0.0509)	(0.0561)
Log Distance	-0.596***	-0.663***	0.0196	-0.0167
	(0.0659)	(0.0900)	(0.0326)	(0.0404)
Common Official Language	1.465***	1.401***	0.150***	0.138**
	(0.145)	(0.157)	(0.0536)	(0.0597)
Log Origin ILO Count	0.869***		0.0516**	0.0781***
	(0.0438)		(0.0202)	(0.0239)
Log Destination ILO Count	0.736***	0.755***	0.0671***	
	(0.0286)	(0.0359)	(0.0231)	
Log Outflow			0.964***	0.939***
			(0.0279)	(0.0280)
Observations	13447	13447	11514	11514
R-Squared	0.801	0.834	0.962	0.970
Origin FE		Y		
Destination FE				Y

Notes: This 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 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	Mig <5	Mig ≥ 5	Mig <5
	(1)	(2)	(3)	(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 less than 5 years and at least 5 years in the destination country, respectively. In column (4), we also add the weighted growth of the neighborhood 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. Statistical significance levels are denoted as follows: *** for p<0.01, ** for p<0.05, * for 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 × Negative	-9.619***	-15.97***	-4.853***	-14.94***	-10.85***
	(1.085)	(2.064)	(0.674)	(1.615)	(1.053)
Firm Growth × 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 × Firm Growth × Negative					-9.182***
					(1.535)
Branch in Origin Country × Firm Growth × 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. Statistical significance levels are indicated as follows: *** for p<0.01, ** for p<0.05, * for 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 (4-5) is the logarithm of Glassdoor salary and Revelio Lab imputed salary data, respectively. Country-by-year fixed effects are incorporated in all columns, while individual fixed effects are controlled in columns (2-5). 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 (5), 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. Statistical significance levels are denoted as follows: *** for p<0.01, ** for p<0.05, and * for 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	0.107***	0.149***		
	(0.0151)	(0.0184)		
Observations	6089	1079		
R-Squared	0.946	0.874		
Panel B: Revelio Salary				
Treatment $\times$ Post	0.102***	0.156***	0.112***	0.198***
	(0.0109)	(0.0198)	(0.0239)	(0.0519)
Observations	92970	12044	2775	455
R-Squared	0.712	0.691	0.736	0.798

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), the last university attended, and the year of initiation of the Bachelor's degree, all contingent upon availability. 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. Statistical significance levels are denoted as follows: *** for p<0.01, ** for p<0.05, * for p<0.1.

A Data Appendix

In this appendix section, our goal is to provide additional insights into our professional profiles dataset. Furthermore, we will delve deeper into explaining the data cleaning procedures and perform validity checks on unprofessional profiles dataset.

We utilize the International Labor Organization (ILO) data on the number of college-educated individuals by country. ILO provides data on the count of college-educated individuals across 186 member countries. Notably, two substantial non-ILO member countries are China and Saudi Arabia. We manually supplement the ILO data with the total number of college-educated individuals in China and Saudi Arabia from independent sources, amounting to 240 million and 6 million, respectively. Countries with fewer than a total of 100,000 college-educated individuals, as reported by the ILO, are excluded from our analyses. Therefore, our primary focus in this paper rests on the remaining 134 ILO members, which are complemented by China and Saudi Arabia, each with at least 100,000 college-educated individuals.

In our analyses, we also utilize the International Monetary Fund's (IMF) classification of Advanced Economies (AE) and Emerging Market and Developing Economies (EM)[1]. Throughout the paper, we consistently refer to Emerging Market (EM) as an abbreviation for Emerging Market and Developing Economies. We also assign a separate category for the United States due to its significant representation in our dataset. Table A1 presents the total number of college-educated individuals in ILO, the number of professional profiles, and categorization as AE or EM for our selected 136 countries. Figure A1 additionally illustrates the ratio of professional profiles in our dataset compared to the ILO college-educated counts.

[1]https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates

Table A1: Country Coverage and Weight Distribution

Part 1

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
2	India	EM	24097	59555	2020	0.40	2.47
3	Brazil	EM	16528	24692	2021	0.67	1.49
4	United Kingdom	AE	15110	15083	2019	1	1
5	France	AE	10118	13245	2021	0.76	1.31
6	Canada	AE	8451	14232	2022	0.59	1.68
7	Italy	AE	5930	5779	2021	1.03	0.97
8	Australia	AE	5840	6107	2020	0.96	1.05
9	Spain	AE	5715	10071	2021	0.57	1.76
10	Germany	AE	5706	13370	2021	0.43	2.34
11	China	EM	5553	240000	2022	0.02	43.21
12	Netherlands	AE	5248	3901	2021	1.35	0.74
13	Indonesia	EM	4466	17582	2022	0.25	3.94
14	Mexico	EM	4402	11488	2021	0.38	2.61
15	Turkey	EM	3529	9142	2021	0.39	2.59
16	South Africa	EM	3142	3705	2021	0.85	1.18
17	Argentina	EM	2896	3319	2021	0.87	1.15
18	Philippines	EM	2595	10471	2018	0.25	4.03
19	Colombia	EM	2489	7247	2021	0.34	2.91
20	U.A. Emirates	EM	2408	2915	2021	0.83	1.21
21	Sweden	AE	2121	2462	2021	0.86	1.16
22	Pakistan	EM	2035	6136	2021	0.33	3.01
23	Poland	EM	1968	6304	2021	0.31	3.20
24	Russia	EM	1944	38060	2021	0.05	19.58
25	Nigeria	EM	1889	11833	2019	0.16	6.26
26	Saudi Arabia	EM	1870	6000	2020	0.31	3.21
27	Chile	EM	1869	2220	2021	0.84	1.19
28	Switzerland	AE	1860	2094	2021	0.89	1.13
29	Belgium	AE	1853	2570	2021	0.72	1.39
30	Malaysia	EM	1811	4497	2020	0.40	2.48
31	Egypt	EM	1685	6113	2021	0.28	3.63
32	Denmark	AE	1561	1203	2021	1.30	0.77
33	Peru	EM	1541	4149	2021	0.37	2.69
34	Portugal	AE	1400	1741	2021	0.80	1.24
35	Singapore	AE	1370	1464	2021	0.94	1.07
36	Ireland	AE	1142	1307	2021	0.87	1.14
37	Bangladesh	EM	1061	4108	2017	0.26	3.87
38	New Zealand	AE	1054	1074	2020	0.98	1.02
39	Norway	AE	966	1333	2021	0.72	1.38
40	Japan	AE	964	33210	2020	0.03	34.42
41	Venezuela	EM	954	5035	2017	0.19	5.28
42	Iran	EM	945	7205	2020	0.13	7.62
43	Romania	EM	932	1842	2021	0.51	1.98
44	Ukraine	EM	886	9494	2021	0.09	10.71
45	Kenya	EM	869	867	2019	1	1
46	Czech Republic	AE	782	1437	2021	0.54	1.84

