Global Migration of Professionals in the 21st Century Disaggregated by Gender, Education and Industry

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Abstract

This paper provides timely and detailed global estimates of trends in the migration of professionals from 2000 to 2023. We leverage a dataset of over 600 million public LinkedIn user profiles' CV entries to construct migration trajectories to provide new insights into gender differentials in global migration flows, and how these flows are shaped by industry and education in different migration corridors. We correlate LinkedIn-based estimates with census data from Eurostat, IPUMS-International, and IPUMS-USA, and propose methods to assess and correct biases using weights generated from official statistics. Our preliminary results indicate steady growth in the global population of professional migrants using LinkedIn, with disruptions associated with the 2008 global financial crisis and the 2020 COVID-19 pandemic. Our raw and unweighted data indicate that in 2023, the top destination countries for professional migrants were the United States, the United Kingdom, Canada, France, and Australia. We observe emergent migration corridors, such as India to the United Arab Emirates, as well as persistently dominant flows, such as India to the United States. We also observe considerable circulation between the US, UK, Australia, Canada, and India, and the results indicate that Europe is the most significant region for migration in- and out-flows. Additionally, we find that on LinkedIn, the top industries employing professional migrants globally are Manufacturing/Trade/Logistics and Consulting. Beyond offering new estimates on professional migration, this paper presents data and analysis that enrich research on the feminization of migration with greater global scale and sociodemographic detail. We find that women comprise an increasing share of professional migrants on LinkedIn since 2000, though the rate of growth has somewhat slowed since 2015. We observe some countries at gender parity among migrant professionals, especially in Europe, while other regions, such as the Middle East, primarily attract male migrants. In particular, we observe gendered migration corridors that are predominantly male (India-UAE) and predominantly female (China-USA). The preliminary estimates from LinkedIn presented in this draft offer a benchmark, which we will use for comparison with weighted data in the full analysis. We discuss the implications of the preliminary findings for understanding changing global professional migration dynamics and future labor force needs.

Keywords: Professionals; Migration; LinkedIn; Digital Trace Data; Gender

Introduction

The global movement of skilled professional migrants makes up a substantial and growing component of international migration flows. The population of highly educated migrants is growing three times faster than less-educated groups, and most immigrants to OECD countries now have a college education (Kerr et al. 2016; d'Aiglepierre et al. 2020; Walton-Roberts 2022).

When professionals move across international borders, they bring skills, knowledge, and expertise that can have significant social and economic impacts. The mobility of professionals is a keystone for economic growth and innovation in modern societies, providing an important source of labor for countries facing skills shortages and shrinking native-born workforces. It also plays a crucial role in fostering economic development, innovation, and the circulation of knowledge in both sending and receiving countries (Docquier and Rapoport 2012; Czaika 2018).

Yet despite its increasing significance, we lack a comprehensive global understanding of skilled, professional migration and how these patterns have changed over time. In particular, our understanding of the determinants of gender differentials in skilled migration flows remains limited. Women are increasingly moving independently for work or study as we observe a "feminization of migration" (Docquier, Lowell, and Marfouk 2009; Kofman 2014; Donato and Gabaccia 2015; Yildiz and Abel 2024; Morellini and Block 2024). Gender is a key factor shaping global migration flows, yet we know little about what factors shape these gendered patterns. There is some indication that the growth of professional women migration is linked to increased female educational attainment in universities and growing employment in specific industries (Kofman 2014; Walton-Roberts 2024; Jacobs et al. 2025). However, we lack a broad, systematic analysis of these dynamics at a global level, or how these trends have shifted over time. Without a longitudinal perspective and a global data coverage, it is difficult to assess shifting dynamics and future areas of growth in specific migration corridors. In addition, prior studies often lack sufficient granularity to examine the determinants of gender differentials in global migration patterns and how they are shaped by educational attainment and industry in specific countries.

Many of these empirical gaps persist due to well-known data limitations in migration research (Willekens et al. 2016; Dańko et al. 2024). Conventional administrative, census, and survey data are typically inconsistent or incomparable across countries, which makes it difficult to examine and compare bilateral flows globally. Further, cross-sectional survey data have issues with examining trends over time, especially related to compositional changes in the migrant population. Additionally, conventional data sources are often too coarse-grained and lack sufficient detail to capture patterns by gender, educational attainment, or industry, leaving many questions unanswered about the complex dynamics of skilled international migration. Finally, in many data-sparse regions of the world like Latin America and Africa, there is little information about professional migration.

To address these challenges, we produce a novel and harmonized database of global flows of professional migrants in the first quarter of the 21st century. Drawing on over 600 million publicly accessible LinkedIn user profiles, we generate a timely and detailed dataset that enables the analysis of gender gaps in the movement of professionals across countries and over time. We provide bilateral migration flows and historical trends for the past 23 years, disaggregated by gender and industry, for the working age population (15-64 years old) with at least some tertiary education. To mitigate biases inherent in LinkedIn data, we propose a weighting approach in line with state-of-the-art techniques in digital trace data research (Drouhot et al. 2022; Chi et al. 2025).

Our analyses of the subset of publicly accessible LinkedIn user profiles reveal trends over time in the global composition and direction of skilled migration flows. We examine how these patterns vary by gender and industry, which provides new insights into global professional migration dynamics and the factors shaping these trends.

This paper offers novel conceptual and methodological contributions. First, it provides insights into global gender gaps in skilled migration at a scope and depth not readily available with other data sources. Moreover, it demonstrates the utility of digital trace data as a complement to conventional survey and census data. The granularity of our data enables us to answer new questions about the composition of the international skilled migrant population across unprecedented levels of disaggregation and time periods. In addition, the global scope and temporal depth of the data enable us to examine migration dynamics in key and emerging corridors. We analyze bilateral migration flows from a single data source, which resolves common issues of data harmonization and definitional inconsistency in administrative data sources from different countries. Because our data have global coverage, we also offer insights into data-sparse regions like Latin America and Africa, where little is known about the dynamics of professional migration.

The data also provide exciting breadth and granularity with relation to time. We offer a longitudinal perspective over the past 23 years. To the best of our knowledge, this is one of the first papers to offer longitudinal global trends in skilled migration patterns at this level of detail or scope. The present results are particularly useful for establish baseline benchmark estimates for comparison with future weighted analysis. Further, they provide insights into countries with high levels of LinkedIn coverage, where we observe strong correlations between our LinkedIn data and IPUMS migration flows.

Data and Methods

LinkedIn Employment Histories

This study leverages 612,328,546 public profiles from LinkedIn to analyze the employment and migration trajectories of professionals moving internationally for work. This includes users from all available countries and, while missing on non-public LinkedIn profiles, it provides some of the most comprehensive data available on LinkedIn users globally.

LinkedIn is the largest professional networking platform used globally. Users post their education and employment histories for professional visibility and potential employer recruitment (Smith and Watkins 2023; Dixon 2023). We leverage the location and duration information in these entries to construct retrospective longitudinal migration histories that follow migrants across career stages and across countries. This digital trace data offers an opportunity to analyze trends in a timely manner and captures a broad population of professional migrants that does not rely on a specific definition based on educational attainment, occupation, or skill category (Parsons et al. 2020). In addition, LinkedIn's public profiles' global reach offers wider coverage of countries than is available in OECD data, which can provide insights into under-studied regions where little is known about professional migration dynamics. LinkedIn data has been increasingly used to study international labor mobility and professional migration, including analyzes of migration flows (State et al. 2014), relocation preferences (Perrotta et al. 2023), spatial distributions of university graduates (Heo, Chang, and Abel 2023), gender differences in professional migrant flows (Jacobs et al. 2025), and the labor market incorporation of skilled migrants (Breschi et al. 2020; Jacobs 2025).

In this paper, we compile a database derived from raw LinkedIn profile data produced by Revelio Labs, a company that collects workforce data from online public profiles and job postings. Revelio Labs collected all publicly available profiles from LinkedIn, with information about users' educational background, employment trajectories, and migration history.

Revelio curates and structures this data with machine learning algorithms and demographic inference techniques (See Revelio Labs, Individual Level Data 2025 and Academic Data Dictionary for detailed methodology[1]). We further refine the measures provided by Revelio with specialized techniques for gender, education and industry classification, described below.

Beginning with the first recorded education spell and ending with the most recent reported job, we construct individual-level, time-varying data containing all reported education and job spells for each LinkedIn user with a public profile. It includes start and end dates, position type, and location. With the time and location information, we measure the population of LinkedIn users in each country in a given year. We report aggregated flows that do not include personal identifying information, such as username, university, or company, and from which it is not possible to identify individuals. These data have been collected, stored, and managed in compliance with GDPR considerations, the Max Planck Society Ethics Review Board (ERB), and the University of Connecticut Institutional Review Board (IRB).

Of the approximately 1.2 billion total LinkedIn accounts, our data include over 711 million profiles that are publicly available. Our dataset focuses on the 612,328,546 profiles that include at least one education or job spell. We use this information to locate users geographically, providing a robust empirical foundation for analyzing global professional migration. In this paper, we restrict our empirical analysis to LinkedIn users who report at least some tertiary education, to provide focused insights into highly educated skilled migrants.

LinkedIn data sourced from Revelio Labs has been used in related fields, such as economics and business administration (Brüstle et al. 2025). To the best of our knowledge, ours is one of the first demographic studies to use Revelio's LinkedIn dataset for large-scale global analysis of professional migration.

[1] https://www.data-dictionary.reveliolabs.com/data.html

Measures.

Our LinkedIn sample population analyzes the 612,328,546 user profiles with at least one education or employment entry reported on the profile. From this information, we develop six key measures for our analysis.

<u>LinkedIn population (according to our curated data).</u> Our dataset spans the period from 2000 to 2023, which allows us to retrospectively reconstruct the coverage based on the information reported in current profiles. Rather than measuring coverage in terms of registered LinkedIn users at a given point in time, we calculate the coverage as the number of profiles with at least one education or employment entry reported in each year within the period 2000 to 2023. This allows us to identify historical patterns of professional activity and mobility prior to LinkedIn's launch in 2003, leveraging retrospective entries reported by users who later joined the platform or in geographical regions where the platform's coverage is substantially lower. Consequently, our coverage metric reflects the temporal distribution of reported career and education entries on public LinkedIn profiles, rather than the platform's user base in a given year. We use the term "LinkedIn users" to refer to the number of people in a given country in a given year reconstructed from the information reported in their current profiles. We are aware that while these cover more than 600 million user profiles, it is still limited to publicly accessible ones. We assign users to the population as a proportion of the months they spent in the country that year, with each month representing 1/12 of the total year. For example, if a user arrived in a country in May, we would count them as part of the population in the country for the remaining seven months of the year.

<u>Country.</u> We use the location information in each job position or education entry to classify a user's country in any given work or study spell. For job positions, we use the "country" category provided by Revelio, which is derived from the location users report for each job entry. For education entries, we use the location that Revelio derives from each reported school or higher education institution.

<u>Migration flows and stocks.</u> We define an international migration as a change in the country of education or employment that lasts more than 12 months. We measure time from the start of one job or education spell to the start of the next position. This 12-month definition of migration is consistent with recent studies (Chi et al. 2025) and the United Nations definition of migration (UNDESA 1998; ECE 2011). We construct migration flows by measuring the number of migrant arrivals from country X to country Y in a given year. We measure migrant stocks as the number of migrants located in each country each year. In other words, we count migrants as part of the population in the destination country for every subsequent year after the migration event, until they report a new country change.

Gender. We infer a user's gender using their first and last name, and a neural network model trained on data from Wikidata on people with an assigned gender as male or female. We then assign a probability that the user is either male or female based on the gender of other people with the same or similar names. This draws on the methodology applied to the Scholarly Migration Database (Akbaritabar et al. 2024). A strength of this method is that we are able to use first and last names, which provides more information about a user's potential gender than just first names on their own, which is the case for the methodology applied by Revelio Labs. The method also provides a confidence value between 0 and 1. We apply a threshold of 0.8 to assign a user's gender and label names with a lower score as "unknown."

Appendix Figure A shows the ROC curves for gender prediction models. The results show that our model outperforms (AUC=0.960) other gender inference models such as Gender API and Genderize (AUC=0.905 and AUC=0.842, respectively). It performs at a similar level as Namsor AUC=0.960), but our model allows us to assign gender to users in millions more cases, i.e., does not have API rate limits as other models' source codes are not publicly accessible.

Our model has less predictive accuracy in contexts with non-Western names or users with gender-ambiguous names. As we detail in the methodological appendix, our research team hand-coded sub-samples of names from different regions to improve the accuracy of the corpus of names and refine our approach.

Even with careful hand-coding and refinement, the gender classification in some countries still included "unknown" or missing cases. The rate of missingness was relatively low in the key countries in our analysis; however, we adjusted for these issues in our analysis to make more consistent comparisons across regions in our dataset. As such, we report the proportion of women among professional migrants, as a share of the total population of users for whom we were able to assign a gender.

Education. We assign time-varying educational information to each user based on the information reported in their profile in each year. This assigns the highest degree reported at each time point based on graduation dates reported in a profile. As we discuss in the methodological appendix, we harmonize information in users' education spells to measure degree level and standardize degree classifications across international education systems. This combines degree classifications inferred by Revelio using machine learning and manual refinements by our research team to improve classification in specific contexts.

Industry. Finally, we code a user's industry of employment based on classifications provided by Revelio Labs. Revelio infers industries based on company names and classifies them into 200 industry categories using the North American Industry Classification System (NAICS), which we then group into 13 industry categories. These include: Manufacturing, Trade and Logistics; Consulting; Education; IT/Telecommunications; Finance; Government; Healthcare; Service/Hospitality; Energy; Real Estate; Business Management; "Other;" and "Unknown." "Other" includes all NAICS industries not included in these groups. "Unknown" includes employment entries where we were unable to classify the industry based on the information provided.

