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MACROECONOMIC DETERMINANTS OF INTERNATIONAL REMITTANCES: EVIDENCE FROM TIME-SERIES AND PANEL METHODS

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At more than three times official development aid flows, remittances are now recognized as a key source of scarce foreign exchange for the developing world. Most papers looking into the macroeconomic determinants of remittance inflows tend to be panel, cross-sectional, or qualitative country-specific studies, understandably due a lack of consistent time-series data. We estimate an econometric model using the bounds-testing approach to cointegration and error-correction modeling (Pesaran et al., 2001) on time-series data as well as by employing traditional panel methods on the same data set. It appears that the generalized evidence based on panel or cross-sectional studies may not apply to individual countries.

Keywords: Remittances, Migration, Development, Bounds-Testing, Altruism, Self Interest
JEL Classification: F22, F24, O19

1. INTRODUCTION

Remittances have grown in both size and importance. Known to surpass official development aid (ODA), remittance flows to the low- and middle- income countries (LMICs) in 2019 are on track to exceed foreign direct investment (FDI) flows as well (World Bank, 2019). This would make remittances the largest source of external development finance to the developing world. Moreover, the scarce foreign exchange that these flows provide tend to be countercyclical and more stable than capital flows (Ratha, 2003; Frankel, 2011), and being mostly intra-family transactions, they also entail fewer problems associated with asymmetric information (viz. adverse selection and moral hazards). Arguably, promoting remittance inflows has emerged as a policy priority for many LMICs who accounted for as much as 77% of global remittance inflows last year. An important question is what the LMICs can do to promote these remittance flows further? This calls for an understanding of the factors driving these flows, both from micro- and macro- standpoints.

Economic factors governing remittance flows are mostly based on the micro-economic reasons to remit - what motivates migrants to send or bring money home.

These motivations fall into one of the following three categories: altruism, self-interest, and enlightened self-interest (Lucas and Stark, 1985). Often a migrant's utility function is an interdependent one in the sense that the well-being of family left-behind enters as an argument there. Optimizing this function also calls for maintaining a threshold of the family members' well-being that the migrant seeks to achieve by remitting money home. Essentially altruistic in nature, this can also be driven by self-interest, at least to some extent. Self-interest can manifest itself as investment back home, in hopes of returning someday, and/or an act of portfolio balancing. It can also involve investment in social assets (e.g., building schools, funding elections/charities, etc. back home) that can have an altruistic appeal. As Lucas and Stark (1985) note, "In the end one cannot probe whether true motive is one of caring or more selfishly wishing to enhance prestige by being perceived as caring." Thus, remittance flows may be attributed to not one or the other, but both altruism and self-interest, "tempered-altruism" or "enlightened self-interest" (ibid).[1]

Macroeconomic variables that motivate remittances - altruism, self-interest, or a combination of both - fall into one of the following categories: (1) variables proxying economic conditions at source and host countries, (2) variables for demographic characteristics, and finally (3) quality of investment opportunities such as interest rates and political risks (Chami et al., 2008). In empirical studies on remittance flows, often the first two categories of variables tend to have the expected signs and significance but the not the third one - the results tend to be country- and model- specific. For example, ceteris paribus, deteriorating economic condition at migrant's country of origin (source), often proxied by GDP or GDP per capita, would likely increase the need for remittances and boost altruistic remittances. However, it might not if bulk of these remittances were motivated by investment (or portfolio) considerations instead. Likewise, economic conditions at host country would determine the migrants' ability to remit. Remittances also respond to economic adversity triggered by economic crises, natural disasters, or conflicts (Spatafora, 2005; Mohapatra et al., 2012). Thus, the frequency and size of remittances would depend on the need, ability and willingness to remit and the sign of the income variable is theoretically ambiguous. Empirically several studies have found that remittances tend to be countercyclical with respect to home country's GDP (Ratha, 2003; Frankel, 2011) and cyclical with respect to the GDP of the host country (Elbadawi and Rocha, 1992; El-Sakka and McNabb, 1999).

