# Drivers of migration: The influence of neighbouring countries on destination choice*

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**Abstract**

Several factors are likely to affect the scale, the origin, and the destination of migration flows. The seminal paper by Borjas (1987) describes the decision to migrate as being determined by the average income differential between two countries, net of migration costs. Further developments have adopted a Random Utility Maximization (RUM) model and included additional location-specific determinants of a prospective migrant's utility. One of the main challenges in estimating RUM models is the Independence of Irrelevant Alternatives (IIA) hypothesis, which limits the ability to explicitly *estimate* the influence of alternative destinations. In this paper we develop a conceptual framework that incorporates the characteristics of alternative destinations among the determinants of migration choices. Based on this framework, we then estimate a RUM model that includes an index of the characteristics of alternative destinations. For the empirical analysis, we use a dataset collected by the OECD, which traces migration flows from over 200 origin countries to 35 OECD destination countries between 2000 and 2021. The results confirm the main findings of the literature while also accounting for the characteristics of alternative destinations, thereby validating our approach. In addition, they show that the presence of migrants from the same country of origin in other destinations discourages the flows to a given country, while the per-capita GDP of alternative destinations is a further pull factor, indicating complex patterns of substitutability and complementarity between destination countries.

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# 1 Introduction

Cross-country migrations have risen substantially in absolute numbers in the past decades. According to the last International Migration Outlook published by the OECD (OECD, 2023), permanent-type migration to OECD countries reached a record level in 2022, with more than 6 million new immigrants. Temporary-labour migration, which includes seasonal migrants, also registered a strong increase, as well as the number of admissions of international students, which neared 2 million for the first time. Understanding the size and the pattern of these movements is of utmost importance to design appropriate economic policies to address the concerns and to reap the benefits that they might create.

The economic profession has answered promptly to this call, and a vast number of academic researches has been published in the recent years, studying theoretically and especially empirically what the determinants of migration flows are.[1]

The starting point for most of this literature is the seminal paper by Borjas (1987), which elaborates on the original intuition of Harris and Todaro (1970) that the choice of migrating is a function of (the difference in) expected income in the destination and in the origin location, net of migration costs, and has decomposed the determinants of such choice into a part due to observable socioeconomic characteristics and a part due to unobserved factors.[2]

Building on these seminal contributions, the empirical literature has analysed extensively how economic and non-economic conditions in both source and destination countries shape international migration flows, using both individual-level microeconomic data on the characteristics of migrants, and aggregate macroeconomic data on total flows. Interestingly, not only the studies using individual-level data, but also a number of studies using aggregate data, employ identification strategies that are consistent with individual-level migration choice based on the Random Utility Maximization (RUM) model of Marschak (1960).[3]

A common characteristic of most of this strand of literature is that it estimates "bilateral migration flows as a function of characteristics in the source and destination countries only" (Hanson (2010), p. 4373), consistent with the RUM model and the original econometric framework of Borjas (1987). From an econometric perspective, this requires that the Independence from Irrelevant Alternatives (IIA) hypothesis is satisfied, and therefore that cross elasticities due to a change in one destination's attributes are identical for all alternatives, including the alternative to stay in the origin country. Clearly, this is a rather restrictive assumption, that also implies that it is impossible to directly estimate the impact of the characteristics of alternative destination countries on the choice to migrate to a given destination. Nonetheless, as convincingly argued by Bertoli and Fernández-Huertas Moraga (2013), since "would-be migrants sort themselves across alternative destinations (p. 79)", controlling for the possible dependence of the migration rate between any pair of countries upon the time-varying attractiveness of other migrants' destinations seems an important step, with crucial policy implications.

[1]A large strand of literature has also studied the consequences of migrations, in both the origin and destination countries, but in the following we will focus only on the determinants of the patterns of migrations.

[2]In turn, this builds on the seminal contribution of Roy (1951), who argued that output of any individual working by hand is the resultant of a large number of random influences.

[3]See, for example, Beine et al. (2011), Grogger and Hanson (2011), Ortega and Peri (2013) and Clark et al. (2007).

Empirical frameworks that relax the IIA assumption while at the same time remaining consistent with the RUM model have been recently proposed. Ortega and Peri (2013), for example, is one of the first attempts, although it only accounts for unobserved differences between migrants and non-migrants, still requiring that IIA holds across all foreign destinations. Borrowing from the international trade theory, that has debated for a long time about a similar problem in the estimation of gravity models (Anderson and Van Wincoop, 2003; Head and Mayer, 2014), Bertoli and Fernández-Huertas Moraga (2013) propose a solution based on accounting for the influence exerted by other destinations through the inclusion of what that they call a 'Multilateral Resistance to Migration' term, whose impact is factored out using the Common Correlated Effects estimator proposed by Pesaran (2006). While this approach allows to rigorously control for the impact of the 'Multilateral Resistance to Migration' term when estimating the elasticity of migration decisions to the characteristics of the country of origin and to dyadic characteristics, its main weakness is that it does not allow to estimate the impact of specific features of alternative destinations on the choice of where to migrate. More recently, Beine et al. (2024) have proposed to estimate a cross-nested logit model, which allows for complicated substitution patterns between destinations and provides structural estimates of such dependence, but this also comes at the cost of requiring to define ex-ante different sets of destination countries (*i.e.*, different nests) and to impose exogenously the degree of dependence across nests. In fact, it is our view that the question is still open on what is the best empirical methodology to address the IIA issue in migration models, and for this reason we propose an alternative approach.

We aim to make two contributions with our paper. We first develop a conceptual framework that is based on a micro-founded random utility model, which allows to include among the determinants of migration choices also the characteristics of the destinations that were possible alternatives to the one chosen. This comes at the cost of imposing exogenous weights – that we model as a function of geographical or cultural distances – on how the characteristics of each alternative destination impacts on the migration choice. However, it has the advantage of allowing to estimate direct elasticities of the migration choice to such characteristics. Next, we estimate our model using a sample of annual migration flows from over 200 origin countries to 35 OECD destination countries between 2000 and 2021. In the empirical specification, we focus on the characteristics of the destination countries, using the interaction of origin-country and time fixed effects to control for the the characteristics of the countries of origin. In choosing the characteristics of the destination country, we follow the empirical literature, which has shown to be the two most important determinants of international migration flows are the presence of other migrants from the same country of origin in the potential destination country and the level of per-capita GDP. As characteristics of the alternative destinations, we include three indices obtained as weighted averages of the geographical distance from the chosen destination country of: (i) the value of per-capita GDP, (ii) the presence of other migrants from the same country of origin, and (iii) the flows of migrants from the same country of origin to the alternative destinations.

Our findings show that, in our sample, the potential bias on the estimates of the elasticities of migration flows with respect to the characteristics of the country of destination that might be introduced by not controlling for features of the alternative destinations is not sizeable (see Bredtmann et al. (2020) for a similar finding and Bertoli and Fernández-Huertas Moraga (2013) for a different result). They also show that, consistent with the literature, migrants are more likely to move to countries that have a higher per-capita GDP (see, e.g., Karras and Chiswick

(1999), Clark et al. (2007) and Mayda (2010)) and a stronger presence of migrants from the same country of origin (Beine et al., 2015).

Remarkably, we also find that the characteristics of neighbouring countries have a statistically and economically significant effect on the choice of where to migrate. In particular, the presence of migrants from the same country of origin in close destinations and the flows of migrants following the same route discourage the flows to a given country, while a higher per-capita GDP in the close alternative destinations is found to be a pull factor, suggesting that migrants not only go to countries where per-capita income is higher, but also to those neighbouring with higher income countries. These findings are robust to alternative estimation methods, including the use of instrumental variables to account for the potential endogeneity of per-capita GDP in the destination country. Interestingly, we provide a set of additional results showing that the impact of the characteristics of the chosen destinations and of the possible alternatives is partly different for migrants coming from origin countries at different level of development. Similarly, the results are partly different when cultural distance is used instead of the geographical distance as a weight to construct the index of the characteristics of the destinations alternative to the chosen one.