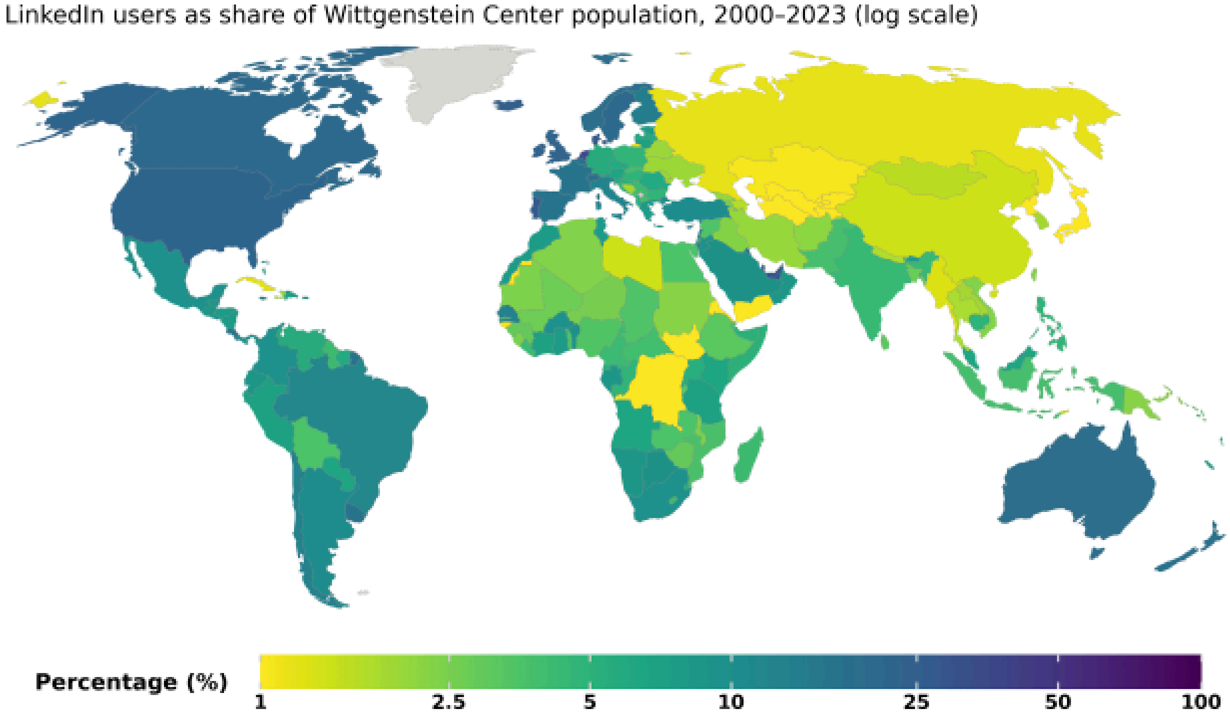
Data Weighting and Validation

To assess the coverage of LinkedIn usership around the world, we examine the size of the population of LinkedIn users across countries and over time. Appendix Figure B shows the global coverage of the 612,328,546 million LinkedIn users in our data. Panel A shows the average coverage across the entire study period of 2000-2023, constructed with retrospective employment and education information. It shows that the United States is the country with the most LinkedIn users, followed by China, India, Canada, Brazil, the United Kingdom, France, Germany, Spain, and Australia. It also shows that while coverage is overall lower in Africa, Central Asia, and parts of Latin America, LinkedIn, according to the publicly accessible profiles used here, is nonetheless used in nearly every country in the world. This is an important contribution of the paper, which provides insights into data-sparse regions where little is known about the dynamics of professional migration.

Panel B disaggregates the coverage into three periods, illustrating how LinkedIn coverage has changed over time. When looking at the panels for the first two periods (2000-2007 and 2008-2015) compared to the most recent period (2016-2023), it shows that coverage has grown across the study period, with increasing coverage across the world in more recent years. In particular, coverage has become even more widespread in established countries like the United States, Brazil and India, and has also become more prevalent in countries like China and Indonesia. There has also been growth in coverage in countries with smaller populations registered on LinkedIn in Africa and Central Asia.

These data, however, only capture information about users on LinkedIn and are only partially representative of the total working or migrant population in any given country. To measure the penetration of LinkedIn usership, based on the publicly available profiles, Figure 1 shows the population of LinkedIn users as a share of the working-age population (15-65 years old), averaged from 2000-2023. It shows that LinkedIn penetration is highest in North America, Western Europe, and Australia, with rates approaching 50 percent. The penetration rate is slightly lower in Central and South America, with rates closer to 25 percent. In Africa and East Asia, the penetration rate is lower.

Figure 1. LinkedIn Penetration Rate, 2000-2023 (Revelio Labs data on public LinkedIn profiles and Wittgenstein Centre for Demography and Global Human Capital)



As shown in the Appendix Figure C, the penetration rates also vary by gender, with higher rates of usership among men compared to women in India, Saudi Arabia, Iran, Eastern Europe, Russia and many countries in Africa. In other regions, such as North and South America and Europe, we observe more comparable penetration rates for men and women.

In addition to variation in the penetration rate across countries and gender, there are other factors to consider when assessing representativeness of LinkedIn data. First, there may be unobserved factors that influence both the propensity to use LinkedIn and the propensity to migrate. Additionally, these data reflect the retrospective employment and education information available on user profiles. This might be an artifact of the age and cohort composition of LinkedIn users in a given country. In other words, older users with longer periods in the labor market may report retrospective employment histories that go further back in time. Thus, countries with a larger share of older users might have more reported coverage at earlier time points.

To address these issues and provide population-level migration estimates that account for biases in the LinkedIn population, we implement a normalization approach that leverages various weighting techniques to adjust our estimates toward known population benchmarks. Specifically, we calibrate our estimates using census-based data accessed through IPUMS-International (Ruggles et al. 2025a), which accumulates and harmonizes 10% of the national census data; IPUMS-USA (Ruggles et al. 2025b), which, unlike IPUMS-International, offers longer time series of migration to the United States, from 2000 to 2023; and Eurostat, which provides complementary European data for weighting.

We adjust our Revelio sample population with population estimates from the Wittgenstein Centre for Demography and Global Human Capital (K.C. et al. 2024), which provides demographic distribution by gender, age group, and educational attainment. For the purpose of this analysis, we restrict the reference population to the segment of working age-population (15-64).

We calibrate our data with this administrative information, and match on educational attainment and gender. Building off Chi et al. (2025)'s methodology, we apply various weighting approaches, including the selection rate, inverse penetration rate, and demographic adjustments. These methods account for differential LinkedIn coverage rates across countries and genders, thereby aligning LinkedIn-based estimates more closely with representative population distributions. In the current version of preliminary findings, these weighted results are not presented.

Methodological Framework

We evaluate LinkedIn-derived migration flows against official census and administrative statistics following the weighting and calibration strategies proposed by Chi et al. (2025). This framework allows us to identify the extent to which LinkedIn data can serve as a proxy for official migration statistics and how weighting schemes reduce systematic biases. We start with administrative data from Eurostat.

Importantly, here we report only country-level formulations of the weighting methods. These will be extended to incorporate additional user characteristics – such as age, gender, educational attainment, and sub-national regions – allowing for finer-grained corrections. We outline generalizable formulas that include this disaggregation. For clarity, we report here the country-level specifications.

Let:

- L_{odx}: LinkedIn-based migration flow estimates from origin *o* to destination *d,* where *x* incorporates additional disaggregation such as gender or education
- O_{odx}: Official statistics-reported migration flows from origin *o* to destination *d,* where *x* incorporates additional disaggregation such as gender or education
- U_c: LinkedIn user base in country *c*
- P_c: population of country *c*

For each method, we evaluate both the Spearman correlation coefficient and the mean absolute error (MAE). We plan to apply the following weighting methods:

1. Raw Estimates

The baseline approach compares LinkedIn flows directly with official statistics:

ρ_{raw}= corr (L_{odx}, O_{odx})

2. Inverse Penetration Rate Weights

To correct for variation in LinkedIn penetration across countries, we define weights based on the inverse penetration rate:

$w_c = 1 / (U_c\, P_c)$

and weight flows by origin country:

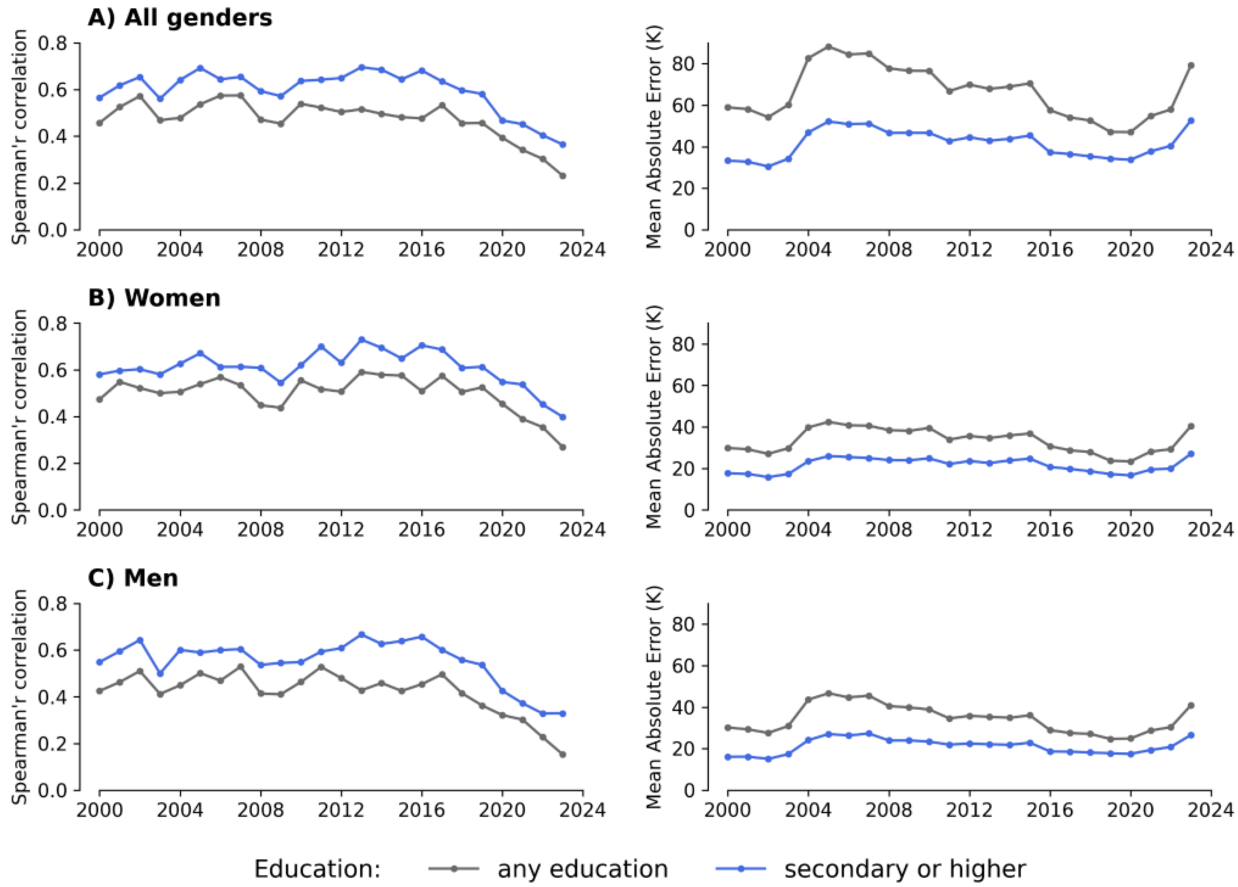
$L_{odx}^{(w)}=L_{odx} \cdot w_o$

3. Selection Rate Adjustment

The Chi et al. 2025 paper notes that penetration-based weights work reasonably well in high-income contexts, but overstate migration in lower-income countries, where the Facebook user base is more selective (e.g., more educated, wealthier, and more mobile than the general population). To address this, they propose a hybrid weight that interpolates between penetration-based correction and a constant adjustment term, depending on the income level of the country. This will need some careful investigation into how it can be adapted to the LinkedIn data.

Figure 2 compares our estimated migration flows to the United States with those obtained from IPUMS, reporting both Spearman correlation metric and mean absolute error (in thousand), by gender and educational attainment. The results show that estimates based on the full sample ("any education") perform systematically worse, with lower correlations and higher errors. In contrast, restricting the analysis to the individuals with secondary education or higher yields stronger correlations and lower errors. This further supports our reasoning to focus on this subgroup, as it better represents the composition of the LinkedIn user base. Over time, we observe a decline in correlation and a corresponding increase in error in the most recent years, likely reflecting an issue of right-censoring in the data. We do not observe significant differences by genders, which show similar performance across groups. In our next step, we will apply weights to migration flows.

Figure 2. Estimated Migration Flows vs. IPUMS Migration Flows, 2000-2023



Caption: Comparison between our estimated (currently unweighted) migrations flows to the United States based on publicly accessible LinkedIn profiles, and IPUMS benchmarks, reporting Spearman correlations and mean absolute error (in thousands), disaggregated by gender and educational attainment, over time (2000-2023).

Analytic Approach

We produce annual estimates of the professional migrant population on LinkedIn by country for every year from 2000 to 2023, calculating in-, out-, and net migration in each country for each year. To construct these measures, we assign individuals to the same country as in the previous year, unless a new location is reported. If a user changes countries mid-year, we assign the person to each country for a proportion of the year based on the duration of reported employment.

Our analysis also measures bilateral flows, defined as the population of migrants that reported on LinkedIn to have left a given origin country and arrived in a given destination country in a given year. These bilateral estimates help us identify major and emerging country-pair migration corridors, shedding light on the global patterns of professional mobility. The second component of our analysis disaggregates these dynamics by gender and industry, allowing for detailed analyses of compositional change over time.

To provide insights into highly educated skilled migrants, we focus our empirical analysis in this paper on LinkedIn users who report at least some tertiary education. This is consistent with other studies using advanced education to identify skilled migrants (d'Aiglepierre et al. 2020; Parsons et al. 2020). We define our population as anyone who has at least some post-secondary education.[2]

In this paper draft, we report unweighted estimates from publicly accessible LinkedIn user profiles. This establishes benchmark patterns of professional migration dynamics on LinkedIn, which we will then use as a point of comparison with the weighted estimates in subsequent analysis.

As we discuss in our section on weighting, we find relatively strong correlations between the unweighted Revelio data and baseline measures from IPUMS-USA. Further, our data provide strong coverage in key migration destinations, which helps us analyze the patterns in these data and benchmark our findings to prior work on skilled migration. The patterns we report in our analysis are largely consistent with previous studies.

Thus, the analysis presented here provides valuable baseline insights for external and internal validation, and promising indicators that LinkedIn offers a valuable window into professional migration dynamics. We will further strengthen these contributions as we refine the measures through additional weighting techniques, which will be particularly useful for areas with lower rates of LinkedIn penetration in more data-sparse areas of the globe.

We report results up to 2023. This is the most recent year with a full 12-month period of observation, which addresses some issues with right-censoring with the 2024 data. Further, the IPUMS data we are using to calibrate our data is currently only available through 2023; when the next year of data become available, we can use this to adjust the 2024 data for further analysis.

Preliminary Results

To understand patterns and trends in the composition of the professional migrant population across countries and over time, we begin our analysis by establishing global patterns of professional migration as reported on LinkedIn.

Professional Migrant Destination Countries

[2] Our approach includes users who may not have yet completed their tertiary education, which we recognize is an important threshold for occupational attainment and labor market entry (Baum, 2014). We employ a more flexible approach to identify the full population of users with some tertiary education based on all of the available pieces of information on a user's profile. This captures the gradient of benefits associated with obtaining some tertiary education (Giani et al. 2020) and expands coverage in our analysis. Education fields on LinkedIn profiles are user-generated, and thus, some profiles have missing information. Our approach balances these fluctuations in user inputted information with the most education coverage possible based on the information reported.

