Migration of Professionals to the U.S.

Evidence from LinkedIn data

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Abstract. We investigate trends in the international migration of professional workers by analyzing a dataset of millions of geolocated career histories provided by LinkedIn, the largest online platform for professionals. The new dataset confirms that the United States is, in absolute terms, the top destination for international migrants. However, we observe a decrease, from 2000 to 2012, in the percentage of professional migrants, worldwide, who have the United States as their country of destination. The pattern holds for persons with Bachelor's, Master's, and PhD degrees alike, and for individuals with degrees from highly-ranked worldwide universities. Our analysis also reveals the growth of Asia as a major professional migration destination during the past twelve years. Although we see a decline in the share of employment-based migrants going to the United States, our results show a recent rebound in the percentage of international students who choose the United States as their destination.

The United States is in the middle of a fierce debate over an immigration reform that would, among others, increase the number of temporary visas for skilled workers, boost the number of visas available to foreign students who earn advanced degrees in STEM disciplines (science, technology, engineering and mathematics), and create new visas awarded on the basis of a scoring system intended to favor "merit" [11].

The United States has always been a country of immigration, a top destination for scientists [6, 16] and, more broadly, for holders of a doctorate degree [2]. It has been found that "individuals making exceptional contributions to science and engineering (S&E) in the United States are disproportionately drawn from the foreign born" [9] and that the US has largely benefited from talent educated abroad [9]. Most of the public discussion around immigration reform has focused on the potential consequences of the immigration bill for employment and wages of United States citizens. Less attention has been paid, however, to the position of the United States in the context of recent changes in the composition and destinations of highly skilled migrants around the world.

The past decades have seen a general increase of worldwide migration [1, 19], including a jump in the migration of professionals [10]. In turn, employment-based migration to the United States has been governed by a complicated system of visa regulations, which in some cases (e.g. the H1-B visa) include absolute caps on the number of individuals admitted to the country.[1] The combination of these two processes leads us to expect the emergence of other destinations for professional migrations, as has been observed at the turn of the century [16].

There is a large body of literature, mainly in the disciplines of sociology, demography, economics, and geography, about international migration, and, more specifically, highly-skilled migration. It is beyond the scope of this article to discuss theories of migration and the rich and healthy debate about them (for an overview see, for instance, [4, 8, 12, 17]). With this article we emphasize an outstanding problem in migration research: the lack of timely, consistent and comparative data sources about international migrants. We address the issue by proposing an analysis based on new and innovative data from LinkedIn, the largest online platform for professionals. More specifically, we investigate recent trends in the composition of international students and highly-educated migrants in the US. We hope that presenting new empirical findings in an interdisciplinary context will contribute to improvements in our theoretical understanding of migration dynamics.

New data for the analysis of migration patterns

Monitoring international flows of migrants is key to designing effective policies. However, migration data tend to be coarse-grained, inconsistent across countries, expensive to gather, and available only with a considerable delay [5, 20]. The increasing availability of geolocated data from online sources or cellphone call records has opened new opportunities to identify migrants and to follow them, in an anonymous way, over time. Cellphone data have been used mainly to evaluate patterns and regularities of internal mobility for a country (e.g., [3, 7]). IP address geolocation has been used to evaluate internal mobility [14]. Analogously, recent trends in international flows of migrants have been estimated by tracking the locations, inferred from IP addresses, of users who repeatedly login into Yahoo! services [18, 21]. More recently, geolocated Twitter 'tweets' have proven useful to monitor trends in short-term international mobility [22].

The relevance of new digital records for migration studies can be evaluated along three main dimensions: i) scope, ii) time series length, and iii) accuracy of geolocation. Most data sources rarely excel in all the three dimensions. For instance, cellphone call detail records are quite accurate in terms of geolocation, but often available only for single countries or small geographic regions. IP geolocated logins to websites are not constrained by country borders, but have low granularity within a country. Geolocated Twitter data provide precise estimates of geographic coordinates and the scope is global. However, the time series are relatively short and little demographic information can be extracted from Twitter profiles.