The rest of the paper is organized as follows. Section 2 describes the literature relevant for our analysis. Section 3 presents the theoretical background and our estimation strategy. Section 4 describes the data used in the empirical analysis, whose baseline results are presented in Section 5. Section 6 presents the results of the robustness checks and some additional findings. Section 7 concludes.

## 2 Review of the Literature

Our research builds on two different strands of literature. From a methodological perspective, we refer to analyses aiming to address the problem of the IIA hypothesis. According to this assumption, the orthogonality between the error component and the main explanatory variables – *i.e.*, the destination-specific sources of attractiveness – requires that variations in the costs of migrating to a country affect homogeneously the bilateral flows between the origin country and all the other alternative destinations. While this hypothesis helps building a direct link between a RUM model and the logit estimates, it imposes very strong restrictions to the data, that are not always satisfied.[4] For this reason, several papers have addressed the problems arising from the violation of the IIA hypothesis in the estimation of the determinants of bilateral migration flows. The most implemented solution – as in Head and Mayer (2014) – is that of including country-time fixed effects (e.g. Bertoli and Ruyssen, 2018; Docquier et al., 2014; Manchin and Orazbayev, 2018). However, as argued by Beine et al. (2024), in many cases the inclusion of country-time fixed effects is insufficient to tackle the problems caused by imposing IIA. This happens for example in presence of unobserved characteristics that are correlated across destinations (Bertoli and Fernández-Huertas Moraga, 2013), or when individuals' rationally decide to limit the costly acquisition of information to a subset of alternative destinations (Bertoli et al., 2020).

[4] Besides, a problem in assessing whether the IIA assumption is satisfied or not is that it requires to estimate an alternative model that does not impose it.

A first step in addressing this problem is to distinguish between home and foreign destinations. In this vein, Ortega and Peri (2013) estimate a gravity model using annual bilateral migration flows covering 15 OECD destination countries and 120 sending countries for the period 1980–2006, allowing for unobserved individual heterogeneity between migrants and non-migrants. Buggle et al. (2023) adopt a similar approach and estimate a nested logit model of the determinants of emigration decisions and destination choices of Jewish refugees during the 1930s in Nazi Germany. Bertoli and Fernández-Huertas Moraga (2013) do not limit the dependence to the distinction between movers and non-movers, but allow for richer patterns among destination countries, assuming that they can be grouped into nests, possibly overlapping with each other. In their setting, the IIA hypothesis needs to be satisfied across nests but not within nests. Interestingly, using the CME estimator developed by Pesaran (2006) to control for the possible dependence of choices within nests, and applying it to data on immigration into Spain from many different origin countries between 1997 and 2009, they obtain estimates that are sizeaby different from those obtained using the standard logit model imposing IIA. Bredtmann et al. (2020), on the contrary, following a different approach and controlling for the robustness of the results obtained assuming IIA by estimating a random parameters logit (RPL) model, find that after controlling for receiving-country and region fixed effects as well as dyad-specific variables, there is no unaccounted heterogeneity across individuals, and that IIA holds even within regions of a country. More recently, Beine et al. (2024) have proposed a different approach, estimating a cross-nested logit (CNL) model on individual decisions to migrate from India to a large set of potential foreign destinations. The CNL hinges on an identical assumption about the dependence of choices within nests of countries as Bertoli and Fernández-Huertas Moraga (2013) but, different from the CME of Pesaran (2006), it allows to estimate the structural parameters of the model. As argued above, the cost is that it requires to impose exogenous weights to each nest.

From an empirical perspective, our paper is closer to the literature studying the macroeconomic determinants of aggregate migration flows. What determines people's choices to migrate has been widely investigated and many empirical studies have confirmed the theoretical intuitions of the Roy model which, in the version by Borjas (1987), predicts that migration decisions are determined by the difference in the average income between two countries and by a *"time-equivalent measure of the costs of emigrating* [...] (p. 4)".[5]. Karras and Chiswick (1999) studies the macroeconomic determinants of immigration in Germany from European countries between 1964 and 1988, showing that long run trends are determined by the degree and speed of per-capita income convergence between the origins and the destination. Clark et al. (2007) studies immigration rates to the United States from a large set of countries between 1971 and 1998, and they also confirm that relative and absolute incomes are a major determinant, matter as predicted by the theory, but also other variables matter, such as the stock of previous immigrants from a given source country (see also Beine et al. (2015) on this issue).[6] Mayda (2010) has been one of the first to unpack migration costs, highlighting the role of migration

[5]See Hatton et al. (2005) for a long view on the patterns of migrations and Ferrie and Hatton (2015) for a more recent survey of the literature

[6]A network, or equivalently a *diaspora* – to specify the ethnic trait of it (Beine et al., 2011) – refers to a group of a country's nationals living in a destination. The channels through which the ethnic network affects the size of migration flows are the lower information and integration costs, and the reduced visa costs. The latter are related to the family reunification programs implemented worldwide, which imply having a relative already settled at destination.

policies and networks in shaping the size of yearly bilateral flows of immigration into 14 OECD countries between 1980 and 1995. In addition, she has also considered the distance-weighted average of the GDP of alternative destinations as an atheoretical measure of a multilateral pull factor of bilateral flows. Following contributions have studied more in detail the relative attractiveness of a destination, often restricting the analysis to a pivotal country. In particular, Bertoli et al. (2016) have looked at the flows to Germany from other European countries and Artuc and Ozden (2018), in a vary interesting contribution, have studied the flows into USA coming from transit destinations.

To our knowledge we are the first to estimate the impact on migration decisions of the relative attractiveness of alternative destinations with a multi-dimensional data set and using a theoretical framework based on a random utility model. This allows us also to estimate the heterogeneity of the effect and to draw more general conclusions on the role of the multilateral pull factors of international migration.

# 3 Empirical model

## 3.1 Theoretical background

Consider the problem of an individual $i$, residing in a generic country $c \in C$ (where $C$ is the set of all world countries and $c = 1, ..., n$), who must choose her preferred location in $C$. For convenience, in the following we will, at times, distinguish between the country of her current residence, denoted by $j$, and all the possible $n-1$ alternatives, denoted by $k = \{1, 2, ..., n-1\}$.

In its most general form, the choice of where to reside does not depend only on the characteristics of the chosen country, but also on those of the neighboring countries. We can think of several reasons. For example, network effects may extend across borders, especially in the case of small and well connected countries, making a large stock of immigrants from the same origin country an attracting factor also for neighboring countries. An obvious example is Central European countries, or Gulf countries. Possibly, the attractiveness of neighboring countries may also increase the expectations to eventually be able to migrate there. In general, migrating to an open and connected area, such as the European Union, can offer opportunities to diversify the risk that economic or social conditions in one of the countries of the area turn out to be worsen than expected, by moving nearby. On the contrary, migrating to a less connected area (e.g., Australia) may offer less such opportunities. Clearly, cross-country spillovers can also be negative. Migrating to a country that neighbors with an economically or socially unstable area is likely to be relatively less attractive, because of the risk that the instability spreads across borders.

