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

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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. Our findings suggest that donors influence the emigration decisions of doctors and nurses through improvements in health infrastructure. 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.

KEYWORDS
aid, development, health personnel, migration

JEL CLASSIFICATION
F22; F35; O15

1 | INTRODUCTION

South–north migration of skilled people has become an increasingly important phenomenon over the past few decades, with the number of high-skilled migrants residing in member countries of the OECD growing at a much faster rate than the respective number of low-skilled migrants (Botezat & Ramos, 2020). The early literature on skilled workers' emigration concluded that it is likely to cause a brain drain, exerting an adverse effect on the welfare of the people who stay in the countries of origin (e.g., Bhagwati & Hamada, 1974). More recently, it has been argued that skilled migration may also contribute to long-term local development, the most relevant transmission mechanism being that emigration possibilities for skilled workers encourage the accumulation of human capital in the migrant-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. According to the World Health Organisation (WHO, 2020), more than 40% of WHO Member States have fewer than 10 medical doctors available per 10 000 population, whereas over 55% have less than 40 nurses and midwives per 10 000 population. Empirical studies have shown that the emigration of doctors is associated with high HIV death rates, child mortality and too few medical workers to meet basic healthcare needs at the local level, pointing to a medical brain drain (see Astor et al., 2005; Bhargava & Docquier, 2008; Chauvet et al., 2013). Yet, the literature also suggests 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 & 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 & 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 that 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.[1] 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 analysed the effects of sector-specific aid so as to account for the heterogeneity of foreign assistance (Gamso & Yuldashev, 2018a; Gamso & Yuldashev, 2018b; Lanati & Thiele, 2018a; Lanati & 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. In a specific analysis for tertiary education, Lanati and Thiele (2020b) conclude that investing in the quality of tertiary education in recipient countries appears to be associated with lower outflows of students to donor countries. These findings are in accordance with the pioneering study by Dustmann and Okatenko (2014), which shows that contentment with various local amenities—including for instance healthcare, schools, air quality and the quality of a country's institutions—turns out to be a more important factor in shaping migration decisions than household wealth. We investigate whether the previous findings hold 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 & Williamson, 2002). Because the migration hump is typically estimated 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 increasing GDP per capita is on average associated with more emigration 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 lead to more labour emigration flows in poorer areas with a strong prevalence of small-scale agriculture, whereas such shocks lower emigration in the most developed rural areas. By contrast, Benček and Schneiderheinze (2020) and Clist and Restelli (2021) 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.[2] We add a disaggregated perspective to this literature by comparing the migration decisions of (relatively poor) nurses and (relatively rich) doctors. In our case, changes in GDP per capita can be regarded as a rough proxy for changes in health workers' wages, which would be the preferable indicator but is not available for the purpose of this analysis. A previous study by Bhargava and Docquier (2008) shows that physicians' wages in the country of origin are negatively related with physicians' emigration rate from developing countries.

Taken together, by considering the impact of aid for health and GDP per capita, we capture important monetary and non-monetary determinants of health workers' migration decisions.

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 specifically targeted at the health sector improves development indicators, such as infant mortality (e.g., Kotsadam et al., 2018; Mishra & 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. Adovor et al. (2021) find that a higher number of physicians per thousand people are associated with less emigration by physicians. 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 existing studies on the link between foreign assistance and emigration 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 (2020) as well as Clist and Restelli (2021) 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.

2 | DATA AND DESCRIPTIVE EVIDENCE

Data on international flows of health personnel are taken from the OECD's Health Workforce Migration dataset. The dataset provides information on annual inflows into OECD countries over the period 2000–2015.[3] 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.[4] 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.[5] 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 heterogeneous. 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.[6] The largest number of doctors emigrates 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 among doctors.

