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Medical brain drain: How many, where and why?☆

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ABSTRACT

We build a new database documenting the evolution of physician migration over a period of 25 years (1990–2014), and use it to empirically shed light on its determinants. In relative terms, the highest emigration rates are observed in small island nations and low-income countries, where needs-based deficits of healthcare workers are often estimated to be most severe. Over time, we identify rising trends in Caribbean islands, Central Asia and Eastern Europe. On the contrary, despite increasing migration flows to Western Europe, physician migration rates from sub-Saharan Africa have been stable or even decreasing. Our empirical analysis reveals that physician migration is a complex phenomenon that results from a myriad of push, pull, and dyadic factors. It is strongly affected by the economic characteristics of origin and destination countries. The sensitivity to these push and pull factors is governed by linguistic and geographic ties between countries. Interestingly, we find that the evolution of medical brain drain is affected by immigration policies aimed at attracting high-skilled workers. In particular, physician migration is sensitive to visa restrictions, diploma recognition, points-based system, tax breaks towards migrants, and the option of obtaining a permanent resident status.

1. Introduction

The global shortage of health workers presents an increasing and palpable concern for governments and policymakers working to ensure the United Nations Sustainable Development Goals for health (SDG3), which prioritize the need for universal and sustained access to health delivery, and the equitable distribution of health services for all are met by 2030. At the cusp of achieving these goals and improving health outcomes are a minimum threshold of physicians, nurses and midwives, and other health workers needed to support an effective healthcare delivery system. However, global disparities and shortages in the supply of healthcare workers exist, with high to severe shortages reported in many low and

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lower-middle income countries where the need for health workers is greatest.[1] Central to the debate on health worker shortages is the emigration of health workers from developing to developed countries and their retention rates. The international migration of doctors in particular, has been an unwaning topic in the discourse of addressing the inequities in the distribution of human resources for health. This has heightened the need to empirically investigate from a policy standpoint, the geographical disparities in the supply of physicians worldwide and to understand the underlying factors causing these disparities.

This paper focuses on the magnitude and causes of physician migration, and presents an opportunity to advance our understanding of their trends, patterns, and drivers using new cross-country estimates. We construct a new data set that more than doubles the size of previous databases, and use it to make *three important and lasting contributions* to the existing evidence on medical brain drain. Firstly, we provide new and useful insights in the global migration of doctors, shedding light on the role of recent events such as the enlargement of the EU, the role of increasing training capacity in sub-Saharan Africa and on the establishment of offshore medical schools in the Caribbean. Secondly, we take advantage of the size of the database to empirically identify the multiple determinants of physician emigration decisions across many countries over a long period of time. Our rich data set allows us to deal with unobserved heterogeneity through the use of a great variety of dyadic, origin-time and destination-time fixed effects. Thirdly, we merge our migration database with recent dyadic and unilateral data on migration policies to assess the role and effectiveness of recruitment practices.

Our paper speaks to two strands of literature. It relates to the literature on high-skilled emigration and development. Much of the earlier literature on the brain drain maintained that the emigration of high-skilled workers in general, and medical doctors in particular, is a waste of talent and a direct fiscal loss for the sending country. The rationale is that doctors in developing countries are mostly trained for free using public funds (e.g., Bhagwati and Dellalfar, 1973; Bhagwati and Hamada, 1974). Notwithstanding, a growing body of literature argues that the emigration of physicians could induce beneficial effects in the form of greater incentives to acquire human capital (e.g., Mountford, 1997; Stark et al., 1997; Beine et al., 2001), remittances (e.g., Niimi et al., 2010; Bollard et al., 2011), and diaspora externalities (e.g., Kerr, 2008; Agrawal et al., 2011). Bhargava et al. (2011) find positive effects of emigration prospects on medical training, though the magnitude is too small for generating a net brain gain. The database developed in our study can be used in future works to assess whether these shortages have an effect on health outcomes and estimate any losses or gains to sending and host countries as a result of international migration.

We also contribute to the literature on the measurement of the medical brain drain and the analysis of its determinants. Our approach and findings can be positioned as following. In the *first part* of the paper, we document the evolution of dyadic migration patterns of physicians from 192 training/origin countries to 22 destination countries over a 25-year period. This is the first data set we are aware of that provides an extensive longitudinal panel data to systematically standardize and quantify the absolute and relative sizes of the medical brain drain over such a long period of time. We build on previous data by Bhargava et al. (2011), which aggregates data on foreign-trained physicians from 18 destination countries (17 OECD member states and South Africa) for the period 1991–2004, by adding observations for 11 additional years (from 2004 to 2014) – and increasing the number of destination countries from 18 to 22.[2] In that respect, our paper enhances the small but growing literature that has attempted to provide comparative evidence to estimate the size and intensity of the brain drain (Clemens and Pettersson, 2006; OECD, 2007).[3] Our database thus provides new evidence to compare migration levels across countries, and to understand how the medical brain drain has evolved to include new corridors and sending sources; given recent key global economic shifts and bilateral country agreements over the last two decades or so.

We find that small island nations, low-income countries, and countries in the Caribbean and sub-Saharan Africa had the highest intensity of physician migration for the period between 2004 and 2014. These regions followed different trends. The Caribbean region experienced the highest emigration rates of physicians from 2004 to 2014; with average rates of migration of 24.0%; compared to rates of 17.5% over the 1990–2003 period.[4] This is due to the growing number of islands that have “offshore” medical schools which train medical doctors from foreign countries. Increasing rates of migration were also observed for Europe and Central Asia (ECA) and Eastern Europe, which experienced more than double emigration rates due to the EU enlargement (from 2.9% in 2004 to 5.9% in 2014). Interestingly, sub-Saharan Africa (SSA), which had the second highest emigration rates of physicians experienced declining emigration rates between 2004 and 2014, due to increasing (albeit limited) training capacities.[5] The most popular destinations of physicians are the United States

[1] According to the World Health Organization, the health related SDGs will not be reached “unless the global shortfall of 18 million health workers by 2030 is averted” (WHO, 2017). Scheffler et al. (2016) estimate the largest needs-based deficits of health workers at 6.9 million in South East Asia and 4.2 million on Africa, respectively.

[2] Including Estonia, Hungary, the Netherlands, Poland and Slovenia, but removing South Africa. South Africa is excluded in the latest wave due to incomplete data.

[3] Clemens and Pettersson (2006) estimate the stock of African-born doctors and nurses in the UK, US, France, Australia, Canada, Portugal, Belgium, Spain and South Africa for the year 2000. OECD (2007) estimates of the stock of doctors and nurses for all regions of the world and by country of training for the year 2005.

[4] Among small island countries with populations less than 2.5 million, emigration rates increased from 12.3% in 1990, to 19.0% in 2004. By 2014, emigration rates had almost doubled to 34.0%.

[5] Among the groups of countries classified by income, low-income countries with a wide geographical reach experienced high intensities of emigration among physicians with an average emigration rate of 10.2% between 1990 and 2004, and 11.8% after 2004. By contrast, countries in the upper middle-income category recorded emigration rates of 2.4% from 1990 to 2004 and 3.0% from 2004 to 2014.

and the United Kingdom, with new and emerging destination countries that include Germany, France, Sweden and Switzerland.

In the *second part* of the paper, we provide an analysis of the determinants of physician emigration across many countries over a long period of time. Our analysis is embedded in the theoretical and empirical literature on push and pull factors influencing skilled workers including wages (as in Padarath et al., 2003), working conditions (as in Awases et al., 2003; Hagopian et al., 2004), and destination country characteristics (as in Docquier and Rapoport, 2012; Bezuidenhout et al., 2009). We quantify the effects of time invariant variables (language, distance, colonial ties, etc.), push factors (governance, public health and economic conditions, etc.), and pull factors (shortage of medical doctors, employment, income levels, etc.). The mechanisms by which host country immigration policies affect the emigration of doctors have not quite been established in the literature. This indicates the need to better investigate and understand how bilateral and unilateral policies of host countries influence the emigration of physicians globally.

Estimates from our empirical analysis of the determinants of physicians' migration reveal the size and evolution of medical brain drain are complex phenomena that results from multiple push, pull, and dyadic factors. Origin-specific characteristics such as GDP per capita influence physician emigration. Training capabilities and governance are also important but less robust to the estimation technique. Given inertia in migration stocks, the long-run responses to changes in explanatory variables are 2.7 times greater than the short-run ones (observed within 5 years). As far as pull-factors are concerned, physician migration is more influenced by economic conditions (as proxied by unemployment rates and wage rates of high-skilled workers) than shortages of health care providers at destination. The sensitivity to these push and pull factors is governed by linguistic and geographic ties between countries. In particular, speaking the same official language increases the dyadic stock of physician migrants by 178% in the long-run which is more important than sharing colonial links.