Ultimately, the choice of where to migrate is not necessarily definitive: people can choose to stay where they already live or to migrate, they can choose to postpone migration to a future point in time, or they can choose to migrate first to one destination and then to another. Indeed, a growing literature shows that migration paths are not linear: a migrant who moves from A to B and stays in B for the rest of her life is the exception rather than the rule (see *e.g.*, Artuc and Ozden, 2018; Dustmann and Görlach, 2016). Notably, the choice an individual makes at each moment in time will affect the options available to her in the future. In fact, when an individual chooses to migrate to another country, other migration opportunities arise, likely because further moving to the countries neighboring the first destination entails lower migration costs than migrating from the country of initial residence. For example, migrating to Australia instead of the US today makes it more affordable to move to New Zealand tomorrow. There is indeed evidence that most prospective migrants consider the future cost of moving when choosing between current alternatives (see *e.g.*, Bertoli et al., 2016).

We adapt the behavioral model of the prospective migrant to include the characteristics of neighboring countries. Formally, we assume that an individual $i$ residing in country $j$, to maximize her utility solves the following problem:

$$\max_{c_k \in C} U(j, c_k) \tag{1}$$

where we drop the index $i$ to simplify the notation, $U(j, c_k)$ is the total expected utility of choosing country $k$ among all possible $n$ alternatives, that include the choice to remain in the origin country $j$.

To make the model more tractable, we assume that utility is linearly separable in the choice of where to migrate, so that the utility in equation (1) can be rewritten as:

$$V(j, c_k) = U(j, c_k) + \lambda f(k, c_l) \tag{2}$$

where we separated the direct utility that individual $i$ living in country $j$ obtains from choosing to live in a country $k$ with some specific characteristics, from the impact of the characteristics of the alternative $n-1$ countries where it could have lived, where we have assumed that such impact depends on the choice of $k$. In other words, the utility that an individual receives from choosing to migrate to a given country $k$ depends also on the available alternatives in a way that is related to $k$.

Formally, we thus assume that the individual $i$ residing in country $j$ maximizes the following utility function:

$$\max_{c_k \in C} V(j, c_k) = U(j, c_k) + \lambda f(k, c_l) \tag{3}$$

From this setting, individual $i$ residing in country $j$ decides to migrate at time $t$ to a generic country $c_k \neq j$ whenever:

$$\sup_{c_k \in C} V(j, c_k) > \sup_{c_j \in C} V(j, c_j) \tag{4}$$

Substituting from equation (3), equation (4) can be rewritten as:

$$U(j, c_k) + \lambda f(k, c_l) > U(j, c_j) + \lambda f(j, c_l) \tag{5}$$

The setting described above abstracts from uncertainty, an issue that needs to be considered especially when bringing the theoretical framework to the data.

In an empirical setting, we need to distinguish between two types of uncertainty. First, an individual may be uncertain about the impact of the characteristics of the alternatives to the choice she is considering – i.e., the term $(\lambda \cdot f(k, c_l))$ in our expression. Second, the idiosyncratic attributes of an individual's utility function are unlikely to be fully known by the researcher.

Allowing for uncertainty from an individual's perspective, equation (3) can be rewritten as:

$$\max_{c_k \in C} V(j, c_k) = U(j, c_k) + \lambda E[f(k, c_l)] = U(j, c_k) + \lambda \int [f(k, c_l|z)]g(z)dz \tag{6}$$

where $E$ is the expectation operator, $z$ is a random variable that takes into account all initially unknown factors on the impact of the alternatives to $k$, and $g(z)$ is the subjective distribution function of individual $i$ over the realizations of $z$.

Under these assumptions, an individual $i$ from country $j$ will decide to migrate to country $k$ if:

$$V(j, c_k) = U(j, c_k) + \lambda E[f(k, c_l)] > U(j, c_j) + \lambda E[f(j, c_l)] = V(j, c_j) \tag{7}$$

Next, we assume that the function $f(k, c_l)$ can be decomposed into two parts. One component $K_2(k, c_l)$ is a function of characteristics known both to the individual and the researcher, and the other component $\epsilon_2(k, c_l)$ is unknown to both of them. In formula:

$$f(k, c_l) = K_2(k, c_l) + \epsilon_2(k, c_l) \tag{8}$$

We further assume that $\epsilon_2(k, c_l)$ follows an extreme value distribution function, i.e. $f(\epsilon_2(k, c_l)) = e^{-e^{-\epsilon_2(k,c_l)}}$, independent of everything else. This unknown factor will become known to the individual in the second period, so the choice in the first period involves maximizing over the known part of $f(k, c_l)$. Under these assumptions:

$$E[\max_{c_k \in C} f(k, c_l)] = \ln \sum_{k=1}^{n-1} e^{K_2(k,c_l)} \tag{9}$$

Similarly, we assume that $U(j, c_k)$ can be decomposed into a part that is a function of characteristics known to both the individual and the researcher, and a part that is unknown, but in this case only to the researcher:

$$U(j, c_k) = K_1(j, c_k) + \epsilon_1(j, c_k) \tag{10}$$

Assuming also in this case that $\epsilon_1(j, c_k)$ follows an extreme value distribution function, we can write:

$$E[\max_{c_k \in C} U(j, c_k)] = \ln \sum_{k=1}^{n} e^{K_1(j,c_k)} \tag{11}$$

Leveraging on the assumptions that both error terms $\epsilon_1(j, c_k)$ and $\epsilon_2(k, c_l)$ follow an extreme value distribution, the previous equation implies that the probability that individual $i$ from country $j$ decides to migrate to country $k$, which we define as $p_{i,j,k}$, is given by the following expression:

$$p_{i,j,c_k} = Prob\left(V(j,c_k) > V(j,c_j)\right) = \frac{e^{K_1(j,c_k)+\lambda K_2(k,c_l)}}{e^{K_1(j,c_k)+\lambda K_2(k,c_l)} + e^{K_1(j,c_j)+\lambda K_2(j,c_l)}} \tag{12}$$

that has a standard nested-logit representation.

The log-odd representation is therefore:

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$$\begin{aligned} ln\left(\frac{p_{i,j,c_k}}{p_{i,j,j}}\right) &= K_1(j,c_k) + \lambda K_2(k,c_l) - K_1(j,c_j) - \lambda K_2(j,c_l) = \\ &= K_1(j,c_k) + \lambda \ln \textstyle\sum_{c=1}^{n} e^{K_2(c_k,c)} - K_1(j,c_j) - \lambda \ln \textstyle\sum_{c=1}^{n} e^{K_2(c_j,c)} \end{aligned} \tag{13}$$

To make this expression operational from an empirical perspective, we only need to define the functions $K_1$ and $K_2$. Following the literature, we assume that, for any triple of countries $j$, $c_k$ and $c_l$, they are log-linear functions of country attributes:

$$K_1(j,c_1) = \ln x(j,c_1)^{\beta'} \tag{14}$$

and:

$$K_2(c_1,c_2) = \ln \gamma' \alpha_{(c_1,c_2)} \mathbf{x}(c_1,c_2) \tag{15}$$

where $\alpha_{(c_1,c_2)}$ is a weight assigned to each characteristic of the dyad $(c_1,c_2)$, $\mathbf{x}(c_1,c_2)$ is a vector of (possibly bilateral) characteristics of $c_1$ and $c_2$, and $\gamma'$ is a vector of coefficients. Similarly, $\mathbf{x}(j,c_1)$ is a vector of characteristics of $j$ and $c_1$, and $\beta'$ is a vector of coefficients.