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

$$EM^h_{ijt} = \frac{M^h_{ijt}}{\sum_j M^h_{ijt} + P^h_{it}},$$

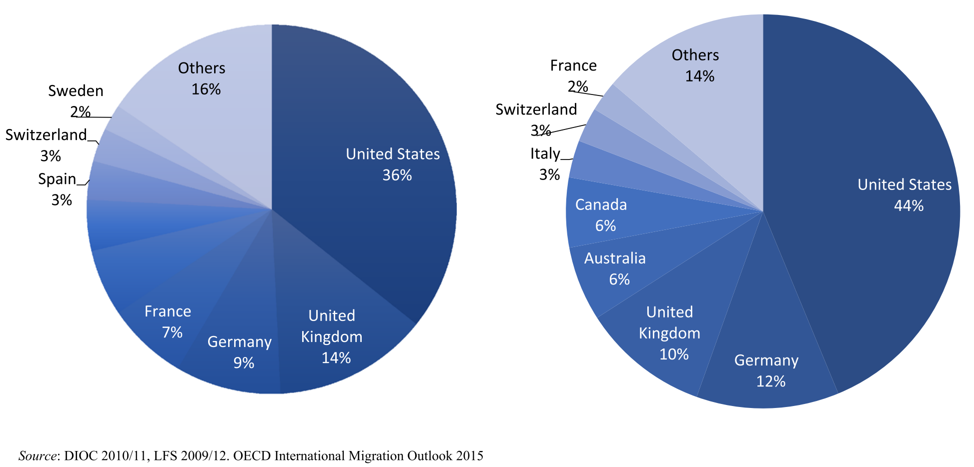

FIGURE 1 Distribution of foreign-born doctors (left) and nurses (right) by country of residence in the OECD, 2010/11. *Source*: DIOC 2010/11, LFS 2009/12. OECD (2015) [Colour figure can be viewed at wileyonlinelibrary.com]

where M^h_{ijt} 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 $\sum_j M^h_{ijt}$ the sum of available emigrant flows from country i.[7] In our baseline estimation, missing values for the 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 assistance, our main explanatory variable under scrutiny alongside GDP per capita, we employ 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 items by sector.[8] 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 & Thiele, 2020a). In order to smooth the volatility in the annual provision of aid disbursements, we use 4-year averages of the aid received.[9] GDP per capita is expressed in purchasing power parities (PPPs) with constant US$ (2011 prices). Table A4 in the appendix lists the sources and provides a brief description of these variables and other covariates that were used as controls in the empirical analysis, and Table A5 shows the summary statistics.

3 | ECONOMETRIC APPROACH

Our empirical analysis relies on a standard gravity model of international migration (e.g., Beine & Parsons, 2015), in which bilateral emigration rates of healthcare workers from country of origin i to country of destination j are related to dyadic $OD_{ijt} - 1$ as well as origin-specific determinants $O_{it} - 1$. $O_{it} - 1$ includes our variables of interest, namely, GDP per capita and the total transferred health aid per capita received by country i. The estimation equation reduces to

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

In addition to the two main variables of interest, we include a standard set of time-varying covariates. These comprise origin-specific factors such as a dummy variable that captures the presence of conflicts; the number of natural disasters in a given year; and a proxy for the quality of governance and local institutions obtained with a principal component analysis (PCA) of the six World Bank Governance Indicators along the lines of Ariu et al. (2016). As a dyadic determinant, we capture time-varying migrant network effects through the inclusion of the lagged bilateral migrant stocks from country i living in country j.

To account for cross-country heterogeneity and attenuate potential estimation biases, the econometric specification includes destination-year ($\alpha_j t$) and asymmetric dyadic ($\alpha_i j$) fixed effects. Although origin-time dummies would fully absorb multilateral resistance to migration (Beine et al., 2015),[10] they cannot be added in our setting as they would completely absorb the effect of our variable of interest. Including destination-year fixed effects, however, fully captures multilateral resistance to migration in countries of destination. This can be assumed to be the dominant factor in the context of international migration, where destination-specific immigration policies play a central role (Beine & Parsons, 2015). In addition, asymmetric dyadic fixed effects address the bias that might result from the omission of unobserved variables and restore the cross-sectional independence of the error terms (Faye & Niehaus, 2012; Bertoli & Moraga, 2015). For instance, bilateral cultural or political affinity—which is unlikely to exhibit strong movements over short periods of time and is often very hard to measure empirically—is plausibly associated with both international mobility and foreign aid flows.

