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Exploring the Macroeconomic Drivers of International Bilateral-Remittance Flows: A Gravity-Model Approach

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Exploring the Macroeconomic Drivers of International Bilateral-Remittance Flows: A Gravity-Model Approach

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Abstract

This paper investigates the macroeconomic determinants of global bilateral remittances flows. Unlike existing studies, which have been often hampered by the lack of comprehensive and large-enough datasets, we use data originally covering 214 World countries over the 2010-2017 period. We employ a gravity-model approach to explore the role payed by dyadic and country-specific covariates in explaining remittances. We find that remittance flows are robustly and strongly impacted by size effects (i.e., number of migrants in the host country and population at home); transaction costs; common social, political and cultural ties; output growth rate and financial development at home. We also document the existence of a robust non-linear relationship between per-capita income at home and remittance flows, both in the aggregate and across income group. Our results suggest that altruistic and self-interested motives non-trivially interact and change across both host/home income groups and income level at home.

KEYWORDS: International remittances; International migration; Gravity Models.

JEL CLASSIFICATION: F24; F22; F63.

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1 Introduction

The last years have witnessed a spectacular increase in worldwide remittance flows[1]. As portrayed in Figure 1, panel (a), aggregate-remittance flows have been steadily growing, in nominal terms, from 37 to around 550 billion (current) US$ over the 1980-2019 period, which, in real terms, is equivalent to a six-fold increase. Furthermore, global remittances grew at a higher pace than merchandise trade, as documented by an almost doubled remittance/trade ratio. In the same period, the share of remittances to world GDP increased by 80%, as compared to a 55% rise in the trade-to-GDP ratio – see panel (b). Such an exponential surge in global remittances can only be partly explained by the increment in the number of (official) international migrants, which between 1980 and 2019 climbed from about 102M to 271M[2].

For many countries, especially low and middle-income ones, remittance inflows have surpassed official development aid (ODA) as well as foreign direct investment (FDI), becoming their largest source of foreign exchange earnings. Overall, remittances make up a share of the country GDP ranging between 5 and 40 per cent, which for some recipients is much larger than their export-to-GDP ratio[3].

Therefore, it comes as no surprise that remittances may have an extremely relevant impact on home-country economies, e.g. in alleviating poverty and contributing to development (Hagen-Zanker and Siegel, 2007; Yang, 2011). Remittances can indeed rise consumption and/or investment and play a crucial role in income smoothing, hence acting as an automatic stabilizer. However, they may also amplify the business cycle and thus destabilize economic activity (Cooray and Mallick, 2013).

Since the seminal paper of Lucas and Stark (1985), several theoretical models have been laid out to explore the determinants underlying individual-migrant remittance behaviors (Rapoport and Docquier, 2006). A wide spectrum of micro motives behind the reason why migrants remit (and how much) have been investigated, ranging between the two extremes of pure altruism and self-interest, but also including tempered forms of altruism and strategic motivations (Carling, 2008). These models have been taken to the data mostly using two approaches. First, remittance determinants have been tested at the micro level, focusing on single-country analyses and using household surveys[4]. Sec-

[1]According to the International Monetary Fund (IMF) and the World Bank (WB), remittances are defined as interpersonal transfers between migrants and their families remained in the country. They include personal transfers and compensation of employees. Throughout this paper, we will employ the terms "sending", "origin" or "host" as defining the country where migrants live and from which they send remittances; whereas "destination", "receiving" and "home" are used to qualify the country where the migrant is from.

[2]See `https://www.un.org/en/development/desa/population/migration/data/estimates2/estimates17.asp`. As a result, the nominal value of remittances per migrant ballooned from about 363US$ to 2409US$.

[3]Cf. `https://blogs.worldbank.org/opendata/money-sent-home-workers-now-largest-source-external-financing-low-and-middle-income`.

[4]For critical surveys of this vast literature, see for example Rapoport and Docquier (2006) and Hagen-

ond, the macroeconomic drivers of aggregate remittances have been explored employing panel-data techniques, where the observational unit is a country and data come from balance-of-payments statistics across the years[5].

Another, albeit less common, stream of literature has exploited the inherent sending-receiving nature of aggregate-remittance flows fitting panel-gravity models to bilateral (origin-destination) remittance flows[6]. A gravity-model approach to remittances has some values added as compared to panel-based econometric models. Those include the possibility: (i) to take separately into account home vs host country-specific characteristics, therefore proxying country masses and frictions, which may limit the volume of remittances due to transaction costs; (ii) to combine a microeconomic foundation with macroeconomic data, since a gravity-like relation emerges from simple micro-founded theoretical models (Schiopu and Siegfried, 2006; Rapoport and Docquier, 2006; McCracken, Ramlogan-Dobson, and Stack, 2017). This last feature is particularly important, as sign predictions coming from the theory can be tested using real world data.

However, existing gravity-based attempts to study international-remittance flows have been often hampered by the lack of comprehensive and large-enough datasets. This has resulted in insufficient coverage for either the cross-sectional dimension (e.g., countries) or for the longitudinal one (e.g., years), or both.

In this paper, we attempt to overcome this limitation fitting a panel-gravity model to the "World Bank Migration & Remittance" database[7]. This repository originally contains estimates for international-remittance flows from 214 sending (host) countries to 214 receiving (home) countries in years 2000-2017. Unlike existing studies, the data we employ define a balanced "squared" panel, with all country pairs featured in each year, which may improve the robustness of coefficient estimates. Obviously, some covariate may present missing values over different years, origins and destinations, which may result in an unbalanced sample estimate. Nevertheless, we are able to fit our gravity model to a very large number of remittance flows, covering a set of host and home countries which is generally larger than those employed so far in the literature (cf. Table D1 in the

Zanker and Siegel (2007). In particular, Yang (2011) discusses the issue of migrant control over remittances, highlighting that migrants may decide to remit more the larger their control over how remittances are used in the receiving country.

[5]See, among others, Vargas-Silva and Huang (2006), Freund and Spatafora (2008), Adams (2009), Posso (2015), Tabit and Moussir (2016) and Kakhkharov, Akimov, and Rohde (2017).

[6]Cf. Schiopu and Siegfried (2006), Lueth and Ruiz-Arranz (2006), Docquier, Rapoport, and Salomone (2012), Nnyanzi (2016), McCracken, Ramlogan-Dobson, and Stack (2017) and Ahmed, Mughal, and Martínez-Zarzoso (2021). The gravity model has been the workhorse model of international trade for more than 50 years (see Baier and Standaert, 2020, and references therein), but it has been successfully applied to several other bilateral-flow data, such as e.g. equity (Portes and Rey, 2005), foreign-direct investment (Harach and Rodriguez-Crespo, 2014), and migration (Beine, Bertoli, and Fernandez-Huertas Moraga, 2016; Fagiolo and Mastrorillo, 2015).

[7]See `worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data`.

Appendix)[8]. At the same time, the large cross-sectional country coverage allows one to address the question whether estimated covariate elasticities differ among host-home country subgroups, e.g. if the determinants of remittance flows from rich or middle-income countries to poor ones are different from those underlying remittance flows in the whole sample.

Furthermore, we contribute to the literature employing gravity models to explain the macroeconomic determinants of bilateral international-remittance flows in four additional dimensions. First, unlike most of the existing papers[9], we explicitly deal with the zero-flow issue (Santos Silva and Tenreyro, 2006) comparing results from OLS and Poisson Pseudo-Maximum Likelihood (PPML) estimators. Second, we flexibly employ different sets of fixed effects (FEs), playing with alternative combinations of host/home and time FEs, so as to possibly mitigate omitted-variable biases. Third, we address potential reverse-causality endogeneity issues coming from using, among our covariates, the stock of migrants in the host country and income at home. Finally, following Cox, Eser, and Jimenez (1998), we test for non-linearities in the relation between income at home and remittance flows, to better explore the interplay between altruistic and self-interested motives.

The rest of the paper is organized as follows. Section 2 briefly discusses some theoretical background and existing papers dealing with a gravity-model perspective to the study of remittance-flow determinants. In Section 3 we describe the data and methods employed. Section 4 presents our main results and reports on robustness checks. Finally, Section 5 concludes.

2 Theoretical Background and Related Literature

2.1 Why Do Migrants Remit?

Disentangling the economic motivations behind migrants' decision about if and how much to remit is not an easy task. Remitting involves indeed a large number of possible interacting determinants, having to do not only with individual preferences and behavioral attitudes of the migrant, but also with economic, social and political factors both at home and in the host country.

Since the seminal work by Lucas and Stark (1985), several theories have been proposed to fill the gap between two extreme views of migrant-remittance behavior (Yang, 2011, and references therein). The first view considers remittances as driven by a pure altruistic motive, fueled by the migrant desire to allow relatives back home to cope with poverty and adverse shocks. The second one models remittance behavior as stemming from a self-

[8] We will come back to the issue of balanced vs. unbalanced estimation samples in Section 4.3.
[9] Cf. Docquier, Rapoport, and Salomone (2012) for an exception.

interested individual who only cares about her/his return to the community s/he left, and therefore remits to increase the likelihood to inherit and/or to buy assets at home. Migrants can however decide to remit because of reasons somewhat in between those two opposite motivations (Hagen-Zanker and Siegel, 2007; Carling, 2008), i.e. driven by a sort of tempered-altruistic behavior wherein migration provides mutual benefits for both the migrant and the family at home. In this framework, remitting can be the consequence of a sort of implicit contractual arrangement, whose motives include loan repayment (i.e., whenever migrants borrow money from their families to cover migration-related cost), exchange (e.g., compensations for child care provided to the migrant by recipients at home), and co-insurance (e.g., when negative shocks occur at home or when the migrant loses her/his job in the host country). Furthermore, the decision to remit can be induced by purely-strategic motives (Stark and Wang, 2002), if e.g. skilled migrants have an incentive to send money back home to avoid further immigration of skilled workers, which might depress wages for skilled jobs.

2.2 Empirical Tests of Remittance Motivations

Trying to empirically discriminate between these competing theories is not always possible. This is because, especially at the micro level, alternative theories often predict similar signs as to the effect of covariates in econometric models explaining remittances. In addition, poor data quality may prevent one to design the appropriate testing strategy (Rapoport and Docquier, 2006). In fact, at the macro level, the lack of high-quality data has been the major hurdle faced by researchers attempting to assess the relative importance of aggregate determinants of country remittance flows.

This is in particular true in the case the dependent variable is not aggregate country (sent or received) remittances, but one aims at explaining bilateral international remittance flows between pairs of countries using a gravity-model approach. Indeed, availability of good-quality datasets featuring, for a large set of country pairs and years, all bilateral remittance flows has always been extremely poor, hence limiting the scope of applied analyses in this field. As we show in the Appendix (Table D1), existing works using remittance gravity models (RGMs)[10] usually focused on a limited number of sending and receiving countries (respectively, in the range 16-89 and 7-75) observed for a short number of years, which is typically inversely related with the country sample size used in the analysis. Furthermore, the panel structure is often strongly unbalanced: the set of sending countries never coincides with that of receiving ones, implying a rectangular dataset. This implies that one may not correctly evaluate the impact of country-specific determinants in the two-way remittance relationship between any two countries in the

[10]See Schiopu and Siegfried (2006), Lueth and Ruiz-Arranz (2006), Docquier, Rapoport, and Salomone (2012), Nnyanzi (2016), McCracken, Ramlogan-Dobson, and Stack (2017) and Ahmed, Mughal, and Martínez-Zarzoso (2021).

sample (we shall come back to that issue in Section 4.3).

