European University Institute

ROBERT SCHUMAN CENTRE FOR ADVANCED STUDIES

EUI WORKING PAPERS

RSCAS 2020/104
Robert Schuman Centre for Advanced Studies
Migration Policy Centre

Aid for health, economic growth, and the emigration of medical workers

Mauro Lanati and Rainer Thiele

European University Institute

Robert Schuman Centre for Advanced Studies

Migration Policy Centre

Aid for health, economic growth, and the emigration of medical workers

Mauro Lanati and Rainer Thiele

EUI Working Paper **RSCAS** 2020/104

Terms of access and reuse for this work are governed by the Creative Commons Attribution 4.0 (CC-BY 4.0) International license. If cited or quoted, reference should be made to the full name of the author(s), editor(s), the title, the working paper series and number, the year and the publisher.

ISSN 1028-3625

© Mauro Lanati and Rainer Thiele, 2020

This work is licensed under a Creative Commons Attribution 4.0 (CC-BY 4.0) International license.
https://creativecommons.org/licenses/by/4.0/

Published in December 2020 by the European University Institute.
Badia Fiesolana, via dei Roccettini 9
I – 50014 San Domenico di Fiesole (FI)
Italy

Views expressed in this publication reflect the opinion of individual author(s) and not those of the European University Institute.

This publication is available in Open Access in Cadmus, the EUI Research Repository:
https://cadmus.eui.eu

Robert Schuman Centre for Advanced Studies

The Robert Schuman Centre for Advanced Studies, created in 1992 and currently directed by Professor Brigid Laffan, aims to develop inter-disciplinary and comparative research on the major issues facing the process of European integration, European societies and Europe's place in 21st century global politics.

The Centre is home to a large post-doctoral programme and hosts major research programmes, projects and data sets, in addition to a range of working groups and *ad hoc* initiatives. The research agenda is organised around a set of core themes and is continuously evolving, reflecting the changing agenda of European integration, the expanding membership of the European Union, developments in Europe's neighbourhood and the wider world.

For more information: http://eui.eu/rscas

The EUI and the RSCAS are not responsible for the opinion expressed by the author(s).

Migration Policy Centre (MPC)

The Migration Policy Centre (MPC) is part of the Robert Schuman Centre for Advanced Studies at the European University Institute in Florence. It conducts advanced research on the transnational governance of international migration, asylum and mobility. It provides new ideas, rigorous evidence, and critical thinking to inform major European and global policy debates.

The MPC aims to bridge academic research, public debates, and policy-making. It proactively engages with users of migration research to foster policy dialogues between researches, policy-makers, migrants, and a wide range of civil society organisations in Europe and globally. The MPC seeks to contribute to major debates about migration policy and governance while building links with other key global challenges and changes.

The MPC working paper series, published since April 2013, aims at disseminating high-quality research pertaining to migration and related issues. All EUI members are welcome to submit their work to the series. For further queries, please contact the Migration Policy Centre Secretariat at migration@eui.eu

More information can be found on: http://www.migrationpolicycentre.eu/

Disclaimer: The EUI, RSCAS and MPC are not responsible for the opinion expressed by the author(s). Furthermore, the views expressed in this publication cannot in any circumstances be regarded as the official position of the European Union.

Abstract

Debates on the extent to which developing countries suffer from a brain drain often focus on the emigration of locally scarce health personnel. In this paper, we empirically examine how two potential determinants - aid for health and local income levels - affect the emigration rates of doctors and nurses from developing countries. Employing a standard gravity model of international migration, we show that aid for health has a negative effect on the emigration of both nurses and doctors. The quantitative impact is moderate but non-negligible: doubling the amount of foreign assistance received by developing countries in the health sector lowers the emigration rates of health personnel by around 10%. Our findings suggest that donors influence the emigration decisions of doctors and nurses through improvements in health infrastructure and health care services. Higher income per capita is also associated with lower emigration from developing countries for doctors and nurses alike. Given that nurses typically belong to the poorer segments of populations in the countries of origin, we can conclude that even at low initial income levels, on balance, economic growth provides an incentive to stay rather than enabling would-be migrants to finance migration costs and encouraging them to leave.

Keywords

Aid; Migration; Health Personnel; Development

JEL classifications: F22; F35; O15

1. Introduction*

The migration of skilled people from poor to rich countries has become an increasingly important feature of international migration. Over the past few decades, the stock of skilled immigrants in member countries of the Organization for Economic Co-operation and Development (OECD) grew at a much faster rate than that of low-skilled workers (Kerr et al. 2017). The early literature on skilled workers' emigration concluded that it is likely to cause a brain drain, adversely affecting the welfare of those who remain in the source countries (e.g. Bhagwati and Hamada 1974). More recently, it has been argued that skilled migration may also contribute to long-term local development. The most relevant transmission mechanism has been that emigration possibilities for skilled workers encourage human capital investment in the sending countries (e.g. Stark et al. 1997).

Medical workers are among the most mobile skilled professions. Their emigration may give rise to large welfare losses given the scarcity of health personnel in many developing countries. Over 40% of WHO Member States report to have fewer than 10 medical doctors per 10 000 population, and over 55% report to have less than 40 nursing and midwifery personnel per 10 000 population (WHO 2020). Empirical studies have shown that the emigration of doctors is associated with high HIV death rates; child mortality; and an insufficient number of medical workers to meet local health care needs, pointing to a medical brain drain (see Chauvet et al. 2013; Bhargava and Docquier 2008; Astor et al. 2005). Yet, the literature also points to instances where emigration prospects for medical workers provide incentives for investment in education that are sufficiently high to bring about a net welfare gain for the country of origin (e.g. Abarcar and Theoharides 2020; Kangasniemi et al. 2007). Despite this empirical ambiguity, there appears to be a justification for the international community to support developing countries in retaining medical workers through improved local conditions. It has been pointed out (e.g. Clemens and McKenzie 2009) that a lack of medical infrastructure is a key reason why medical professionals in poor countries are unproductive. This might in turn, as we argue in this paper, constitute a main mechanism underlying their emigration.

Against this background, the present paper investigates how two potential determinants, aid for health and local income levels, affect emigration rates of doctors and nurses from developing countries. By including nurses, we adopt a broader definition of medical brain drain than is found in most previous studies which were only concerned with the emigration of physicians. The ultimate objective is to obtain an indication of whether international efforts to improve local health infrastructure through foreign aid and to provide the right conditions for economic growth can actually help mitigate a potential medical brain drain in developing countries. Employing data on international flows of health personnel obtained from the OECD Health Workforce Migration dataset for the period 2000-2015, we estimate a gravity model of international migration.

Our contribution to the literature is threefold. Firstly, by considering aid and income effects jointly, we speak to two related strands of literature on the determinants of emigration, which have largely been treated separately in empirical research so far. On the one hand, several studies have accounted for the heterogeneity of foreign assistance by disaggregating it along sectoral lines (Gamso and Yuldashev 2018a; Gamso and Yuldashev 2018b; Lanati and Thiele 2018a; Lanati and Thiele 2018b). A common conclusion of these studies is that aid can be effective in reducing aggregate migration if it is spent on the provision of public services. We investigate whether this finding holds in the specific case of health personnel. On the other hand, there is a strand of research that investigates the link between economic development and migration. By comparing the emigration rates of countries at different stages of economic development, an inverse u-shape emerges, giving rise to the notion of a “migration hump” (e.g. Clemens 2014; Hatton and Williamson 2002). Since the migration hump is typically estimated

* We thank Christopher Parsons, Martin Ruhs, and Claas Schneiderheinze and participants of the MPC webinar “‘Migration and Development: Revisiting the Migration Hump’” for helpful comments and suggestions.

using cross-country data, it is best interpreted as capturing the long-term association between economic development and emigration.

In contrast, recent studies that employ a panel data approach and thus tend to focus on short- to medium-term effects within countries have come up with opposing results. Clemens (2020), for example, finds that emigration rises on average with increasing GDP per capita in poor countries, and that the effect reverses only after GDP per capita exceeds about $10,000. In a similar vein, Bazzi (2017) shows that in Indonesia, positive agricultural income shocks increase labor emigration flows in poorer areas with more small landholders. Whereas, in the most developed rural areas, persistent income shocks reduce emigration. By contrast, Benček and Schneiderheinze (2019) and Clist and Restelli (2020) find that even at low initial levels of income, the relationship between economic growth and aggregate emigration is negative for a large sample of OECD destinations and for Italy specifically, even though the effects tend to be small.[1] We add a disaggregated perspective to this literature by comparing the migration decisions of (relatively poor) nurses and (relatively rich) doctors.

Second, we shed light on the key mechanism through which aid for health is likely to affect the incentives of medical workers to emigrate from developing countries. Previous studies have consistently shown that aid allocated to the health sector improves development indicators, such as infant mortality (e.g. Kotsadam et al. 2018; Mishra and Newhouse 2009). We are the first to test whether sector-specific foreign assistance leads to improvements in the quality of health infrastructure. This arguably has a more direct bearing on medical workers' migration decisions than health-related development outcomes as they affect their working conditions. We use an instrumental variable (IV) approach based on a shift-share instrument along the lines of Nunn and Qian (2014) to come closer to a causal interpretation of our estimates.

Third, most of the previous studies on the relationship between aid and migration have focused on total migrant flows despite strong potential heterogeneity across sectors and skill levels, thus rendering any inference from aggregate data difficult. Exceptions include Lanati and Thiele (2020b), who investigate the impact of aid for education on international student mobility, and Moullan (2013), who considers the link between aid for health and physicians' emigration. Our investigation of health aid is closely related to Moullan (2013). We extend his work by taking the emigration of nurses into account. We also address various methodological concerns by employing the Pseudo-Poisson Maximum Likelihood (PPML) estimator with higher-dimensional fixed effects, which represents the current state of the art in the estimation of gravity models.

We find that aid for health improves various components of local health infrastructure and has a negative effect on the emigration of both nurses and doctors. Higher income per capita is also associated with lower emigration from developing countries for doctors and nurses alike. Given that nurses typically belong to the poorer segments of populations in the countries of origin, the link appears to hold across income levels, corroborating what Benček and Schneiderheinze (2019) as well as Clist and Restelli (2020) previously found at the aggregate level.