All covariates are predetermined—lagged one period—with respect to the emigration of medical workers. This to some extent addresses concerns that our variables of interest may be endogenous due to reverse causality. In addition, regarding the foreign aid variable, only the bilateral part of the total amounts allocated to country *i* possibly responds to migration from country *i* to country *j*. This may be due to the fact that migrants successfully lobby the destination countries' governments to increase disbursements to their home countries (Lahiri & Raimondos-Møller, 2000; Lanati & Thiele, 2018a). Hence, we argue that reverse causality should not severely affect our results, at least as far as foreign aid is concerned. In any case, given that a minor role played by simultaneity bias cannot be ruled out, we still desist to make strong causal claims. The standard procedure to tackle the issue of reverse causality is to employ an IV strategy: in our gravity setting, however, we would have to come up with an IV with an *ijt* dimension, while 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.[11] To address this issue, we follow the approach implemented by Cameron et al. (2011) as well as Faye and Niehaus (2012) and include non-nested multiway clusterings of standard errors along all three dimensions of the panel, that is 'donors', 'recipients' and 'years'.

Following previous analyses based on gravity models (e.g., Bertoli & Moraga, 2015; Beine & Parsons, 2015; Lanati & Thiele, 2018a), we apply the PPML approach when estimating Equation 1. The rationale for doing so is that our sample contains a fairly high share of zeros—around 23% and 17% of total observations for nurses and doctors, respectively. As Silva and Tenreyro (2006) have shown, a significant share of zero observations creates a correlation between the covariates and the error term, rendering ordinary least squares (OLS) estimates inconsistent.

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 and 2). We only include the set of fixed effects in line with Beine and Parsons (2017) and Cattaneo and Peri (2016). Although this specification is potentially subject to model misspecification, its advantage is that it does not include any covariate that could absorb 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 and 5) to check whether our core results survive their inclusion. The results suggest that the time variation of both per capita income and health aid is negatively associated with bilateral emigration of the healthcare workforce. In substantive terms, the effect of per-capita health aid is very close to previous estimates based on gravity models for international migration (e.g., Lanati & 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 non-monetary dimensions of well-being in developing countries including 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. Although there appears to be some consensus on the role of improved public services in reducing emigration from developing countries (Dustmann & Okatenko, 2014), the impact of a rise in income on emigration decisions is subject to contrasting

TABLE 1 Impact of per capita transferred health aid on migration of nurses (bilateral rates): 2006–2015

Estimator Dep. variable Sample destinations	(1) PPML Migration rate Whole	(2) PPML Migration rate Whole	(3) PPML Migration rate Whole	(4) PPML Migration rate Whole	(5) PPML Migration rate Whole
Log health ODA pc (o)	−0.131* (−2.06)		−0.100* (−2.29)	−0.100 (−1.93)	−0.101* (−2.23)
Log GDP pc const. $ PPP (o)		−2.462*** (−6.29)	−2.277*** (−7.53)	−2.276*** (−6.45)	−2.412*** (−7.04)
Log diaspora (o to d)				−0.00627 (−0.05)	−0.0224 (−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%

Note: *z* statistics are in parentheses. Robust standard errors in parentheses in Columns 1–5 are multiway clustered by donor, recipient and year. Columns 1–5 show the estimates using the enlarged sample that 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, and 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, the United Kingdom and the United States.

Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

forces. It not only provides an incentive to stay by narrowing the income gap, but it also makes it easier to incur the cost of emigration, with no clear prediction regarding its net effect. According to the migration hump hypothesis (e.g., Clemens, 2014; Hatton & Williamson, 2002), the effect is non-linear: At low levels of per capita GDP, additional income makes it easier for would-be migrants in countries of origin to incur 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, which involves the comparison of emigration rates from richer and poorer developing countries (e.g., Clemens, 2014), while evidence is mixed so far with panel data. Our results corroborate the previous findings obtained by Benček and Schneiderheinze (2020) and Clist and Restelli (2021) that there is a negative but quantitatively moderate impact of per capita GDP on emigration regardless of sending countries' level of income 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, which corroborates previous findings by Adovor et al. (2021) and Moullan (2013), could still be in accordance with the migration hump hypothesis as doctors may lie on the

TABLE 2 Impact of per capita Transferred Health Aid on Migration of Doctors (Bilateral Rates) 2006–2015

Estimator Dep. variable Sample destinations	(1) PPML Migration rate Whole	(2) PPML Migration rate Whole	(3) PPML Migration rate Whole	(4) PPML Migration rate Whole	(5) PPML Migration rate Whole
Log health ODA pc (o)	−0.100** (−2.62)		−0.0964** (−2.63)	−0.0936* (−2.16)	−0.0927* (−2.07)
Log GDP const. $ PPP (o)		−0.636* (−2.04)	−0.605* (−2.14)	−0.568 (−1.86)	−0.630* (−2.37)
Log diaspora (o to d)				−0.116 (−1.69)	−0.118 (−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%

Note: Robust standard errors in parentheses in Columns 1–5 are multiway clustered by donor, recipient and year. *z* statistics are in parentheses. 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 that 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, the United Kingdom and the United States.
Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

downward-sloping segment of the curve.[13] 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-sectional and time-series estimates of the development-migration nexus may point in different directions is 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 and 2) and leads to a positive and significant relationship between health aid and the emigration of doctors from developing countries (Columns 3 and 4).[14]

This finding is in line with previous research. As shown, for instance, by Benček and Schneiderheinze (2020) and Ortega and Peri (2013) in their analysis of the relationship between income and emigration rates, there tend to be large differences between panel and cross-sectional estimates. Their findings show that a pure cross-sectional

TABLE 3 Not accounting for cross-country heterogeneity at the origin

Estimator Dep. variable Sample destinations	(1) PPML Migration rate nurses Whole	(2) PPML Migration rate nurses Whole	(3) PPML Migration rate doctors Whole	(4) PPML Migration rate doctors Whole
Log health ODA pc (o)	0.113 (0.85)	0.107 (0.82)	0.325*** (3.74)	0.323*** (3.69)
Log GDP const. $ PPP (o)	0.0650 (0.58)	0.0548 (0.50)	−0.0173 (−0.10)	−0.0133 (−0.08)
N	2,541	2,541	4,387	4,387
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%

Note: *z* statistics are in parentheses. Robust standard errors in parentheses are multiway clustered by donor, recipient and year. Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.
$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

exercise leads to a positive relationship; by contrast, when exploiting the variation over time and accounting for heterogeneity across countries of origin and destination through an appropriate set of fixed effects, they consistently find a negative association between income and emigration. This result is independent of the level of income a country starts out at.

4.1 | 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 healthcare 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.

The pattern for GDP per capita shown in Table 4 might be explained by the fact that financial constraints are more binding for nurses as compared with doctors. For doctors, the falling impact with rising incomes would then simply indicate lower incentives to emigrate as the income gap between origin and destination narrows. For nurses, the negative incentive effect of rising incomes would partly be offset by a loosening of budget constraints which are most binding in low-income settings. A larger provision of health aid—if not wasted—can be expected to improve the supply and the quality of local healthcare infrastructures in developing countries (see below). As Dustmann and Okatenko (2014) pointed out, the quality of local amenities and public services—including healthcare

TABLE 4 Impact of health aid and GDP per capita at different levels of income

Estimator	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML	(9) PPML	(10) PPML
Dep. variable	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate	Migration Rate
Sample destinations	Nurses Whole	Nurses Whole	Nurses Whole	Nurses Whole	Nurses Whole	Doctors Whole	Doctors Whole	Doctors Whole	Doctors Whole	Doctors 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

Note: *z* statistics are in parentheses. Robust standard errors in parentheses are multiway 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

Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

infrastructures—is an important determinant of emigration decisions, especially from poor and deprived areas whose healthcare system suffers from insufficient financial and human resources as well as limited institutional capacity and infrastructure. Against this background, our finding that the aid effect on nurses' emigration lowers with higher levels of per capita income might indicate that the marginal productivity of one dollar of foreign aid spent in the healthcare system decreases with better quality/larger supply of healthcare infrastructure. The reverse pattern for doctors might indicate that they benefit relatively less from the international support typically forthcoming in low-income settings—for instance the improvement of rural health posts or the provision of basic equipment such as syringes—and relatively more from the health aid provided in higher income settings, which also tends to include more sophisticated equipment that improves the conditions for doctors working in hospitals.