In this paper, we use instead data from the "World Bank Migration & Remittance" database, originally reporting estimates for international-remittance bilateral flows from 214 sending (host) countries to 214 receiving (home) countries in years 2000-2017. As discussed in more details below, we are eventually able to retain 176 countries in our regression analyses, after removing those that never remit nor receive and for which some covariates are missing. Therefore, we still cover most remittance flows in the World in a squared panel, i.e. all incoming and outgoing (zero or positive) remittance flows are present in the dataset in each year (see Table C1 in the Appendix and cf. the discussion in Section 4.3). Despite World Bank data are not empirically observed but come from estimates, this is, to the best of our knowledge, the best choice if one aims at a large country-coverage for a sufficiently long number of years —we shall go back on this point in Section 5.

In addition to heterogeneity in country sample size and composition, there are further issues limiting comparability of results (and their robustness) across existing RGM works. First, all studies except that by Docquier, Rapoport, and Salomone (2012) apply an OLS estimator only, thus excluding ex-ante the possibility of dealing with zero-remittance flows. It is well known that, under heteroskedasticity, this may imply biased estimates of the true elasticities (Santos Silva and Tenreyro, 2006). Second, existing papers employ different assumptions as to the set of sending-receiving country and time FEs[11]. As discussed at length in Anderson and van Wincoop (2003), failing to properly control for cross-sectional origin-destination heterogeneity may lead to strong unobserved-variable biases.

In our exercises, we instead explicitly address these two issues. Firstly, we check the robustness of our OLS estimates against those obtained via a PPML estimator, which explicitly includes zero flows in the estimation. Secondly, we experiment with different assumptions as to FEs employed in the regressions (more on that in Section 3).

Furthermore, following most of existing papers (see Table D1 in the Appendix), we test for potential (reverse-causation) endogeneity of some right-side variables, namely the stock of migrants at the origin of remittance flows (i.e., in the host country) and income at destination. Finally, our enlarged country sample size allow us to run separate gravity regressions, where sending vs receiving countries belong to subgroups defined according to their income (i.e., high, middle and low income), and therefore to assess how the aggregate drivers of remittances change depending on the development levels of the home

[11]For example, Schiopu and Siegfried (2006) only employ receiving-country and year FEs, whereas Lueth and Ruiz-Arranz (2006) and Docquier, Rapoport, and Salomone (2012) introduce separate FEs for the sending and receiving country, as well as for years. Ahmed, Mughal, and Martínez-Zarzoso (2021) opt instead for bilateral and year dummies only, thus neglecting cross-sectional unobservable heterogeneity at the level of sending and receiving countries. This happens also in Nnyanzi (2016), where only time FEs are considered.

and host country.

2.3 Gravity Models of Bilateral Remittance Flows

As mentioned, a gravity-model framework is particularly appealing if the researcher aims at assessing the macroeconomic determinants of remittances. To begin with, remittance flows at the macro level have an intrinsic sending-receiver essence. Therefore, they naturally lend themselves to a modeling setup where flows are explained using separate origin and destination characteristics, as well as features related to the dyadic interaction between host and home country, capturing the role of frictions induced by transaction costs.

More importantly, a gravity specification for remittance flows emerges as the equilibrium prediction of a 2-period model where migrants care about consumption and invest in a host-country safe asset as well as in a home-country risky asset (Schiopu and Siegfried, 2006; Rapoport and Docquier, 2006; McCracken, Ramlogan-Dobson, and Stack, 2017). This allows one to derive precise implications about the expected sign of remittance macroeconomic drivers, stemming from microeconomic assumptions about altruistic vs self-interested migrant behaviors. For example, the model predicts that, if migrants are sufficiently altruistic[12], remittances to relatives in the home country should decrease the larger income at destination (net of that in the origin).

Existing empirical evidence about the role of macroeconomic determinants of remittances is nevertheless not conclusive (cf. Table D1 in the Appendix). Sign predictions are indeed often contrasting and sometimes uncertain, possibly because of data limitations and estimation issues discussed above. For instance, the impact of economic conditions at home (i.e., country income, GDP growth, etc.), as well as that of transaction costs (as modeled using geographical distance and traditional gravity dyadic relations), may be biased and highly sensitive to the FE specification, treatment of zero flows and presence of endogeneity. Additionally, the sample of countries included in the analysis —either as sending or receiving— greatly varies across exiting studies. Even in Ahmed, Mughal, and Martínez-Zarzoso (2021), who employ the "World Bank Migration & Remittance" database as in the present work, only the most important migration corridors are considered[13].

This paper aims at reassessing in a more robust way the role of macroeconomic drivers of international remittance flows. In our RGM approach, we control for three types of covariates, net of various combinations of origin country (i), destination country (j) and year (t) FEs. The first one is the stock of migrants in the host country, which varies

[12] In addition, remittance cost must be sufficiently low and host-home income differential large enough.

[13] This implies that only 30 sending countries and 75 receiving countries are left in the sample, also because of the presence of many missing values in the covariate controlling for transaction costs, see also Section 4.3.

across origins and destinations of remittance flows (i.e., respectively, migrant host and home countries) and time (i.e., over the ijt triplet). In line with existing literature (Freund and Spatafora, 2008), we expect remittances to increase with the stock of migrants in the host country ("Number of Migrants" thereafter), due to a sheer size effect[14].

The second family of covariates are time invariant and vary across pairs of countries (i.e. across the ij dyad). These include geographical distance, contiguity and typical gravity-model bilateral dummies capturing ties between home and host countries (i.e., common language, and religion, as well as existence of any former colonial relationship). Remittances are expected to decrease with distance and increase if host and home country share a border, as they both proxy transaction costs[15]. The impact of contiguity may however be negative if, net of geographical distance, sharing a border enhances informal remittances and discourages formal ones, as travel costs are lower and migrants find it easier to remit by unofficially transferring money across borders (Lueth and Ruiz-Arranz, 2006). We also expect holding ties with the host country to boost remittances. Indeed, migrants already speaking host-country language or sharing the same religion may be more integrated in the new society and hence they may more easily get a job. Similarly, a common past of colonial relationships typically implies some degree of institutional similarity and political ties between home and host countries. This may facilitate migration towards the former colonizer and subsequent integration.

The third class of potential remittance determinants includes origin and destination country-specific factors, which vary both across countries and time (along the it and/or jt dimensions). More specifically, we focus on covariates proxying for country economic conditions (i.e., per-capita GDP and GDP growth), size effects (i.e., population), agriculture (i.e., share of rural population), education (i.e. expenditure share of education over GDP and enrollment rate) and efficiency of financial institutions (as proxied by the share of bank branches)[16]. Net of host-country and other destination covariates, we expect remittances to increase: (i) the larger population size at home (as, net of the number of migrants at the origin, the greater will be the basin of potential recipients)[17]; (ii) the larger the share of home rural population and education level, as this may reflect loan repayment or exchange motives, and more generally that remittances are used for invest-

[14]An alternative strategy is to use as dependent variable the ratio of remittances to the number of migrants. However, we chose not to adopt this approach as it implicitly constrains the elasticity of the stock of migrants to one and it is not usually employed in the gravity-model literature.

[15]Interpreting geographical distance as a proxy for time-invariant transaction costs is common in the gravity-model literature. After all, sheer geography should have largely decreased its impact on international bilateral flows in the era of globalization, not only in the case of trade or migration, but also when immaterial goods are concerned (Coe, Subramanian, and Tamirisa, 2007). However, geographical distance still appears to be a large and growing obstacle to bilateral flows even when it proxies immaterial transport costs (Brei and von Peter, 2018).

[16]See Section 3 and Tables A1 and B1 in the Appendix for more details.

[17]We have also experimented with specifications where country GDP instead of population is used to proxy country size, without any substantial differences in our results.

ment purposes rather than to boost consumption; cf. see Hagen-Zanker and Siegel (2007); Yang (2011)[18]; (iii) the more developed financial system at destination, because this eases formal-money transfers both at home and in the host country (Giuliano and Ruiz-Arranz, 2009); and (iv) the lower home GDP growth rate, as it may be correlated with a less dynamic economic environment at home and, therefore, may proxy for sender-receiver differences in the business cycles (Kakhkharov, Akimov, and Rohde, 2017).

The impact of per-capita GDP (as a proxy for income) on remittances is instead less straightforward. Given host-country income, we expect that, if altruistic motives dominate, then a larger income at home would decrease remittance flows. Instead, if migrants are more self-interested and care about investment, an increasing income at home should boost remittances. However, as shown Cox, Eser, and Jimenez (1998), altruistic and self-interested motives may switch as home income increases. This means that one may possibly observe U-shaped (or inversely U-shaped) relations when investigating the impact of income on remittances. For example, migrants from poor home countries may mostly remit to help relatives back home coping with poverty and adverse shocks. On the contrary, migrants from high-income countries may start remitting pushed by tempered-altruistic or even purely self-interested motivations (e.g., loan repayment, exchange or co-insurance). Therefore, in order to explore whether this is the case in our data, we test for possible non linearities in the (home) income-remittance relationship.

A number of other macroeconomic determinants may be potentially affect international remittance flows (Carling, 2008). These include, among others, climate and disasters, interest and exchange rate differentials, poverty and fragility indicators. However, as discussed in the next Section (see also Table B1), their detected impact in our regression exercises was neither conclusive nor robust across alternative specifications and estimation methods, and therefore were discarded from the analysis.

3 Data and Methods

We fit to the data a panel gravity model whose non-linear formulation reads:

$$R_{ij}^t = \kappa \exp\{\alpha_{(i)(j)}^{(t)} + \beta\delta^t + \gamma\mathbf{D}_{ij} + \phi M_{ij}^t + \theta\mathbf{X}_{(i)(j)}^{(t)}\}\epsilon_{ij}^t, \tag{1}$$

where R_{ij}^t are remittances (in levels) from i (origin/host country) to j (destination/home country) in year t; κ is a constant; $\alpha_{(i)(j)}^{(t)}$ is a set of country specific dummies accommodating different origin, destination and time fixed-effect (FE) specifications (more on that below); δ^t are time dummies; $\mathbf{D_{ij}}$ is a set of time-invariant, bilateral covariates; M_{ij}^t is the number of migrants, i.e. the stock of people born in country i and living in country

[18]A positive effect of education on remittances is also found by Bollard, McKenzie, Morten, and Rapoport (2011) using using microdata in 11 major host countries

j in year t; $\mathbf{X}_{(i)(j)}^{(t)}$ is a set of country-specific, time dependent, regressors that vary across origins, destinations, and time, depending on chosen FE specification; and ϵ_{ij}^{t} are the errors.