Additionally, financial macroeconomic variables such as exchange rate, interest rate and financial innovations can impact remittance flows. Currency devaluation, for example, can boost trade balances (e.g., Ratha and Kang, 2013). Since it pushes down the real value of remittances in terms of foreign goods (Faini, 1994), migrants may remit more as the real value of remittances increase in terms of home country goods. Thus,

[1] For example, individual family members may also migrate as part of an insurance- or risk-sharing arrangement that would protect family members from spatial income-shocks, such as drought, civil war, and the like.

exchange-related remittances - remittance to boost family's income back home, would go up. However, compensatory remittances - remittance ensuring a certain threshold of purchasing power of family members back home, would go down, making the net effect theoretically indeterminate. Moreover, both volatility of and expectations about exchange rate matter too (Lianos, 1997). In most empirical studies, however, it appears that remittances increase in response to currency depreciation.

The same is true of financial sector development and innovations as they help promote competition, lower transaction cost, broaden the reach while facilitating better record keeping (Freund and Spatafora, 2008).

However, as mentioned earlier, the empirical evidence on the sign and significance of the interest rate variables have not been clear in the literature. For example, Straubhaar (1986) found that the interest rate differential was not a significant factor in determining the size of remittance from Germany to Turkey during the 1962-1982 period, while El-Sakka and McNaab (1999) found a significant and negative impact of interest rate differential on the remittance inflows to Egypt and suggested that a high interest rate spread reflects the instability of home countries and it reduces the remittance flows. On the other hand, Castillo-Ponce et al. (2011) and Peters and Kamau (2015) found that the interest rate differential had a positive and significant impact on the remittance to El Salvador and Guyana, respectively. The positive relationship between interest rate spread and remittance inflows is attributable to altruism and/or investment motives. The altruism hypothesis would predict that the amount of remittances would increase when it becomes more difficult for the families at home to obtain credit to maintain their normal consumption as their credit tightens and interest rates rise. Also, remittance flows will increase if the interest rates spread rises as the return on investment at home is higher.

Similarly, the empirical evidence from various panel studies of the effect of interest rate differential on remittances in the literature were also split. For example, Faini (1994), in a study of five Mediterranean countries, found the rate of returns on asset to have a positive and significant effect on the remittance flows. Alleyne et al. (2008) also found similar results in their study of eight Caribbean countries - the interest rate differential had a positive and significant impact on remittance flows in three out of five panel estimations. On the other hand, Singh et al. (2011) found a negative and significant impact of interest rate differential on the remittance flows in their study of 36 Sub-Saharan African countries. They interpreted that a high inflation and widening interest rate spread at home discourage the investment purpose of remittance from abroad. Recently, Jackman (2013) also produced similar evidence in his panel study of 93 countries. The study found that the nominal interest rate volatility of remittance receiving countries had a significant and negative impact on the remittance flows. The inconsistent empirical evidence on the effect of interest rate differential on the remittance flows seem to be the results of approaching the issue with different data sets (country-specific and cross-sectional panel) and different proxies for interest rate differential (real and nominal rates).

Recent empirical studies linking macroeconomic variables to remittance flows into LMICs include: economic conditions and/or standard of living at home and source country (Singh et al., 2011), business cycles (Vargas-Silva, 2008; Frankel, 2011), volatility in the macro-variables (Higgins et al., 2004; Jackman, 2013), exchange rate (Straubhaar, 1986; Faini, 1994; Chami et al., 2008), interest rate differential (El-Sakka and McNabb, 1999), financial development (Freund and Spatafora, 2005), gravity variables such as distance and language (McCracken et al., 2017), migrants' stock, skill composition, and demographic characteristics like age-dependency ratio (Adams, 2009).

While the literature is quite rich and growing fast, most studies tend to use panel or cross-sectional data - possibly due to a lack of consistent time-series data (Faini, 1994, p. 241). Some of the earlier empirical studies using panel data include: Swamy (1981) for Greece, Yugoslavia, and Turkey; Elbadawi and Rocha (1992) for Algeria, Morocco, Portugal, Tunisia, Turkey, and Yugoslavia; Buck and Kuckulenz (2004) for 87 developing countries; Higgins et al. (2004) for 9 Latin American countries; Schiopu and Siegfried (2006) for 7 EU neighbor countries (Algeria, Egypt, Tunisia, Morocco, Tunisia, Croatia, FYR of Macedonia, Serbia and Montenegro). Cross-countries studies, being aggregative in nature, could involve an implicit aggregation bias. While they increase the degrees of freedom, they can also introduce heterogeneity into the models that might not apply to some of individual countries - country-specific, time-series study may overcome this problem (Singh et al., 2011).