The remainder of the paper is structured as follows. In Section 2, we describe the data used in the empirical analysis and provide some descriptive evidence on the emigration patterns of the health workforce. Section 3 introduces our econometric approach. In section 4, we present the regression results. In doing so, we start with a baseline specification, add several robustness checks and finally deal with the mechanisms through which aid for health potentially affects the emigration of medical workers. Section 5 concludes.

[1] Note that Clist and Restelli (2020) are mainly concerned with irregular migrant flows, for which they do not obtain robust evidence in favor of a negative association between GDP per capita and emigration.

2. Data and Descriptive Evidence

Data on international flows of health personnel is taken from the OECD's Health Workforce Migration dataset. The dataset provides information on annual inflows into OECD countries over the period 2000-2015.[2] These inflows are defined as (a) *doctors* who have obtained their first medical qualification (degree) in another country and are receiving new authorization in a given year to practice in the receiving country and (b) the number of *nurses* who have obtained a recognized qualification in nursing. The sources from which data are collected vary by destination. The preferred source is professional registers. Alternatively, data are also taken from working permits delivered to immigrants. [3] The quality of the OECD's Health Workforce Migration dataset is high even though the coverage is not complete. A relatively large number of missing observations prevents us from performing a proper panel-data analysis.[4] It is only for the United States, which is by far the main migrant destination for medical workers, that we have information on health workforce emigration for all the countries of origin over the whole period under consideration. We therefore present estimates based on a pooled gravity model for the whole set of available OECD destinations using a dataset which is representative of all South-North emigration of medical workers. In a robustness check we estimate a panel-data model with the United States as the only migrant destination.

As shown in Figure 1, the United States is clearly ahead of all other OECD countries as the main destination for nurses (44% of foreign-born workers) as well as doctors (36% of foreign-born workers). Emigration patterns among countries of origin are fairly heterogenous. In absolute terms, the Philippines is by far the leading emigration country for nurses with an average of over 8000 emigrants per year, followed by India with about 2700.[5] The largest number of doctors emigrate from India and Pakistan (2300 and 1150, respectively). When it comes to assessing the severity of the medical brain drain in a specific developing country, it is more relevant to look at the share of domestic medical workers that actually leave their home. The emigration rates of nurses are particularly high among Caribbean countries and in the Philippines, whereas several African countries exhibit high emigration rates amongst doctors.

Along the lines of Beine and Parsons (2015) as well as Bhargava and Docquier (2008), we define bilateral emigration rates as:

$$EM_{ijt}^{h} = \frac{M_{ijt}^{h}}{\sum_j M_{ijt}^{h} + P_{it}^{h}}$$

where M_{ijt}^{h} denotes the flow of healthcare workforce of type h (nurses or doctors) from country *i* to country *j* at time *t*, while P_{ijt} is the total healthcare workforce of type *h* in the home country and $\sum_j M_{ijt}^{h}$ the sum of available emigrant flows from country *i*.[6] In our baseline estimation, missing values for the

2 The time span is restricted by the information available for nurses migrating to the United States.

3 Although the data on migration of health personnel is not perfectly comparable across OECD countries (OECD 2019), it is reasonable to assume that changes over time can be compared. In addition, in the robustness section we address potential inconsistencies in the measurement of emigration flows of medical workers across destinations by including US as the only country of destination. The results are qualitatively very similar to the baseline estimates, which we find reassuring.

4 In the OECD Health database, missing values are indicated by empty cells, and zero values are indicated with 0. The missing information means data are not available (either not provided by the country, or not available at all), and should not be replaced with a 0.

5 Tables A1 and A2 in the Appendix list the number of emigrating doctors and nurses as well as the respective emigration rates for all the countries of origin included in the regression analysis.

6 We include the term $\sum_j M_{ijt}^{h}$ even though we don't have a complete set of origins for each destination because we deem this ratio as closest to the rate of medical brain drain proposed by Bhargava & Docquier (2008) and Moullan (2013). In a robustness check, we re-estimate our benchmark specification by omitting the term $\sum_j M_{ijt}^{h}$ in the denominator. The results are virtually unaffected; they are available upon request.

population of doctors and nurses in the denominator are imputed using the average population density of the nurses and doctors multiplied by the recipient country's population. We perform a robustness check where missing values are imputed by allowing the number of nurses and doctors to vary proportionally to a country's total population.

For foreign aid, our main explanatory variable of interest, along with GDP per capita, the data are gross disbursements of Official Development Assistance (ODA) in the health sector expressed in constant US dollars from the OECD Creditor Reporting System (CRS) dataset that disaggregates aid flows by sector.[7] Following the methodology proposed by Qian (2015), we only use the transferred share of health ODA. This means that we subtract the portion of foreign assistance that is mostly spent within donor borders from total aid, including for example, "*In-Donor Scholarships*", "*Administrative Costs*", and "*Donor Personnel*". The rationale behind this is that only those resources that are actually transferred to recipient countries have the potential to affect migration decisions (Lanati and Thiele 2020a). We take four-year averages of the aid received to account for the volatility of annual aid flows. GDP per capita is expressed in purchasing power parities (PPP) with constant US$ (2011 prices). Table A4 in the appendix provides sources as well as a brief description of these variables and other controls that were used in the empirical analysis, while Table A5 shows the summary statistics.

3. Econometric Approach

Our econometric specification is based on a standard gravity model of international migration (e.g. Beine and Parsons 2015). Bilateral emigration rates of healthcare workers from aid recipient *i* to donor *j* are a function of dyadic OD_{ijt-1} as well as origin-specific factors O_{it-1}, where the latter includes per-capita income and the overall transferred per-capita health aid received by country i. The baseline estimation equation is given by:

$$\ln\left(EM_{ijt}\right) = \alpha_{ij} + \alpha_{jt} + \ln(O_{it-1}) * \Delta + \ln(OD_{ijt-1}) * \vartheta + e_{ijt} \qquad (1)$$

In addition to the two main variables of interest, we consider a standard set of time-varying control variables. These comprise origin-specific factors such as a dummy that takes the value of one for the presence of conflicts; the number of natural disasters in a given year; and a synthetic indicator of the quality of governance based on a principal component analysis (PCA) of the six World Bank Governance Indicators (see Ariu et al., 2016). As a dyadic determinant, we capture time-varying migrant network effects through the inclusion of the pre-determined stock of migrants from country i living in country j.

To account for cross-country heterogeneity and attenuate potential estimation biases, the econometric specification includes destination-year (α_{jt}) and asymmetric dyadic (α_{ij}) fixed effects. While origin-time dummies would fully account for multilateral resistance to migration (Beine et al 2015)[8], they cannot be added in our setting as they would completely absorb the effect of our variable of interest. The inclusion of destination-year fixed effects, however, completely captures multilateral resistance to migration in receiving countries. This is likely to be the most important factor in the context of international migration, given the key role that the destination country's migration policies play (Beine and Parsons, 2015). In addition, asymmetric dyadic fixed effects address the bias that might result from

[7] Table A3 in the Appendix lists the different components of aid for health.

[8] Multilateral resistance to migration denotes the fact that the choice of a potential migrant to move to a given destination country does not only depend on the attractiveness of the country of destination relative to the country of origin, but also on how this relates to the opportunities to move to other destinations. Failing to account for multilateral resistance to migration in the gravity framework could lead to significant biases in the estimated coefficients of the determinants of migration (Bertoli and Fernandez-Huertas Moraga, 2013).

the omission of unobserved variables and restore the cross-sectional independence of the error terms (Faye and Niehaus, 2012 and Bertoli and Moraga, 2015).[9] For example, political or cultural proximity between countries, which does not vary much over time and is often difficult, if not impossible, to measure with quantitative data, is likely to be positively correlated with both migration and foreign aid flows.

All covariates are predetermined - lagged one period - with respect to the emigration of medical workers. This at least partly addresses concerns that our variables of interest may be endogenous due to reverse causality. In addition - as far as foreign aid is concerned - only the bilateral part of the total health ODA country *i* receives is potentially affected by migration from country *i* to country *j*. This is because migrants successfully lobby the destination country's government to allocate more aid to their country of origin (Lahiri and Raimondos-Møller, 2000). Hence, we argue that reverse causality should not be a major issue in our estimation at least for the aid variable, but we still refrain from making strong causal claims. The standard procedure to deal with the issue of reverse causality is to use instrumental variables. However, in our gravity setup we would have to look for an instrument that has an *ijt* dimension, whereas our variables of interest are origin-specific. We are not aware of an instrument that is suitable in such a setting.

A further potential methodological concern relates to the consistency of the standard errors. The error term in the gravity specification might be correlated within dimensions of the panel, leading to inconsistent estimates of Equation (1).[10] To address this issue, we follow the approach implemented by Cameron, Gelbach, and Miller (2011) as well as Faye and Niehaus (2012) and include non-nested multi-way clusterings of standard errors along each of the three dimensions of the panel - donors, recipients, and years. While this is our preferred approach, results remain similar when we use more restrictive approaches, such as clustering on donor-recipient pairs to allow for autocorrelation.[11]

In line with previous gravity model applications (e.g. Bertoli and Moraga 2015; Beine and Parsons 2015), we rely on the PPML approach to estimate Equation (1). This choice is driven by the fairly high share of zeros - around 23% and 17% of total observations for nurses and doctors, respectively. As Silva and Tenreyro (2006) pointed out, the presence of zeros creates a correlation between the covariates and the error term, leading to inconsistent OLS estimates.

4. Results

Equation (1) is estimated separately for *nurses* and *doctors*. The results are presented in Tables 1 and 2, respectively.[12] We first show estimates of the isolated effect of health aid and per capita income without any further controls (Columns 1-2). We only include the set of fixed effects in line with Beine and Parsons (2017) and Cattaneo and Peri (2016). While this specification is prone to omit variable bias, it

---

[9] If we define b(i) as a nest of countries i characterized by similar levels of geographical, cultural or/and political proximity with n, a bilateral shock between n and i may introduce a correlation in the stochastic component of Equation (1). For instance, the impact of a more restrictive visa policy in the US towards South African medical workers will affect the relative attractiveness of other potential destinations which we realistically assume as being highly dependent on the proximity between South Africa and third countries (i.e. on whether or not they belong to the same nest b(i)).In other words, if the unobserved components that create interdependencies across cross-sections within nests are correlated with the included regressors, the PPML estimator will be biased and inconsistent. Bertoli and Moraga (2015) restored the cross-sectional independence of the error terms through the inclusion of origin-nest dummies. Similarly, this paper proposes a richer analysis in which we generate a nest for each country-pair through α_{ij}, alleviating potential estimation problems deriving from an incorrect specification.