Part 2

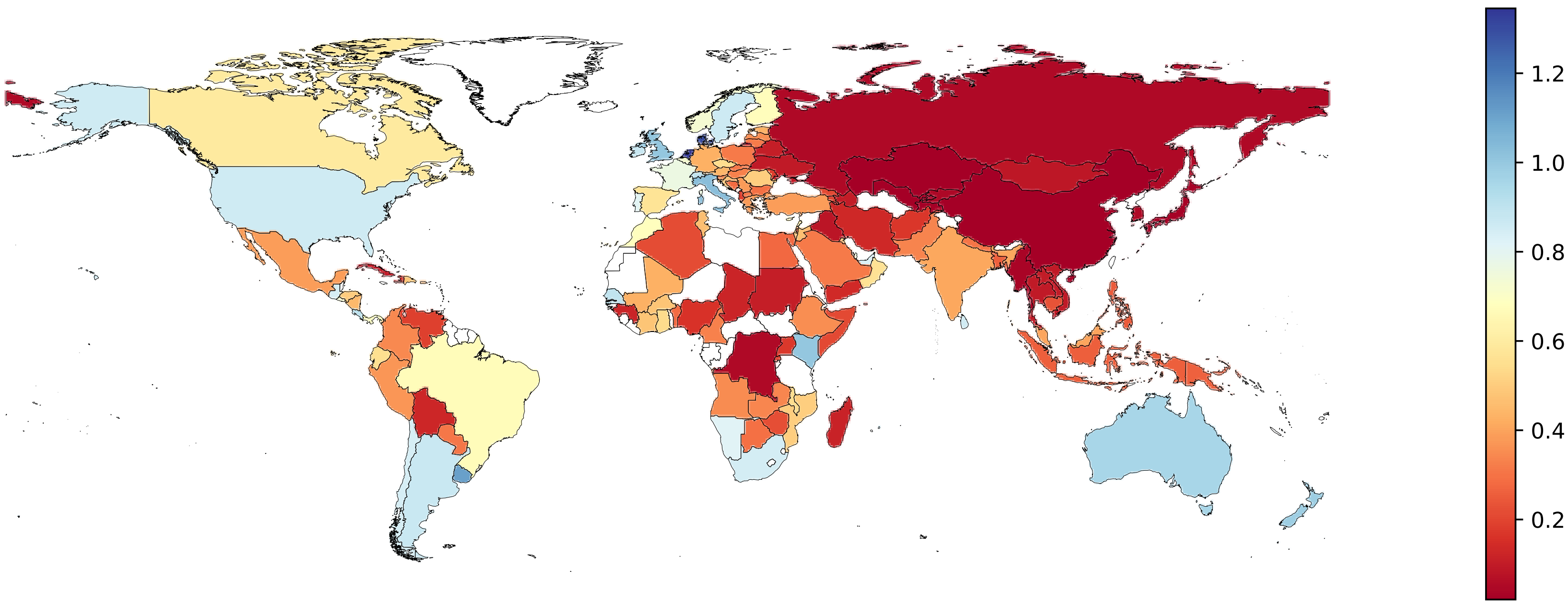
N (1)	Country (2)	Cat. (3)	Link (4)	ILO (5)	ILO Yr (6)	Covrg (7)	W (8)
47	Finland	AE	770	1144	2021	0.67	1.49
48	Morocco	EM	770	1131	2021	0.68	1.47
49	Israel	AE	765	1580	2021	0.48	2.07
50	Vietnam	EM	759	7774	2021	0.10	10.24
51	Austria	AE	743	1672	2021	0.44	2.25
52	South Korea	AE	740	15887	2022	0.05	21.44
53	Hong Kong	AE	734	1259	2021	0.58	1.71
54	Ecuador	EM	700	1273	2021	0.55	1.82
55	Greece	AE	654	1731	2021	0.38	2.64
56	Thailand	EM	652	6697	2021	0.10	10.26
57	Hungary	EM	491	1485	2021	0.33	3.02
58	Algeria	EM	489	2293	2017	0.21	4.68
59	Ghana	EM	455	845	2017	0.54	1.86
60	Costa Rica	EM	453	502	2021	0.90	1.11
61	Sri Lanka	EM	450	529	2020	0.85	1.18
62	Qatar	EM	425	558	2021	0.76	1.31
63	Tunisia	EM	418	900	2017	0.46	2.15
64	Lebanon	EM	356	600	2019	0.59	1.68
65	Serbia	EM	333	872	2021	0.38	2.61
66	Jordan	EM	332	715	2021	0.47	2.15
67	Dominican Rep.	EM	323	664	2021	0.49	2.05
68	Bulgaria	EM	311	1062	2021	0.29	3.41
69	Guatemala	EM	301	358	2019	0.84	1.19
70	Uruguay	EM	289	260	2019	1.11	0.90
71	Kuwait	EM	275	530	2016	0.52	1.93
72	Slovakia	AE	247	801	2021	0.31	3.23
73	Croatia	AE	244	513	2021	0.48	2.10
74	Puerto Rico	AE	243	587	2015	0.42	2.41
75	Panama	EM	235	344	2021	0.68	1.46
76	Oman	EM	230	411	2021	0.56	1.79
77	Nepal	EM	228	751	2017	0.30	3.29
78	Ivory Coast	EM	227	473	2019	0.48	2.08
79	Lithuania	AE	221	695	2021	0.32	3.14
80	Uganda	EM	213	1235	2021	0.17	5.78
81	Zimbabwe	EM	207	953	2021	0.22	4.58
82	Iraq	EM	200	2477	2021	0.08	12.34
83	Bolivia	EM	186	1470	2021	0.13	7.89
84	Luxembourg	AE	185	168	2021	1.10	0.91
85	Kazakhstan	EM	183	7486	2020	0.02	40.90
86	Cameroon	EM	180	548	2014	0.33	3.04
87	Belarus	EM	179	1714	2021	0.10	9.58
88	Senegal	EM	166	186	2019	0.89	1.12
89	Zambia	EM	161	479	2021	0.34	2.96
90	El Salvador	EM	161	224	2021	0.72	1.39
91	Angola	EM	153	438	2021	0.35	2.86
92	Paraguay	EM	152	494	2017	0.31	3.24

Part 3

N (1)	Country (2)	Cat. (3)	Link (4)	ILO (5)	ILO Yr (6)	Covrg (7)	W (8)
93	Azerbaijan	EM	151	1476	2021	0.10	9.77
94	Ethiopia	EM	150	427	2013	0.35	2.83
95	Myanmar	EM	150	4379	2020	0.03	29.05
96	Cyprus	AE	145	225	2021	0.65	1.55
97	Slovenia	AE	143	438	2021	0.33	3.05
98	Honduras	EM	138	277	2019	0.50	2.01
99	Georgia	EM	135	650	2020	0.21	4.80
100	Latvia	AE	134	381	2021	0.35	2.84
101	Cambodia	EM	128	561	2019	0.23	4.38
102	Estonia	AE	125	289	2021	0.43	2.31
103	Nicaragua	EM	123	275	2014	0.45	2.23
104	Sudan	EM	113	1080	2011	0.11	9.50
105	Mozambique	EM	106	210	2015	0.51	1.98
106	Albania	EM	102	564	2019	0.18	5.50
107	Mauritius	EM	102	110	2020	0.92	1.08
108	Botswana	EM	95	328	2020	0.29	3.45
109	Armenia	EM	88	463	2021	0.19	5.23
110	DR Congo	EM	87	1715	2020	0.05	19.61
111	Afghanistan	EM	86	506	2021	0.17	5.87
112	Namibia	EM	83	102	2018	0.81	1.24
113	Bosnia and Herz.	EM	80	284	2021	0.28	3.56
114	Macedonia	EM	79	519	2021	0.31	3.27
115	Cuba	EM	76	793	2010	0.10	10.40
116	Rwanda	EM	64	327	2021	0.20	5.09
117	Burkina Faso	EM	62	130	2018	0.48	2.08
118	Papua New Guinea	EM	62	240	2010	0.26	3.84
119	Mali	EM	62	145	2020	0.43	2.34
120	Madagascar	EM	61	540	2015	0.11	8.73
121	Malawi	EM	61	112	2020	0.55	1.83
122	Uzbekistan	EM	59	2681	2020	0.02	44.92
123	Palestine	EM	57	404	2021	0.14	7.02
124	Benin	EM	53	189	2018	0.28	3.53
125	Haiti	EM	53	388	2012	0.14	7.26
126	Yemen	EM	52	383	2014	0.14	7.37
127	Moldova	EM	51	279	2021	0.19	5.40
128	Mongolia	EM	43	515	2021	0.08	11.96
129	Guinea	EM	41	338	2019	0.12	8.21
130	Somalia	EM	36	174	2019	0.21	4.82
131	Kosovo	EM	35	147	2021	0.24	4.15
132	Macao	AE	33	134	2016	0.25	3.96
133	Kyrgyzstan	EM	26	566	2018	0.05	21.77
134	Laos	EM	25	257	2017	0.10	10.05
135	Chad	EM	16	134	2018	0.12	8.22
136	Tajikistan	EM	12	581	2016	0.02	48.37

