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“Do neighboring countries matter when explaining bilateral remittances?”

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Do neighboring countries matter when explaining bilateral remittances?*

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Abstract

We measure to what extent neighboring countries affect the amount of remittances between a source and a recipient country, controlling for the commonly used macro determinants of remittances (such as, economic activity, inflation, distance and transaction costs). For the study, we rely on bilateral remittances' data involving 67 source countries and 129 recipient countries all over the word. We provide novel evidence on the importance of neighbouring countries on remittance flows, with the parameter estimates capturing origin- and destination-spatial dependence being both positive and significant. This result is crucial, because disregarding the role of neighbouring countries leads to biased estimates for the determinants of remittances and misprediction. Indeed, prediction errors decrease by 67% when we correctly account for the role of neighbouring countries (relative to the standard non-spatial model for bilateral remittances). By properly accounting for the role of neighboring countries, we then re-examine the altruism and investment motives to remit. Finally, we apply our model estimates to quantify the expected negative impact of the COVID pandemic shock on the bilateral remittances. Interestingly, we find that remittances may be more resilient for low- and middle-income countries, which are the ones that rely on remittances the most.

Keywords: Bilateral remittances, migrants, network effects.

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1 Introduction

Recorded remittances to low- and middle-income countries (LMIC) have grown at an impressive 11% annual rate since 2000, to reach USD 554 billions in 2019, constituting the largest source of foreign capital of LMIC, even before foreign direct investment or FDI (World Bank, 2020). However, projections are that remittances will decline sharply by about 20 percent in 2020 due to the economic crisis induced by the COVID pandemic. While decreasing in value, the relative importance of remittance flows as a source of external financing for LMIC is still expected to rise. This is because FDI and private capital flows are expected to decline by even more as they are more volatile and less resilient (see for instance Balli and Rana, 2015), due to travel bans, disruption of international trade, and wealth effects of declines in the stock prices of multinational companies (Ratha et al., 2020). In this context, understanding the determinants of remittances is important, especially when we consider that these remittance flows reduce poverty (Adams Jr and Page, 2005; Jongwanich, 2007; Le Goff, 2010), allow recipients to smooth consumption (Balli and Rana, 2015) and are used for investment purposes (Adams Jr and Cuecuecha, 2010; Cooray and Mallick, 2013; Yang, 2008).

This paper quantifies to what extent neighbouring countries affect the amount of bilateral remittances (between a source and a recipient country), controlling for the determinants of remittances that the macro-literature has already identified (such as, economic activity, inflation, remittance costs and former colony relations). The impact of neighbouring countries in our context means that larger observed remittance flows from a source country A to a recipient country Z might be accompanied by: (1) larger remittance flows from countries nearby the source country A to the recipient country Z; (2) larger remittance flows from the source country A to countries neighboring the recipient country Z and (3) larger flows from countries that are neighbors to the source country to countries that are neighbors to the recipient. (1) is called an origin-dependence effect; (2) a destination-dependence effect and (3) an origin-to-destination dependence effect. Relying on bilateral remittance data involving 67 source countries and 129 recipient countries all over the word, we find positive and significant origin- and destination- spatial dependence. This finding is crucial, because disregarding the role of neighbouring countries leads to biased estimates for the determinants of remittances and misprediction. As a matter of fact, prediction errors decrease by 67% when we account for the role of neighbouring countries (relative to the standard non-spatial model for remittances). As an application of our model, we quantify the expected negative impact of the COVID pandemic shock on bilateral remittances.

There are two main mechanisms that explain why neighbouring countries may have an impact on bilateral remittances, namely, migration to countries with historical or cultural ties (Fenoll and Kuehn, 2018) and regional business cycles (Balli and Rana, 2015; Bettin et al., 2017; Cooray and Mallick, 2013). To build intuition and illustrate how these mechanisms are active in the case of origin-dependence, consider the following situation: A large number of migrants from a given country Z, say Venezuela, move into a country A, for example Spain, because of favorable labor market and economic conditions in A. It is then likely that we also observe migrants from country Z moving into other countries B and C in the neighbourhood of A, for instance Italy and Portugal, if there are favorable economic conditions in those other countries as well. We should hence expect to observe more remittances from countries A, B and C to the home country of these migrants, Z. The latter situation would be consistent with an origin-based spatial dependence for remittance flows. Figure 1 illustrates this idea for Venezuela. The left panel shows how Venezuelan people have migrated to Spain and to the neighboring countries of Spain, namely, Italy and Portugal (these three countries were among the top five destinations of Venezuelan migrants in 2017). The right panel shows that among the top five countries remitting money to Venezuela in 2017, they were Spain, Italy and Portugal.

To illustrate the destination-dependence, consider now a large number of migrants moving away from a country Z, say Algeria, to another country W, say France. We may expect to see migrants from other countries X and Y, say Morocco and Tunisia, near Z, also moving away from these countries to country W, if there are unfavorable economic conditions at their home countries. We should then observe larger remittances from country W to countries Z, X and Y, when migrants in W send money back home. The latter description is consistent with a destination-dependence. Figure 2 illustrates this situation by depicting the countries receiving money from France in 2017. We observe in that Figure that Algeria, Morocco and Tunisia are among the main recipient countries of remittances sent from France (and they are also in the top five ranking of countries of origin of migrants to France). Therefore, these examples show that migration and regional business cycles are important reasons for neighboring countries affecting the bilateral remittance flows.[1] The main contribution of this paper is that, for the very first time, we quantify to what extent these neighbouring countries affect bilateral remittance flows, controlling for the standard remittances' determinants. To the best of our knowledge, the existing macro-literature on remittances, up to present, has not considered them.

Data on bilateral remittances come from the World Bank: They are derived from a global estimation of bilateral remittance flows worldwide, building upon the methodology developed by Ratha and Shaw (2007).[2] Our dataset comprises 67 source countries and 129 recipient countries all over the world, for which workers' remittances are reported in 2017, with 60 countries being both source and recipient countries. For a robustness exercise, we also report estimates for 2012. As macro determinants of the remittances, we include the use of electricity per capita, which is a proxy for economic activity; inflation (as measured by GDP deflator); the political stability index; dummy variables for the occurrence of natural disasters; the existence of multiple exchange rates and/or capital controls and foreign exchange volatility, which are proxies for financial frictions; the average transfer fee at the source country;[3] and gravity variables characterizing the country pairs in the bilateral remittance flows, such as distance, whether the two given countries have had colony relations, among others. All country characteristics are lagged two years to mitigate reverse causality. Last, we define proximity in the set of source (recipient) countries, based on the 3-nearest neighbours.

[1]Figure 3 highlights the importance of the neighbouring countries when studying remittance flows, this time, grouping countries by geo-economic zones. This Figure makes clear that remittances are a regional phenomenon.

[2]The global estimation of bilateral remittance flows worldwide rely on source and recipient country incomes, as well as estimated migrant stocks (at country level).

[3]Following Freund and Spatafora (2008), we instrument transactions costs in the source country using the two year-lagged financial development index and a dollarization dummy variable.

Our work has three main contributions. First, we provide novel evidence about the effect of neighbouring countries on the remittance flows. We find that the parameter estimates capturing the origin- and destination- spatial dependence are positive and statistically significant, thus confirming that larger observed remittance flows from a source country A to a recipient country Z are likely to be accompanied by, larger remittance flows from countries that are neighbors to the source country A (and the neighbours of its neighbours) to the recipient country Z, and by larger remittances from the source country A to countries that are neighbors to the recipient Z (and the neighbours of its neighbours). This result is crucial, because it means that omitting to account for spatial dependence leads to biased estimates for the determinants of remittances, inefficient standard errors and misprediction. Indeed, we show that accounting for neighbouring countries reduces prediction errors by 67% when we express bilateral remittances in nominal terms and by 27% when remittances are in logarithm (as measured by the changes in the mean average percentage error of the spatial and the non-spatial model). To the best of our knowledge, no previous work has documented the role of neighbouring countries on bilateral remittances at the macro level.

Second, by properly accounting for the role of neighbouring countries, we re-examine the altruism and investment motives to remit[4] and we assess the relative importance of each motive. Interestingly, our results show that the altruism motive is the most important motive for remitting money, followed by the investment motive. Specific to the altruism hypothesis, we find that remittances: i) increase when the economic activity of the source country increases;[5] ii) grow after the occurrence of a natural catastrophe (possibly, to help family members at home to overcome the damages); iii) are smaller if the purchasing power of the overseas workers in the source country decrease, which is the case when the country is under a high or moderate inflation regime; iv) are larger if the recipient country is under a high or moderate inflation regime. Regarding the investment hypothesis, we find that remittances increase when the economic activity of the recipient country expands and that remittances are sensitive to the investment and political climate in the recipient country. On top of that, we confirm Freund and Spatafora (2008)'s findings that remittances decrease with transfer costs and with financial frictions (with the latter being proxied by the existence of multiple exchange rates and/or capital controls and foreign exchange volatility in the source countries). Last, we show that the gravity variables (such as, whether the two countries in a given country pair have had colony relations, whether the countries share a language, a border or the currency) are key determinants of bilateral remittances.

Third, we show that a shock to an origin characteristic at a particular location, say economic activity, has a greater impact on remittance flows, relative to a shock to a destination characteristic. This is because we find that local (country-specific) origin effects (which summarize the impact of changing an

[4]According to the altruism hypothesis, overseas workers and/or migrants may send more remittances home when their home country's relative income declines, so as to compensate for the lost income of family members owing to economic downturn back home, and when the relative income of the country where they live in and work increases. In turn, the investment motive states that remittances would be used to seize investment opportunities at the migrant's home; hence, when income there grows, remittances to the migrants' home should increase.

[5]To give an order of magnitude, a 6% expansion in the electricity use per capita of a typical source country is expected to increase the remittance flows originating from that representative location by 6% to 8%, depending on the model specification.

origin characteristic on the flows departing from that given changed location), tend to be larger than destination effects (which measure the impact of changing a destination characteristic on the flows arriving at that given location). Interestingly, this finding holds regardless of the level of economic development of the country under analysis and is also true at the aggregate (cumulative) level. In contrast, we find that network effects (which measure the impact of a change in a given characteristic on all the remittance flows that do not originate nor arrive at that representative location) are non-negligible at the aggregate level, and are heterogeneous across countries. Precisely, we find that economies sending or receiving money from a largest number of countries, and the more central source countries (in the sense of a country being connected to many other countries which are, in turn, connected to many others) are the ones exhibiting the largest network effects. This is an interesting finding. The way we read it is that these economies exhibit large network effects because they can transmit shocks to and/or may be exposed to shocks from many more countries, that is, they are subject to higher order effects. Higher order effects arise when a shock to a given country is transmitted to other countries not directly linked to the stressed country (with the transmission being due to, for example, real (trade) or financial linkages in the form of common investors between countries).

To conclude, this article is a first study of the importance of neighbouring countries to explain bilateral remittances at the macro level. It hence sharply contrasts with the existing macro literature on remittances which does not account for these neighbouring effects. For this study, we propose a flexible methodology that has the capacity to accommodate for multiple spatial weight matrices (capturing origin- and destination- dependence), a different list of locations for origins and destinations, as well as different characteristics for the source and the recipient countries.[6] Furthermore, following Laurent et al. (2021), we distinguish between local (country-specific) and cumulative (aggregated) origin, destination, network and total effects. However, the study is subject to one drawback, as it includes data only from formal providers of remittance services. By some estimates, one third of the remittances are sent through informal channels (Freund and Spatafora, 2008). This limitation notwithstanding, the article offers novel evidence on the importance of neighboring countries that should stimulate further data collection on bilateral remittances.

