Global Gender Gaps in the International Migration of Professionals on LinkedIn

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Abstract

This paper examines gender differentials in the international migration of professionals, and how this varies by country, industry, age, and years of experience. We construct an immigrant and emigrant Gender Gap Index (iGGI and eGGI) to measure gender gaps in inflows and potential outflows. We use the LinkedIn Advertising and Recruiter platforms as a novel data source, which provides timely and detailed complements to standard migration data.

The findings indicate that, among Linkedin users, the global population of immigrant professionals is at gender parity. In contrast, the potential emigrant population is largely male. Thus, men have higher migration aspirations, but men and women have similar rates of mobility. Overall, we find that about 1 in 5 people convert migration aspirations into a move.

Our results show that country-level variation in the gender composition of migrants is associated with gender equality, migration policy and wages. Further, women are more mobile in female-dominated industries and at younger ages, while men are more mobile in junior employment cohorts. Finally, we find evidence of positive selection among women migrant professionals in key destination countries for skilled migrants like the United States, Australia, the United Kingdom, France and Germany.

The global migration of high-skilled professionals is an important and increasingly large component of international migration. The number of highly educated migrants grew three times faster than less-educated migrants between 1990 and 2010 (Kerr et al. 2016) and is continuing an upward trend. By 2020, there were more highly educated migrants living in OECD countries than low-educated migrants (d'Aiglepierre et al. 2020). Professional migration is an important source of labor for countries with advanced skills shortages and shrinking native-born workforces, and has important implications for economic development, innovation and the circulation of global knowledge in both sending and receiving countries (Docquier and Rapoport 2012; Czaika 2018).

Despite its importance, many dynamics related to skilled migration remain poorly understood. In particular, gender differentials in skilled migration have not been systematically analyzed at a macro-level scale, in part due to data limitations including a lack of sufficient detail for analyses disaggregated by country, gender and industry. The migration literature has emphasized a process of feminization in recent years, with an increasing share of women among all international migrants (Ehrenreich and Hochschild 2003; Abel 2022). However, closer examination across a wider range of migration corridors, and consideration of longer time trends has made this feminization process more ambiguous (Donato and Gabaccia 2015). Further, little is known about the gender composition of professional migrants by industry, age, or level of experience. With specific dynamics of gender inequality in professional occupations, and gender differences in professional recruitment and migration networks, the gender composition of skilled migrants might differ considerably from less-skilled migrant groups (Walton-Roberts 2022; Kofman and Raghuram 2022).

This paper examines gender gaps in the international migration of professionals. We consider how these patterns vary across countries by age, industry and years of experience. We construct an immigrant and emigrant Gender Gap Index (iGGI and eGGI) to measure these differentials. The paper explores three migration dynamics: recent migrant arrivals, potential migrant outflows, and the gap between migration aspirations and realizations. We use LinkedIn Advertising and Recruiter platforms as a novel data source, which provides timely aggregate-level information about professional migrants at a richer level of detail than is available in survey data on migrants.

We ask three questions. First, what is the gender composition of professional immigrants and emigrants on LinkedIn? Second, how do these gender differentials vary across potential sending and receiving countries, and by industry, age, and years of employment? Finally, how big is the gap between the population of people expressing migration aspirations and the population of people realizing those goals and relocating to a foreign country?

The paper contributes to the research gap in gender and skilled migration by providing timely analysis of professional migrants on LinkedIn at a rich level of detail by potential sending and receiving country, industry, age, and employment cohort. Further, it offers insights into the gap between migration aspirations and observed migration behavior. Further, it contributes to the growing research digital data sources to complement limitations in conventional migration data to study global patterns of professional mobility.

Literature Review

The International Mobility of Professionals

Labor migration has long been one of the primary drivers of international migration, as people move abroad for higher wages and better economic prospects (Piore 1979). Skilled migration among highly educated professionals has become an increasing share of the labor migration system as university systems and labor markets have globalized, and human capital facilitates international mobility (Iredale 2001; Faggian et al. 2007). Globally, skilled migration is growing at a faster rate than less-educated migrants (d'Aiglepierre et al. 2020). In fact, since 2020, the number of skilled migrants exceeds low-skilled migrants in OECD countries (d'Aiglepierre et al. 2020). The emigration rate of skilled migrants from origin to destination countries is also generally higher than the overall migrant population, due to more financial resources to migrate and migration policies in destination countries aimed to attract skilled migration, which has sparked debates and concerns about "brain drain" (Docquier and Rapoport 2012; d'Aiglepierre et al. 2020). Thus, skilled migration is a crucial dynamic for both origin and destination countries.

The growth in the international migration of skilled professionals is driven by a combination of labor demand for skilled workers, global economic integration and targeted migration policies designed to attract highly educated migrants (Czaika and Parsons 2017; Czaika 2018). Economic demand for specialized skilled labor in sectors like technology and business attracts skilled migrants (Sassen 2007; Kerr et al. 2016). Further, countries have developed specialized skilled migration policies to attract the best and brightest workers that prioritize their entry (Czaika 2018). In countries with highly selective migration policies, the share of skilled migrants is approaching or exceeds the majority of migrants (47% of Australian migrants have tertiary degree; 60% of Canadian migrants have tertiary degree (Czaika 2018; d'Aiglepierre et al. 2020).

The majority of skilled migrants move to OECD countries, responding to targeted migration policies and labor opportunities (Czaika and Parsons 2018). The United States, Canada, United Kingdom, Australia and Israel are the top five migrant receiving countries in the OECD (Czaika and Parsons 2018). Due to data limitations, there is less known about more current patterns, or destinations in non-OECD countries, though there are indicators that China, Japan, South Korea, Brazil, Argentina, Korea and Russia are also important destinations for skilled migrants (d'Aiglepierre et al. 2020; Zhao 2023).[1]

Amid growing interest from policymakers to understand the dynamics of skilled migration, there has been a growth in data sources on professional migrants from the OECD and occupation-specific datasets, which has contributed to the recent growth in research in this area(Arslan et al. 2015; Czaika and Parsons 2016; Clemens and Petterson 2008; Bhargava et al. 2011) However, these data have a number of limitations.

First, these studies are based on varied definitions of "skilled migrant," sometimes defined by educational attainment, occupation, or skill level (Parsons et al. 2020). Without consistent comparable categories, it is difficult to make comparisons across countries or over time. Relatedly, these data often lack a level of detail that make it possible to look at multiple dimensions of skilled migration simultaneously. For example, measures of gender, age, and industry are rarely available, or it is difficult to disaggregate the data across multiple characteristics. These measures provide important insights into changes in the migrant composition in younger age groups, and industry differences highlight key entry pathways for labor migrants. Finally, the most reliable data on skilled migration focuses on surveys on OECD countries and are only made available at large time intervals. For example, the most recent data used in many studies was published in 2015/2016. This misses important dynamics in recent years, as well as different political-economic dynamics from non-OECD countries like China and India that play an increasingly important role as both origin and destination countries for skilled migrants (Kerr et al. 2016; d'Aiglepierre et al. 2020). Thus, there are many outstanding questions about skilled migration to non-OECD countries, industry-specific dynamics across multiple settings, and gender differences in professional international migration (Kerr et al. 2017).

Gender patterns in professional migration

In particular, despite the growth of skilled migration and its increasing political and economic importance, there is still much to be understood about gender differentials among skilled

[1] Different definitions of skilled migrant, based on education level (tertiary degree) or occupational definitions (defined by ISCO) can lead to different estimates in different country or regional contexts depending on data availability. See Parsons et al. 2020 Table A.1 for different definitions of migrant skill in different studies.

migrant professionals (Boucher 2018). Scholars have long called to "bring gender in" to research on labor migration, and skilled workers in particular (Morokvasic 1984; Sassen 1998; Kofman 2004; Donato et al. 2017; Bailey and Mulder 2017). The evidence for whether skilled women are more migratory than their male counterparts is ambiguous, and less is known about the factors shaping highly-skilled female migration compared to male skilled migrants.

Recent interest in the "feminization" of skilled migration has emphasized the growing share of the global professional migrant population comprised by women (Docquier et al. 2009; Abel 2022). Among OECD countries, the average share of all women migrants in 2016 was 51.8%, and the share of immigrant women holding tertiary degrees was only three percentage points below that of men (OECD 2016; d'Aiglepierre et al. 2020). The leading destination countries for highly educated migrant women are USA, UK, Canada, New Zealand, Ireland and Israel, with the main origin countries being Philippines, China and India (IOM 2014). These destination countries have relatively high rates of female labor force participation and higher measures of gender egalitarianism (Donato and Gabbaccia 2016; Kofman and Raghuram 2022).

Women are increasingly moving as individuals rather than trailing family members (Shauman and Xie 1996; Hochschild and Ehrenreich 2003; Andall 2013; Gabaccia 2016). The primary pathways for skilled women migrants are educational channels as international students and employment pathways in specific industries (Batalova 2006; Donato and Gabaccia 2015; Kofman and Raghuram 2022). Migration can function as a compensation mechanism for gender bias in the education and labor markets. For example, Docquier et al. (2009) show that the gender gap in highly skilled migration is strongly related to the gender gap in educational attainment in the origin country, reflecting unequal access to education. Further, Faggian et al. (2007) find that women university graduates in the UK are more migratory when entering the labor market than men, moving to more egalitarian labor markets.

Given this "feminization" of skilled migration and the increasing share of women professional migrants, we expect (H_{1a}) women and men to be near parity in the global immigrant population. At the destination country level, we expect (H_{1b}) to see women-majority immigrant populations in more gender-egalitarian countries with more employment opportunities for women. With respect to patterns of potential out-migration, we expect (H_{1c}) to see higher rates of female potential emigration from less gender-egalitarian origin countries, as a result of limited employment opportunities and constrained gender norms for women.

Despite these indicators of an increasingly female skilled migrant population, additional factors and complexities related to gender egalitarianism might constrain professional migration opportunities for women. A combination of political-economic factors can influence the gender composition of the skilled migrant pool in different countries. Policies that facilitate skilled immigration and emphasize employment on certain industries can have effects on the sex-composition of this migration flow (Boucher 2018; Kofman and Raghuram 2022). In some cases, gender disparities in educational attainment and labor force participation in mobile industries like STEM fields are associated with lower levels of female migration (McCann, and Sheppard 2007; Malakhov, 2019). Docquier et al. 2012 find that skilled women are not necessarily more migratory than men, and do not respond with the same intensity to the traditional determinants of labor mobility as men. Further, Beine and Salomone (2013) find that the agglomeration effects and productivity spillovers related to concentrations of skilled workers have less of an influence of female skilled migration than male skilled migration patterns. Finally, Zhao et al. (2022) note that gender imbalances in return migration can further amplify gender disparities in skilled migration.

Further, gender gaps in employment across different industries can influence the gender composition of the professional migrant population (Bossavie et al. 2022). For example, STEM fields tend to be male-dominated, while nursing and carework tends to be female-dominated (Harvey-Wingfield 2019; Williams 2023). Thus, the economic structure in different countries can influence the gender composition of the professional migrant pool. Further, admissions policies can prioritize employment in certain industries or entry pathways like student visas, which also influences the gender composition of the migrant pool (Kofman 2014; Donato and Gabaccia 2016; Boucher 2018; Jacobs 2022). For example, in Australia in 2011, 76 percent of migrants arriving on temporary skilled visas were men and 24 percent were women (Boucher 2018).

With respect to industry-specific dynamics, we expect (H_{2a}) to see a women-majority migrant population in more feminized industries like Healthcare and Education (Hochschild and Ehrenreich 2002; Walton-Roberts 2022). Further, we expect (H_{2b}) to see women-majority migrant populations in younger age groups and for migrants in earlier career stages. This compositional change should reflect national and global trends towards more gender equality in more recent age and employment cohorts. With respect to patterns of potential out-migration, we expect (H_{2c}) to see higher rates of female potential emigration in female-dominated industries, because these are the primary employment mobility pathways for women migrants (Walton-Roberts 2022; Kofman and Raghuram 2022).