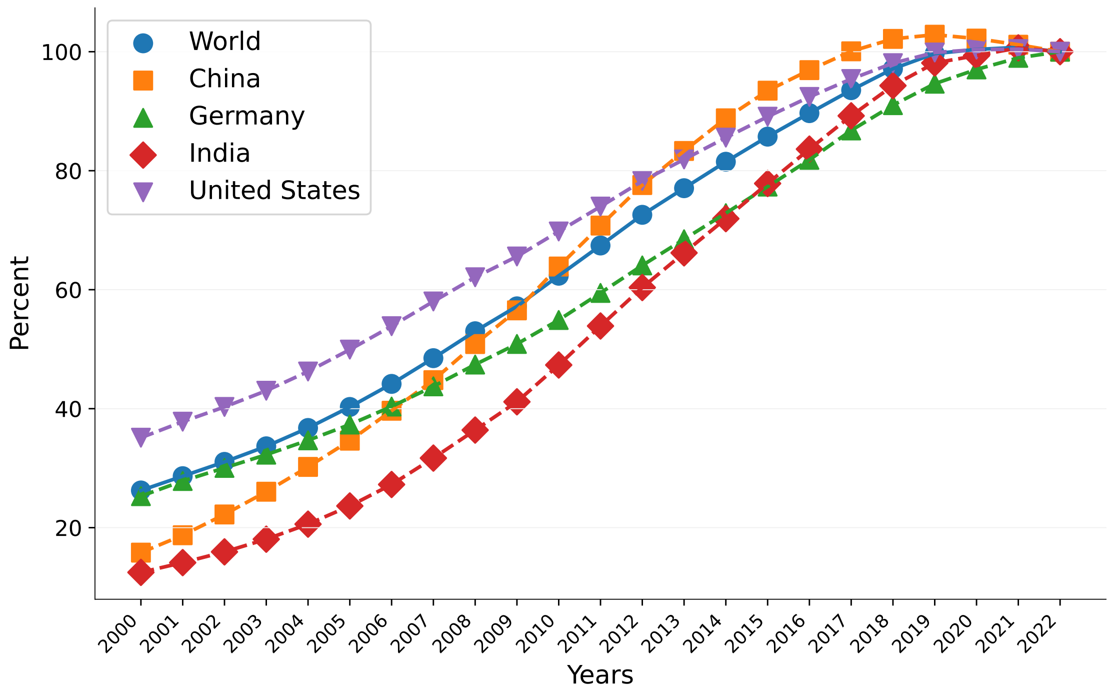
Notes: The table is divided into three sections and presents the order (1), country name (2), IMF country category (3), professional profile counts (4), ILO college-educated counts (5), ILO data year (6), country coverage (7), and country weight (8). ILO counts indicate the number of college-educated individuals in each country according to the International Labor Organization. Professional profile count includes users within the country during the ILO year, two years before, and after that year. Columns (4, 5) represent values in units of 1000 individuals. Country coverage is the professional profile count divided by ILO counts, and country weights are the inverse of that. The table is focused on 134 ILO member countries with over 100,000 college-educated individuals, plus China and Saudi Arabia. We assume 240 million and 6 million college-educated individuals in China and Saudi Arabia, respectively.

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



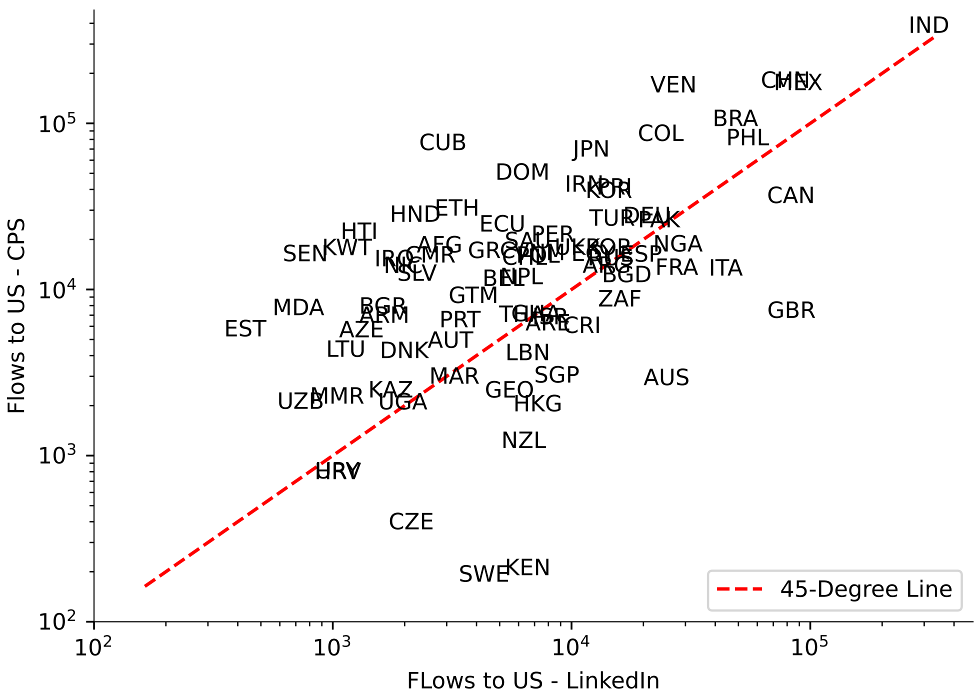
Notes: Refer to the notes on Table A1. This map illustrates the country coverage (Column (7) in Table A1) for the selected 136 countries.