We experiment with different FE formulations as to $\alpha_{(i)(j)}^{(t)}$. In particular, we are mostly interested in controlling for both cross-sectional and longitudinal variation across origins of the remittance flows, while focusing on time-varying observable characteristics of destination/home countries —once their unobservable cross-sectional differences are controlled for. Therefore, our benchmark FE specification will be:

$$\alpha_{(i)(j)}^{(t)} = \eta_i^t + \psi_j. \tag{2}$$

As a consequence, country-specific variables only depends on destinations, i.e., $\mathbf{X}_{(i)(j)}^{(t)} = \mathbf{X}_j^t$. This means that coefficient estimates of destination time-varying covariates are to be interpreted as "net of the country-origin covariates".

To check for robustness of bilateral-variable coefficient estimates (especially as far as M_{ij}^t is concerned), we also fit a structural-gravity specification where $\alpha_{(i)(j)}^{(t)} = \eta_i^t + \psi_j^t$ and country-specific covariates $\mathbf{X}_{(i)(j)}^{(t)}$ are omitted (more on that in Section 4.3).

Remittance and migrant data come from the "World Bank Migration & Remittance" database[19]. Bilateral matrices originally report estimated remittance flows (in millions of US$) from 214 sending (host) countries to 214 receiving (home) countries in years 2000-2017 —we shall go back to discussing some possible issues related to using estimated rather than observed data in Section 5.

We also employ data about migration stocks, which contain estimates of the number of people M_{ij}^t, born in the destination country j and living in the host country i (i.e., the origin of the remittance flow from i to j) in years 2010, 2013 and 2017. Estimates are based on the "Migration and Remittances Factbook" (various years) and are used here as a covariate controlling for bilateral migration-size effects at the origin. Since we do not have bilateral-migration observations for all the years covered in the remittance database, we employ two alternative strategies. First, we estimate Eq. (1) only for the three waves where both remittance and migration are available. In this setup, the number migrants M_{ij}^t enter as a contemporaneous co-variate for R_{ij}^t, $t = 2010, 2013, 2017$. We label this case in our results as "Year=t". Second, we fit our model in all the years for which we do have remittance data ($t = 2010, \dots, 2017$), building a stepwise migrants-at-destination variable reading $\tilde{M}_{ij}^t = M_{ij}^{2010}$ for $t = 2010, 2011, 2012$, $\tilde{M}_{ij}^t = M_{ij}^{2013}$ for $t = 2013, \dots, 2016$, and $\tilde{M}_{ij}^t = M_{ij}^{2017}$ for $t = 2017$. We label this case in our results as "Stepwise". Descriptive statistics for bilateral remittances and the number of migrants in three selected years (2010, 2013 and 2017) are reported in the Appendix, cf. Table C2.

In addition to M_{ij}^t, we account for two sources of variation. The first one ($\mathbf{D}_{ij}$) includes

[19]See Table A1 for descriptions and sources of all variables used in our analysis.

usual bilateral, time-invariant, standard gravity regressors such as geographical distance, contiguity, common language, common religion and existence of any colonial relationship in the past. We have also experimented with additional bilateral, time-invariant effects such as common ethnic language, common currency, weighted versions of geographical distance, as well as different definitions of colonial relationships, see Table B1 for details. However, these covariates have been excluded from our preferred specification as they turned out to be not significant in almost all our regressions and contained too many missing values for our selected sample of 176 countries.

The second one ($\mathbf{X}_{(i)(j)}^{(t)}$) controls for origin or destination country-specific factors that may affect remittance flows and vary both longitudinally and cross-sectionally. These are: income (as proxied by per-capita GDP, pcGDP henceforth), GDP growth rates, population, the share of rural population, expenditure in education (as a % of GDP), enrollment rate, the share of bank branches[20]. Since, as mentioned, we mainly focus on destination-country characteristics, they will enter as $\mathbf{X}_j^t$ in our preferred specifications. Since, as mentioned, we are interested in exploring possible non-linearities in the relation between home income and remittances, we also insert among our covariates the square of per-capita GDP.

After removing countries that never remit nor receive in at least one year (12 in total), and those for which our selected covariates are seldom observed (26 countries), we end up with a final sample covering 176 countries (see Table C1 in the Appendix) for the period 2010-2017. The remittance-flow panel has a squared format, i.e. all in/out (zero and positive) remittance flows are featured in the dataset in each year (more on this point in Section 4.3).

We begin fitting Eq. (1) with a standard OLS estimator. This requires to log-linearize the gravity model and therefore does not allow one to account for zero-remittance flows that, as Table C2 suggest, is a sensible issue in our data. It is well-known that, under heteroskedasticity, this implies potentially-biased coefficient estimates (Santos Silva and Tenreyro, 2006). Therefore, we check the robustness of our OLS baseline results estimating (1) with a Poisson pseudo-maximum likelihood (PPML) estimator, using remittances in level and including their zero observations.

Endogeneity may also be a possible source of bias in our exercises. Indeed, in addition to omitted-variable biases, which are in partly reduced by origin and destination fixed effects, reverse causation (RC) may be an issue. In particular, we are concerned with RC generated by the number of migrants and per-capita GDP, which can both cause and be

[20] Also in this case, the explaining power of many additional, potentially-interesting, factors has been explored. Due to their non significance in most of the regression exercises performed, they have been excluded form our preferred specification. These additional regressors are: domestic credit share, poverty gaps, educational attainment, enrollment and literacy rates, the number of displaced persons, real exchange and interest rates, intensity of natural disasters, and country-fragility indicators (see Table B1 for details)

affected by remittances[21]. In order to address endogeneity of the number of migrants, we double-check our baseline results by replacing M_{ij}^t and $\tilde{M}_{ij}^t$ with the observation at $t = 2010$, i.e. we set $M_{ij}^t = M_{ij}^{2010}$, for all $t = 2010, \ldots, 2017$ (Altonji and Card, 1991)

To further check for robustness, we perform two additional exercises. In the first one, we employ less-recent observations to instrument M_{ij}^t, using past observations from the Global Bilateral Migration database for the years 1960, 1970, 1990 and 2000[22]. In the second exercise, we instrument M_{ij}^t using a structural-gravity model that reads: $\log(M_{ij}^t) = a + b_{it} + c_{jt} + d\Delta_{ij} + \epsilon_{ij}^t$, where b and c are time-dependent origin and destination FEs and Δ_{ij} is geographical distance. We use the OLS predictions $\hat{M}_{ij}^t$ from this model in our main equation (1). Overall, both exercises confirm the results obtained using $M_{ij}^t = M_{ij}^{2010}$. Therefore, we only report the latter case in discussing our main findings, see Section 4.

Furthermore, we investigate whether the possible endogeneity of per-capita GDP at destination may lead to biased estimates. We implement a two-stage model where in the first step the endogenous covariate is regressed against a set of independent variables that are country (and time) dependent. These are geographical and climate-related factors including precipitation and temperature anomalies, percentage of land that is arable, average elevation, coastline length, distance from the equator and country remoteness (defined as the sum of geographical distances between a country and all the others), see Table A1. In order to limit over-identification issues, we end up with a parsimonious first-stage model where, in addition to time and continent dummies, only distance from the equator and temperature anomalies are kept in the regression (R^2=0.437). As expected, in the first stage regression, per-capita GDP at destination is positively related to temperature anomalies and negatively associated to distance from the equator. Both coefficients are statistically significant at 1% and standard F-based tests reject the hypothesis that instruments are weak. In the second stage, we fit our main gravity equation using OLS (2SLS, see Wooldridge, 2001), considering per-capita GDP as an endogenous covariate[23]. According to Sargan-Hansen J-test ($\chi^2(1)$=4.26), instruments are not over-identified (p-value=0.039).

Finally, we double-check our results against a number of possible sources of bias, including the effect of missing values in the covariates, multicollinearity between population-related regressors, and the presence of trends in technological advances, which may have

[21]In principle, other covariates may reverse-cause remittances, e.g. GDP growth. However, existing literature failed so far to establish a robust causal link from remittances to country growth (Perez-Saiz, Dridi, Gursoy, and Bari, 2019; Yang, 2011). We briefly return to this point in Section 5.

[22]Due to the well-known persistence of bilateral migration stocks over time (Parsons, Skeldon, Walmsley, and Winters, 2007), these appear to be a valid instrument for 2010 stocks. Of course, here we do not argue that they may actually explain more recent remittance behavior, as structural changes induced by globalization may have substantially altered migration trends.

[23]For robustness purposes, we have also employed a Poisson two-stage IV estimator (2SP, see Windmeijer and Santos Silva, 1997). In the next section, we only report results from OLS, as 2SP regressions lead to similar outcomes. Details are available from the authors upon request.

led to remittance costs unevenly decreasing in time (cf. Section 4.3).

4 Results

4.1 Whole-Sample Regressions

Table 1 reports coefficient estimates obtained when Eq. (1) is fitted to whole-sample data. We show two sets of specifications. The first set —columns (1)-(4)— includes baseline OLS and PPML estimates where empirically-observed values for both the number of migrants and per-capita GDP are employed. The second set —last three columns— reports results obtained instrumenting the number of migrants (with its 2010 values, cf. columns 5-6) and per-capita GDP (column 7). As discussed in Section 3, we also experiment with two alternative setups as far as the number-of-migrants covariate is concerned, according to whether only years 2010, 2013 and 2017 are considered ("Year=t", cf. columns 1 and 2) or the "Stepwise" version of M_{ij}^t is employed (columns 2 and 4)[24].

As a first general observation, both diagnostics and the signs of estimated coefficients turn out to be very stable across our first four baseline specifications, i.e. the R^2 is always very high and we do not detect sign inconsistencies as the estimation method and the definition of the number-of-migrant covariate change.

Notice also that the number of observations actually fitted substantially varies across specifications. This is due to two related issues. First, the squared remittance matrix contains 176*175=30,800 observations per year, that is 246,400 observations in total, of which only 55,731 are strictly positive (cf. Table C2). When using the "Year=t" version for the number of migrants, there are only about 21,000 strictly positive observations notionally available with the OLS estimator. Second, the presence of missing values in the covariates (on average, about 40% of the observations), scattered across years and countries, further limits the number of observations actually available and makes the panel unbalanced. This implies that in the OLS case one can fit only about 12,500 observations in the "Year=t" case and about 33,400 observations when using either the "Stepwise" option or when instrumenting the number of migrants with year 2010. Notwithstanding missing values in the covariates, the sample size becomes much larger when we employ the PPML estimator, as all zero-flows are considered. We will explicitly address the robustness of our results to the presence of missing values in the covariates in Section 4.3.

As far as significance and magnitude of coefficients are concerned, there appears to be a small subset of covariates that, overall, seem to impact remittances in a less robust way across specifications. For instance, colonial ties sometimes become not significant, whereas the magnitude of coefficient estimates for geographical distance, GDP growth

[24]This version of M_{ij}^t is used also in column (7), when we instrument per-capita GDP. Similar results are obtained using the "Year=t" definition.

and common language occasionally change.