Digital Trace Data for Migration Studies

This paper builds on an emergent research stream using digital trace data for the study of international migration with the aim of addressing long-standing data limitations on migration data. Migration data are often coarse-grained, inconsistent across countries, cross-sectional, and constrained to a single country, making it difficult to conduct dynamic analysis across countries and over time (Jacobs 2022; Drouhot 2023). However, digital data sources offer information at more detailed temporal and spatial scales than conventional data sources and have exciting potential for migration research, offering insights about displacement and migration flows, and other processes such as integration (Kashyap 2021; Sîrbu et al. 2021; Druhout et al. 2023; Salah et al. 2022).

New technologies have generated an explosion in digital data generated by social media, cell phones, mobile applications, and web browsers that leave "digital traces" (Latour 2007). Digital trace data exploit information recorded in newspapers, cell phones, credit card transactions, and online platforms including Facebook, Twitter, LinkedIn and TikTok. Digital data can include hard-to-reach populations that may be excluded from traditional data sources, identify highly mobile groups within narrow time-frames, and contain rich information (Tjaden 2021; Bail et al. 2019; Kashyap et al. 2020; Coimbra Vieira et al. 2023; Kim et al. 2022; Akbaritabar et al. 2023; Luca et al. 2023). Highly-skilled migrants leave online traces about their employment histories which allow for analysis of their migration patterns and labor market outcomes (State et al. 2014; Perrotta et al. 2022).

To complement existing work on the international migration of professionals, we offer LinkedIn as a data source that can provide timely and detailed information about the international movement of skilled migrants. LinkedIn offers an opportunity to analyze trends in a timely manner, with data collected in 2023, and the potential for ongoing data collection to allow for more continuous analysis of skilled migration trends in more countries. LinkedIn has been used as a source to study the flows of professional migrants (State et al. 2014; Perrotta et al. 2023), the spatial distribution of university graduates (Heo, Chang and Abel 2023) and the labor market incorporation of skilled migrants (Breschi et al. 2021; Jacobs 2022). The LinkedIn Advertising platform offers information on gender differentials by industry, examining all professional migrants rather than specific definitions based on educational attainment or occupational categories. This study is among the first to leverage the gender information on the Advertising platform to conduct this timely, detailed analysis across industries, age, and employment cohorts.

Data and Methods: LinkedIn Dataset

Data. This article improves our understanding of gender gaps in professional migration by analyzing aggregate-level information of migrant professionals on LinkedIn. LinkedIn is a professional networking site with over 900 million registered users. It is used by employment recruiters and job seekers who report their past employment and education in an online resumé. This includes information about employment location, which allows for the study of spatial mobility as it relates to employment. Thus, LinkedIn is especially valuable for studying professional migrants, who are highly mobile and often not captured in administrative and survey data sources (Breschi et al. 2021; Jacobs 2022; Perrotta et al. 2023). LinkedIn offers a rich complement to standard data on migration, which are often costly, coarse-grained, and inconsistent across countries (Drouhout 2023). These data also provide more timely estimates across a wider range of countries.

We access these data through the LinkedIn Advertising and Recruiter platforms. The Advertising platform provides an estimate of LinkedIn users with specific demographic and employment traits, such as gender, age group, and industry. It also provides information about users recently relocated internationally for work, which allows us to measure the recently arrived migrant stock in different countries. The platform includes information about the number of people open to relocating internationally from any given origin country, giving us a measure of the potential migrant outflow of professionals.

The Recruiter platform enables employers to identify job candidates through user profile characteristics like education, industry and years of experience, but does not capture direct measures of age or gender to avoid discriminatory hiring practices. However, it does include rich information about users open to job-related relocation, which allows us to identify potential future migrant in-flows to destination countries as a measure of migration aspirations (Perrotta et al. 2023). We thus combine data from the Advertising and Recruiter platforms to leverage the information from both data sources. This is, to our knowledge, the first paper to analyze these data in parallel.

We collected audience counts of LinkedIn users from the Advertising platform API in August and September 2023. We collected the aggregate number of LinkedIn users in each country and the number who had recently relocated or were open to relocation, along with key demographic and employment characteristics. On the Recruiter platform, we collected data every two weeks from January through November 2022. Due to the variability in the dataset, here we use median country-level flows across all dates of data collection. See Perrotta et al. (2023) for more on the nature of data on the Recruiter platform.

On both platforms, we collect anonymous, aggregate-level data, from which it is not possible to identify individuals. The Advertising platform provides information above a threshold of 300 users to protect individual identifiers; targeted queries below this threshold do not return results (LinkedIn API).[2] There are some tradeoffs between the level of detail and data sparsity in aggregate-level data (Kashyap and Verkroost 2021). In our study, this is most pronounced in specific industry categories and for countries with smaller population sizes. (Appendix in full paper will include a detailed analysis of missingness).

To manage computational loads and maximize audience counts beyond the aggregated threshold, this study focuses on the 50 largest migrant sending and receiving countries, as measured by the size of the skilled migrant population.[3] It was not possible to collect data from Russia and Syria due to limited access to the platforms in these countries amidst ongoing violent conflict. We also collect information at the continent-level to increase audience sizes, excluding Oceania because we report Australia and New Zealand at the country-level. Finally, we group industries, age groups

[2] The Recruiter platform provides information at a more granular level but we only collect aggregate-level data to maintain data privacy.

[3] This focus on larger populations likely captures migration to and within countries in the Global North, which are more common destinations for skilled migrants. We focus on these countries as the primary sites of skilled labor migration but future work targeting South-South migration among professional migrants would enrich our overall understanding of global labor migration dynamics and might reveal a unique set of patterns.

and employment-tenure cohorts for ease of interpreting the results and to increase audience count sizes.

This paper contributes to a growing line of research leveraging the potential of digital data sources (Druhout et al. 2023). As with many of these sources, which are not originally designed for scientific research, LinkedIn is not representative of country-level populations (Zagheni and Weber 2015). For example, the population on LinkedIn is younger and more male than the underlying population (Kashyap and Verkroost 2021; Cruz 2021). This study offers an analysis of LinkedIn users and the findings should be interpreted within this context, rather than for the underlying population in a country.

That said, these data capture information about over 930 million LinkedIn users around the world, and provide important insights into international job search and relocation behavior among professionals moving internationally. LinkedIn is an important job seeking tool and is the most commonly used professional networking platform globally, with a continuously growing usership (Smith and Watkins 2020; Dixon 2023). In many industries central to international migration, it is considered standard practice to create and maintain a LinkedIn profile (Garg and Telang 2012; Hosain and Liu 2020). Thus, the findings of this study reflect important dynamics about the employment and migration of professionals on a key online platform.

Further, recent work indicates that LinkedIn usership largely reflects ground truth data from the International Labor Organization and is a useful predictor of gender gaps in professional populations (Kashyap and Verkroost 2021). In an analysis of LinkedIn advertising data, Kashyap and Verkroost (2021) find that women are significantly underrepresented on LinkedIn in STEM fields, at older ages and more senior positions, and in Africa, the Middle East and South Asia. These findings largely reflect ILO reports on the same dynamics, but the advertising data allow the authors to expand the analysis to countries missing from ILO data with additional measures. Additional studies by the World Economic Forum (2023) have recently used LinkedIn advertising data as a source to supplement to its own survey data and have reached similar conclusions about gender gaps reflected on LinkedIn and in the general population.

We take these studies as a foundation establishing the validity of LinkedIn data for gender analysis among professionals. Our paper extends this work and sharpens the focus on migrants to understand gender gaps among migrant professionals. For the purposes of this study, we assume that migrants behave similarly to native-born populations on LinkedIn when searching for jobs in destination countries, though further work about the online behavior of job-seeking migrants would enrich this work (Hosain and Liu 2020).

Measures

We include the following measures in our analysis, based on the definitions provided by the LinkedIn Advertising platform (LinkedIn Advertising 2023 and LinkedIn Help 2023). As others have noted in recent studies using digital trace data, social media platforms are often a "black box" with regards to the specific ways they infer measures provided to researchers (Stewart et al. 2019). Some of the explanations provided by the platform are vague; for example, LinkedIn does not provide a time frame for its definition of "recently" relocated, or how it infers user age and gender. We take the measures provided as estimates but recognize that precise details are not explained to researchers and the results should thus be interpreted as indicators of patterns rather than exact measures. For more on considerations in demographic inference techniques, see Wang et al. 2019 and Lockhart, King and Munsch 2023.

Recently relocated (international). Members who recently relocated to another country. This is based on a country change in the location of employment between two job titles. We interpret this as an estimate of recently arrived migrant stock in destination countries.

Open to international relocation. Members who are seeking jobs in a different country. This is based on job search behavior in a country outside of a user's current location. The Advertising platform provides information about openness to relocate, which we use as a measure of potential outflows from an origin country. The Recruiter platform provides the specific country of potential relocation, which we use to estimate migration aspirations to a destination (see Perrotta et al. 2022 for more on the use of Recruiter platform data for studying potential migration flows).

Member age. LinkedIn estimates how old a member is based on profile information such as years since high school or college graduation and years in the labor force. We construct three age groups for our analysis: 18-24 year olds; 25-34 year olds; 34-55 year olds. We also collected information on users over 55, but due to consistently low audience sizes across all categories we do not report this group in our analysis due to high variability and missingness in the data.

Member gender. LinkedIn infers whether a user is male or female based on profile information such as user name and profile picture. When inference is not possible, LinkedIn does not assign a gender to all users; on average, 75 percent of LinkedIn users are labeled as male or female on the Advertising platform.[4] We analyze the two gender categories provided by LinkedIn (male and female) but recognize the need for future research on nonbinary users, if this measure becomes available (Lagos 2022).

Years of experience. Accumulated years of professional experience, excluding gaps in employment. Overlapping positions are not double-counted. We group the years of experience into three employment cohorts (1-3 years; 4-7-years; 8+) to capture early an career stage at initial labor market entry, a slightly more advanced career stage, and more senior career stages.

Company Industry. The primary industry of the company where the member is employed, as stated by the company. Additional industries may be inferred by LinkedIn about the company. We group the 20 industry categories on LinkedIn into 10 categories for ease of interpretation and to manage computational load and increase audience count sizes in our data collection. The categories are: Construction and Agriculture; Education; Finance; Government; Healthcare; Manufacturing, Supply Chains and Logistics; Oil, Gas and Mining; Consulting; Real Estate; Tech, Information Technology and Media; and "other."

Socio-economic indicators from external sources

To explore the relationship between the iGGI and eGGI established in our LinkedIn data and broader socioeconomic indicators, we incorporate measures from additional data sources. First, we use the World Economic Forum's Global Gender Gap Index which measures gender parity across four key dimensions (Economic Participation and Opportunity, Educational Attainment, Health and Survival, and Political Empowerment). The index ranges from 0-1, with a value of 1

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[4] Because we do not have access to LinkedIn's gender assignment algorithm, we are not able to test for systematic bias in the algorithmic assignment of men and women. However, we can examine gender assignment by country, and its implications for the assigned gender composition of users on LinkedIn. We find that countries in East Asia and Southeast Asia have lower rates of gender assignment for all LinkedIn users, at 41 percent and 65 percent respectively. This is consistent with prior work showing that demographic inference using algorithms is less effective at ascribing demographic characteristics to racial minorities (Lockhart, King and Munsch 2023) and highlights an important avenue for improved techniques across race and nationality categories. This gap in gender assignment among Asian LinkedIn users might introduce some bias in the findings of this paper because Asian-origin labor migration streams from countries such as the Philippines, Indonesia, China and Thailand are female-dominated (Terrazas and Batalova 2010; Abel 2022). As such, the findings of this paper might be underestimating the share of women migrants. Other Asian countries like India with more male-dominated labor migration streams have a higher rate of gender assignment in our dataset, at 84 percent of all users in India, for example (Abel 2022).

indicating parity.[5] Second, we incorporate the World Bank's measure of GDP per capita (purchasing power parity).[6] Third, we include a measure of skilled migrant wages, provided by the OECD for member countries.[7] Using the same OECD database, include a measure of the gender wage gap between men and women.[8] Next, we use a measure of welcoming long-term migration policy context for skilled migrants in OECD destination countries, measured by immigrant integration, ease of legal status adjustment and access to citizenship. Finally, we include a measure of internet penetration from the United Nation's International Telecommunication Union.[9] A full description of the methodology of each of these measures is available in the documentation provided in each reference.