Figure A2: Professional Profiles Coverage Over Time



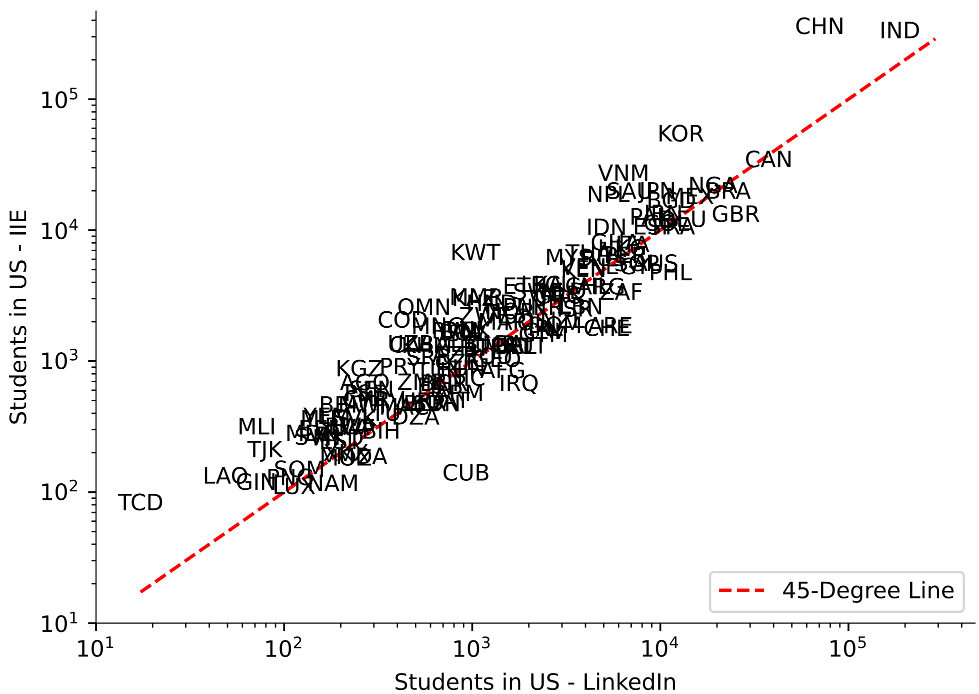
Notes: The figure showcases the professional profile coverage over time for the world average and selected countries. To calculate the country coverage trend, we standardize the country coverage in the year 2022 (the final year in our dataset) to 100. Subsequently, we divide the count of professional 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)



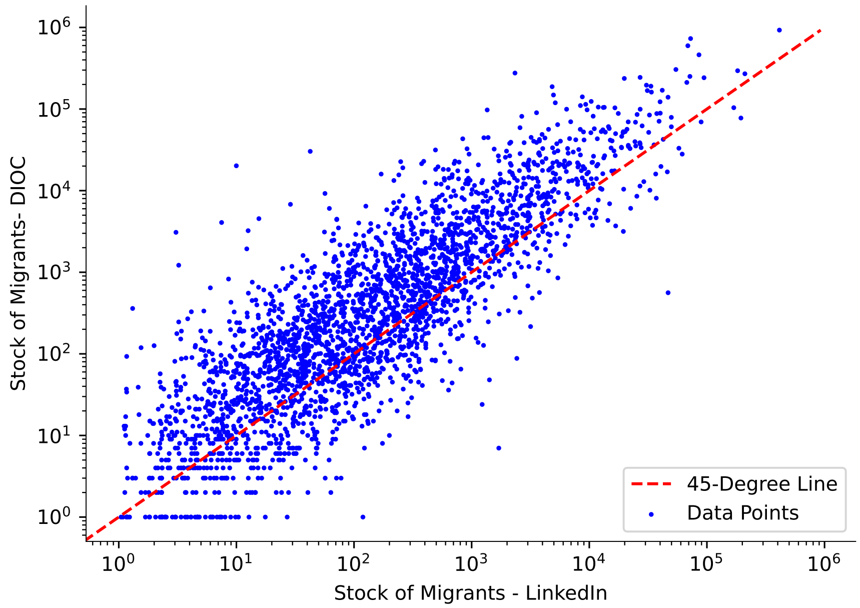
Notes: This figure compares the inflows to the United States in our professional profiles data versus the inflows of people with a college degree in the Current Population Survey (CPS) 2022 data. The CPS 2022 data specifically represents individuals residing in the US in 2022. Similarly, we restrict our professional profiles 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.

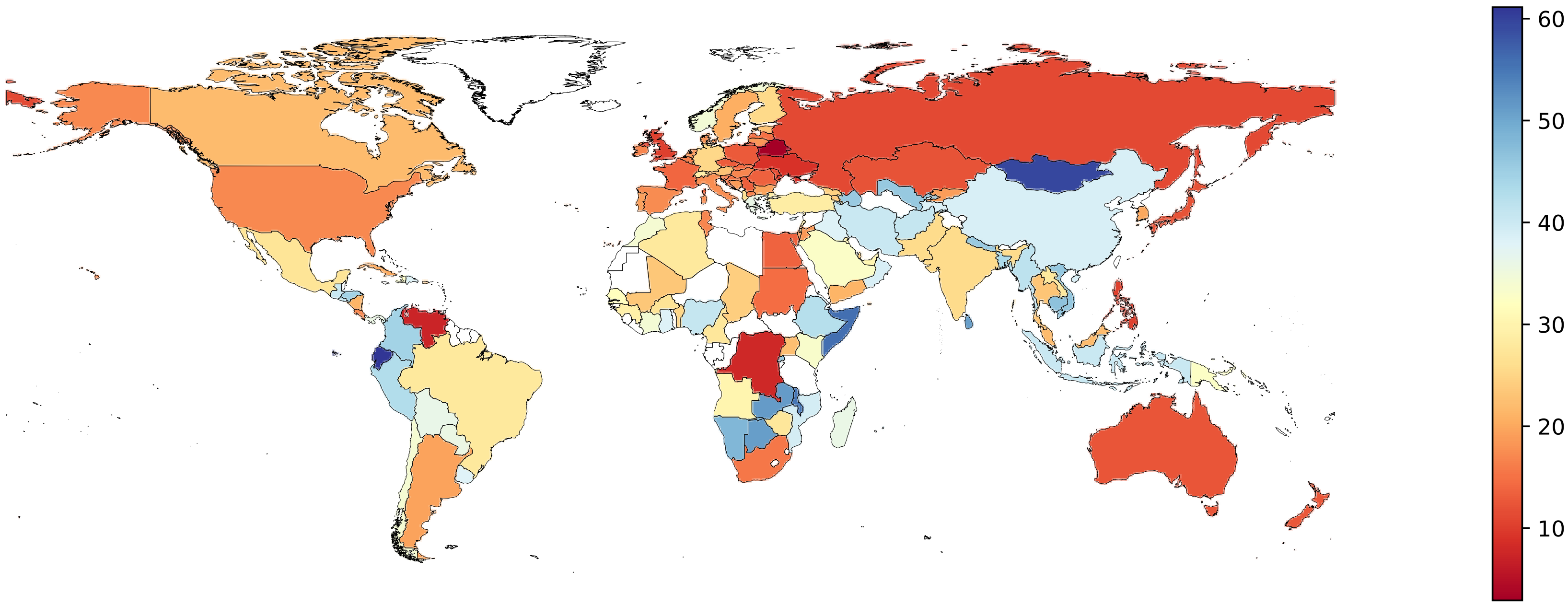
Table A2: Regression of Log Stock of Migrants in DIOC Data on Professional Profiles

	(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.