Table 1 Panel A. Top 10 Destination Countries, 2000-2023

	2000		2005		2010		2015		2020		2023	
1	USA	1315454	USA	2119886	USA	3504380	USA	5883274	USA	8445696	USA	9813771
2	UK	510921	UK	890622	UK	1549725	UK	2555685	UK	3595838	UK	4199799
3	Canada	262015	Canada	461886	Canada	816609	Canada	1404747	Canada	2281014	Canada	2914277
4	France	224343	France	412250	France	750140	France	1348723	France	2221462	France	2657535
5	Australia	204056	Australia	381467	Australia	695850	Australia	1141298	Australia	1673689	Germany	1926511
6	Germany	165093	Germany	302136	Spain	562874	Germany	1014139	Germany	1606962	Australia	1900086
7	Netherlands	156023	Spain	300519	Germany	543520	India	991034	India	1570986	India	1880387
8	Spain	140168	Netherlands	249025	India	511248	Spain	908892	Spain	1502625	Spain	1815846
9	India	98818	India	212002	UAE	454968	UAE	897258	UAE	1343310	UAE	1656310
10	Switzerland	90517	UAE	184107	Netherlands	420695	Netherlands	692892	Netherlands	1094636	Netherlands	1282646

Table 1 Panel A shows the top destination countries for professional migrants on LinkedIn, which are derived directly from Revelio data and are not yet weighted using IPUMS or Eurostat data. It indicates that in 2023, the top 10 countries with the largest professional migrant stocks were the United States, the United Kingdom, Canada, France, Germany, Australia, India, Spain, the United Arab Emirates, and the Netherlands.[3]

The table also shows the top destinations over time, in five-year increments. It shows that the leading destination countries have been relatively consistent since 2000, and concentrated in Europe, North America, and Australia. At the same time, we observe the emergence of India and the United Arab Emirates as destination countries. In the case of India, this may reflect some patterns of return migration from other destination countries, which we explore further below in our discussion of bilateral country flows. For the UAE, this likely reflects the increasingly dominant share of the labor force comprised by foreign-born workers (over 90 percent), and significant economic growth in key industries like Energy, Consulting and Manufacturing/Trade/Logistics (De Bel-Air 2018). While these results might be updated after weights are applied, nonetheless, they offer insights into UAE's current condition based on public LinkedIn profiles.

The table indicates growth in the LinkedIn migrant stock in the top 5 destination countries from 2000 to 2023. It shows that the population of professional migrants has grown in all five destinations since 2000, with more growth in the U.S., relative to other countries. This reflects an increasing number of migrant professionals in these destinations, as well as organic growth in LinkedIn coverage over time, which will be further refined in our subsequent weighted analysis.

[3] These results provide insights into the countries employing the largest number of highly educated professional migrants with LinkedIn profiles. As we note above, these patterns reflect both the population size of the country and LinkedIn usership. Because the data in these key destination countries are already highly correlated with migration flows, these results provide a useful window into professional migration in these destination countries, which will be further refined in our subsequent weighted analysis. The raw numbers reported here should be interpreted as indicators of the relative magnitude of migrant stocks among LinkedIn users, rather than population estimates.

Destination Countries by Gender

Table 1 Panel B. Top 10 Destination Countries by gender, 2000-2023

Men

	2000		2005		2010		2015		2020		2023	
1	USA	802162	USA	1219062	USA	1873626	USA	2949644	USA	4050494	USA	4687679
2	UK	305715	UK	501079	UK	816465	UK	1254758	UK	1701172	UK	1981149
3	Canada	155965	Canada	260438	Canada	428589	Canada	689242	Canada	1075317	Canada	1366544
4	France	131606	France	228864	France	390285	France	661222	France	1060637	France	1256160
5	Australia	124948	Australia	218305	Australia	369134	India	653454	India	1022940	India	1222311
6	Germany	106412	Germany	185847	India	347310	UAE	578507	Germany	850725	UAE	1030061
7	Netherlands	86693	Spain	164213	Germany	313826	Australia	563159	UAE	842373	Germany	1017104
8	Spain	81664	India	147988	UAE	306886	Germany	552079	Australia	788046	Australia	884628
9	India	70559	Netherlands	132838	Spain	286759	Spain	441053	Spain	715981	Spain	860422
10	Switzerland	58684	UAE	131937	Netherlands	213585	Saudi Arabia	417985	Saudi Arabia	570504	Saudi Arabia	667434

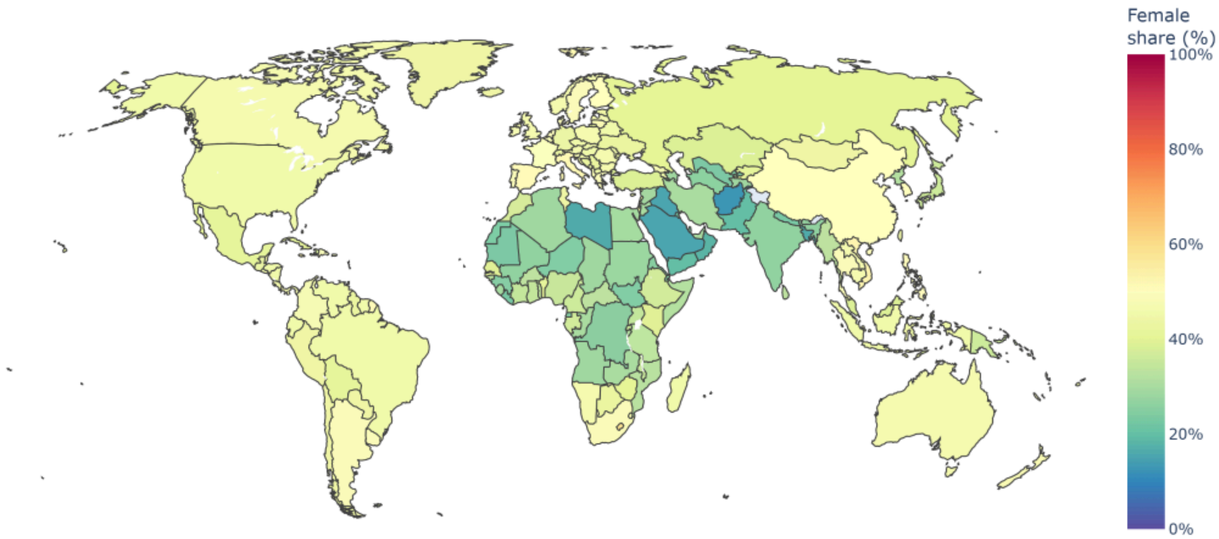
Women

	2000		2005		2010		2015		2020		2023	
1	USA	378608	USA	672485	USA	1219862	USA	2183015	USA	3269433	USA	3806910
2	UK	167053	UK	313909	UK	585889	UK	1039817	UK	1504321	UK	1735221
3	Canada	82103	France	162286	France	318176	France	608146	France	1028721	France	1241716
4	France	81918	Canada	155671	Canada	301446	Canada	551168	Canada	911398	Canada	1160478
5	Australia	61160	Australia	126177	Australia	253151	Australia	446171	Spain	725673	Spain	883140
6	Netherlands	60131	Spain	124327	Spain	252899	Spain	429443	Australia	670681	Germany	775895
7	Spain	52744	Netherlands	100741	Germany	195754	Germany	393963	Germany	644786	Australia	764913
8	Germany	50450	Germany	98512	Netherlands	179233	Netherlands	309682	Netherlands	505448	Netherlands	592180
9	Italy	29895	Italy	65911	Italy	134392	Brazil	279331	Brazil	460343	Brazil	546999
10	Sweden	29558	Switzerland	54851	Brazil	116555	Italy	246836	Italy	403830	Italy	479021

We next disaggregate migrant destination countries by gender, which reveals distinct patterns for men and women. Table 1 Panel B shows the top destination countries for men and women LinkedIn users by year. It indicates that in 2023, the United Arab Emirates and Saudi Arabia were top destinations for men, while Brazil and Italy were more common destinations for women. This highlights gendered migration streams in contexts like the Middle East, where employment in sectors like energy and oil is largely male-dominated (De Bel-Air 2018).

When exploring these dynamics over time, we see that the overall composition of major destination countries has remained relatively consistent in Western countries. We observe notable growth in male migration to India, the United Arab Emirates and Saudi Arabia, suggesting that this is a gendered migration stream driving the growth of migration to the Middle East and South Asia. These results could also be affected by return migration of professionals who create their profile elsewhere and return to their country of origin but do not have CV entries for education or employement in their country of origin.

Figure 3 Panel A. Women migrants as share of all professional migrants on LinkedIn with secondary or higher education by country, 2023



Beyond raw estimates, we also explore the gender composition of the migrant population in destination countries. Figure 3 Panel A shows a map of women as a share of all professional migrants on LinkedIn in 2023. The figure indicates that some countries like Vietnam (52%), Italy (51%), Spain (51%), Finland (50%), China (50%), the Philippines (50%) and Korea (50%) are at gender parity in the professional migrant population. We also observe considerable gender inequality in destination countries. Some countries like Pakistan, Oman, Saudi Arabia, Iraq and Afghanistan have largely male professional migrant populations, with women comprising less than 20 percent of all professional migrants. In contrast, women comprise the majority of professional migrants in many countries in the Caribbean, including Martinique (58%), Barbados (57%) and Jamaica (54%).

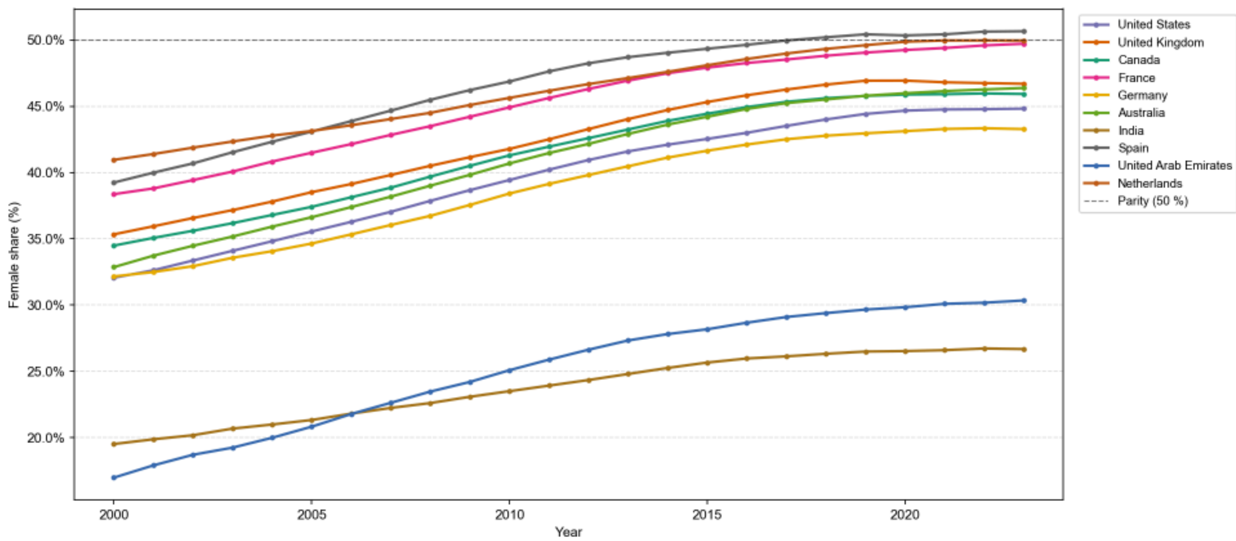
In most of the top destination countries, the population was slightly more male than female, with percents ranging from 42 to 47 percent in the United States, UK, Canada, Germany and Australia. India (27%) and the UAE (30%) were notable exceptions, with largely male populations of professional migrants.

These results indicate gendered migration patterns across regions. In particular, host countries in the Caribbean, Europe and East Asia are larger destinations for women migrants, while the Middle East is a larger destination for male migrants. However, we caution the interpretation of results in East Asia, where our gender assignment coverage is less widespread.

Overall, these patterns are broadly in line with estimates of gender ratios generated from analysis of data from the LinkedIn Advertising Platform (Jacobs et al. 2025) and broader indicators that women are making up a larger share of the skilled migrant population globally

(Yildiz and Abel 2024). This suggests that the data presented here is an informative indicator of gender patterns in migration, even before we refine our estimates with weights.

Figure 3 Panel B. Women migrants as share of all professional migrants on LinkedIn with secondary or higher education by country, 2000-2023



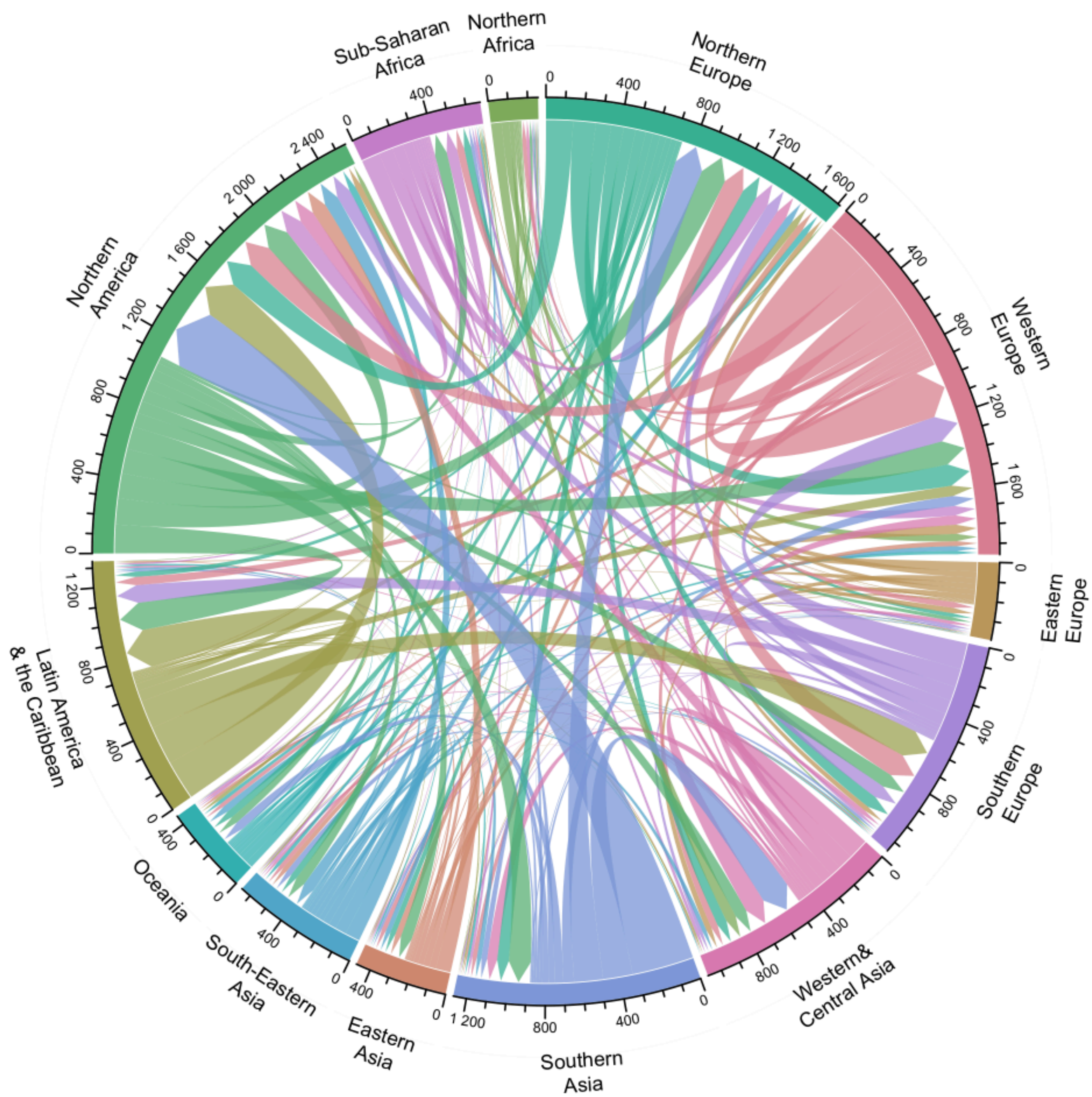
To understand changing dynamics in the share of men and women migrants in the professional workforce, Figure 3 Panel B shows the gender composition of LinkedIn users from 2000-2023 for the top 10 destination countries. It shows that the share of women has increased in all destination countries since 2000. We observe an increase between 8 and 13 percentage points in all countries except UAE, which had an increase of 22 percentage points.