Methods. We compute a female-to-male migrant ratio that measures the Immigrant and Emigrant Gender Gap Index (iGGI and eGGI) among migrant professionals. We also calculate an Overall Gender Gap Index (oGGI) as a reference point for the total (migrant and non-migrant) LinkedIn population in each country. This extends Kashyap and Verkroost's previous work (2021) estimating country-level gender gaps on the LinkedIn Advertising platform. A GGI value below one indicates that the migrant professional population is more male in a given country; a value over one indicates that women comprise a larger share of the migrant pool than men. The iGGI measures recent immigrant arrivals in destination countries; the eGGI measures potential emigrant departures from origin countries.

We calculate the female-to-male gender ratio among recently arrived immigrant inflows (iGGI) through the stock of LinkedIn users on the Advertising platform who recently relocated internationally, given by:

$$iGGI = \frac{Recently\ relocated\ women}{Recently\ relocated\ men}$$

We calculate the female-to-male gender ratio of potential emigrant outflows (eGGI) through the stock of LinkedIn users on the Advertising platform who have indicated that they are open to relocate internationally:

$$eGGI = \frac{Women\ open\ to\ relocate\ internationally}{Men\ open\ to\ relocate\ internationally}$$

Finally, to provide a baseline for gender gaps in the overall population of LinkedIn users in each country, we calculate the female-to-male gender ratio of the audience size on the LinkedIn advertising platform (oGGI) through the total stock of LinkedIn users on the Advertising platform:

$$oGGI = \frac{Women\ audience\ size\ on\ LinkedIn\ Advertising\ Platform}{Men\ audience\ size\ on\ LinkedIn\ Advertising\ Platform}$$

We also calculate a relocation-to-aspiration gap as the number of people who recently relocated to a destination country as a share of the total number of migrants who indicated they were open to relocate to that country. These results should be interpreted as population-level estimates of aspirations and relocations, rather than individual-level conversion of migration aspirations into migration behavior.

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[5] https://www3.weforum.org/docs/WEF_GGGR_2023.pdf
[6] https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD?most_recent_value_desc=true&year_high_desc=true
[7] https://www.oecd.org/migration/talent-attractiveness/2019/how-does-your-country-compare-in-each-dimension.htm
[8] https://data.oecd.org/earnwage/gender-wage-gap.htm#indicator-chart
[9] https://www.itu.int/itu-d/reports/statistics/facts-figures-2022/index/

To calculate the gap between migration aspirations and actual relocation behavior, we combine data from the Advertising and Recruiter platforms. We calculate the behavior-aspiration gap as the number of recently relocated migrants in a destination country (from the Advertising platform) as a share of the total number of migrants who indicated they were open to relocate to that country (from the Recruiter platform). We employ a standard weighting approach to adjust for rounding differences in the user numbers reported on the Advertising and Recruiter platforms. The Advertising platform provides population estimates that are on average 20 percent higher than the Recruiter platform. Thus, to calculate the migration behavior-to-aspiration gap, we use the formula:

$$Relocation - Aspiration\ Gap = \frac{Recently\ relocated\ to\ country * \frac{Advertising}{Recruiter} ratio}{Open\ to\ relocate\ to\ country}$$

Results

Gender Gaps in Recent Migrant Arrivals[10]

Figure 1 Panel A shows a matrix of the Immigrant GGI for the global migrant population, five regions, and the 38 largest skilled migrant receiving countries. The matrix disaggregates the iGGI by industry, age and years of experience. Values of 1 or above are shown in green to indicate gender parity or a women-majority population of migrant professionals.

Immigrant gender gaps across countries

At the global level, the Immigrant GGI is 0.99, meaning that the overall population of men and women immigrants on LinkedIn worldwide is very close to parity. We hypothesized that the global professional immigrant population would be near gender parity (H_{1a}), and this result confirms our expectations.

Figure 1 Panel B shows a map of the iGGI for the 38 host countries in our analysis. It shows that there is considerable variation in the gender composition of migrants across different countries and regions on LinkedIn. At the regional level, the North American international migrant population on LinkedIn is women-majority (iGGI=1.56), the European population is almost at parity (iGGI=0.96) and South America, Asia and Africa have male-majority professional migrant populations on LinkedIn.

At the country level, we identify three categories of host countries. First, we observe countries at parity or with women-majority migrant stocks (iGGI>1). This includes the United States, South Korea and France, as examples. The second category is countries close to parity with slightly male-majority migrant stock (0.85<iGGI<0.99). For example, this includes Italy, China and Canada. Finally, we identify countries with largely male-dominated migrant stocks (iGGI<0.85) such as India, Mexico, Japan and Saudi Arabia).

Immigrant gender gaps across industries

The results in the iGGI matrix indicate that there are important industry-level differences in the gender composition of the migrant population. Globally, Construction/Agriculture as well as Oil/Gas/Mining are very male-dominated industries mostly employing male migrants, with Immigrant GGIs of iGGI=0.39 and iGGI=0.34 respectively. In contrast, Healthcare, Finance and Real Estate are primarily comprised of female migrants, with Immigrant GGIs of iGGI=1.67, iGGI=1.31 and iGGI=1.28 respectively. Other industries were slightly female-dominated, including Education (iGGI=1.12), Government (iGGI=1.08) and Consulting (iGGI=1.02), or slightly male-dominated, including Manufacturing/Supply Chain/Logistics (iGGI=0.97). Finally, Tech/IT/Media

[10] As noted in the Data section, LinkedIn does not provide a precise measure of the time frame defined by “recent” relocation, but this is likely a country change within the last 6 months or 1 year.

had a Migrant GGI of 0.82, meaning the industry employs more men, but with a smaller gap than Construction/Agriculture and Oil/Gas/Mining. This is consistent with our hypothesis (H_{2a}) expecting more international mobility of women in feminized industries like Healthcare and Education (Hochschild and Ehrenreich 2002; Walton-Roberts 2022; Kofman and Raghuram 2022).

At the country level, the gender composition of immigrant professionals employed in different industries varies considerably. The United States is a notable exception, where all industries except oil/gas/mining have female-majority immigrant professional populations. For example, education, finance, healthcare, manufacturing, consulting, real estate and technology are considerably female-majority, with iGGI>1.2. France is another exception with women-majority immigrant professional employment in education, finance, government, healthcare, manufacturing, and consulting.

Other developed Western countries which are important destinations for skilled migrants including Australia, Germany, Canada and the United Kingdom have a mixed composition across industries. In these countries, construction/agriculture, finance, manufacturing, oil/gas/mining and tech are male-majority industries. In contrast, other countries like India and Saudi Arabia have male-majority immigrant professional populations in all industries with available data.

Immigrant gender gaps across age and years of experience

The iGGI matrix indicates that the gender composition of the migrant population varies across age and years of experience, but follows a V-shaped pattern rather than a linear trend. The age distribution of recent migrant arrivals shows that women professionals move internationally before age 24 or after age 34 at higher rates than men. Women outnumber men in the youngest (18-24 years old) and oldest (35-54 years old) age groups globally, but men outnumber women in the mid-range age group (25-34 years old). This indicates that men move abroad for work at slightly older ages than women in their mid-20's, and a second group of women professionals move when they are older than 34. It is possible that the high levels of mobility among 18-24 year old migrant women includes some international students who are simultaneously studying and working.

Years of experience follows the opposite pattern globally, with male-dominated migrant populations in the most junior (1-3 years) and senior (8+ years) employment cohorts, but female dominated migrant populations in the middle cohort (4-7 years). This indicates that male professionals are more internationally mobile at the earliest career stages, while women move internationally slightly later in their careers. A separate cohort of men are more internationally mobile in more advanced career stages.

These results challenge our hypothesis (H_{2b}) that women would be more internationally mobile in younger age groups and earlier career stages (Hochschild and Ehrenreich 2002; Walton-Roberts 2022; Kofman and Raghuram 2022). Instead, we find that men are more internationally mobile at earlier career stages, while women are more mobile at younger ages, perhaps before fully entering the labor market. This might reflect higher levels of career flexibility for men with fewer family-care obligations.

At the country level, we identify four classes of dynamics in newer age and years of experience cohorts: 1) countries with persistently male-dominated migrant populations across cohorts (e.g. India for age); 2) countries approaching parity from male-majority migrant populations in younger and more junior groups (e.g. Chile for age); 3) countries switching from male- to female-majority migrant populations (e.g. South Korea for age); 4) countries with persistently female-dominated migrant populations (e.g. United States for age). Few countries were approaching parity from female-dominated migrant populations across age cohorts, and only one country (Germany) switched from female- to male-majority migrant populations.

Gendered Patterns in Immigrant Selectivity

To better understand how the professional immigrant population differs from the overall population of professionals on Linkedin, we compare the oGGI[11] with the iGGI. This helps us identify whether the migrant population has a higher share of women compared to the overall population in a given destination country.

The global population of all migrant and non-migrant users on LinkedIn is oGGI=0.77, meaning that men use LinkedIn at higher rates than women globally. Comparing the global iGGI (0.99) and overall LinkedIn oGGI indicates that women are overrepresented in the migrant population compared to the global population of LinkedIn users by 0.22 points. This suggests that women professionals may be a highly selected group, given their representation in the workforce relative to larger gender inequality in the professional workforce.

Figure 2 analyzes these dynamics by host country. It shows the oGGI on the x-axis and the iGGI on the y-axis, with a 45º line to illustrate gender parity with a GGI value of 1.First, the figure shows that the regression line closely fits the 45º line, suggesting that the gender composition of both migrant and non-migrant professionals globally is close to parity, echoing the indicators from the iGGI matrix.

We find important variation in key skilled migrant destination countries. The figure indicates that in most Westernized developed countries such as the United States, United Kingdom, France and Germany, the iGGI is higher than the oGGI, indicating that the immigrant population is more female than the overall population. For example, the iGGI in the United Kingdom is 0.22 points higher than the oGGI, 0.24 points higher in France and 0.25 points higher in Germany. The gap is even wider in the United States, where the iGGI in the United States is 0.92 points higher than the oGGI. This indicates that the population of immigrant professionals is more female than the overall population of professionals in developed Western countries and suggests that women immigrant professionals might be highly selected on certain employment characteristics relative to the total professional workforce in these countries.

We further disaggregate these dynamics by industry. Globally, immigrant women professionals on LinkedIn are overrepresented in finance, manufacturing, consulting, real estate, and technology. All of these industries have relatively high levels of male-dominated gender inequality in the overall professional population, with iGGIs of 0.82 or less. These patterns suggest that immigrant women professionals on LinkedIn are highly selected in male-dominated industries of finance, manufacturing, consulting, real estate and technology.

In contrast, immigrant women are underrepresented in education and healthcare, which are female-dominated industries in the overall professional population. Education has a global oGGI of 1.24 and Healthcare has a global oGGI of 1.79. Finally, immigrant women are employed at relatively similar rates to the overall professional population in construction, government, and oil/gas/mining. While government is close to parity in the overall professional population with an oGGI of 1.01, construction and oil/gas/mining are largely male-dominated industries with oGGI=0.39 and 0.35, respectively.