We analyzed recent trends in international migration of highly skilled workers using a dataset of unprecedented detail, extracted from LinkedIn, the social networking website for professionals. LinkedIn counts over 200 million members in more than 200 countries and territories [13]. People typically use their LinkedIn profiles to post their

[1] The American Community Survey documents a flat trend in the number of college-educated individuals who migrated to the United States during the period 2000-2010.

employment and educational history. When aggregated and anonymized, that information provides the most comprehensive and up to date picture of international flows of highly skilled migrants.

Trends in highly skilled migration to the US

We tracked the proportion of migrants whose destination was the United States, out of all migrants observed during a particular calendar year, for the period 1990-2012. Figure 1 shows the fraction of world migrants who moved to the United States, over time. The trends are broken down by level of education and by sector of employment (STEM vs. non-STEM). In our sample of LinkedIn users we observed a slight increase of the conditional probability of migrating to the United States during the 1990s, followed by a downward trend after the year 2000. The trend that we observed suggests

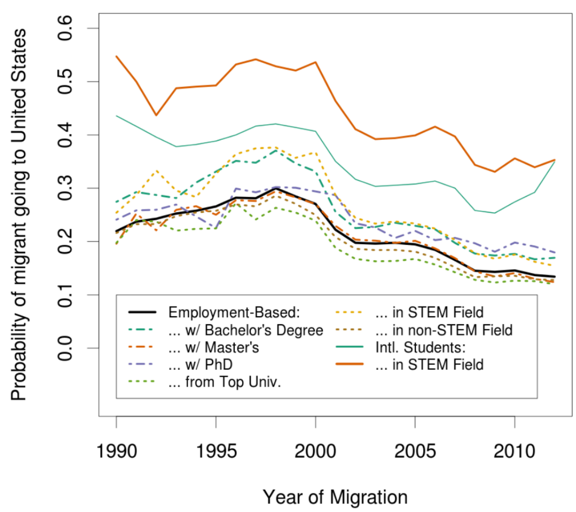

Fig. 1. Conditional Probability of Migration to United States by Year, 1990-2012.

that a smaller fraction of highly skilled migrants seeking employment have made their way to the United States as the first decade of the 21st century progressed. The patterns that we observed could be related to both increasing opportunities outside the United States or a reduction of the demand in the United States. For instance, during the first decade of the 21st century, the United States experienced two major economic crises: the collapse of the "dot-com bubble" during 1999-2001, and the financial crisis of 2008. These crises adversely affected opportunities for immigrants in the United States. The nature of our dataset has allowed us to assess the decline in migration likelihoods by educational attainment at the time of migration. As Figure 1 shows, 33% of professional migrants with Bachelors' degrees achieved by the time of migration were likely to reach the US in the year 2000, compared to 17% in 2012. Analogous figures are 27% in 2000 and 12% in 2012 for migrants with Master's degrees, 29% (2000) and 18% (2012) for migrants with PhDs.

The current policy debate has centered around the availability of temporary and permanent visas for highly-skilled migrants in STEM fields. To address this area of interest we classified individuals according to their broad occupational field. A downward trend is observed in STEM as well as non-STEM fields, although the overall decrease in the probability of migrating to the US was higher in STEM (22 percentage points, from 37% to 15%) as compared to non-STEM fields (12 percentage points, from 25% to 13%). Our findings suggest that, in addition to short-term crises, such as the "dot-com bubble", there are long-term structural changes in the global system of employment-based, highly-skilled migration. The United States continues to occupy a central place in the global migration system. However, its dominant position is no longer indisputable. Figure 2 shows that, while the U.S. became a less prominent destination for professional migrations during the 2000s, Europe and Canada also saw a decrease in their share[2] of the world's professional migration flows – albeit a gentler one – while Australia and Oceania, Africa and Latin America increased their proportional intake.[3] The most prominent increase was recorded for Asian countries, which attracted, in our sample, a cumulative 25% of the world's professional migrants in 2012, compared to only 10% in the year 2000. The observed decline of the United States as a professional