While relatively sparse, there exist several time-series studies on specific individual countries in the literature, which include for Egypt (ElSakka and McNabb, 1999), Greece (Lianos, 1997), India (Gupta, 2006), Mexico (Vargas-Silva and Huang, 2006), Turkey (Straubhaar, 1986; Alper and Neyapti, 2006), among others. This paper contributes to this sparse literature by investigating the macroeconomic factors driving remittance flows to LMICs. It has three novelties: One, now that we have some 30 plus years of annual data for many of the top remittance receiving countries, we estimate a time-series model linking remittance inflows to key macro- determinants for some of the top remittance-recipients, both in absolute and relative terms. The sample comprises of a diverse set of countries based on the size of remittance inflows in 2018 (Word Bank estimate), both in absolute and relative terms (i.e., % of GDP), subject to availability of consistent data over the 1980-2017 time period. The top 10 in absolute terms include India, China, Mexico, Philippines, Egypt, Nigeria, Pakistan, Bangladesh, Indonesia, and Guatemala; and top 11 in relative terms include Tonga, El Salvador, Honduras, Jamaica, Lesotho, Dominica, Senegal, Togo, Ghana, Morocco, and Thailand.2 Together these countries account for more than half of global remittance inflows and more than two-thirds of remittance inflows to LMICs. Two, since the short-run dynamics can be different from the underlying long-run relation, we employ cointegration and

[2] Vietnam and Ukraine respectively rank 8th and 10th in absolute terms but could not be included due to gaps in the data. Data limitations, likewise, prevented including most of the top ranked countries in relative terms - Kyrgyz Republic (2nd), Tajikistan (3rd), Haiti (4th), Nepal (5th), Comoros (8th), West Bank (9th), and Samoa (10th).

error-correction modeling, specifically, the bounds-testing approach (Pesaran et al., 2001) - a relatively recent technique also deemed appropriate for small samples such as the case in hand. Three, in order to identify consistent macroeconomic determinants of remittance flows, we also employ traditional panel methods on the same data set. This helps demonstrate some inconsistencies in empirical evidence produced by the two methods. Such studies are remarkably absent in the empirical literature.

The rest of the paper is organized as follows. In the next section, we introduce a reduced form model incorporating the key macro variables widely used in the literature. Section 3 discusses the methodology and empirical results in two parts: (a) the bounds-testing approach to cointegration (time-series approach) and (b) the panel fixed and random effects modelling. Section 4 concludes. The data, definitions, and sources are provided in the appendix.

2. THE MODEL

While numerous factors influence migrants' decisions to send money home (say, country j), we incorporate a reduced form model incorporating the key macro- variables extensively used in the literature: exchange rate, returns on investment and economic conditions (standard of living) at migrants' source and host country, and state of financial markets at source:

$$\ln REMSR_t = a + b\ln REX_t + cINTR_t + d\ln PCIR_t + e\ln M2SR_t + \varepsilon_t, \qquad (1)^3$$

where $\ln X$ stands for the natural log of variable X, $REMSR$ is the remittance inflows, measured as a share of GDP; REX is the real exchange rate, defined such that an increase implies appreciation of country j's currency; $INTR$ and $PCIR$ stand for, respectively, real interest rate, and real per capita income in country j relative to the corresponding US values; $M2SR$ is broad money (M2) as a % of GDP - a proxy for financial market development.[4]

These variables capture some of the most important economic reasons behind migration and remittances - the migrant's desire to return and hence invest, and/or help family (altruism) back home. The ability and incentive to remit (and the amount) depends on, among other things, the macroeconomic conditions at source and host

[3] The small sample size calls for a relatively parsimonious model, accomplished here by using variables in ratio forms. For example, GDPR is GDP of country j relative to US GDP. This saves on degree on degrees of freedom without sacrificing the critical information - the relative movements between two. Moreover, it rules out the variable being negative thus the model can be run in log form and the coefficient estimates can then be interpreted as elasticities. Since real interest rate can be negative, INTR is the only variable without log.