Nevertheless, results in Table 1 suggest quite a robust and consistent pattern as to the association between macroeconomic determinants and bilateral remittances. Indeed, remittances increase the larger the pool of migrants at the origin; whether home/host countries share a language, colonial or religion tie; and the larger total population, rural population share, expenditure in education, enrollment rate and bank branches at home. Instead, remittances decrease the larger geographical distance between origin and destination and GDP growth at home; and whether home and host countries share a border.

Taken together, the foregoing results imply a number of considerations as to the role played by alternative macroeconomic drivers of remittances. First, the stock of migrants at the origin appears to exert a very stable and strong size effect on remittance flows, net of the magnitude of the basin of recipients at home, controlled for by total population. This is confirmed also in column (5)-(6), where we instrument the stock of migrants with its year-2010 observations. Second, the negative impact of geographical distance hints at transaction costs as being a relevant factor in explaining remittances. Note, however, that sharing a border reduces formal flows of money towards home. This indicates that contiguity may be an incentive to boost informal ways to remit (we shall further comment on this interpretation in Section 4.3). Third, our exercises confirm that remittances are facilitated if origin and destination countries hold social, cultural and political ties, as this may further decrease transaction costs. Fourth, the positive impact of rural population share, expenditure in education and enrollment rate suggests that, as mentioned in Section 2, remittances are employed relatively more for investment motives rather than as a way to boost consumption at home. Finally, relatively to the origin, a less dynamic but more financially-developed home economy is able to attract more remittances.

We also detect a consistent and robust non-linear impact of income (pcGDP) at destination. More precisely, as Table 1 shows, we find that the relation between home income and remittances is U-shaped, with remittance flows decreasing for low-income levels and increasing for high-income ones. As column (7) suggests, this result is robust to possible endogeneity biases. Indeed, a 2SLS estimation procedure (when in the first stage per-capita GDP is regressed against country distance from the equator and temperature anomalies) yields similar coefficient estimates for pcGDP and its squared term.

The U-shaped relationship between (per-capita) income and remittances observed in the whole data sample, is depicted in Figure 2. There, we plot the marginal effect of pcGDP (across its observed range) on bilateral-remittance flows in a log-log scale (for the specification in Table 1, column 2) and we add in background the histogram of the observed whole-sample distribution of pcGDP at destination.

This evidence suggests that for relatively poor destination countries, altruistic motives dominate in the sending behavior of migrants (net of host income), whereas self-interest seems to be more relevant in the decision to remit as income at home —relatively to that at the origin— becomes larger than a given threshold. This is in contrast with results obtained by Cox, Eser, and Jimenez (1998), who find that, in the case of private transfers in Peru, exchange motives prevail for low-income recipients and altruistic motives predominate for those with high income.

In order to dig further on this point —and more generally to better understand if whole-sample results still hold when we consider subsamples of remittance flows— we now move to a more disaggregated analysis, where both origin and destination countries are classified according to their income group.

4.2 Remittance Flows by Origin and Destination Income Group

We categorize countries in our sample in three income groups (poor, middle and rich), using the 2020 WB income-group classification based on the Atlas method[25]. In our exercises, countries are defined as: (i) "Poor" (PC) if they belong to the "Low" or "Lower-middle" WB income group; (ii) "Middle" (MC) if they are classified as "Upper middle "; (iii) "Rich" (RC) if they belong to the "High" WB income group.

This allows us to form 9 non-overlapping subsamples for our dependent variable, according to whether the origin and the destination country of remittance flows are classified as PC, MC or RC.

We are particularly interested in focusing on two subsamples, namely those where remittances are sent to a PC either from a RC ("Rich to Poor") or a MC one ("Middle to Poor"). This is because of two main reasons. First, poor countries are those where remittances can impact the most in terms alleviating poverty and promote economic growth. Second, as discussed above, there exists literature (see, e.g., Cox, Eser, and Jimenez, 1998) showing that in poor (home) countries exchange and self-interested motives prevail for low-income levels, while altruistic motives predominate when income grows. This suggests that an inverse U-shaped relation might be observed when focusing on poor home countries, contrary to what we have found in our whole sample estimates.

Table 2 summarizes our main outcomes. We report OLS coefficient estimates and significance levels obtained when fitting Eq. 1 to the two subsamples of interest, and comparing them with whole-sample results from Table 1, columns (1)-(2)[26].

To begin with, note that the sign and significance of most macroeconomic drivers of remittances, as identified in the whole data sample, are confirmed also when disaggregating by origin and destination income groups. In particular, size effects exerted by migrants in the host country and home-country population continue to be strong determinants of remittances also in the "Rich to Poor" and "Middle to Poor" subsamples.

[25]See `https://datahelpdesk.worldbank.org/knowledgebase/articles/906519`

[26]Overall, the main insights from Table 2 robustly hold with PPML estimation and instrumentation.

The same observation applies for GDP growth, rural population share, education-related covariates and bank branches.

On the contrary, the impact on remittances of macroeconomic drivers associated to transaction costs and bilateral ties differs between whole-sample (column 3) and income-group (columns 1-2) regressions. On the one hand, a larger geographical distance now boosts remittances from rich to poor countries. This is in line with evidence found in de Sousa and Duval (2010) for Romania, and is in general consistent with the idea that migrants from poor countries, who travel longer distances, remit more because they cannot visit their home country rather frequently —and therefore they cannot carry in-kind or cash with them. In addition, distance may be positively associated with remittances to poor countries due to a loan-repayment motive: if family members living in distant, low-income countries partly covered the higher migration cost, such a loan may be repaid in the form of larger remittances thereafter. These interpretations are also consistent with the almost not significant effect of contiguity on remittances from high-middle income countries to poor ones, also because poor countries do not tend to share a border with richer ones (i.e., informal remitting channels become irrelevant). Nevertheless, our disaggregated regressions do not pick up any positive association between contiguity and formal-remittance flows in income-disaggregated samples, as perhaps one may have expected.

Second, common ties related to religion, former colonial relationships and (partly) language become much less important than in the aggregate while explaining remittances from middle and rich countries to poor ones. Although the interpretation of why this happens is less straightforward, the significance loss of social, cultural and political ties as macroeconomic drivers of remittances may be in line with the idea that migrants from poor areas, hosted by richer countries, are less integrated in their societies, and therefore cannot sufficiently enjoy the potential transaction-cost mitigation effect of common ties.

Third, and more importantly, we still find a strong and non-linear effect of per-capita GDP on remittances in income-group regressions. However, while whole-sample exercises suggested a U-shaped relation —with remittances first decreasing and then increasing with income at destination— estimates in Table 2, columns (1)-(2), show that an inverse U-shaped relation is now in place. Therefore, contrary to what happens when one takes into account all global remittance flows, when we discriminate between origin and destination income groups, investment or exchange motives seem to be behind remittances from rich and middle countries to poor ones when home per-capita GDP is low. Instead, when income of a poor destination country grows, altruistic motives seem to dominate remittance behaviors of migrants sending money from richer countries, see Figure 3. This is in line with studies focusing on private transfers in less-developed countries (Cox, Eser, and Jimenez, 1998).

4.3 Robustness Checks

The impact of macroeconomic determinants on bilateral remittance flows estimated in the previous subsections can be biased due to a number of possibly concurrent issues. In this subsection, we attempt to address three of them in order to discuss the robustness of our foregoing findings.

First, our estimates employ an originally balanced sample of 176×175 remittance flows in each year. As discussed above, this is one of the main contributions of the paper, as our aim was to have a country coverage over time as large as possible. However, the number of bilateral flows actually employed in the regressions is much smaller than the notional maximum. This is true not only in OLS estimates (when zero flows are automatically excluded) but also when PPML is employed. In both cases, the net reduction in the observations used in estimation is due to the presence of missing values in destination-country covariates, which makes unbalanced the sample actually employed for estimation. We investigate whether this may be a source of bias in our results in a series of additional exercises in which we either shrink the sample of countries or we fit a structural-gravity model where destination-country specific covariates are replaced by country-time fixed effects (as it happens in all specifications for origin countries). In the first case, we select only the countries that do not have any missing values in all the covariates used in our baseline regressions. This allows us to focus on a smaller sample of 110 countries (see Table E1), out of the original 176 available. In the second case, we fit to both the reduced sample and to the 176-country sample a structural-gravity specification (Baldwin and Taglioni, 2006) where:

$$\alpha^{(t)}_{(i)(j)} = \eta^t_i + \psi^t_j. \tag{3}$$

In this case, all country-specific variables $\mathbf{X}^{(t)}_{(i)(j)}$ are omitted and only dyadic ones ($\mathbf{D}_{ij}$) are retained. Table E2 in the Appendix reports results for the case of baseline OLS estimates using the "Stepwise" version of M^t_{ij}. We compare four different specifications, depending on whether the full 176-country sample or the reduced 110-country sample is employed, and whether FEs are as in Eq. (2) or as in the structural-gravity model of Eq. (3)[27]. Overall, our main results seem to be confirmed, suggesting that sample unbalancing due to the presence of missing values in country covariates does not bias the main conclusions of our analysis. In particular, both the sign and magnitude of the size effect exerted by the number of migrants in the host country appears to be extremely robust in all specifications.

Our second concern is related to multicollinearity issues, possibly arising in relation to population-related variables. These are the number of migrants in the host country,

[27]Some missing values are obviously present in dyadic time-invariant covariates, but we decided not to shrink the country sample size further to keep a sufficiently large country coverage

total population and % of rural population at home, which were all included in the baseline specification. If these variables are strongly correlated, e.g. because the number of migrants at the origin of remittance flows heavily depends on population at home or its share living in rural areas, estimated coefficients may be biased. To check for this potential source of bias, we have performed additional regressions where one excludes either the covariate "Population" or the covariate "Rural Population Share" from the list of regressors. Results are reported in Table E3, columns (2)-(3), vis-à-vis the baseline correspondent estimates from Table 1 (column 1). Apart from the impact of contiguity, which becomes less relevant, all our main results robustly hold, in particular as far as population-related regressors are concerned.