In the finance sector, migrant women are overrepresented relative to the overall population in Australia, Egypt, France, Netherlands, the United Kingdom and the United States. In technology, women are overrepresented in the UK, the US, Sweden, Ukraine, Singapore, Netherlands, Germany, France, and Australia. Remember that this does not necessarily indicate that these industries are female-dominated, but rather, that women immigrants are employed at higher rates than women in the non-migrant population. For example, in the technology industry in the UK, the oGGI is 0.61 while the iGGI is 0.86.

The Consulting and Manufacturing/Supply Chain/Logistics industries have even more countries with a larger share of immigrant women professionals than the overall population. In consulting, this includes Australia, Canada, Denmark, Egypt, France, Germany, Ireland, Italy,

[11] See Appendix Table A for full results of oGGI values.

Japan, Malaysia, Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Ukraine, United Kingdom and United States. In Manufacturing/Supply Chain/Logistics, this includes, Australia, Belgium, Denmark, Egypt, France, Germany, Ireland, Italy, Netherlands, New Zealand, Singapore, Spain, United Kingdom and United States.

Factors related to Immigrant Gender Gap

As discussed in the literature review, the gender composition of the professional immigrant population is influenced by political-economic factors that vary across different countries. We explore the relationships between country-level iGGI and six economic and political indicators by calculating the Pearson correlations. The results are reported in Table 1 and the statistically significant relationships are visualized in Figure 3.

First, we explore the relationship between iGGI and gender egalitarianism indicated by the World Economic Forum's Global Gender Gap Index.[12] We find a moderate positive relationship in the Pearson correlation (r=-0.49) between these measures, which indicates that countries with a higher iGGI are positively associated with countries with a smaller gender gap. In other words, more gender egalitarian countries are positively associated with having a larger share of women in the professional immigrant population. This provides support to H_{1b}, where we expected the gender composition of the migrant population to be more female in more gender-egalitarian countries. This relationship visualized in Figure 3 Panel A.

With respect to economic indicators, the results in Table 2 show a positive but insignificant relationship between the iGGI and GDP per capita (PPP). We also explore the relationship between the iGGI and skilled wages, as well as the gender gap in earnings between men and women, but do not find a statistically significant association. Further, the relationship between iGGI and internet penetration is also not significant.

Finally, we consider the migration policy context in host countries. We find a significant moderate positive relationship between the iGGI and future prospects of long-term settlement in OECD countries. This indicates that countries with more welcoming immigration policies promoting integration and long-term settlement for skilled migrants are associated with a higher share of women in the immigrant population. This relationship is visualized in Figure 3 Panel B for the 21 countries for which the "future prospects" indicator was available from the OECD.

<u>Gender Gaps in Potential Migrant Outflows</u>

We now turn our analysis to potential outflows of professionals leaving an origin country for employment abroad. Figure 4 Panel A shows the matrix of the Emigrant GGI by potential sending country, industry, age, and years of employment. This includes the 43 largest migrant sending and receiving countries[13] to look at potential emigration from both origin and destination contexts, including contexts of displacement like Ukraine and Venezuela.

The results show a markedly different picture of the gender composition of potential emigrant outflows, compared to the recently arrived immigrant stock in the prior analysis. Globally, regionally and at the country level, all potential emigrant outflows are predominantly male, with an eGGI below one. These dynamics are visualized in Figure 4 Panel A, which shows the spatial distribution of the emigrant gender gap and underscores the male-majority eGGI across all countries. Further, potential migrant men are overrepresented compared to the oGGI overall population of LinkedIn users in every country.

[12] WEF reports an index of global gender gaps as the distance from parity on a 0-1 scale. See WEF 2023 Global Gender Gap report for full methodology of this measure.

[13] Belgium, Denmark, Hong Kong, Iceland, Jamaica, Philippines and Singapore are excluded from the Emigrant GGI analysis because of insufficient audience counts.

These results run counter to our expectation in H_{1c} that openness to relocation would have a female-majority eGGI in countries with higher levels of gender inequality. Instead, the results suggest that more gender unequal countries have higher levels of potential male emigration, perhaps due to higher opportunity to migrate or more labor market participation.[14]

Globally, all industries are male-dominated, though there is some country-level variation in Education, Government and Healthcare. This provides some credence to our expectation H_{2c} that rates of female potential emigration would be higher in female-dominated industries. With respect to age and years of experience, all cohorts are male-dominated, but are moving closer to parity in more junior and younger cohorts, though the gap is still large (eGGI ranges from 0.67 to 0.07).

Factors Related to Potential Emigrant Gender Gap

We explore the relationship between eGGI and political-economic factors in Table 2, which reports the Pearson correlations between eGGI and six indicators. The statistically significant relationships are visualized in Figure 5.

First, we consider the relationship between eGGI and gender egalitarianism indicated by the World Economic Forum's Global Gender Gap Index. We find a significant moderate positive relationship in the Pearson correlation (r=0.38) between these measures. This indicates that countries with a higher eGGI are positively associated with countries with a relatively smaller gender gap. In other words, more gender egalitarian countries are positively associated with having a more-female potential emigrant population, even if it is not at parity. Put another way, while the findings in Figure 4 indicate that men have considerably higher levels of potential emigration in all countries, more gender-equal countries in this study are associated with slightly higher levels of potential female out-migration. This relationship is visualized in Figure 5 Panel A.

We also test the relationship between eGGI and the other factors. With respect to economic indicators, we find a moderate negative relationship between the iGGI and skilled wages, significant at the p=.05 level. This is visualized in Figure 4 Panel B. This result indicates a higher level of potential emigration in countries with lower wages for skilled migrants, suggesting low wages can function as a push factor for professional migrants. However, as indicated in the prior analysis reported in Table 1, there is not a significant relationship between destination countries and skilled migrant wages, suggesting it is more of a push factor than a pull factor to specific destinations. Further, the relationship between the gender wage gap and the eGGI is not significant, indicating that wage differentials between countries, rather than gender-specific disparities in wages, might be a more important factor.

We do not find a significant relationship between eGGI and GDP per capita or internet penetration. We do not explore the relationship between migration policy and potential emigration from sending countries because it is difficult to interpret the results without being able to differentiate between native- and foreign-born potential emigrants, for whom the migration policy context is very different because of their citizenship status.

<u>Migration Aspirations and Behavior</u>

Finally, we are interested in the conversion of professional migration aspirations into observed migration behavior on LinkedIn. We calculate a relocation-to-aspiration gap as the number of people who recently relocated to a country for work as a share of the number of people who indicated that they are open to relocate to that country for work. This analysis combines

[14] This persistent male-dominated gap in eGGI may also be explained by gender differences in job search behavior on LinkedIn. Men may actively pursue jobs in other countries at higher rates than women, reflecting broader gender differences in both online behavior (Hasan 2010; Hassan 2019.) and job-seeking behavior (Obukhova and Kleinbaum 2022; Cortes et al.2021). This difference in online networking may also reflect gender differences in the structure of in-person professional networks (Zhou and Logan 1989; Wynn and Correll 2017).

information about the recently relocated immigrant stock from the Advertising platform and the population open to relocating to a destination from the Recruiter platform. Because the Recruiter platform does not collect information on gender to avoid discriminatory hiring practices, we focus our analysis on the gap between aspirations and relocation among the general population. This analysis is intended to broadly illustrate the gap; deeper analysis of the factors related to these patterns will be the focus of a parallel paper.

Figure 6 shows the results for the 39 destination countries with available data. The table shows a large gap between professionals on LinkedIn who aspire to migrate and professionals on LinkedIn who actually relocate. The median relocation-aspiration score across the 39 countries with available data was 22 percent, indicating that almost 4 out of 5 people who express migration aspirations do not move.

There is considerable variation in the relocation-to-aspiration ratio across countries. In India, the recently relocated population was more than half (60%) of the aspiring migrant population. In six countries, (Pakistan, Philippines, Poland, Brazil, USA, Egypt and France), the gap ranged from 47% to 33%. In the remaining 32 countries, the relocated population of migrant professionals represented less than a third of professionals open to relocate to that country.

Discussion

This paper utilizes an emergent digital data source to offer fresh, detailed insights into gender gaps in the international immigration and potential emigration of professionals. We use information from the LinkedIn Advertising platform to take a close look at how gender differentials vary across countries, industries, age, and years of experience.

We find that, among Linkedin users, the global immigrant population is at gender parity, while the population of those open to international relocation is largely male. Thus, while men have considerably higher migration aspirations, globally, men and women have similar rates of mobility. As a brief illustration of the gap between aspirations and actual migrations, we estimate that about 1 in 5 people who express aspirations convert them into an actual move. We find that men are more internationally mobile at earlier career stages, while women are more mobile at younger ages, perhaps before fully entering the labor market.

We find considerable variation at the host country level, with female-majority populations of immigrant professionals in USA, Singapore, France, South Korea, Australia and the UK. In contrast, countries like India, United Arab Emirates and Saudi Arabia have considerably male-majority professional immigrant populations, and others like Sweden, Canada and Spain have slightly male-majority professional migrant populations. We find that country-level variation in the gender composition of professional immigrants on LinkedIn is associated with gender equality, migration policy and wages. In particular, countries with a larger share of women professional immigrants are positively associated with higher levels of gender egalitarianism, more welcoming migration policies, and higher wages.

These results are consistent with recent related work estimating the global skilled migrant population, but we are able to provide more detail in the composition of the migrant population (Abel 2022). Our results show that men on LinkedIn are more internationally mobile at earlier career stages, while women are more mobile at younger ages, perhaps before fully entering the labor market.

Further, we find that women LinkedIn users are more mobile in female-dominated industries. Key industries driving female professional migration include education, finance, healthcare, and real estate, where the female-to-male gender ratio exceeds iGGI>1.1. In some countries, these industries are prioritized in migration policies that create targeted entry pathways for skilled migrants and gendered migration channels (Kofman and Raghuram 2022). The age dimension suggests

These findings suggest women migrant professionals on Linkedin might be positively selected in countries with advanced economies like the United States, Australia, the UK, France and Germany. In these countries, migrant women are overrepresented relative to the country-level population of professionals, especially in industries including consulting, finance and information technology.

This paper lays the groundwork for further analysis with these data. As we continue collecting these data across multiple time points, they lend themselves to future longitudinal analysis of shifting gender dynamics over time. Further, more detailed country-specific analysis might reveal useful insights into the gender patterns in professional migration from such as Ukraine and Venezuela to countries like Poland and Colombia, where large populations are being displaced amid violent conflict and economic collapse and detailed, timely data are scarce. Finally, we aim to conduct deeper analysis of the gap between migration aspirations and actual moves as the focus of a parallel paper.