However, the figure also indicates that the rate of change has slowed since 2015. We observe a plateauing effect in most countries, and a slight decrease in the female share for the United Kingdom, possibly associated with Brexit. We also observe that while India and UAE have significantly lower shares of women migrants in the professional population on LinkedIn, the share has grown in both countries since 2000, with a faster growth rate in UAE than in India.

Migration Corridors

To understand global patterns in migration dynamics, we next explore migration flows across regions, and specific bilateral migration corridors.

Figure 4. Migration Flows by Region, 2023.



Caption: Estimated unweighted international migration flows in 2023 across regions, in thousands of people. Each tick corresponds to 100,000 people. The arrow lines represent the total number of people migrating between all country pairs within each region and are sorted in descending order. Please note, these flows are not yet weighted.

The chord diagram in Figure 4 shows the unweighted estimated migration flows across country pairs within and between regions in 2023. Europe emerges as the primary hub in global professional migration, with the largest total outflows (2.4 million) and the largest total inflows (2.7 million). It is followed by Asia and North America, while Africa, South America, and Oceania account for comparatively smaller shares of global migration. These patterns highlight Europe's prominent role as both a major origin and destination of professional migrants, according to the unweighted results. To facilitate comparison across regions of different sizes, we normalize bilateral flows on the total turnover (defined as the sum of outflows and inflows), which allows us to express flows as shares of migration activity. For instance, about 25% of all migration in Europe occurs within Europe itself, compared to about 18% in Asia, 11% in South America, 10% in Northern America, 8% in Africa, and 4% in Oceania. Within Europe, intra-regional migration is mostly pronounced in Western Europe (about 13% of its total turnover), followed by Eastern Europe (8%), Southern Europe (6%), and Northern Europe (5%).

At the same time, several inter-regional corridors emerge, particularly from Asia to Oceania (24% of the total turnover in Oceania) and from Asia to Northern America (20%), highlighting Asia's role as a key origin in global migration. More broadly, outflows are highest in Southern Asia (approximately 70% of the total turnover in Southern Asia), Sub-Saharan Africa (57%), and Latin America and the Caribbean (55%). In contrast, inflows are most concentrated in Oceania (60%), Northern America (58%), and Western & Central Asia (55%).

Finally, comparing unweighted inflows and outflows across regions, we observe important asymmetries. Regions such as Northern America and Northern Europe act as net attractors, with inflows exceeding outflows. In contrast, regions like Southern Asia and African regions show higher outflows than inflows, indicating their role as net sending regions. Together, these patterns highlight the uneven geography of global migration, characterized by strong regional clustering alongside a limited number of dominant inter-regional corridors.

Table 2 Panel A. Top 10 origin-destination migration corridors, 2000-2023

	2000		2005		2010		2015		2020		2023	
1	India-USA	168316	India-USA	301405	India-USA	503181	India-USA	818146	India-USA	1194376	India-USA	1530471
2	UK-USA	142437	UK-USA	217851	UK-USA	342073	UK-USA	5482	UK-USA	746585	UK-USA	824922
3	USA-UK	136250	USA-UK	214209	USA-UK	334366	USA-UK	512193	USA-UK	693267	USA-UK	774713
4	Canada-USA	133603	Canada-USA	191708	USA-Canada	279837	USA-Canada	436142	USA-Canada	632328	USA-Canada	744651
5	USA-Canada	105248	USA-Canada	171281	Canada-USA	275484	Canada-USA	402999	China-USA	537769	Canada-USA	598370
6	China-USA	54766	China-USA	95153	China-USA	194193	China-USA	371180	Canada-USA	531568	China-USA	587315
7	Germany-USA	51734	USA-India	89091	USA-India	188779	USA-India	317161	USA-India	470161	USA-India	57478
8	USA-Australia	50118	UK-Australia	82476	UK-Australia	143386	India-UAE	266765	India-UAE	421740	India-UAE	533274
9	UK-Australia	45013	USA-Australia	81128	USA-Australia	131624	UK-Australia	216558	USA-Brazil	306826	India-Canada	468931
10	USA-India	43114	Germany-USA	75098	India-UAE	131185	USA-Australia	208295	China-Taiwan	300451	India-UK	402313

To dig deeper into the particular migration corridors contributing to shifting dynamics in migrant destination countries, we next explore bilateral country flows. Table 2 Panel A shows key migration corridors, with the 10 largest origin-destination pairs reported every five years from 2000-2023. Panel A shows that in 2023, the largest professional migration corridor on LinkedIn was from India to the United States. This was followed by bi-directional circulation between the UK, USA, and Canada. It also shows that migration between China and the USA is a top migration corridor, as well as migration from India to the United Arab Emirates, Canada and the United Kingdom. Further, we observe migration from the United States to India, which indicates that professionals are circulating between India and the United States in both directions.

The table also reports the largest migration corridors for every five years between 2000-2023. It indicates that migration from India to the United States has consistently lead professional migration during this period, and circulation between Canada, the United States, and the United Kingdom has also been consistently prominent. Migration from China to the United States has also persisted across this period.

While there have been some stable patterns in migration corridors, the table also shows shifting dynamics with emergent and receding corridors. In particular, migration from India to the United Arab Emirates has emerged as a growing corridor since 2010. The table also shows that migration from Germany to the United States has become less prevalent, as well as migration to Australia from the United Kingdom and the United States in 2023. This may be associated with Australia's strong entry restrictions during the COVID-19 pandemic, which were lifted in 2022, but may have ongoing effects on employment in subsequent years.

Table 2 Panel B. Top 10 origin-destination migration corridors by gender, 2000-2023
Men

	2000		2005		2010		2015		2020		2023	
1	India-USA	118304	India-USA	201799	India-USA	321761	India-USA	501608	India-USA	694121	India-USA	874334
2	UK-USA	90895	UK-USA	130548	UK-USA	188530	UK-USA	276952	UK-USA	358295	UK-USA	391057
3	USA-UK	83730	USA-UK	123692	USA-UK	180971	USA-UK	260565	USA-UK	340777	USA-UK	376277
4	USA-UK	83463	Canada-USA	113134	Canada-USA	152014	USA-Canada	218560	USA-Canada	304636	India-UAE	370815
5	USA-Canada	61653	USA-Canada	96251	USA-Canada	148346	Canada-USA	211411	India-UAE	300699	USA-India	360266
6	Germany-USA	35264	USA-India	61390	USA-India	125500	USA-India	202723	USA-India	295369	USA-Canada	354334
7	Australia-USA	30446	Germany-USA	48878	India-UAE	98303	India-UAE	196759	Canada-USA	271190	Canada-USA	303784
8	USA-India	30427	UK-Australia	48839	UK-Australia	77944	USA-Brazil	109123	USA-Brazil	173672	India-Canada	241989
9	UK-Australia	28998	USA-Australia	46437	India-UK	74240	UK-Australia	109024	India-Canada	147776	India-UK	218902
10	Mexico-USA	27380	India-UAE	44660	USA-Australia	71203	USA-Australia	105780	USA-Australia	143398	USA-Brazil	205900

Women

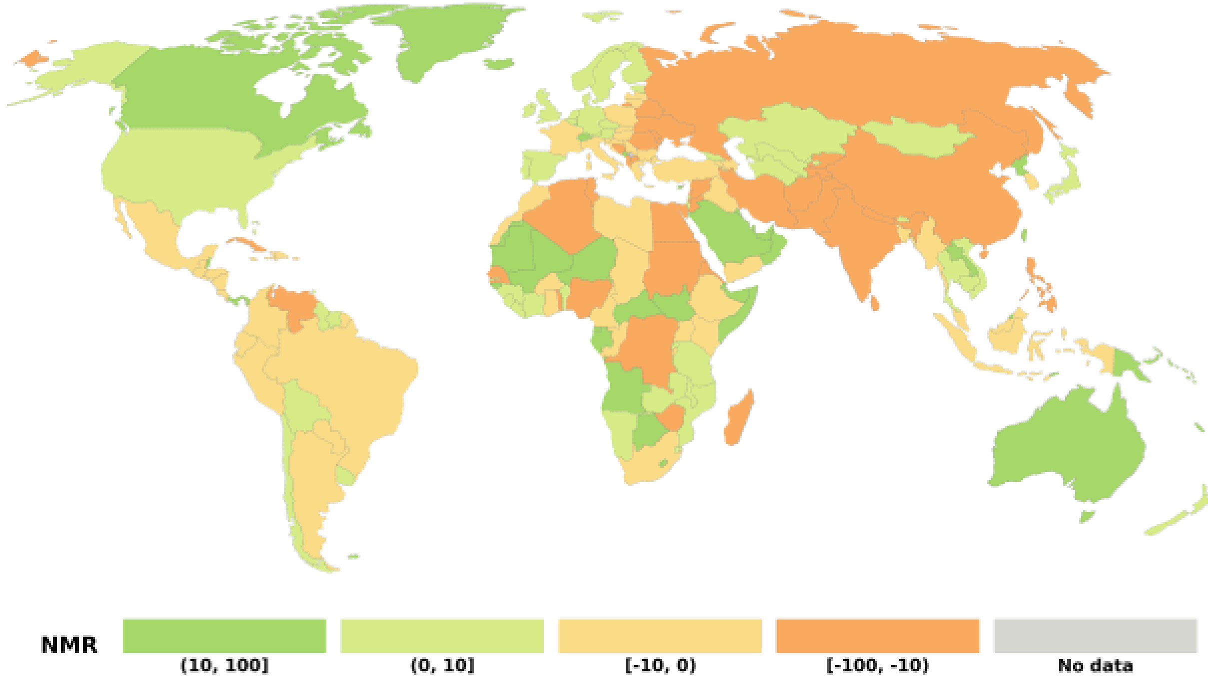
	2000		2005		2010		2015		2020		2023	
1	USA-UK	44599	USA-UK	76243	USA-UK	129010	UK-USA	222868	India-USA	354826	India-USA	463814
2	UK-USA	41560	UK-USA	71156	UK-USA	126073	India-USA	220264	UK-USA	317639	UK-USA	353273
3	Canada-USA	38993	India-USA	65530	India-USA	124174	USA-UK	211133	USA-UK	293892	USA-UK	330807
4	USA-Canada	35751	Canada-USA	62055	USA-Canada	107267	USA-Canada	175522	USA-Canada	259107	USA-Canada	305853
5	India-USA	30994	USA-Canada	61326	Canada-USA	97734	Canada-USA	151141	Canada-USA	202868	Canada-USA	227547
6	USA-Australia	16522	USA-Australia	29168	UK-Australia	56366	China-USA	94961	China-USA	141032	China-USA	154167
7	Philippines-USA	16273	UK-Australia	28805	China-USA	51532	UK-Australia	92605	UK-Australia	125757	India-Canada	151896
8	France-USA	15931	UK-France	26860	USA-Australia	50498	USA-Australia	84979	USA-Australia	123556	USA-India	149323
9	UK-France	14881	Philippines-USA	26304	UK-France	47311	USA-India	79658	USA-Brazil	122869	USA-Brazil	149259
10	USA-Netherlands	14559	USA-France	24892	USA-India	43110	UK-France	79611	UK-France	122496	USA-Australia	139157

Table 2 Panel B reports gender-disaggregated dynamics in migration corridors across the study period. It shows that in 2023, certain corridors, like India to the United Arab Emirates, employed significantly more men, while other corridors, like China to the United States, employed more women. These two corridors have both grown across the study period, highlighting the expansion of gendered migration corridors.

These patterns are likely driven by employment in certain industries such as oil/gas, consulting, and logistics in the case of India-UAE, where over 90 percent of the labor force is foreign-born, and over three-quarters male (De Bel-Air 2018; ILO 2025). In the case of Chinese migration to the U.S., this is likely associated with educational migration, where women students are more likely to remain in the United States for work after their studies (Greene and Batalova 2025; Laczko and Esipova 2025).

Net Migration Rates

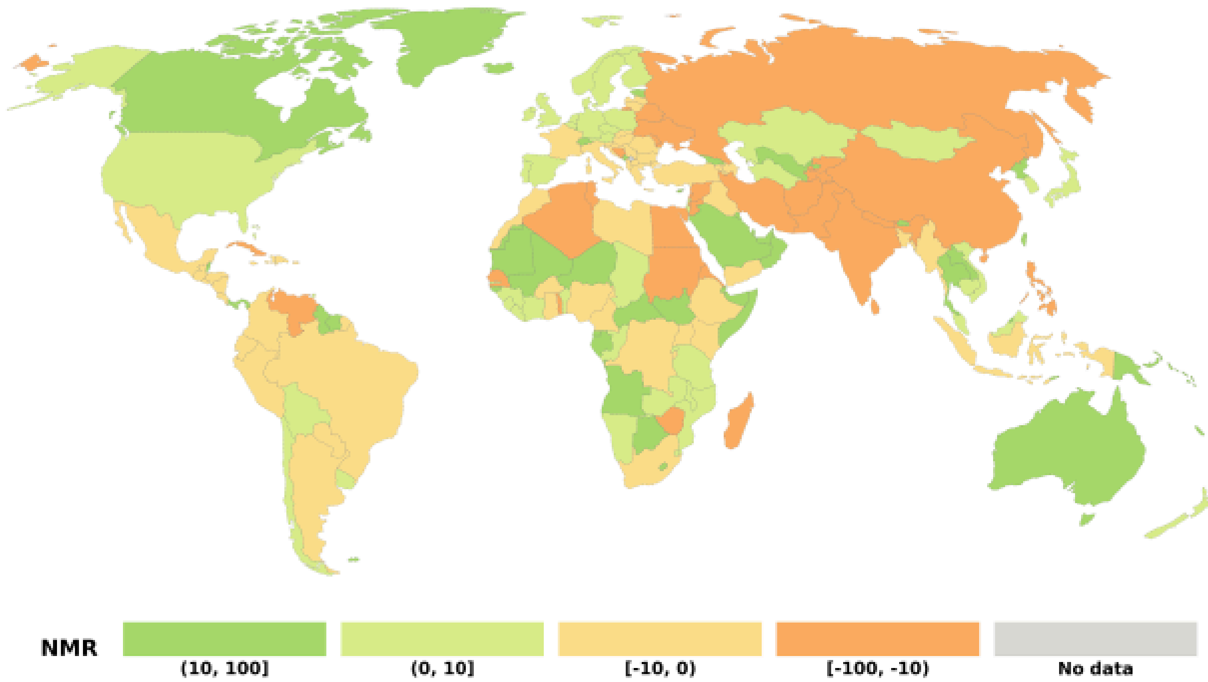
Figure 5 Panel A. Net Migration Rate per 1,000 LinkedIn users, 2000-2023