Substituting these expressions into the log-odd ratio and averaging over the population yields an expression that can be used to estimate our model using aggregate country-level data:

$$\begin{aligned} ln\left(\frac{p_{i,j,c_1}}{p_{i,j,j}}\right) &= \beta'[\ln x(j,c_1) - \ln x(j,j)] + \\ &+\lambda[\ln \textstyle\sum_{c=1}^{n} \gamma' \alpha_{(c_1,c)} \mathbf{x}(c_1,c) - \ln \textstyle\sum_{c=1}^{n} \gamma' \alpha_{(j,c)} \mathbf{x}(j,c)] \end{aligned} \tag{16}$$

## 3.2 Estimation strategy

We estimate the empirical counterpart of (16) using country level information on bilateral migration rates from origin countries to destination countries. Since our main focus is on the value of choosing country $k$ while explicitly controlling for the characteristics of all possible alternatives, our empirical specification controls for as many of the other characteristics of the optimal choice as possible by means of fixed effects. To this purpose, we estimate the following specification:

$$
\begin{aligned}
emigration\ rate_{jkt} = \alpha &+ \tilde{\beta}_1 \ \ln direct\ network_{jkt-1} + \tilde{\beta}_2 \ \ln per\text{-}capita\ GDP_{jkt-1} + \\
&+ \tilde{\gamma}_1 \ \ln weighted\ network_{jkt-1} + \tilde{\gamma}_2 \ \ln weighted\ per\text{-}capita\ GDP_{jkt-1} + \\
&+ \ln \left[ 1 - \sum_{l \neq k, l=1}^{n} \frac{\alpha_{jl}}{dist(l,k)} \left( \sum_{c \in C, c \in S} \frac{\gamma_c}{\phi_{jl}^c \beta_c} \right) \right] + \\
&- \ln \left[ 1 - \sum_{l \neq j, l=1}^{n} \frac{\alpha_{jj}}{dist(l,j)} \left( \sum_{c \in C, c \in S} \frac{\gamma_c}{\phi_{jl}^c \beta_c} \right) \right] + \epsilon_{jkt}
\end{aligned}
\tag{17}
$$

In equation (17), the dependent variable is the rate of emigration from origin country $j$ to destination country $k$, defined as the ratio of the flow of migrants from $j$ to $k$ and the population of origin country $j$. As explanatory variables, the time varying characteristics of origin countries – which refer to $x_{jjt}$ in equation (16) – are captured by a set of $j$x$t$ fixed effects. The characteristics of destination countries – $x_{kt}$ in equation (16) – include a time invariant component, that is captured by $j$ x $k$ fixed effects, and a time varying component, that is what allows us to identify the $x_{jkt}$ characteristics of the destination country in equation (16). We consider two groups of characteristics that vary with time and destinations. The first group includes typical time-varying characteristics of the destination country, that in our specification are the stock of migrants from origin country $j$ already living on country $k$ at time $t$, that measures the *direct network* effect, and per-capita GDP in country $k$ at time $t$. The second group, which is the main innovation of our framework, includes characteristics of countries $l \neq k$, weighted by the inverse of the distance from $k$ to $l$. Consistent with the choice of the characteristics of country $k$, we include in the second group the weighted average of the stock of migrants from country $j$ that live in country $l$ at time $t$, that measures the *weighted network* effect, and per-capita GDP in country $l$ at time $t$.[7] Recalling equation (16), $\tilde{\beta}_s = \frac{\beta_s}{\tau}$ and $\tilde{\gamma}_c = \frac{\gamma_c}{\tau}$. In the baseline specification we use as weights the inverse of the geographical distance, but we also present additional results using a measure of cultural distance.

A problem with estimating equation (17) is that the parameters $\beta_s$ and $\gamma_c$ to be used to calculate the expressions in the two log terms $\ln \left[ 1 - \sum_{l \neq k, l=1}^{n} \frac{\alpha_{jl}}{dist(l,k)} \left( \sum_{c \in C, c \in S} \frac{\gamma_c}{\phi_{jl}^c \beta_c} \right) \right]$ and $\ln \left[ 1 - \sum_{l \neq j, l=1}^{n} \frac{\alpha_{jj}}{dist(l,j)} \left( \sum_{c \in C, c \in S} \frac{\gamma_c}{\phi_{jl}^c \beta_c} \right) \right]$ are unknown ex-ante. For this reason, we proceed iteratively. We first estimate the empirical model excluding these terms, and obtain values of $\tilde{\beta}_s$ and $\tilde{\gamma}_c$ that we use as starting points to estimate the log terms. Next we re-estimate equation (17) including the two log terms and obtain new values of $\tilde{\beta}_s$ and $\tilde{\gamma}_c$, that we use to re-calculate the log terms. We then proceed iteratively until the estimates of $\tilde{\beta}_s$ and $\tilde{\gamma}_c$, which measure the direct effect of the changes in the characteristics destination countries alternative to the chosen ones, converge to a stable value.

Our sample includes several countries of origin and of destination at different points in time, and the dependent variable is an emigration rate, that by construction cannot assume negative values. The structure is thus identical to that of the gravity models of international trade.

[7] Unfortunately, our data do not allow us to control for the flows of migrants from country $j$ residing in country $k$ that eventually decide to move to country $l$, as in Artuc and Ozden (2018).

For these reasons, we borrow from the ample discussion in that field of literature and adopt in our baseline specification a Poisson pseudo-maximum-likelihood specification (PPML) of Silva and Tenreyro (2006).[8] In a set of robustness checks, we have also estimated our model using instrumental variables to account for the possible endogeneity of per-capita GDP in the destination country and using a GMM framework to include the lagged value of migration flows, to account for time persistence.

# 4 Data and summary statistics

The main dataset we rely on to implement the empirical analysis is the OECD International Migration Database that contains information on stocks, in- and out- flows of people who are foreign citizen or foreign born, originating from 210 countries and living in 35 reporting countries, all OECD countries.[9] The time period covered by the panel dataset is from 2000 to the last available year – *i.e.*, 2021. The data come from different sources, mainly local administrative registers, and are harmonized.[10]

We combine the OECD data with the CEPII data to obtain information on variables that might affect migration decisions, such as the GDPs, the populations of the two countries, and the geographical distance.

More in detail, the dependent variable of the regression model is the emigration rate, computed as the yearly outflows over the country population. The destination-specific characteristics that we consider are the per-capita GDP and the (lagged) stock of compatriot migrants as share of the population at origin. The characteristics of neighbouring countries, instead, are the average per-capita GDP, the average stock, and the average outflows of migrants from the same origin to all the destination countries, but the destination of the bilateral flow. All the average characteristics of the neighbouring countries are weighted by the inverse of the geographical distance.

Table 1 provides the summary statistics of the variables included in the empirical specification computed over the period of the analysis. The average rate of migration is 0.5, but with a very high variability across countries and time. The network of migrants from the same country of origin is just above 0.2 and also shows a high variability. Our distance-weighted measures of the characteristics of alternative destinations show instead lower variability, partly by construction.

# 5 Baseline Results

Table 2 reports the results of the estimation of equation (17) on the whole sample using a PPML specification, that is our baseline empirical model. The coefficients are expressed as elasticities

[8] In particular, to allow for the inclusion of the set of fixed effects described above – bilateral time-invariant $j$ x $k$ and origin-country time-varying $j$ x $t$ level – we estimate equation (17) using the Stata routine *ppmlhdfe* developed by Correia et al. (2020). In unreported regressions, available upon request, we have verified that the coefficients estimated using a standard fixed effects model, with the dependent variable expresses either in levels or in logarithms, are severely biased, confirming the discussion in Silva and Tenreyro (2006).

[9] last accessed on June $15^t h$, 2023 at https://www.oecd.org/els/mig/oecdmigrationdatabases.htm.