Finally, we investigate possible biases due to the omission of bilateral covariates controlling for technological advances, which may have contributed to reduce transaction costs. In our baseline specification, all bilateral variables are indeed time invariant. Geographical distance alone can hardly control for technological developments that, together with an increased competition in the financial-service industry, may have unevenly led to a reduction of transfer costs of remittances in particular, and of transaction costs in general (Ahmed, Mughal, and Martínez-Zarzoso, 2021; Kakhkharov, Akimov, and Rohde, 2017)[28]. To address this issue, columns (4)-(8) in Table E3 present estimation results where one adds to the baseline specification some proxies controlling for cost-reducing technological advances. To begin with, we have explored the impact that a larger diffusion of internet technologies at home —net of that in the host country, controlled for by origin FEs as usual— may have on remittance flows. We did that using two additional covariates, i.e. fixed broadband subscriptions (per 100 people) and the individuals using the Internet (as a % of population), see Table A1 for sources and definitions. Results in Table E3, columns (4)-(5) show that both variables enhance remittances, but the estimated effect of geographical distance, number of migrants, as well as those of other time-invariant bilateral variables, remain roughly in line with our baseline specification (see column 1). Furthermore, we have exploited data on remittance costs from the World Bank "Remittance Prices Worldwide" database to build a bilateral, time-varying covariate defined as the average total cost of all remittance flows between any two countries as a percentage of the total transaction (for a similar perspective, see Ahmed, Mughal, and Martínez-Zarzoso, 2021). Unfortunately, a very small number of remittance costs are reported in that database, leading to a huge decrease in the estimation sample size. Nonetheless, results in columns (6)-(8) of Table E3 hint to a picture that is quite consistent with our baseline regressions. More specifically, average remittance cost appears to exert a weak negative (or a statistically insignificant) impact on remittance flows when

[28]It must be noted that our only time-varying bilateral variable (i.e., "Number of Migrants") might partly control for differences in transaction costs, as the corridors with a larger number of migrants and higher competition tend to exhibit consistently lower remittance costs.

inserted in the baseline specification with FEs as in Eq. (2), together or without geographical distance[29]. Furthermore, we are still able to observe a negative (albeit weaker) effect of our contiguity covariate. In Section 4.1, this was interpreted as suggesting that sharing a border could have been an incentive to boost informal ways to remit. However, in presence of financial development there could be a counter effect, as a more efficient financial industry could reduce remittance prices and thus enhance formal remittances. That counter effect was not entirely controlled for in our baseline regressions, since financial development was proxied only by bank branches at destination, whereas all bilateral covariates were time invariant. Recovering a negative effect of contiguity in this set of regressions indicates instead that sharing a border reduces formal remittances, net of the counter-acting effect of financial development and technological advances.

Notice that the weak impact of remittance costs is detected also when one removes time-invariant bilateral variables and replaces them with a set of paired, time-invariant FEs (Baldwin and Taglioni, 2006). Column (8) in Table E3 reports indeed estimates when the FEs specification reads:

$$\alpha_{(i)(j)}^{(t)} = \eta_i^t + \psi_j + \lambda_{ij}. \tag{4}$$

In this case, once all time-invariant transaction costs are fully controlled for, average remittance costs weakly and negatively affect remittance flows. More importantly, however, our main results seem to be confirmed, particularly those related to the impact of migrant networks and per-capita income.

5 Concluding Remarks

In this paper, we have explored the macroeconomic determinants of bilateral-remittance flows between world countries, using the "World Bank Migration & Remittance" database, which originally covers 214 sending and receiving countries over the period 2010-2017. Exploiting the inherent origin-destination nature of remittance flows, we have fitted the data using a number of gravity-model specifications, controlling for host-, home- and time-specific fixed effects, to a subset of 176 countries.

As discussed in Section 2, using a gravity-model approach allowed us to investigate in more details the drivers of remittance flows, separating as much as possible host, home and bilateral effects. Furthermore, a gravity specification can be derived by micro-founded models (Schiopu and Siegfried, 2006; Rapoport and Docquier, 2006; McCracken,

[29] This is partly in contrast with findings in Ahmed, Mughal, and Martínez-Zarzoso (2021), who find a strong negative impact of remittance costs in absence of geographical distance. Such discrepancy may be due to a number of reasons. First, we employ a richer FEs specification to control for origin and destination unobserved heterogeneity and a larger set of covariates. Second, the definition of the average cost of remittances somewhat differs, as Ahmed, Mughal, and Martínez-Zarzoso (2021) build a covariate computing the cost sending USD200 as a percentage of the amount remitted.

Ramlogan-Dobson, and Stack, 2017), which is helpful in identifying expected signs of coefficients in terms of migrant motives.

Results from whole-sample exercises clearly indicate that size effects (controlled for by the number of migrants at the origin and home-country population), transaction costs (distance and contiguity) and common host-home country ties, strongly influence global remittance flows. Furthermore, the important remittance-enhancing effect of rural population and education-related covariates hint at the existence of investment motives behind the migrant-remittance behavior. We have also found that economic growth and financial development at home play an important role in impacting remittances.

Most of those macroeconomic determinants (e.g. size effects, education, economic growth and financial development) are also important in explaining remittance flows from rich and middle countries to poor ones. However, when one conditions on the income group of host and home countries, interesting discrepancies emerge. First, the impact of transaction costs on remittances substantially change: a higher origin-destination geographical distance between middle/rich country and poor ones boosts remittances, while sharing a border becomes less relevant. Second, common political, social and cultural ties lose their importance in explaining remittance flows.

We have also documented the existence of a robust non-linear relationship between income at home and remittance flows. Globally, a U-shaped relation emerge, suggesting that altruistic motives dominate when per-capita GDP at destination is small, whereas self-interested or exchange motives become more relevant for higher levels of home income. On the contrary, remittance sent from middle/rich nations to poor countries are explained by self-interested motives for low-income levels and then by investment or exchange, as income at home increases (i.e., an inverted U-shaped relation between per-capita GDP at destination and remittances emerges). This suggests that altruistic and self-interested motives non-trivially interact and may change across both host/home income groups and the level of income at home.

Our main results robustly hold vis-à-vis a number of alternative estimation strategies and specifications. First, as PPML-based exercises show, the most important findings are not influenced by the presence of zero-flow observations in the data. Second, coefficient estimates do not seem to be strongly affected by omitted-variable biases, since host-time fixed effects control for cross-country and longitudinal factors at the origin, destination-specific and time invariant fixed effects control for unobserved cross-country heterogeneity at home, and year dummies for time trends. Third, we have employed two different specifications for the covariate controlling for the number of migrants, in order to mitigate the bias coming from the fact that migrant stocks are not observed in every year. Fourth, results appear to be quite robust to endogeneity issues related to a possible reverse-causation link involving migrant stocks in the host country and per-capita GDP at home. Fifth, we do not detect strong departures from our main results when a number of possible additional sources of bias are considered. These include the effect of missing values in the covariates, multicollinearity between population-related regressors, and the presence of trends in technological advances, which may have led to remittance costs unevenly decreasing in time.

One of the contributions of this paper was to employ a large panel of bilateral-remittance flows among world countries, in the attempt to overcome data limitations that, so far, have prevented existing studies from reaching robust and conclusive predictions on the impact of macroeconomic determinants on remittance flows (cf. Table D1 in the Appendix). However, it must be noted that the wide cross-sectional coverage of the "World Bank Migration & Remittance" database comes at a cost. Indeed, bilateral-remittance flows in the database are not empirically observed but comes from an estimation procedure proposed in Ratha and Shaw (2007). As discussed in Mallela, Singh, and Srivastava (2020), remittance estimates may be inaccurate in terms of volumes, especially for certain countries (Alvarez, Briod, Ferrari, and Rieder, 2015). Nevertheless, the database has been successfully employed in many existing works (see, e.g., Aggarwal, Demirguc-Kunt, and Peria, 2011; Arvin and Lew, 2012; Azizi, 2017). Furthermore, remittance flows are estimated using alternative weighting schemes and do not make use of gravity models, which may introduce biases in our analysis. In absence of better comprehensive data on bilateral-remittance flows, this is still the best choice if one aims at a large country-coverage for a sufficiently long number of years.

Exploring in more details the possible biases that this type of remittances data may generate on gravity-model estimates is certainly one of our future avenues of research. The present work, however, may be extended in at least three additional ways. First, the analysis of remittance flows disaggregated by income groups has only focused on remittances from middle and rich countries towards poor ones. Studying the behavior and determinants of other income-conditioned flows (e.g., those between rich or middle countries), as well as their geographical breakdown (e.g., north to south) may complement the present analysis. Second, the presence and shape of non-linearities in per-capita GDP (and other co-variates) can be explored more deeply. Finally, endogeneity issues may be investigated in a more consistent way, e.g. using system GMM techniques as in Olivero and Yotov (2012) and Anderson and Yotov (2020).

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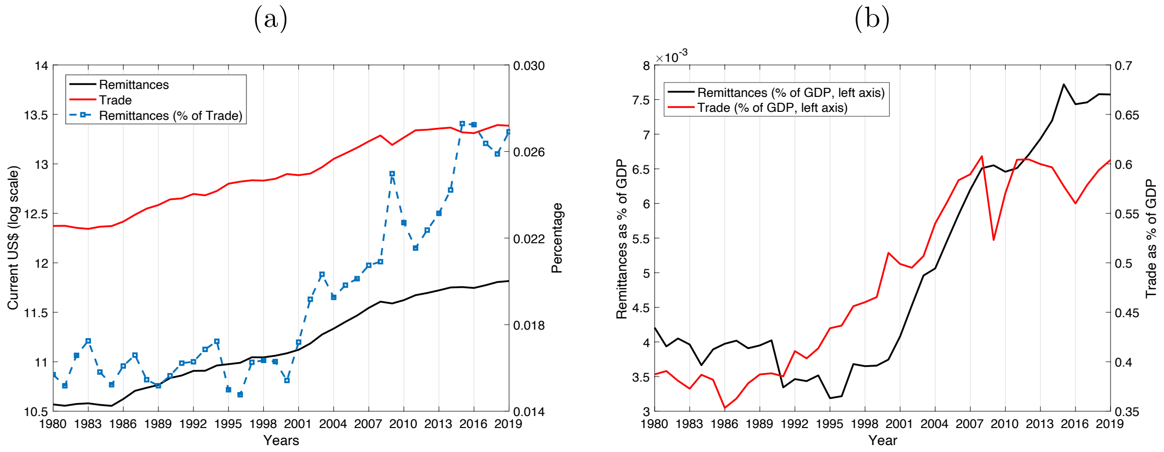


Figure 1: Aggregate flows of international remittances. Panel (a): Aggregate World remittance and trade flows (current US$). Panel (b): Remittances and trade as a percentage of World GDP. Source: Authors caluclation based on World Bank WDI data.