[4] Giuliano and Ruiz-Arranz (2009) uses M2 as a broad measure of financial development.

countries, captured by the relative income difference, $PCIR$; the real exchange rate, REX (analogous to the relation between price and quantity supplied of a foreign currency); optimizing investment by comparing alternatives, $INTR$; and the cost and ease of remittance, measured by $M2SR$, the degree of monetization. Since financial deepening and innovations facilitate transactions, the coefficient of $M2SR$, e, is expected to be positive. However, the sign and significance of the other variables are theoretically indeterminate. If the altruistic motive is dominant, when $PCIR$ is falling due to an economic slowdown, or natural disaster, migrants would step up their remittances to help people back home. Similarly, when REX is rising - to compensate for the appreciation of domestic currency, they would need to remit more dollars (to maintain the standard of living of family back home). Thus, $b > 0$ and $d < 0$ likely imply altruism being the dominant motive behind remittances, whereas the opposite would point to the investment motive. Under both the altruistic and investment motives, the theoretical impact of $INTR$ on remittances is ambiguous. Since interest rate hikes usually imply a tightening of credit, migrants would likely send more money home to alleviate the credit crunch. However, it also depends on how the remittance money is used by the migrants' family - if bulk of it spent on basic needs, perhaps remittance would not change much under the altruistic motive. Moreover, the state and sophistications of the financial markets varies from country to country - the poor is still unbanked in many of the $LMICs$ comprising our sample. Thus, it appears that the investment (portfolio) motive would be the dominant factor determining the coefficient of $INTR$, and since investment also depends on, among other things, perceptions of risk - the underlying coefficient, c, is theoretically ambiguous. Since the coefficient-estimates can go either way and, also vary cross-sectionally, country-specific studies, in contrast to aggregate panel studies, are likely to shed valuable insights into the finer dynamics.

3. METHODS AND DATA

3.1. The Bounds-Testing Approach to Cointegration

Equation (1) outlines the long-run relation (cointegration) among the variables of interest and is estimated using the bounds-testing approach to co-integration (Pesaran et al., 2001). The underlying short-run dynamics (or the error-correction model) are as follows:

$$\begin{aligned}\Delta\ln REMSR_t = a_i &+ \textstyle\sum_{i=1}^{n_1} b_i \Delta\ln REMSR_{t-i} + \sum_{j=0}^{n_2} c_j \Delta\ln REX_{t-j} \\ &+ \textstyle\sum_{k=0}^{n_3} d_k \Delta INTR_{t-k} + \sum_{l=0}^{n_4} f_l \Delta\ln PCIR_{t-l} + \sum_{m=0}^{n_5} g_m \Delta\ln M2SR_{t-m} \\ &+ \delta_1 \ln REMSR_{t-1} + \delta_2 \ln REX_{t-1} + \delta_2 \ln REX_{t-1} + \delta_3 INTR_{t-1} \\ &+ \delta_4 \ln PCIR_{t-1} + \delta_5 \ln M2SR_{t-1} + \varepsilon_t. \end{aligned} \tag{2}$$

The procedure then comprises of two steps: (i) selection of the optimal lag structure for (2) and (ii) *a variable addition test* testing the null of "*non-existence of cointegration*" (i.e., H_0: $\delta_1=\delta_2=\delta_3=\delta_4=\delta_5=0$) against its alternative. Given the smaller sample size and annual frequency of the data, a maximum lag of 2 was imposed in each case. Also, the Schwartz-Bayesian Criterion (SBC), being a parsimonious model, is employed for step (i). The critical values for the F-test employed in step (ii) are non-standard and obtained from Pesaran et al. (2001) and Narayan (2005). If the calculated F-statistic exceeds the upper bound, then the null hypothesis of no co-integration is rejected, establishing cointegration among the variables. If it falls below the lower bound, then the null hypothesis cannot be rejected. If it falls between the lower and upper bounds, the results are inconclusive. The calculated values of F-statistics are reported in Table 1.