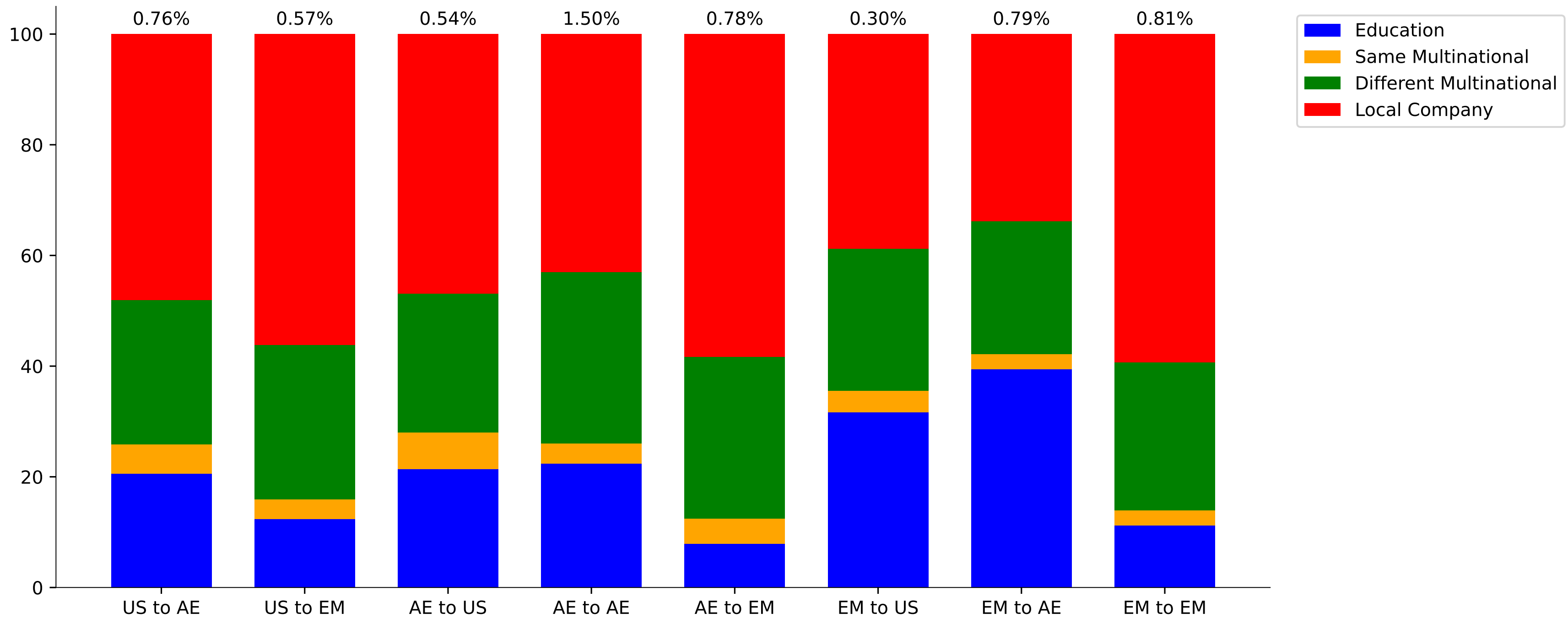
B Appendix Figures

Figure B1: Share of Out-Migration for Education



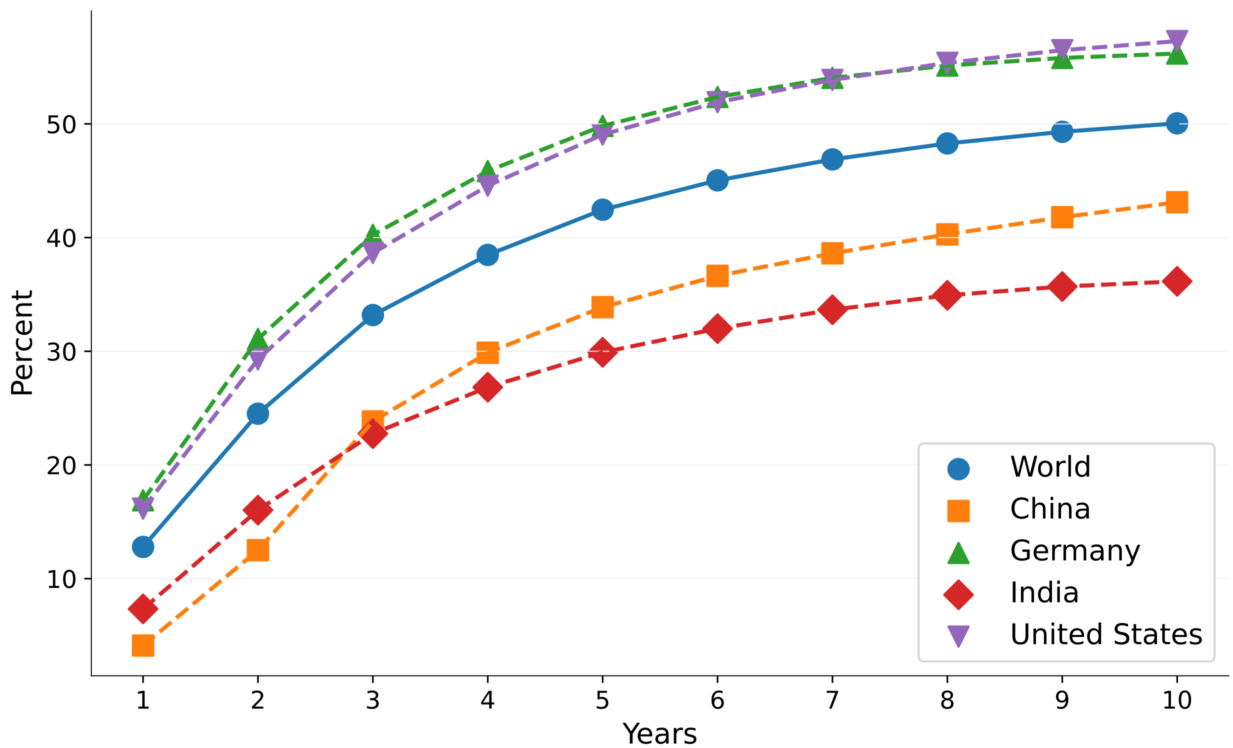
Notes: Refer to the notes in Figures 1 and 2. This figure illustrates the proportion of the total outflows after 5 years that are in education in the destination country.

Figure B2: Outflow to Education and Multinational Companies



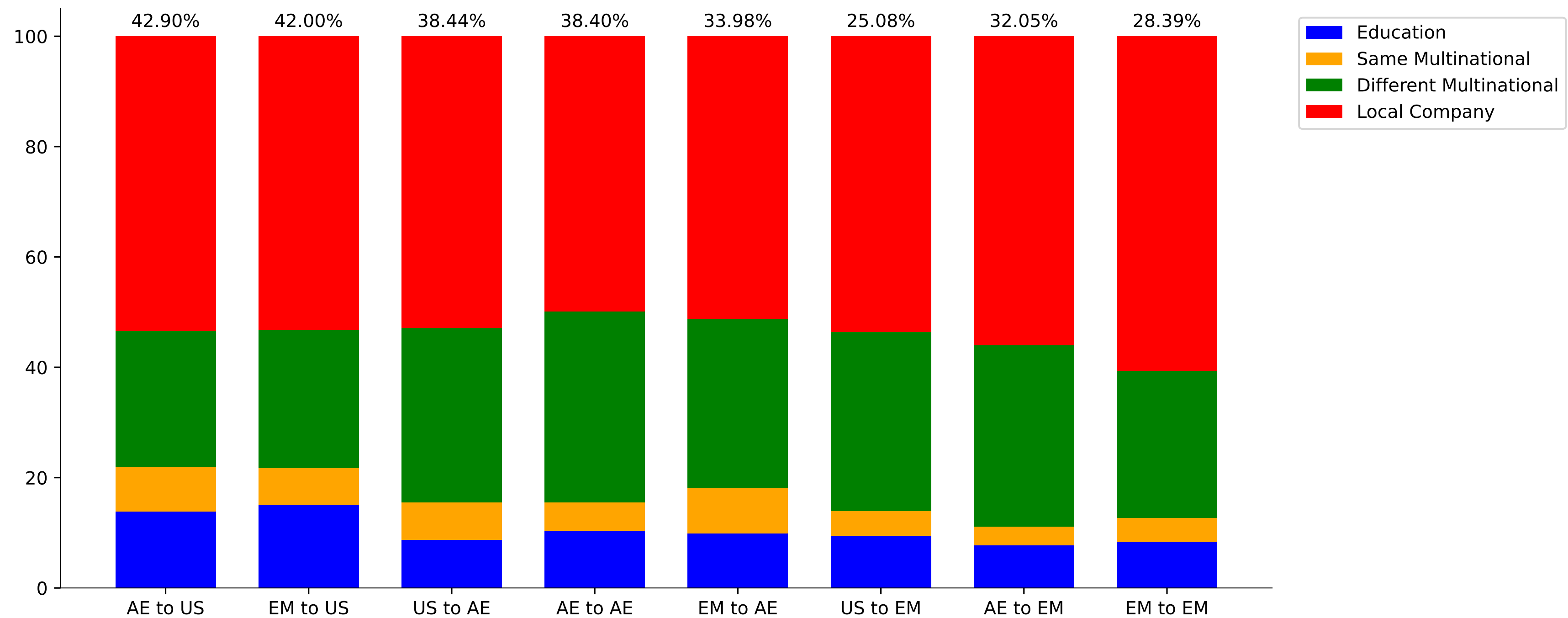
Notes: See notes on Figure 1. This figure shows the distribution of outflows across various origin and destination country categories. The numerical values displayed on the bars represent the outflow rate after 5 years. The color divisions within the bars signify the total outflows categorized into education 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