The paper is organised as follows. Section 2 describes the spatial autoregressive interaction model we consider to model bilateral remittance flows and discusses how to interpret the model estimates. Section 3 lists the hypotheses we test, whereas section 4 presents the data and details the construction of the neighbourhood matrices. Section 5 presents the main results: It first presents the baseline model estimates, it then discusses the evidence for the hypotheses to remit and, last, it presents the local origin, destination and network effects. As an application, section 6 quantifies the impact of the COVID pandemic shock on bilateral remittance flows. Finally, section 7 concludes. An online appendix contains

[6]To the best of our knowledge, we know of a single paper, Lee and Pace (2005), that considers different lists for origin and destination locations in a spatial gravity model. Their application is in the geo-marketing literature where the flows happen between a retail store and consumers. Their model includes a single spatial weight matrix combining customer proximity and store proximity. Moreover, they use the restrictive assumption that customers from a given area go shopping at a single store. In contrast, in this paper, we demonstrate that a gravity model with spatial dependence can be defined with a more flexible specification.

all the R codes used to produce the results exhibited in the paper.

Figure 1: Left: Three of the top five destinations of Venezuelan migrants in 2017. Right panel: Three of the top five countries remitting money to Venezuela in 2017

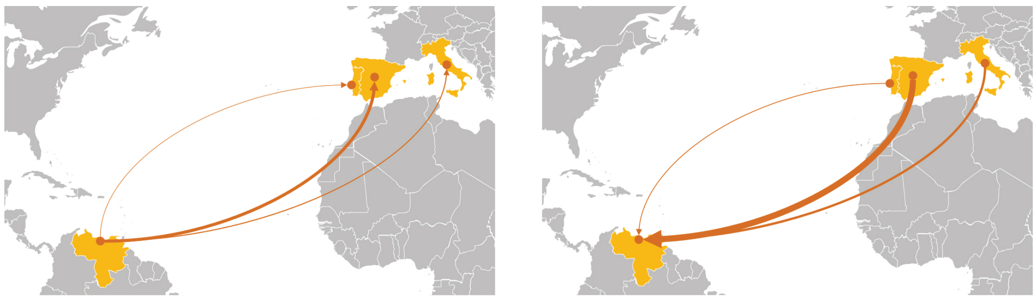


Figure 2: Countries receiving money from France in 2017

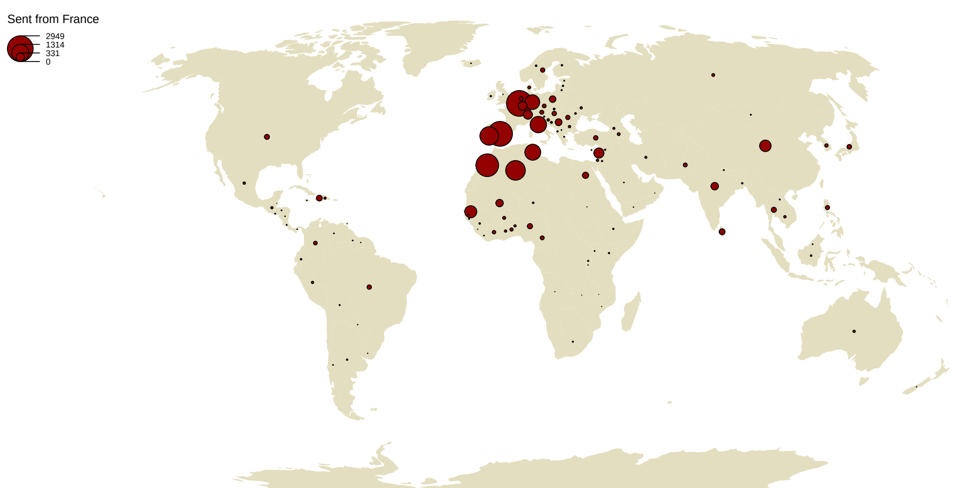
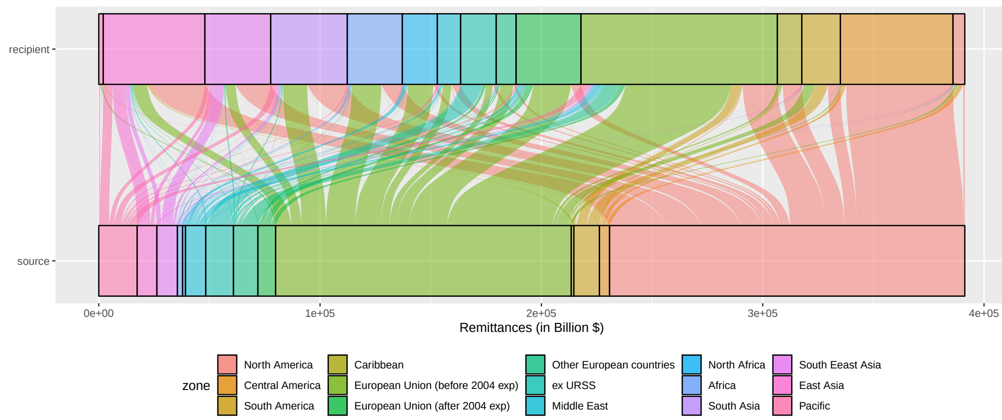


Figure 3: Bilateral remittance flows, by geo-economic zones in 2017



2 Spatial autoregressive interaction models for remittance flows

The objective of this paper is to model bilateral remittances accounting for the role of neighbouring countries. In our context, the impact of neighbouring countries, or spatial dependence as the spatial econometric literature calls it, means that larger observed remittance flows from a source country A to a recipient country Z might be accompanied by: (1) larger remittance flows from countries nearby the source country A to the recipient country Z, say countries B and C that are neighbors to country A; (2) larger remittance flows from the source country A to countries neighboring the recipient country Z; and (3) larger flows from countries that are neighbors to the source country to countries that are neighbors to the recipient. (1) is called an origin dependence effect, (2) a destination-dependence effect and (3) an origin-to-destination dependence effect (see LeSage and Pace, 2008, for details).

To model bilateral remittances accounting for the role of neighbouring countries, we rely on spatial autoregressive interaction models. Interaction or gravity models attempt to explain the interaction between origin and destination locations using: (i) origin-specific attributes characterizing the ability of the origins to generate flows; (ii) destination-specific characteristics representing the attractiveness of destinations; (iii) variables that characterize the way spatial separation of origins from destinations constrains or impedes the interaction. Acknowledging that using spatial separation variables, such as distance between origin and destination locations, is generally not enough to eradicate the spatial dependence among the sample of OD flows, spatial autoregressive interaction models augment the gravity equation with spatially lagged dependent and independent variables. In a typical spatial interaction model, the sample involves n locations being origins and destinations at the same time and k variables characterizing the origins as well as the destinations.

2.1 Interaction model with spatial dependence and different origin and destination sets.

In this paper, we allow for n_o origins, or source countries, and n_d destinations, or recipient countries, resulting in $N = n_o \times n_d$ pairs (o, d) of origin-destination (OD) remittance flows, and k_o and k_d source and recipient country characteristics, respectively. In a first step, we will assume that all possible OD-pairs indeed correspond to an observed remittance flow making the set of couples (o, d) a cartesian product. Later on, we will deal with the case of unobserved flows and non-cartesian OD-sets. Let Y be the remittance flow matrix at period t,[7] where the n_d columns represent the recipient countries 1 to n_d and the n_o rows correspond to source countries 1 to n_o:

$$Y = \begin{pmatrix} o_1 \to d_1 & o_1 \to d_2 & \dots & o_1 \to d_{n_d} \\ o_2 \to d_1 & o_2 \to d_2 & \dots & \dots \\ & & & o_{n_{o-1}} \to d_{n_d} \\ & & & o_{n_o} \to d_{n_d} \end{pmatrix} \tag{1}$$

We denote by $Y_{o:d}$ an OD remittance flow from source country o to recipient country d. Two possible vectorizations of the flow matrix Y are possible, depending on whether we stack its columns (destination centric) or its rows (origin centric). In this paper, we choose a destination centric ordering and denote by $\mathbf{y}$, the flow vector, of length $N \times 1$. Hence, the first n_d elements of $\mathbf{y}$ represent remittance flows from source country 1 to all n_d recipients. All formulas below can be adapted to the origin-centric scheme.

Let OW be a $n_o \times n_o$ matrix characterizing the proximity in the set of source countries, with the proximity being defined in this application based on m-nearest neighbours, with $m = 3$.[8] OW represents a non-negative, sparse matrix, with element $ow_{lp} > 0$ if country l is one of the m-nearest neighbours to country p and $\sum_j ow_{lp} = 1$. Similarly, let DW of dimension $n_d \times n_d$, be a matrix characterizing the proximity in the set of recipient countries. We consider the following two types of neighborhood structures,

- $W_o = OW \bigotimes I_{n_d}$ is the origin based spatial neighborhood matrix,
- $W_d = I_{n_o} \bigotimes DW$ is the destination based spatial neighborhood matrix,

where $\bigotimes$ stands for the Kronecker product of two matrices. Note that the two weight matrices W_o and W_d are of dimension $N \times N$.

Regarding the country characteristics, we define OX as the matrix of the k_o characteristics of the source countries, which is of dimension $n_o \times k_o$, and we denote as DX that of the k_d recipient characteristics, with dimension $n_d \times k_d$. We now construct the following two matrices

- $X_o = OX \bigotimes \iota_{n_d}$, of dimension $(n_o n_d \times k_o)$, characteristics of the source countries,

[7] Note that hereafter we omit the subindex t for notational convenience.

[8] Note that the methodology and the to-be presented spatial autoregressive model specification are still valid for other definitions of proximity and neighborhood structures.

- $X_d = \iota_{n_o} \bigotimes DX$, of dimension $(n_o n_d \times k_d)$, characteristics of the recipient countries.

Let G be the matrix of variables characterizing both the source and the recipient country (for example, distance). The spatial autoregressive model in its reduced form can be written as follows

$$(I_{N\times N} - \rho_o W_o - \rho_d W_d)y = X_o\beta_o + X_d\beta_d + G\gamma + \epsilon, \tag{2}$$

where the parameters ρ_o and ρ_d capture the strength of the origin and destination spatial dependence, respectively; β_o, β_d and γ are vectors of parameters whose dimensions correspond to the number of variables in OX, DX and G, respectively. LeSage and Pace (2009) consider a specific treatment for intraregional flows but these are not relevant in our application and will be automatically null.

Let us denote by $A(W) = (I_{N\times N} - \rho_o W_o - \rho_d W_d)^{-1}$ the $N \times N$ filter matrix. It could be any of the other filters for the nine flow submodels described in LeSage and Pace (2009). Concerning parameter estimation, in this paper, we focus on Bayesian estimation with Markov Chain Monte Carlo (MCMC), which is easy to implement when several weight matrices are involved.