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.[15] 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 that 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 & 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.[16] 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.[17] 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

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 whole	Migration rate whole	Migration rate whole	Migration rate whole	Migration rate whole	Migration rate whole
Sample destinations	*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	2,580	2,230	1921	4,441	4,000	3,620
Destination-year FE	X	X	X	X	X	X
Origin-destination FE	X	X	X	X	X	X

Note: *z* statistics are in parentheses. Robust standard errors in parentheses are multiway clustered by donor, recipient and year. The regressions do not include controls other than our two variables of interest.

Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE 6 Addressing endogeneity: Augmented gravity model

Estimator Dep. variable Sample destinations	(1) PPML Migration rate Whole Nurses	(2) PPML Migration rate Whole Nurses	(3) PPML Migration rate Whole Nurses	(4) PPML Migration rate Whole Doctors	(5) PPML Migration rate Whole Doctors	(6) PPML Migration rate Whole 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

Note: *z* statistics are in parentheses. Robust standard errors in parentheses in Columns 1–5 are multiway 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 Tables 1 and 2. All regressors are lagged at *t*-1.
Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

nurses over and above what is captured by the full set of fixed effects.[18] Importantly, both income per capita and health aid effects are largely unaffected; that is, 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 healthcare 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 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.

4.2 | Potential mechanisms

The empirical analysis presented in the previous subsection suggests that a rise in foreign assistance in the health sector leads to lower emigration among medical workers from developing countries. Our hypothesis is that foreign

TABLE 7 Panel setting: The United States as the only destination

Estimator Dep. variable Sample destinations	(1) Nurses PPML Migration rate Whole	(2) Doctors PPML Migration rate Whole
Log health ODA pc (o)	−0.155* (−2.18)	−0.158 (−1.81)
Log GDP pc const. $ PPP (o)	−2.265 (−1.88)	−0.237 (−0.34)
N	973	937
Year FE	X	X
Origin FE	X	X
Destinations	1	1
Origins	102	96
% Zeros	35.2%	20.8%

Note: *z* statistics are in parentheses. Robust standard errors are multiclustered by recipient and year.
Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.
**p* < 0.05. ***p* < 0.01. ****p* < 0.001.

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 healthcare. 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 healthcare 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), the probability of receiving aid from donor j is defined as $\overline{p_{j,i}} = \frac{1}{11}\sum_{t=1}^{11} p_{j,i,t}$. p_j, i, t denotes 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, that is, $\sum_j FRAC_{jt} * \overline{p_{j,i}}$. 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, p. 1172) 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" (Dreher & Langlotz (2020, p. 1173). 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 & Qian, 2014).[19]

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 healthcare workers in the populations of recipient countries.[20] 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 healthcare infrastructure such as a higher number of health posts, health centres, etc. Overall, there is evidence supporting our hypothesis that aid for health leads to better working conditions for health personnel in developing countries.

Whether better working conditions in health facilities do indeed provide an incentive for health workers to stay in their home countries is not well established in the literature. For the case of physicians' emigration, Adovor