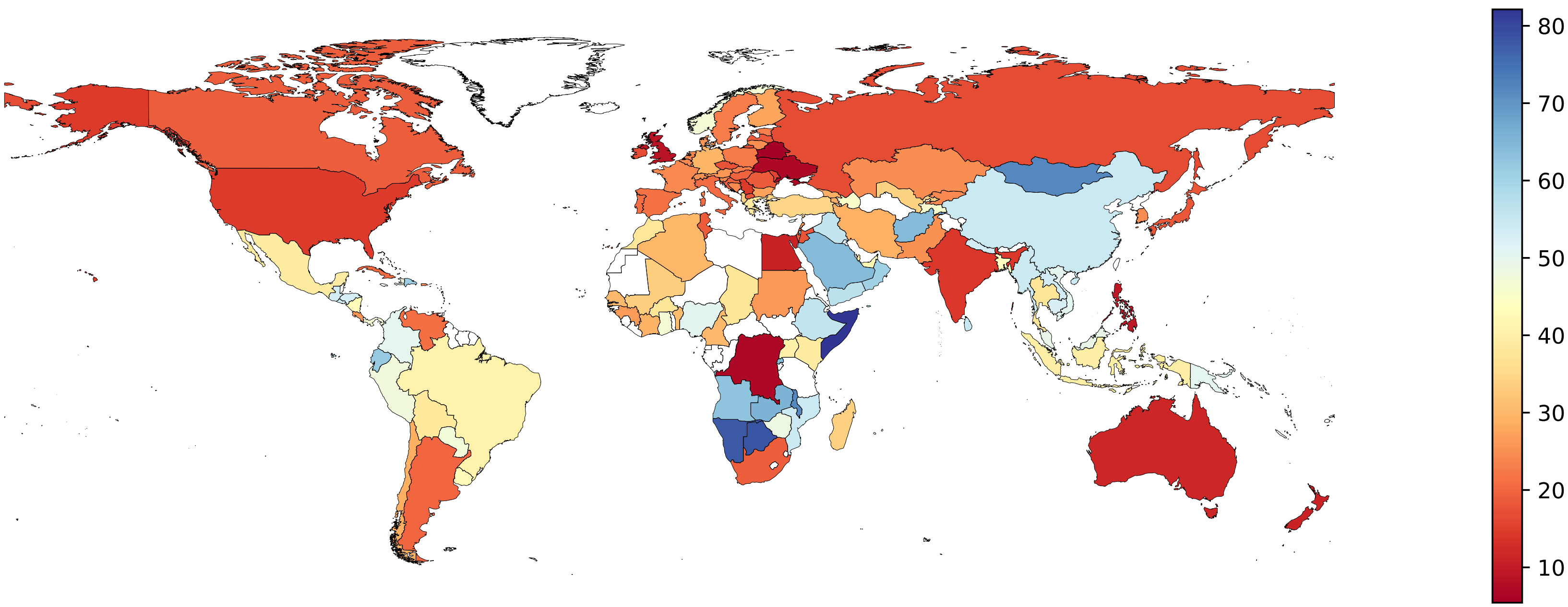
Notes: See notes on Figure 3. This figure is similar to Figure 3, but it now encompasses migrants who depart the destination country to a third country (not solely returning to the origin country). In essence, this figure depicts the percentage of migrants who leave the destination country, either returning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

Figure B4: Return to Education and Multinational Companies



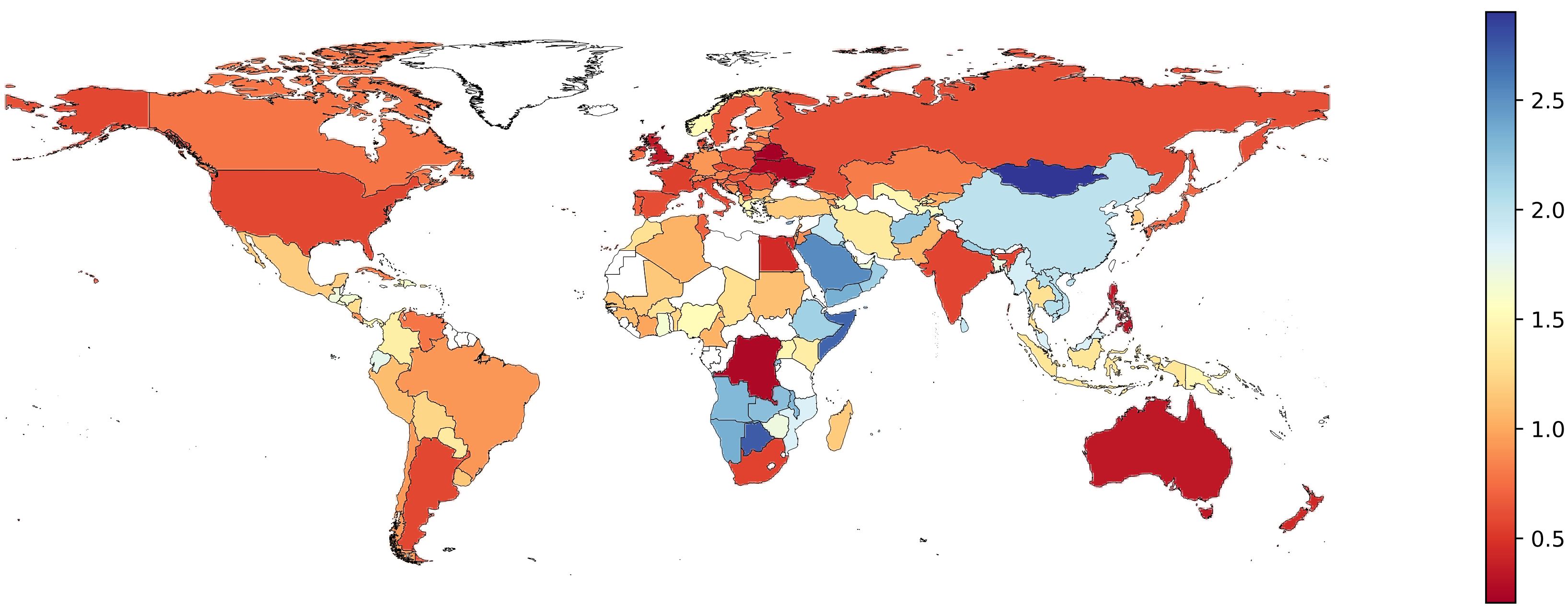
Notes: See the notes on Figure 3. This figure illustrates the distribution of returns across various origin and destination country categories. The numerical values displayed on the bars represent the return rate after 5 years of migration. The color divisions within the bars represent the total returns 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