Several reasons may lead to unobserved flows for some OD pairs. For instance, in the context of air passenger flows between city pairs, there may be no flights between two cities, because, for example, it is not profitable for the airlines to open that route. Another example of this situation is our current study, with no reported information on bilateral remittances between certain pairs of countries. In that case, our OD-set is not anymore a cartesian product which prevents us from using the convenient tool of Kronecker products as before. Nevertheless, what we do is that we first construct the two neighbourhood matrices W_o and W_d as before. The remittance flow matrix, as well as the weight matrices can then be vectorized by stacking their columns, for example. After the vectorization operation, we perform an elimination of the non-observed OD-country pairs (because of non-observed remittances between them) in these four matrices, as well as in the vectorized versions of the explanatory variables X_o and X_d. The elimination of some OD-pairs may result in a final version of the weight matrices involving pairs without a neighbour. In Section 4, we describe a way to deal with this problem. In the vectorized form, we can then use ordinary code for fitting a Bayesian spatial autoregressive model; our code is adapted from the LeSage Spatial Econometrics Matlab toolbox.

2.2 Model interpretation

Interpretation of explanatory variable's effects in simultaneous spatial autoregressive models requires the computation of the so-called direct and indirect impacts introduced in LeSage and Pace (2006). Indeed, due to the presence of the filter matrix, the parameters of explanatory variables no longer coincide with the increment of the dependent variable resulting from an increment of the explanatory as is the case in the classical (non-spatial) linear models. The two consequences are that this increment is no longer the same for all locations and that an increment of a given explanatory variable at a location may result in non null increments at all other locations. Note that, due to the linearity of the expected value of the dependent variable with respect to the explanatory variable, these increments can be indifferently thought of as infinitesimal or finite increments in the case of continuous covariates. These impact measures have been extended to the spatial interaction models by LeSage and Thomas-Agnan (2015) for models with endogenous spatial interaction and later by LeSage and Fischer (2016) to the case of exogenous spatial interactions. These last two papers further decompose the total effects into origin, destination and network effects, but they are concerned with the case where the list of origins coincide with the list of destinations and where the characteristics of origins are the same as the characteristics of destination. If we now consider the present framework where this is no longer the case, the definition of the total impact TE itself is unchanged but its decomposition has to be adapted (see for instance Laurent et al., 2021). Let TE denote the total impact of a continuous characteristic X, which is given by

$$TE = \sum_{o \in O, d \in D} \sum_{s \in S} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_s}, \tag{3}$$

where the set S is O when X is an origin characteristic only, is D when X is a destination characteristic only and $O \cap D$ when X is both an origin and a destination characteristic. In LeSage and Thomas-Agnan (2015), the total origin effect TOE is the sum of all changes on the flows resulting from a change in the characteristic at the origin of the flow. Therefore, this effect only has a meaning for origin characteristics. Symmetrically, the total destination effect TDE only has a meaning for destination characteristics. Let us define the total origin effect of a characteristic of origin X to be

$$TOE = \sum_{o \in O, d \in D} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_o}, \tag{4}$$

and the total destination effect for a characteristic of destination X to be

$$TDE = \sum_{o \in O, d \in D} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_d}. \tag{5}$$

For a variable X which may characterize origin, destination or both, the network effect is now defined to be:

$$TNE = \sum_{o \in O, d \in D} \sum_{s \neq o, s \neq d} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_s}, \tag{6}$$

and the total effect is then the sum of the origin, destination and network effects $TE = TOE + TDE + TNE$, when these terms have a meaning (replaced by zero otherwise). LeSage and Thomas-Agnan (2015) introduce a scalar measure of the origin effect (resp: destination effect, network effect) by normalizing the total origin effect (respectively, total destination effect, network effect) by the square of the number of locations. In our case, replacing this scaling factor by the total number of flows N, this measure represents the impact of an origin characteristic change on a typical flow originating at its origin location (respectively, the impact of a destination characteristic on a typical flow going to its destination location). Note that the number of flows is now defined by $N = \sum_{o \in O} nd(o) = \sum_{d \in D} no(d)$, where $nd(o)$ is the number of destinations that one can reach from origin o, $no(d)$ is the number of origins that can lead to destination d.

Furthermore, Laurent et al. (2021) propose additional summary measures that give more detail about the full matrix of effects by defining the contributions of each location (local effects) to the total effects. For a given X, this matrix, with general term $\frac{\partial \mathbb{E}(Y_{o:d})}{\partial x_s}$ has a dimension of $N \times \#S$, where $\#S$ is the cardinality of S which is as above O, D, or $O \cup D$ according to the nature of X. For example, for each origin $o \in O$, let $OE(o) = \sum_{d \in D} \frac{\partial Y_{o:d}}{\partial X_o}$ be the local origin effect due to changing the explanatory variable at location o, so that we have $TOE = \sum_{o \in O} OE(o)$. Similarly for a destination $d \in D$, let $DE(d) = \sum_{o \in O} \frac{\partial Y_{o:d}}{\partial X_d}$ be the local destination effect due to changing the explanatory variable at location d so that we have $TDE = \sum_{d \in D} DE(d)$. In the total network effect, we can isolate the contribution $N_o E(o) = \sum_{d \in D} \sum_{s \neq o, s \neq d} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_s}$ due to origin o, the contribution $N_d E(d) = \sum_{o \in O} \sum_{s \neq o, s \neq d} \frac{\partial \mathbb{E}(Y_{o:d})}{\partial X_s}$ due to destination d. Depending on whether s is in O, D or $O \cup D$, $TE(s)$ will be sum of two or three terms among $OE(s), DE(s)$, and $NE(s)$.

In this application, we are also interested in characterizing the impact of a dummy variable. In that case, it amounts to compare the difference in the mean flow between the two levels of the dummy. For positive autocorrelation, this difference turns out to have the same sign as the parameter of the dummy variable (opposite sign in case of negative autocorrelation) as can be seen by the classical expansion of the filter matrix.

3 Hypotheses we test

Starting from the seminal paper of Lucas and Stark (1985) on the motivations to remit, the literature has identified three main motives for individuals to remit, that is, pure altruism; self-interest in the form of investment and/or risk-diversification motives; and intermediate motivations that represent contractual agreements between the migrant and the family at the origin (see Bettin et al., 2017, for a complete literature review). Given that empirically investigating the third motive requires micro data at the household level, in this paper we focus on the first two motives. On top, following Freund and Spatafora (2008), we consider an additional hypothesis, which is the role of financial frictions, capital controls and transfer costs. We now detail the three hypotheses we test in this paper, properly accounting for the role of neighboring countries on bilateral remittance flows.

Hypothesis 1: Altruism motive

Overseas workers and/or migrants may send more remittances when their home country's relative income declines, so as to compensate for the lost income of family members owing to economic downturn back home, and when the relative income of the country where they live in and work increases. According to this hypothesis, we should then expect a positive effect for the income of the source country (in the remittance flow) and a negative effect for the recipient country's income. Furthermore, from this hypothesis, we test the following additional predictions:

- Higher inflation in the recipient country of the remittance flow (home country of the migrant or overseas worker) should encourage more remittances sent to compensate for the loss of purchasing power at the migrant's home (Lueth and Ruiz-Arranz, 2008). Conversely, higher inflation in the source country should reduce the purchasing power of overseas workers in that country and hence, result in smaller remittance flows originating from that country.

- Remittances should increase in the wake of natural disasters, to substitute for less efficient financial markets in the recipient country (of the migrant flow), and/or they may be larger in countries having experienced natural disasters in the past, as part of an ex ante risk management strategy (Bettin and Zazzaro, 2018).

Hypothesis 2: Investment motive

Remittances should increase with output in the recipient country, if remittances are used to seize investment opportunities at home. Consistent with this idea, remittances should also be sensitive to the investment and political climate in the recipient countries (Bettin et al., 2017).

Hypothesis 3: Financial frictions, multiple exchange rates and capital controls, and transfer costs

Remittances should decrease with the financial frictions and restrictions to remit money in the source country (of the remittance flow), with these frictions possibly taking the form of exchange rate volatility, multiple exchange rate and capital controls. In addition, remittances should decrease when the cost of sending money abroad increases (Beck and Martínez Pería, 2011; Freund and Spatafora, 2008).

In the next section, we present the way we proxy each of the previously mentioned hypotheses.

4 Data and definition of neighbourhood structure

Data on bilateral remittances come from the World Bank (World Bank 2017). Data are derived from a global estimation of bilateral remittance flows worldwide, relying on source and recipient country incomes, as well as estimated migrant stocks. The methodology builds upon Ratha and Shaw (2007). Our dataset comprises 67 source countries and 129 recipient countries all over the world, for which workers' remittances are reported in 2017, with 60 countries being both source and recipient countries. For a robustness exercise, we also report estimates for 2012. The caveats attached to these bilateral remittance estimates are: (a) Data on migrants in some recipient countries are incomplete; (b) the incomes of migrants abroad and the costs of living are proxied by per capita incomes in purchasing power parity terms; and (c) the data do not capture remittances flowing through informal, unrecorded channels (World Bank 2017).

Regarding the factors characterizing both the source and the recipient countries, we consider the use of electricity per capita in log, which is a proxy for economic activity (source: Central Intelligence Agency, USA); inflation, as measured by GDP deflator (source: United Nations) and total population, which proxies for the county's size. Note that both the use of electricity per capita and the deflator at the source and recipient countries (in the remittance flow) allow us to test the altruism hypothesis

(hypothesis one), whereas the use of electricity per capita at the recipient country should provide evidence in favor or against the investment hypothesis (an estimated negative sign for the destination effect for electricity use per capita would be consistent with hypothesis two). In particular, in the case of GDP deflator, instead of using the continuous variable, we build two indicator variables, which we denote as high (moderate) inflation. Specifically, the high (moderate) inflation indicator takes the value of 1 if the country has experienced over the previous two years an inflation rate above the percentile $90th$ (between the percentile $90th$ and the $10th$) of the empirical distribution of the GDP deflator (of the source or recipient countries, when corresponding). The reason for modeling inflation in this manner is to account for the non-linearities of this variable, where a few countries exhibit very high inflation rates (e.g. Venezuela).

The additional determinants characterizing only the source countries (in addition to elextricity use per capita and GDP deflator) comprise whether the source country is an island, whether the country exhibits dual or multiple exchange rates and/or capital controls (source: IMF's Annual Report on Exchange Arrangements and Exchange Restrictions or ARREAR), exchange rate volatility, as measured by the standard deviation of monthly exchange rates (source: World Bank), and finally, the average transfer fee, associated with sending remittances from each source country (source: Western Union website). These transaction costs were computed assuming a remittance size of 200 Euros, and are quoted in nominal terms. The reason for using the prices charged by Western Union is to alleviate concerns about bias due to differences across remittance service providers. We hence choose a leading remittance service provider with worldwide operations (Beck and Martínez Pería, 2011). Finally, all the previously mentioned proxies, with the exception of whether the source country is an island, aim at assessing the third hypothesis.

Concerning the controls characterizing only the recipient countries, we include the political stability index (source: World Bank), whether the country is landlocked, and whether the country has experienced a natural disaster (including floods, earthquakes or storms, source EM-DAT, CRED/UCLouvain dataset on international disasters). Note that while the political stability should provide evidence to test the investment hypothesis (hypothesis two), the occurrence of natural disaster might be useful to examine the altruism hypothesis (hypothesis one). In addition, we include variables typically used in the gravity models to characterize the pair of OD countries, namely, whether the two countries involved in the country pair share a border; whether the countries share the language; whether they share the currency; whether they have had some colony relation; and the distance between the source and the recipient country (Lueth and Ruiz-Arranz, 2008). Table 8.1, in the appendix, details the variables we use, together with their data sources. In turn, Tables 5 and 6 report the descriptive statistics of the continuos and the indicator variables, respectively.