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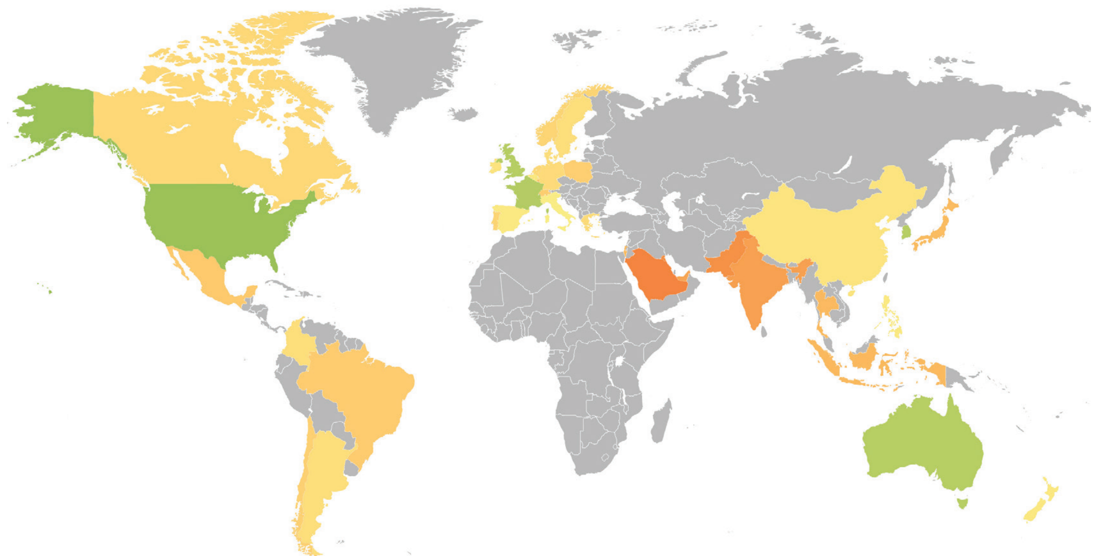
Figure 1

Panel A. Immigrant Gender Gap Index (iGGI)

	iGGI	INDUSTRY											AGE			YEARS OF EXPERIENCE		
	Immigrant GGI	Construction and Agriculture	Education	Finance	Government	Healthcare	Mfg., Supply Chain, Logistics	Oil, Gas and Mining	Consulting	Real Estate	Tech, IT and Media	Other	18-24	25-34	34-55	1-3	4-7	8+
Global	0.99	0.39	1.12	1.31	1.08	1.67	0.97	0.34	1.02	1.28	0.82	1.03	1.07	0.89	1.13	0.96	1.08	0.92
North America	1.56	0.75	1.18	2.44	1.14	2.39	1.68	0.62	1.41	2.75	1.23	1.29	1.49	1.32	1.97	1.14	1.72	1.54
Europe	0.96	0.39	1.23	0.84	1.39	1.77	0.80	0.38	1.01	1.14	0.73	1.12	1.04	0.98	0.88	1.10	1.08	0.81
South America	0.80	0.41	1.12	0.61	1.36	1.84	0.65	0.22	0.87		0.51	1.08	0.91	0.91	0.65	0.96	0.91	0.65
Asia	0.53	0.17	0.86	0.59	0.75	0.97	0.46	0.17	0.63	0.51	0.52	0.57	0.65	0.55	0.47	0.60	0.61	0.43
Africa	0.53	0.21	0.75	0.64	0.69	0.93	0.42	0.24	0.61		0.39	0.67	0.72	0.54	0.40	0.63	0.57	0.40
United States	1.91	1.02	1.25	2.94	1.12	2.47	2.20	0.74	1.61	3.29	1.43	1.47	1.77	1.52	2.41	1.36	2.21	1.91
Singapore	1.52	0.60	1.64	0.92			1.54		2.04		1.20	1.80	1.46	1.43	1.68	1.23	1.82	1.38
France	1.17	0.31	1.26	1.06	1.35	1.72	1.08	0.79	1.09		0.86	1.33	1.09	1.31	1.06	1.39	1.38	0.93
South Korea	1.05						0.84		1.19				1.53	1.18	0.72	1.43	1.26	0.78
Australia	1.04	0.44	1.21	0.94	1.32	2.06	0.85	0.40	1.31	1.25	1.00	1.14	1.04	1.01	1.18	1.00	1.27	1.00
United Kingdom	1.01	0.40	1.16	0.83	1.16	1.60	1.01	0.38	1.07	1.09	0.86	1.07	1.05	0.97	1.07	1.04	1.18	0.91
Italy	0.99		1.26	0.82	1.24		0.87		1.19		0.84	1.53	1.14	1.07	0.86	1.18	1.33	0.84
Spain	0.97	0.55	1.57	0.80	1.55	2.00	0.80		1.07	0.97	0.63	1.18	1.16	1.07	0.81	1.17	1.18	0.83
Philippines	0.96			1.03			0.71		1.21		0.90	1.10	1.18	1.13	0.75	1.18	1.27	0.75
New Zealand	0.96			1.00			0.83		1.00		0.69	1.02	1.32	1.00	0.82	1.17	1.20	0.78
Belgium	0.94		1.32		0.73		0.93		0.70	1.19			0.77			0.62	0.92	
Ireland	0.93		1.45	0.81		1.58	0.76		0.95		0.70	1.18	1.00	0.94	0.84	1.10	1.06	0.79
China	0.93		0.69	1.16			1.07		0.86		0.83	0.94	1.17	0.95	0.74	1.09	1.01	0.71
Sweden	0.90						0.68		0.92		0.88	1.04	1.13	0.89	0.77	0.98	0.99	0.76
Colombia	0.90						0.76		0.95		0.35	1.04	1.00	1.00	0.73	1.03	0.99	0.74
Argentina	0.89						0.73		0.97		0.38	1.20	1.06	0.94	0.70	1.10	0.94	0.73
Denmark	0.89						0.74		0.93			1.15	1.08	0.92	0.73	1.15	1.07	0.73
Germany	0.89	0.44	1.23	0.67	1.00	1.40	0.64		1.06		0.80	1.14	0.91	0.95	1.06	0.92	1.00	0.77
Greece	0.88								0.93			1.16		1.02			1.15	0.70
Canada	0.86	0.37	1.07	0.87	1.20	1.69	0.68	0.41	1.06	1.02	0.69	0.92	0.79	0.85	0.90	0.85	1.08	0.82
Netherlands	0.86		1.41	0.72	1.29	1.68	0.70		0.94		0.67	1.06	1.05	0.92	0.74	1.06	1.00	0.75
Portugal	0.84		1.28	0.71	1.27		0.63		0.82		0.42	1.12	0.91	0.84	0.81	1.01	0.94	0.72
Norway	0.81						0.58		0.90			1.03	1.05	0.85	0.71		0.94	0.69
Chile	0.80						0.62		0.85			1.95	0.94	0.90	0.67	1.09	0.90	0.67
Poland	0.78			0.79			0.63		0.79		0.62	0.98	0.87	0.81	0.54	1.26	0.86	0.56
Switzerland	0.76		0.97	0.58	1.21	1.48	0.60		0.69		0.54	0.92	0.73	0.81	0.64	0.96	0.76	0.66
Brazil	0.75	0.53	1.02		0.59		0.67		0.41	1.00			0.58			0.53	0.71	
Mexico	0.73		1.09				0.55		0.79		0.43	0.93	0.85	0.83	0.59	0.87	0.94	0.58
Japan	0.64		0.92	0.65	0.65		0.52		0.75		0.47	0.71	1.09	0.77	0.42	0.76	0.61	0.46
Luxembourg	0.63			0.78					0.82				0.97	0.84	0.82	0.89	0.93	0.75
Thailand	0.62								0.74			0.72	0.83	0.69	0.51		0.81	0.45
Indonesia	0.62						0.58		0.77			0.92	0.97	0.79	0.48	1.06	0.81	0.48
Israel	0.60								0.67					0.74	0.57		0.76	0.58
United Arab Emirates	0.46	0.19	1.00	0.43	0.77	1.00	0.34	0.17	0.49	0.46	0.41	0.48	0.52	0.48	0.39	0.53	0.51	0.37
India	0.40	0.14	0.67	0.48	0.71	0.72	0.27		0.49		0.42	0.41	0.54	0.41	0.33	0.55	0.47	0.26
Kuwait	0.28													0.29				
Pakistan	0.23						0.16		0.25		0.24		0.32	0.23	0.16	0.32	0.23	0.15
Saudi Arabia	0.19		0.49		0.39	0.65	0.12		0.22		0.21	0.20	0.24	0.20	0.14	0.22	0.20	0.14

Panel B. Spatial Distribution of iGGI

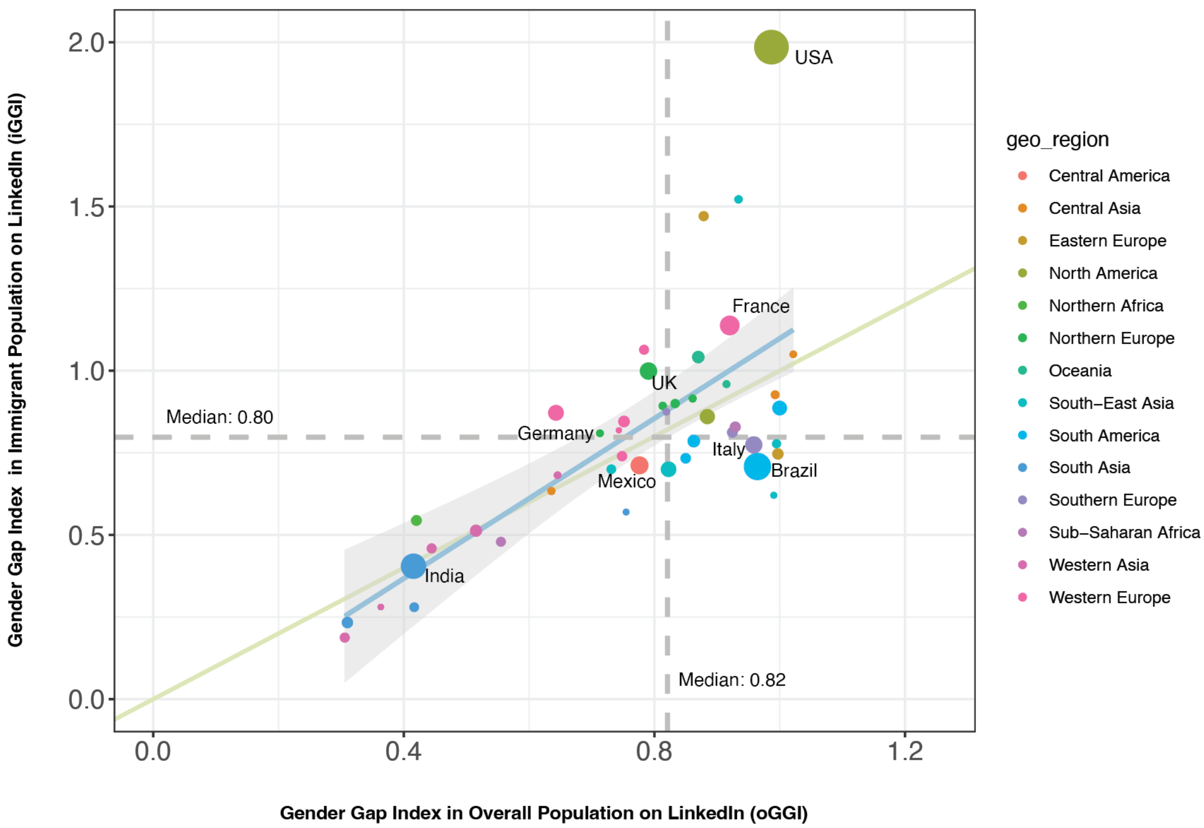


iGGI color scale

Source: LinkedIn Advertising Platform

Note: A GGI value below one indicates that women are underrepresented relative to men in the migrant population in the host country; a value over one indicates that women comprise a larger share of the migrant pool than men. Values of 1 or larger are scaled to darker shades of green to indicate parity or a more female migrant pool; values less than 1 are scaled from yellow to orange to indicate an increasingly male share of the migrant population. Missing data is shown in white in the matrix. Countries in grey on the map were not included in the analysis.