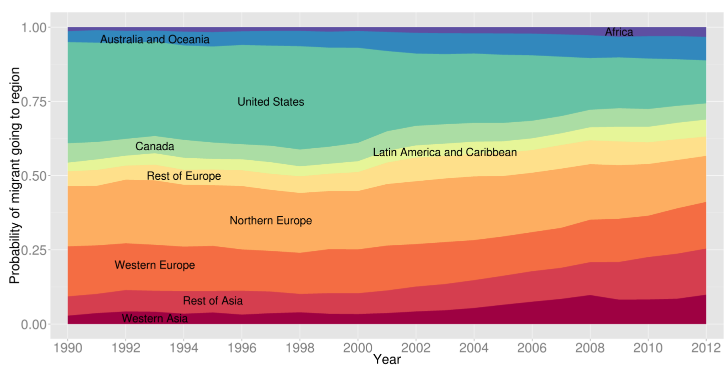

Fig. 2. Distribution of Migration Flows, by year and region of destination, 1990-2012.

migration destination may be a reflection of increased competition for highly skilled migrants from other countries, of declining demand for highly skilled migrants in the

[2] Europe attracted 40.8% of the world's professional migrants in 2000, and 37.8% in 2012, while Canada attracted 6.2% of the flow in 2000 and 5.5% in 2012.

[3] Africa increased from 1.3% in 2000 to 3.3% in 2012, Australia and Oceania from 5.7% in 2000 to 7.9% in 2012, Latin America and the Caribbean increased from 3.7% in 2000 to 5.7% in 2012.

United States, of an increased worldwide supply of highly skilled migrants, or of inefficiencies created by current US migration laws. While the mechanism is most likely a multi-factorial one, the overall conclusion seems to suggest the possibility of a fundamental change in the international migration patterns of professionals.

Robustness of the results

Although our dataset allows an otherwise-unattainable glimpse into the global system of highly skilled migration, there are a number of limitations that we would like to acknowledge and discuss. First, we do not know the citizenship status of individuals in our sample. As a result, our dataset does not directly distinguish between the return migration of US expatriates and in-migration of foreign persons. However, this is expected to be a minor factor, as relatively few American professionals migrate outside of the United States, and fewer return to their country of origin.[4] Another relatively minor source of uncertainty in our data concerns cases of circular migrations, back and forth from the United States, of foreign persons, which are expected to be rare events. Indeed, 92% of migration events in our dataset were due to individuals who generated only one migration event.

LinkedIn users are not a representative sample of the entire population of highly-skilled migrants. As a result our estimates may be biased. A potential problem of our data is the mechanism through which individual migrants are selected into the sample. We thus verified the robustness of our main result, the downward trend in fraction of migrants to the United States, with further analyses. Since LinkedIn is a United States company, those individuals who joined earlier were more likely to be located in the United States at the time of their registration, and thus more immigrants to the United States are expected to be included in the early sample of our data. However, we checked that the size of this potential source of bias is small and does not affect our results. In order to control for unobserved users' characteristics associated with the choice of registering with LinkedIn, we divided our dataset into ten separate subsets, one for each annual cohort[5] of new LinkedIn users since 2004. For all of the ten cohorts we found a statistically significant downward trend in migrants' likelihood to move to the United States after the year 2000.[6]

As a further test of the validity of the results, we compared predictions derived from our model against the American Community Survey (ACS) (`http://www.census.gov/acs`), using a dataset provided by the IPUMS project (`https://usa.ipums.org/usa/sda/`). To our knowledge, the ACS – a survey continuously run by the US

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[4] This consideration is even more likely to hold for graduates of non-US top global universities.