[10] see OECD (2020) for technical details.

of the emigration rate with respect to each explanatory variables. All specifications include bilateral time-invariant $j$ x $k$ and origin-country time-varying $j$ x $t$ dummy variables. Standard errors, reported in brackets, are clustered at the origin-country and year level. Regressions are weighted by the population of the origin country $j$ observed on the initial year, $t_0 = 2000$.

Column 1 reports the results of a regression model that includes only characteristics specific to the destination country $k$ at time $t$: per-capita GDP and the stock of migrants from country $j$ already living in country $k$, capturing the *direct network* effect. Consistent with the basic theoretical model of migration, and with most of the empirical literature, the estimated elasticity of the emigration rate with respect to per-capita GDP of the destination country is positive and significant at the 99-percent level. The coefficient show little variations also in the following specifications of Table 2, where we include as additional explanatory variables the characteristics of the alternative destination countries (Columns 2 and 3), implying that an increase of 1 per cent in the per-capita GDP of country $k$ induces an increase of about 0.5 per cent in the migration flows from $j$ to $k$.

Existing empirical evidence has already emphasized the role of the presence at destination of migrants from the same origin in reducing the migration costs. The coefficient of 0.048, that is statistically significant at the 99-percent level, suggests that a 10 per cent increase in the stock of migrants from $j$ in $k$ increases the emigration rate by about 0.5 per cent. Reassuringly, also the coefficient of the emigration rate with respect to the stock of compatriots living at destination – *i.e.*, the *direct network* effect – is broadly unchanged across all the specifications of Table 2 (see also Columns 2 and 3).

Column 2 reports the results obtained including among the regressors also the characteristics of countries $l \neq k$, weighted by the inverse of the geographical distance from $k$ to $l$. The most remarkable result is that they all have an impact on the emigration rate that is statistically significant at the 99-percent level. In this regard, our attempt to model the multilateral resistance term can be considered successful. More in detail, the elasticity with respect to the weighted average of the stock of migrants from country $j$ that live in country $l$ at time $t$, that captures the impact of the network in the alternative destinations – *i.e.*, the *weighted network* effect– is equal to $-0.169$, suggesting that migrants are less likely to choose a destination that is surrounded by countries with a larger number of compatriots. A change in this index from its value at the $25^{th}$ percentile of its distribution to that at the $75^{th}$ percentile (the inter-quartile change) causes a drop of 8 percent of the emigration rate.

Although we cannot directly control for subsequent migration flows from one destination country to another, this results is at odd with the view that migrants are more likely to choose a destination if they expect that they can use it as a bridge to eventually move to a (close) third country.

The coefficient of the weighted level of per-capita GDP in the alternative destinations is instead positive and equal to 3.067, suggesting that migrants are more likely to move to destinations that are surrounded by faster growing countries. In this case, the inter-quartile change causes a massive 1.25-fold increase of the emigration rate. This large effect might be due to the geographical distribution of the potential destinations, with a large cluster of countries in mainland Europe and high mobility among them. One possible explanation might be that migrants tend to locate close to growing countries in order to take advantage of the increasing job opportunities there and, at the same time, reside where the costs of living are lower. Indeed, cross-border workers are well documented, especially within smaller areas (see *e.g.* Bello, 2020).

However, the previous explanation might be conflated by a potential spatial correlation in the growth rate of per-capita GDP. To contrast this alternative explanation we computed the spatial correlograms (as in Wheeler, 2001). Reassuringly, Figure 1 shows that in our sample there is no clear declining pattern in the correlation of the growth rate of per-capita GDP with respect to geographical distance.

Column 3 reports the results of a specification that includes one additional measure of the characteristics of alternative destinations, that is the outflows of migrants from the origin country $j$ to each possible destination country $l$ except $k$, weighted by the inverse of the distance with respect to country $k$. This index can be seen as the flow counterpart of the *weighted network* effect. The estimated coefficient is negative ($-0.627$), implying that the emigration rate to a given destination is lower when the emigration rate to close alternative destinations is higher. The inter-quartile change causes in this case a 47-percent drop of the emigration rate. Migrants thus see the possible destinations as substitute, and this prevails with respect to a possible wave-effect towards groups of neighbouring countries.

Reassuringly, the inclusion of this additional control has almost no impact on the estimated elasticities with respect to the specific characteristics of country $k$, *direct network* and pre-capita GDP, but it nearly halves the elasticities with respect to the weighted average of those same characteristics in the alternative destinations. All effects remain statistically significant at the 99-percent level, but the coefficient of the *weighted network* which is now significant at the 90-percent level.

# 6 Robustness and Additional Results

## 6.1 Robustness checks

In principle, our baseline results can be obtained also by implementing a log-linearised regression model. The results of the OLS estimation method are presented in Column 1 of Table 3, and – as expected – are consistent in the sign but not in the magnitude nor in the statistical significance with our baseline results, obtained through a Poisson pseudo maximum likelihood model and replicated, on a comparable sample, in Column 4 of Table 3. In particular the per-capita GDP of the destination country is now very small and not significant.

More generally, there might be concerns regarding the consistency of the estimated effect of destination-country GDP on migration flows. As already stressed, per-capita GDP at destination is an important pull factor for prospect migrants, but at the same time it might be affected by the arrival of new immigrants. There is a vast literature that shows that (high-skilled) migration positively affects economic growth at destination through innovation. This effect becomes more pronounced with a higher degree of assimilation among immigrants, and consequently, with a longer time span over which the effect is evaluated (see, *e.g.*, Ottaviano and Peri, 2006 and Burchardi et al., 2020).

To address concerns regarding potential bias from a reverse-causality issue in estimating the effect of destination-country GDP on migration flows all our specifications include lagged per-capita GDP. Furthermore, we estimate a 2SLS regression model and results are presented in Column 2 of Table 3. To instrument per-capita GDP, we leverage exogenous variations caused by financial crises – specifically sovereign debt crises – using the database introduced by Nguyen et al. (2022). The dataset covers 200 debt crises for 206 countries over more than 50 years, specifically from 1960 to 2019. The exclusion restriction requires that the debt crises in year $t$ affects migration flows at year $t + 1$ only through its effect on per-capita GDP. We argue that the instrument is plausibly exogenous, given that our dataset consists exclusively of economic migrants who are more likely to be responsive to variations in local-market conditions rather than changes in public spending or transfers. Furthermore, the instrument is deemed relevant, as indicated by the F-statistic of the first stage regression, which is approximately 21.

The effect of per-capita GDP at the destination is now significant at the 99-percent level, implying an elasticity of migration flows approximately equal to 1. Obviously, the IV coefficient is more accurate for those destination countries where per-capita GDP dropped during our sample period due to sovereign debt crises.[11] Instrumenting per-capita GDP in the destination country also impacts on the coefficient of the per-capita GDP of neighbouring countries, which is larger in absolute value than that obtained using OLS, but is estimated with much less precision and it is therefore statistically insignificant. Likely, this is explained by the fact that with IV estimates the effect of per-capita GDP of the destination country is controlled for only during debt crises, and therefore in other years it is partly captured by the evolution in neighbouring countries.

An additional aspect that might affect our estimates is that migration flows are persistent through time. To address this issue we have also controlled for past migrations, including among the explanatory variables the one-year lagged of the dependent variable and estimating our model employing the Generalized Method of Moments (GMM) of Arellano and Bond (1991). The results are shown in Column 3 of Table 3. As expected, the coefficient of the lagged dependent variable is 0.928 and it is statistically significant at the 99-percent level, confirming the high degree of persistence of migration flows. The sign and significance of all other coefficients is broadly consistent with that of the baseline specification, with the exception of the *weighted network*.