Table 1. The F-test

Country	Model with relative real interest rate	Model with relative nominal interest rate
Bangladesh	4.42**	2.87$^+$
China	4.91***	4.35**
Dominica	2.62$^+$	2.65$^+$
Egypt	2.49$^+$	3.06$^+$
El Salvador	2.67$^+$	4.64**
Ghana	10.26***	7.78***
Guatemala	5.35*	5.70***
Honduras	1.35	1.43
India	2.57$^+$	2.54$^+$
Indonesia	1.83	2.13
Jamaica	2.10	2.60$^+$
Lesotho	3.49**	2.75$^+$
Mexico	1.55	0.69
Morocco	1.77	1.89
Nigeria	1.39	3.00$^+$
Pakistan	1.11	2.27$^+$
Philippines	3.57*	3.61*
Senegal	2.03	1.91
Thailand	1.76	1.85
Togo	4.61**	2.85$^+$
Tonga	2.74$^+$	5.27***

Notes: Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The corresponding upper (lower) bound critical values with 4 repressors and an intercept are 4.781 (3.516), 3.805 (2.649), and 3.367 (2.262), respectively. $^+$ denotes inconclusive at the 10% level. These preceding values are for large samples and based on Pesaran et al. (2001). For smaller samples, Narayan (2005) proposes a different set of critical values - 5.532 (4.093), 4.088 (2.947), 3.460(2.460) at 1%, 5%, and 10% levels, respectively. However, the inferences on the F-test remain the same.

Table 2A. The Error-Correction Model (with Relative Real Interest Rates)

Country	Intercept	$\Delta LREX$	$\Delta LREX1$	$\Delta INTR$	$\Delta INTR1$	$\Delta LPCIR$	$\Delta LPCIR1$	$LM2SR$	$\Delta LM2SR1$	EC_{t-1}
Bangladesh	-1.31*	-1.47***		0.01	0.05***	0.79***		0.31	-0.61**	-0.29***
	(1.71)	(5.77)		(0.40)	(2.82)	(3.50)		(1.06)	(2.49)	(2.95)
China	-2.63	1.35		0.01		6.45*		0.66		-1.00
	(0.24)	(1.09)		(0.13)		(1.78)		(0.32)		(∞)
Dominica	-8.35***	-3.55	8.08**	-0.002		-2.93**		-0.68		-0.43***
	(2.62)	(0.88)	(2.35)	(0.58)		(2.58)		(1.01)		(3.13)
Egypt	-1.09	0.37	-0.85**	-005		0.67		0.93*		-0.19*
	(0.50)	(1.09)	(2.50)	(0.32)		(1.57)		(1.89)		(1.89)
El Salvador	0.46	0.01		0.01		-1.14	-2.78***	-0.29		0.11
	(0.42)	(0.47)		(0.54)		(0.88)	(3.02)	(1.62)		(1.12)
Ghana	14.65***	-1.60***		-0.001		7.73**	-16.56***	0.48	-2.50***	-1.20***
	(4.55)	(5.57)		(1.64)		(2.49)	(4.75)	(0.61)	(3.64)	(7.44)
Guatemala	-18.32**	3.37		0.01		-7.65	28.85***	0.66		-0.53***
	(2.62)	(1.60)		(0.50)		(0.70)	(2.94)	(0.74)		(4.73)
Honduras	-4.51	-0.44		-0.0002		-0.23		0.81		-0.26**
	(0.89)	(0.56)		(0.05)		(1.10)		(1.21)		(2.23)
India	-0.24	-0.46***		0.002		0.43		2.36**		-0.33***
	(0.12)	(3.13)		(0.27)		(1.47)		(2.52)		(3.01)
Indonesia	-8.21**	-1.28***		0.000		1.20**		-0.12		-0.44***
	(2.50)	(2.64)		(0.19)		(1.91)		(0.26)		(3.57)
Jamaica	-4.24**	-0.64***		0.001		-3.97***	2.58**	-0.26		-0.16
	(2.54)	(2.90)		(0.45)		(3.27)	(2.13)	(0.88)		(1.65)

Notes: *LX* stands for the natural log of variable *X*; $\Delta LREX = LREX_t - LREX_{t-1}$, $\Delta LREX1 = LREX_{t-1} - LREX_{t-2}$, and EC_{t-1} denotes lagged error-correction term. Figures in parentheses are absolute values of t-statistic. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Ghana also had a positive and significant $\Delta LREMSHR1 = LREMSHR_{t-1} - LREMSHR_{t-2}$.