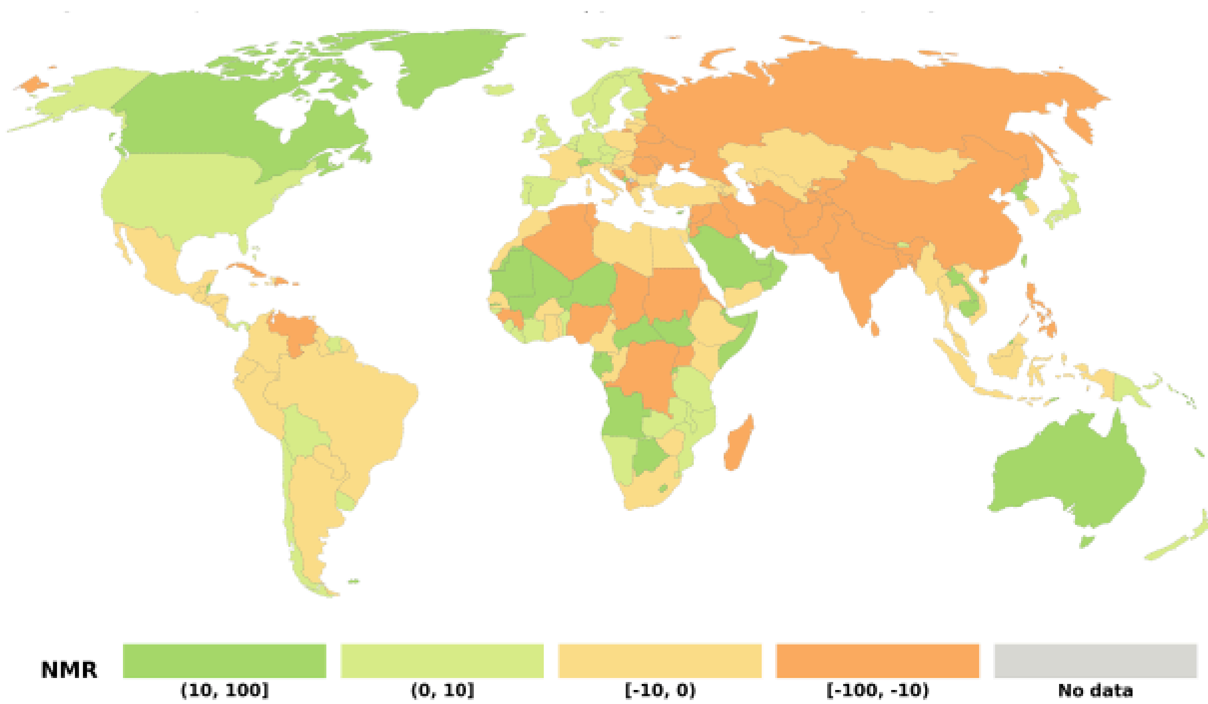
To further understand the in- and out-flow migration dynamics indicated in our regional flow analysis, we explore net migration rates across countries and over time. We measure net migration by counting in-migrations, subtracting out-migrations, and standardizing this using the population of professionals in a given country and year. Figure 5 Panel A shows the net migration rate per 1,000 LinkedIn users from 2000-2023, averaged across the entire period of study. It shows that overall, countries in North America, Western and Northern Europe (except for France), Australia, the Arabian peninsula, and some countries in Southeast Asia and Africa have a positive net migration rate (i.e., are depicted with greenish colors) and receive more professionals than they send abroad. In contrast, most countries in South and East Asia, as well as South America and Northern Africa, are migrant-sending countries.

Figure 5 Panel B. Net Migration Rate per 1,000 LinkedIn users by gender, 2000-2023

Men



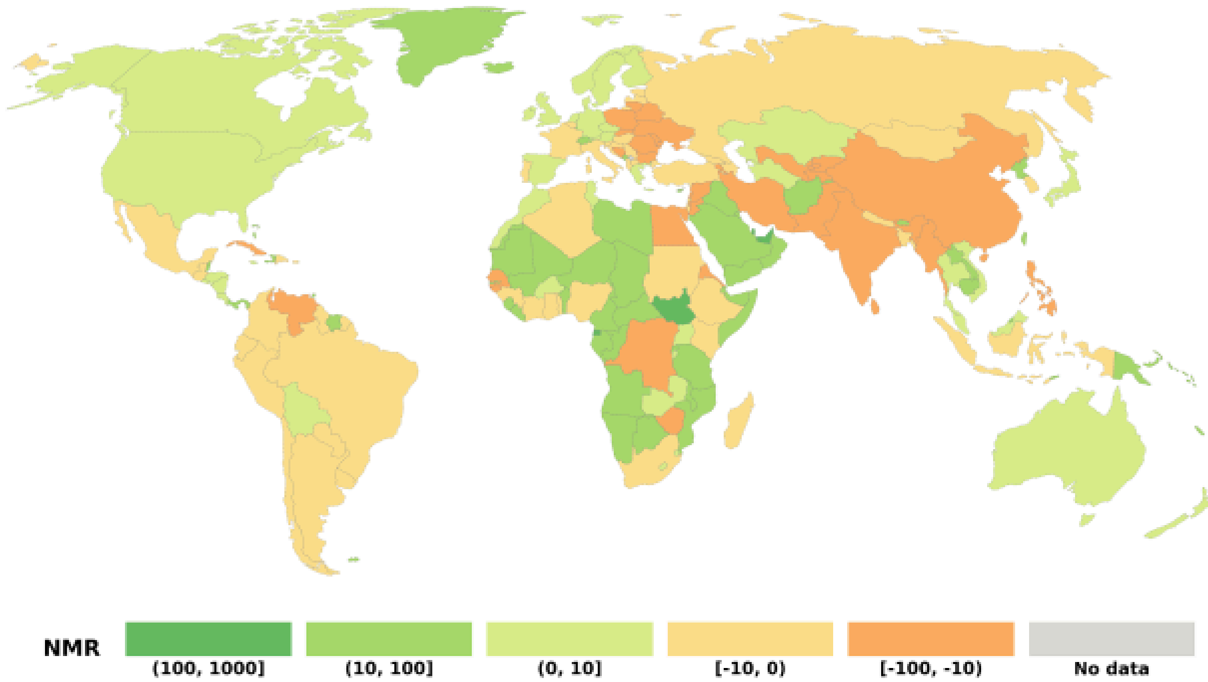
Women



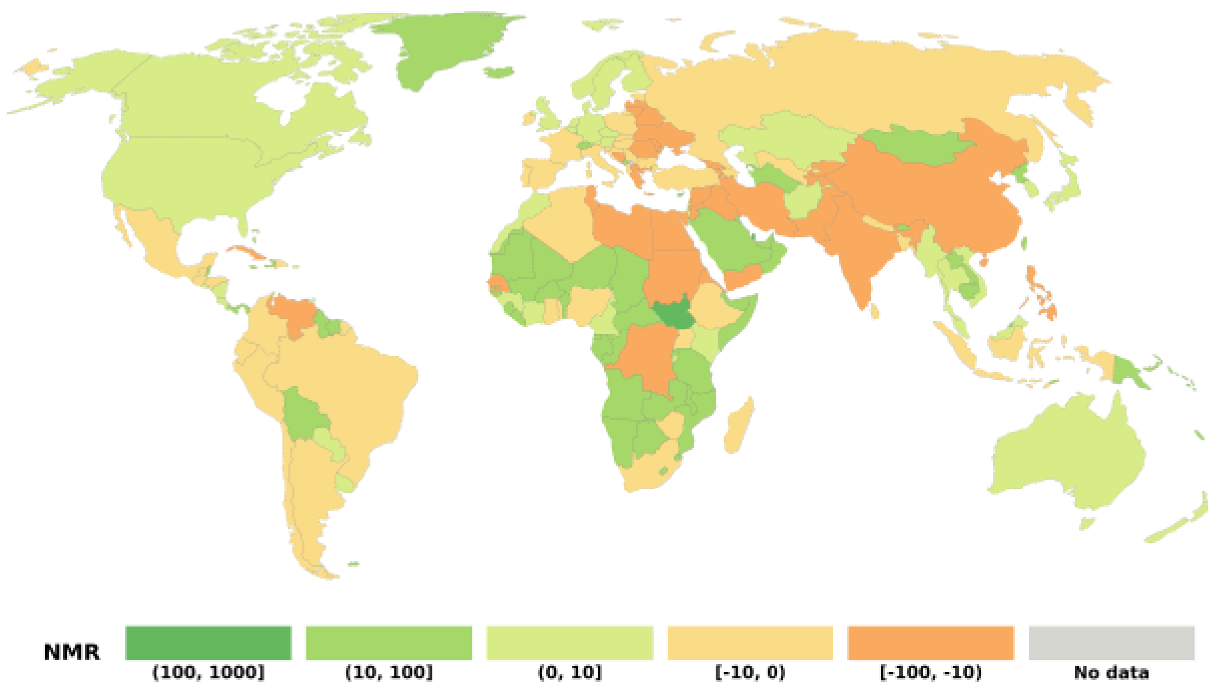
To see how these dynamics vary for men and women, Figure 5 Panel B disaggregates net migration rates by gender. It shows that some countries are sending countries for women, but receiving countries for men. For example, Thailand, Vietnam and Korea receive more men migrants and send more women migrants.

Figure 5 Panel C. Net Migration Rate per 1,000 LinkedIn users over 7-year periods

2000-2007



2008-2015



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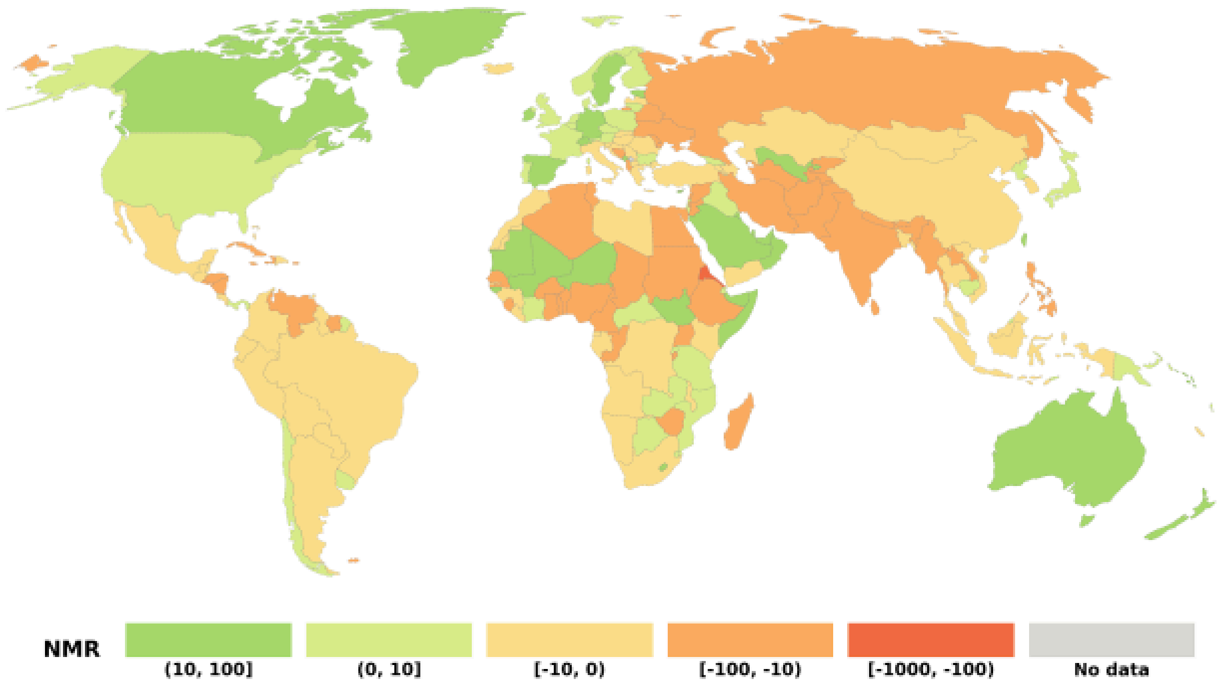
2016-2023



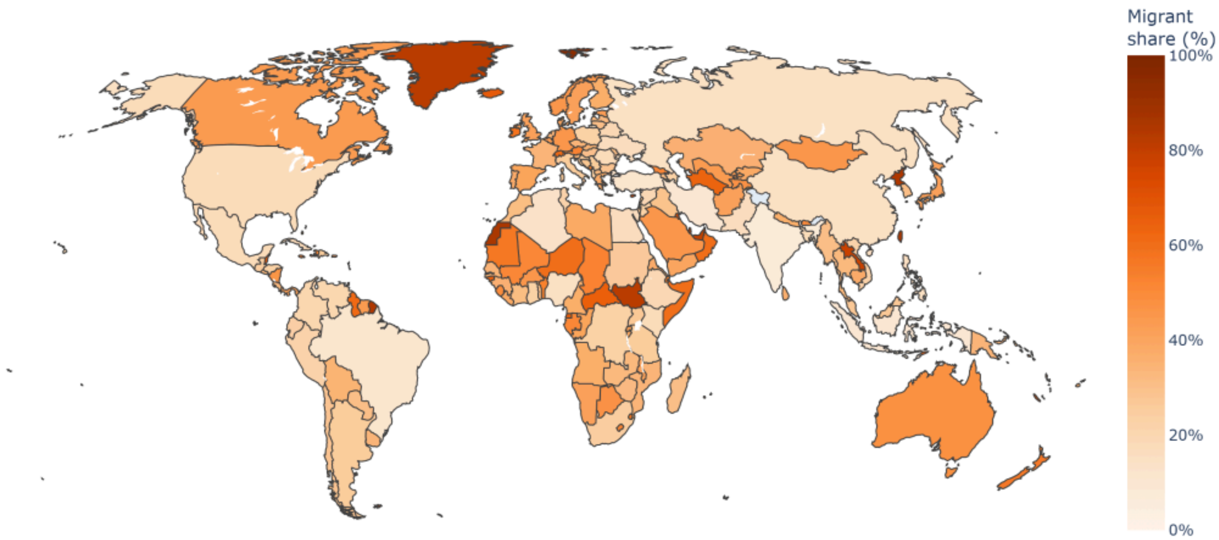
Finally, we consider how net migration rates have changed over time. Figure 5 Panel C disaggregates the net migration rates into three periods, which offers insights into changing migration dynamics over the past three decades. For example, it demonstrates how China has shifted from being largely a migrant-sending country between 2000-2007 and 2008-2015, with about 100 migrants per 1,000 sent, to a more balanced mix of in- and out-migration in the most recent period (2016-2023), with about 10 migrants per 1,000 sent. Other countries, like Chile, have transitioned from migrant-sending to migrant-receiving countries during this period. Canada, Germany and Sweden have become more significant migrant-receiving countries, receiving up to 100 per 1,000 migrants in 2016-2023.

A case such as Saudi Arabia is interesting as it has always been a receiving country for professionals using LinkedIn, receiving up to 100 per 1,000 migrants in all time periods. Additionally, in the most recent period, we observe increased levels of out-migration from areas of conflict like Russia and Ukraine (which has a higher outmigration rate of 100 per 1,000 professionals starting already in 2006-2015 continued to the latest period, while Russia's outmigration peaks in the latest period in 2016-2024 to 100 per 1,000 migrants sent). We also observe countries experiencing economic collapse, like Venezuela, or political unrest and conflict like Iran, Afghanistan, and Pakistan, which have a net outmigration surpassing in-migration in 2016-2024 up to 100 per 1,000 migrants sent. Additionally, these maps show that most of the Continental and Western European countries became a receiving destination with greener colors after 2015, while they were sending countries in earlier periods.