To mitigate the problem of reverse causality from remittances to the macroeconomic variables that we consider in this paper (due to the fact that in some recipient countries, remittances represent a non-negligible share of GDP), all country characteristics are lagged two years. On top of that, following Freund and Spatafora (2008), we instrument transactions costs in the source countries using the two year-lagged financial development index and a dollarization dummy variable.

There is an additional technical but important point to make regarding the presence of zero flows, which in our application represents around 20% of total remittance flows. In order not to bias the parameter estimation, we eliminate them, before fitting the model. This elimination results in some remittance flows having no longer a neighbor. We hence take a two-step sequential procedure to address this issue. Specifically, for those flows without neighbors, we first look for new nearest neighbors, that is, we increase the number of nearest neighbors for them, until all flows have at least one neighbor. In the second step, we eliminate those neighbors with a distance above 3000 km, to avoid abnormal neighbors. This procedure results in 622 remittance flows being eliminated due to the fact that their neighbours were above the threshold of 3000 kms in W_o or W_d. The distribution of the number of neighbors per flow follows in Table 1.

Table 1: Distribution of the number of neighbors per flow (in percent points)

Number of neighbors:	3	2	1
Weight matrix W_o	0.69	0.26	0.04
Weight matrix W_d	0.85	0.12	0.03

5 Results

5.1 Baseline model estimates

Table 2 presents the estimation results for the year 2017, with the independent variables being lagged two years: The Table first presents the ordinary linear model (OLM) estimates, assuming no spatial dependence (first and second columns of results); it then exhibits the estimates allowing for origin-dependence (third and fourth columns of results) and for destination-dependence (fifth and sixth columns). Finally, the last two columns of results show the model estimates when the origin and destination neighbourhood matrices are simultaneously present.

Table 2: Ordinary linear model and Bayesian spatial autoregressive model estimates for 2017. Spatial neighbourhood matrices W_o and W_d, with 3 nearest neighbors

Variables	OLM	T-stat	Est Wo	T-stat	Est Wd	T-stat	Wo Wd	T-stat
Spatial parameter O			0.449	52.872			0.304	33.869
Spatial parameter D					0.383	42.182	0.385	45.316
Source country								
Log(Electric Use PC)	1.321	42.633	0.955	32.974	0.86	27.487	0.642	22.53
Log(Population)	0.995	50.199	0.935	51.049	0.626	30.116	0.652	35.126
High Inflation	-1.519	-12.781	-1.306	-11.715	-0.844	-7.692	-0.802	-7.859
Medium Inflation	-1.077	-12.827	-0.882	-11.375	-0.679	-8.692	-0.592	-8.36
Island	0.694	7.129	0.453	5.158	0.441	4.802	0.292	3.607
Multiple FX	-0.689	-10.635	-0.415	-7.233	-0.518	-8.455	-0.317	-5.758
FX Volatility	-0.003	-4.796	-0.004	-7.46	-0.001	-3.013	-0.003	-5.691
Transfer Cost	-0.076	-12.359	-0.073	-12.501	-0.046	-7.933	-0.049	-9.275
Recipient country								
Log(Electric Use PC)	0.296	4.61	0.365	17.869	0.44	20.623	0.262	13.25
Log(Population)	0.615	27.817	0.499	27.675	0.767	44.352	0.459	26.544
High Inflation	0.887	47.674	0.662	6.379	1.041	9.341	0.63	6.353
Medium Inflation	1.174	9.93	0.634	7.861	0.924	11.27	0.513	6.804
Pol Stability	1.173	13.342	0.117	3.279	0.241	6.523	0.133	3.885
Landlocked	0.244	6.09	-0.021	-0.29	-0.28	-3.966	-0.255	-4.013
Natural Disaster	0.026	0.344	0.179	2.95	0.296	4.93	0.197	3.624
Country pair								
Com Border	0.272	1.6	0.552	3.556	0.513	3.151	0.71	4.898
Com Language	1.802	20.307	1.355	16.512	1.448	17.048	1.138	15.09
Com Currency	-0.089	-0.645	-0.122	-0.96	-0.304	-2.387	-0.285	-2.47
Colony	1.834	10.817	1.532	9.961	1.357	8.401	1.195	8.29
Distance	-1.555	-43.43	-0.872	-25.213	-0.995	-27.578	-0.524	-15.269

Notes: O and D correspond to origin and destination, respectively. FX stands for exchange rate, PC for per capita and Pol for Political. Com stands for common. Obs and T-stat stand for number of observations and t statistics, respectively. Intercept is not reported.

Table 2 shows strong evidence of the importance of neighboring countries on bilateral remittances, above and beyond the macro determinants of remittances, with both parameter estimates for the origin- and the destination-spatial dependence, ρ_o and ρ_d, respectively, being always positive and statistically significant. Intuitively, a positive parameter estimate for ρ_o is reflecting that observed remittance flows from a source country A to a recipient country Z are likely to be accompanied by larger remittance flows from countries nearby the source country A to the recipient country Z. To make this concrete, consider the situation of migrants from country Z moving to country A, because of favorable labor market and economic conditions at A. We would then expect to see migrants from country Z also moving into other countries B and C in the neighbourhood of A, presumably because of favorable regional economic conditions. If this is the case, we should hence observe more remittances from countries A and also from countries B and C to the home country of these migrants, Z. A positive estimated parameter ρ_o is consistent with this description and it is what we call origin-dependence.

Similarly, a positive estimated parameter for ρ_d as Table 2 exhibits, is indicating that larger observed remittance flows from a source country A to a recipient country Z are likely to be accompanied by larger remittance flows from country A to countries neighboring the recipient country Z. As an illustration, consider migrants moving away from a country Z to another country A. If there are unfavorable economic conditions in country Z and its neighbourhood, we might then see migrants from other countries, say X and Y in the neighbourhood of Z, also moving away to other countries, in particular, to the same country A. It is hence more likely to observe larger remittances from country A to countries Z, and also from country A to countries X and Y (near Z), when these migrants (living in country A) decide to send money back to their home countries (in Z, X and Y). The latter interpretation is consistent with a destination-dependence. Finally, the last two columns of results in Table 2 show that when the two spatial neighbourhood matrices are simultaneously present, both the origin- and destination-dependence parameters are almost equally important, with the estimates ranging between 0.30 to 0.39. The latter reinforces the idea that bilateral remittances are a regional phenomenon, as Figure 3 shows.

As a robustness check, Table 7 in the appendix, examines the stability of the estimated spatial dependence parameters across time. Specifically, we compare the results for two estimation years, 2017 and 2012. To do so, we first estimate the same model specification than in Table 2 for 2017 (with control variables as of 2015), but excluding the electricity use per capita and the transfer cost. We then estimate this reduced model specification with data on remittances as of 2012 (with control variables as of 2010) and compare the two model estimates. The reason for modifying the model specification is that for 2010, we do not have access to the information on the use of electricity per capita or the transfer costs for all the countries that we consider in this paper. Table 7 shows that the estimated spatial dependence parameters are stable through time, thus confirming the importance of origin- and destination- spatial dependence.

The next natural question is how much we improve estimations when we properly account for the role of neighbouring countries. To address this point, we focus on predicted remittances and compare the OLM and the spatial model in terms of prediction errors. Precisely, we first predict (in-sample) the bilateral remittances, both for the OLM and for the spatial model specification that includes simultaneously the spatial neighbourhood matrices W_o and W_d (first two columns and last two columns in Table 2, respectively). For the predicted bilateral remittances in the spatial model, we consider the 'trend–signal–noise' or TS predictor formula (refer to Goulard et al., 2017, for details). The remittance predictions for the OLM and for the spatial model follow:

$$\hat{y}^{OLM} = X_o\hat{\beta}_o + X_d\hat{\beta}_d + G\hat{\gamma} \tag{7}$$

$$\hat{y}^{TS} = \hat{\rho}_o W_o y + \hat{\rho}_d W_d y + X_o\hat{\beta}_o + X_d\hat{\beta}_d + G\hat{\gamma} \tag{8}$$

with $\hat{y}^{OLM}$ and $\hat{y}^{TS}$ being the vectors of predicted remittances according to the OLM and the TS predictor formula, respectively and $\hat{\rho}_o$, $\hat{\rho}_d$, and $\hat{\beta}_o$, $\hat{\beta}_d$ and $\hat{\gamma}$ being the estimated parameters in the corresponding model specification, as exhibited in Table 2. Second, we compute the mean absolute percentage error or MAPE for the OLM and for the spatial model as,

$$MAPE^{OLM} = \frac{1}{N}\sum_{o,d}\frac{|\hat{Y}^{OLM}_{o:d} - Y_{o:d}|}{Y_{o:d}}$$

$$MAPE^{TS} = \frac{1}{N}\sum_{o,d}\frac{|\hat{Y}^{TS}_{o:d} - Y_{o:d}|}{Y_{o:d}}$$

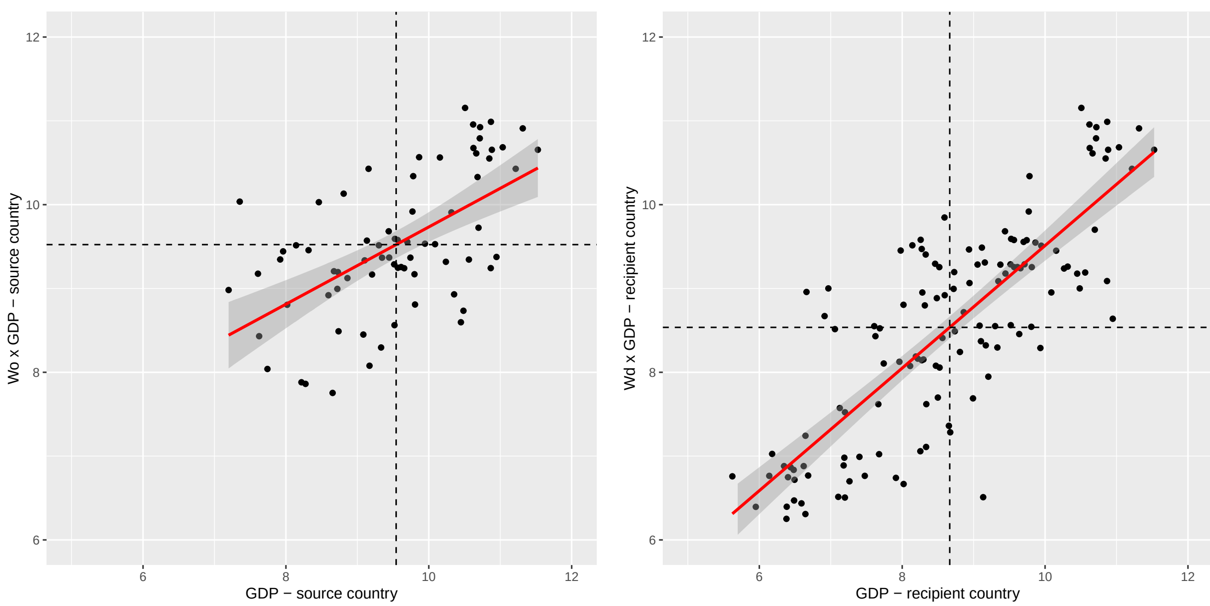
Third, we compute the reduction in the MAPE thanks to accounting for the impact of neighbouring countries. The crucial result is that accounting for origin- and destination- spatial dependence leads to a 67% reduction of the MAPE if we consider bilateral remittances in nominal terms and to a 27% decrease if bilateral remittances are in logarithm. Therefore, the latter offers a way to quantify the importance of neighbouring countries, when studying the determinants of remittances.