In the *third part* of the paper, we assess the role of migration policies influencing the global migration of high-skilled workers in general, and migration of doctors in particular. Based on previous work by Czaika and Parsons (2017), who provide a comprehensive assessment of 9 policies aimed at attracting high-skilled workers across 10 destination countries, we estimate how bilateral agreements and unilateral policies of host countries, including the ease of work and residency permits, and diploma recognition affect the emigration of medical doctors globally. For instance, what new insights might we gain from policies which agree on the mutual recognition of diplomas of professionals including doctors? Could recruitment practices by countries that introduce work permits as a requirement for all foreign medical graduates against a previously open door policy affect the attraction of medical doctors to countries with stricter immigration policy? An understanding of these policies may help policy-makers better project their human resources planning and staffing needs.

We find that the evolution of medical brain drain is affected by immigration policies aimed at attracting high-skilled workers. In the long-run, the dyadic stock of physician migrants increases by 132% when a destination country implements a points-based system, by 124% when it offers a path to permanent residency, or by 65% when tax cuts are targeted towards immigrants. In the same vein, removing dyadic visa restrictions or recognizing foreign diplomas increases the long-run stock by 54% and 28%, respectively. Overall, of the nine policy instruments we introduce to assess the role of immigration policy of destination countries in attracting physicians, we find that the implementation of points-based system and the ease of obtaining permanent residency in the destination country appear to be the most effective policies for attracting doctors.

The rest of our paper is organized as follows. Section 2 presents an overview of our data sources. We then describe the current patterns and trends in the evolution of the medical brain drain in Section 3. Section 4 lays out the foundations of our empirical model and describes our results. We conclude with a discussion of our results and of their implications.

2. Data sources and imputation techniques

We define a migrant doctor as a medical doctor practicing in a country other than her/his country of training (preferably, her/his country of first qualification). Using the country of training as a definition is very relevant to the policy debate on the medical brain drain due to the fiscal implications of training costs for sending countries. We also (and mostly) use country of training rather than country of birth because data on country of birth are only collected using census data, and are available at a very low frequency.[6] On the contrary, data by country of training are available on a yearly basis from national medical associations. We are aware that a major limitation of this definition is the potential to skew the data in favor of the growing number of countries that have "offshore" medical schools which train medical doctors from foreign countries. We address this by identifying these countries in our estimates of the trends.

We analyze registers from the medical associations of 22 destination countries, and collect data on the size of annual stocks of foreign-trained physicians and their structure by country of origin for each year (1990–2014). Table 1 describes our data sources. In order to harmonize the scale and efficiency of the data across countries, we adjust our data based on individual country definitions and data availability. As explained in the last two columns, we categorize these adjustments into four groups by country:

- Our first category of countries – Canada, France, Finland, Germany, Hungary, Italy, New Zealand, Portugal, Sweden, the United Kingdom, and the United States – provide data for the entire period 2004–2014, using the same definition of emigrant doctors as defined in the 1990–2004 database (see Bhargava and Docquier, 2008; Bhargava

[6] Census data are available every five years in a few countries, and every ten years in the majority of them.

Table 1
Data sources and concepts.

Country	Source	Origin def.	Raw data	Adj. 1990–2004	Adj. 2005–2014
Australia	Australian Bureau of Census	Birth	1991, 1996, 2001	Estimated	Estimated
Austria	Austrian medical chamber	Training	2000–2015	Harmonized	None
Belgium	Ministère de la Santé – DG Soin de Santé	Training	2000–2014	Harmonized	None
Canada	Canadian Medical Association	Training	1996–2015	Adjusted	None
Denmark	National Board of Health	Training	1990–2004	None	Estimated
Estonia	Health Board – Bureau of the Registers and Licenses	Training	2004–2014	Estimated	None
Finland	THL – National Institute for Health and welfare	Training	2009–2012	None	None
France	ADELI and RPPS register from Ministry of Health (DREES)	Training	2000–2013	Adjusted	None
Germany	German Medical Association (Bundesärztekammer)	Citizenship	2004–2014	Adjusted	None
Hungary	Health Registration and Training Center, Dept of Migration and Human Resources	Training	1990–2014	None	None
Ireland	Medical Council of Ireland (Medical Workforce Intelligence Report)	Training	1991, 2002, 2012–14	Harmonized	Estimated
Italy	Federazione Nazionale degli Ordini dei Medici Chirurghi e degli Odontoiatri	Training	1990–2015	None	None
Netherlands	Ministry of Health – BIG register (office for registration of healthcare professionals)	Training	1998–2014	Estimated	None
New Zealand	Medical Council of New Zealand	Training	2000–2015	Adjusted	None
Norway	Department of labor market statistics, Statistics Norway	Training	2008–2014	Estimated	Estimated
Poland	Polish Chamber of Physicians and Dentists Centre of recognition of qualifications – International Cooperation Dep.	Training	2010–2015	Estimated	None
Portugal	Doctor's order Portuguese Medical Association	Training	1990–2014	None	None
Slovenia	National Institute of Public Health (NIJZ), Health Data Center	Training	2010–2013	Estimated	Predicted
Sweden	National Board of Health and Welfare, National Planning Support	Training	1990–2014	None	None
Switzerland	Department Data, Demography and Quality (DDQ) FMH	Training	2002–2014	Estimated	None
UK	General Medical Council	Training	1990–2014	None	None
USA	American Medical Association	Training	1990–2015	None	None

Notes. Authors' inventory of sources and summary of hypotheses. In cols. 5–6, "Adjusted" means that the levels observed in 1990–2004 have been slightly rescaled to match the new levels. The term "Harmonized" means that data by country of birth have been rescaled to match the concept of country of training. The term "Estimated" means that interpolations or extrapolations have been used for a large number of periods (relying on a few data points).

et al., 2011). In the case of Finland, Hungary, Italy, Portugal, the United Kingdom and the United States, new data collection covers the entire period 1990–2014. It is worth noticing that for Italy, we now use the concept of country of training while the data provided in Bhargava and Docquier (2008) was based on country of birth. In the case of Canada, France, Germany and New Zealand, we collected new data for a period covering the years 2000–2014. Due to data register updates, a small break is observed for the years that are common between the first wave (1990–2004) and the second wave (2004–2014). We use the most recent data when available, and rescale the uncovered part of first-wave data to smooth the gap in the data by multiplying the stocks by the ratio of the new total number of immigrants with the previous total for a year that is common across the two waves. The correlation between data previously collected and that recently observed is above 0.9, which suggests strong accuracy of previous data collected.

- In a second category of countries, the medical associations provide updated data for recent years (2004–2014) with a different definition of emigrant doctor that differs from 1990 to 2004. Although our preference is for the definition based on country of training, recent data refers to country of education while the previous database used a definition based either on country of birth or country of citizenship. This applies to five countries: Austria, Belgium, Switzerland, Ireland and Norway. As before, we

use the data previously collected on country of birth or citizenship and rescale the data based on a ratio of the new total number of foreign-trained and the previous total number of foreign-born (or foreign-citizen) physicians for a year which is common across the two waves. For Ireland, data received begins in 2012. Based on these data on foreign-trained definition, we, thus, extrapolated these data backward based on the ratio of the total number of foreign-trained from 2012 to 2014 and the previous number of foreign born in 1991 and 2002. By doing so, these five countries whose data were not based on country of training are now considered in line with the country of training-based definition that we adopt.
- In a third set of countries, the data are available for the recent period but not for prior years. This is the case for four European countries: Estonia, the Netherlands, Poland and Slovenia. Data for Poland and Slovenia are only provided beginning 2010. In order to have a long-term perspective for these countries, we extrapolate the data backwards based on the 5 year average annual growth observed in the available data. For the Netherlands, the data begins in 1998, which allows us to refine our backward extrapolation to observed average annual growth between 1998 and 1999. In the case of Estonia, data begin in 2004 and backward extrapolation is based on annual growth observed in Hungary between 1991 and 2004. These estimations affect a very small number of medical doctors trained in Eastern European countries in particular.
- Finally, two countries did not provide any data for the recent period, namely Australia and Denmark. For these two countries, recent data have been estimated based on the growth rate observed in the previous data set for the period 2000–2004.[7]

As in Bhargava and Docquier (2008) and Bhargava et al. (2011), we analyze the medical brain drain in both absolute and relative terms. For each (origin) country of training i and for each year t, the dyadic stocks to all destinations j ($M_{ij,t}$) are aggregated over the 22 destinations. This gives the absolute level of medical brain drain ($M_{i,t} \equiv \sum_j M_{ij,t}$). Since the most important destination countries are well covered by our database, this implies that or imputation techniques have little impact on the aggregate stocks.