Industry and Employment Dynamics

The final section of our analysis explores migrant professionals in destination country labor markets. We consider the composition of migrants in the labor force, as well as industry dynamics.

Figure 6 Panel A. Migrants as share of all professionals on LinkedIn with secondary or higher education by country, 2023

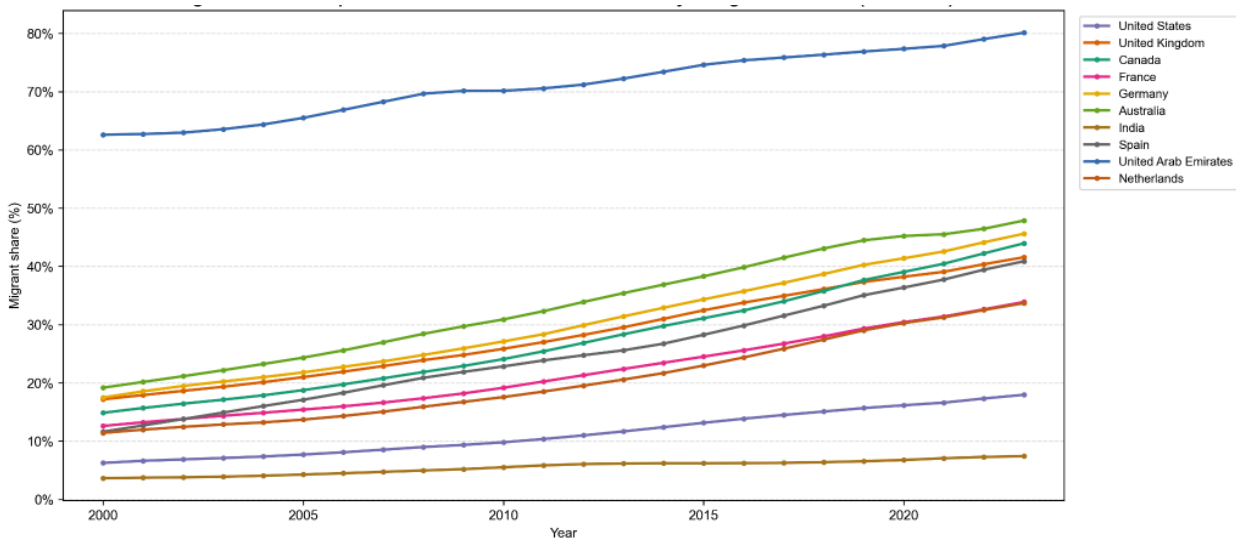


To understand how much of the professional population in destination countries is comprised of immigrants, Figure 6 Panel A shows a map of the LinkedIn professional migrant stock as a share of all LinkedIn users. It shows that in some regions, especially the Middle East, migrants comprise well over the majority of professionals on LinkedIn. For example, Qatar (84%), the United Arab Emirates (80%), and Oman (60%) employ significantly more migrants than native-born workers with some tertiary education. This suggests that migrants play a central role in the economies of this region, and countries are increasingly dependent on migrant labor. In contrast, in other countries like India (7%) and Indonesia (9%), migrants make up less than a tenth of the professional workforce. This might be related to relatively large native-born populations in these countries and the significant expansion of higher education (Froumin and Platonova 2020).

In key destination countries, migrants comprise between a third and a half of the LinkedIn population in Australia (48%), Canada (44%), Germany (46%), Spain (41%), the UK (42%), the Netherlands (34%), and France (34%). In the United Arab Emirates (80%), migrants make up the vast majority of the highly skilled labor force, emphasizing the key role migrants play in the Emirati economy. In contrast, migrants comprise a smaller share of the professional population in the United States (17%) and India (7%).

These patterns are slightly higher than labor force participation data from administrative sources in each country. Because our data detect mobility at the monthly level, our results may capture higher levels of mobility at shorter time intervals than what is typically measured in survey data identifying migrants, which is often collected at one-year or larger intervals. Further, we employ a broader definition of "skilled migrant" as any professional with some tertiary education, which harmonizes different definitions of skilled migrant across occupation, education and migrant class of admission (Parsons et al. 2020). This helps capture dynamics of professional migration and emergent patterns that may be overlooked in more narrow definitions.

Figure 6 Panel B. Migrants as share of all professionals on LinkedIn with secondary or higher education by country, 2000-2023



To understand changing dynamics in the migrant composition of the labor force over time, Figure 6 Panel B shows the migrant share of all professionals on LinkedIn in the top 10 destination countries from 2000 to 2023. It shows that migrants comprise an increasing share of the highly educated workforce in all destinations since 2000. Most countries, including Australia, Germany, Canada, the UK, Spain, the Netherlands, and France, had increases between 25 and 30 percentage points. In these countries, migrants as a share of the professional workforce range from 30 to almost 50 percent.

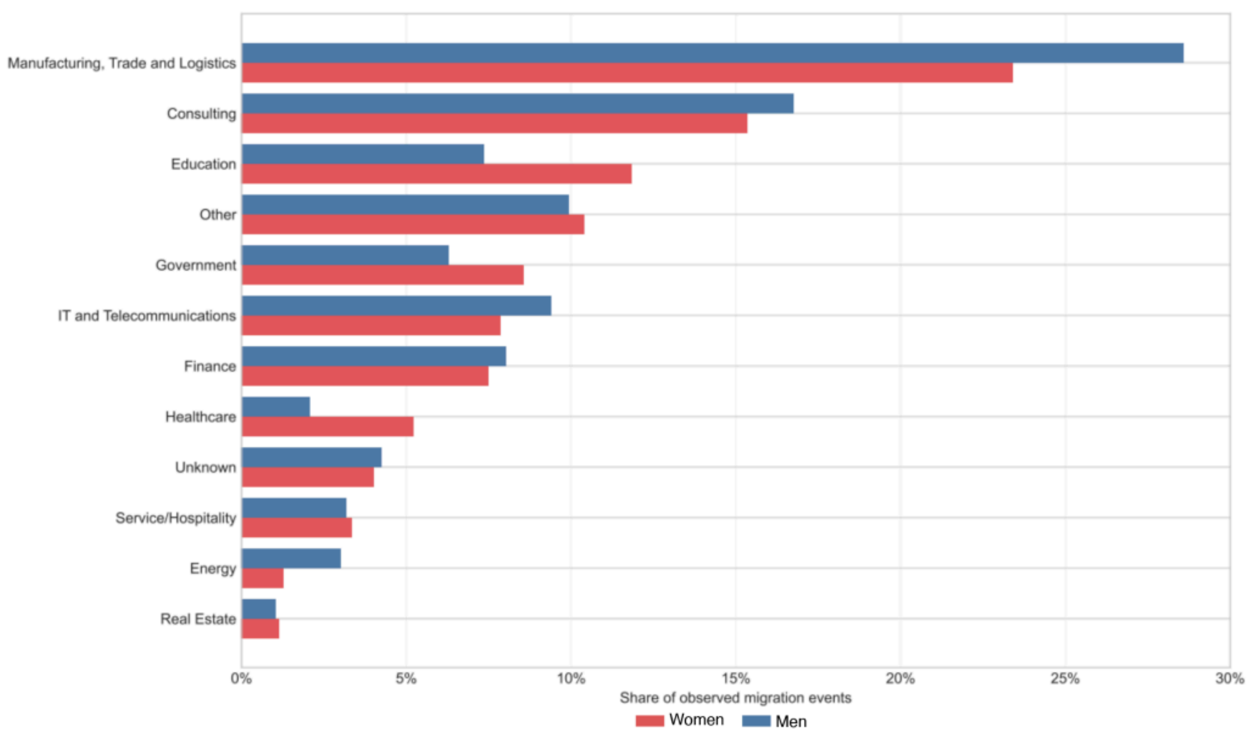
In contrast, the United States and India have smaller migrant shares of the professional workforce and lower rates of growth. The United States and India had the lowest relative growth, with an increase of 12 and five percentage points, respectively, over the study period. This indicates that migrants comprise an increasingly significant share of the labor force of key destination countries, but the rate of growth varies. The figure also shows that, consistent with the results for 2023, the United Arab Emirates has had a larger share of migrant workers in the labor force relative to other top destinations since 2000. To account for gender inequality in the labor force of each country, we further disaggregate our analysis to understand what share of the male and female workforce is comprised of migrants. The results are available in Appendix Figure D.

Table 3. Migration events by industry, worldwide (aggregated from 2000-2023)

Industry	Number of migration events	Percent
Manufacturing, Trade and Logistics	27,371,151	26.1%
Consulting	16,797,456	16.0%
Other	10,424,652	10.0%
Education	9,882,858	9.4%
IT and Telecommunications	9,226,067	8.8%
Finance	8,373,213	8.0%
Government	7,414,313	7.1%
Unknown	4,683,709	4.5%
Healthcare	3,504,763	3.3%
Service/Hospitality	3,364,783	3.2%
Energy	2,353,613	2.2%
Real Estate	1,105,569	1.1%
Business Management	203,322	0.2%

Finally, we consider industry dynamics in the migration of professionals on LinkedIn, and how these vary over time and by gender. Table 3 examines migration events by industry. It shows the total number of migration events that occurred between 2000 and 2023 in each industry, and what percent of all migrations are comprised by each industry. The table indicates that Manufacturing/Trade/Logistics is the largest industry employing professional migrants, with 26 percent of moves. Consulting is second, with 16 percent of migration events, with "Other," Education, IT/Telecommunications, Finance, and Government each comprising between 7 and 10 percent of all migration events.

Figure 7. Migration events by industry and gender



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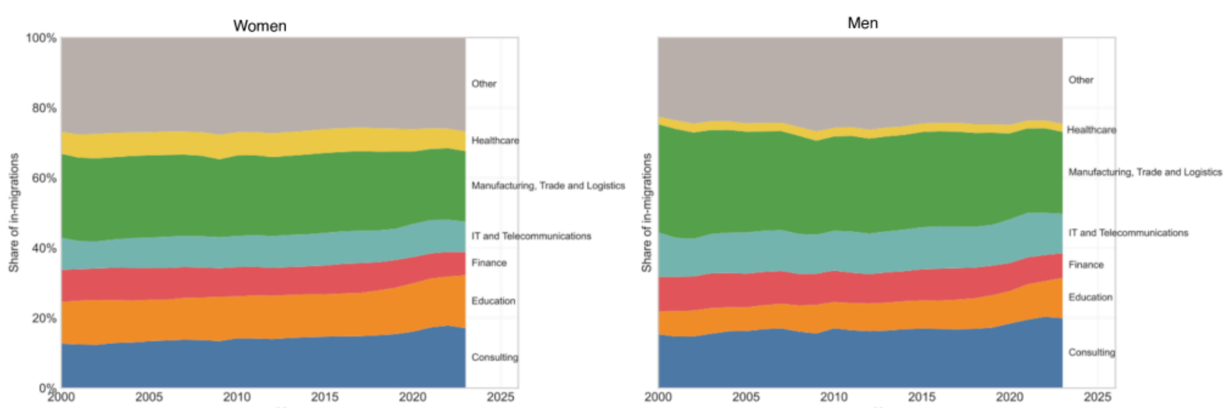
To see how industries vary by gender, we disaggregate our results for men and women migrants. Figure 7 shows the breakdown of migration events by both industry and gender. It shows that Manufacturing/Trade/Logistics had the largest share of migration events for both men and women, but a larger share of men (28%) migrated into this industry compared to women (23%). Consulting was the second largest industry for both men and women, with a slightly larger share of men (17%) working in this field compared to women (15%). In contrast, a larger share of women (13%) migrated for a job in education sectors compared to men (7%). A larger share of women also work in “other,” government, healthcare, service/hospitality and real estate than men. Compared to women, a larger share of men work in IT/Telecommunications, finance, “unknown,” and energy.

Finally, we examine industry dynamics over time in the particular case of the United States, the largest destination country for professional migrants on LinkedIn. Figure 8 shows the industry composition of migrations to the United States by gender between 2000-2023. The left panel shows these dynamics for women, and the right panel shows the trends for men. It shows that for both men and women, the share of migration events has grown in Consulting, Education and IT/Telecommunications from 2000-2023, with particular growth in Education for women. In contrast, Finance and Manufacturing/Trade/Logistics have both declined slightly, though Manufacturing/Trade still comprises the largest share for both groups. The share of migration events in healthcare and “other” has remained relatively stable during the study period for both groups. We observe some decrease in employment in finance and consulting for men around 2008, likely associated with the global financial crisis.

Figure 8. Industry composition of in-migrations to USA by gender, 2000-2023



Discussion and Future Directions

This paper provides detailed global estimates of trends in professional migration of LinkedIn users in the first quarter of the 21st century. We employ a novel and harmonized dataset of over 600 million publicly accessible LinkedIn user profiles to provide comprehensive insights into gender differentials and industry dynamics across the world and over time. Leveraging the global coverage of our data, we introduce new weighting techniques to adjust for biases in

LinkedIn usership across countries. While we still need to apply weights to migration flows, however, this helps provide new insights and shifting dynamics in data-sparse regions of the world with less empirical research.

Our preliminary results and analysis of publicly accessible LinkedIn users indicates steady growth in the global population of professional migrants, with disruptions associated with the 2008 global financial crisis and the 2020 COVID-19 pandemic. Our data show that in 2023, the top destination countries for professional migrants using LinkedIn were the United States, the United Kingdom, Canada, France, and Australia. We observe emergent migration corridors, such as India to the United Arab Emirates, as well as persistently dominant flows, such as India to the United States. We find considerable circulation between the US, UK, Australia, Canada, and India, and the results indicate that Europe is the most significant region for migration in- and out-flows. Additionally, we observe countries that transitioned from sending to receiving destinations, such as Chile, or became more significant receiving countries, such as Canada, Germany and Sweden. With the global reach of our data, we observe patterns in regions with relatively less empirical research due to data sparsity, such as the Caribbean, East Asia, and the Middle East.

With respect to labor market dynamics, the preliminary results indicate that migrants comprise an increasing share of the professional workforce using LinkedIn, with shares approaching one-half in Europe, and over three-quarters in parts of the Middle East. Further, we find that the top industries employing professional migrants globally are Manufacturing/Trade/Logistics and Consulting. The composition of industries has remained relatively stable over time in most countries, with a slight decline in Manufacturing/Trade/Logistics and a modest increase in most other industries, including Consulting, Education and IT/Telecommunications.

Beyond offering new estimates, this paper presents data and analysis that enrich research on the feminization of migration with greater global scale and sociodemographic detail (Kofman 2014; Donato and Gabaccia 2015; Walton-Roberts 2024; Yildiz and Abel 2024; Jacobs et al. 2025). The results show that women are comprising an increasing share of professional migrants using LinkedIn since 2000, though the rate of growth has somewhat slowed since 2015. We identify some countries that have reached gender parity among migrant professionals, such as Italy and Spain, and others with significant gender inequality, such as Pakistan and Saudi Arabia, which are largely male. These preliminary results indicate gendered migration patterns across regions. In particular, host countries in Europe, the Caribbean, and parts of East Asia are larger destinations for women migrants, while the Middle East is a larger destination for male migrants. We also find that some countries, like Thailand, Vietnam and Korea, are sending countries for women, but receiving countries for men.