Last, in the literature, there are two main mechanisms that explain why neighbouring countries may have an impact on bilateral remittances, namely, migration to countries with historical or cultural ties (Fenoll and Kuehn, 2018) and regional business cycles (Balli and Rana, 2015; Bettin et al., 2017; Cooray and Mallick, 2013). While testing the relative importance of these mechanisms is out of the scope of this paper, Figures 4 and 5 examine the previously discussed interpretations for the origin- and destination-dependence (with the origin- and destination-dependence being reflected in the model by the positive and significant estimated parameters $\hat{\rho}_o$ and $\hat{\rho}_d$, respectively, Table 2). Specifically, Figures 4 and 5 depict the Moran scatter plots for GDP and the stock of migrants, respectively: The left (right) panel in each Figure represents the relationship between the values of the variable of interest, GDP or number of migrants, and the spatially averaged values of the same variable according to W_o (W_d). Note that, unfortunately, we do not observe bilateral migration data; we only have access to the stock of migrants in a given country.

Figures 4 and 5 show, on the one hand, that the economic activity of neighbouring countries are spatially correlated (regardless of whether we consider W_o and W_d, Figure 4); on the other hand, that there is positive spatial autocorrelation between the number of migrants of neighbouring countries (Figure 5). Both pieces of evidence are hence consistent with: i) the origin-dependence for remittances flows, according to which it is likely that people moving away from a given country Z, might move into country

A or into other countries B and C in the neighbourhood of A, if there are favorable regional economic conditions; ii) the destination-dependence interpretation, according to which if there are unfavorable economic conditions in country Z and its neighbourhood, we might then expect to see people from country Z and also from countries X and Y in the neighbourhood of Z, moving away to other countries, in particular, to the same country A.[9] Summing up, the evidence in Figures 4 and 5 provides plausible explanations for neighboring countries (and the neighbors of their neighbors) exerting an influence on bilateral remittance flows.

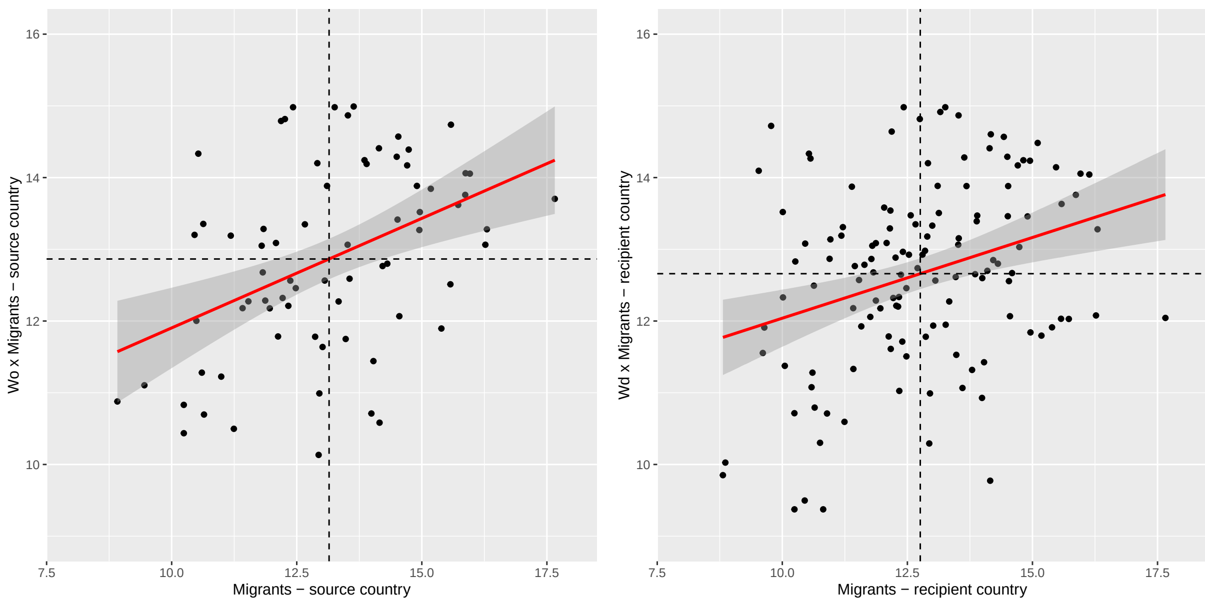
Figure 4: Moran scatter plots. Left panel: GDP and spatially averaged GDP of neighbouring countries at origin (W_o). Right panel: GDP and GDP of neighbouring countries at destination (W_d)



The Figures depict the Moran scatter plots for GDP (as of 2017). The left (right) panel depicts the relationship between GDP and the averaged values of GDP at neighboring locations according to W_o (W_d).

[9]As a matter of fact, the Moran's I statistic equal 0.461 and 0.731 in the case of GDP according to W_o and W_d, respectively, and 0.305 and 0.225 for the number of migrants, according to W_o and W_d, respectively.

Figure 5: Moran scatter plots. Left panel: Number of migrants and spatially averaged migrants of neighbouring countries at origin (W_o). Right panel: Number of migrants and spatially averaged migrants of neighbouring countries at destination (W_d)



The Figures depict the Moran scatter plots for the number of migrants per country (as of 2017). The left (right) panel depicts the relationship between number of migrants and the averaged values of migrants at neighboring locations according to W_o (W_d).

5.2 Evidence on the hypotheses to remit

We now proceed to analyse the evidence for the three hypotheses which we state in section 3. For the latter, we combine the model estimates reported in Table 2 with Table 3 which presents the total, the total origin, the total destination and the total network effects, as defined in equations (3), (4), (5) and (6), respectively, for the continuous variables electricity use per capita, population, political stability, foreign exchange volatility and transfer cost, with the scaling factor being the total number of flows N. To compute the effects, we assume that the corresponding characteristic of each country (acting as an origin or a destination when corresponding) registers an increase of 1% in the range of the variable in question. As explained in 2.2, recall that in the case of the simultaneous spatial autoregressive interaction models, interpretation of explanatory variables' effects is not straightforward and requires the computation of the origin, destination and network impacts (LeSage and Thomas-Agnan, 2015).

Table 3: Impact computation

	Log(Electric Use PC)			**Log(Population)**			**Pol Stability**		
Effects	W_o	W_d	W_o, W_d	W_o	W_d	W_o, W_d	W_o	W_d	W_o, W_d
TOE	0.060	0.081	0.066	0.099	0.100	0.115	x	x	0.000
t-stat	33.211	27.990	22.156	50.852	30.367	31.334	x	x	3.722
TDE	0.038	0.027	0.025	0.089	0.079	0.073	0.010	0.011	0.010
t-stat	17.948	20.765	13.426	28.557	44.500	25.069	3.287	6.522	3.876
TNE	0.041	0.015	0.078	0.068	0.043	0.165	x	0.006	0.010
t-stat	23.722	17.735	16.093	26.760	23.972	17.836	x	6.319	3.810
TE	0.139	0.122	0.168	0.257	0.223	0.353	0.010	0.018	0.019
t-stat	34.567	33.133	21.707	48.238	45.253	27.490	3.287	6.486	3.856

	FX Volatility			**Transfer Cost**		
Effects	W_o	W_d	W_o, W_d	W_o	W_d	W_o, W_d
TOE	-0.014	-0.009	-0.017	-0.015	-0.014	-0.017
t-stat	-7.458	-3.020	-5.678	-12.485	-8.008	-9.167
TDE	x	x	-0.000	x	x	-0.000
t-stat	x	x	-5.302	x	x	-7.675
TNE	-0.010	x	-0.014	-0.010	x	-0.014
t-stat	-7.225	x	-5.485	-11.488	x	-8.299
TE	-0.024	-0.009	-0.031	-0.026	-0.014	-0.031
t-stat	-7.404	-3.020	-5.644	-12.241	-8.008	-8.956

Notes: FX stands for exchange rate, PC for per capita and Pol for Political. TE, TOE, TDE and TNE correspond to the total effects, the total origin effects, total destination effects and total network effects, as defined in equations (3), (4), (5) and (6), respectively. T-stat stands for t statistics.

The first element to highlight from Table 3 is that the total, the total origin, the total destination and the total network effects are always statistically significant for all the continuous variables under analysis, that is, electricity use per capita, population, political stability at destination, and foreign exchange volatility and transfer cost at origin. To interpret results in Table 3, recall that when a variable only characterizes the source countries (recipients), such as foreign exchange volatility and transfer cost (e.g. political stability), the destination (origin) effect is null. Also, the network effects of these variables (being only origin (destination) characteristics) are also null when we consider as neighbourhood matrix W_d (W_o).

Focusing on the evidence for the various hypotheses, Table 3 supports the altruism motive for remittances (hypothesis one), as we find a positive and statistically significant total origin effect for electricity use per capita, which is our proxy for economic activity. The way to interpret this result is that when the economic activity of the country where overseas workers live in and work increases (as reflected in a higher use of electricity per capita at the source country), we would expect that these migrants may also increase their incomes and hence, are more likely to remit more money home. As a matter of fact, Table 3 shows that a 6% expansion in the electricity use per capita[10] of a typical source country is expected to increase the remittance flows originating from that representative location by 6% to 8% depending on the model specification considered, that is, depending on whether we include the spatial neighbourhood matrix W_o, W_d or W_o and W_d.

Also consistent with the altruism hypothesis, Table 2 shows a positive relation between the occurrence of a natural disaster at a recipient country and remittances, with these remittances possibly being a way to help family members at home to overcome the damages. Furthermore, Table 2 exhibits that remittances are smaller if they come from a source country registering a high inflation regime (that is, with an inflation rate above the $90th$ percentile of the GDP deflator distribution), relative to the base category (which is the low inflation regime). The same holds for source countries under a moderate inflation regime, that is, we find a negative coefficient estimate for the dummy variable medium inflation regime in Table 2. Both results are in line with the interpretation that inflation reduces the purchasing power of people and, in particular, of overseas workers and migrants, which in turn should result in smaller remittances originating from their country of residence. Conversely, remittances are larger if the recipient country is under a high or moderate inflation regime, which is also consistent with the altruism hypothesis. This is because we would expect more remittances if there is high inflation in the recipient country to compensate for the loss of purchasing power at the migrant's place of birth. Summing up, the evidence on the dummy variables for the inflation regimes confirms the altruism hypothesis in what relates to the purchasing power of the individuals in the source and recipient countries.