## 6.2 Additional results: Origins' income class

The impact of the characteristics of the destination countries on the decision to migrate may also vary depending on the conditions in the origin country. This hypothesis reflects the individual migration-choice model, particularly highlighting the so-called *Sympson's Paradox*. Specifically, the literature has shown that due to the presence of liquidity constraints and the nature of migration as an inferior good, the elasticity of migration with respect to individual income is smaller in both the lower and upper tails of the income distribution (Clements and Mendola, 2020). To partly test this hypothesis on a larger scale, in Table 4 we present the results of our baseline specification estimated on four sub-samples obtained by splitting the original sample depending on the income level of the origin country (see Table 4).

[11] More specifically, the coefficient on per-capita GDP estimated using our instrumental variables measures the *local treatment effect* during periods when the debt crises affected GDP.

Consistent with the individual migration-choice model, the elasticity of migration with respect to per-capita income is negative and not statistically significant for migrants from high-income countries ($-0.191$). Conversely, it is positive and statistically significant for poorer countries, reaching its highest value (1.899) among upper-middle income countries. In the latter case, the elasticity with respect to the number of migrants from the same country of origin, the *direct network* effect, is negative and statistically insignificant, suggesting that among this group of countries emigration flows primarily respond to expected income at the destination.

The *direct-network* exhibits a positive and statistically significant effect at the 90-percent level among high-income countries. However, this effect becomes statistically more significant, reaching the 99-percent level, when considering samples of origin countries in lower income classes, with values of 0.108 for the lower-middle income class and 0.055 for the low-income class.

Among the characteristics of alternative countries, the *weighted network* effect is never statistically significant. On the contrary, the distance-weighted flows from the origin country to all possible destinations alternative to $k$ have a negative and statistically significant effect, with values decreasing as we consider lower-income countries. Finally, the coefficient of the weighted level of per-capita GDP in the alternative destinations is negative and statistically insignificant for the sample of high-income origin countries. However, it is positive and statistically significant in all other sub-samples except the lower-middle income subgroup, and its magnitude decreases as we consider origin countries with progressively lower income.

### 6.3 Additional results: Cultural distance

So far, we have weighted the characteristics of the $l$ destinations alternative to destination $k$ using the inverse of the geographical distance between $k$ and $l$. While this is an obvious assumption if one considers that migration costs have been shown to be well proxied by geographical distance, alternative measures of the distance between country couples could be considered.

An increasing consensus is emerging that cultural distance between countries does play a role in determining the different dimensions of international exchanges and, especially for migration, it might be an even more important component of moving costs than geographical distance.

The literature on international trade has used different measures of cultural distance, often approximated with common religion, language, or ethnicity (see e.g. Melitz, 2008; Rauch and Trindade, 2002), but also non-dummy measures have been proposed. For example, Felbermayr and Toubal (2010) have considered the score given to music songs performed in an international contest by referees from different countries, and White and Tadesse (2008) have used data from the European Value Survey to built a measure of cultural proximity based on shared norms and values.

In the sociological literature, Hofstede (2011) has been one of the first to give an operational definition of national culture, gauged along six dimensions: Power distance, uncertainty avoidance, individualism, masculinity, long-term orientation, and indulgence. Among these dimensions, two of them – *i.e.*, long-term orientation and indulgence – can be assessed with data of the World Value Survey Database and, therefore, observed for all the country pairs in our dataset.

As a metrics of cultural distance, we follow Rapoport et al. (2021) and compute the Euclidean distance. Therefore, for each country pair, we compute:

$$Dist(Cult)_{k,j} = \sqrt{|Long_k - Long_j|^2 + |Ind_k - Ind_j|^2} \tag{18}$$

where $Dist(Cult)_{k,j}$ is the cultural distance between countries $k$ and $j$, $Long_i$ and $Ind_i$ are degree of, respectively, long-term orientation and indulgence in country $i$ (with $i = k, j$).[12]

This different measure of distance is then used to compute the weighted average of the characteristics of neighbouring countries considered in the baseline specification – *i.e.*, the average per-capita GDP, the average stock, and the average outflows of migrants from the same origin.

Figure 2 shows the average stock of migrants from the same origin, living in alternative destinations, over the period of analysis, weighted by the inverse of the geographical distance in panel (a) and by the inverse of the cultural distance in panel (b). It is easy to grasp, for example, that the USA shows a network of compatriots in the geographically close country much greater than the network of compatriots in the culturally close country.

To assess whether and to which extent the alternative destinations are differently weighted by prospect migrants we re-estimate the regression models by including the cultural-distance weighted characteristics of neighboring countries.

Column (1) of Table 5 shows that destination countries with greater networks and higher per-capita GDP in the (cultural) neighbours attract higher flows of migrants, pointing at a complementarity effect among culturally similar countries. However, these effects are no longer significant once we include also concurrent flows to the culturally similar destinations (see Column (2) of Table 5).

The coefficient of the weighted average of outflows is negative and consistent to the inclusion of the geographical-distance weighted average characteristics of neighbouring countries (Columns 2 and 3 of Table 5).

More in detail, if the cultural-distance weighted average of outflows to other countries increases, passing from the $25^{th}$-percentile value to $75^{th}$-percentile value, the predicted value of emigration rate decreases by about 5 percentage points. The conclusion we drawn from these results taken together is a general competition effect among alternative destinations that are culturally close.

# 7 Concluding remarks

Most of the empirical literature on migrations models the destination choice as a decision between two alternatives, staying at home and going to a given destination. In fact, the typical IIA (Independence of Irrelevant Alternatives) assumption implies that the decision to stay in country $j$ or migrate to country $k$ only depends on the characteristics of $j$ and $k$.

In practice, however, a more general framework would be preferable, in which a change in the relative attractiveness of given potential destination impacts heterogeneously on the migration

[12] According to Hofstede (2011) long-term orientation deals with change and indulgence is about the good things in life (see `https://geerthofstede.com/` for more details and data).

flows to alternative locations. In fact, everybody would agree that a wall between Serbia and Hungary is likely to have a stronger impact on migration flows from Serbia to Croatia than from Serbia to Japan.

The typical solution adopted in the empirical literature to address the problem caused by the IIA assumption is to introduce in the estimation model country-year specific dummy variables, thus controlling for the impact of the 'Multilateral Resistance Term". Although this approach allows to obtain unbiased estimates of the variables that can be identified also in presence of the country-year fixed effect, it does not permit to measure the economic impact of the relative attractiveness of the potential alternative destinations. For this reason, in this paper we explicitly model the relative attractiveness of destinations, with both a theoretical and an empirical approach. First, we extend the Random Utility Model (RUM) by Marschak (1960) in order to include distance-weighted average of the characteristics of neighbouring countries and, secondly, we estimate a Pseudo-Poisson regression model consistent with the theory.

The results suggest that migrants positively respond to the economic improvements, measured as the per-capita GDP, and the presence of compatriots at destination, confirming the well-documented network effect. Moreover, they show that the characteristics of alternative destinations have a statistically and economically significant effect on the choice of where to migrate: The presence of migrants from the same country of origin in other destinations discourages the flows to a given country, while a higher per-capita GDP in the alternative destinations exerts instead a pull effect.