[5] A cohort of users comprises all those individuals who joined LinkedIn during the same calendar year. Regardless of when a user joins, we observe events both before and after their joining of LinkedIn, from the user's professional history as reported on their LinkedIn profile.

[6] Statistical significance was established using a logistic regression where the year of migration and the year of user registration were dummy-coded. The ratio between the cohort-specific likelihoods of migrating to the United States in 2012 and 2000 ranged between 0.47 and 0.72. The similar ratio against the year 1999 ranged between 0.47 and 0.62. There was no monotonic relation between user cohort and decrease of likelihood of migrating to US.

Census Bureau – represents one of the most authoritative data sources available to estimate migrations to the United States. We compared the yearly rate of change in the US in-migration rate estimated from our data and from the ACS, for the period 2001 to 2010. ACS and LinkedIn estimates were computed for individuals who had at least a Bachelor's degree at the time of migration. Pearson's ρ between the two time-series is 0.70, whereas Spearman's rank-correlation coefficient is 0.83. The time-series are plotted together in Figure 3. The plot shows the two time-series tracking each other quite closely until 2005 (Pearson's $\rho = 0.96$, Spearman's rank-correlation coefficient 0.9). After 2005, estimates based on LinkedIn data give a higher immigration rate. It is possible that ACS underestimates professional migration, due to underreporting. Alternatively, our approach based on LinkedIn data may tend to overestimate professional migration to the US during the late 2000s. This observation further strengthens our main result. If estimates of migration rates from our LinkedIn dataset tend to overestimate recent migration of professionals to the US (i.e., if the population of LinkedIn users is more mobile than the overall population of highly-skilled professionals), then the downward trend in conditional probabilities of professional migration to the United States may be even steeper than what we expect. In other words, in spite of the fact that LinkedIn data may overestimate recent migration of highly-skilled individuals to the United States, in our sample professional migrants appear less likely to go to the United States in the second half of the last decade than in the first.

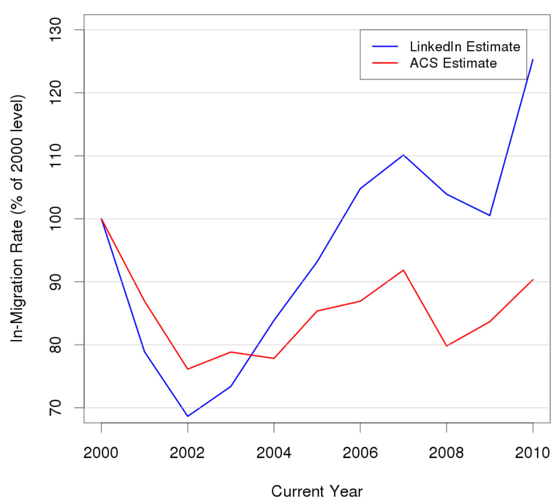

Fig. 3. U.S. In-Migration rate, computed from LI and ACS data.

An additional potential confounding factor in our data concerns the definition of a "highly-skilled migrant". A skeptical argument would be that the quality of university degrees might have been diluted by increases in the number of higher education institutions worldwide. By this token, the United States is receiving the same share of the "truly" highly-skilled migrants in the world, but the (likely) increasing number of university graduates is hiding this fact. We falsified this hypothesis by computing the conditional migration probability to the United States for a subset of individuals in our sample: those whose latest degree at the time of migration came from one of the top-500 worldwide universities, as listed in the Quacquarelli-Symonds (QS) ranking (2013).[7] Once more we observed the same overall pattern of decreasing probabilities of migration to the United States: in our sample, 24% of migrants who were graduates of the top 500 universities worldwide went to the United States in the year 2000, but only 12% did so during 2012.