It may be noted that value the F-statistic depends on the optimal lag-structure which in turn is determined by the selection criterion employed - in this case SBC, due to the smaller sample size. Given the 90% upper (lower) critical bound of 3.367 (2.262), the null could be rejected in 7 cases (establishing cointegration), and the results were inconclusive in another[5]. As an indirect evidence of cointegration, the sign and the significance of the lagged error correction term (EC_{t-1}) in the error-correction model is examined. According to Kremers et al. (1992) a negative and significant coefficient of EC_{t-1} indicates cointegration. As may be noted from Table 2A, the error-correction model, coefficient of the lagged error-correction term is negative in all but 1 cases and is significant in 16 out of the 21 cases.5 Thus, it appears that there exists a long run relation among the variables of the model.[6]

Table 2A also shows the short-run dynamics involving the other variables as well: how *changes* in a specific argument effects *changes* in the dependent variable, and for how long. For example, the coefficient of $\Delta \ln REX$ is negative in majority of cases and is negative and significant for Bangladesh, Egypt (at lag 2), Ghana, India, Indonesia, Jamaica, Mexico, Morocco, Nigeria, Pakistan (at lag 2), Philippines, Senegal, Togo, and Tonga. This could mean the dominance of the investment channel as currency appreciation (depreciation) at country of origin has a dampening (favorable) effect on remittance inflows to these countries. On the other hand, for Dominica, the coefficient is positive, i.e., migrants send more money home when the East Caribbean Dollar, XCD, gets stronger. This would be mostly altruistic transfers.

Table 2C. Short Run Results: Tempered Altruism?

Dominant Factor	$\Delta LREX$ (+/-)	$\Delta LINTR$ (-/+)	$\Delta LPCIR$ (-/+)
Altruism	*Dominica* (at lag 2)	**Mexico** and **Togo** (lag 1)	*Dominica*, El Salvador (lag 2), Ghana (lag 2), **Jamaica** (lag 1), **Lesotho**, and **Mexico**
Investment	***Bangladesh***, Egypt (at lag 2), ***Ghana***, **India**, ***Indonesia***, *Jamaica*, Mexico, Morocco, Nigeria, Pakistan (at lag 2), ***Philippines***, Senegal, ***Togo***, and **Tonga**	*Bangladesh* (lag 2), Lesotho (lag 2) and *Togo* (lag 2)	*Bangladesh*, China, *Ghana* (lag 1), Guatemala (lag 2), *Indonesia*, *Jamaica* (lag 2), and *Philippines*.

Notes: *Italics* indicate results consistent across at least two variables; **Bold** indicates consistent with long run results.

[5] Although, the error-correction coefficient was positive for El Salvador, the F-test result was inconclusive. For Jamaica, Mexico, Nigeria, and Senegal the coefficient was insignificant but negative.

[6] The size of the error correction coefficient negative and less than one in majority of cases, indicating a mild to moderate speed of adjustment to the long run equilibrium.

Are the preceding observations consistent with the rest of the short-run dynamics? Table 2B summarizes the short run results, classifying countries into two groups based on the dominant factor, *altruism* or *investment*, and by variables $-\Delta LREX$, $\Delta LINTR$, and $\Delta LPCIR$.[7] If at least two of these variables point to the same dominant motive - altruism or investment - the country's name is italicized.

While both factors are important, it appears that investment might be the dominant factor driving remittance flows to many countries. Also, many of these short run dynamics last to the long run but not all. The long run results corresponding to (2) are reported in Table 3A and the possible interpretations are summarized in Table 3C

It is noteworthy that M2SR carries the hypothesized positive in sign in majority of cases, and significant in many. Financial innovations and development boost remittance flows. They also facilitate better record keeping. However, remittance behavior is governed by both altruism and investment considerations and it is difficult to establish a single motive behind remittance flows.[8] Nevertheless, country-specific time-series studies can help identify the relatively dominant motive and design appropriate policy. For example, investment seems to the dominant motive behind remittance flows to Bangladesh, Ghana, and Indonesia, both in the short- and long- run (Tables 2C and 3C). For Lesotho and Togo, on the other hand, altruism seem to be the driving force. Moreover, some of the short run effects reverse themselves in the long run, e.g., China, Guatemala, and Jamaica with respect to PCIR; Lesotho and Togo, with respect to INTR, etc. Also, in line with Chami et al. (2008), it is intriguing to note that INTR is negative in most cases and, also the least significant of all. Since many of the developing countries tend to have high inflation, the real interest rate, INTR can be negative at times and hence could not be logged. In any case, to check the robustness, we replaced it with nominal interest rate and ran the log-linear model. The results did not seem to change much and are reported in Tables 2B and 3B.[9] Moreover, we also ran a panel version of the same model that we turn to next.