Further, we observe specific gendered migration corridors that are predominantly male (India-UAE) and predominantly female (China-USA). These patterns are likely driven by employment in key industries such as oil/gas, as well as educational migration linked to labor market entry in destination countries (De Bel-Air 2018; ILO 2025; Greene and Batalova 2025;

Laczko and Esipova 2025). We also observe a higher share of male migrants working in Manufacturing/Trade/Logistics and Consulting, and a larger share of women migrants in Education, Government and Healthcare.

Our findings are currently restricted to publicly accessible LinkedIn users with some tertiary education, and they are going to be updated after we apply weights to migration flows. Further analysis of weighted data may reveal some distinct dynamics, especially in areas with less LinkedIn coverage. Nonetheless, the preliminary results have important implications for understanding changing dynamics in global professional migration and emerging regions in the global economy. The growth of migration in the Middle East, especially from India to the United Arab Emirates, signals the increasing importance of foreign-born workers contributing to economic growth and the expansion of key industries like energy and logistics. The dominant share of migrants in the UAE labor force also highlights a shift towards dependence on migrant labor in emerging destination countries, which might have important implications for migration and economic policy. These dynamics also signal an expansion of migration corridors beyond established Western channels, suggesting a diversification of global migration pathways. We observe largely male migration to this region, which provides a window into the factors shaping the gender composition of the labor force. In contrast, we observe some indication that destination countries in Europe and East Asia are hosting a larger share of women migrants, and thus, we should expect different patterns of employment migration in these regions.

Further, the results observed in this paper are instructive for addressing future labor force needs. Understanding the foreign-born and gender composition of the labor force can highlight areas for economic growth. Foreign-born workers play a central role in addressing labor demand in key economic sectors. Migrants can help address skill shortages among the native-born population in rapidly growing economic sectors like technology and energy. They can also help address growing imbalances in the age structure of Western nations. By joining the working-age population, migrants can help balance the demands of aging populations with increasing healthcare needs and pensions and shrinking taxbases.

Our results identify a number of areas for potential growth to address these issues, especially related to gender disparities in global migration. In particular, we find that a number of key migrant destination countries, including the United States and Germany, are not at gender parity. This highlights an opportunity for additional growth in the female professional migrant population to help address these labor force needs. We also find that the United States and India have lower proportions of migrants as a share of the skilled labor force relative to other top destination countries and slower rates of growth, highlighting another area for growth.

Beyond the immediate scope of this paper, the richness of these data opens up multiple lines of future inquiry to address ongoing debates in international migration. The dynamic patterns of circulation we observe in our results highlight additional questions about circular migration and return; these data particularly lend themselves to examining the drivers and effects of return and onward migration among skilled migrants. The data are also well-positioned to conduct in-depth industry analysis from supply- and demand-side perspectives, focusing on key migration corridors with bilateral country flows data. Additionally, the temporal granularity of our data enables us to examine case-based studies, such as contexts of forced migration from Ukraine or policy-induced shocks on migration flows to and from the United Kingdom before and after Brexit.

Author Contribution Statement: TT, AA, EJ, DP, CC and EZ designed the research; TT, AA, EJ, DP and CC performed research; TT, AA and DP curated data; TT, AA, EJ, DP and CC analyzed data; TT, AA, DP and CC visualized results; TT, AA, EJ, DP, CC and EZ wrote the paper.

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Appendix

Methodology and Detailed Appendix

Data Curation

Migration.

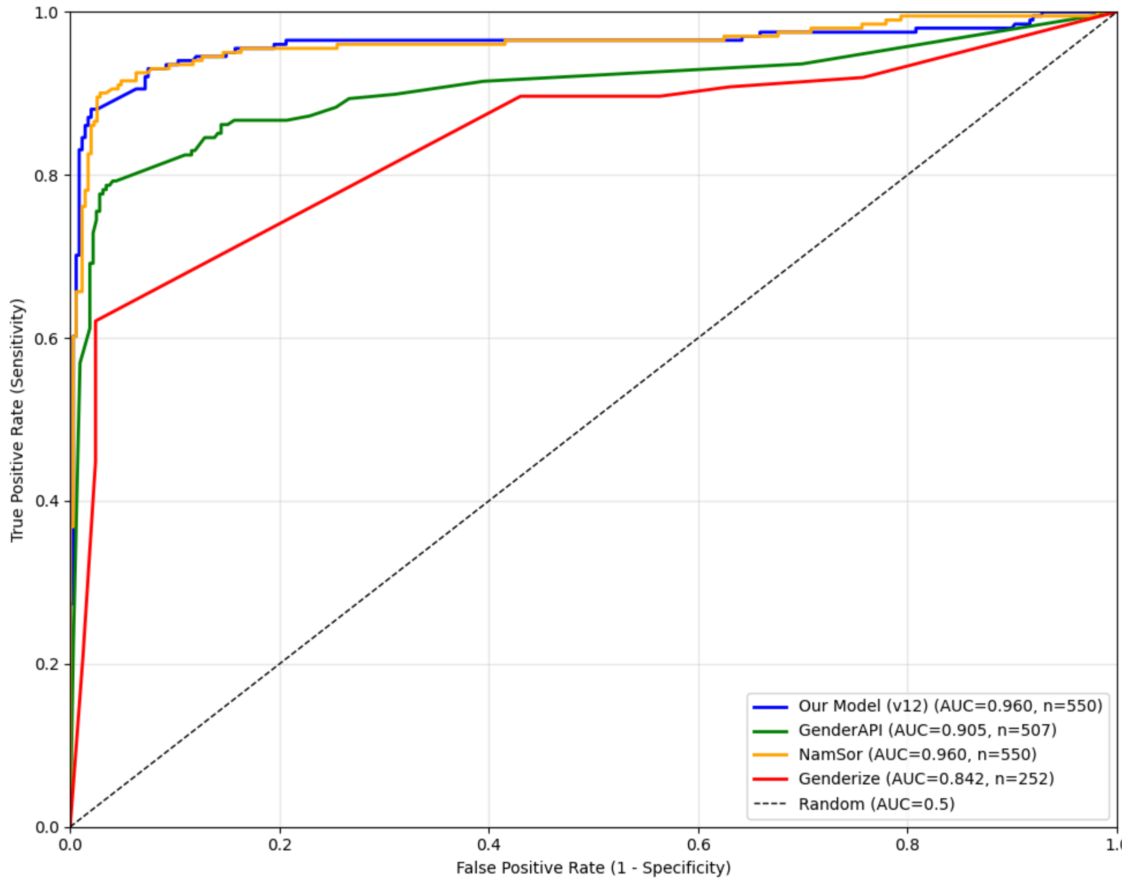
We define an international migration as a change in the country of education or employment that lasts more than 12 months. We calculate the duration using the start and end date information on a job or education spell. This 12-month definition of migration is consistent with recent studies (Chi et al. 2025) and the United Nations definition of migration (UNDESA 1998; ECE 2011).

Gender.

We infer a user's gender using their first and last name, and a neural network model trained on data from Wikidata on people with an assigned gender as male or female. We then assign a probability that the user is either male or female based on the gender of other people with the same or similar names. This draws on the methodology applied to the Scholarly Migration Database (see Akbaritabar et al. 2024 for more details). A strength of this method is that we are able to use first and last names, which provides more information about a user's potential gender than just first names on their own, which is the case for the methodology applied by Revelio Labs. The method also provides a confidence value between 0 and 1. We apply a threshold of 0.8 to assign a user's gender and label names with a lower score as *unknown*.

Overall, our model outperforms similar gender inference models. As we report in Appendix Figure A which shows the ROC curves for gender prediction models, our model outperforms (AUC=0.960) other gender inference models such as Gender API and Genderize (AUC=0.905 and AUC=0.842, respectively). It performs at a similar level as Namsor AUC=0.960), but our model allows us to assign user gender to millions more cases.

Appendix Figure A. ROC Curves for Gender Prediction Models



This approach provides coverage for 88 percent of names in our dataset, but presents some challenges for names where the name may be gender-neutral (Jamie in the United States, for example). In other cases, the gender may be ambiguous across different regions (for example, Simone is often female in English or French, but male in Italian). Further, our algorithm did not perform as well for names in non-Western characters, or where naming conventions emphasize initials rather than full given names.

To address this, our research team hand-coded sub-samples of names from different regions to improve the accuracy of the corpus of names to train the data. We used Google Images to search the name and assign a gender (male, female or unknown) based on the gender of the people in the search results. This approach gives a broader sense of the gender associated with the name across multiple people, rather than the particular individual in a LinkedIn profile. We also use name databases such as genderize.io, which provides the probability of a name having a certain gender in a certain country.

The research team included individuals from multiple regions of the world, and we recruited additional regional experts with local knowledge on regions, like China, where our expertise was limited.

Even with careful hand-coding and refinement, the gender classification in some countries still included "unknown" or missing cases. In particular, in 2023, some East Asian countries were unknown or missing in more than half of cases, including Mongolia (71%), Cambodia (61%), Vietnam (58%) and China (58%). There was also unknown/missingness in about a third of cases in some African countries, including Botswana (41%), Ethiopia (35%) and Zambia (33%).

In the largest migrant destination countries, the range of unknown cases varied from four percent (Spain) to 13 percent in USA, Canada and Australia. France (6%), Germany (7%), Netherlands (8%), UAE (10%), India (11%), UK (12%) close out the top ten. Thus, there is less missingness in the gender coverage for the key countries in our analysis, increasing our confidence in the gender dynamics we observe. However, we recognize the limitation of gender coverage in other regions, and subsequent analysis will further refine our gender assignment through weighting and additional algorithmic techniques.

Education.

We assign time-varying educational information to each user based on the information reported in their profile before a move. This includes the level and field of the degree, and the country where the degree was obtained. We infer the country of degree based on location predictions provided by Revelio Labs, and assign the latest degree information in each year based on graduation dates reported in a profile.

318 million users in our data had at least one education entry in their profile. Because much of this information is user-generated data, there were inconsistencies in the data entries that required further refinement. In particular, many entries had missing or ambiguous degree level or field of study information. To address this, we leveraged other pieces of information in the education information to infer these details. We used Revelio's algorithmic inferences about degree level as a baseline and refined this approach to address issues with ambiguous degree information and non-English degrees.

First, we coded a degree at the Bachelor's, Master's, Doctorate, Associate or Professional level for degrees not recognized by Revelio, such as B.Tech, a common degree in Indian technology institutes, or A-Levels to indicate secondary school completion in the United Kingdom. We used international degree equivalencies from the World Higher Education database, the French, Spanish and British Departments of Labor, the U.S. National Collegiate Athetics Association Core Course Equivalencies and the admissions websites at NYU, Cornell University, University of Michigan and University of Pisa to translate and match degree equivalencies from education systems with differences across countries.

This approach also accounted for translation of degree information from non-English languages, and the associated degree level in that country's education system. For example, we translated

“Bacharel” from Portuguese to “Bachelor’s” in English, but “Bachillerato” in Spanish to the equivalent of a secondary school diploma in English.

This doubled our coverage of degree level from one third of education entries having degree information to two thirds of entries having degree information. By focusing on non-English degrees and different international education systems, this strategy not only increased coverage but especially helped to reduce systematic biases in degree coverage in non-English speaking countries and non-Western education systems, which has important implications for estimating educational attainment around the world.

To further increase our coverage of people with a tertiary education, in cases where a user reported a school name but no specific degree, we use school names reported on user’s profiles. We differentiate between universities and high schools, to infer whether someone has a tertiary education, which we measure as “Bachelor’s degree or higher.” A limitation with this approach is we cannot differentiate between Bachelor’s and advanced degree levels, but it helps expand our broader understanding of tertiary educational attainment.

We identified universities by using an LLM, and manually refined the classifications to check for inconsistencies across languages and educational systems in different regions. The agreement between human classification and the LLM was very high.

Industry.

Finally, we code a user’s industry of employment based on predictions provided by Revelio Labs. Revelio infers industries based on company names and classifies them into 200 industry categories, which we will then group into 11 broad industry categories using the North American Industry Classification System (NAICS).

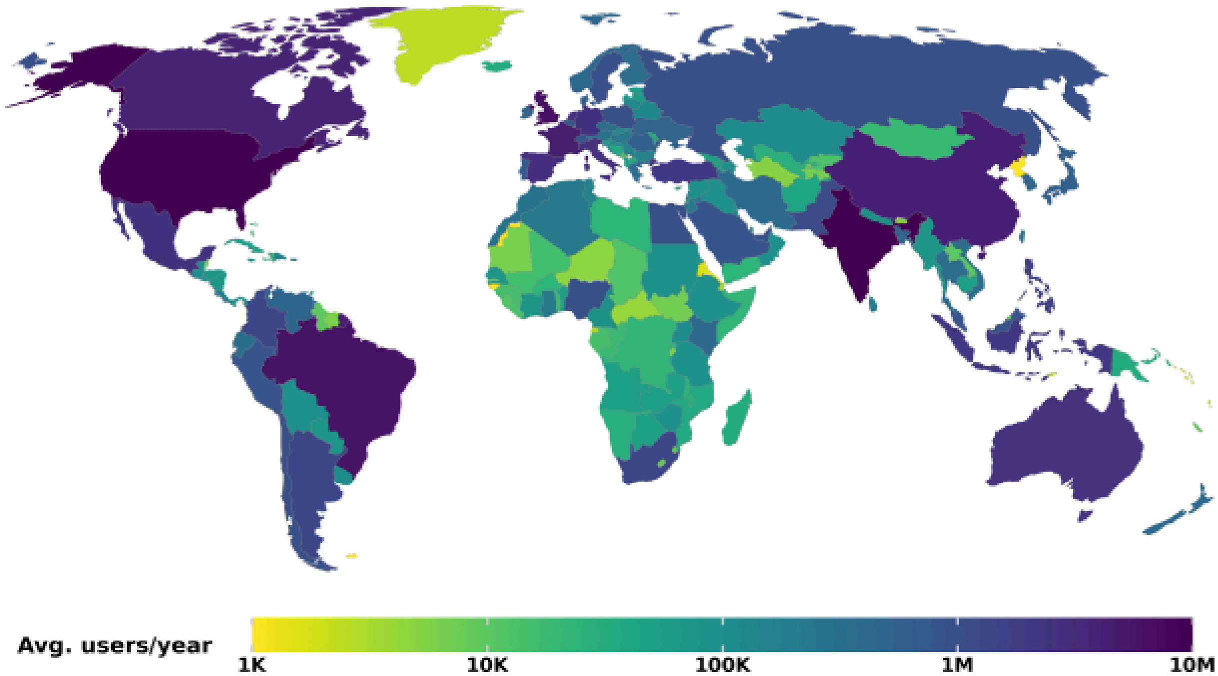
Data Calibration and Weighting

To provide population-level migration estimates that account for biases in the LinkedIn population, we apply a normalization approach that leverages various weighting techniques to adjust our estimates toward known population benchmarks.