The relative intensity of medical brain drain ($m_{i,t}$) is proxied by the ratio of the stock of domestically trained physicians abroad ($M_{i,t}$), to the sum of the stock of physicians practicing in the home country ($R_{i,t}$) and the stock of domestically trained physicians who are employed abroad ($M_{i,t}$). Data on doctors practicing in their country of origin are obtained from the World Health Organization (WHO) online database. More specifically, we collect WHO data on the density of physicians per 1000 people for all countries and years, and multiply them by the population in 1000 inhabitants taken from the United Nationas Population Division (UNPOP) website. Missing information can be linearly interpolated, or extrapolated (assuming the density of the closed year is constant). This allows us to compute the 25-year trend of physician density for all countries. The advantage of this relative measure ($m_{i,t}$) is to express the stock of physicians abroad as a percentage of the potential stock that the home country would have if all domestically trained physicians had stayed:

$$m_{i,t} \equiv \frac{M_{i,t}}{M_{i,t}+R_{i,t}} \equiv \frac{M_{i,t}}{T_{i,t}}, \tag{1}$$

where $T_{i,t} \equiv M_{i,t}+R_{i,t}$ is the total stock of domestically trained physicians at time t. Some countries export a significant number of their medical doctors, but because of their simultaneous huge training capacity (i.e., large $T_{i,t}$), we do not expect that this will affect the quantity and quality of health services provided at origin. However, the same export of doctors for a country with a small medical capacity could have severe implications because of the difficulty of their replacement.

Equivalently, the density of physicians is denoted by:

$$r_{i,t} \equiv \frac{R_{i,t}}{P_{i,t}}, \tag{2}$$

where $P_{i,t}$ is the population in 1000 inhabitants, whereas the number of trained physicians per 1000 people is defined as:

$$\tau_{i,t} \equiv \frac{R_{i,t}+M_{i,t}}{P_{i,t}} \equiv \frac{r_{i,t}}{1-m_{i,t}}, \tag{3}$$

which reflects the country's training capacity.

3. Stylized facts

Firstly, we characterize the *relationship between emigration and the domestic supply of physicians, in absolute and in relative terms*. Panels 1a and 1b in Fig. 1 map the stocks of domestic physicians ($R_{i,t}$) and emigrant physicians ($M_{i,t}$) per country in the year 2014. In logs and after excluding countries without a medical school, the cross-country correlation between these stocks for 2014 equals 0.68. A 10% increase in the stock of domestic physicians is associated with a 6.9% increase in the stock of physician emigrants. The correlation is even larger (0.79) when comparing emigrants ($M_{i,t}$) with domestically trained physicians ($T_{i,t}$), the denominator in Eq. (1) (i.e., domestic physicians plus emigrants). A 10% increase in the stock of domestically trained physicians is associated with a 8.7% increase in the stock of physician emigrants. This correlation is obviously guided by country size and training capacity at origin.

The correlations are different when expressing the numbers in relative terms. Panels 1c and 1d in Fig. 1 provide an overview of physician density and emigration rates of physicians for countries globally in 2014, using quintiles of the distributions. After excluding countries without a medical school, the cross-country correlation between the density of domestic physicians ($r_{i,t}$ computed as in Eq. (2)) and the physician emigration rate ($m_{i,t}$ computed as in Eq. (1)) equals −0.16 in the year 2014. A 10% increase in the stock of domestic physicians per 1000 inhabitants is associated with a 2% decrease in the physician emigration rate. This means that countries exhibiting the largest emigration

[7] Based on these backward extrapolations, the year 1990 is estimated except for countries which provide the foreign-trained medical doctors over the entire period.

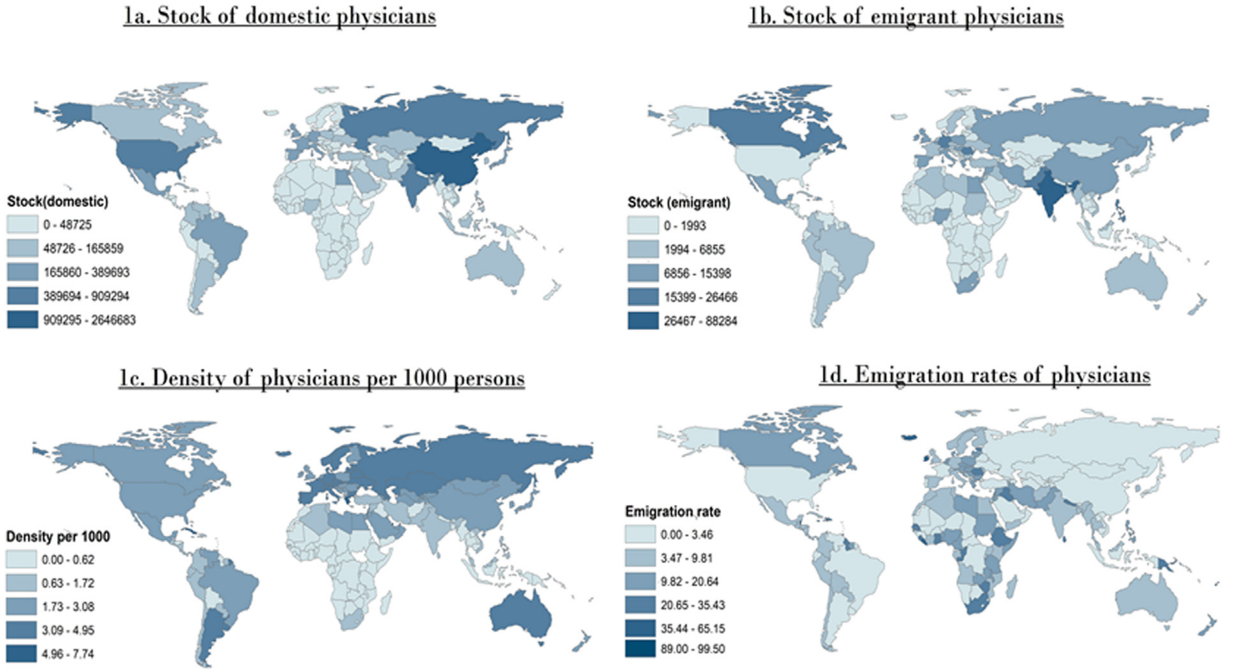

Fig. 1. Maps of domestic and emigrant physicians worldwide in the year 2014. Notes. Authors' own computation based on aggregate data for the year 2014. Panels 1a and 1b map the distribution of aggregated variables $R_{i,t}$ and $M_{i,t}$, respectively. Panels 1c and 1d map the distribution of relative measures $r_{i,t}$ and $m_{i,t}$, respectively. These rates are defined in Eqs. (2) and (1).

rates are those facing the largest needs-based deficits of health workers. On the contrary, the correlation between the number of domestically trained physicians per 1000 inhabitants ($\tau_{i,t}$ computed as in Eq. (3)) and emigration rates ($m_{i,t}$) is positive and equals 0.56. A 10% increase in the stock of domestically trained physicians per 1000 inhabitants is associated with a 0.8% increase in the physician emigration rate. In other words, countries training more medical doctors per capita are those exhibiting the greatest emigration rates. Our data reveals that a majority of sending countries recorded emigration rates of less than 10%.[8]

Secondly, Table 2 shows the *top-20 countries with the highest emigration stocks and rates of physicians*. Of the countries in the top 20 emigration rates, four are located in Europe (Iceland, Ireland, Estonia and Malta), five are in sub-Saharan Africa (Liberia, Ghana, Congo, Zimbabwe and Ethiopia), and the rest in the Caribbean. Six countries (Congo, Rep, Estonia, Zimbabwe, Guyana, Ethiopia and Malta) appear in the top-20 emigration rates for the first time in 2014 with Guyana (up 50 spots from 2004), Estonia (up 39 spots from 2004) and Congo, Rep (up 33 spots from 2004) showing the largest increases. South Africa, Sri Lanka, Lebanon, Hong Kong, Zambia, and Canada, countries that were previously in the top-20 countries with the highest emigration rates in 2004 dropped outside of the top-20 countries in our 2014 data.

In absolute terms, India retains the top spot with the largest number of physicians (88,243) practicing in the 22 destination countries in 2014 – almost double the number (46,404) in 1990. Despite the high numbers of Indian doctors practicing abroad, compared to the share of size of doctors practicing abroad, India is not included in the top 20 origin countries by emigration rate. Pakistan remains the second biggest exporter of physicians in 2014, followed by Germany (up four spots from 2004), and the Philippines (down 2 spots from 2004). Greece and Grenada appear among the top-20 countries with the largest stock of physicians in 2014 for the first time after increasing their physician stock by 91% and 117% respectively between 2004 and 2014.

Thirdly, we focus on the *dyadic dimension of our database*. Fig. 2 identifies the main migration corridors. Panel 2a relies on the stock data at the beginning of the period (i.e., in the first year 1990), while Panel 2b depicts dyadic migration flows (as proxied by the variation in migration stocks between 1990 and 2014). In absolute terms, the United States and the UK were the top destination countries of doctors globally in 1990, accounting for more than half of the stock of physician emigrants. The largest stocks of foreign-trained doctors in 1990 were from high-income countries to the United States, and from the Latin America and Caribbean region to the United States. South Asia and the Latin America and Caribbean regions also had a large share of doctors emigrate to the United States. The USA maintains its position as the largest recipient of migrating physicians in 2014 – serving as host to about 50% of the world's physicians, although the numbers declined from 55% in 2004 and 1990. In relative terms, this

[8] China, the United States and Turkmenistan recorded emigration rates of less than 0.5% in 2014.