Discussion

Highly-skilled migration is an important demographic phenomenon with relevant consequences, for instance in terms of human capital formation, a central issue in the study of economic development. Despite the importance of highly-skilled migrations for a number of disciplines and for policy making, it is extremely difficult to find reliable data on the flows of highly-skilled migrants. This is due to a number of factors. There is no uniform international definition of migration, and even migration data sources that provide time-series data caution against assuming either within- or between-country consistency in the measurement of migrations. In some cases the data sources are so indirect as to render them useless in a comparison against our dataset. For instance, data for the United States in the OECD international migration database come from the Department of Homeland Security count of new permanent residencies, though a great number of migration episodes to the United States start out with a "non-immigrant" visa status (e.g., the H1-B, F-1 visa, etc.).

For this article, our aim is to measure highly-skilled – rather than overall – migration flows. There is even less consistent data available for this task, and to our knowledge no large-scale survey of the world's professional migration flows has currently been compiled. The boundaries of the concept of a "highly-skilled" migrant are relatively porous, rendering its measurement difficult with traditional demographic instruments. We believe that complementing existing data sources with social media data may improve our understanding of migration patterns. LinkedIn, with a website interface in 20 languages and an aggressive strategy emphasizing growth outside of the United States, provides innovative data to investigate population processes for highly-skilled professionals.

In this article, we showed that LinkedIn data provide important insights about recent trends in migrations of highly-skilled migrants to the United States. At the same time, the sample of LinkedIn users is a convenience sample. It is a large and interesting sample, but not representative of the entire population of highly-skilled migrants. We provided analyses that support the robustness of our results. Nonetheless, there is a

[7] There were 406 non-US universities in the Quacquarelli-Symonds top 500. We only included non-US universities because individuals who have attended US schools and are currently abroad are by definition return migrants to the United States, whereas we are primarily interested in first-time migrants.

tradeoff between generating new information from social media, and the statistical confidence in the results. Whenever large datasets exist for calibration of estimates from social media data, then our uncertainty about the outcomes is low. In those situations, the novelty of the results is also low. Whenever little traditional data exist for calibration, social media may provide more novel information, but with higher uncertainty. The challenge for social scientists and computer scientists is to incorporate existing data sources, from official statistics to social media data, into a unified framework.

The rise of very large datasets has the potential to reshape both science and policy in innumerable ways, as long as appropriate methods will be developed to make inference from unstructured data. Traditional measurement methods have not been enough to generate timely estimates consistent across countries. We believe that the use of social media data in this area will be very fruitful, especially in combination with existing data sources. Measuring migrations is a relatively well-defined problem. Thus it will be possible to evaluate the predictive power of models that incorporate social media data. Our article is intended to provide a first step towards the study of highly-skilled migrations using social media data. As such, we hope to stimulate the discussion about the use of social media data to improve our understanding of population processes. We believe that social scientists will not only benefit from new and large data sets, but also increasingly contribute to the emerging field of Web science by developing new and innovative methods.

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Appendix

Extracting information from LinkedIn profiles

From the initial population of over 200 million LinkedIn users worldwide, we extracted the subset of inter-country migration events related to changes in individuals' places of employment, for migrations lasting at least one calendar year between 1990 and 2012. We measured migrations by examining country-level locations associated with positions held by individuals across their careers, as listed in their LinkedIn profiles. Part of the geolocated positions are standardized data, where the user selects the position's location from a drop-down menu. We inferred the remaining positions' location by combining various sources of information: free-text entered by the user (addresses), IP geo-location, location of the company associated with the position, colleagues' locations, and the location associated with the next and previous positions in the individual's profile. To combine the various sources of information, we used a Naive Bayes classifier trained on the standardized location data. The decision threshold that we chose achieved 99% precision and 54% recall against a held-out dataset.