TABLE 8 Mechanisms: Aid effectiveness

Estimator Model	(1) OLS	(2) 2SLS
Dep. variable:		
Doctors (per 10 000 people)		
Log health ODA pc (o)	0.00687 (0.59)	0.277 (1.97)
N	1,382	1,382
Kleibergen–Paap *F* statistic		13.933
Dep. variable:		
Nurses (per 10 000 people)		
Log health ODA pc (o)	0.0204 (0.93)	0.296 (1.78)
N	1,413	1,413
Kleibergen–Paap *F* statistic		13.901
Dep. variable:		
Immunization, DPT (% of children ages 12–23 months)		
Log health ODA pc (o)	0.0132 (2.02)	0.170* (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* (2.51)	0.151* (2.46)
N	1711	1711
Kleibergen–Paap *F* statistic		10.936
Dep. variable:		
Hospital beds (per 10 000 people)		
Log health ODA pc (o)	0.00517 (0.26)	0.184 (0.89)
N	1692	1692
Kleibergen–Paap *F* statistic		10.439

Note: z statistics are in parentheses. Robust standard errors in parentheses are multiway 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 3- (t-1 to t-3) and 2-year periods (t-1 and 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.
Abbreviations: 2SLS, two-stage least squares; ODA, Official Development Assistance; OLS, ordinary least squares.
*p < 0.05. **p < 0.01. ***p < 0.001.

et al. (2021) show that the stock of emigrant doctors increases less than proportionately with the number of physicians in the home country—that is, the physician emigration rate decreases with 'increases' in the number of domestic physicians. In our view this is not surprising, a rise in the number of domestic physicians—especially in poor and deprived areas characterized by scarcity of qualified healthcare personnel—improves the productivity of the labour force and the overall working conditions of healthcare workers. This in turn creates more incentives for doctors and nurses to stay in their home country rather than leaving. Combining this reasoning with our evidence on the positive relationship between foreign assistance and the number of physicians (Table 8), we can cautiously conclude that the

TABLE 9 Mechanisms–cross-sectional 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 centres	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 (1.78)	0.520** (3.24)	0.269** (2.77)	0.384*** (3.81)	0.233* (2.31)	0.257*** (4.23)
N	82	78	86	80	85	97

Note: *t* statistics are in parentheses. Robust standard errors are 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 1 year and is the average over 4-year periods (*t*-1 to *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

Abbreviations: ODA, Official Development Assistance; OLS, ordinary least squares.

$^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

TABLE 10 Mechanisms: Subtracting bilateral flows

Estimator **Dep. variable** **Sample destinations**	**(1)** **PPML** **Migration rate nurses** **Whole**	**(2)** **PPML** **Migration rate nurses** **Whole**	**(3)** **PPML** **Migration rate doctors** **Whole**	**(4)** **PPML** **Migration rate doctors** **Whole**
Log minus bil. health ODA pc (o)	−0.100* (−2.29)	−0.0980 (−1.71)	−0.0964** (−2.63)	−0.0780* (−1.96)
Log bilateral health ODA pc (d to o)		−0.0113 (−1.44)		0.0172* (2.33)
Log GDP Const. $ PPP (o)	−2.277*** (−7.53)	−2.233*** (−7.96)	−0.605* (−2.14)	−0.631* (−2.20)
N	2,541	2,541	4,387	4,387
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%

Note: *t* statistics are in parentheses. 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.

$^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

rise in the number of domestic physicians induced by foreign aid leads to lower doctors' (and possibly also nurses') emigration rates.

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 investigate 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 & 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 analysed 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 that is targeted at improving health infrastructure can help mitigate medical brain drain. The same is true for more general growth-enhancing activities by various actors—for example, governments who provide the institutional framework, private enterprises who invest in new equipment, and donors who ideally complement local development initiatives. 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 that 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. Another interesting question for future work is whether local governments or NGOs could affect health infrastructure in a similar way as donors. Finally, it would be promising to investigate the impact of aid and income shocks. Negative aid shocks, for instance, may lead to cuts in healthcare spending, with implications for medical workers' incomes and workplace conditions.

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DATA AVAILABILITY STATEMENT

Data used in this paper are openly available from public sources (see Table A4).

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ENDNOTES

[1] This is not to deny that OECD countries may also aim to attract foreign health personnel to fill gaps in their own health systems. See, for example, Adovor et al. (2021) for a recent account of how different immigration policy instruments affect physicians' migration patterns.

[2] Note that Clist and Restelli (2021) are mainly concerned with irregular migrant flows, for which they do not obtain robust evidence in favour of a negative association between GDP per capita and emigration.