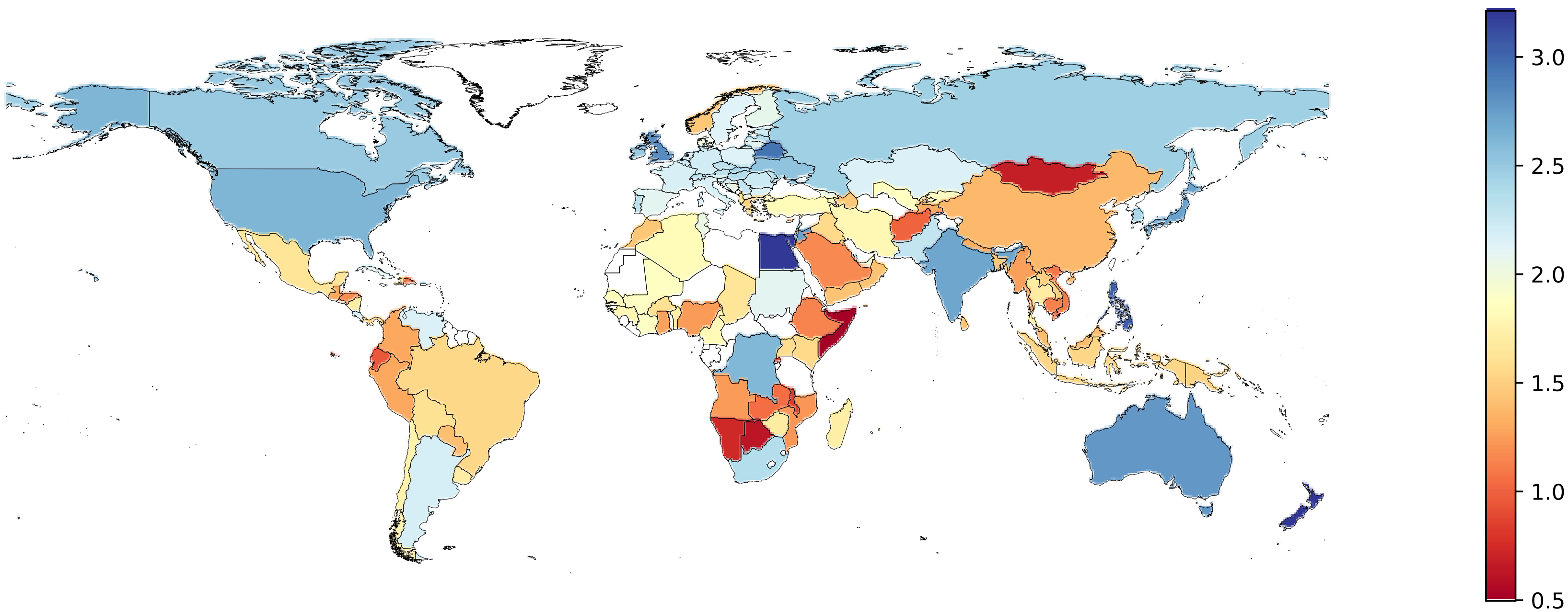
Notes: See notes on Figure 3. This figure presents the percentage of education migrants who promptly return to their origin country immediately after graduating without accumulating any job experience abroad. This percentage is derived from the subset of education migrants, defined as individuals engaged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

Figure B6: Average Accumulated Education Years Abroad Prior to Return



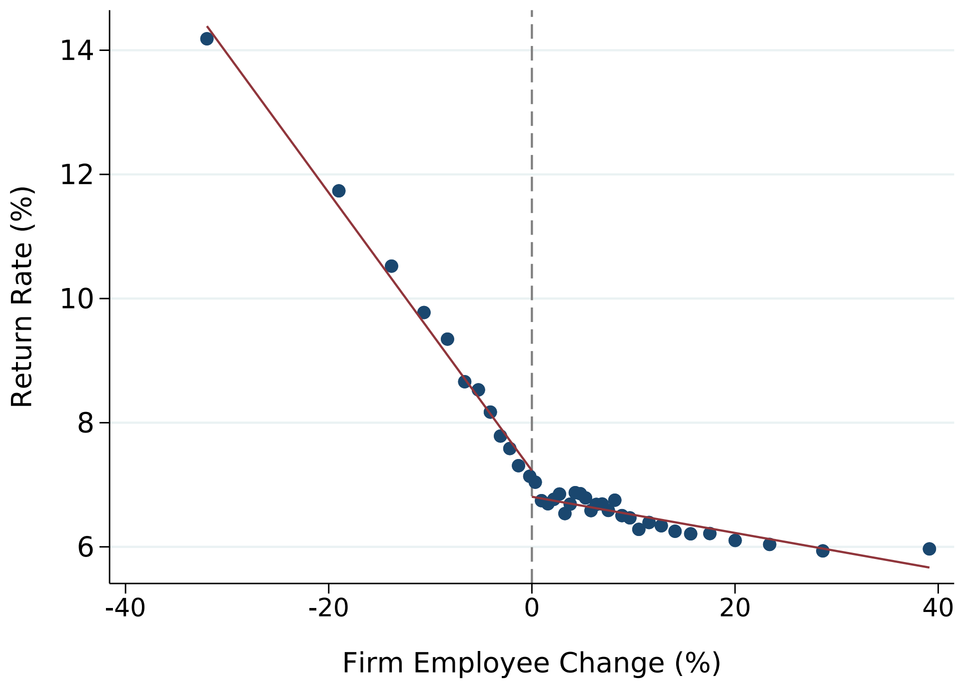
Notes: See notes on Figure 3. This figure illustrates the total number of education years accumulated abroad by returnees before their return to their origin country. The average is calculated across all returnees, not solely those who migrated for education.

Figure B7: Average Accumulated Job Experience Abroad Prior to Return



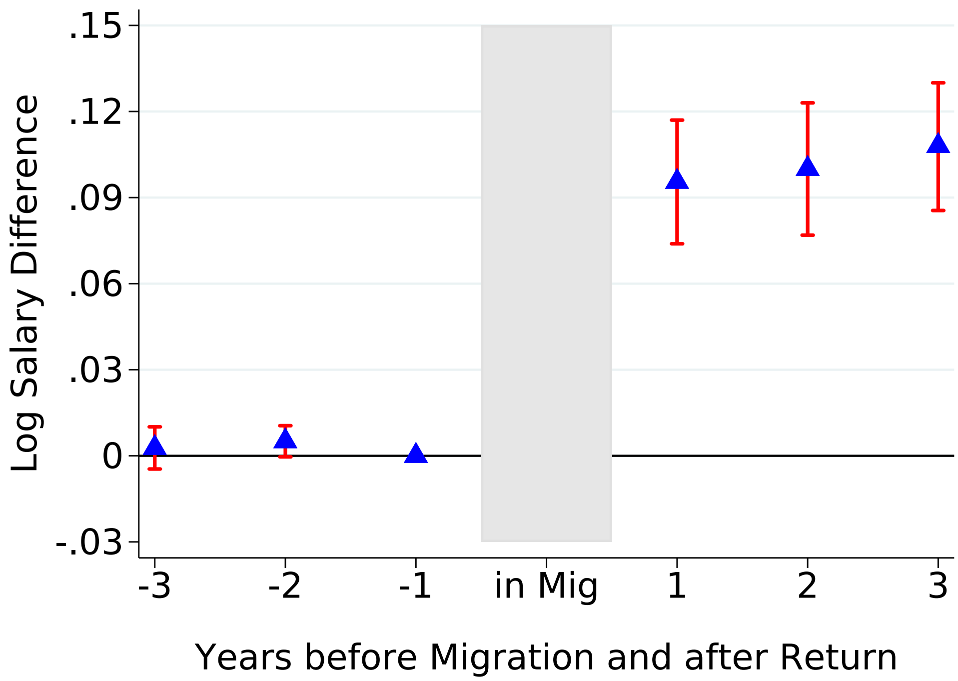
Notes: See notes on Figure 3. This figure depicts the total number of job experience years accumulated abroad by returnees before their return to their origin country. The average is calculated across all returnees and specifically includes those who migrated for education and returned after graduation.