# 8 Figures

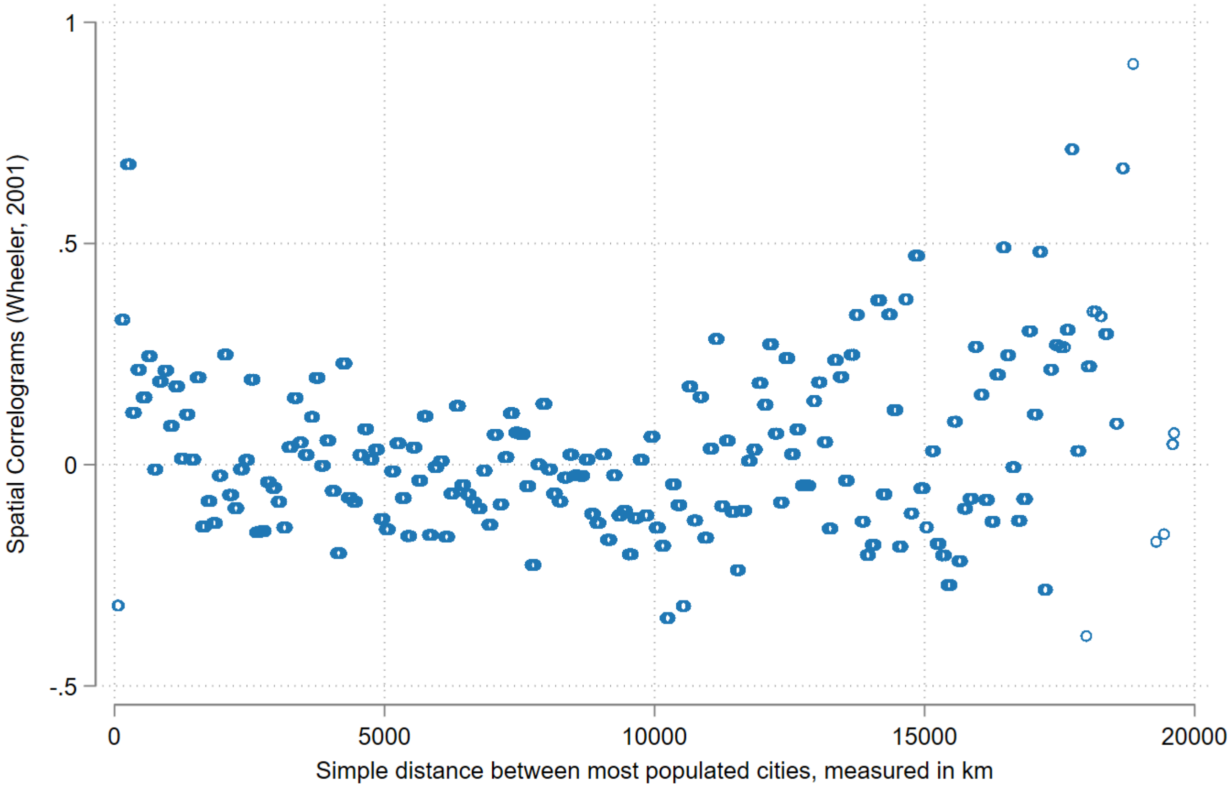
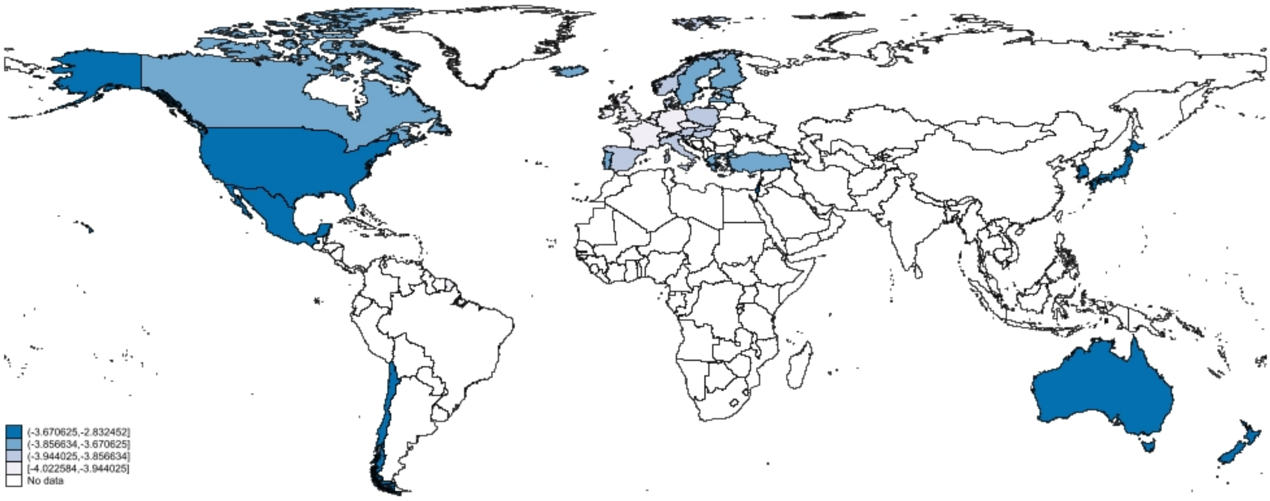
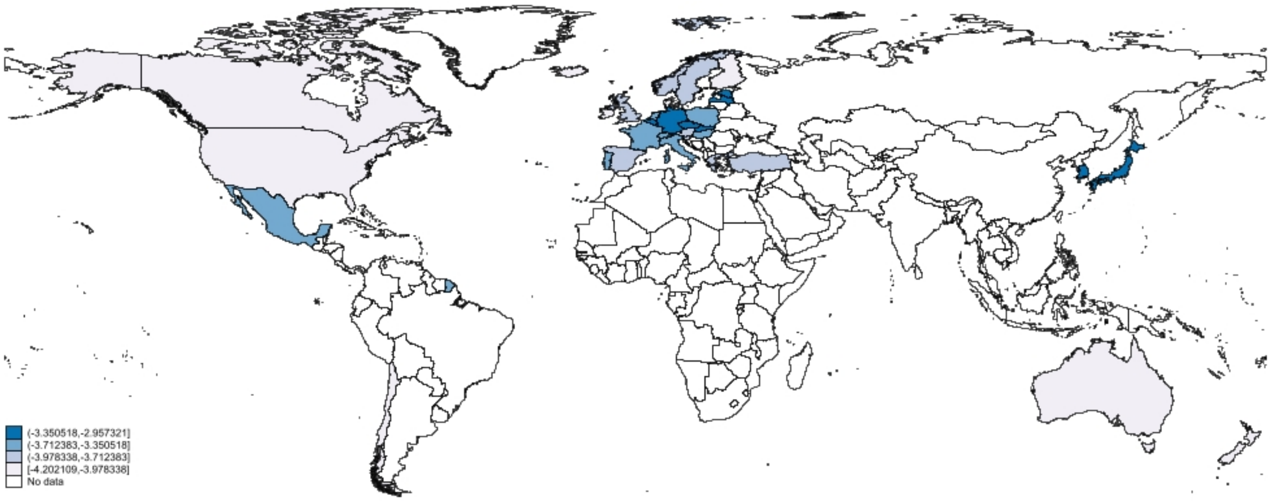



Figure 1: Spatial correlation of per-capita GDP growth rates




(a) Geographical-distance weighted average network




(b) Cultural-distance weighted average network

Figure 2: Distance-weighted average network in alternative destinations

# 9 Tables

Table 1: Summary statistics of the regression variables

| | mean | st. dev. | min | max | obs. |
|---|---|---|---|---|---|
| migration flow to k | 0.492739 | 2.107821 | 0 | 38.57347 | 146832 |
| migrant network in k | 0.232039 | 1.249441 | 0 | 26.11202 | 146851 |
| GDPpc of k | 34978.46 | 14075.72 | 9709.896 | 95503.24 | 122850 |
| GDPpc of j | 28618.74 | 18550.24 | 0 | 95503.24 | 150920 |
| dist-w-to-k migrants in l | -3.65381 | 0.415717 | -5.75897 | -2.11281 | 145296 |
| dist-w-to-k GDPpc of l | -3.70065 | 0.483778 | -4.0726 | -2.37094 | 122850 |
| dist-w-to-k migrant flows to l | -3.7235 | 0.541988 | -5.43929 | -2.0159 | 137402 |

*Notes*: Authors' elaboration on OECD International Migration database (last accessed on June 15, 2023) and CEPII data. Migrantion flows and migrant networks are computed as ratios over the population of the origin country. The GDP and the population are measured in thousand. Statistics are population weighted. Distance-weighted averages are expressed in logarithms. A log transformation is applied to all the variables that enter the estimated equation.