We represented each individual's career as an ordered tuple $(p_{i,1}; p_{i,2}; \ldots p_{i,k})$, where $p_{i,j}$ denotes the j-th position held by individual i, with the order determined by each position's start date. We projected each person's tuple of geolocated positions into month-level observations that specify their location during a particular month. In cases where location information is missing from a person's career for a period of less than or exactly twelve months, we interpolated the location with respect to the nearest (in time) non-missing observation. Where two non-missing and different observations are equally close (e.g. location A six months before and location B six months later), we selected an imputation at random from the two possibilities. We then inferred the place of residence for each user, at regular intervals of time (i.e., during the month of January) over the course of several years.

We define a migration event by querying the location of each individual at the beginning of every calendar year. If the individual's estimated place of residence is in a different country, compared to the beginning of the previous year, we assume that a migration event has occurred during the past calendar year. For the purposes of this article, immigration rates are defined as the ratio $N^{(y)}_{\to C}/N^{(y)}_{C}$ between the number of individuals who moved to country C during year y ($N^{(y)}_{\to C}$), and the number of individuals who were observed in country C at the end of year y ($N^{(y)}_{C}$).

We mapped employment-based positions to their Standard Occupational Classification (SOC) code. From each position we extracted the job title as reported by the user. Job titles were then mapped through an internal algorithm to a number of standardized titles, which in turn were mapped by human coders to their Standard Occupational Classification code. Positions were considered to be STEM if their SOM code was either 15-1000 (Computer Occupations), 15-2000 (Mathematical Science Occupations) 17-1000 (Architecture and Engineering Occupations), 19-0000 (Life, Physical and Social Science Occupations), and 25-1000 (Postsecondary Teachers). The decision to include all Postsecondary Teachers in the STEM field is motivated by the great deal of overlap between academia and STEM fields.

Table 1: Probability that Migration Destination is U.S. (cf. Figure 1)

Year		**Employment-Based Migration**							**Education-Based**	
	Overall	**Degree Prior to Migration**				**Top**	**STEM Field**		**Overall**	**STEM**
		Bac.	**Mst.**	**PhD**	**School**	**Yes**	**No**		**Field**	
1	1990	0.22	0.27	0.20	0.24	0.20	0.25	0.22	0.44	0.55
2	1991	0.24	0.29	0.25	0.26	0.24	0.29	0.23	0.42	0.50
3	1992	0.24	0.29	0.22	0.26	0.24	0.33	0.23	0.40	0.44
4	1993	0.25	0.28	0.26	0.27	0.22	0.30	0.25	0.38	0.49
5	1994	0.26	0.31	0.27	0.25	0.22	0.28	0.25	0.38	0.49
6	1995	0.27	0.33	0.25	0.23	0.22	0.33	0.26	0.39	0.49
7	1996	0.28	0.35	0.28	0.30	0.27	0.36	0.27	0.40	0.53
8	1997	0.28	0.35	0.28	0.29	0.24	0.37	0.27	0.42	0.54
9	1998	0.30	0.37	0.29	0.30	0.26	0.38	0.29	0.42	0.53
10	1999	0.28	0.35	0.28	0.30	0.25	0.36	0.27	0.41	0.52
11	2000	0.27	0.33	0.27	0.29	0.24	0.37	0.25	0.41	0.54
12	2001	0.22	0.26	0.23	0.29	0.19	0.29	0.21	0.35	0.46
13	2002	0.20	0.23	0.20	0.23	0.17	0.24	0.19	0.32	0.41
14	2003	0.20	0.23	0.20	0.23	0.16	0.23	0.18	0.30	0.39
15	2004	0.20	0.24	0.20	0.21	0.16	0.24	0.18	0.31	0.39
16	2005	0.19	0.23	0.20	0.22	0.17	0.23	0.18	0.31	0.40
17	2006	0.18	0.22	0.19	0.20	0.16	0.22	0.17	0.31	0.42
18	2007	0.17	0.20	0.17	0.21	0.14	0.20	0.15	0.30	0.40
19	2008	0.15	0.18	0.14	0.20	0.13	0.18	0.13	0.26	0.34
20	2009	0.14	0.17	0.13	0.18	0.12	0.17	0.13	0.25	0.33
21	2010	0.15	0.18	0.14	0.20	0.13	0.18	0.14	0.27	0.36
22	2011	0.14	0.17	0.13	0.19	0.13	0.16	0.13	0.29	0.34
23	2012	0.13	0.17	0.12	0.18	0.12	0.15	0.13	0.35	0.35