Figure B8: Firm Employee Count Change and Return Migration



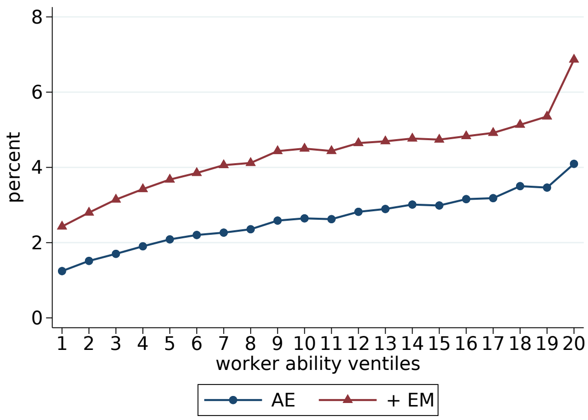
Notes: Figure displays a binscatter depicting the relationship between the return migration of a migrant and the changes in the employee count of the firm where the migrant is currently employed. We establish an individual-level panel of migrants employed (excluding those in education) in their destination 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

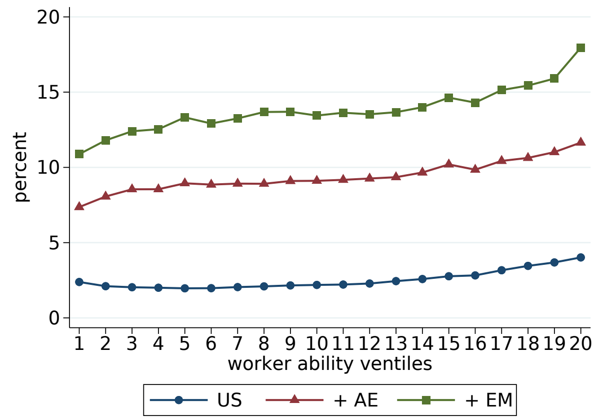


Notes: Refer to the notes on Table 5. In this figure, we apply the matching procedure detailed in section 6.3 and the associated notes from Table 5. However, our focus now extends to comparing the treatment and control groups over a broader temporal window: specifically, from 3 years before migration (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 possess 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.

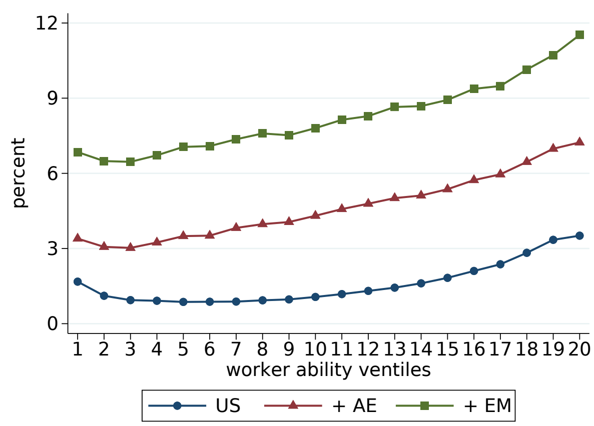
Figure B10: Share of Worker Ability Ventiles Across Different Regions



(a) United States



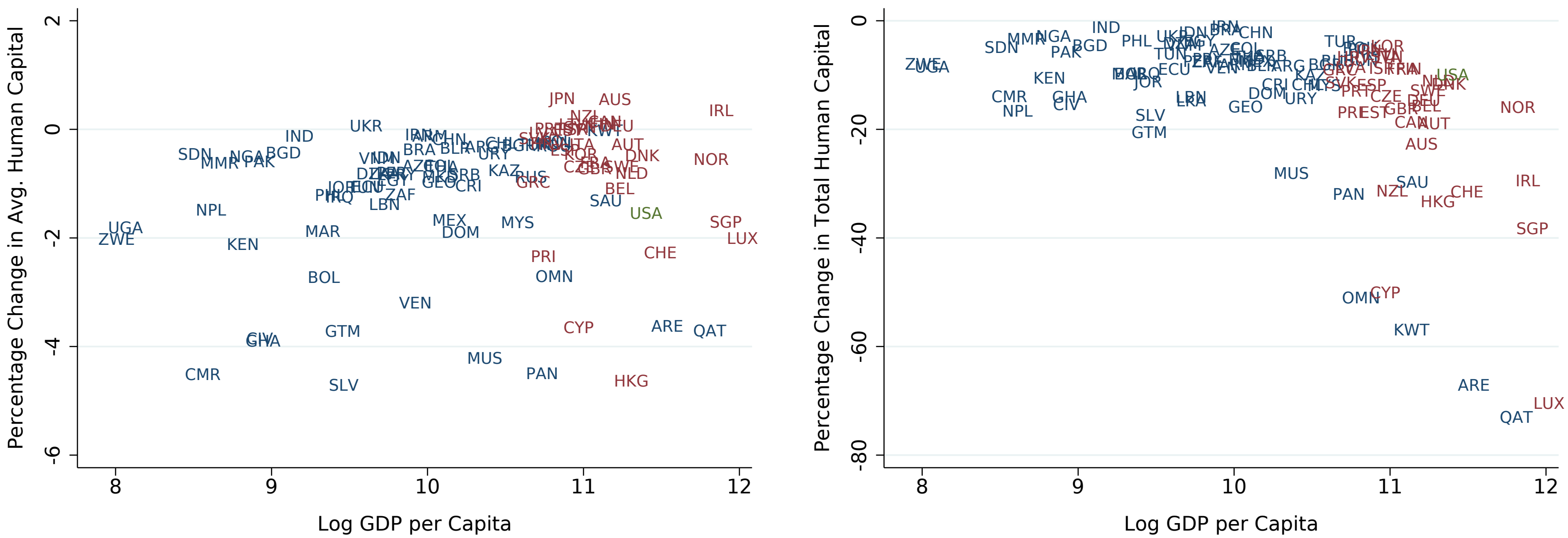
(b) Advanced Economies



(c) Emerging Market

Notes: Refer to notes of Figure 5. We divide the original populations of the three main regions into 20 ventiles using their individual fixed effects (worker mobility) and then for each ventile, find the share of individuals migrating to the US, advanced economies (AE), and emerging markets (EM). Panels a, b, and c display the shares for people originally from the US, AE, and EM, respectively. Each line represents the cumulative sum of the preceding lines. Ventiles 1 to 20 denote worker abilities sorted from low to high.

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: 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 C2: Returns to Job Experience - All Individuals

Revelio Salary	Glassdoor 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.