[7] $\Delta LM2SR$ is omitted here as its coefficient estimate, while mostly positive as expected, does not lend itself to such interpretation.

[8] See, for example, Lucas and Stark (1985) for a microeconomic application and Chami et al. (2008) for a macroeconomic one. While consistent, by and large with the latter, our findings from time-series estimations yield a negative coefficient for real exchange rate (implying remittances increase in response to currency depreciation) and therefore tend to be opportunistic- rather than compensatory, as found by the latter. This may be due to using different samples and estimation methods (cross-section versus time-series). Nevertheless, the results are in agreement for the latter's sub-sample post- 9/11 (Table 4.3, pg., 28). Another caveat is that they use nominal exchange rate instead of real.

[9] The Stability Test Results based on CUSUM and CUSUMSQ are reported in Table 4.

Table 3A. The Long Run Model (with Relative Real Interest Rates)

Country	Intercept	$LREX$	$INTR$	$LPCIR$	$LM2SR$
Bangladesh	-4.56 (1.44)	-5.08*** (2.93)	-0.09 (1.30)	2.73*** (2.92)	-0.47 (0.83)
China	-2.63 (0.24)	1.35 (1.09)	-0.01 (0.13)	-0.03 (0.25)	0.66 (0.32)
Dominica	-19.32** (2.29)	3.10 (0.50)	-0.005 (0.56)	-6.78 (2.40)	2.41 (1.31)
Egypt	-5.87 (0.48)	1.81 (1.64)	-0.03 (0.33)	3.63 (1.09)	5.02 (1.30)
El Salvador	4.09 (0.45)	-0.11 (0.40)	-0.05 (0.44)	4.92 (0.86)	5.13 (1.46)
Ghana	12.25*** (5.27)	-1.34*** (8.41)	-0.001* (1.69)	5.79*** (10.50)	2.60*** (8.24)
Guatemala	-34.28** (2.52)	-0.99 (0.38)	0.01 (0.50)	-10.29* (1.96)	1.24 (0.74)
Honduras	-17.18 (0.97)	-1.68 (0.64)	-0.001 (0.05)	-0.87 (0.10)	3.10* (1.98)
India	-0.73 (0.12)	-1.41*** (2.67)	-0.01 (0.27)	1.30 (1.47)	0.21 (0.22)
Indonesia	-18.77 (2.63)	-2.94*** (3.16)	0.003 (0.02)	2.76** (2.58)	-0.27 (0.26)
Jamaica	-26.40 (1.42)	-3.98 (1.34)	0.005 (0.43)	-7.62** (2.51)	-1.64 (0.99)
Lesotho	-17.91*** (4.82)	2.04*** (2.98)	-0.23* (1.96)	-5.85*** (6.62)	1.17** (2.15)
Mexico	-6.40 (1.68)	-0.13 (0.14)	-0.01* (1.72)	-4.17*** (3.36)	-0.02 (0.03)
Morocco	-0.46 (0.13)	-1.20 (1.53)	-0.001 (0.68)	0.32 (0.35)	0.13 (0.60)
Nigeria	-8.48 (0.12)	-6.33 (0.85)	-0.06 (0.29)	5.41 (0.26)	-1.51 (0.13)
Pakistan	-188.61 (0.05)	-72.92 (0.05)	0.07 (0.05)	103.46 (0.05)	68.90 (0.05)
Philippines	-7.52*** (6.66)	-0.79*** (2.83)	0.01 (0.93)	-0.49 (1.58)	1.25*** (8.88)
Senegal	-22.71** (2.23)	-2.22 (1.02)	-0.004 (0.87)	-2.25 (1.20)	0.98 (0.80)
Thailand	-6.87 (0.97)	2.78* (1.87)	0.004 (0.06)	-2.31 (1.64)	2.42 (1.51)
Togo	-70.74*** (2.86)	-7.54* (1.96)	-0.06** (2.19)	-3.08** (2.46)	3.39*** (2.89)
Tonga	-0.85 (1.41)	-1.05*** (2.65)	0.003 (0.43)	1.06 (0.65)	1.60*** (5.07)