However, results in Tables 2 and 3 do not confirm the altruism hypothesis in regards to the income of the recipient country, as we find, in contrast to that hypothesis, a positive total destination effect for the log of electricity use per capita. As a matter of fact, the positive destination effect for electricity use is consistent with the investment hypothesis (hypothesis two), according to which remittances would be used to seize investment opportunities at the migrant's home, when economic activity there expands (as proxied by the increase of electricity use per capita at the recipient country). Furthermore, the finding that the destination effect for political stability is statistically significant and positive is also in accordance with hypothesis two, as remittances should be sensitive and positively related to better investment and political climate in the recipient countries.

In relation to hypothesis three, we find that remittances decrease with the transfer costs at the source country (negative origin effect). Indeed, Table 3 shows that a 1% increase in the range of the (residual) cost of remitting 200 dollars abroad of a typical source country (which is equivalent to a 19% expansion in the residual cost of remitting 200 dollars abroad) appears to reduce between 1% and 2% the remittance flows originating from that representative location (depending on the model specification considered). While the negative sign for the origin effect is indicating that at least partially, migrants

[10]In the case of electricity use per capita, since the variable is in logarithm, the 1% increase in the range of the variable we suppose represents a 6% in the electricity use per capita in level.

either refrain from sending money home or remit through informal channels when costs increase, the small percentage reductions suggest that remittances would be relatively inelastic to increases in the cost of remittances, with the latter being in contradiction with previous literature (Aycinena et al., 2010; Gibson et al., 2019). However, we would like to examine this finding with caution, based on the following three elements: i) we are focusing on the costs of only one remittance service provider, Western Union; ii) we are computing the impact of increasing the transfer cost on a representative corridor departing from each source country in our dataset, therefore, the computation provides an average impact, setting aside disparities between corridors due to competition, market structure, regulatory framework, among others (Beck and Martínez Pería, 2011); iii) we do not have access to data on remittances through informal channels. In addition, our results show that remittances are smaller when financial frictions in the source country exists, as measured by the existence of multiple exchange rates and/or capital controls (Table 2) and/or larger foreign exchange volatility (Table 3).

Furthermore, Table 2 shows that the inclusion of variables typically used in gravity models to characterise the pair of OD countries perform well. Specifically, we find that sharing a common language, borders, and having had a colony relation in the past, exhibit significant and positive coefficient estimates, whereas sharing the same currency and distance display coefficient estimates which are negative and statistically significant. It is worth to highlight that the coefficient estimate for distance considerably decreases when we simultaneously include the two neighbourhood matrices, a result which is to be expected though, given that in this specification, we are more extensively capturing the spatial dependence present in the remittance flows.

A complementary way to read Table 3 is to examine the contribution of the total origin, total destination, and total network effects, relative to the total effects. Interestingly, Table 3 shows that for the continuous variables under analysis, the total network effects are non-negligible; on the contrary, they represent between one-sixth and one half of the total effects, depending on the variable under analysis. Therefore, these results confirm the importance of accounting for network effects when studying the determinants of the remittance flows. Omitting to do so would result not only in biased estimated parameters for the determinants of bilateral remittances (as we have already shown) and inefficient standard errors, but in addition, it would lead, for example, to incorrect estimations of the impact of a shock to a country or group of countries, on remittances.

Two natural further questions would be which of the four subsets of determinants (namely, the three motives to remit and the gravity variables) is the most important one and how these relative contributions change, if any, when not accounting for spatial dependence. To answer these questions, we first classify the determinants of remittances into the four subset of variables, namely, those that account for the altruism motive, the investment motive, the financial friction and the transfer cost hypothesis, and last, the gravity variables. Precisely, to capture the altruism motive, we consider electricity use per capita in the source countries, the indicator variables for high and medium inflation both in the source and recipient countries, the occurrence of natural disasters in the recipient countries, and population both in the source and recipient countries. To measure the investment hypothesis, we include the electricity use per capita and the political stability index, both in the recipient countries. In order to account for the financial friction and cost of transfer hypothesis, we consider the existence of multiple exchange rates, capital controls and foreign exchange volatility in the source countries. Finally, the remaining variables that appear in the model specifications in Table 2 are part of the gravity variables. Note that in the case of the electricity use per capita in the recipient countries, we decide to include it as part of the investment hypothesis, the reason being that its destination effect was positive (Table 3), which is consistent with this hypothesis. Second, we predict the contribution of the four subsets of determinants both for the OLM and for the spatial model specification that includes simultaneously the spatial neighbourhood matrices W_o and W_d (equations (7) and (8)). We define the relative contribution of each subset by the ratio of the variance of the block prediction to the total variance of bilateral remittances.

Table 4: Relative contribution of each subset of determinants to total remittance variance

Hypothesis	**OLM**	$\mathbf{SAR_{TS}}$
Altruism	0.491	0.616
Gravity	0.229	0.420
Investment	0.092	0.342
Fin Frictions	0.016	0.289

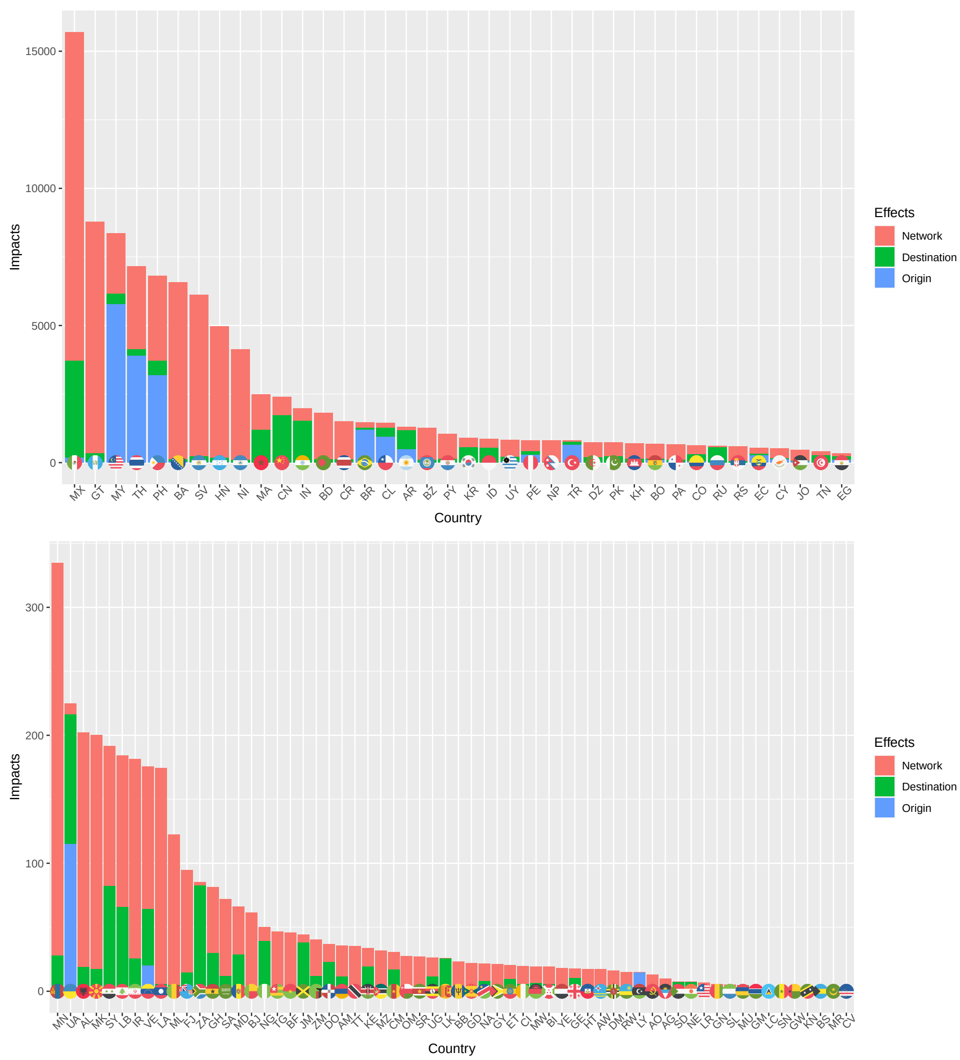
Notes: Fin stands for financial and TS for 'trend–signal–noise' predictor.

Table 4 shows that the altruism motive is the most important hypothesis to explain bilateral remittances, followed by the gravity variables and the investment motive. Interestingly, the above ranking remains valid in the non-spatial model specification.

5.3 Analyzing the local origin, destination and network effects

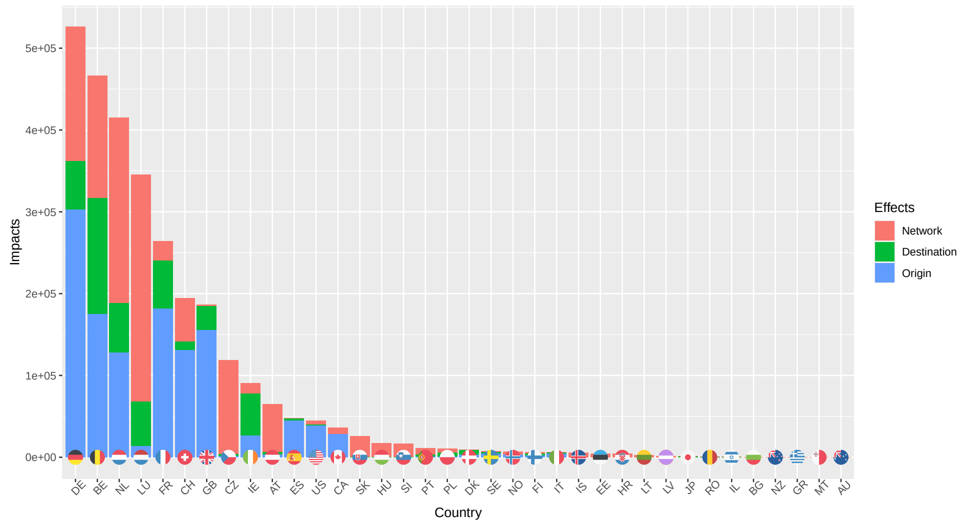
To dig more deeply into the matrix of origin, destination and network effects and the possible heterogeneities between countries, we now analyze the local effects, that is, the country-specific relative importance of the origin, destination and network effects. Without loss of generality, for the exercise, we will consider the model estimate which includes simultaneously the two neighbourhood matrices W_o and W_d (last two columns in Table 2). To make the analysis richer, we will distinguish between emerging and advanced economies and we will report the impacts expressed in millions of USD (instead of logarithms). Figures 6 and 7 depict the local origin, local destination and local network effects, which result from increasing by 1% the range of the electricity use per capita in each emerging and advanced economy (one at a time), with the countries being indexed in the x axis of the corresponding Figure. Note that the conclusions that we will derive from studying the local impacts due to an increase in the use of electricity will be qualitatively valid also for population (which is the other continuous variables in our model specification characterizing both the source and the recipient countries), provided of course, we assume an equivalent change of variation for population. This is because: i) the estimated β_o and β_d coefficients for electricity use per capita and population, both in logarithms, are positive and such that $\beta_o > \beta_d$ in the two cases; ii) the country-specific impacts depend on the filter matrix $(I - \rho_o W_o - \rho_d W_d)^{-1}$, with this filter matrix being scaled by the different variable-specific contributions as given by the vectors β_o and β_d.

Figure 6: Origin, destination and network effect, in USD millions of dollars, after increasing electricity use per capita by 1% of its range. Top and bottom panels: Emerging economies.