Table 2
Top-20 countries by emigrant stocks and rates (1990–2014).

Total stock				Emig rates (%)			
Country	1990	2004	2014	Country	1990	2004	2014
India	46,404	74,132	88,243	Grenada	97.04	98.58	99.36
Pakistan	7752	18,080	26,500	Dominica	95.69	97.13	98.85
Germany	7956	15,628	22,850	St Lucia	70.59	84.36	96.95
Philippines	17,009	19,648	21,160	St Kitts & Nevis	34.88	61.90	95.00
Romania	2947	6329	18,709	Antigua & Barbuda	16.18	47.48	89.15
Canada	13,237	18,680	17,326	Jamaica	48.50	55.34	65.15
United Kingdom	14,083	16,572	15,380	Liberia	48.91	45.40	54.81
Mexico	10,993	13,200	14,503	Iceland	50.72	50.31	52.72
Poland	3984	7389	14,201	Fiji	23.74	37.93	44.64
Italy	6647	7988	12,968	Ireland	67.07	48.82	43.48
South Africa	10,734	16,773	12,803	Belize	1.04	31.56	42.49
Egypt	5361	9005	12,014	Dominican Rep	34.18	34.89	35.43
Grenada	1638	4987	10,834	Ghana	34.37	25.83	33.74
Spain	5739	8073	10,418	Congo, Rep.	3.15	11.65	33.59
Greece	3276	5363	10,240	Estonia	2.08	10.22	32.99
Russia	1773	6451	10,020	Zimbabwe	11.48	19.85	32.86
Dominica	822	3758	9864	Guyana	0.93	7.78	32.64
Ireland	12,234	10,818	9478	Haiti	64.67	33.48	32.11
Nigeria	1517	5775	9049	Ethiopia	9.39	18.99	28.35
Dominican Rep	4945	7318	8507	Malta	31.91	23.08	28.28

Notes: Countries are ranked on the basis of the stock ($M_{i,t}$) or rate ($m_{i,t}$) observed in 2014.

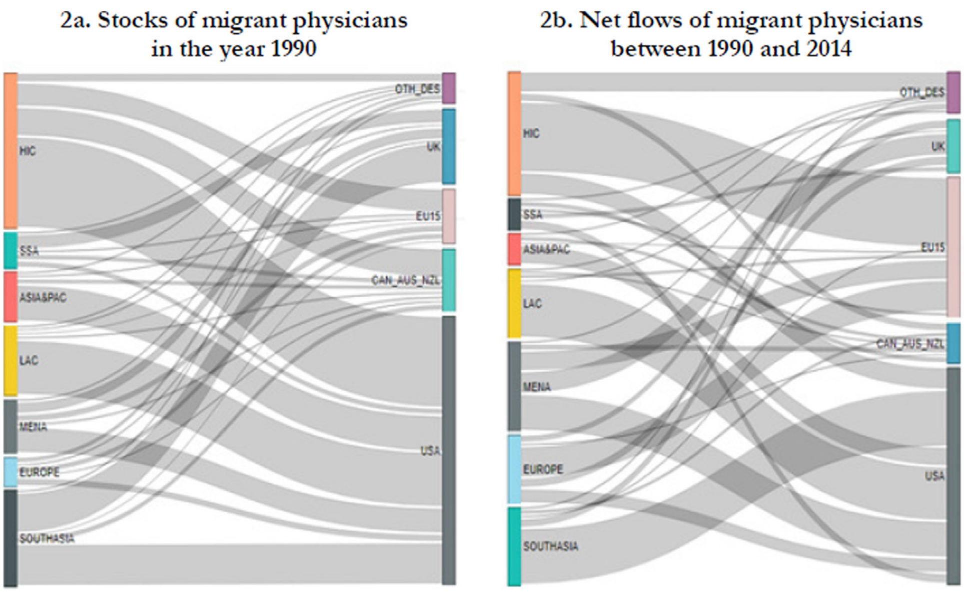

Fig. 2. Stocks and flows of physicians 1990 and 2014 by source and destination region. Notes: The left and right axes represent the share of origin and destination regions in the total stock/flow of physician emigrants. Stocks are measured in 1990 ($M_{i,1990}$). Net flows are defined as variations in stocks: $M_{i,2014} - M_{i,1990}$. Regions are defined as: HIC = high-income countries, SSA = sub-Saharan Africa, ASIA&PAC = Asia and Pacific islands, LAC = Latin America and the Caribbean, MENA = Middle East and Northern Africa, EAP = East Asia and Pacific, EE = Eastern Europe, ECA = Europe and Central Asia; LAC = Latin America; USA = United States, EU15 = European Union (see Footnote [9]), CAN_AUS_NZL = Canada, Australia and New Zealand, UK = United Kingdom, OTH_DES = other destinations.

suggests that the United States has become a less attractive destination country for doctors – similar to the United Kingdom, which attracted fewer than 20% of physicians in 2014 compared to 24% in 1990. Flows of migrant doctors to the USA were from South Asia, the Latin America and the Caribbean region and MENA regions. The EU15 becomes the second largest host destination for migrating physicians in 2014,[9] replacing the UK and attracting doctors primarily from high-income countries, Europe and MENA. The EU15's share as a destination region for immigrant doctors increased, due to the emergence of new destinations including Sweden, Slovenia, Portugal, Norway, Netherlands, Hungary and Germany.

[9] EU15 countries for which data are available: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Sweden. The UK usually appears separately.

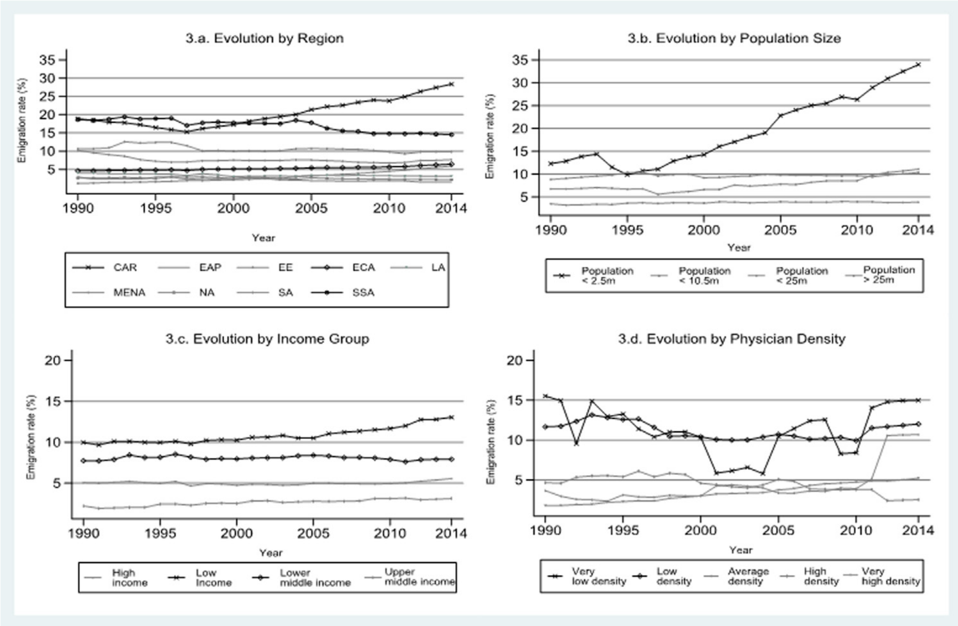

Fig. 3. Evolution of the medical brain drain by country group. Note: Medical brain ($m_{i,t}$) is defined in Eq. (1). Regions are defined as: CAR = Caribbean, EAP = East-Asia and Pacific; EE = Eastern Europe, ECA = Europe and Central Asia; LA = Latin America; MENA = Middle East and Northern Africa, NA = North America, SA = South Asia, SSA = sub-Saharan Africa. Density thresholds used in Panel 3d: Very low (*leq*0.16); Low (*leq*0.60); Average (*leq*0.71); High (*leq*2.94); Very high (*leq*2.94).