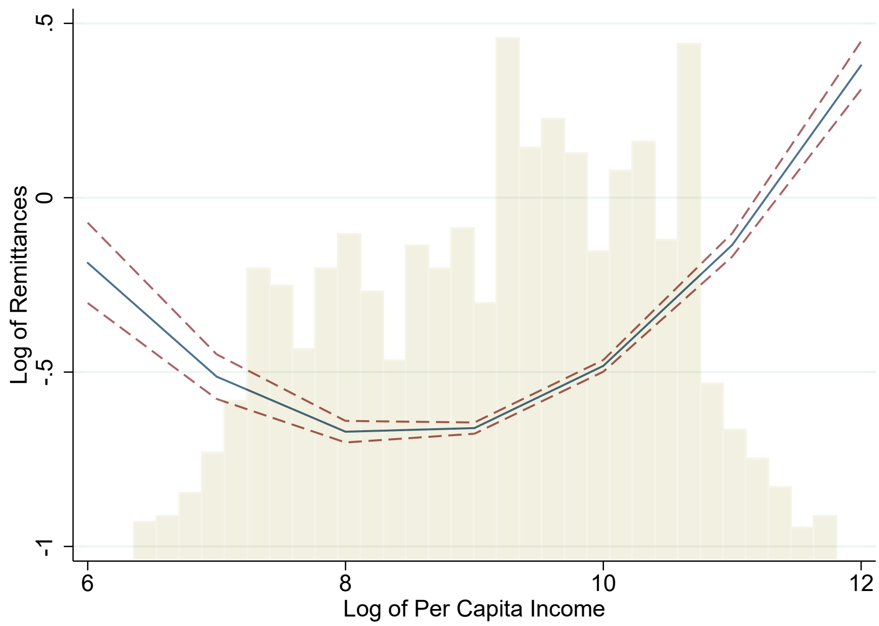
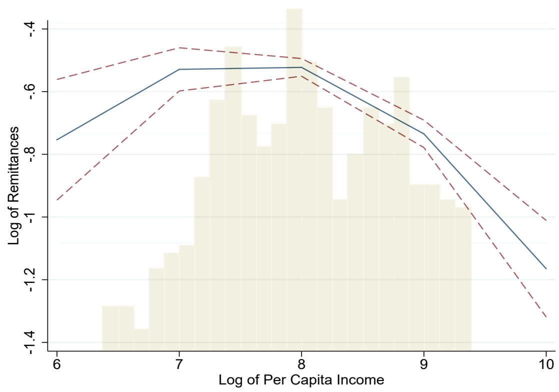


Figure 2: Non-linear marginal impact of (per-capita) Income (pcGDP) on remittances. Whole sample OLS estimates from Column (2), Table 1. X-Axis: Log of (Per-Capita) Income (pcGDP) in the observed whole-sample range of the covariate. Y-Axis: Log of Remittance Flows. The histogram in background depicts the whole-sample distribution of pcGDP at destination, across countries and years (bar heights are proportional to observed frequencies). Dashed-lines: 95% confidence bands.

(a)



(b)

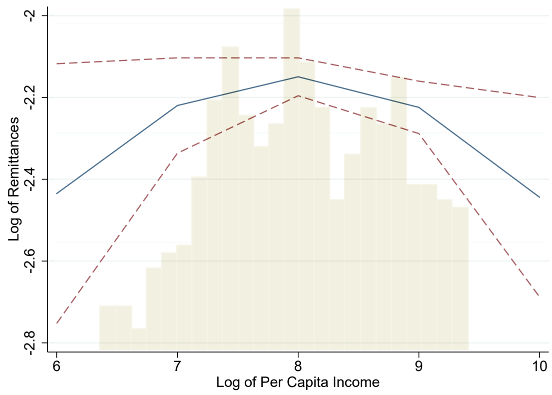


Figure 3: Non-linear marginal impact of (per-capita) Income (pcGDP) on remittances by origin and destination country-income groups. (a) Rich to Poor; (b) Middle to Poor. OLS estimates from Columns (1)-(2), Table 2. X-Axis: Log of (Per-Capita) Income (pcGDP) in the observed whole-sample range of the covariate. Y-Axis: Log of Remittance Flows. The histogram in background depicts the distribution of pcGDP at destination for countries in the poor-income group across the years (bar heights are proportional to observed frequencies). Dashed-lines: 95% confidence bands.

	Baseline Regressions				Instrumenting Number of Migrants		Instrumenting pcGDP
	OLS		PPML		OLS	PPML	2SLS
Dependent Variable: Bilateral Remittance Flows	(1) Number of Migrants: Year=t	(2) Number of Migrants: Stepwise	(3) Number of Migrants: Year=t	(4) Number of Migrants: Stepwise	(5) Number of Migrants: Year=2010	(6) Number of Migrants: Year=2010	(7) Number of Migrants: Year=t
Number of Migrants	0.993*** (0.008)	0.992*** (0.004)	0.858*** (0.021)	0.837*** (0.013)	0.930*** (0.005)	0.781*** (0.015)	1.012*** (0.001)
Distance	-0.096*** (0.019)	-0.104*** (0.010)	-0.181*** (0.040)	-0.243*** (0.025)	-0.209*** (0.012)	-0.253*** (0.028)	-0.033*** (0.005)
Contiguity	-0.360*** (0.069)	-0.355*** (0.035)	-0.216* (0.091)	-0.222*** (0.053)	-0.329*** (0.043)	-0.106* (0.040)	-0.184*** (0.020)
Common Language	0.040* (0.039)	0.049* (0.021)	0.183* (0.076)	0.207*** (0.045)	0.013* (0.027)	0.248*** (0.049)	0.069*** (0.011)
Colonial Relationship	0.164* (0.072)	0.002 (0.039)	0.093 (0.112)	0.006 (0.062)	0.112* (0.048)	0.037* (0.066)	0.062*** (0.022)
Common Religion	0.101* (0.048)	0.217*** (0.025)	0.233* (0.101)	0.331*** (0.060)	0.239*** (0.032)	0.267*** (0.074)	-0.060 (0.016)
pcGDP	-1.599*** (0.186)	-1.420*** (0.101)	-1.669*** (0.448)	-2.479*** (0.280)	-1.097*** (0.129)	-2.734*** (0.331)	-2.921** (0.749)
pcGDP Squared	0.090*** (0.010)	0.084*** (0.005)	0.080*** (0.024)	0.130*** (0.015)	0.067*** (0.007)	0.140*** (0.017)	0.135*** (0.039)
GDP Growth	-0.044*** (0.005)	-0.021*** (0.002)	-0.021* (0.009)	-0.002* (0.006)	-0.017*** (0.003)	-0.005* (0.004)	0.154*** (0.003)
Population	0.118*** (0.009)	0.100*** (0.005)	0.171*** (0.019)	0.178*** (0.012)	0.149*** (0.006)	0.191*** (0.013)	0.188*** (0.001)
Rural Population Share	0.005*** (0.001)	0.007*** (0.001)	0.006* (0.003)	0.008*** (0.002)	0.007*** (0.001)	0.008*** (0.002)	-0.083 (0.188)
Exp in Education (% of GDP)	0.045*** (0.009)	0.075*** (0.004)	0.015 (0.028)	0.033* (0.016)	0.067*** (0.006)	0.043** (0.016)	0.016*** (0.009)
Enrollment Rate	0.013*** (0.002)	0.007*** (0.001)	0.018*** (0.003)	0.017*** (0.002)	0.012*** (0.001)	0.021*** (0.002)	0.003*** (0.002)
Bank Branches	0.014*** (0.001)	0.019*** (0.000)	0.010*** (0.001)	0.011*** (0.001)	0.018*** (0.001)	0.011*** (0.001)	0.009*** (0.001)
Obs	12510	33408	55406	147740	33406	147737	12502
R^2	0.881	0.902	0.941	0.936	0.877	0.926	0.988
Prob>F	0.000	0.000	-	-	0.000	-	0.000

Table 1: Regression results. Dependent variable: Bilateral remittance flows. Whole-sample estimates of gravity-model coefficients (Eq. 1). Fixed effects specification: $\alpha_{(i)(j)}^{(t)} = \eta_i^t + \psi_j$. Columns (1)-(4): Baseline regression w/o instrumentation. Columns (5)-(6): The covariate "Number of Migrants" is instrumented using year-2010 observations. Column (7): The covariate "pcGDP" is instrumented using 2SLS. Columns (1), (2), (5): OLS estimates. Columns (3), (4), (6): PPML estimates. Columns (1), (3), (7): The covariate "Number of Migrants" is observed only in years 2010, 2013, 2017. Columns (2), (4): The "stepwise" version of the covariate "Number of Migrants" is employed (see Section 3 for more details). Standard errors in round parentheses. Significance levels: * p<0.05; ** p<0.01; *** p<0.001.

Dependent Variable: Bilateral Remittance Flows	Number of Migrants	Income Group (Origin → Destination)		
		(1) Rich → Poor	(2) Middle → Poor	(3) Whole Sample
Number of Migrants	Year=t	1.044***	1.035***	0.993***
	Stepwise	1.026***	1.037***	0.992***
Distance	Year=t	0.107*	0.043*	-0.096***
	Stepwise	0.117***	0.029*	-0.104***
Contiguity	Year=t	-0.029	-0.388*	-0.360***
	Stepwise	-0.122	-0.406	-0.355***
Common Language	Year=t	0.146	0.279*	0.040*
	Stepwise	0.075	0.240***	0.049*
Colonial Relationship	Year=t	0.287	0.074	0.164*
	Stepwise	0.210*	0.004	0.002
Common Religion	Year=t	-0.593	-0.122	0.101*
	Stepwise	-0.088	0.161*	0.217***
pcGDP	Year=t	1.709*	2.146*	-1.599***
	Stepwise	1.644***	1.158*	-1.420***
pcGDP Squared	Year=t	-0.132**	-0.154*	0.090***
	Stepwise	-0.109***	-0.073*	0.084***
GDP Growth	Year=t	-0.140***	-0.152***	-0.044***
	Stepwise	-0.096***	-0.097***	-0.021***
Population	Year=t	0.282***	0.326***	0.118***
	Stepwise	0.232***	0.255***	0.100***
Rural Population Share	Year=t	0.004*	0.001*	0.005***
	Stepwise	0.004***	0.005**	0.007***
Exp in Education (% of GDP)	Year=t	0.034*	0.058**	0.045***
	Stepwise	0.042***	0.039***	0.075***
Enrollment Rate	Year=t	0.015***	0.012**	0.013***
	Stepwise	0.009***	0.003*	0.007***
Bank Branches	Year=t	0.048***	0.051***	0.014***
	Stepwise	0.039***	0.039***	0.019***
Obs	Year=t	2293	1009	12510
	Stepwise	5561	3604	33408
R^2	Year=t	0.937	0.938	0.881
	Stepwise	0.990	0.983	0.941
Prob>F	Year=t	0.000	0.000	0.000
	Stepwise	0.000	0.000	0.000

Table 2: Regression results. Dependent variable: Bilateral remittance flows. OLS estimates of gravity-model coefficients (Eq. 1) in subsamples defined according to the income group of origin and destination remittance-flow country. Column (1) Rich to poor; column (2): Middle to poor; column (3): whole-sample estimates from columns (1)-(2) in Table 1. Fixed effects specification: $\alpha^{(t)}_{(i)(j)} = \eta^t_i + \psi_j$. Number of Migrants: "Year=t" means that the covariate is observed only in years 2010, 2013, 2017); "Stepwise": means that the stepwise version of the covariate is employed (see Section 3). Significance levels: * p<0.05; ** p<0.01; *** p<0.001.