[10] Egger and Tarlea (2015) have shown that ignoring multi-way clustering in a gravity setting leads to misleading inference, which appears to be particularly relevant under the Poisson PML–GLM estimator we employ.

[11] The estimates are available upon request.

[12] Appendix Table A6 reports the results of a robustness check in which missing values of the dependent variable are imputed by letting the number of nurses and doctors vary proportionally to a country's total population.

has the advantage that it includes no control variable which could possibly take up part of the overall effect of the variables of interest. We then consider health aid and income per capita jointly in the same specification (Column 3), and finally add several controls (Columns 4-5) to test whether our main results are robust to their inclusion. The results suggest that the time variation of both per capita income and health aid are negatively associated with bilateral emigration of the healthcare workforce. The magnitude of the effect of per-capita health aid is very close to previous estimates based on gravity models for international migration (e.g. Lanati and Thiele 2018a) and is similar across the two healthcare workforce categories. According to our point estimates, doubling the volume of transferred foreign assistance received by developing countries in the health sector would lower the healthcare workforce's emigration rates by around 10%.

Both coefficients of interest are very similar across specifications. As shown in columns 3-5, the effect of health aid and per capita income maintain roughly the same magnitude when included together in the same regression. This suggests that the impacts of health aid and per capita income are not collinear and that in fact they influence healthcare workers' migration decisions through separate and distinct channels. More specifically, the provision of health aid is most likely to affect the non-monetary dimensions of well-being in developing countries such as the quality and supply of healthcare infrastructure and services. A rise in GDP per capita, on the other hand, proxies for higher wages and better income opportunities in recipient countries. While there appears to be some consensus on the role of improved public services in reducing emigration from developing countries (Dustmann and Okatenko 2014), the impact of a rise in income on emigration decisions is subject to contrasting forces. It provides an incentive to stay by narrowing the income gap but it also makes it easier to incur the cost of emigration, and its net effect is less clear-cut. According to the migration hump hypothesis (e.g. Hatton and Williamson 2002; Clemens 2014), the effect is non-linear: At low levels of development, additional income enables a larger share of the population in countries of origin to finance migration costs thus raising the number of people who leave. At higher development levels, incentives to stay eventually become more important than budgetary considerations. The migration hump hypothesis receives empirical support in cross-sectional settings where the emigration rates of countries at different stages of economic development are compared (e.g. Clemens 2014), while evidence is mixed so far with panel data. Our results corroborate the previous findings obtained by Benček and Schneiderheinze (2019) and Clist and Restelli (2020) that there is a small but negative association between income and emigration irrespective of the level of income a country starts out at once cross-country heterogeneity is accounted for.

When looking at the two groups of medical workers, the estimated negative relationship between GDP per capita growth and the emigration of doctors could still be in accordance with the migration hump hypothesis as doctors may lie on the downward-sloping segment of the curve (see Moullan 2013). However, when we extend the analysis to nurses, who are poorer than doctors and more likely to be located on the upward-sloping part of the hump, there is an even stronger negative relationship. Hence, even for nurses, migration decisions are on balance more strongly affected by the incentive effects of higher incomes (i.e. a greater incentive to stay) than by the loosening of budgetary constraints (and the consequent greater financial ability to emigrate).

The fact that cross-section and time-series estimates of the development-migration nexus may point in different directions is further illustrated in Table 3, where regression results are reported based on Equation (1), but without including dyadic fixed effects that account for cross-country heterogeneity. Omitting country-pair fixed effects reverses the sign of the relationship between development and emigration of nurses (Columns 1-2) and leads to a positive and significant relationship between health aid and the emigration of doctors from developing countries (Columns 3-4).[13]

[13] Lanati and Thiele (2018a) find the same discrepancy between time series and cross-country estimates for the impact of total foreign aid on total emigration.

Robustness

The negative relationship between development and the emigration of healthcare workforce that emerges from our benchmark estimates presented in Tables 1 and 2 could in principle be driven by a small subset of relatively rich recipient countries. To address this issue, we progressively drop recipient countries with the highest GDP per capita by yearly income quintile (Table 4). The results suggest that income per capita is negatively related to the emigration of healthcare workforce across different income categories. Interestingly, as we progressively omit the richest countries from the sample, the provision of foreign aid becomes relatively more important for the emigration decisions of nurses at the expense of GDP per capita. In other words, in poorer contexts the quality and supply of health care services and infrastructures induced by foreign aid matter relatively more for migration decisions than monetary dimensions of well-being. The opposite applies for doctors, whose decision on whether to emigrate or not is relatively more sensitive to the level of income in more deprived areas.

Despite the large set of fixed effects which attenuate omitted variable bias and the pre-determined (lagged) covariates with respect to emigration rates that mitigate potential biases deriving from reverse causality, our specification might still suffer from endogeneity. First, we address reverse causality, and at same time test for the timing of aid and income effects by introducing longer time lags.[14] The results shown in Table 5 suggest that both the negative effects of health aid and income per capita remain statistically significant and become larger when passing from the very short to the short-to-medium term. The result for foreign aid is in accordance with Dreher et al. (2019) and indicates that it takes time for aid projects to have an impact on wellbeing and thus to influence emigration rates. As for per capita GDP, we interpret this finding as the "natural" lagged effect of emigration decisions in response to income variations: migration decisions are not taken overnight and require some planning ahead of settling into a new country.

Second, there might be time-varying dyadic-specific omitted variables which could be correlated with the error term and thus could bias our parameters of interest. For instance, the allocation of ODA is in large part affected by donors' strategic motivations (see Alesina and Dollar 2000), such as bilateral economic and political alignments, which can plausibly have an effect on emigration rates (see Campaniello 2014). We address this issue by including bilateral trade flows (exports) and an affinity index of the UN General Assembly voting created by Voeten et al (2009) as additional control variables in the econometric specifications.[15] The estimates are reported in Table 6. The newly added controls do not significantly influence the emigration of health personnel. Their insignificance points to the absence of network effects through trade and political relations.[16] This corroborates the finding reported in Tables 1 and 2 that diaspora networks do not appear to play a role in determining the emigration pattern of doctors and nurses over and above what is captured by the full set of fixed effects.[17] Importantly, both income per capita and health aid effects are largely unaffected, i.e. our key results are robust to the inclusion of political affinity scores in the UN assembly and export variables.

Finally, we investigate whether our baseline results based on a pooled gravity model with multiple destinations hold when we estimate a panel-data model, with the United States as the only migrant destination. This econometric exercise automatically rules out any potential inconsistencies in the measurement of health-care workforce emigration flows across destinations. As shown in Table 7, the findings are qualitatively similar to the benchmark estimates despite a considerable loss of statistical

---

[14] Given the relatively low number of observations on bilateral emigration of nurses we cannot extend the analysis over the 3-year lag.

[15] We use the affinity score "*s3un*". Data are taken from the updated version of the "*United Nations General Assembly Voting Data*" dataset available in the Erik Voeten Harvard Dataverse webpage https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LEJUQZ.

[16] The statistically not significant trade coefficient is in line with Lanati and Thiele (2018a).

[17] See below for an analysis of a further potential network effect running through bilateral aid relations.

power due to the lower number of observations. More specifically, all the parameters of interest have the expected sign and the effects are statistically significant with the exception of income per capita for doctors' emigration.

Potential Mechanisms

The empirical analysis presented in the previous sub-section suggests that a rise in foreign assistance in the health sector leads to lower emigration amongst medical workers from developing countries. Our hypothesis is that foreign assistance influences doctors and nurses' emigration decisions through the improvements to local amenities, in particular regarding health infrastructure. To test this hypothesis, we use proxies of the quality of health infrastructure such as the number of doctors, nurses, and hospital beds per capita as well as the percentage of immunized children. The latter can be regarded as a quality indicator for primary health care. All of these variables arguably cover relevant dimensions of working conditions for health personnel.

We first run OLS regressions with country and year fixed effects, in which we focus on the relationship between the time variation of per capita health aid and the quality of health care infrastructure in the recipient country. In contrast to the baseline regressions above, we now depart from the standard dyadic gravity framework and can use time-varying and country-specific IVs. Hence, in a second step we instrument foreign assistance in the health sector with a shift-share instrument along the lines of Nunn and Qian (2014) as well as Dreher and Langlotz (2020). Specifically, we first construct a time-invariant variable which is the probability of each recipient country *i* to receive aid from a particular donor *j* in the period for which data are available (2002-2018). Following Dreher et al. (2019), we define the probability of receiving aid from donor j as $\overline{p_{j,i}} = \frac{1}{11}\sum_{t=1}^{11} p_{j,i,t}$. $p_{j,i,t}$ is a binary indicator that is equal to one if recipient *i* receives foreign assistance in the health sector from donor *j* at time *t*. We then multiply this term by donor-government fractionalization, $FRAC_{jt}$, and aggregate over all donors, i.e. $\sum_j FRAC_{jt} * \overline{p_{j,i}}$. The instrument varies across recipients *i* and years *t*. As concerns the relation of the instrument with the volume of aid received, Dreher and Langlotz (2020) argue that higher fractionalization increases donor–government expenditures, which in turn increases the total amount of aid given by a donor. Countries that receive more aid from a given donor have a higher probability of receiving a larger share of increases in aid compared to countries that hardly receive any aid from the donor. We test the strength of the IV using the standard F statistics for weak instruments. In contrast, it is not possible to test for the exogeneity of the instrument through the Hansen-J test given that the model is exactly identified. Yet, our identifying assumption is unlikely to be violated. It requires that the quality of health infrastructure in countries with differing probabilities of receiving aid will not be affected differently by changes in donor–government fractionalization, other than via the impact of health aid, when controlling for country and year fixed effects. The first stage Kleibergen-Paap F-statistic for the excluded instrument is above 10 in all the specifications, which is in line with previous research using this kind of IV (e.g. Nunn and Qian 2014).[18]

The results are reported in Table 8. According to the IV estimates, a rise in health aid enhances the percentages of vaccinated children and improves the share of health-care workers in the populations of recipient countries.[19] We corroborate these findings with some cross-sectional evidence, where we exploit various measures of health infrastructure from the WHO for which there is not enough variation over time. The estimates shown in Table 9 indicate that countries that receive relatively higher levels of health aid per capita display better indicators of health-care infrastructure such as a higher number of

[18] As in Nunn and Qian's (2014) baseline specifications, the Kleibergen–Paap F statistics fall between the Stock and Yogo critical values for a maximum bias in the IV of less than 15 percent (critical value: 8.96) and less than 10 percent (critical value: 16.38), respectively.