Fourthly, Fig. 3 characterizes the *evolution of physician emigration rates by group of countries*. Panel 3a describes the evolution of the medical brain drain by geographical groups. The Caribbean region experiences the highest rate of physician emigration – with an increasing trend from 18.9% in 1990 to 20.0% and 28.4% in 2004 and 2014 respectively – a corresponding increase of over 55% from 1990 to 2014. The largest increase in emigration rates occurs in Antigua and Barbuda, which experiences a 85% increase in the emigration of doctors between 2004 and 2014. A number of reasons could explain the rising trend in emigration from the Caribbean. It is possible there is a small labor market in the region, which makes it impossible for physicians to integrate once they graduate. Secondly, the numbers may represent the willingness or strategy for countries to train an excess number of physicians for the global labor market. Third and more importantly, the Caribbean region is host to over 15 “Offshore Medical Schools,” which specialize in the training of foreigners, especially from the United States and Canada. The high emigration rates of doctors from the Caribbean reflects the number of US and other foreign citizens who are trained in medical schools in the Caribbean but return to their origin countries to practice. Since 2004, more than 20 offshore medical schools have been established in the Caribbean region. The density of physicians per 1000 people in the Caribbean shows an upward trend with an average of 0.9 physicians per 1000 people in 1990 and 1.6 per thousand people in 2014.

To a lesser extent, Eastern Europe experiences increasing rates of migration, from 1.2% in 1990, to 2.9% in 2004. By 2014, emigration rates doubled to almost 6%. The increase in the size and density of physicians from Eastern Europe may be the result of new memberships to the European Union after 2004, and of the EU directive recognizing diplomas across all its member states for certain categories of workers including medical doctors. Romania and Poland had the highest emigration rates of Eastern European countries. In Romania, emigration rates increased from 6.3% in 1990, to 13.4% in 2004. By 2014, Romania had among the highest emigration rates of doctors worldwide, at 27.8%. The intensity of emigration in Poland increased from 4.5% in 1990 to almost double the rate (8.0%) in 2004 and 13.5% in 2014.

A decreasing trend is observed for East Asia and the Pacific (EAP), the Middle East and North Africa (MENA) region, and South Asia (SA). Sub-Saharan Africa is a region of particular interest, as its density of physicians is very low. It increased from 0.12 physicians per 1000 in 1991 to 0.19 physicians per 1000 in 2014, a figure far below the 3.56 physicians per 1000 in Europe and 1.92 in Latin America and the Caribbean regions. Sub-Saharan Africa (SSA) exhibits declining rates of migration in the recent period. More precisely, the SSA migration rate remained steady between 1991 and the year 2004 (at an average rate of 18.2%), but a decreasing trend began in 2005, with emigration rates dropping to 14.5% in 2014. A number of demand and supply factors could be responsible for the declining emigration rates in SSA. On the demand side, increasing immigration restrictions and lower diploma recognition may have played a role. For example, SSA's share of doctors to the UK, one of its largest hosts began to decline after 2005, corresponding to overall declines in non-EU skilled migration to the UK. On the supply side, the rise in the number of physicians trained in SSA has led to a less than proportional increase in the stock of emigrants. Still, sub-

Saharan Africa (SSA) records the second highest emigration rates after the Caribbean region.

In comparing emigration rates according to variations in the size of the population (Panel 3b), we observe that higher population size corresponds to a lower emigration rate of physicians. This relationship can be driven by the specific situation of Caribbean states. In 2014, the average medical brain drain in small countries (population less than 2.5 million) was about 34%, almost ten times higher than large countries (population higher than 25 million) with emigration rates of 3.9%. We observe the highest increasing trend for small countries between 1991 and 2014 with emigration rates increasing from 9.9% to 34% – about 2.5 times their initial medical brain drain rate.

Panel 3c in Fig. 3 shows emigration rates by income group. Countries in the low-income group (GDP per capita of $995 or less) were the most affected by the emigration of physicians followed by lower-middle income (GDP per capita between $996 and $3895). Countries that make up the low-income group vary over geographical region, although the majority (27) of them are in SSA. The rest are in the Middle East (2); South Asia (2); the Caribbean (1); and Europe and Central Asia (1). A majority of countries in the low-income group have emigration rates below 40% and a physician density ratio of less than 0.5 per thousand of the population. Liberia had the largest emigration rate – at 55% and 0.01 physicians per 1000 people in 2014. Tajikistan on the other hand had a higher density of physicians (1.98 physicians per 1000 individuals) and an emigration rate of 1%. In 2014, low income countries had a 13% emigration rate, compared to 8% for lower middle income countries; 6% for high income (GDP per capita of more $12,056) and 3% for upper middle income countries (GDP per capita between $3896 and $12,055).

Finally, Panel 3d compares emigration rates using the density of physicians per 1000 people. Our results are revealing: higher emigration rates were observed for countries with a very low doctor to patient ratio, but with fluctuating emigration rates. Emigration rates in countries with very low density decreased from 15.5% in 1990 to 9.5% in 1992. The numbers increased again to 14.9% in 1993. By 2001, emigration rates for countries with very low doctor to population ratio had fallen by about 60% to 5.9% but increased again to almost 15% by 2014. Countries with a low physician density had slightly lower emigration rates, but a more stable pattern in emigration rates is observed. Emigration rates fell from 11.6% to 10.4% from 1990 until 2004, but increased to 12.0% in 2014.

4. Empirical analysis

The goal of this section is to analyze the determinants of physician emigration and its evolution over the period 1990–2014. In Section 4.1, we first develop the microfoundations underlying our two-step empirical model, relying on the standard random utility framework. We then discuss our results of the first-step and second-step regressions in Sections 4.2 and 4.3, respectively.

4.1. Empirical strategy

The recent migration literature has produced a consensus tool for modelling dyadic migration decisions. The Random Utility Model (RUM) provides the state-of-the-art microfoundations for most recent gravity models of migration (Beine et al., 2016). It assumes the utility of someone moving from country i to country j is the sum of a deterministic component – capturing the mean utility attainable in country j, net of moving costs – and a stochastic component – a vector of person-specific random taste shocks representing the unobservable determinants which enter the utility functions and are orthogonal to the deterministic component. The latter is used to account for the fact that not all individuals decide to move and not all migrants choose to settle in the same destination country. In our context, consider a physician trained in country i and practicing in country j at time t. Abstracting from individual subscripts to simply notations, her utility is given by:

$$U_{ij,t} = V_{ij,t} + \varepsilon_{ij,t}, \tag{4}$$

where $V_{ij,t}$ denotes the deterministic level of utility that is common to all physicians, and $\varepsilon_{ij,t}$ is the stochastic component of utility that varies across individuals and destinations. The deterministic component captures the average level of utility that each physician derives from moving from i to j, net of migration costs. The latter includes monetary costs, assimilation costs, and legal or visa costs. The stochastic component captures diverse factors such as heterogeneity in preferences, heterogeneity in capabilities of realizing migration aspirations, or bounded rationality.

If the stochastic component of utility follows an independent EVT-1 distribution, the probability $p_{ij,t}$ that country j is the utility-maximizing alternative follows the multinomial logit expression:

$$p_{ij,t} = \frac{\exp\left(V_{ij,t}\right)}{\sum_k \exp\left(V_{ik,t}\right)}. \tag{5}$$

The probability that staying in the country is the best alternative ($p_{ii,t}$) follows the same expression. Hence, the relative probability of emigrating to j over staying at origin (which is equivalent to the ratio of dyadic migrants to stayers) only depends on the characteristics of the origin and destination countries. Taking the logs of this ratio gives:

$$\ln\left(\frac{M_{ij,t}}{M_{ii,t}}\right) = \ln\left(\frac{p_{ij,t}}{p_{ii,t}}\right) = V_{ij,t} - V_{ii,t}. \tag{6}$$

Let us emphasize three characteristics of our empirical gravity model. Firstly, we have to account for the fact that there is inertia in migration stocks and possible network effects. This is due to the fact that the stock of physician migrants at time t ($M_{ij,t}$) includes migrants who already settled in period $t-1$ ($M_{ij,t-1}$), and that previous migrants ($M_{ij,t-1}$) may attract new waves of migrants at time t. We thus include the lagged stock of one plus physician migrants, $\ln(1 + M_{ij,t})$, in the set of dyadic regressors (i.e., in $V_{ij,t}$), which leads to a dynamic specification. The one-plus correction is used to avoid losing observations with $M_{ij,t-1} = 0$.

Secondly, our empirical strategy is structured in two steps which is common in gravity models applied to international trade (Combes et al., 2008; Combes and Gobillon, 2015). Firstly, we estimate $V_{ij,t}$ and $V_{ii,t}$ as functions of a full set of fixed effects. We consider origin-time ($\alpha_{i,t}$), destination-time ($\alpha_{j,t}$), and dyadic fixed effects (α_{ij}). These fixed effects greatly reduce the biases driven by omitted variables and improve the estimation of the lagged stock. In the *second step*, we regress each set of fixed effects on potential explanatory variables, using the standard OLS estimator or weighting observations by the inverse of the standard error of the coefficient in order to give more weight to the most significant fixed effects.