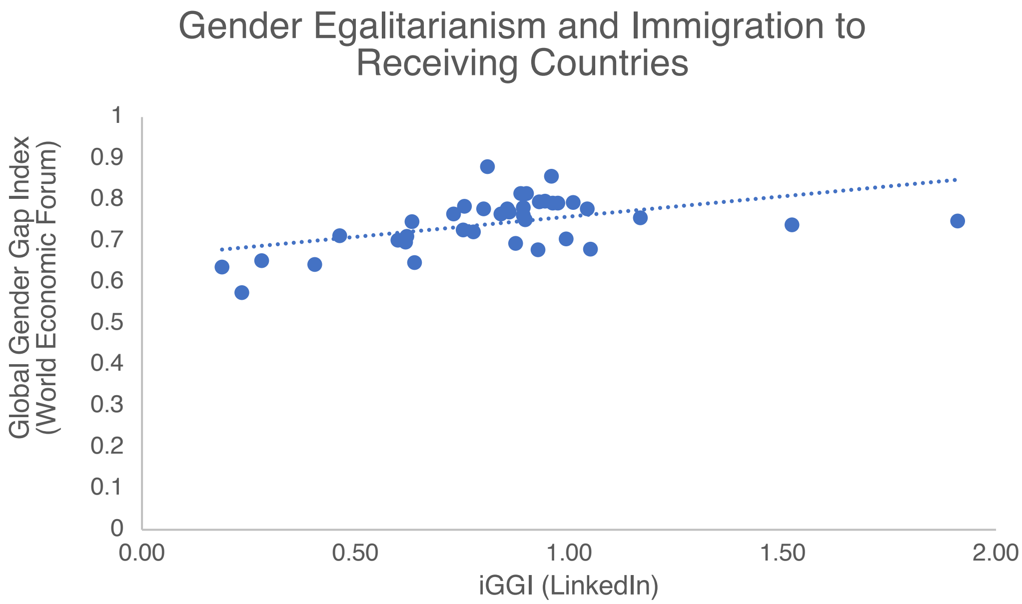
Figure 2. Gender ratios among immigrant and total LinkedIn users



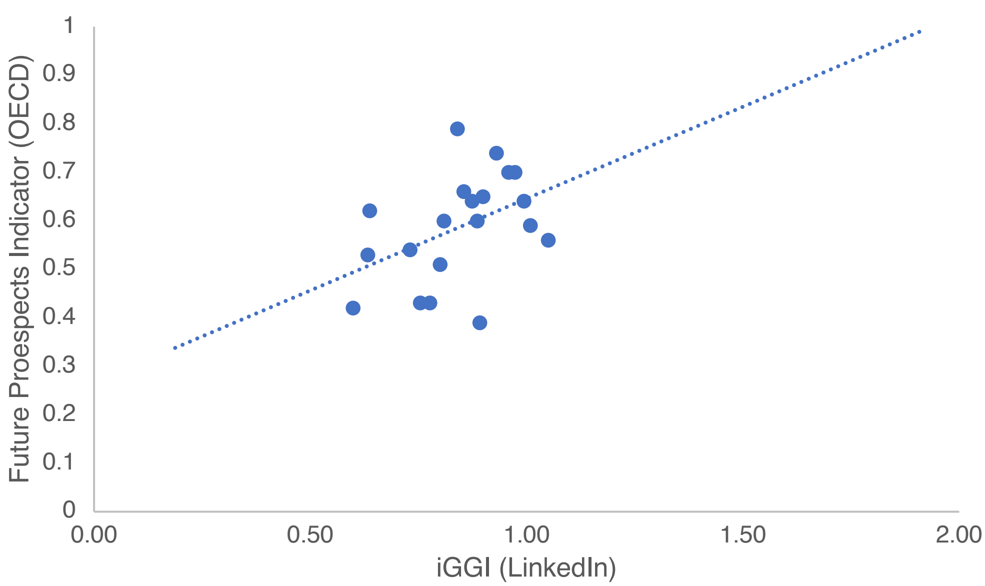
Notes:

The size of each country's circle is proportional to the number of female researchers who migrated from and to this country. The vertical and horizontal dashed lines indicate the median gender ratios of all professionals and immigrant professionals. The 45◦ line in each subfigure is used to help compare the gender ratios of these two categories compared to parity with a value of 1. The shaded grey region indicates the 95% confidence interval.

Figure 3
Panel A. Gender Egalitarianism and iGGI



Panel B. Migration Policy Openness and iGGI



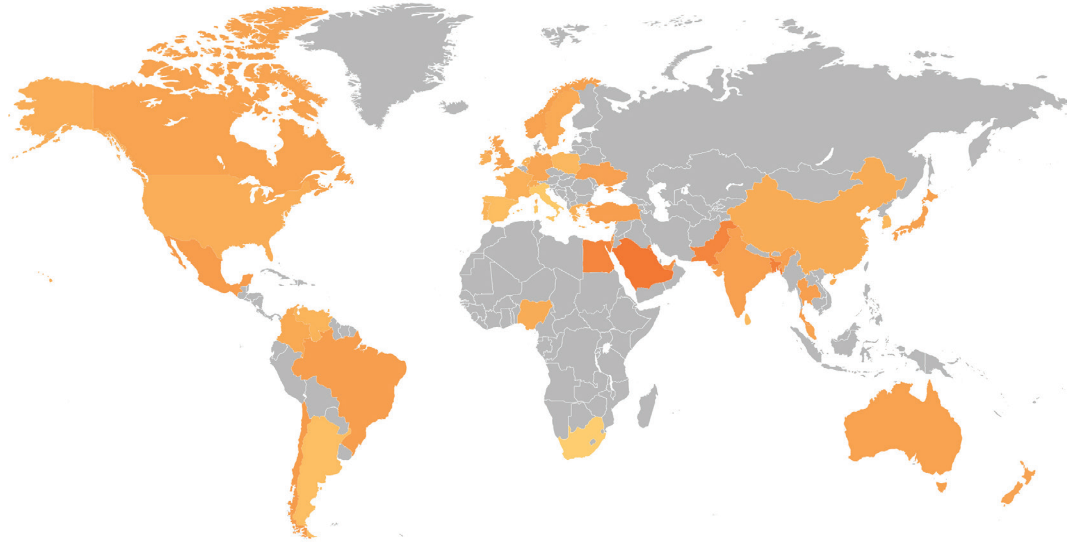
Source: Authors' analysis of data from LinkedIn Advertising Platform

Figure 4

Panel A. Emigrant Gender Gap Index (eGGI)

	eGGI	INDUSTRY											AGE			YEARS OF EXPERIENCE		
	Emigrant GGI	Construction and Agriculture	Education	Finance	Government	Healthcare	Mfg., Supply Chain, Logistics	Oil, Gas and Mining	Consulting	Real Estate	Tech, IT and Media	Other	18-24	25-34	34-55	1-3	4-7	8+
Global	0.42	0.22	0.66	0.40	0.67	0.75	0.31	0.17	0.45	0.33	0.36	0.54	0.49	0.44	0.34	0.47	0.45	0.34
Europe	0.57	0.32	0.86	0.41	0.85	1.07	0.48	0.22	0.59	0.58	0.48	0.86	0.62	0.65	0.52	0.62	0.65	0.52
South America	0.49	0.33	0.84	0.46	0.88	1.25	0.40	0.23	0.53	0.43	0.35	0.85	0.50	0.55	0.45	0.52	0.57	0.46
North America	0.46	0.27	0.66	0.44	0.72	0.90	0.35	0.15	0.46	0.58	0.38	0.60	0.52	0.49	0.38	0.49	0.52	0.39
Africa	0.43	0.20	0.65	0.52	0.67	0.90	0.31	0.19	0.49	0.35	0.38	0.53	0.52	0.43	0.36	0.49	0.43	0.36
Asia	0.37	0.15	0.55	0.34	0.52	0.56	0.22	0.13	0.40	0.24	0.34	0.36	0.47	0.36	0.25	0.46	0.39	0.24
South Africa	0.76	0.39	1.13	0.83	1.07	1.88	0.55	0.33	0.79		0.61	0.96	0.97	0.80	0.65	0.94	0.83	0.67
Italy	0.72	0.44	1.06	0.54	1.14	1.28	0.60	0.21	0.68		0.67	1.06	0.74	0.78	0.64	0.79	0.78	0.62
Argentina	0.64	0.38	1.11	0.54	1.05	1.50	0.50	0.26	0.74		0.44	1.10	0.70	0.77	0.56	0.65	0.77	0.62
Spain	0.63	0.38	0.98	0.46	1.16	1.26	0.53		0.63		0.51	0.94	0.61	0.66	0.62	0.59	0.69	0.63
Sri Lanka	0.62						0.52		0.67		0.71		0.65	0.70	0.59	0.73	0.67	0.58
Poland	0.60		0.90	0.56			0.53		0.63		0.47	1.01	0.58	0.66	0.54	0.63	0.74	0.54
South Korea	0.60													0.72				
Portugal	0.57	0.19	0.85	0.47	0.51	1.33	0.49		0.59		0.45	0.85	0.57	0.62	0.52	0.64	0.65	0.51
Venezuela	0.57		0.77	0.60	0.98		0.48	0.25	0.67		0.39	0.79	0.70	0.63	0.54	0.60	0.61	0.51
Netherlands	0.56		0.96	0.37			0.48		0.57		0.46	0.77	0.71	0.63	0.45	0.71	0.70	0.47
Greece	0.55		1.00				0.45		0.57		0.36	0.77	0.63	0.59	0.48	0.57	0.62	0.45
France	0.55		0.49	0.39	0.87		0.50		0.53		0.45	0.87	0.66	0.55	0.47	0.57	0.59	0.49
Ireland	0.54		0.80	0.46			0.48		0.53		0.48	0.74	0.54	0.57	0.50	0.53	0.59	0.50
United States	0.53	0.32	0.68	0.50	0.67	0.94	0.46		0.50		0.43	0.59	0.56	0.56	0.47	0.52	0.58	0.47
Indonesia	0.51		0.78	0.53	0.85		0.43	0.18	0.59		0.39	0.53	0.65	0.54	0.29	0.68	0.54	0.36
Switzerland	0.51		0.65	0.32			0.42		0.52		0.39	0.75	0.53	0.47	0.47	0.61	0.64	0.36
China	0.50													0.51	0.47			0.45
Nigeria	0.50	0.28	0.61	0.55	0.79	1.17	0.40	0.28	0.49		0.41	0.61	0.54	0.53	0.44	0.60	0.53	0.43
Sweden	0.49						0.32		0.56		0.44	0.76	0.69	0.57	0.40	0.61	0.62	0.39
Colombia	0.49	0.35	0.70	0.55	0.82	1.03	0.44		0.48		0.31	0.71	0.48	0.53	0.41	0.50	0.53	0.44
Germany	0.46	0.25	0.73	0.34	0.69	0.85	0.36		0.52		0.41	0.79	0.53	0.51	0.42	0.53	0.56	0.40
Luxembourg	0.46																	
United Kingdom	0.45	0.24	0.67	0.33	0.65	0.85	0.38		0.47		0.40	0.59	0.55	0.52	0.40	0.55	0.54	0.41
Malaysia	0.45			0.51			0.39		0.50		0.45	0.60	0.61	0.49	0.35	0.56	0.58	0.36
New Zealand	0.45													0.53	0.39			0.43
Canada	0.43	0.24	0.65	0.39	0.65	0.84	0.35		0.46		0.35	0.59	0.45	0.48	0.39	0.44	0.52	0.37
Japan	0.42													0.47				
Norway	0.41													0.48				0.39
Australia	0.41		0.48				0.33		0.44		0.35	0.61	0.57	0.47	0.33	0.56	0.52	0.35
Ukraine	0.41								0.52		0.38			0.60	0.46			0.43
India	0.40	0.18	0.59	0.38	0.59	0.60	0.24	0.15	0.44	0.27	0.37	0.40	0.48	0.41	0.28	0.49	0.42	0.25
Thailand	0.39																	
Brazil	0.39	0.30	0.64	0.35	0.72	0.99	0.31	0.20	0.39		0.29	0.68	0.38	0.44	0.36	0.41	0.46	0.34
Turkey	0.39	0.25	0.69	0.38	0.64	0.86	0.32	0.20	0.44		0.31	0.53	0.46	0.39	0.31	0.46	0.40	0.32
Mexico	0.38	0.14	0.67	0.40	0.74	0.80	0.29		0.43		0.33	0.60	0.49	0.43	0.31	0.46	0.47	0.32
Chile	0.37								0.41				0.25	0.41	0.29		0.44	0.31
Israel	0.34								0.39		0.29			0.39	0.38			0.35
United Arab Emirates	0.27	0.13	0.67	0.29	0.49	0.71	0.21	0.12	0.35	0.26	0.26	0.28	0.34	0.30	0.24	0.41	0.32	0.22
Pakistan	0.19	0.07	0.38	0.17	0.33	0.31	0.11	0.06	0.20		0.21	0.27	0.26	0.19	0.12	0.26	0.19	0.11
Egypt	0.19	0.07	0.43	0.18	0.41	0.31	0.13		0.25		0.21	0.26	0.28	0.18	0.15	0.23	0.20	0.14
Kuwait	0.16																	
Bangladesh	0.15						0.10		0.15		0.14	0.19	0.17	0.16	0.11	0.19	0.14	0.10
Saudi Arabia	0.09					0.33	0.06		0.10			0.10	0.14	0.10	0.07	0.13	0.10	0.07