[19] Only the availability of hospital beds is not significantly affected by increases in health aid.

health posts, health centers etc. Overall, there is evidence supporting our hypothesis that aid for health leads to better working conditions for health personnel in developing countries.

Berthélemy et al. (2009) have pointed to another possible transmission mechanism. They demonstrate that bilateral aid relationships between donor and recipient can positively affect emigration. This occurs through a network effect, which is similar to the one known for migrant networks, as they give rise to regular contacts and exchange of information. To test the relevance of this channel, we re-estimate Equation (1) distinguishing between bilateral and non-bilateral components of health aid. The results reported in Table 10 suggest, in accordance with previous studies covering the general aid-migration link (Berthélemy et al. 2009; Lanati and Thiele 2018a) , that there is evidence of network effects running through bilateral aid relations for the specific case of doctors, but not for nurses. The discrepancy between doctors and nurses tends to confirm the hypothesis put forward by Berthélemy et al. (2009) that network effects are expected to be stronger among more skilled people because, for example, they interact more intensively with experts from donor countries.

5. Concluding Remarks

In this paper, we analyzed how aid for health and changes in GDP per capita affect the emigration rates of doctors and nurses from developing countries. Our empirical results show that additional health aid and higher GDP per capita are both associated with lower emigration for both groups of medical workers. The estimated effects capture short-to-medium term variations over time within countries and would therefore still be consistent with the existence of a migration hump in the long term.

From a development policy perspective, the paper's findings imply that foreign assistance which is targeted at improving health infrastructure can help mitigate medical brain drain. The same is true for more general efforts by the international community and local governments to raise growth prospects. It has to be noted, however, that our estimates point to quantitatively modest impacts and therefore suggest only a minor role for development-oriented measures in containing the emigration of medical workers.

By focusing on conditions in countries of origin, our analysis neglects the destination country perspective even though OECD countries tend to have policy instruments in place which aim at attracting skilled people such as medical workers. Providing a detailed account of how destination countries use immigration policy in pursuit of their own interests, and combining this with the developmental perspective adopted in this paper, would be a fruitful avenue for future research. This would contribute to a more complete picture of the determinants of medical brain drain.

References

Abarcar, P., and C. Theoharides (2020). Medical Worker Migration and Origin-Country Human Capital: Evidence from US Visa Policy. SocArXiv Papers, August, 3.

Alesina, A., and D. Dollar (2000). Who gives foreign aid to whom and why? *Journal of Economic Growth* 5(1): 33–63.

Ariu, A., F. Docquier, and M. Squicciarini (2016). Governance quality and net migration flows. *Regional Science and Urban Economics* 60: 238-248.

Astor, A., Akhtar, T., Matallana, M. A., Muthuswamy, V., Oluwu, F.A., Tallo, V., and Lie, R. K. (2005). Physician migration: Views from professionals in Columbia, Nigeria, India, Pakistan, and the Philippines. *Social Science and Medicine* 61: 2492–2500.

Bazzi, S. (2017). Wealth Heterogeneity and the income elasticity of migration. *American Economic Journal: Applied Economics* 9(2): 219-255.

Beine, M., and C. Parsons (2015). Climatic Factors as Determinants of International Migration. *Scandinavian Journal of Economics* 117(2): 723-767.

Beine, M., Bertoli, S., & Fernandez-Huertas Moraga, J. (2015). A practitioners' guide to gravity models of international migration. *The World Economy* 39(4), 496–512.

Beine, M., and C. Parsons (2017). Climatic Factors as Determinants of International Migration: Redux. *CESifo Economic Studies* 63(4): 386–402.

Berthélemy, J.-C., Beuran, M., Maurel, M. (2009). Aid and migration: Substitutes or complements? *World Development* 37 (10): 1589–1599.

Bertoli, S., and J. Fernandez-Huertas Moraga (2013). Multilateral resistance to migration. *Journal of Development Economics* 102(May): 79-100.

Bertoli, S., and J. Fernandez-Huertas Moraga (2015). The size of the cliff at the border. *Regional Science and Urban Economics* 51: 1-6.

Benček, D., and C. Schneiderheinze (2019). More development, less emigration to OECD countries – Identifying inconsistencies between cross-sectional and time-series estimates of the migration hump. Kiel Working Paper 2145, December 2019.

Bhagwati, J., and K. Hamada (1974). The brain drain, international integration of markets for professionals and unemployment: A theoretical analysis. *Journal of Development Economics* 1(1): 19-42.

Bhargava, A., and F. Docquier (2008). HIV pandemic, medical brain drain, and economic development in sub-Saharan Africa. *World Bank Economic Review* 22: 345-366.

Cameron, A.C., J.B. Gelbach, and D.L. Miller (2011). Robust Inference with Multiway Clustering. *Journal of Business and Economic Statistics* 29(2): 238-249.

Campaniello, N. (2014). The causal effect of trade on migration: Evidence from countries of the Euro-Mediterranean partnership. *Labour Economics* 30(C): 223-233.

Cattaneo, C., and G. Peri (2016). The Migration Response to Increasing Temperatures. *Journal of Development Economics* 122: 127–146.

Chauvet, L., F. Gubert, and S. Mesplé-Somps (2013). Aid, Remittances, Medical Brain Drain and Child Mortality: Evidence Using Inter and Intra-Country Data, *The Journal of Development Studies*, 49:6, 801-818.

Clemens, M.A. (2014). Does Development Reduce Migration? In: *International Handbook on Migration and Economic Development* 8592: 152–185.

Clemens, M.A. (2020). The Emigration Life Cycle: How Development Shapes Emigration from Poor Countries. Center for Global Development Working Paper 540, August 2020.

Clemens, M.A., and D. McKenzie (2009). Think Again: Brain Drain. *Foreign Policy*, October 22.

Clist, P., and G. Restelli (2020). Development Aid and International Migration to Italy: Does Aid Reduce Irregular Flows? *The World Economy*, forthcoming.

Dreher, A., and S. Langlotz (2020). Aid and growth. New evidence using an excludable instrument. *Canadian Journal of Economics* 53(3): 1162-1198.

Dreher, A., A. Fuchs, and S. Langlotz (2019). The effects of foreign aid on refugee flows. *European Economic Review* 112: 127-147.

Dustmann, C., and A. Okatenko (2014). Out-migration, wealth constraints, and the quality of local amenities. *Journal of Development Economics* 110: 52-63.

Egger, P.H., and F. Tarlea (2015). Multi-way clustering estimation of standard errors in gravity models. *Economics Letters* 134: 144-147.

Faye, M., and P. Niehaus (2012). Political aid cycles. *American Economic Review* 102(7): 3516-30.

Gamso, J., and F. Yuldashev (2018a). Does rural development aid reduce international migration? *World Development* 110: 268-282.

Gamso, J., and F. Yuldashev (2018b). Targeted foreign aid and international migration: Is development-promotion an effective immigration policy? *International Studies Quarterl*y 62(4): 809-820.

Hatton, T.J., and J.G. Williamson (2002). What fundamentals drive world migration? NBER Working Paper 9159.

Kangasniemi, M., L.A. Winters, and S. Commander (2007). Is the medical brain drain beneficial? Evidence from overseas doctors in the UK. *Social Science and Medicine* 65: 915–923.

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

Kotsadam, A., G. Østby, S. A. Rustad, A. Forø Tollefsen, and H. Urdal (2018). Development Aid and Infant Mortality: Micro-level evidence from Nigeria. *World Development* 105(May): 59-69.

Lahiri, S., and P. Raimondos-Møller, P. (2000). Lobbying by Ethnic Groups and Aid Allocation. *Economic Journal* 129: 879–900.

Lanati, M., and R. Thiele (2018a). The impact of foreign aid on migration revisited. *World Development* 111: 59-74.

Lanati, M., and R. Thiele (2018b). Foreign assistance and migration choices: Disentangling the channels. *Economics Letters* 172: 148-151.

Lanati, M., and R. Thiele (2020a). Foreign Assistance and Emigration: Accounting for the Role of Non-Transferred Aid. *The World Economy* 43(7): 1951-1976.

Lanati, M., and R. Thiele (2020b). International Student Flows from Developing Countries: Do Donors Have an Impact? *Economics of Education Review* 77(August): 101997.

Mishra, P., and D. Newhouse (2009). Does Health Aid Matter? *Journal of Health Economics* 28: 855-872.

Moullan, Y. (2013). Can Foreign Health Assistance Reduce the Medical Brain Drain? *Journal of Development Studies* 49(10): 1436-1452.

Nunn, N., and N. Qian (2014). US Food Aid and Civil Conflict. *American Economic Review* 104(6): 1630-1666.

OECD (2015), International Migration Outlook 2015, OECD Publishing, Paris, https://doi.org/10.1787/migr_outlook-2015-en.

OECD (2019). OECD Health Statistics 2019 Definitions, Sources and Methods, available at https://www.oecd.org/els/health-systems/Table-of-Content-Metadata-OECD-Health-Statistics-2019.pdf

Qian, N. (2015). Making Progress on Foreign Aid. *Annual Review of Economics* 7(1): 277-308.

Silva, J.S., and S. Tenreyro (2006). The Log of Gravity. *The Review of Economics and Statistics* 88(4): 641-658.

Stark, O., C. Haldenstein, and A. Prskawetz (1997). A Brain Gain with a Brain Drain. *Economic Letters* 55: 227-234.

World Health Organisation (WHO) (2020). Global Health Observatory (GHO) data.