Thirdly, the high prevalence of zero values for the dependent variable is another source of concern in the first step. The use of the log specification in (6) drops the zero observations which constraint the estimation to a subsample involving only dyadic pairs with positive stocks. This causes some biases in OLS estimation, as in many other dyadic contexts. Santos Silva and Tenreyro (2006) and Santos Silva and Tenreyro (2010) specifically tackle this problem and proposed an appropriate technique that minimizes the estimation bias of the parameters, namely the Poisson pseudo maximum likelihood (hereafter PPML). In case of a significant proportion of zero values, the PPML estimator generates unbiased estimators of the parameters of (6). Furthermore, the PPML estimates are found to perform quite well under various heteroskedasticity patterns and under rounding errors for the dependent variable. Therefore, our *first-step model* relies on the PPML estimation techniques and can be written as:

$$M_{ij,t} = \exp\left[\alpha_{i,t} + \alpha_{j,t} + \alpha_{ij} + \beta \ln(1 + M_{ij,t-1}) + \gamma x_{ij,t} + \varepsilon_{ij,t}\right], \quad (7)$$

where $x_{ij,t}$ is a vector of observable time-varying and dyadic factors, β and γ for the set of parameters to be estimated, and $\varepsilon_{ij,t}$ is the error term. Note that the origin-time fixed effects $\alpha_{i,t}$ on the right-hand side of Eq. (7) also capture $\ln M_{ii,t}$ as well as corrections for multilateral resistance to migration (Bertoli and Fernandez-Huertas Moraga, 2013).

Our set of dyadic factors ($x_{ij,t}$) includes bilateral agreements and origin-specific visa waivers, which may ease the migration process and determine whether physicians stay in the host country permanently. We employ two unique data sets developed by Czaika and Parsons (2017) and Czaika et al. (2018), the only longitudinal data sets we are aware of that synthesize and harmonize high-skilled immigration and visa policies across 12 host countries and 185 origin countries (Appendix Tables 8 and 9). We add a dummy equal to one when there is a visa restriction to move from i to j, a dummy equal to one when a social security agreement exists between the two countries, or when an agreement of recognition of diplomas exists. Evidently, high-skilled migration policies have not specifically targeted emigrating physicians on a large scale, neither have any specific policies designed for emigrating physicians in all but few cases. Rather, like other skilled migrants, physicians are mostly governed by host country stance on its highly skilled migrants – although in notable exceptions, simplified procedures including shorter processing times, and fast-track may be offered to ease or facilitate the recruitment of foreign doctors depending on their shortage needs by host countries, residency. However, this program is only to facilitate recruitment and does involve a specific policy of high-skilled migration towards medical doctors. In the *second step*, we regress each set of fixed effects on potential explanatory variables to shed light on explicit determinants. The second-step regressions rely on the standard OLS estimator. As standard in the gravity literature, we also use weighted regressions, weighting observations by the inverse of the standard error of the coefficient in order to put higher importance to significant β.

The regression $\alpha_{ij} = d\left(X_{ij}\right)$ allows us to capture the dyadic determinants. Our gravity variables (X_{ij}) include bilateral geographic variables including distance as a measure of relative geographic proximity between the origin and destination countries to represent the actual and psychological costs of migration. We also include genetic distance to account for the genetic variation between countries. Genetic distance is hypothesized to be positively associated with emigration rates, as countries that share a common ancestry also tend to have similar preferences, language and culture (see Spolaore and Wacziarg, 2016). We include a dummy variable if the two countries in a dyad share a border, and a dummy variable if the countries have a common language. A dummy is also included if two countries have a colonial relationship, to test whether higher physician flows occur between countries that have historic colonial ties (e.g., Head et al., 2010).

The regression $\alpha_{j,t} = g\left(X_{j,t}\right)$ allows us to capture the time-varying pull factors at destination. Economic conditions in the host country may serve as incentive for emigrating physicians to seek opportunities abroad. High employment opportunities for physicians due to shortages of medical doctors in destination countries also serve as a pull indicator. We include the unemployment rate in the destination country to assess whether high unemployment rates in destination countries decrease the emigration of physicians. The appeal of wages in the destination country is proxied by the high-skilled wage rate. We used the ratio of gross earnings for the 9th over the 5th decile from the OECD online database as proxy. Data on unemployment rates are also taken from the OECD online database. To assess the capacity of human resources for health in the destination country, we also include the density of physicians per 1000 people as a measure of quality of healthcare.

As far as policy variables are concerned, we use the unilateral policy variables provided in Czaika and Parsons (2017). The policy instruments in the data set are based on the two distinct skill-selective immigration systems: (i) demand-driven systems used by host country employers to initiate the demand for high-skilled workers and based on employers' immediate needs to fill a vacancy; and (ii) supply-driven systems where skilled migrants are invited to apply for either temporary or permanent residency based on a variety of factors which may include educational attainment, work experience and language proficiency. Countries have used either of these systems or a combination of both systems to attract high-skilled migrants to fulfil immediate or longer-term labor needs. Based on these systems, Czaika and Parsons (2017), develop six policy instruments: (i) job offer; (ii) points-based system; (iii) labor market test; (iv) shortage list; (v) permanent residency offer; (vi) financial incentives. To account for dyadic bilateral agreements and programs that may exist between countries and their role in the movements of medical doctors, three additional policy instruments that relate to (vi) social security (vii) double taxation and (viii) recognition of diplomas between countries are included to capture the movement of high-skilled migrants. The database also controls for unilateral policy that allows free mobility in areas which share a mutual agreement to facilitate mobility of high-skilled migrants, for example the European Economic Area. In these second-step regressions, we use the standard OLS estimator and control for destination and time fixed effects.

The regression $\alpha_{i,t} = f\left(X_{i,t}\right)$ allows us to capture the time-varying push factors from the origin countries. Our push factors examine the motivating characteristics of source countries that lead physicians to seek employment opportunities abroad. We use GDP per capita – a widely used indicator of relative per capita distribution across origin countries wealth and economic development. Given evidence that suggests wages are a strong predictor of physicians' migration, and the deterioration of economic conditions, including the inability to find employment in the source country associated with physician migration, we expect that large variations in incomes between countries will be associated with the emigration of physicians for better wages and living standards (e.g., Vujicic et al., 2004; Hussey, 2007).

The human resources for public health capacity is an important indicator showing how well a country's health system performs. Hagopian et al. (2004) note that countries with struggling health systems and particularly those without sufficient human resources will provide poorer health outcomes for its citizens. This, compounded by a lower density of physicians may overburden the already low number of physicians with longer hours and higher patient to doctor ratios and push physicians to seek opportunities abroad. Thus, we include the number of physicians per 1000 people in the origin country as an indicator of the capacity for human resources for health of a sending country. We create a public health index which is a PCA of (i) the percentage of the population with access to clean water; (ii) the percentage of the population with access to improved sanitation facilities and (iii) the under-5 mortality rate.

We also assess the institutional determinants of the medical brain drain by investigating the role of source country institutions on the emigration of physicians. This is rooted in the theory that political institutions and economic governance are functions of economic development. We capture the effect of governance and institutions on the magnitude of the medical brain drain using a confirmatory factor analysis of the World Bank's World Governance Indicators (WGI). Using a PCA, we create a "governance" indicator that captures the institutional quality and political stability based on an optimally weighted combination of these indicators; (i) Voice and accountability (ii) Political stability and absence of violence (iii) Government effectiveness (iv) Regulatory quality (v) Rule of law and (vi) Control of Corruption. We hypothesize that physicians experience a higher incentive to migrate given lower institutional quality and political instability (Bang and Mitra, 2011). Thus, we expect a higher governance index to be negatively associated with the emigration of physicians from source countries.

4.2. First-step regressions

In our empirical analysis, a period represents five years. Hence, we compute the average levels of dyadic emigrant stocks and explanatory variables over five-year intervals. In addition, we limit our analysis to 12 destination countries for which data on migration policy variables and dyadic migration data include a minimum of estimates.[10]

Table 3 gives the results of our first-step PPML regressions. Errors are clustered at the dyadic level. In col. (1), the specification includes the lagged migration stock only. We identify a strong inertia in migration stocks, with a coefficient of the lagged stock of 0.972. In cols. 2 and 3, we add two sets of fixed effects, $\alpha_{i,t}$ and $\alpha_{j,t}$. The coefficient of the lagged stock is stable and the fixed effects slightly improves the quality of fit. In col. (4), we add the dyadic fixed effects, α_{ij}, which capture the unobserved dyadic factors that do not vary over time. The coefficient of the lagged stock falls to 0.740 and is now identified using the variations of the dyadic migrant stocks over time. Col. (5) combines the three sets of fixed effects. The coefficient of the lagged stock reaches 0.627.