Notes: Employment-based migration: migrant (first) obtains job in destination country. Education-based migration: migrant (first) pursues educational program in destination country. If migrant pursues both employment and education upon arriving in destination country, migration event is assumed to be education-based. Prior degree must have been received during the previous year. “Top schools” are all non-US schools in the top 500 universities in the Quacquarelli-Symonds ranking. For STEM field identification, see main text.

Table 2: Definition of Regions used in Figure 2

Region	Countries
Africa	Algeria; Angola; Benin; Botswana; Burkina Faso; Burundi; Cameroon; Cape Verde; Central African Republic; Chad; Comoros; Congo, Republic Of; Congo, The Democratic Republic Of; Cote D'ivoire; Djibouti; Egypt; Equatorial Guinea; Eritrea; Ethiopia; Gabon; Gambia; Ghana; Guinea; Guinea-bissau; Kenya; Lesotho; Liberia; Libyan Arab Jamahiriya; Madagascar; Malawi; Mali; Mauritania; Mauritius; Mayotte; Morocco; Mozambique; Niger; Nigeria; Reunion; Rwanda; Saint Helena; Sao Tome And Principe; Senegal; Seychelles; Sierra Leone; Somalia; South Africa; Sudan; Swaziland; Tanzania, United Republic Of; Togo; Tunisia; Uganda; Zambia; Zimbabwe
Australia and Oceania	American Samoa; Australia; Cook Islands; Fiji; French Polynesia; Guam; Kiribati; Marshall Islands; Micronesia, Federated States Of; Nauru; New Caledonia; New Zealand; Northern Mariana Islands; Palau; Papua New Guinea; Samoa; Solomon Islands; Tonga; Tuvalu; Vanuatu
Canada	Canada
Latin America and Caribbean	Anguilla; Antigua And Barbuda; Argentina; Aruba; Bahamas; Barbados; Belize; Bermuda; Bolivia, Plurinational State Of; Brazil; Cayman Islands; Chile; Colombia; Costa Rica; Cuba; Dominica; Dominican Republic; Ecuador; El Salvador; Falkland Islands (Malvinas); French Guiana; Greenland; Grenada; Guadeloupe; Guatemala; Guyana; Haiti; Honduras; Jamaica; Martinique; Mexico; Montserrat; Netherlands Antilles; Nicaragua; Panama; Paraguay; Peru; Puerto Rico; Saint Kitts And Nevis; Saint Lucia; Saint Pierre And Miquelon; Saint Vincent And The Grenadines; Suriname; Trinidad And Tobago; Turks And Caicos Islands; Uruguay; Venezuela, Bolivarian Republic Of; Virgin Islands, British; Virgin Islands, U.s.
Northern Europe	Aland Islands; Denmark; Estonia; Faroe Islands; Finland; Guernsey; Iceland; Ireland; Isle Of Man; Jersey; Latvia; Lithuania; Norway; Svalbard And Jan Mayen; Sweden; United Kingdom
Rest of Asia	Afghanistan; Bangladesh; Bhutan; Brunei Darussalam; Cambodia; China; Hong Kong; India; Indonesia; Iran, Islamic Republic Of; Japan; Kazakhstan; Korea, Democratic People's Republic Of; Korea, Republic Of; Kyrgyzstan; Lao People's Democratic Republic; Macao; Malaysia; Maldives; Mongolia; Myanmar; Nepal; Pakistan; Philippines; Singapore; Sri Lanka; Tajikistan; Thailand; Timor-leste; Turkmenistan; Uzbekistan; Vietnam
Rest of Europe	Albania; Andorra; Belarus; Bosnia And Herzegovina; Bulgaria; Croatia; Czech Republic; Gibraltar; Greece; Holy See (vatican City State); Hungary; Italy; Macedonia, The Former Yugoslav Republic Of; Malta; Moldova, Republic Of; Montenegro; Poland; Portugal; Romania; Russian Federation; San Marino; Serbia; Slovakia; Slovenia; Spain; Ukraine
United States	United States
Western Asia	Armenia; Azerbaijan; Bahrain; Cyprus; Georgia; Iraq; Israel; Jordan; Kuwait; Lebanon; Oman; Palestinian Territory, Occupied; Qatar; Saudi Arabia; Syrian Arab Republic; Turkey; United Arab Emirates; Yemen
Western Europe	Austria; Belgium; France; Germany; Liechtenstein; Luxembourg; Monaco; Netherlands; Switzerland