Author contacts:

Mauro Lanati

MEDAM Post-Doctoral Research Fellow

Migration Policy Centre, Robert Schuman Centre for Advanced Studies, EUI

Villa Malafrasca, Via Boccaccio 151

50133 Florence

Italy

Email: mauro.lanati@eui.eu

Rainer Thiele

Adjunct Professor, Kiel University

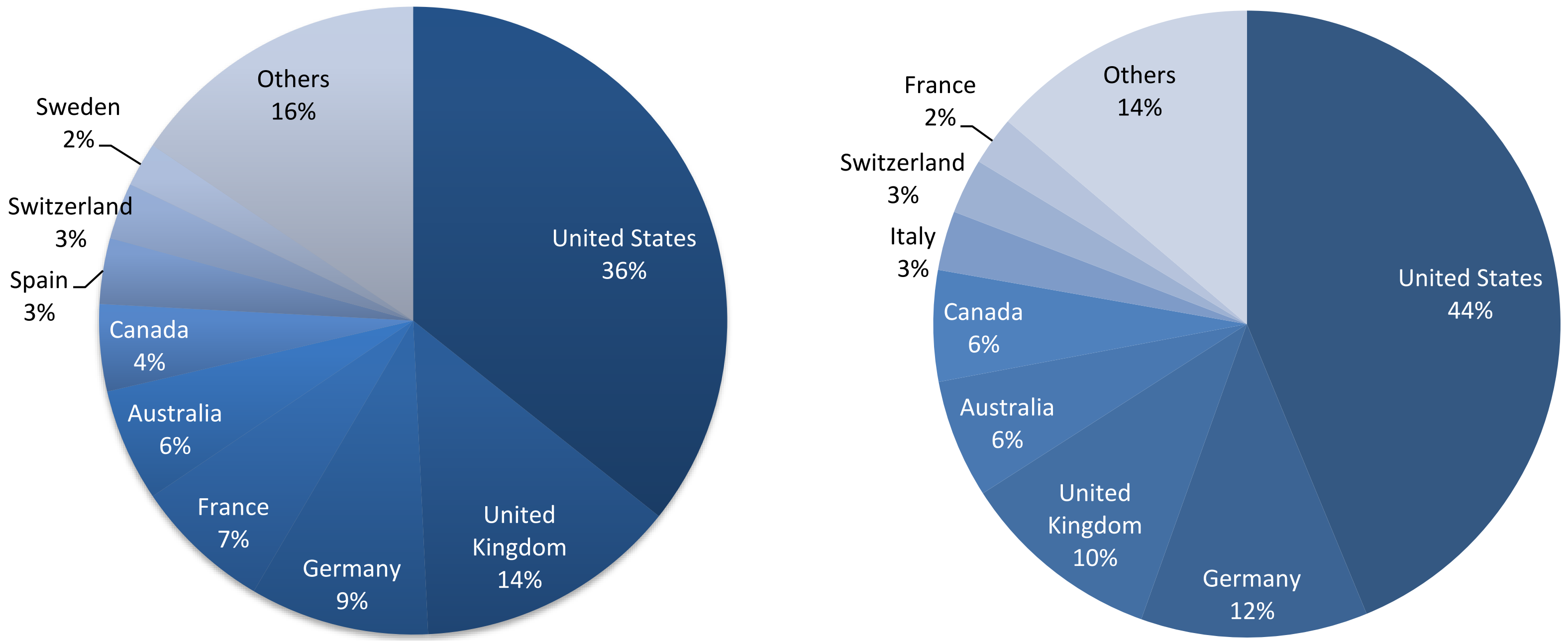
and Director of Kiel Institute Africa Initiative, Kiel Institute for the World Economy

D-24105 Kiel

Germany

Email: rainer.thiele@ifw-kiel.de

Figure 1: Distribution of foreign-born doctors (Left) and nurses (Right) by Country of Residence in the OECD, 2010/11



Source: DIOC 2010/11, LFS 2009/12. OECD International Migration Outlook 2015

Table 1: Impact of per capita Transferred Health Aid on Migration of Nurses (Bilateral Rates) - 2006-2015

	(1)	(2)	(3)	(4)	(5)
Estimator	PPML	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate
Sample Destinations	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*
Log Health ODA pc (o)	-0.131*		-0.100*	-0.100	-0.101*
	(-2.06)		(-2.29)	(-1.93)	(-2.23)
Log GDP pc Const. $ PPP (o)		-2.462***	-2.277***	-2.276***	-2.412***
		(-6.29)	(-7.53)	(-6.45)	(-7.04)
Log Diaspora (o to d)				-0.00627	-0.0224
				(-0.05)	(-0.34)
Quality of Institutions (o)					0.116
					(1.45)
Conflict (o)					-0.196
					(-0.47)
Natural Disasters (o)					0.0199***
					(7.83)
N	2541	2541	2541	2541	2541
Destination-Year FE	X	X	X	X	X
Origin-Destination FE	X	X	X	X	X
Destinations	18	18	18	18	18
Origins	108	108	108	108	108
% Zeros	23,6%	23,6%	23,6%	23,6%	23,6%

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses in Columns (1-5) are multi-way clustered by donor, recipient, and year.

Columns (1-5) show the estimates using the enlarged sample which includes all destinations for the years 2006-2015. All origin specific variables are lagged at t-1. For foreign aid, we take the 4-year average. So total transferred ODA received at time t is the 4-year average between t-1 and t–4. Emigration rates are calculated using interpolated values of Nurses Population at the missing values of Doctors population are imputed using the average of the Nurses Population ratio multiplied by country's total population. The OECD destination countries included in the sample are the following - Belgium, Canada, Denmark, Germany, Greece, Hungary, Ireland, Israel, Italy, Latvia, Netherlands, New Zealand, Norway, Poland, Switzerland, Turkey, United Kingdom and United States.

Table 2: Impact of per capita Transferred Health Aid on Migration of Doctors (Bilateral Rates) 2006-2015

	(1)	(2)	(3)	(4)	(5)
Estimator	PPML	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate
Sample Destinations	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*
Log Health ODA pc (o)	-0.100**		-0.0964**	-0.0936*	-0.0927*
	(-2.62)		(-2.63)	(-2.16)	(-2.07)
Log GDP Const. $ PPP (o)		-0.636*	-0.605*	-0.568	-0.630*
		(-2.04)	(-2.14)	(-1.86)	(-2.37)
Log Diaspora (o to d)				-0.116	-0.118
				(-1.69)	(-1.71)
Quality of Institutions (o)					0.0419
					(0.37)
Conflict (o)					-0.0450
					(-0.64)
Natural Disasters (o)					-0.00761
					(-0.59)
N	4387	4387	4387	4387	4387
Destination-Year FE	X	X	X	X	X
Origin-Destination FE	X	X	X	X	X
Destinations	23	23	23	23	23
Origins	107	107	107	107	107
% Zeros	16,7%	16,7%	16,7%	16,7%	16,7%

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses in Columns (1-5) are multi-way clustered by donor, recipient, and year.

The following small countries of origin - Antigua and Barbuda, Belize, Dominica, Grenada, Saint Kitts and Nevis, Saint Lucia and Saint Vincent and the Grenadines - are excluded from the sample. Columns (1-5) show the correspondent estimates using the enlarged sample which includes all destinations for the years 2006-2015. All origin specific variables are lagged at t-1. For foreign aid, we take the 4-year average. So total transferred ODA received at time t is the 4-year average between t-1 and t–4. Emigration rates are calculated using interpolated values of Doctors Population at the denominator and missing values of Doctors population are imputed using the average of the Doctors Population ratio multiplied by country's total population. The OECD destination countries included in the sample are the following - Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Israel, Latvia, Lithuania, Netherlands, New Zealand, Norway, Slovenia, Sweden, Switzerland, Turkey, United Kingdom and United States

Table 3: Not Accounting for Cross-Country Heterogeneity at the Origin

	(1)	(2)	(3)	(4)
Estimator	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Doctors	Migration Rate Doctors
Sample Destinations	*Whole*	*Whole*	*Whole*	*Whole*
Log Health ODA pc (o)	0.113	0.107	0.325***	0.323***
	(0.85)	(0.82)	(3.74)	(3.69)
Log GDP Const. $ PPP (o)	0.0650	0.0548	-0.0173	-0.0133
	(0.58)	(0.50)	(-0.10)	(-0.08)
N	2541	2541	4387	4387
Destination-Year FE		X		X
Destination FE	X		X	
Year FE	X		X	
Destinations	18	18	23	23
Origins	108	108	107	107
% Zeros	23,6%	23,6%	16,7%	16,7%

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Robust standard errors in parentheses are multi-way clustered by donor, recipient, and year.

Table 4: Impact of Health Aid & GDP per Capita at Different Levels of Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Doctors	Migration Rate Doctors	Migration Rate Doctors	Migration Rate Doctors	Migration Rate Doctors
Sample Destinations	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*	*Whole*
Class GDP (Percentile)	0-100th	0-95th	0-90th	0-85th	0-80th	0-100th	0-95th	0-90th	0-85th	0-80th
Log Health ODA pc (o)	-0.100*	-0.106*	-0.113**	-0.123***	-0.160***	-0.0964**	-0.0697*	-0.0427	-0.0406	-0.0624
	(-2.29)	(-2.13)	(-2.91)	(-4.80)	(-7.84)	(-2.63)	(-1.99)	(-1.74)	(-1.51)	(-1.02)
Log GDP Const. $ PPP (o)	-2.277***	-1.808***	-1.795***	-1.789***	-1.736***	-0.605*	-1.001*	-1.076**	-1.078**	-1.082*
	(-7.53)	(-4.64)	(-4.50)	(-4.66)	(-4.40)	(-2.14)	(-2.53)	(-2.69)	(-2.63)	(-2.35)
N	2541	2414	2272	2142	1999	4387	4143	3944	3699	3456
Destination-Year FE	X	X	X	X	X	X	X	X	X	X
Destination-Origin FE	X	X	X	X	X	X	X	X	X	X

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Robust standard errors in parentheses are multi-way clustered by donor, recipient, and year.
The percentiles are calculated for each year's sample distribution of income per capita over the time span covered in the analysis.