Finally, col. (6) adds three proxies for dyadic migration policies, x_{ij}, that vary over time. These include a dummy equal to one if a visa is requested to travel from country i to j, a dummy equal to one if there is an agreement of diploma recognition between the two countries, and a dummy equal to one if there is a social security agreement between the two countries. From Eq. (7), the estimated coefficient of these dyadic variables ($\frac{d \ln M_{ij,t}}{dx_{ij,t}} = \gamma$) gives their impact on the stock of migrant physicians in the short-run (i.e., after five years and for a given level of $M_{ij,t-1}$). Except for the latter, they have a significant impact on the dynamic of physician migrant stocks. The existence of a visa restriction reduces the stock of migrant physicians by 20%, whereas the diploma recognition agreement increases it by 10%.

The coefficient of the lagged stock is stable (0.630) compared to (0.627) in col. (5).[11] Because our estimates strongly support $0 < \beta < 1$, this coefficient determines the speed of convergence of each dyadic migrant stock to its steady state

[10] The list of destination countries is included in Table 8 in Appendix C, whereas the list of origin countries is provided in Table 9. In Appendix B, we provide descriptive statistics for our explanatory variables.

[11] Note that Beine et al. (2011) find a very similar coefficient of the lagged stock in their analysis of network effects. They obtain a coefficient of 0.75 when aggregating college-educated and less educated migrants, and of 0.625 when focusing on college graduates only. However, our coefficient is not totally comparable for two reasons. Firstly, we use the log of the current stock as a dependent variable, while Beine et al. (2011) use the log of the variation in migrant stocks. Secondly, the length of a period is 5 years in our study, whereas it amounts to 10 years in Beine et al. (2011).

Table 3
PPML regressions with and without fixed effects (dependent = $M_{ij,t}$).

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(1+M_{ij,t-1})$	0.972***	0.962***	0.977***	0.740***	0.627***	0.630***
	(0.0114)	(0.00686)	(0.0122)	(0.0313)	(0.0347)	(0.0339)
Visa restriction	–	–	–	–	–	−0.199***
						(0.0539)
Dipl. recognition agreement	–	–	–	–	–	0.104**
						(0.0491)
Social security agreement	–	–	–	–	–	−0.0128
						(0.0464)
Obs.	4484	4483	4484	4483	4483	4483
R-sq	0.9837	0.9900	0.9860	0.9916	0.9949	0.9950
$\alpha_{i,t}$	No	Yes	No	No	Yes	Yes
$\alpha_{j,t}$	No	No	Yes	No	Yes	Yes
α_{ij}	No	No	No	Yes	Yes	Yes

Notes. Errors are clustered at the dyadic level; Robust standard errors in parentheses. PPML stands for Poisson pseudo-maximum likelihood estimation.
* Significant at the 10% threshold.
** Significant at the 5% threshold.
*** Significant at the 1% threshold.

level, $\ln M^*_{ij}$, which is obtained after imposing $M_{ij,t} = M_{ij,t-1}$ in Eq. (7). This gives:

$$\ln M^*_{ij} = \frac{\alpha^*_i + \alpha^*_j + \alpha_{ij} + \gamma x^*_{ij}}{1-\beta}, \tag{8}$$

where α^*_i and α^*_i are the stationary levels of $\alpha_{i,t}$ and $\alpha_{j,t}$, whereas x^*_{ij} is the stationary level of $x_{ij,t}$.

This means that the long-run effect of a permanent change in x^*_{ij} on the dyadic stock of physician migrants is given by $\frac{d\ln M^*_{ij}}{dx^*_{ij}} = \frac{\gamma}{1-\beta}$. In our model, the long-run effect of each shock is roughly 2.7 times (i.e., $1/(1-0.63)$) the short-run effect. This implies that the existence of a visa restriction reduces the stock of migrant doctors by 54%, and the diploma recognition agreement increases it by 28%. The regression in col. (6) is used as our benchmark regression.

4.3. Second-step regressions

In the second step, we use OLS regressions to explain the structure of our fixed effects using appropriate sets of explanatory variables.

Table 4 presents our results for the dyadic fixed effects (α_{ij}). Our set of variables of interest include the geographic distance between country i and country j (a proxy for the actual and psychological costs of moving), a dummy for contiguous countries, a dummy equal to one for countries sharing a colonial link, a dummy equal to one for countries sharing the same official language (a variable that affects the transferability of human capital), and a measure of genetic distance (as a proxy for cultural distance). Before considering these variables, we clean the dyadic data from origin- and destination-specific factors in cols. 1–3. Origin and destination fixed effects capture 31% and 23% of variability in α_{ij}, respectively. Combined, they explain 55% of the variations in α_{ij}.

In col. (4), we find that the dyadic determinants influencing the physician migrant stocks are geographic distance, colonial link and linguistic proximity. The estimations in col. (5) confirm the previous results once we weight observations by the inverse of the standard error of the fixed effect estimates. The coefficient in Table 4 can be interpreted as the short-run effect of dyadic determinants on the log of physician migrant stocks ($\frac{d\ln M_{ij,t}}{dX_{ij}}$). Remember the long-run effect of each shock is roughly 2.7 times greater. Hence, the short-run and long-run elasticities of the dyadic physician stock to distance equal −0.45 and −1.22, respectively. Sharing a colonial tie increases the physician stock by 51% in the short-run and 138% in the long-run. The short-run and long-run responses to the common language variable equal 66% and 178%, respectively. Increases in geographical distance reduce the migration of physicians. Sharing a common colonial heritage and a common language have strong and positive effects on the dyadic stock of physicians. We find no evidence that genetic distance and contiguity affect the migration of physicians.

Table 5 presents our results for the origin-time fixed effects ($\alpha_{i,t}$). Our set of variables of interest include the level of GDP per capita, the stock of domestically trained physicians, the quality of governance, and a proxy for public health infrastructure. As $\alpha_{i,t}$ captures the determinants of the variation in the stock of physicians over time, all variables are lagged one period. Before considering these variables, we clean the dyadic data from origin- and time-specific factors in cols. 1–3. Origin and time fixed effects capture 91% and 0.5% of variability in $\alpha_{i,t}$, respectively. Combined, they explain 92% of the variations in $\alpha_{i,t}$. The coefficient in Table 5 can be interpreted as the short-run effect of origin-specific determinants on the log of physician migrant stocks ($\frac{d\ln M_{ij,t}}{dX_{i,t}}$). As usual, the long-run effect of each shock is 2.7 times greater.

In col. (4), we find that greater physician migration is strongly associated with less wealth and quality of life in the source country. A 1% increase in the GDP per capita in the source country is associated with a short-run decline in physician migrant stocks by 0.29% in our model. The long-run effect varies between 0.78%.

In col. (5), we find negative and robust associations between our governance indicator and physician emigration, which intuitively explains that improvements in

Table 4
OLS regressions on time-invariant dyadic fixed effects (dependent = α_{ji}).

	(1)	(2)	(3)	(4)	(5)
Geog. distance (logs)				−0.460***	−0.450***
				(0.0353)	(0.0352)
Contiguity				−0.227	−0.228
				(0.163)	(0.161)
Colony				0.512***	0.507***
				(0.110)	(0.103)
Common language				0.692***	0.657***
				(0.0871)	(0.0954)
Genetic dist. (logs)				−0.0171	−0.0154
				(0.0183)	(0.0192)
Constant	−1.568	−0.544***	−1.573	1.737	3.565***
	(1.275)	(0.197)	(1.212)	(1.252)	(0.486)
Obs.	4483	4483	4483	4483	4483
R-squared	0.311	0.231	0.550	0.659	0.657
Weight ($\frac{1}{SD_\alpha}$)	No	No	No	No	Yes
α_i	Yes	No	Yes	Yes	Yes
α_j	No	Yes	Yes	Yes	Yes

Notes. Errors are clustered at dyadic level. Robust standard errors in parentheses. In col. (5), observations are weighted by the inverse of the standard error of each fixed effect estimate. OLS stands for Ordinary Least Squares estimation.
* Significant at the 10% threshold.
** Significant at the 5% threshold.
*** Significant at the 1% threshold.

Table 5
OLS regressions on origin-time fixed effects (dependent = $\alpha_{i,t}$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP pc (logs)				−0.291***	−0.361***	−0.395***	−0.236**
				(0.0718)	(0.101)	(0.105)	(0.107)
Dom. phys. (logs)				0.0755	0.151***	0.127***	0.0460
				(0.0509)	(0.0422)	(0.0443)	(0.0286)
Governance (logs)					−0.0853***	−0.0829***	−0.0548
					(0.0284)	(0.0298)	(0.0371)
Pub. health (logs)						0.140*	0.113
						(0.0768)	(0.0759)
Constant	−0.297	−0.898***	−0.382	−2.215***	0.972	3.420***	2.179**
	(0.607)	(0.0614)	(0.599)	(0.504)	(1.273)	(1.020)	(0.969)
Obs.	4483	4483	4483	4249	2208	2176	2176
R-squared	0.913	0.005	0.919	0.921	0.977	0.977	0.996
Weight ($\frac{1}{SD_\alpha}$)	No	No	No	No	No	No	Yes
α_i	Yes	No	Yes	Yes	Yes	Yes	Yes
α_t	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Errors are clustered at the origin-time level; Robust standard errors in parentheses. In col. (7), observations are weighted by the inverse of the standard error of each fixed effect estimate. OLS stands for Ordinary Least Squares estimation.
* Significant at the 10% threshold.
** Significant at the 5% threshold.
*** Significant at the 1% threshold.

political stability and political institutions are associated with declines in the migration of doctors from sending countries. In addition, the effect of medical training in the source country on physician migrant stocks is positive and much below unity. In line with our stylized facts, this means that the stock of emigrants increases less than proportionately with the number of physicians in the home country (i.e., the physician emigration rate decreases with "increases" in the number of domestic physicians). In col. (6), the health system of the country, proxied by our public health indicator, is a positive determinant of emigration, although the coefficient is weakly significant (likely due to collinearity between public health and the density of physicians).