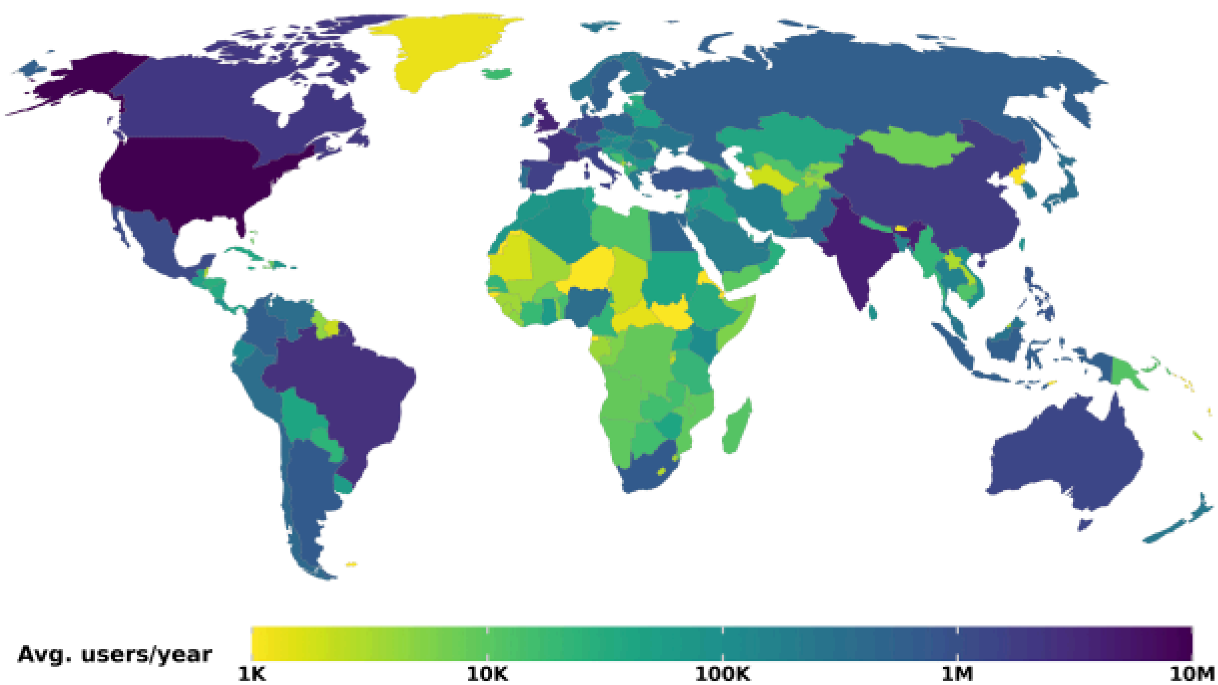
We start by calibrating the population of LinkedIn users to country-level population estimates from Census data. These data are accessed through IPUMS-International (Ruggles et al. 2025a), which accumulates and harmonizes 10% of the national census data, and Eurostat, which provides complementary European data for weighting.

We calibrate our data with this administrative information, and match on educational attainment. We measure the extent to which our population of migrant professionals with a Bachelor’s degree or higher is correlated with the migrant population in each country with a Bachelor’s degree or higher.

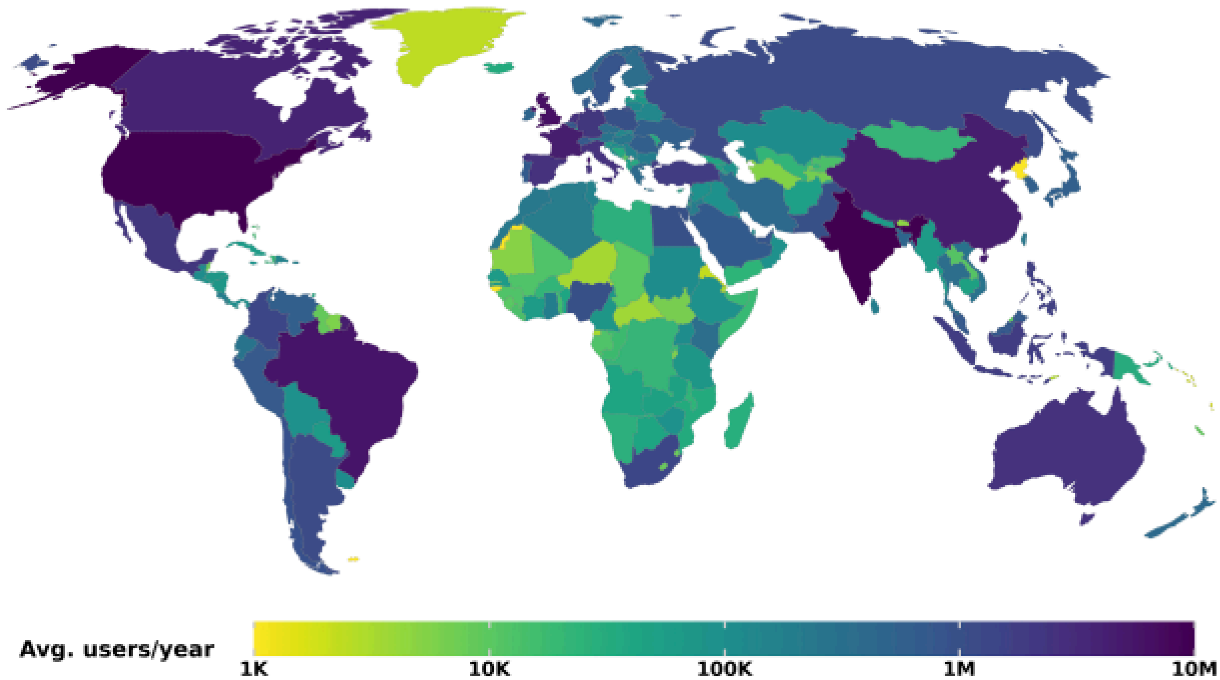
Figure B. Global distribution of users as reported in LinkedIn profiles
Panel A. Average over 2000-2023 (log scale)



Panel B. Average over seven-year intervals (log scale)
2000-2007



2008-2015



2016-2023

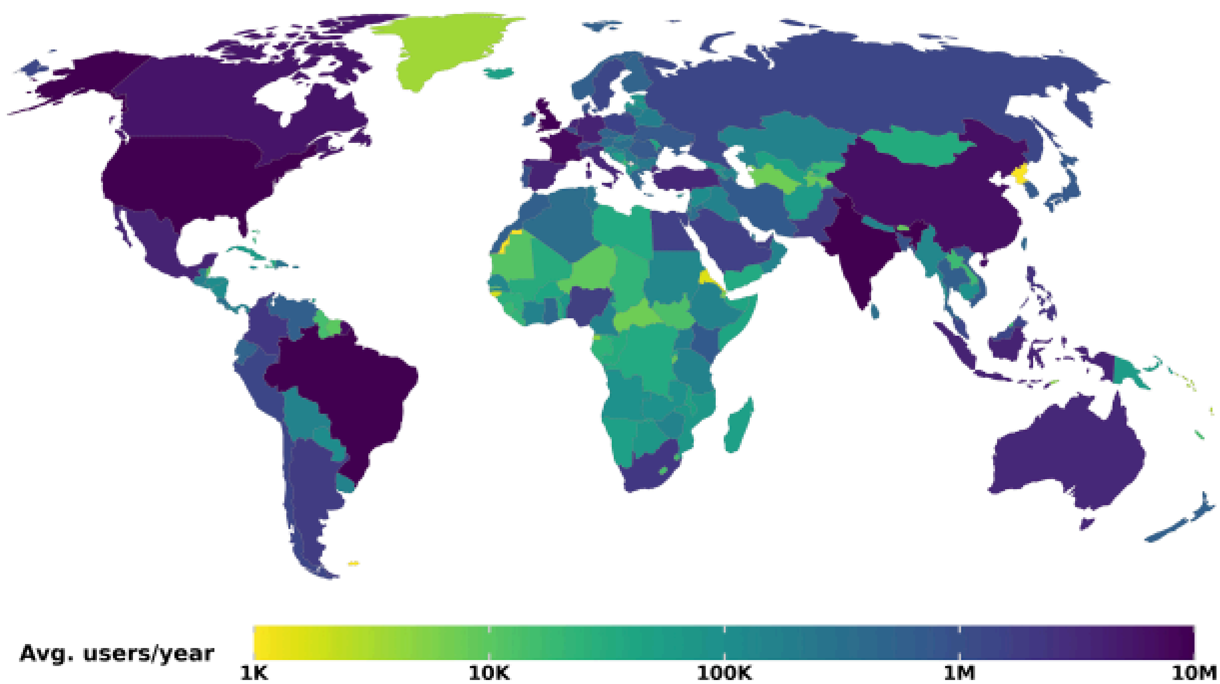
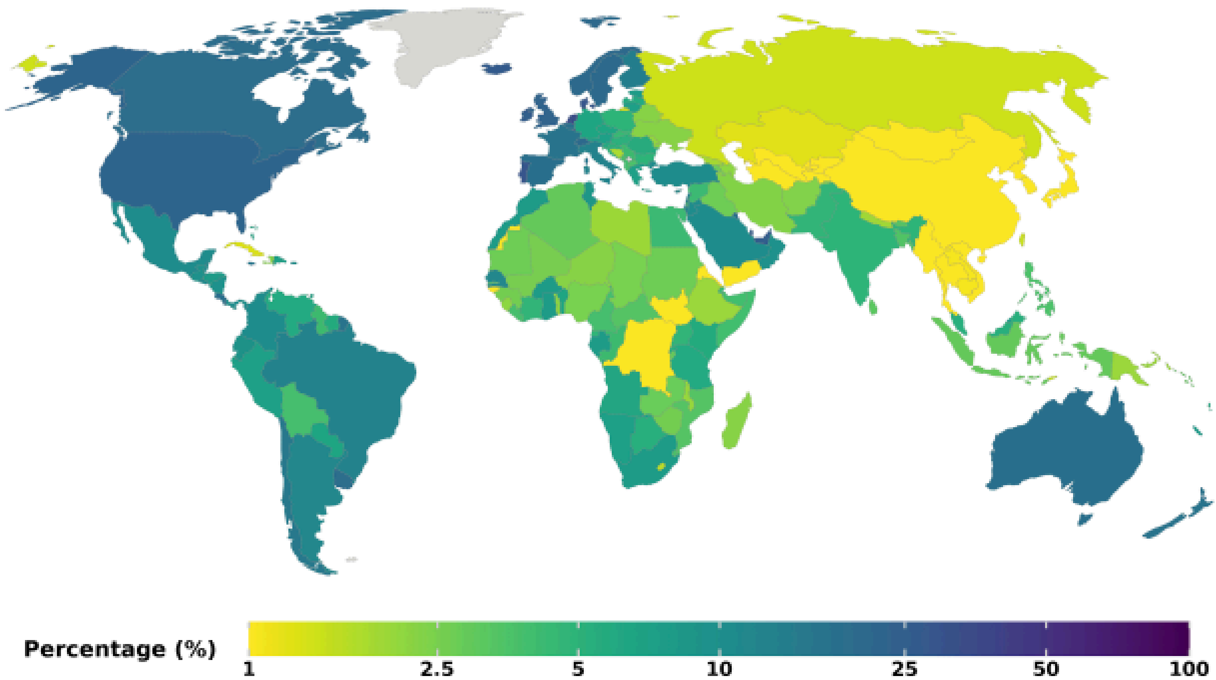
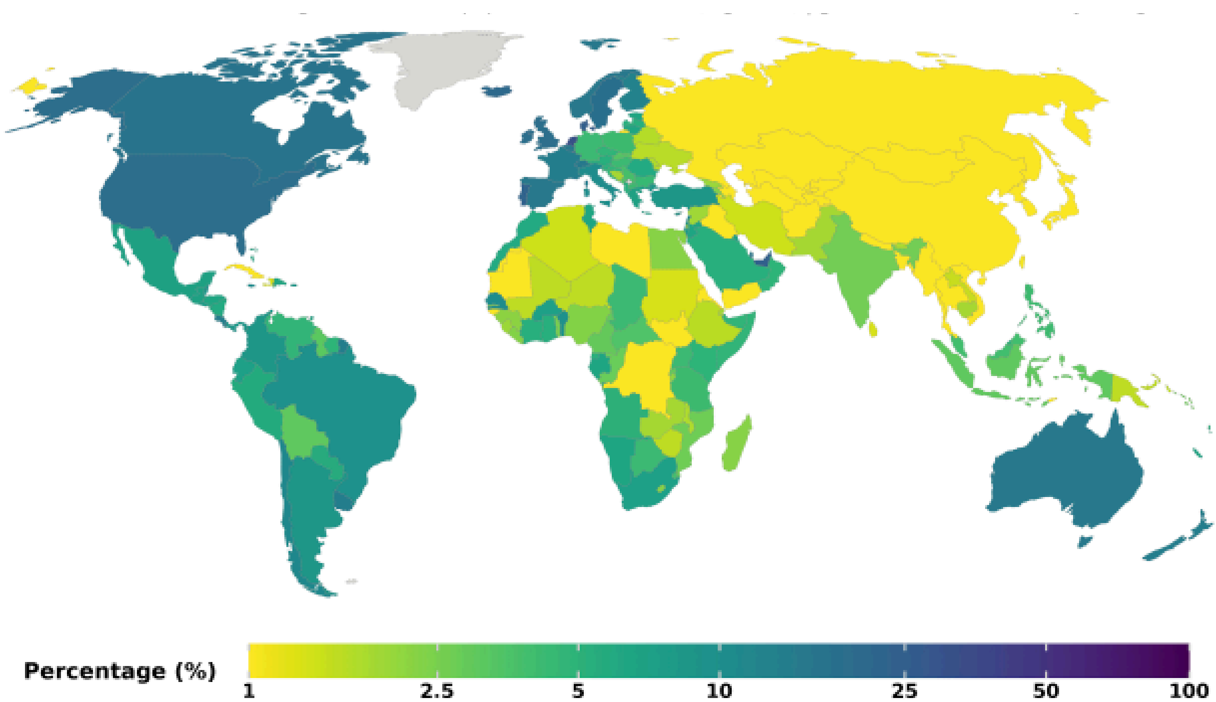


Figure C. LinkedIn Penetration Rate, by gender 2000-2023 (Revelio Labs LinkedIn data and Wittgenstein Centre for Demography and Global Human Capital)

Men



Women



Supplementary analysis

Our analysis explores the composition of the professional workforce in destination countries by migration and gender. To account for gender inequality in the labor force, we further disaggregate our analysis to understand what share of the male and female workforce is comprised of migrants. Appendix Figure D shows the migrant stock as the share of all professionals on LinkedIn with secondary or higher education, disaggregated by gender from 2000 to 2023.

The figure shows that in most countries, men and women migrants make up less than half of the professional workforce, though this has steadily increased since 2000. In some countries, including France, Spain, and the Netherlands, men and women migrants comprise a similar share of the overall professional population, and increased between 20 and 25 percent over the study period. In some countries like Canada, Australia, and the UK, migrants comprised a slightly lower share of the professional female workforce earlier in the study period, but have converged on similar rates to male migrants in more recent years. The UAE follows a similar pattern, despite migrants comprising a larger overall share of the professional workforce. In Germany, women migrants comprise a slightly larger share of the professional workforce compared to men, and the gap is growing. Finally, in the United States and India, we observe slower rates of growth among migrants as a share of the male and female population. In the US, men consistently comprise a slightly higher share of the population, and in India, there is some indication that the share of women migrants is decreasing slightly since 2018.

Appendix Figure D. Migrant stock as share of all professionals on LinkedIn with secondary or higher education by gender, 2000-2023