Table 3: Distribution of World Migrations (cf. Figure 2)

	Afr.	Aus.	Can.	L. Am.	N.Eur.	R.of Asia	R.of Eur.	U.S.	W. Asia	W. Eur.	Total
1990	0.01	0.04	0.07	0.03	0.20	0.06	0.05	0.34	0.03	0.17	1.00
1991	0.01	0.04	0.06	0.04	0.20	0.06	0.05	0.33	0.04	0.16	1.00
1992	0.01	0.04	0.06	0.03	0.21	0.07	0.05	0.32	0.04	0.16	1.00
1993	0.01	0.04	0.06	0.04	0.22	0.07	0.05	0.32	0.04	0.15	1.00
1994	0.01	0.05	0.06	0.04	0.21	0.08	0.05	0.32	0.03	0.15	1.00
1995	0.02	0.05	0.06	0.04	0.20	0.07	0.05	0.32	0.04	0.15	1.00
1996	0.01	0.05	0.05	0.04	0.21	0.08	0.05	0.33	0.03	0.14	1.00
1997	0.01	0.05	0.06	0.04	0.21	0.07	0.05	0.34	0.04	0.14	1.00
1998	0.01	0.05	0.06	0.03	0.20	0.06	0.06	0.35	0.04	0.14	1.00
1999	0.02	0.05	0.06	0.03	0.20	0.07	0.06	0.33	0.03	0.15	1.00
2000	0.01	0.06	0.06	0.04	0.20	0.07	0.06	0.32	0.03	0.15	1.00
2001	0.02	0.06	0.07	0.04	0.21	0.08	0.07	0.27	0.04	0.15	1.00
2002	0.02	0.07	0.07	0.04	0.21	0.08	0.08	0.24	0.04	0.14	1.00
2003	0.02	0.07	0.07	0.04	0.21	0.09	0.08	0.24	0.05	0.14	1.00
2004	0.02	0.07	0.06	0.04	0.21	0.09	0.08	0.23	0.05	0.13	1.00
2005	0.02	0.07	0.06	0.04	0.20	0.10	0.08	0.23	0.06	0.13	1.00
2006	0.02	0.07	0.06	0.04	0.20	0.10	0.08	0.22	0.08	0.13	1.00
2007	0.02	0.08	0.06	0.04	0.20	0.10	0.08	0.20	0.08	0.13	1.00
2008	0.03	0.08	0.06	0.04	0.19	0.11	0.08	0.17	0.10	0.14	1.00
2009	0.03	0.07	0.06	0.05	0.18	0.13	0.08	0.17	0.08	0.15	1.00
2010	0.03	0.08	0.06	0.05	0.17	0.14	0.07	0.17	0.08	0.14	1.00
2011	0.03	0.08	0.06	0.06	0.16	0.15	0.07	0.16	0.09	0.15	1.00
2012	0.03	0.08	0.05	0.06	0.16	0.16	0.07	0.14	0.10	0.16	1.00

Note: Table reflects all observed migrations, whether employment- or education-based.