Appendix

A Data Sources

Variable	Description	Data Source
Bilateral Remittances	Yearly Bilateral Remittance Estimates, million of US$ (years: 2010-2017)	World Bank Migration and Remittances Data*
Number of Migrants	Bilateral Estimates of Migrant Stocks (years: 2010,2013,2017)	World Bank Migration and Remittances Data*
Distance	Distance between most populated cities (km)	Cepii Gravity Database (`cepii.fr`)
Contiguity	Dummy variable; 1 = Country pair shares a border	Cepii Gravity Database (`cepii.fr`)
Common Language	Dummy variable; 1 = Country pair shares common official or primary language	Cepii Gravity Database (`cepii.fr`)
Colonial Relationship	Dummy variable; 1 = Country pair ever in colonial relationship	Cepii Gravity Database (`cepii.fr`)
Common Religion	Dummmay variable; 1 = Country pair shares common religion	Cepii Gravity Database (`cepii.fr`)
pcGDP	per-capita GDP, PPP (constant 2011 international $)	World Bank Open Data (`data.worldbank.org`)
GDP Growth	GDP growth (annual %)	World Bank Open Data (`data.worldbank.org`)
Population	Population, total	World Bank Open Data (`data.worldbank.org`)
Rural Population Share	Rural population (% of total population)	World Bank Open Data (`data.worldbank.org`)
Exp in Education (% of GDP)	Government expenditure on education, total (% of GDP) pgap_550	World Bank Open Data (`data.worldbank.org`)
Enrollment Rate	Adjusted net enrollment rate, primary (% of primary school age children)	World Bank Open Data (`data.worldbank.org`)
Bank Branches Share	Commercial bank branches (per 100,000 adults)	World Bank Open Data (`data.worldbank.org`)
Broadband Subs	Fixed broadband subscriptions (per 100 people)	World Bank Open Data (`data.worldbank.org`)
Internet Usage	Individuals using the Internet (% of population)	World Bank Open Data (`data.worldbank.org`)
Remittance Cost	Average total cost of the transaction in %	Remittance Prices Worldwide (`remittanceprices.worldbank.org`)
Precipitation Anomalies	Yearly total precipitation anomalies (z-score based on 1901-2018 obs)	Climatic Research Unit - CRU (`www.cru.uea.ac.uk`)

Temperature Anomalies	Yearly average temperatures anomalies (z-score based on 1901-2018 obs)	Climatic Research Unit - CRU (`www.cru.uea.ac.uk`)
Arable Land	Land cultivated for crops (% of total land area)	CIA World Factbook (`www.cia.gov`)
Average Elevation	Country average elevation above sea level (mt)	CIA World Factbook (`www.cia.gov`)
Coastline Length	Country total length of the boundary between the land area (including islands) and the sea (km)	CIA World Factbook (`www.cia.gov`)
Distance from the equator	Absolute value of country latitude	CIA World Factbook (`www.cia.gov`)
Remoteness	Sum of distances between a country and all the others	Our own calculation based on Cepii Gravity Database (`cepii.fr`)

Table A1: Description and sources of variables used in our preferred specifications. (*) See `https://www.worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data`

B Additional Covariates

Variable	Description	Data Source
Common Ethnic Language	Dummy variable; 1 = Country pair shares common language (spoken by at least 9 % of the population)	Cepii Gravity Database (cepii.fr)
Common Colonizer	Dummy variable; 1=Country pair shares a common colonizer post 1945	Cepii Gravity Database (cepii.fr)
Colonial Relation Post 1945	Dummy variable; 1 = country pair in colonial relationship post 1945	Cepii Gravity Database (cepii.fr)
Common Currency	Dummy variable; 1 = country pair share common currency	Cepii Gravity Database (cepii.fr)
Weighted Distance	weighted distance (pop-wt, Km), year= 2010	Cepii Gravity Database (cepii.fr)
Domestic Credit Share	Domestic credit to private sector (% of GDP)	World Bank Open Data (data.worldbank.org)
Poverty Gap (1.90$)	Poverty gap at $ 1.90 a day (2011 PPP) (%)	World Bank Open Data (data.worldbank.org)
Poverty Gap (3.20$)	Poverty gap at $ 3.20 a day (2011 PPP) (%)	World Bank Open Data (data.worldbank.org)
Poverty Gap (5.50$)	Poverty gap at $ 5.50 a day (2011 PPP) (%)	World Bank Open Data (data.worldbank.org)
Poverty Gap Share at NPL	Poverty gap at national poverty lines (%)	World Bank Open Data (data.worldbank.org)
Educational Attainment Share	Educational attainment, at least completed primary, population 25+ years, total (%) (cumulative)	World Bank Open Data (data.worldbank.org)
Displaced Persons	Internally displaced persona, total displaced by conflict and violence (number of people)	World Bank Open Data (data.worldbank.org)
Enrollment Rate	Adjusted net enrollment rate, primary (% of primary school age children)	World Bank Open Data (data.worldbank.org)
Literacy Rate	Literacy rate, adult total (% of people ages 15 and above)	World Bank Open Data (data.worldbank.org)
Real Exchange Rate	Real effective exchange rate index (2010 = 100)	World Bank Open Data (data.worldbank.org)
Real Interest Rate	Real interest rate (%)	World Bank Open Data (data.worldbank.org)
Natural Disasters	Total number of persons affected by natural disasters	EM-DAT (www.emdat.be)
Fragility	Dummy variable; 1 = country in fragile situation (conflict, violence and instability)	World Bank Open Data (data.worldbank.org)

Table B1: Additional covariates used in the analysis and not included in our preferred specifications, because they turned out to be not significant in almost all our regressions.

C List of Countries and Summary Statistics

Country	ISO3	Country	ISO3	Country	ISO3
Afghanistan	AFG	Georgia	GEO	Nicaragua	NIC
Albania	ALB	Germany	DEU	Niger	NER
Algeria	DZA	Ghana	GHA	Nigeria	NGA
Angola	AGO	Greece	GRC	Norway	NOR
Argentina	ARG	Grenada	GRD	Oman	OMN
Armenia	ARM	Guatemala	GTM	Pakistan	PAK
Australia	AUS	Guinea	GIN	Panama	PAN
Austria	AUT	Guinea-Bissau	GNB	Papua New Guinea	PNG
Azerbaijan	AZE	Guyana	GUY	Paraguay	PRY
Bahamas, The	BHS	Haiti	HTI	Peru	PER
Bahrain	BHR	Honduras	HND	Philippines	PHL
Bangladesh	BGD	Hungary	HUN	Poland	POL
Barbados	BRB	Iceland	ISL	Portugal	PRT
Belarus	BLR	India	IND	Qatar	QAT
Belgium	BEL	Indonesia	IDN	Russian Federation	RUS
Belize	BLZ	Iran, Islamic Rep.	IRN	Rwanda	RWA
Benin	BEN	Iraq	IRQ	Samoa	WSM
Bhutan	BTN	Ireland	IRL	Sao Tome and Principe	STP
Bolivia	BOL	Israel	ISR	Saudi Arabia	SAU
Bosnia and Herzegovina	BIH	Italy	ITA	Senegal	SEN
Botswana	BWA	Jamaica	JAM	Seychelles	SYC
Brazil	BRA	Japan	JPN	Sierra Leone	SLE
Brunei Darussalam	BRN	Jordan	JOR	Singapore	SGP
Bulgaria	BGR	Kazakhstan	KAZ	Slovak Republic	SVK
Burkina Faso	BFA	Kenya	KEN	Slovenia	SVN
Burundi	BDI	Kiribati	KIR	Solomon Islands	SLB
Cabo Verde	CPV	Korea, Dem. Rep.	PRK	Somalia	SOM
Cambodia	KHM	Korea, Rep.	KOR	South Africa	ZAF
Cameroon	CMR	Kuwait	KWT	Spain	ESP
Canada	CAN	Kyrgyz Republic	KGZ	Sri Lanka	LKA
Central African Republic	CAF	Lao PDR	LAO	St. Lucia	LCA
Chad	TCD	Latvia	LVA	St. Vincent & Grenadines	VCT
Chile	CHL	Lebanon	LBN	Suriname	SUR
China	CHN	Lesotho	LSO	Sweden	SWE
Colombia	COL	Liberia	LBR	Switzerland	CHE
Comoros	COM	Libya	LBY	Syrian Arab Republic	SYR
Congo, Rep.	COG	Lithuania	LTU	Tajikistan	TJK
Costa Rica	CRI	Luxembourg	LUX	Tanzania	TZA
Cote d'Ivoire	CIV	Macedonia, FYR	MKD	Thailand	THA
Croatia	HRV	Madagascar	MDG	Togo	TGO
Cuba	CUB	Malawi	MWI	Tonga	TON
Cyprus	CYP	Malaysia	MYS	Trinidad and Tobago	TTO
Czech Republic	CZE	Maldives	MDV	Tunisia	TUN
Denmark	DNK	Mali	MLI	Turkey	TUR
Djibouti	DJI	Malta	MLT	Turkmenistan	TKM
Dominica	DMA	Marshall Islands	MHL	Uganda	UGA
Dominican Republic	DOM	Mauritania	MRT	Ukraine	UKR
Ecuador	ECU	Mauritius	MUS	United Arab Emirates	ARE
Egypt, Arab Rep.	EGY	Mexico	MEX	United Kingdom	GBR
El Salvador	SLV	Micronesia	FSM	United States	USA
Equatorial Guinea	GNQ	Moldova	MDA	Uruguay	URY
Eritrea	ERI	Mongolia	MNG	Uzbekistan	UZB
Estonia	EST	Morocco	MAR	Vanuatu	VUT
Ethiopia	ETH	Mozambique	MOZ	Venezuela, RB	VEN
Fiji	FJI	Myanmar	MMR	Vietnam	VNM
Finland	FIN	Namibia	NAM	Yemen, Rep.	YEM
France	FRA	Nepal	NPL	Zambia	ZMB
Gabon	GAB	Netherlands	NLD	Zimbabwe	ZWE
Gambia, The	GMB	New Zealand	NZL		

Table C1: List of countries included in the baseline regression sample (176 countries).

Remittances				
Year	2010	2013	2017	Whole Sample
% of Obs = 0	0.83	0.74	0.73	0.77
No. of Obs > 0	5154	8043	8035	55731
Mean	12.50	15.61	17.18	15.27
Std Dev	208.92	244.42	282.25	249.38
Min	0.00	0.00	0.00	0.00
Max	21693.42	22587.29	30019.19	30019.19
Skewness	55.27	47.43	56.01	53.01
Kurtosis	4451.01	3237.19	4655.12	4150.52

Number of Migrants				
Year	2010	2013	2017	Whole Sample
Mean	5401.53	6559.25	6869.20	6165.94
Std Dev	88789.56	98966.07	96213.84	94942.28
Min	0.00	0.00	0.00	0.00
Max	11600000.00	13000000.00	11600000.00	13000000.00
Skewness	78.22	75.82	63.50	75.22
Kurtosis	9159.62	8989.80	6570.46	8802.70

Table C2: Descriptive statistics for bilateral remittances and number of migrants at the origin in selected years. 176 Countries. Whole sample: All 8 years from 2010 to 2017.