The two diagrams in Figure 6 exhibit the origin, destination and network effects, by emerging economy (on the x axis), due to an increase of 1% in the range of electricity use per capita. Impacts are based on the model estimates in the last two columns of Table 2; they are expressed in millions of USD dollars. Emerging economies are sorted in decreasing order of total impacts.

Figure 7: Origin, destination and network effect, in USD millions of dollars, after increasing electricity use per capita by 1% of its range: Advanced economies.



The two diagrams in Figure 7 exhibit the origin, destination and network effects, by advanced economy (on the x axis), due to an increase of 1% in the range of electricity use per capita. Impacts are based on the model estimates in the last two columns in Table 2; they are expressed in millions of USD dollars. Advanced economies are sorted in decreasing order of total impacts.

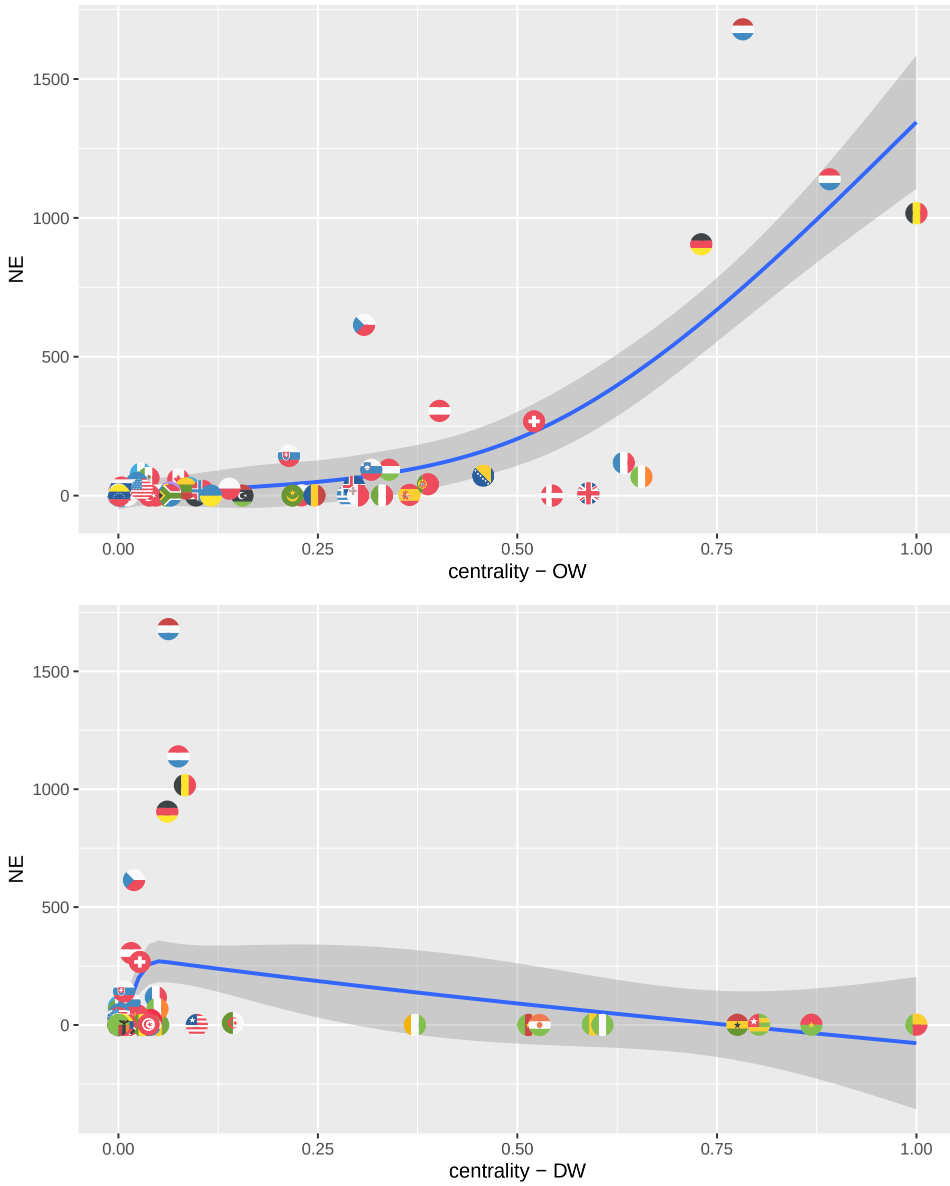
To begin with, Figures 6 and 7 show that for those countries whose origin effects are non-zero (several emerging economies register zero origin effects as they do not remit money abroad), origin effects tend to be larger than the destination effects, thus indicating that a shock to an origin characteristic has a larger impact on the remittance flows relative to an equivalent change in a destination characteristic. This result is in line with the model estimates in Table 2, since the β_o coefficient for electricity use per capita is larger than β_d (last two columns in Table 2). This finding also holds for the impacts of population (which acts as an origin and destination characteristic as well).

The second result to highlight from Figures 6 and 7 is that there is considerable heterogeneity across countries in their local network effects, specially within advanced economies, with some countries recording large network effects and some others smaller impacts. There are two forces that may be driving this heterogeneity across countries: On the one hand, there is the number of counterparties that a given source or recipient country might have in the bilateral remittance matrix, that is, the number of recipient countries to which a given source country remits, or conversely, the number of source countries, from which a recipient country receives remittances from. On the other hand, how central a country is, in the sense of having several neighbors (countries) which in turn, may or may not be connected to several other countries.

To better understand this phenomenon, Figure 8 exhibits the local network effects, as a function of countries' eigenvector centrality. Eigenvector centrality, according to one spatial proximity matrix OW

or DW, is a measure of the influence a country has on the given spatial neighborhood matrix (Bonacich, 2007). Relative scores are assigned to all countries in the neighborhood matrix based on the concept that connections to high-scoring countries contribute more to the score of the country in question than equal connections to low-scoring countries. Hence, countries with high eigenvector centralities (close to 1) for a given weight matrix OW or DW, are those which are connected to many other countries which are, in turn, connected to many others (and so on). The Figure in the top panel computes the eigenvector centrality based on the origin-based spatial proximity matrix OW, whereas the bottom panel computes the eigenvector centrality based on the destination-based spatial proximity matrix DW.

Figure 8: Network effects and eigenvector centrality indexes: Emerging and advanced economies.



The Figures exhibit the local network effects, as a function of eigenvector centrality. Top panel focuses on the eigenvector centrality according to the origin-based (destination- based) spatial proximity matrix OW (DW). Network effects are computed based on the model estimates in the last two columns of Table 2.

Figure 8 indicates that local network effects are increasing in the eigenvector centrality of the source countries, as computed from the origin-based spatial neighborhood matrix OW. The way we read this finding is that the more central source countries are the ones exhibiting the largest network effects, because they may be subject to higher order effects. Higher order effects arise when a shock to a given country is transmitted to other countries not directly linked to the stressed country, with the transmission being due, for example, to real or financial linkages in the form of trade or common investors between countries, respectively. Therefore, the more central source countries may transmit shocks to and/or may be exposed to shocks from many more countries, thus impacting a larger number of remittance flows. Oppositely, there is no clear pattern when we consider the centrality based on the spatial proximity matrix DW. In particular, note that there is a considerable number of countries in the bottom left of the eigenvector centrality distribution exhibiting very small values for that centrality index.

There is an additional point to make regarding the heterogeneous network effects across countries: When expressed in millions of USD, the network effects tend to be much larger for advanced than for emerging economies. As a matter of fact, the total network effects of advanced economies are 1756% larger than the corresponding sum for emerging economies. The latter is due to a size effect, that is, the remittance inflows and outflows are considerably larger for advanced economies, relative to emerging economies. Consistent with the previous finding, the countries with the largest network effects are all advanced economies, precisely, Luxembourg, Netherlands, Germany, and Belgium. In turn, the emerging economies with the largest network effects are Mexico, Guatemala, Bosnia and Herzegovina, and Salvador, with the sum of the network effects of these four emerging economies being 4% of the network effects of the top-four advanced economies.

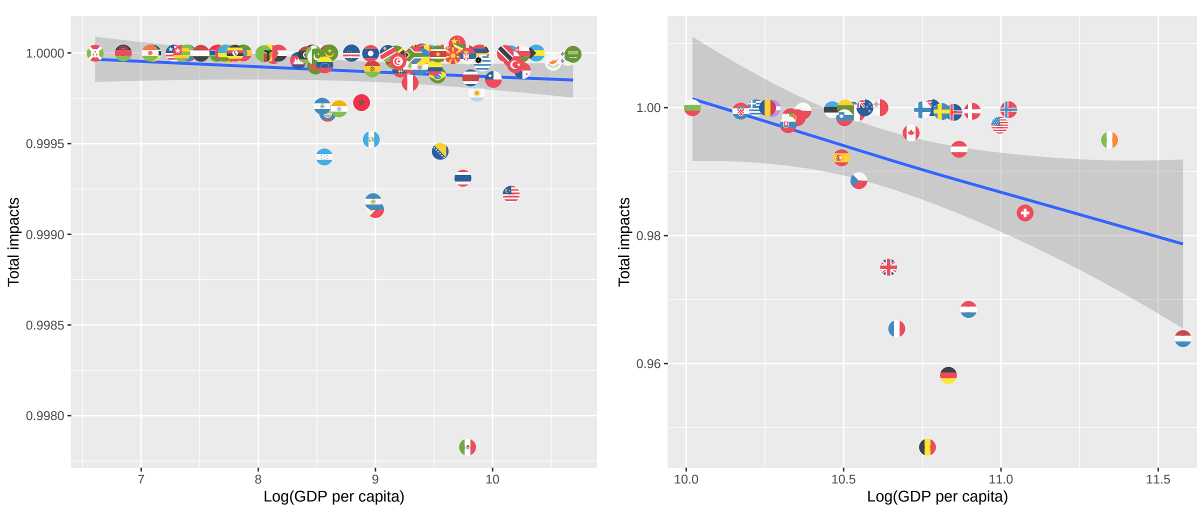
6 Application: Quantifying the impact of the COVID pandemic shock on bilateral remittance flows

The ongoing COVID pandemic constitutes an unprecedented negative economic shock to the global economy. On the one hand, the economy of each country is already affected by local shocks due to lockdowns imposed in some (or all) cities to protect the population's health, which is a 'direct' effect of the COVID pandemic on economic activity. On the other hand, the economy of each country will also be impacted by the transmission of these domestic shocks from other countries, which represents an 'indirect' effect, generated by the international spread of the COVID virus. Both direct and indirect effects of the COVID shock are expected to severely impact the remittances that countries send and receive from abroad. The latter is particularly important for LMIC, for which remittances constitute their largest source of foreign capital, even before foreign direct investment or FDI (World Bank, 2020).

In this section, we apply our methodology to predict the likely impact of the country-specific shocks to economic activity generated by the COVID virus, on the bilateral remittance flows. To quantify the economic damage, we rely on the IMF's WEO projections (for December 2020) for GDP growth in each individual country (which were released in October 2020). We then apply the country-specific expected changes in GDP (as computed by the IMF) to stress the electricity use per capita in each country (which is our proxy for economic activity), assuming that changes in expected GDP will equivalently affect electricity use. Finally, we predict the impact on bilateral remittance flows due to the stressed electricity use following the COVID shocks to each country.