Table 5: Addressing Endogeneity - Past Values of Aid and Income Per Capita

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Lag	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Dep. Variable	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate
Sample Destinations	Whole	Whole	Whole	Whole	Whole	Whole
	Nurses	*Nurses*	*Nurses*	*Doctors*	*Doctors*	*Doctors*
Log Health ODA pc (o)	-0.112*	-0.172**	-0.330*	-0.0966**	-0.124*	-0.127*
	(-2.34)	(-2.86)	(-2.50)	(-2.64)	(-2.18)	(-2.23)
Log GDP Const. $ PPP (o)	-2.288***	-3.130***	-4.065***	-0.616*	-0.704**	-0.802**
	(-7.66)	(-49.31)	(-6.16)	(-2.15)	(-2.69)	(-2.91)
N	2580	2230	1921	4441	4000	3620
Destination-Year FE	X	X	X	X	X	X
Origin-Destination FE	X	X	X	X	X	X

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses are multi-way clustered by donor, recipient, and year. The regressions do not include controls other than our two variables of interest.

Table 6: Addressing Endogeneity – Augmented Gravity Model

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	PPML	PPML	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate
Sample Destinations	Whole	Whole	Whole	Whole	Whole	Whole
	Nurses	*Nurses*	*Nurses*	*Doctors*	*Doctors*	*Doctors*
Log Health ODA pc (o)	-0.0986^{*}	-0.100	-0.0978	-0.0900^{*}	-0.0860^{*}	-0.0834^{*}
	(-2.15)	(-1.92)	(-1.92)	(-2.12)	(-1.96)	(-2.02)
Log GDP Const. $ PPP (o)	-2.282^{***}	-2.421^{***}	-2.292^{***}	-0.635^{*}	-0.598^{*}	-0.603^{*}
	(-5.55)	(-6.69)	(-5.33)	(-2.48)	(-2.33)	(-2.44)
Log Diaspora (o to d)	-0.0215	-0.0233	-0.0219	-0.118	-0.115	-0.116
	(-0.28)	(-0.32)	(-0.26)	(-1.70)	(-1.71)	(-1.71)
Quality of Institutions (o)	0.112	0.115	0.111	0.0527	0.0436	0.0546
	(1.38)	(1.44)	(1.37)	(0.45)	(0.39)	(0.47)
Conflict (o)	-0.177	-0.198	-0.179	-0.0260	-0.0463	-0.0273
	(-0.41)	(-0.50)	(-0.43)	(-0.38)	(-0.61)	(-0.38)
Natural Disasters (o)	0.0185^{***}	0.0197^{***}	0.0183^{***}	-0.00678	-0.00743	-0.00661
	(6.05)	(6.98)	(5.29)	(-0.50)	(-0.59)	(-0.50)
Log Trade Flows (d to o)	-0.0871		-0.0866	-0.0363		-0.0369
	(-1.32)		(-1.35)	(-0.89)		(-0.91)
UN Votes Affinity Index (d to o)		-0.437	-0.440		0.289	0.286
		(-0.60)	(-0.61)		(1.16)	(1.14)
N	2497	2541	2497	4350	4380	4343
Destination-Year FE	X	X	X	X	X	X
Origin-Destination FE	X	X	X	X	X	X

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses in Columns (1-5) are multi-way clustered by donor, recipient, and year. The regressions include *Log Trade Flows (d to o)* and *UN Votes Affinity Index (d to o)* on top of the covariates included in the model estimated in Column 5 of Table 1 and 2. All regressors are lagged at t-1.

Table 7: Panel Setting – USA as the only Destination

	(1)	(2)
	Nurses	*Doctors*
Estimator	PPML	PPML
Dep. Variable	Migration Rate	Migration Rate
Sample Destinations	*Whole*	*Whole*
Log Health ODA pc (o)	-0.155*	-0.158
	(-2.18)	(-1.81)
Log GDP pc Const. $ PPP (o)	-2.265	-0.237
	(-1.88)	(-0.34)
N	973	937
Year FE	X	X
Origin FE	X	X
Destinations	1	1
Origins	102	96
% Zeros	35,2%	20,8%

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Robust standard errors are multi-clustered by recipient and year.

Table 8: Mechanisms – Aid Effectiveness

Estimator *Model*	(1) OLS	(2) 2SLS
Dep. Variable: **Doctors (per 10000 People)**		
Log Health ODA pc (o)	0.00687	0.277
	(0.59)	(1.97)
N	1382	1382
Kleibergen-Paap F-statistic		13.933
Dep. Variable: **Nurses (per 10000 People)**		
Log Health ODA pc (o)	0.0204	0.296
	(0.93)	(1.78)
N	1413	1413
Kleibergen-Paap F-statistic		13.901
Dep. Variable: **Immunization, DPT (% of children ages 12-23 months)**		
Log Health ODA pc (o)	0.0132	0.170*
	(2.02)	(2.42)
N	1711	1711
Kleibergen-Paap F-statistic		10.936
Dep. Variable: **Immunization, Measles (% of children ages 12-23 months)**		
Log Health ODA pc (o)	0.0181*	0.151*
	(2.51)	(2.46)
N	1711	1711
Kleibergen-Paap F-statistic		10.936
Dep. Variable: **Hospital Beds (per 10000 People)**		
Log Health ODA pc (o)	0.00517	0.184
	(0.26)	(0.89)
N	1692	1692
Kleibergen-Paap F-statistic		10.439

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors in parentheses are multi-way clustered by recipient and year. The regressions include a dummy for the presence of conflicts, along with country and year fixed effects, and cover the period 2004-2016. ODA variable is lagged one year and is the average over four-year periods (t-1 , t-4); for the years 2005 and 2004 ODA is the average over three (t-1 – t-3) and two-year periods (t-1 – t-2), respectively. Iran and North Korea are excluded from the sample because they exhibit values of health infrastructures incredibly high with respect to the sample average, and whose reliability may not be completely accurate.

Table 9: Mechanisms – Cross-Section Correlations: Effect of Health Aid on Health Infrastructures (Source: WHO)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Dependent Variable (in Log)	*Health Posts*	*Health Centers*	*District/Rural Hospitals*	*Provincial Hospitals*	*Specialized Hospitals*	*Number Hospitals*
Data Source:	WHO	WHO	WHO	WHO	WHO	WHO
Independent Variables (Lagged at t-1)						
Log Health ODA pc (o)	0.188	0.520**	0.269**	0.384***	0.233*	0.257***
	(1.78)	(3.24)	(2.77)	(3.81)	(2.31)	(4.23)
N	82	78	86	80	85	97

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
The dependent variables are expressed in per capita terms. In Column 6, for instance, the dependent variable is the log of the per capita number of hospitals in a given country at time t. ODA variable is lagged one year and is the average over four-year periods (t-1 – t-4). The regressions include GDP per capita (log) and a Conflict dummy as controls, whose coefficients are not reported. Data are from the World Health Organization and available for the years 2013 and 2010: hence, as dependent variable we take the average of the 2010 and 2013 cross sections.

Table 10: Mechanisms - Subtracting Bilateral Flows

	(1)	(2)	(3)	(4)
Estimator	PPML	PPML	PPML	PPML
Dep. Variable	Migration Rate Nurses	Migration Rate Nurses	Migration Rate Doctors	Migration Rate Doctors
Sample Destinations	*Whole*	*Whole*	*Whole*	*Whole*
Log Minus Bil. Health ODA pc (o)	-0.100*	-0.0980	-0.0964**	-0.0780*
	(-2.29)	(-1.71)	(-2.63)	(-1.96)
Log Bilateral Health ODA pc (d to o)		-0.0113		0.0172*
		(-1.44)		(2.33)
Log GDP Const. $ PPP (o)	-2.277***	-2.233***	-0.605*	-0.631*
	(-7.53)	(-7.96)	(-2.14)	(-2.20)
N	2541	2541	4387	4387
Destination-Year FE	X	X	X	X
Origin-Destination FE	X	X	X	X
Destinations	18	18	23	23
Origins	108	108	107	107
% Zeros	23,6%	23,6%	16,7%	16,7%

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The specification distinguishes between bilateral and non-bilateral health aid. In order to maintain the same sample size as in Tables 1 and 2, ODA is expressed in log form as ln(1+ODA). Therefore, the coefficients in this table should be interpreted as *semi-elasticity* rather than *elasticity*. All specifications include GDP per capita and Diaspora as controls.

Table A1: Countries of Origin in the Sample - Emigration of Nurses (Average 2006-2015)

Destination Origin	Emigration Flows All	Emigration Rates (per thousand) All	Emigration Flows USA	Emigration Rates (per thousand) USA
Philippines	**8180.7**	**20.95703**	**6860.1**	**17.22766**
India	2737.1	1.758528	1444.1	0.9585693
China	274.2	0.1503812	175.3	0.0977455
Nigeria	226.3	1.871048	120	0.9771218
Jamaica	**142.7**	**40.43991**	**123**	**35.13354**
Peru	142	3.038256	9	0.1942262
Ukraine	114.7	0.340169	58.6	0.1716908
Nepal	**112.6**	**6.627877**	**66.7**	**3.009881**
Albania	**96.5**	**7.225455**	**2.6**	**0.1956698**
Iran	79.9	0.6064556	31.7	0.2393595
Kenya	70.3	3.447183	54.1	2.551132
Pakistan	65.3	0.9926745	19.5	0.272438
Haiti	**62.9**	**14.77263**	**37**	**9.309366**
Serbia	59.8	1.330521	1.4	0.0308062
South Africa	58.2	0.2644542	20.8	0.0957353
Bosnia and Herzegovina	55.7	2.651538	3.3	0.1600073
Jordan	55.3	2.418612	17.2	0.816414
Brazil	54.4	0.043777	13.1	0.01074
Ghana	49.9	2.389431	29.5	1.271906
Thailand	45.8	0.4001828	39.9	0.3545504
Croatia	45.6	1.635021	0.8	0.0305131
Lebanon	45	4.868343	16.5	1.991756
Colombia	43.7	1.280499	16.2	0.4791895
Ethiopia	37.5	1.490754	35.3	1.388901
Tunisia	32	1.281189	0	0
Moldova	31.3	1.380396	2.8	0.1246556
Zimbabwe	29.1	1.775189	3.8	0.231459
Zambia	22.4	3.400619	3.8	0.574237
Uzbekistan	21.8	0.0689952	14	0.0441387
Mexico	21.3	0.0821314	20.1	0.0774789
Cameroon	19.7	1.740258	13.4	1.152891
Algeria	17.7	0.2413027	0.2	0.0034155
Mauritius	14.2	3.955087	2.9	0.8787879
Armenia	14.1	0.9284419	13.5	0.8888873
Paraguay	13.9	1.792687	0	0
Belarus	13.5	0.1456247	7.4	0.0802217
Argentina	13.1	0.1643732	3.4	0.0342739
Saudi Arabia	12	0.1002258	7.8	0.05315
Guyana	**11.5**	**12.33052**	**9.7**	**10.42093**
Morocco	10.9	0.3678156	0.8	0.0283095
Sri Lanka	10.5	0.3554476	2.6	0.0834831
Kazakhstan	10.4	0.0810475	1.9	0.0151688
Dominican Republic	9.2	0.7739995	2.6	0.2213296
Georgia	9.1	0.6310956	6.8	0.4768947
Turkey	8.8	0.0674964	3.7	0.0284758
Myanmar	8.6	0.3813467	8.3	0.3683174
Ecuador	8.3	0.3187849	1.7	0.0673425
Indonesia	7.9	0.0537667	4.8	0.0322645
Chile	7.6	5.919086	5.2	3.846919
Sierra Leone	**7.6**	**7.035678**	**5**	**4.62423**
Eritrea	7.4	2.59919	6.4	2.099469
Gambia	**6.6**	**6.785609**	**4.8**	**4.119517**
North Macedonia	6.5	0.7639533	0.4	0.0461547
Bolivia	5.9	0.7384278	0.2	0.0299439
Malaysia	5.9	0.0904427	4	0.0557578
Barbados	5.8	4.032954	1.8	1.274562
Côte d'Ivoire	5.8	0.5508842	0	0
Uganda	5.8	0.1675797	3.8	0.1154601
Panama	5.7	0.7343604	3.3	0.4339516
Trinidad and Tobago	5.6	1.237301	4.5	0.9956094
Egypt	5	0.0332034	4.1	0.0272123
Bangladesh	4.8	0.1925811	1	0.0297319
Suriname	4.8	2.598411	0.1	0.0515836
Venezuela	4.8	0.1467497	2.2	0.0667287