D Gravity Models of International Remittance Flows: Summary of the Literature

	Paper					
	Schiopu & Siegfried (2006)	Lueth & Luiz-Arranz (2008)	Docquier et al (2012)	Nnyanzi (2016)	McCracken et al (2017)	Ahmed et al (2020)
Sample sizes						
No. Sending Countries	21	16	89	African Countries	18	30
No. Receiving Countries	7	11	47	10	27	75
No. of Years	6	25	4	21	10	7
Time Period	2000-2005	1980-2004	2002-2005	1990-2011	1998-2007	2011-2017
Estimation						
Panel type	Unbalanced	Unbalanced	Unbalanced	Unbalanced	Balanced	Unbalanced
Estimation Method	OLS	OLS	OLS, POISSON	OLS	OLS	OLS
Fixed effects employed	(j, t)	(i,j,t)	(i,j,t)	(t)	(t)	(ij,t)
R^2	0.35 - 0.57	0.69 - 0.72	0.49-0.91	NR	0.72-0.92	0.46-0.70
Econometric issues						
Zero-flow treatment	No	No	Yes	No	No	No
Endogenity	No	Yes (lagged vars)	No	Yes (lagged vars)	Yes (lagged vars)	Yes (GMM)
Non linearity in income	No	No	No	No	No	No
Rich vs poor breakdown	No	No	Yes	No	No	No
Predictions						
Number of Migrants	- †	+	+	+		+
Distance		-	?	-	-	?
Contiguity		-		?	+	?
Common Language		+	+	?	+	?
Colonial Relationship		+		?	?	?
Income (diff)	+			+	+	
Income (home)		-		-		
Income (host)		+		+		
GDP (diff)	?					
GDP (home)		+	?		+	+
GDP (host)		+	+		+	?
GDP Growth (home)		?				
GDP Growth (host)		-				
Real interest rate diff	?			+	?	
Inequality	?					
Remittance cost	+ ‡					
Natural disasters (home)		?			+	
Inflation (diff)		+		+		
Credit to private sector (home)				+	+	
Credit to private sector (host)				+	-	
Unemployment				?		

Table D1: Sample sizes, estimation, econometric issues, and predictions in existing papers fitting gravity models to international bilateral-remittance flows. Notes: (†) unskilled workers only; (‡) number of Western Union agents.

E Robustness Checks

Country	ISO3	Country	ISO3	Country	ISO3
Albania	ALB	Guatemala	GTM	Nicaragua	NIC
Angola	AGO	Guinea	GIN	Niger	NER
Argentina	ARG	Guinea-Bissau	GNB	Norway	NOR
Armenia	ARM	Guyana	GUY	Oman	OMN
Australia	AUS	Honduras	HND	Pakistan	PAK
Azerbaijan	AZE	Hungary	HUN	Panama	PAN
Barbados	BRB	Iceland	ISL	Paraguay	PRY
Belarus	BLR	India	IND	Peru	PER
Belgium	BEL	Indonesia	IDN	Poland	POL
Belize	BLZ	Iran, Islamic Rep.	IRN	Portugal	PRT
Benin	BEN	Ireland	IRL	Qatar	QAT
Bolivia	BOL	Israel	ISR	Russian Federation	RUS
Brazil	BRA	Italy	ITA	Rwanda	RWA
Burkina Faso	BFA	Japan	JPN	Samoa	WSM
Burundi	BDI	Kazakhstan	KAZ	Sao Tome and Principe	STP
Cabo Verde	CPV	Kenya	KEN	Senegal	SEN
Cambodia	KHM	Korea, Rep.	KOR	Sierra Leone	SLE
Cameroon	CMR	Kyrgyz Republic	KGZ	Slovenia	SVN
Chile	CHL	Lao PDR	LAO	South Africa	ZAF
Colombia	COL	Latvia	LVA	Spain	ESP
Comoros	COM	Lebanon	LBN	Sri Lanka	LKA
Costa Rica	CRI	Liberia	LBR	St. Vincent & Grenadines	VCT
Cote d'Ivoire	CIV	Luxembourg	LUX	Sweden	SWE
Croatia	HRV	Malaysia	MYS	Switzerland	CHE
Cyprus	CYP	Maldives	MDV	Tajikistan	TJK
Denmark	DNK	Mali	MLI	Tanzania	TZA
Ecuador	ECU	Malta	MLT	Togo	TGO
El Salvador	SLV	Mauritius	MUS	Tunisia	TUN
Estonia	EST	Mexico	MEX	Turkey	TUR
Ethiopia	ETH	Micronesia, Fed. Sts.	FSM	Uganda	UGA
Fiji	FJI	Moldova	MDA	Ukraine	UKR
Finland	FIN	Mongolia	MNG	United Kingdom	GBR
France	FRA	Mozambique	MOZ	United States	USA
Gambia, The	GMB	Myanmar	MMR	Uzbekistan	UZB
Georgia	GEO	Namibia	NAM	Vanuatu	VUT
Germany	DEU	Nepal	NPL	Vietnam	VNM
Ghana	GHA	New Zealand	NZL		

Table E1: List of countries included in the reduced regression sample (110 countries).

	(1)	(2)	(3)	(4)
Dependent Variable: Bilateral Remittance Flows	Sample: 176 Countries	Sample: 110 Countries	Sample: 176 Countries	Sample: 110 Countries
Number of Migrants (Stepwise)	0.992*** (0.004)	0.995*** (0.003)	0.992*** (0.000)	0.995*** (0.000)
Distance	-0.104*** (0.010)	-0.091*** (0.016)	-0.082*** (0.001)	-0.073*** (0.001)
Contiguity	-0.355*** (0.035)	-0.256*** (0.041)	-0.012*** (0.004)	-0.023*** (0.005)
Common Language	0.049* (0.021)	0.037*** (0.022)	0.039*** (0.002)	0.049*** (0.004)
Colonial Relatioship	0.002 (0.039)	0.061*** (0.032)	0.057*** (0.004)	0.0449*** (0.006)
Common Religion	0.217*** (0.025)	0.122** (0.026)	0.111*** (0.003)	0.119*** (0.005)
pc GDP	-1.420*** (0.101)	-1.493*** (0.094)	–	–
pc GDP Squared	0.084*** (0.005)	0.048*** (0.005)	–	–
GDP Growth	-0.021*** (0.002)	-0.006*** (0.001)	–	–
Population	0.100*** (0.005)	0.147*** (0.007)	–	–
Rural Population Share	0.007*** (0.001)	0.037*** (0.001)	–	–
Exp in Education (% of GDP)	0.075*** (0.004)	0.051*** (0.003)	–	–
Enrollment Rate	0.007*** (0.001)	0.0122*** (0.002)	–	–
Bank Branches	0.019*** (0.000)	0.009*** (0.000)	–	–
Origin FEs	(it)	(it)	(it)	(it)
Destination FEs	(j)	(j)	(jt)	(jt)
Destination Country Covariates	YES	YES	NO	NO
Obs	33408	18937	55731	18943
R^2	0.902	0.984	0.997	0.998
Prob>F	0.000	0.000	0.000	0.000

Table E2: Assessing the effect of missing values in the covariates. Dependent variable: Bilateral remittance flows. OLS estimates of gravity-model coefficients. Columns (1) and (3): Full sample (176 countries, see Table C1). Columns (2) and (4): Reduced country sample size (110 countries, see Table E1). Columns (1) and (2): FEs are as in Eq. (2) and destination-country covariates are included. Columns (3) and (4): Columns (1) and (2): FEs are as in Eq. (3) and destination-country covariates are not included. Number of Migrants: the stepwise version of the covariate is always employed (see Section 3). Significance levels: * p<0.05; ** p<0.01; *** p<0.001.

Dependent Variable: Bilateral Remittance Flows	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Migrants (Stepwise)	0.992***	0.995***	0.995***	0.995***	0.995***	0.989***	0.986***	0.801***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.029)	(0.028)	(0.011)
Distance	-0.104***	-0.127***	-0.126***	-0.108***	-0.127***	-0.088**	-	-
	(0.010)	(0.004)	(0.005)	(0.004)	(0.005)	(0.032)	-	-
Contiguity	-0.355***	-0.024	-0.025*	-0.025*	-0.022*	-0.019*	-0.048*	-
	(0.035)	(0.015)	(0.015)	(0.015)	(0.010)	(0.009)	(0.009)	-
Common Language	0.049*	0.032***	0.031***	0.030***	0.031***	0.015*	0.019*	-
	(0.021)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.111)	-
Colonial Relatioship	0.002	0.058***	0.058***	0.058***	0.058***	0.005	0.015	-
	(0.039)	(0.017)	(0.017)	(0.017)	(0.017)	(0.110)	(0.108)	-
Common Religion	0.217***	0.286**	0.309**	0.310**	0.329**	0.027	0.027	-
	(0.025)	(0.105)	(0.114)	(0.114)	(0.117)	(0.150)	(0.150)	-
pc GDP	-1.420***	-1.292***	-1.025***	-1.790***	-1.679***	-1.146**	-1.129**	-1.059*
	(0.101)	(0.410)	(0.382)	(0.295)	(0.282)	(0.426)	(0.418)	(0.481)
pc GDP Squared	0.084***	0.251***	0.352***	0.438***	0.378***	0.614**	0.605**	0.556
	(0.005)	(0.029)	(0.031)	(0.032)	(0.031)	(0.306)	(0.305)	(0.360)
GDP Growth	-0.021***	-0.038***	-0.050***	-0.055***	-0.025**	-0.016	-0.016	-0.007
	(0.002)	(0.012)	(0.010)	(0.011)	(0.008)	(0.010)	(0.010)	(0.011)
Rural Population Share	0.007***	0.052***	-	0.037***	0.033***	0.219***	0.219***	0.171***
	(0.001)	(0.006)	-	(0.006)	(0.006)	(0.053)	(0.053)	(0.058)
Exp in Education (% of GDP)	0.075***	0.043***	0.046***	0.039***	0.040***	0.258***	0.258***	0.219***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.044)	(0.044)	(0.047)
Enrollment Rate	0.007***	0.012***	0.007***	0.013***	0.008***	0.012	0.012	0.009
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.010)
Bank Branches	0.019***	0.003***	0.005***	0.006***	0.007***	0.033***	0.032***	0.034***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)	(0.011)	(0.011)
Population	0.100***	-	0.085***	0.053***	0.167***	0.314***	0.313***	0.073***
	(0.005)	-	(0.021)	(0.012)	(0.046)	(0.085)	(0.077)	(0.021)
Broadband Subs	-	-	-	0.034***	-	-	-	-
	-	-	-	(0.003)	-	-	-	-
Internet Usage	-	-	-	-	0.010***	-	-	-
	-	-	-	-	(0.001)	-	-	-
Remittance Cost	-	-	-	-	-	-0.008*	0.010	-0.020*
	-	-	-	-	-	(0.003)	(0.011)	(0.008)
Origin FEs	(it)	(it)	(it)	(it)	(it)	(it)	(it)	(it)
Destination FEs	(j)	(j)	(j)	(j)	(j)	(j)	(j)	(j)
Paired FEs	-	-	-	-	-	-	-	(ij)
Obs	33408	33417	33421	31015	31751	1581	1581	1581
R^2	0.902	0.984	0.984	0.984	0.985	0.981	0.981	0.984
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table E3: Further robustness tests. OLS estimates using the full sample size (176 countries) and the stepwise verion of the covariate "Number of Migrants". FE specification in Columns (1)-(7) is as in Eq. (2), in Column (8) as in Eq. (4). Column 1: Results from the baseline specification, see Table 1. Significance levels: * p<0.05; ** p<0.01; *** p<0.001.