Panel B. Spatial Distribution of eGGI

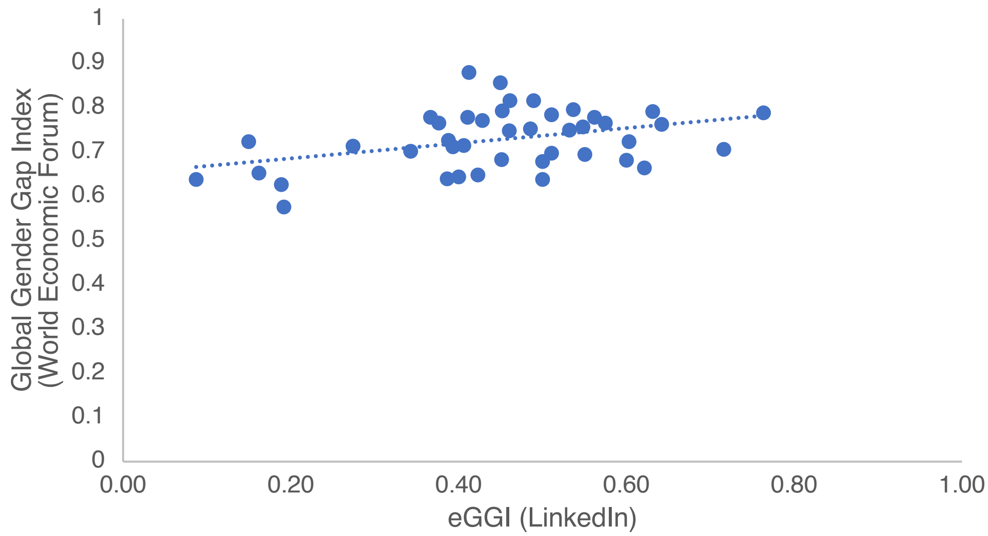


eGGI color scale

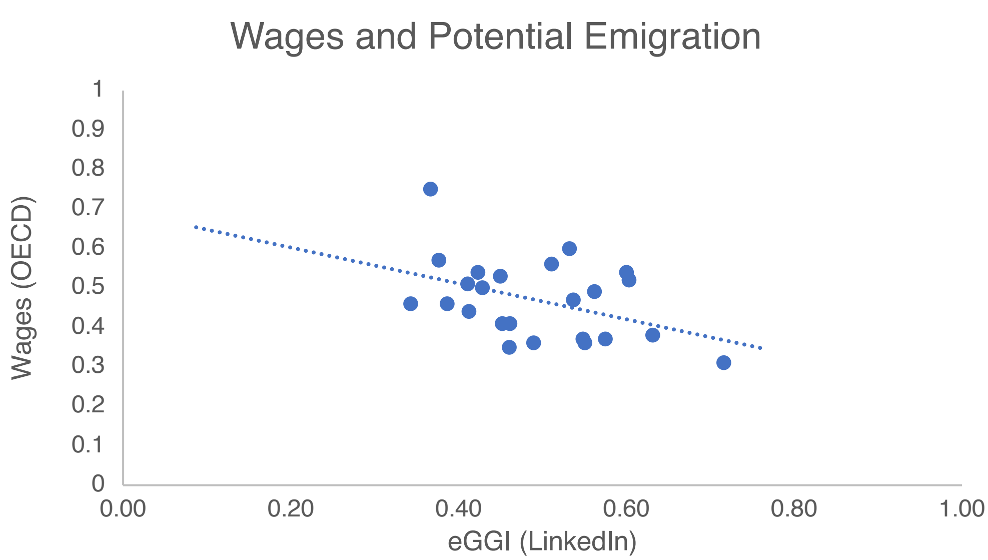
Source: LinkedIn Advertising Platform

Note: A GGI value below one indicates that women are underrepresented relative to men in the migrant population in the host country; a value over one indicates that women comprise a larger share of the migrant pool than men. Values of 1 or larger are scaled to darker shades of green to indicate parity or a more female migrant pool; values less than 1 are scaled from yellow to orange to indicate an increasingly male share of the migrant population. Missing data is shown in white in the matrix. Countries in grey on the map were not included in the analysis.

Figure 5
Panel A. Gender Egalitarianism and eGGI

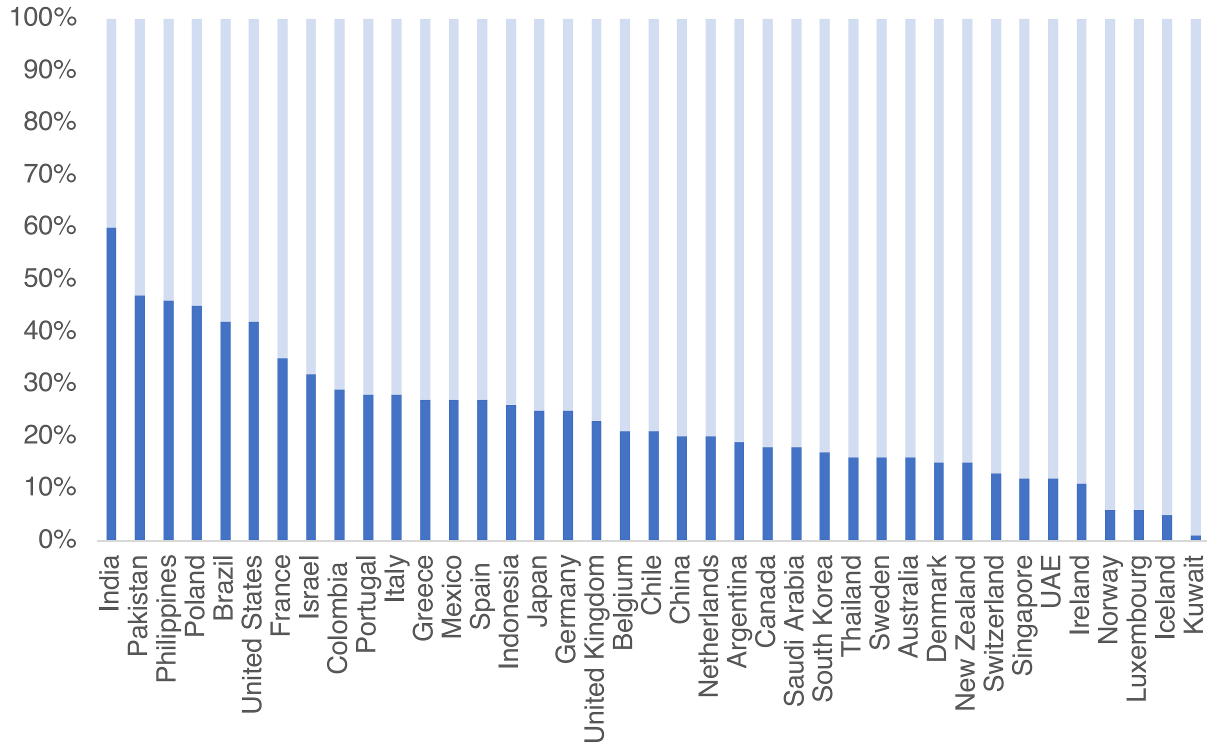


Panel B. Skilled Wages and eGGI



Source: Authors' analysis of data from LinkedIn Advertising Platform

Figure 6. Relocation-Aspiration Gap



Source: Authors' analysis of data from LinkedIn Advertising and Recruiter Platform
Note: Dark blue indicates population of people who recently relocated as a share of population open to relocate (light blue).

Table 1. Pearson Correlations between Migrant Gender Gap Index and Five Socio-Political-Economic Indicators

	Immigration	Emigration
	r	*r*
Gender Equality	0.49***	0.38**
GDP	0.28	0.05
Skilled Wages	0.09	-0.43*
Gender Wage Gap	-0.27	-0.32
Migration Policy Openness	0.44*	--
Internet Penetration	0.14	-0.10

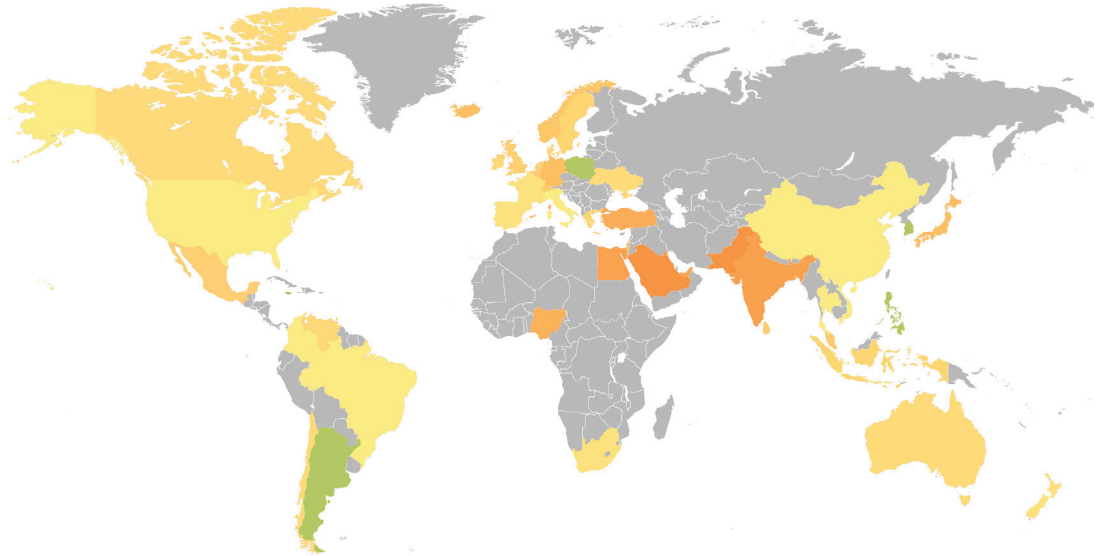
*** $p \leq 0.001$, **$p \leq 0.01$, * $p \leq 0.05$

Source: Authors' analysis of data from LinkedIn Advertising and Recruiter Platforms. Gender Equality indicator from World Economic Forum (2023); GDP from World Bank (2023); Wages from OECD (2023); Migration Policy from OECD (2023); Internet Penetration from UN International Telecommunciation Union (2023).