Nevertheless, the effects of governance, training capacity and public health become insignificant when observations are weighted by the standard errors of the fixed effect estimates. In col. (7), the weighted regression suggests that GDP per capita is the only variable which remains statistically significant at the 5% level and negative. This highlights the role of the level of economic development in the source countries on physician emigration.

Finally, Table 6 presents our results for the destination-time fixed effects, $\alpha_{j,t}$. Our set of variables of interest include the rate of unemployment, the average wage of high-skilled workers, the density of physicians, and a set of dummies capturing the unilateral immigration policy of the destination country. Before considering these variables, we

Table 6
OLS regressions on destination-time fixed effects (dependent = $\alpha_{j,t}$).

	(1)	(2)	(3)	(4)	(5)	(6)
log(unemployment)				−0.370***	−0.181***	−0.128**
				(0.0812)	(0.0330)	(0.05549)
log(wage ratio)				1.229	0.998	0.0648
				(1.226)	(0.857)	(1.202)
log(Phys. density)				−0.238*	−0.326***	−0.201*
				(0.119)	(0.101)	(0.118)
Constant	−0.461***	−0.356***	−0.530***	−0.695	−0.778	−0.515
	(0.123)	(0.0902)	(0.0804)	(1.326)	(0.730)	(1.220)
Policy dummies						
Perm. residence					0.459***	0.439***
					(0.065)	(0.068)
Fin. incentives					0.216***	0.242***
					(0.041)	(0.046)
Cont. on job offer					0.160**	0.258***
					(0.060)	(0.085)
Labor market test					−0.262***	−0.275***
					(0.031)	(0.037)
Shortage list					0.0950*	0.129**
					(0.053)	(0.051)
Points based					0.492***	0.594***
					(0.0858)	(0.114)
Obs.	4483	4483	4483	3338	3129	3129
R-squared	0.699	0.132	0.829	0.912	0.988	0.989
Weight ($\frac{1}{SD_\alpha}$)	No	No	No	No	No	Yes
α_j	Yes	No	Yes	Yes	Yes	Yes
α_t	No	Yes	Yes	Yes	Yes	Yes

Notes. Errors are clustered at the destination-time level; Robust standard errors in parentheses. In col. (6), observations are weighted by the inverse of the standard error of each fixed effect estimate. OLS stands for Ordinary Least Squares estimation.
* Significant at the 10% threshold.
** Significant at the 5% threshold.
*** Significant at the 1% threshold.

clean the dyadic data from destination- and time-specific factors in cols. 1–3. Destination- and time fixed effects capture 70% and 13% of variability in $\alpha_{j,t}$, respectively. Putting them together explains 83% of the variations in $\alpha_{j,t}$. The coefficient in Table 6 can be interpreted as the short-run effect of destination-specific determinants on the log of physician migrant stocks ($\frac{d \ln M_{ij,t}}{dX_{j,t}}$). The long-run effect of each shock is 2.7 times greater.

Again, in col. (4), we add labor market and macroeconomic variables and find that the stock of physician migrants decreases with the rate of unemployment in the destination country. Our estimates confirm that physicians are less attracted by host countries that experience high levels of unemployment. The short-run elasticity is equal to −0.37% in case of a 1% increase in the unemployment rate. In the long-run, elasticity becomes inversely proportional to unemployment, meaning that, a 1% increase in unemployment rate corresponds to a 1% decrease in physician migrants. The wages of high-skilled workers are not significant. The number of physician migrants decreases with the physician density at destination but with weak significance.

In col. (5), the immigration policies of host countries show strong and positive associations with physician migration, except the labor market test. Controlling for other characteristics of host countries, we find that the points-based system is the most effective policy for attracting physicians for host countries (+49% in the short-run and +132% in the long-run), relative to demand-led policies which require a job offer (+16% in the short-run and +43% in the long-run). In fact, the labor market test has a strong and negative association to migrant physician stocks (−26% in the short-run and −70% in the long-run). Once physicians migrate to host countries, the path to permanent residency is the most important instrument to attract foreign physicians. A country with a policy with a clear path to permanent residency increases the attractiveness of the host country and increases physician migration by almost 46% in the short-run and 124% in the long-run. Our results also reveal that financial incentives such as tax breaks targeted towards migrants are attractive for physicians (elasticity is equal to 65% in the long-run). In col. (6), results obtained with weighted regressions confirm our previous findings and highlight the importance of the points-based system and of the option of obtaining permanent residency offer in attracting foreign physicians. Note that dummies for financial incentives, visa contingent on job offer, shortage list and labor market test gain in magnitude and significance in the weighted-regression framework.

5. Concluding remarks

This paper makes a threefold contribution to the existing literature on the medical brain drain. Firstly, it provides the most extensive longitudinal database documenting the evolution of physician migration from 192 training/origin countries to 22 destination countries over a 25 year period. Secondly, it uses empirical models to quantify the effects of time invariant dyadic variables and push/pull factors. Thirdly, it assesses the effectiveness of migration policies in influencing the global migration of medical doctors.

Our database reveals new and interesting patterns. Small island nations, low-income countries and countries in the Caribbean and sub-Saharan Africa have the highest intensity of physician migration. Over time, we identify rising trends in Caribbean islands, Central Asia and Eastern Europe. On the contrary, despite increasing migration flows to Western Europe, physician migration from sub-Saharan Africa has been stable or even slightly decreasing. The most popular destinations of physicians are the United States and the United Kingdom, with new and emerging destination countries that mostly include European countries (such as Germany, France, Sweden and Switzerland).

Our empirical analysis shows that medical brain drain is a complex phenomenon that results from multiple push, pull, and dyadic factors. Physician emigration is influenced by the level of economic development at origin. As far as pull-factors are concerned, physician migration is more influenced by economic conditions (as proxied by unemployment rates) than shortages of health care providers at destination. Dyadic dimension is governed by linguistic, cultural and geographic ties between countries. In particular, speaking the same official language increases the dyadic stock of physician migrants by 178% in the long-run, which is more important than the historical links and geographic distance.

Interestingly, we find that the evolution of the medical brain drain is affected by immigration policies aimed at attracting high-skilled workers. In the long-run, the dyadic stock of physician migrants increases by 132% when the destination countries starts implementing a points-based system, by 124% when it offers a path to permanent residency, or by 65% when tax cuts are targeted towards immigrants. In the same vein, removing dyadic visa restrictions or recognizing foreign diplomas increases the long-run stock by 54 and 28%, respectively. Overall, of the nine policy instruments we introduce to test the effectiveness of immigration policy of destination countries in attracting physicians, we find that the implementation of point based system and the ease of obtaining permanent residency in the destination country appear to be the most effective policies for attracting doctors.

Although we limit our analysis to understanding the evolution of physicians' emigration and critically assessing its determinants, the tools developed here can be used to revisit the consequences of medical brain drain. In particular, the effects of the medical brain drain on health outcomes in sending countries are largely unresolved and also remains a highly contentious policy issue.[12] In addition, existing accounts have failed to resolve the paradox of whether the emigration of physicians constitutes a brain drain or a brain gain, which highlights the need for additional empirical studies on its effects and outcomes. This newly extended panel data set will provide for these future impact analyses.

[12] Anand and Barnighausen (2004) find a positive and significant association between the high density of health professionals and lower infant and maternal mortality, suggesting that the medical brain drain may negatively affect health outcomes. Clemens (2007) on the other hand finds no evidence for a causal impact of the number of physicians and nurses abroad on child mortality, infant mortality under the age of one, vaccination rates, or the prevalence of acute respiratory infections in children under the age of five. Bhargava et al. (2011) show that the supply of physician per capita improves infant mortality and vaccination indicators once literacy rates cross the approximate threshold of 60%. Together these studies provide important insights into the possible short and long run effects of the medical brain drain.

Authors' contribution

Ehui Adovor and Yasser Moullan: investigation, formal analysis. Mathias Czaika: investigation, writing. Frédéric Docquier: conceptualization, investigation, writing, supervision.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhealeco.2020.102409.

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