Table A1: Countries of Origin in the Sample - Emigration of Nurses (Average 2006-2015) (Continued)

Destination / Origin	Emigration Flows All	Emigration Rates (per thousand) All	Emigration Flows USA	Emigration Rates (per thousand) USA
Belize	**4.4**	**9.522161**	**4.4**	**9.522161**
Oman	4	0.2850941	3.3	0.2187251
Malawi	3.8	0.8862253	0.4	0.078309
Liberia	3.5	4.780256	3.1	4.164471
Costa Rica	3.2	0.8581653	2.8	0.7509885
Congo	3.1	0.6464056	0.3	0.0463896
Grenada	2.5	6.268998	2.4	6.177742
Fiji	2.4	1.040033	0.5	0.234008
Saint Lucia	**2.4**	**7.864879**	**2.2**	**7.225972**
Kyrgyzstan	2.3	0.0757268	2.2	0.0723151
Iraq	2.1	0.0381274	0.1	0.001996
Montenegro	2	0.6070369	0.2	0.0607304
Saint Vincent and the Grenadines	2	5.330025	1.6	4.2294
Uruguay	2	0.1163822	0.7	0.0361962
Dominica	1.8	4.117162	1.7	3.888329
Tanzania	1.8	0.1401211	1.6	0.1266371
El Salvador	1.7	0.2304212	1.5	0.2131381
Burkina Faso	1.6	0.3376669	0.6	0.1121517
Democratic Republic of the Congo	1.6	0.0607717	0.3	0.0120173
Rwanda	1.5	0.2088685	0.9	0.1261212
Azerbaijan	1.4	0.0215921	0.6	0.0091657
Mongolia	1.4	0.1483296	1.2	0.1283927
Tajikistan	1.4	0.053328	1.1	0.0401001
Antigua and Barbuda	1.3	4.354342	1.2	4.008681
Botswana	1.3	0.2376453	0.5	0.094316
Burundi	1.2	0.2590637	0.4	0.0710422
Turkmenistan	1.2	0.0470595	1.1	0.0429275
Afghanistan	1	0.0805427	0.2	0.0115895
Guatemala	0.9	0.0737653	0.8	0.0651893
Nicaragua	0.9	0.1192116	0.5	0.0668522
Seychelles	0.8	1.929535	0	0
Viet Nam	0.8	0.0119424	0.3	0.0054131
Honduras	0.5	0.0824309	0.5	0.0824309
Niger	0.5	0.2511229	0.2	0.1088159
Senegal	0.5	0.0969995	0.2	0.0533526
Benin	0.4	0.0724381	0.2	0.0346921
Sudan	0.4	0.0170096	0.2	0.0085078
Angola	0.3	0.0119913	0	0
Mauritania	0.3	0.1332767	0	0
Togo	0.3	0.1363779	0.1	0.0806452
Cape Verde	0.2	0.4081785	0	0
Chad	0.2	0.063674	0.2	0.063674
Lesotho	0.2	0.1613617	0.1	0.0825861
Palau	0.2	1.797824	0.2	1.797824

Notes: Data are from the Health Workforce Migration dataset (OECD). Emigration Rates are calculated as the average of the ratio between total nurse emigration and nurse population for a given origin over the period 2006-2015. Countries that exhibit the 10 highest emigration rates are in **bold.**

Table A2: Countries of Origin in the Sample - Emigration of Doctors (Average 2006-2015)

Destination	Emigration Flows	Emigration Rates (per thousand)	Emigration Flows	Emigration Rates (per thousand)
	All	All	USA	USA
Origin				
India	2304.8	2.882875	1433.4	1.796239
Pakistan	1146.7	7.60231	400.9	2.699812
Nigeria	412	8.109043	120.4	2.372758
Egypt	398.2	6.448642	107.6	1.767312
Colombia	305.5	3.872108	91.8	1.26513
China	302.4	0.1507115	208.8	0.1053215
Iraq	279.7	12.90946	56.3	2.407793
Saudi Arabia	277.2	4.316364	48.4	0.7068645
Iran	266.6	3.892691	130	1.897496
South Africa	214.4	5.653528	8	0.212638
Philippines	213.7	1.825997	174.9	1.500527
Sudan	**204.8**	**15.3922**	**26.3**	**2.043601**
Ukraine	200.3	1.309034	41.1	0.2630349
Mexico	194.5	0.7783738	147.4	0.5903127
Ecuador	183.4	6.486145	31	1.168861
Sri Lanka	177.3	11.35529	9	0.601445
Jordan	149.6	8.614302	78.3	4.593152
Dominican Republic	139.5	10.22293	103	7.746138
Lebanon	138.7	11.21378	101.1	8.229341
Algeria	127.2	2.141443	2.8	0.061832
Brazil	126.6	0.350875	47.4	0.1336313
Argentina	125.8	0.8122889	30.8	0.2117717
Venezuela	108.9	1.932402	48.4	0.8699451
Bangladesh	108.5	1.96693	40.2	0.7524307
Nepal	108.2	9.49886	82.5	7.418213
Peru	98.2	2.881515	53.4	1.499017
Serbia	96.5	4.372436	12.9	0.5898249
Libya	92.6	8.019333	22.5	1.871946
Croatia	69.7	5.436932	4.4	0.3717145
Myanmar	68.8	2.622294	40.6	1.544932
Tunisia	65.1	4.813971	0.8	0.0676192
Turkey	64.2	0.5306244	34.4	0.284619
Thailand	51.6	2.152255	31.2	1.319654
Jamaica	42.4	36.37971	21.3	18.03208
Ethiopia	41.9	13.59927	35.5	11.32594
Bolivia	41.3	6.707798	6.4	1.318226
Belarus	39.4	1.11326	13.9	0.3980393
Morocco	38.8	1.85496	4	0.1987994
Moldova	33.3	3.168495	5.3	0.523632
Ghana	32.9	12.87158	20.6	8.437406
Chile	30.5	1.692652	5	0.2801868
Trinidad and Tobago	29.4	12.87136	19	8.822237
Oman	28.1	4.016767		
Malaysia	27.8	0.8479177	3.9	0.1221095
Uruguay	23.3	1.743797	1.7	0.1294087
El Salvador	22.3	2.06079	17.3	1.599299
Haiti	18.8	11.97603	11.8	7.511956
Costa Rica	18	3.35376	13	2.422282
Armenia	17.5	2.102971	10.3	1.239882
Senegal	**17.5**	**17.4416**	**13.4**	**16.13781**
Afghanistan	15.8	2.742256	0.9	0.1447743
Guatemala	14.7	1.348318	11.2	1.016194
Zimbabwe	**14.5**	**16.07612**	**2.3**	**2.651986**
Bosnia and Herzegovina	14.4	2.089409	1.5	0.2186312
Georgia	14.3	0.7380721	6.1	0.3131043
Kenya	14.1	1.887595	7	0.9725859
Uzbekistan	13.8	0.1963244	5.7	0.0819058
Uganda	13.2	3.85506	4.5	1.324414
Paraguay	12.8	1.75106	6.6	0.9262583
Albania	12.2	3.332708	5.1	1.388962
Cameroon	11.9	7.353657	3.4	2.252609
Macedonia	11.4	2.022879	1.4	0.2481517
Honduras	10.7	1.719401	6.5	1.117638
Kazakhstan	10.7	0.1877249	3.4	0.0599548

Table A2: Countries of Origin in the Sample - Emigration of Doctors (Average 2006-2015) (Continued)