Appendix A
Panel A. Overall Gender Gap Index (oGGI)

	oGGI	INDUSTRY											AGE				YEARS OF EXPERIENCE		
	Overall GGI	Construction and Agriculture	Education	Finance	Government	Healthcare	Mfg., Supply Chain, Logistics	Oil, Gas and Mining	Consulting	Real Estate	Tech, IT and Media	Other	18-24	25-34	34-55	55+	1-3	4-7	8+
Global	0.79	0.39	1.25	0.80	1.01	1.79	0.62	0.35	0.78	0.82	0.64	0.94	0.85	0.82	0.77	0.49	0.95	0.91	0.73
North America	0.98	0.36	1.45	0.96	1.09	2.27	0.69	0.36	0.86	1.02	0.74	1.04	1.02	0.96	0.92	0.62	1.05	1.05	0.87
South America	0.93	0.46	1.44	0.94	1.10	1.98	0.69	0.33	0.92	0.80	0.66	1.07	1.05	0.97	0.81	0.46	1.11	1.00	0.76
Europe	0.85	0.39	1.29	0.80	1.15	1.88	0.65	0.41	0.80	0.82	0.64	1.00	0.91	0.89	0.81	0.49	1.06	1.02	0.75
Africa	0.58	0.32	0.72	0.70	0.64	0.92	0.45	0.29	0.62	0.56	0.48	0.60	0.63	0.56	0.52	0.34	0.72	0.59	0.47
Asia	0.54	0.28	0.79	0.55	0.72	0.79	0.41	0.27	0.56	0.44	0.48	0.55	0.59	0.53	0.47	0.26	0.68	0.59	0.44
Jamaica	1.33	0.47	2.03	1.64	1.91	2.89	0.97	0.54	1.44	1.10	1.00	1.29	1.55	1.28	1.20	0.73	1.86	1.60	1.19
Philippines	1.18	0.57	1.54	1.41	2.00	1.90	0.93	0.50	1.15	1.23	0.94	1.17	1.25	1.23	1.01	0.68	1.30	1.26	1.00
South Korea	1.02	0.75	1.16	0.94	1.11	1.40	0.87	0.68	1.08	0.98	0.99	1.15	1.06	1.09	0.85	0.54	1.41	1.31	0.86
Argentina	1.00	0.39	2.03	0.76	1.26	2.14	0.67	0.29	0.98	0.82	0.71	1.00	1.07	1.03	0.86	0.53	1.12	1.06	0.78
Poland	1.00	0.46	1.59	1.20	1.27	2.11	0.81	0.56	1.07	1.16	0.69	1.22	1.06	1.00	0.87	0.40	1.19	1.14	0.86
Hong Kong	1.00	0.46	1.15	0.94	1.08	1.37	1.00	0.60	0.94	0.90	0.83	1.06	1.09	1.04	0.89	0.42	1.19	1.25	0.89
China	0.99	0.88	1.02	1.07	1.08	1.08	1.06	0.88	1.04	1.00	0.85	1.19	1.10	0.99	0.96	0.40	1.37	1.36	1.01
Vietnam	0.99	0.60	1.27	1.18	1.21	1.16	1.04	0.78	1.04	1.10	0.92	1.10	0.97	1.00	0.99	0.56	1.30	1.18	0.93
Colombia	0.99	0.56	1.25	1.07	1.17	1.96	0.83	0.39	0.96	1.03	0.70	0.96	1.03	1.01	0.86	0.42	1.13	1.04	0.80
Thailand	0.99	0.69	0.94	0.96	0.89	1.15	0.96	0.77	0.95	0.74	1.19	0.75	1.68	0.85	0.63	0.22	1.12	0.94	0.55
United States	0.99	0.35	1.51	1.00	1.07	2.44	0.73	0.36	1.00	1.04	0.78	1.07	1.13	1.02	0.96	0.65	1.12	1.14	0.90
Brazil	0.96	0.48	1.46	0.94	1.08	2.10	0.71	0.33	0.95	0.75	0.67	1.17	1.06	1.00	0.83	0.44	1.15	1.02	0.75
Italy	0.96	0.47	1.75	0.82	1.00	1.73	0.74	0.45	0.92	0.83	0.83	1.02	1.08	0.99	0.93	0.49	1.31	1.21	0.82
Singapore	0.93	0.53	1.06	0.93	1.05	1.62	0.80	0.50	0.92	0.96	0.78	0.94	0.82	0.94	0.86	0.47	1.06	1.15	0.87
South Africa	0.93	0.46	1.36	1.11	1.16	1.90	0.72	0.44	0.96	1.11	0.75	1.00	1.02	0.91	0.84	0.57	1.06	1.00	0.77
Portugal	0.92	0.43	1.63	0.84	1.21	2.32	0.69	0.43	0.92	0.89	0.62	1.12	1.00	0.95	0.90	0.52	1.22	1.07	0.82
France	0.92	0.41	1.21	0.95	1.22	2.22	0.71	0.45	0.88	1.04	0.63	1.07	1.02	0.94	0.83	0.59	1.12	1.09	0.82
New Zealand	0.92	0.37	1.51	0.92	1.43	2.26	0.64	0.35	0.88	0.90	0.66	1.14	0.94	0.97	0.91	0.51	1.08	1.11	0.85
Spain	0.91	0.43	1.48	0.78	1.18	1.88	0.68	0.42	0.87	0.79	0.63	1.00	1.00	0.94	0.85	0.46	1.12	1.07	0.76
Canada	0.88	0.34	1.41	0.96	1.29	2.42	0.65	0.34	0.87	0.82	0.63	1.17	0.96	0.95	0.90	0.58	0.93	1.01	0.87
Ukraine	0.88	0.45	1.96	1.23	1.30	1.88	0.70	0.49	0.94	1.17	0.64	1.21	0.97	0.91	0.77	0.54	0.95	0.90	0.70
Australia	0.87	0.31	1.35	0.82	1.35	2.19	0.64	0.33	0.84	0.92	0.62	1.07	0.91	0.92	0.84	0.45	1.04	1.07	0.79
Chile	0.86	0.42	1.61	0.97	1.23	2.17	0.62	0.28	0.78	0.82	0.63	0.93	0.93	0.90	0.75	0.44	0.94	0.89	0.69
Ireland	0.86	0.24	1.29	0.83	1.25	2.08	0.65	0.31	0.77	0.71	0.65	0.95	0.93	0.92	0.82	0.42	0.95	0.92	0.76
Venezuela	0.85	0.47	1.42	0.87	1.15	1.43	0.62	0.36	0.92	1.00	0.60	0.73	0.83	0.85	0.78	0.50	0.92	0.84	0.74
Sweden	0.83	0.30	1.26	0.79	1.82	2.17	0.58	0.38	0.71	0.67	0.54	1.00	0.86	0.89	0.79	0.58	0.86	0.94	0.81
Indonesia	0.82	0.49	1.12	0.88	1.00	1.47	0.67	0.42	0.81	0.66	0.68	0.76	1.03	0.79	0.54	0.35	1.06	0.84	0.57
Greece	0.82	0.42	1.32	0.82	1.13	1.24	0.58	0.45	0.84	0.75	0.60	0.87	0.85	0.87	0.01	0.00	1.03	0.99	0.70
Denmark	0.81	0.31	1.24	0.71	1.48	2.37	0.57	0.36	0.76	0.56	0.57	1.16	0.80	0.93	0.85	0.65	0.90	0.92	0.84
United Kingdom	0.79	0.29	1.27	0.69	1.19	2.03	0.60	0.28	0.75	0.69	0.61	0.92	0.91	0.85	0.73	0.43	0.94	1.00	0.69
Belgium	0.78	0.28	1.23	0.73	1.07	1.94	0.56	0.39	0.76	0.65	0.53	0.90	0.86	0.85	0.76	0.50	1.00	0.96	0.72
Mexico	0.78	0.40	1.19	0.75	0.98	1.23	0.56	0.35	0.72	0.80	0.56	0.74	0.85	0.80	0.68	0.34	0.86	0.77	0.57
Sri Lanka	0.76	0.60	1.20	0.81	1.00	1.00	0.60	0.58	0.75	0.58	0.68	0.64	0.88	0.73	0.68	0.48	1.00	0.78	0.64
Netherlands	0.75	0.24	1.36	0.59	0.91	2.31	0.47	0.31	0.64	0.60	0.49	0.89	0.79	0.76	0.75	0.51	0.91	1.00	0.74
Switzerland	0.75	0.27	1.01	0.64	0.96	1.72	0.53	0.43	0.65	0.75	0.53	0.92	0.82	0.80	0.68	0.41	0.90	0.92	0.66
Luxembourg	0.75	0.25	1.09	0.75	0.87	1.63	0.57	0.46	0.77	0.67	0.54	0.92	0.84	0.83	0.71	0.43	0.95	0.90	0.68
Malaysia	0.73	0.49	0.90	0.88	0.97	1.09	0.61	0.41	0.81	0.73	0.63	0.75	0.79	0.74	0.66	0.40	0.81	0.77	0.65
Norway	0.71	0.28	1.21	0.72	1.36	1.77	0.52	0.34	0.72	0.51	0.53	0.91	0.77	0.74	0.73	0.46	0.81	0.89	0.74
Israel	0.65	0.33	0.82	0.56	0.74	1.03	0.46	0.34	0.64	0.46	0.46	0.74	0.59	0.67	0.62	0.41	0.60	0.61	0.53
Germany	0.64	0.34	0.80	0.60	0.82	1.18	0.49	0.38	0.62	0.63	0.56	0.83	0.73	0.69	0.57	0.34	0.81	0.78	0.54
Japan	0.64	0.34	0.69	0.56	0.65	0.77	0.48	0.35	0.54	0.59	0.49	0.76	0.67	0.69	0.54	0.23	0.74	0.72	0.47
Iceland	0.62	0.42	1.50	0.88	1.28	2.00	0.69	0.38	0.88	0.00	0.67	0.96	1.00	0.56	0.75	0.57	1.08	1.13	0.89
Nigeria	0.56	0.30	0.64	0.64	0.61	0.89	0.48	0.35	0.54	0.54	0.52	0.59	0.62	0.57	0.46	0.30	0.78	0.64	0.44
Turkey	0.52	0.26	0.92	0.62	0.64	1.07	0.38	0.27	0.59	0.43	0.43	0.46	0.55	0.49	0.47	0.23	0.77	0.63	0.42
United Arab Emirates	0.44	0.19	1.09	0.42	0.64	1.09	0.35	0.21	0.50	0.48	0.42	0.45	0.46	0.47	0.42	0.20	0.63	0.55	0.40
Egypt	0.42	0.17	0.69	0.43	0.63	0.60	0.29	0.14	0.46	0.39	0.39	0.40	0.51	0.43	0.32	0.18	0.54	0.45	0.28
Bangladesh	0.42	0.30	0.41	0.48	0.33	0.43	0.34	0.58	0.40	0.26	0.48	0.40	0.51	0.38	0.19	0.13	0.30	0.23	0.17
India	0.42	0.21	0.71	0.39	0.56	0.56	0.25	0.19	0.48	0.28	0.42	0.43	0.49	0.42	0.35	0.19	0.58	0.45	0.30
Kuwait	0.36	0.16	0.79	0.38	0.61	0.71	0.29	0.17	0.36	0.24	0.32	0.36	0.45	0.38	0.32	0.18	0.52	0.41	0.29
Pakistan	0.31	0.12	0.50	0.25	0.46	0.47	0.16	0.11	0.29	0.21	0.27	0.30	0.36	0.30	0.20	0.11	0.39	0.27	0.16
Saudi Arabia	0.31	0.08	0.59	0.28	0.42	0.73	0.17	0.12	0.34	0.18	0.29	0.27	0.38	0.31	0.16	0.10	0.50	0.30	0.14

Panel B. Spatial Distribution of iGGI



iGGI color scale

Source: LinkedIn Advertising Platform

Note: A GGI value below one indicates that women are underrepresented relative to men in the migrant population in the host country; a value over one indicates that women comprise a larger share of the migrant pool than men. Values of 1 or larger are scaled to darker shades of green to indicate parity or a more female migrant pool; values less than 1 are scaled from yellow to orange to indicate an increasingly male share of the migrant population. Missing data is shown in white in the matrix. Countries in grey on the map were not included in the analysis.