Table 2: Estimation results of the baseline specification

| | (1) migration | (2) migration | (3) migration |
|---|---|---|---|
| GDPpc of k | 0.528*** | 0.598*** | 0.537*** |
| | (0.098) | (0.100) | (0.092) |
| stock of migrants from j to k / population of j | 0.048*** | 0.040*** | 0.039*** |
| | (0.013) | (0.014) | (0.014) |
| dist-w-from-k migrant stocks from j to l / population of j | | -0.169*** | -0.071* |
| | | (0.036) | (0.038) |
| dist-w-from-k GDPpc of l | | 3.067*** | 2.260*** |
| | | (0.656) | (0.607) |
| dist-w-from-k outflows from j to l / population of j | | | -0.627*** |
| | | | (0.023) |
| Observations | 118,961 | 116,669 | 113,311 |
| num. of clusters | 3481 | 3472 | 3419 |
| origin-destination FE | yes | yes | yes |
| origin-year FE | yes | yes | yes |

*Notes*: Authors' elaboration on OECD International Migration database (last accessed on June 15, 2023) and CEPII data. In all models, the dependent variable is the emigration rate from the origin country, measured as the number of yearly outflow over the country population. The estimation method is a PPML model with fixed effects (Correia et al., 2020). Regressions are weighted by the population of the country of origin on the initial year. Errors are clustered at the origin-year level. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Robustness test - Comparing different estimation methods.

| | (1) OLS | (2) IV | (3) GMM | (4) PPML |
|---|---|---|---|---|
| GDPpc of k | 0.014 | 0.988*** | 0.022** | 0.569*** |
| | (0.046) | (0.233) | (0.009) | (0.099) |
| stock of migrants from j to k / population of j | 0.964*** | 1.033*** | 0.147*** | 0.038*** |
| | (0.089) | (0.211) | (0.057) | (0.015) |
| dist-w-from-k migrant stocks from j to l / population of j | -0.374*** | -0.402** | 0.030 | -0.070* |
| | (0.067) | (0.168) | (0.019) | (0.041) |
| dist-w-from-k GDPpc of l | 4.811** | 8.608 | 0.071** | 2.413*** |
| | (1.946) | (5.186) | (0.034) | (0.667) |
| dist-w-from-k outflows from j to l / population of j | -0.974*** | -0.980*** | -0.109** | -0.663*** |
| | (0.084) | (0.205) | (0.045) | (0.027) |
| one-year-lag emigration rate from j to k | | | 0.928*** | |
| | | | (0.034) | |
| Observations | 109,547 | 109,547 | 107,176 | 109,547 |
| num. of clusters | 3311 | 3402 | . | 3419 |
| origin-destination FE | yes | yes | yes | yes |
| origin-year FE | yes | yes | no | yes |
| Weak IV test | . | 20.774 | . | . |

*Notes*: Authors' elaboration on OECD International Migration database (last accessed on June 15, 2023) and CEPII data. In all models, the dependent variable is the (log of) emigration rate from the origin country, measured as the number of yearly outflow over the country population. In columns (1) the regression model is a FE-panel model estimated by OLS. In column (2) the regression model is a FE-panel model estimated by 2SLS. The endogenous regressor is the per-capita GDP of the destination country, instrumented by currency crises (data source: Nguyen et al. (2022) - last accessed on February 28, 2024). The reported Weak IV test is the Kleinbergen-Paap rk Wald statistics. In column (3) the regression model is a GMM model with one-year lag. In columns (4) the estimation method is a Poisson pseudo maximum likelihood model with fixed effects (Correia et al., 2020). Marginal effects are reported. All the regression models are weighted by the population of the origin country on the initial year. Errors are clustered at the origin-year level. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Estimation results by income class

| | (1) H | (2) UM | (3) LM | (4) L |
|---|---|---|---|---|
| GDPpc of k | -0.191 | 1.899*** | 0.599*** | 0.185*** |
| | (0.337) | (0.199) | (0.131) | (0.056) |
| stock of migrants from j to k / population of j | 0.068* | -0.018 | 0.108*** | 0.055*** |
| | (0.041) | (0.045) | (0.020) | (0.019) |
| dist-w-from-k migrant stocks from j to l / population of j | 0.219 | -0.142 | -0.044 | -0.008 |
| | (0.144) | (0.156) | (0.052) | (0.016) |
| dist-w-from-k GDP of l | -5.442** | 10.425** | 1.084 | 0.903* |
| | (2.515) | (4.666) | (1.180) | (0.500) |
| dist-w-from-k outflows from j to l / population of j | -1.894*** | -0.661*** | -0.370*** | -0.131*** |
| | (0.148) | (0.060) | (0.035) | (0.010) |
| Observations | 30,184 | 24,700 | 29,654 | 25,809 |
| num. of clusters | 932 | 762 | 902 | 790 |
| origin-destination FE | yes | yes | yes | yes |
| origin-year FE | yes | yes | yes | yes |

*Notes*: Authors' elaboration on OECD International Migration database (last accessed on June 15, 2023) and CEPII data. In all models, the dependent variable is the emigration rate from the origin country, measured as the number of yearly outflow over the country population. Marginal effects of a Poisson pseudo maximum likelihood model with FE (Correia et al., 2020) and weighted by the population of the country of origin on the initial year are reported. Errors are clustered at the origin-year level. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimation results of the baseline specification with cultural-distance

| | (1) migration | (2) migration | (3) migration |
|---|---|---|---|
| GDPpc of k | 0.542*** | 0.386*** | 0.602*** |
| | (0.089) | (0.078) | (0.080) |
| stock of migrants from j to k / population of j | 0.062*** | 0.058*** | 0.055*** |
| | (0.014) | (0.013) | (0.013) |
| cult-dist-w-from-k migrant stocks from j to l / population of j | 0.131*** | 0.020 | 0.023 |
| | (0.034) | (0.028) | (0.030) |
| cult-dist-w-from-k GDPpc of l | 2.692*** | -0.929 | -0.085 |
| | (0.695) | (0.610) | (0.603) |
| cult-dist-w-from-k outflows from j to l / population of j | | -0.693*** | -0.429*** |
| | | (0.030) | (0.032) |
| dist-w-from-k migrant stocks from j to l / population of j | | | -0.049 |
| | | | (0.039) |
| dist-w-from-k GDPpc of l | | | 3.147*** |
| | | | (0.555) |
| dist-w-from-k outflows from j to l / population of j | | | -0.479*** |
| | | | (0.030) |
| Observations | 113,209 | 109,641 | 106,651 |
| num. of clusters | 3472 | 3419 | 3419 |
| origin-destination FE | yes | yes | yes |
| origin-year FE | yes | yes | yes |

*Notes*: Authors' elaboration on OECD International Migration database (last accessed on June 15, 2023) and CEPII data. In all models, the dependent variable is the emigration rate from the origin country, measured as the number of yearly outflow over the country population. Marginal effects of a Poisson pseudo maximum likelihood model (Correia et al., 2020) and weighted by the population of the country of origin on the initial year are reported. Errors are clustered at the origin-year level. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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