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

[4] Although the data on migration of health personnel are 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 the United States as the only country of destination. The results are qualitatively very similar to the baseline estimates, which we find reassuring.

[5] 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.

[6] 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.

[7] We include the term $\sum_j M_{ijt}^h$ even though we do not 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 and 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.

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

[9] Results are similar when using averages of ODA over different periods.

[10] Multilateral resistance to migration indicates the fact that the volume of bilateral migration between country pairs depends not only on the barriers between them, but also on the barriers and relative attractiveness of all potential destinations. Not accounting for multilateral resistance to migration in the gravity framework could significantly bias in the estimated coefficients of the determinants of migration (Bertoli & Moraga, 2013).

[11] Egger and Tarlea (2015) have shown that ignoring multiway clustering in a gravity setting leads to misleading inference, which appears to be particularly relevant under the Poisson pseudo maximum likelihood (PML)–generalized linear model (GLM) estimator we employ.

[12] 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.

[13] Adovor et al. (2021) obtain a considerably stronger negative effect of increases in GDP per capita on the emigration of physicians as compared with our estimates.

[14] 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.

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

[16] 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.

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

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

[19] 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% (critical value: 8.96) and less than 10% (critical value: 16.38), respectively.

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

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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

TABLE A1 (Continued)

Destination Origin	Emigration flows All	Emigration rates (per thousand) All	Emigration flows USA	Emigration rates (per thousand) USA
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
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

(Continues)

TABLE A1 (Continued)

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

Note: 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 Origin	Emigration flows All	Emigration rates (per thousand) All	Emigration flows USA	Emigration rates (per thousand) USA
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

(Continues)

TABLE A2 (Continued)

Destination Origin	Emigration flows All	Emigration rates (per thousand) All	Emigration flows USA	Emigration rates (per thousand) USA
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
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

TABLE A2 (Continued)

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		

Note: 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 1 year of the covered time span (2006–2015). Countries that exhibit the 10 highest emigration rates are in **bold**.

TABLE A3 Official Development Assistance (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, specialized clinics and hospitals (including equipment and supplies); ambulances; dental services; medical rehabilitation. Excludes noncommunicable diseases (123xx).
122			**Basic health**	
	12220		Basic healthcare	Basic and primary healthcare programmes; paramedical and nursing care programmes; supply of drugs, medicines and vaccines related to basic healthcare; activities aimed at achieving universal health coverage.
	12230		Basic health infrastructure	District-level hospitals, clinics and dispensaries and related medical equipment; excluding specialized 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 programmes (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 43,072 for household food security.
	12250		Infectious disease control	Immunization; 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.

TABLE A3 (Continued)

DAC 5 code	CRS code	Voluntary code	Description	Clarifications/additional notes on coverage
	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	Immunization, prevention and control of tuberculosis.
	12281		Health personnel development	Training of health staff for basic healthcare 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

(Continues)

TABLE A4 (Continued)

Variable	Short description	Source
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 10 000 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 10 000 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 10 000 people)	Hospital beds include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centres. 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	0.0008794	0.0011317
	St. Dev.	0.0035844	0.0033195
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	0.2581661	0.2607705
	St. Dev.	0.437712	0.439105
Natural Disasters (o)			
	Mean	3.884691	3.310007
	St. Dev.	6.321231	5.38602

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

TABLE A6 Alternative treatment of missing values in dependent variable

Estimator Dep. variable Sample destinations	(1) Nurses PPML Migration rate Whole	(2) Doctors PPML Migration rate Whole
Log health ODA pc (o)	−0.094* (−2.14)	−0.094* (−2.47)
Log GDP pc const. $ PPP (o)	−2.134*** (−7.44)	−0.644* (−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%

Note: *z* statistics are in parentheses. Robust standard errors are multiway 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.

Abbreviations: FE, fixed effect; ODA, Official Development Assistance; PPP, purchasing power parity; PPML, Pseudo–Poisson maximum likelihood.

**p* < 0.05. ***p* < 0.01. ****p* < 0.001.