Destination / Origin	Emigration Flows All	Emigration Rates (per thousand) All	Emigration Flows USA	Emigration Rates (per thousand) USA
Democratic Republic of the Congo	10.4	1.697194	0.7	0.122788
Madagascar	9.8	2.59971		
Viet Nam	9.8	0.15364	5.7	0.0933435
Azerbaijan	9	0.2781734	2	0.0618904
Congo	**8.4**	**15.67677**		
Fiji	**8.2**	**15.50962**	**0.4**	**0.9697205**
Côte d'Ivoire	8	1.882643	0.3	0.0792042
Panama	7.7	1.499756	6.4	1.263744
Nicaragua	7.3	1.657719	5	1.181286
Yemen	7	0.9204105	1.7	0.2223279
Benin	6.4	4.750658	0.3	0.3913727
Mali	6.1	3.18857	0.1	0.0945477
Togo	6.1	10.11518	0.3	1.053733
Indonesia	5.8	0.1204532	3.7	0.0778868
Mauritius	5.6	3.042079	3.1	1.682254
Barbados	5.3	9.047723	4.4	7.649174
Kyrgyzstan	5.2	0.4611956	1.8	0.1537166
Suriname	5.1	12.47111		
Guyana	**5**	**17.43943**	**3.1**	**10.88167**
Tanzania	4.2	2.899789	1.8	1.297851
Guinea	4.1	4.246116	0.2	0.2116307
Zambia	3.9	4.385025	0.9	1.14264
Burundi	3.5	7.980649	0.1	0.3667482
Mongolia	2.4	0.290329	0.6	0.0772801
Seychelles	**2.3**	**24.19407**	**2**	**20.92074**
Rwanda	2.1	1.698783	0.1	0.0905797
Tajikistan	2	0.1489328	0.9	0.0658948
Gabon	1.9	3.1007	0.1	0.1452785
Malawi	1.8	6.695682	0.1	0.3697834
Sierra Leone	**1.7**	**13.80994**	**0.3**	**1.908212**
Montenegro	1.6	1.207785		
Niger	1.6	2.444605	0.2	0.689688
Samoa	**1.2**	**15.21255**	**0.9**	**11.56805**
Burkina Faso	1.1	1.249676		
Central African Republic	0.9	3.436592		
Turkmenistan	0.9	0.0650089	0.3	0.0208804
Cambodia	0.6	0.1950206	0.1	0.0303582
Mozambique	0.6	0.5499114		
Papua New Guinea	0.6	1.494658	0.1	0.2496391
Angola	0.5	0.1812168		
Liberia	0.4	4.153479	0.3	3.422485
Mauritania	0.3	0.6950803		
Chad	0.1	0.1542417		

Notes: Data are from the Health Workforce Migration dataset (OECD). Emigration Rates are calculated as the average of the ratio between total doctor emigration and doctor population for a given origin over the period 2006-2015. Dominica, Grenada, Antigua and Barbuda, Saint Kitts and Nevis, Belize, Saint Vincent and Grenadines and Saint Lucia are dropped because they exhibit emigration flows that are disproportionate with respect to the country's population and therefore do not appear in the list of countries of origin. Dominica and Grenada are the second and fourth overall country of origin of doctors, respectively. While the other countries lie above the 70th percentile in the distribution of doctors' emigration in at least one year of the covered time span (2006-2015). Countries that exhibit the 10 highest emigration rates are in bold.

Table A3: ODA Health Sectors

DAC 5 Code	*CRS Code*	*Voluntary Code*	*Description*	*Clarifications / Additional Notes on Coverage*
120			**Health**	
121			**Health, General**	
	12110		Health policy and administrative management	Health sector policy, planning and programmes; aid to health ministries, public health administration; institution capacity building and advice; medical insurance programmes; including health system strengthening and health governance; unspecified health activities.
		12196	Health statistics and data	Collection, production, management and dissemination of statistics and data related to health. Includes health surveys, establishment of health databases, data collection on epidemics, etc.
	12181		Medical education/training	Medical education and training for tertiary level services.
	12182		Medical research	General medical research (excluding basic health research and research for prevention and control of NCDs (12382)).
	12191		Medical services	Laboratories, specialised clinics and hospitals (including equipment and supplies); ambulances; dental services; medical rehabilitation. Excludes noncommunicable diseases (123xx).
122			**Basic Health**	
	12220		Basic health care	Basic and primary health care programmes; paramedical and nursing care programmes; supply of drugs, medicines and vaccines related to basic health care; activities aimed at achieving universal health coverage.
	12230		Basic health infrastructure	District-level hospitals, clinics and dispensaries and related medical equipment; excluding specialised hospitals and clinics (12191).
	12240		Basic nutrition	Micronutrient deficiency identification and supplementation; Infant and young child feeding promotion including exclusive breastfeeding; Non-emergency management of acute malnutrition and other targeted feeding programs (including complementary feeding); Staple food fortification including salt iodization; Nutritional status monitoring and national nutrition surveillance; Research, capacity building, policy development, monitoring and evaluation in support of these interventions. Use code 11250 for school feeding and 43072 for household food security.
	12250		Infectious disease control	Immunisation; prevention and control of infectious and parasite diseases, except malaria (12262), tuberculosis (12263), HIV/AIDS and other STDs (13040). It includes diarrheal diseases, vector-borne diseases (e.g. river blindness and guinea worm), viral diseases, mycosis, helminthiasis, zoonosis, diseases by other bacteria and viruses, pediculosis, etc.
	12261		Health education	Information, education and training of the population for improving health knowledge and practices; public health and awareness campaigns; promotion of improved personal hygiene practices, including use of sanitation facilities and handwashing with soap.
	12262		Malaria control	Prevention and control of malaria.
	12263		Tuberculosis control	Immunisation, prevention and control of tuberculosis.
	12281		Health personnel development	Training of health staff for basic health care services.

Table A4: Variables Used and Related Sources

Variable	Short description	Source
Dependent variable		
Health Workforce Emigration Rates	Bilateral Emigration Flows of Doctors and Nurses divided by the respective Population in their country of origin	Number of nurses who have obtained a recognized qualification in nursing/doctors who have obtained their first medical qualification (degree) in another country and are receiving a new authorization in a given year to practice in the receiving country.
Explanatory variables		
ODA Health Sector, Total	Total transferred ODA received by country *i* from all donors in the Health Sector, normalized by the total population of country *i*, gross disbursements in Constant US dollars (2 years average).	CRS-OECD DAC
GDP Per Capita	GDP per capita, expressed in PPP constant US$ (2011 prices)	World Bank
Diaspora	Stock of migrants born in country n and resident in country i at time t-1. Values for intermediate years are linearly interpolated.	World Bank
Governance Quality	A synthetic indicator of quality of governance based on a Principal Component Analysis (PCA) of the six World Bank Governance Indicators (*Voice and Accountability*, *Political Stability and Absence of Violence*, *Government Effectiveness*, *Regulatory Quality*, *Rule of Law* and *Control of Corruption*)	World Development Indicators, World Bank
Conflict	Dummy = 1 in the presence of conflict in the country of origin, 0 otherwise	UCDP Monadic Conflict Onset and Incidence Dataset
Natural Disasters	Calculated as the total number of natural disasters in a given year	International Disaster Database, Centre for Research on the Epidemiology of Disasters
UN Votes Affinity Index (d to o)	Values for the Affinity index "*S3UN"* using 3 category vote data (1 = "yes" or approval for an issue; 2 = abstain, 3 = "no" or disapproval for an issue.)	Voeten, Erik; Strezhnev, Anton; Bailey, Michael, 2009, "United Nations General Assembly Voting Data", https://doi.org/10.7910/DVN/LEJUQZ, Harvard Dataverse (updated version)
Log Trade Flows (d to o)	Trade flows in current US$ from destination to origin	BACI, CEPII

Instrumental Variable Analysis

Govt. Fractionalization	Government Fractionalization Index	Database of Political Institutions 2015. Inter-American Development Bank
Probability of Receiving Aid	For each dyad - it is calculated as the number of years for which there's a positive ODA flow over total number of years in the sample.	CRS-OECD DAC
Mechanisms		
Doctors (per 10000 People)	Includes generalists, specialist medical practitioners and medical doctors not further defined, in the given national and/or subnational area. Depending on the nature of the original data source may include practising (active) physicians only or all registered physicians.	World Health Organization
Nurses and Midwifery Personnel (per 10000 People)	Number of nursing and midwifery personnel includes nursing personnel and midwifery personnel in the given national and/or subnational area. Depending on the nature of the original data source may include practising (active) nursing and midwifery personnel only or all registered nursing and midwifery personnel	World Health Organization
Immunization	Child immunization, DPT, measures the percentage of children ages 12-23 months who received DPT vaccinations before 12 months or at any time before the survey. A child is considered adequately immunized against diphtheria, pertussis (or whooping cough), and tetanus (DPT) after receiving three doses of vaccine.	World Health Organization
Immunization Measles	Child immunization, measles, measures the percentage of children ages 12-23 months who received the measles vaccination before 12 months or at any time before the survey. A child is considered adequately immunized against measles after receiving one dose of vaccine.	World Health Organization
Hospital Beds (per 10000 people)	Hospital beds include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centers. In most cases beds for both acute and chronic care are included.	World Health Organization

Table A5 – Summary Statistics

Variable / ***Destination***	**Nurses** *All*	**Doctors** *All*
Emigration Rate (o to d)		
Mean	.0008794	.0011317
St. Dev.	.0035844	.0033195
Per Capita Health ODA (o)		
Mean	2.367332	2.257906
St. Dev.	3.161005	3.003967
GDP Per Capita (o)		
Mean	8803.38	9605.757
St. Dev.	6235.072	6610.046
Diaspora (o to d)		
Mean	156928.6	93581.3
St. Dev.	769636.9	589544.6
Conflict (o)		
Mean	.2581661	.2607705
St. Dev.	.437712	.439105
Natural Disasters (o)		
Mean	3.884691	3.310007
St. Dev.	6.321231	5.38602

Notes: Means and standard deviation refer to Column 5 of Tables 1 and 2, respectively

Table A6: Alternative Treatment of Missing Values in Dependent Variable

	(1) *Nurses*	(2) *Doctors*
Estimator	PPML	PPML
Dep. Variable	Migration Rate	Migration Rate
Sample Destinations	*Whole*	*Whole*
Log Health ODA pc (o)	-0.094*	-0.094*
	(-2.14)	(-2.47)
Log GDP pc Const. $ PPP (o)	-2.134***	-0.644*
	(-7.44)	(-2.23)
N	2541	4387
Destination-Year FE	X	X
Origin-Destination FE	X	X
Destinations	18	23
Origins	108	107
% Zeros	23,6%	16,7%

z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Robust standard errors are multi-way clustered by donor, recipient, and year.
Migration rate is calculated using annual bilateral flows of Nurses/Doctors emigration over Nurses/Doctors Population. Missing values of Nurses/Doctors population are linearly interpolated when possible, or imputed by letting the number of nurses vary proportionally to country's total
population.

With the support of the Erasmus+ Programme of the European Union

The European Commission supports the EUI through the European Union budget. This publication reflects the views only of the author(s), and the Commission cannot be held responsible for any use which may be made of the information contained therein.