To analyse the impact of the COVID pandemic on remittances, we consider two pieces of evidence. First, we stress the economic activity of each country (as predicted by the IMF) one at a time, and examine the ratio between the total predicted remittances, by country, following the COVID shock and the total expected remittances, by country, that would have prevailed had the COVID pandemic not taken place. The two scatter plots in Figure 9 depict the above ratio as a function of GDP per capita; one scatter plot corresponds to emerging economies (left) and one to advanced economies (right). Second, we consider the overall impact of stressing the economic activity of all the countries in our dataset at the same time. The two scatter plots in Figure 10 hence depict the expected reduction in the remittance inflows of each source country, due to the COVID pandemic shock, relative to the expected incoming remittances (of each source country) that would have prevailed had the COVID pandemic not taken place, as a function of GDP per capita. As before, the left (right) panel in Figure 10 focuses on emerging (advanced) economies.[11] Note that the second exercise is different from the first one, as it aims at quantifying the global impact on remittance flows.

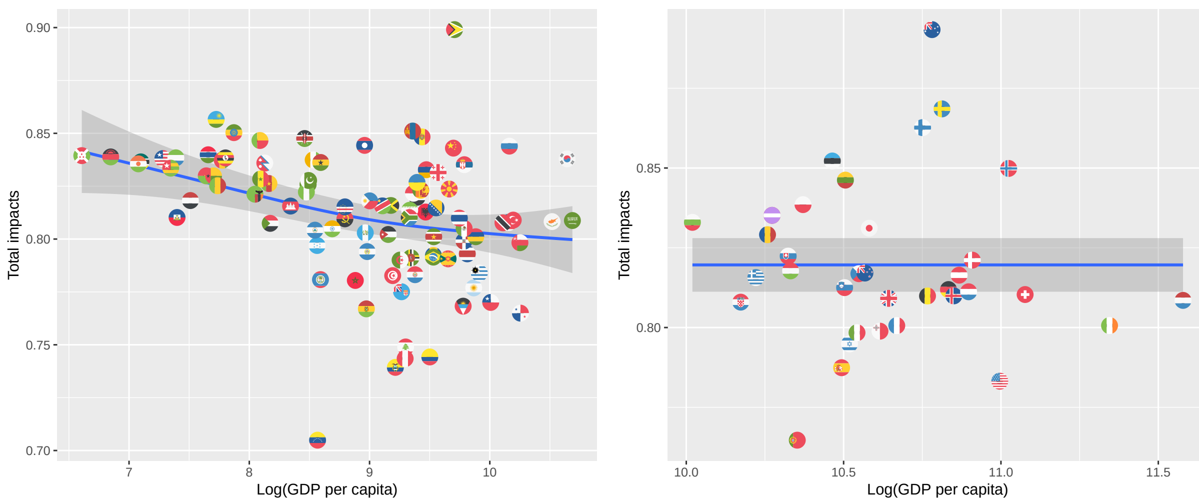
Figure 9: Country-specific relative total impacts due to the COVID shock (with one country at a time being shocked). Left panel: Emerging markets. Right panel: Advanced economies.



The two scatter plots exhibit the fraction between the total predicted remittances, per country, due to the COVID shock and the total expected remittances, by country, that would have prevailed had the COVID pandemic not taken place, as a function of GDP per capita. The plots are computed assuming that the electricity use per capita of one country at a time is shocked. The Figures are based on the model estimates in the last two columns of Table 2.

[11] It is important to add that in these exercises we are only computing the predicted effect on remittances, accounting for the impact on economic activity due to the pandemic. Therefore, we are not considering any increase in international aids that countries, in particular LMIC, might have received to mitigate the COVID impact on the population.

Figure 10: Relative total impact due to the COVID shock due to a global change. Left panel: Emerging markets. Right panel: Advanced economies.



The two scatter plots exhibit the fraction between the predicted incoming remittances due to the COVID shock and the expected incoming remittances that would have prevailed had the COVID pandemic not taken place, as a function of GDP per capita. The Figures are based on the model estimates in the last two columns of Table 2.

Figure 9 provides two interesting findings: On the one hand, China and Surinam (Dutch Guyana) are the two countries for which the ratio between the predicted remittances due to the COVID shock and the expected remittances that would have prevailed had the COVID pandemic not taken place is above one. The reason for such a situation is that while the economic activity of these countries was negatively affected by the COVID shock, the total year economic activity in each of them (as predicted by the IMF WEO projections) has still increased, relative to the previous year. On the other hand, the two scatters in Figure 9 show that, when shocking the economic activity of one country at a time, the most severely affected countries are those advanced economies with higher GDP per capita. In the case of emerging economies, the relation between the above ratio and GDP per capita is less clear.

In turn, Figure 10 shows that, when considering the simultaneous effect of all countries being affected by the COVID pandemic, countries with higher GDP per capita exhibit larger expected reductions in incoming remittances following the COVID pandemic (relative to the expected values that were predicted assuming the COVID shock had not taken place). This result is good news for LMIC, as it is showing that remittances may be more resilient for those countries that rely more on remittances. Another implication from this exercise is that it is likely that the relative importance of remittance flows as a source of external financing for LMIC would indeed rise, which is consistent with Ratha et al. (2020)'s predictions (who examine the impact of travel bans, disruption of international trade, and wealth effects of declines in the stock prices of multinational companies), among others.

7 Conclusions

This paper measures to what extent neighboring countries affect the amount of remittances between a source and a recipient country, controlling for the commonly used macro determinants of remittances in the literature (such as, GDP, population and transaction costs). Our work has three main contributions. First, we provide novel evidence on the effect of networks on remittance flows. Second, by properly accounting for the role of neighboring countries, we re-examine the altruism and investment motives to remit. Third, we propose a flexible modelling. This flexibility implies not only having multiple spatial neighbourhood matrices capturing origin- and destination- and spatial dependence, but on top of that, it has the capacity to accommodate for different characteristics for the source and the recipient countries, as well as for a different list of locations for origins and destinations. To conclude, one venue of future research could be to extend the analysis to a panel data estimation. The shortcoming of such a development would possibly be that there might be fewer countries of analysis.

8 Appendix

8.1 Variables Description

Variable	Description	Source
GDP per capita	(Constant USD) GDP as a proportion of total population, in log	World Bank
Electricity use PC	Use of electricity as a proportion of total population, in log	Central Intelligency Agency
Deflator	Growth of Deflator, with Deflator = GDP current US$/GDP constant	World Bank
Population	Total population	World Bank
Political Stability	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5	World Bank
Transfer Costs	Transfer fee for 200 euros, measured in current US$. The original dataset contained the fee for a 200 euros transfer, it was then converted to dollars. Available only for 2015	Western Union
Migrants	Stock of Migrants: Number of people born in a country other than that in which they live, in log	World Bank
Multiple FX	=1 if the country has restrictions, controls and/or multiple currency practices, dual and/or multiple exchange rates	IMF Annual Report on Exchange Arrangements and Exchange Rate Restrictions
Natural Disaster	Dummy that indicates the occurrence of the natural disaster (Earthquake, Flood and Storm)	EM-DAT: The OFDA/CRED International Disaster database
FX Average	Annual average of monthly exchange rates (1)	World Bank Global Economic Monitor
FX Vol	Standard deviation of monthly average exchange rates	World Bank Global Economic Monitor
Island	=1 if country is an island	CEPII
Landlocked	=1 if country is landlocked	CEPII
Com Border	=1 if the country pair shares a border	CEPII
Com Language	=1 if the country pair shares the language	CEPII
Com Currency	=1 if the country pair shares the currency	CEPII

Notes: Own elaboration. FX stands for foreign exchange and CEPII stands for the Center for Research and Expertise on the World Economy. (1) For those countries for which the monthly exchange rates were not available at the World Bank dataset for some period of time, the IMF dataset was used. The 10 countries involved were the following: South Sudan, Serbia, French Polynesia, New Caledonia, Montenegro, Saint Martin, Macau, Isle of Man, Cayman Islands, and Jersey. In the case of Latvia and Lithuania, which started using the EURO in January 2014 and 2015, respectively, the exchange rate used for the computations was the local currency unit to dollar until the incorporation to the Eurozone.

8.2 Descriptive statistics - 2017

Table 5: Descriptive statistics of the continuous variables of interest. 2017

	Min.	**Max.**	**Mean**	**Median**	**Std. Dev.**
Log(Remittances)	-11.66	10.31	-0.86	-0.84	3.58
Source country					
Log(Electric Use PC)	5.08	10.87	8.24	8.38	0.97
Log(Population)	10.84	19.59	16.17	16.15	1.71
FX Volatility	0.00	366.47	9.77	0.03	51.95
Transfer cost	-9.96	9.51	0.09	0.89	4.96
Recipient country					
Log(Electric Use PC)	3.01	10.87	7.36	7.76	1.54
Log(Population)	11.17	21.04	16.39	16.24	1.78
Pol Stability	-2.97	1.52	-0.12	0.01	0.93
Landlocked	0.00	1.00	0.16	0.00	0.36

Notes: Remittances are expressed in millions of USD. Min., Max. and Std. Dev. stand for minimum, maximum and standard deviation, respectively. FX stands for exchange rate, PC for per capita and Pol for Political.

Table 6: Frequency table of indicator variables

	0	**1**
Source country		
Island	5730	889
High inflation	5816	803
Medium inflation	1551	5068
Multiple FX	4743	1876
Recipient country		
Natural Disaster	4685	1934
High inflation	5862	757
Medium inflation	1447	5172
Landlocked	5573	1046
Country pair		
Com Border	6422	197
Com Language	5839	780
Com Currency	6334	285
Colony	6444	175

Notes: FX stands for exchange rate, Com stands for common.

8.3 Comparison estimates 2017 and 2012

Table 7: Bayesian model estimates with the two neighbourhood matrices W_o and W_d. Comparison between 2012 and 2017

	2012		**2017**	
Variables	**Coeff**	**T-stat**	**Coeff**	**T-stat**
Spat par O	0.386	39.4	0.375	48.805
Spat par D	0.475	47.517	0.429	48.951
Intercept	-13.083	-17.923	-10.557	-18.659
Source country				
Log(Population)	0.542	23.303	0.571	30.819
Island	0.568	4.908	0.353	4.061
High Inflation	0.473	2.8	-0.763	-8.471
Medium Inflation	0.782	5.729	-0.236	-4.068
Multiple FX	-0.367	-4.923	-0.226	-3.795
FX Volatility	-0.011	-4.222	-0.003	-6.964
Recipient country				
Log(Population)	0.364	15.629	0.415	22.825
High Inflation	-0.391	-2.676	0.451	4.055
Medium Inflation	-0.11	-1.014	0.349	4.311
Pol Stability	0.138	3.777	0.306	9.677
Landlocked	-0.363	-3.836	-0.475	-7.323
Natural Disaster	-0.001	-0.009	0.234	3.971
Country pair				
Com Border	0.826	4.534	0.81	5.379
Com Language	0.892	9.779	0.913	11.834
Com Currency	-0.056	-0.361	-0.179	-1.421
Colony	1.23	6.825	1.17	7.714
Distance	-0.152	-3.631	-0.367	-10.665

Notes: O and D correspond to origin and destination, respectively. FX stands for exchange rate, PC for per capita and Pol for Political. Com stands for common. Obs and T-stat stand for number of observations and t statistics, respectively.

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