Notes: LX stands for the natural log of variable X; Figures in parentheses are absolute values of t-statistic. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3B. The Long Run Model (with Relative Nominal Interest Rates)

Country	Intercept	$LREX$	$LINTN$	$LPCIR$	$LM2SR$
Bangladesh	-3.06	-6.29**	0.40	3.49**	-1.46
	(0.83)	(2.39)	(1.26)	(2.47)	(1.41)
China	-3.23	1.40	0.20	-0.14	0.73
	(0.31)	(1.28)	(0.61)	(0.12)	(0.40)
Dominica	-9.75	-2.69	0.38	-4.13*	0.11
	(1.64)	(0.52)	(0.70)	(1.83)	(0.01)
Egypt	-4.26	1.98*	-0.35	5.05	5.78
	(0.30)	(1.73)	(0.39)	(1.02)	(1.41)
El Salvador	52.24	1.38	-6.51	-1.25	-12.22
	(0.41)	(0.53)	(0.43)	(0.11)	(0.45)
Ghana	13.10***	-1.29***	-0.03	6.00***	2.62***
	(3.80)	(7.46)	(0.28)	(6.75)	(7.10)
Guatemala	-35.28***	-0.75	-0.29	-10.94*	1.25
	(2.40)	(0.28)	(0.28)	(1.84)	(0.73)
Honduras	-36.22	0.13	0.30	-9.95	-1.75
	(1.62)	(0.34)	(0.24)	(0.84)	(0.70)
India	-1.46	-1.36***	-0.15	1.23	0.41
	(0.25)	(2.78)	(0.49)	(1.48)	(0.45)
Indonesia	-18.55***	-3.23***	-0.79	3.41***	-0.32
	(2.89)	(3.58)	(1.16)	(3.19)	(0.34)
Jamaica	-26.86	-7.28	0.36	-2.90	-3.47
	(0.45)	(0.43)	(0.50)	(0.33)	(0.42)
Lesotho	3.31	1.40	-3.11*	-1.50	0.13
	(0.25)	(1.59)	(1.90)	(0.59)	(0.13)
Mexico	-2.77	-0.98	-0.27	-0.37	0.33
	(0.67)	(1.43)	(0.36)	(0.35)	(1.61)
Morocco	-2.77	-0.98	-0.03	-0.37	0.33
	(0.67)	(1.43)	(0.36)	(0.35)	(1.61)
Nigeria	39.55	-1.67	8.96*	8.18	-11.50
	(0.68)	(0.50)	(1.85)	(0.63)	(0.99)
Pakistan	-42.26	2.02	0.56	-11.35	1.92
	(1.07)	(1.11)	(1.42)	(1.24)	(0.72)
Philippines	-7.55***	-0.79***	0.14	-0.47	1.26***
	(6.44)	(2.73)	(0.85)	(1.45)	(8.62)
Senegal	-28.58	-2.70	-0.24	-2.85	1.39
	(1.28)	(0.77)	(0.47)	(0.99)	(0.72)
Thailand	2.48	2.84*	-0.01	-2.35	2.48
	(1.51)	(1.69)	(0.02)	(1.61)	(1.51)
Togo	-95.93	-12.97	-0.23	-1.34	3.10
	(0.97)	(0.81)	(0.31)	(0.31)	(0.85)
Tonga	6.46	-1.15***	0.037*	4.03**	1.64***
	(1.61)	(2.78)	(1.81)	(2.33)	(4.75)

Notes: LX stands for the natural log of variable X; Figures in parentheses are absolute values of t-statistic. Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3C. Long Run Results

Dominant Factor	*LREX* (+/-)	*LINTR* (-/+)	LPCIR (-/+)
Altruism	*Lesotho* and Thailand	Ghana, **Mexico**, *Lesotho*, and ***Togo***	China, **Dominica**, Guatemala, **Jamaica**, ***Lesotho***, **Mexico**, and *Togo*
Investment	***Bangladesh***, ***Ghana***, **India**, ***Indonesia***, **Philippines**, **Togo**, and **Tonga**.		*Bangladesh*, *Ghana*, and *Indonesia*

Notes: *Italics* indicate results consistent across at least two variables; **Bold** indicates consistent with short run results.

Table 4. Stability Test

Country	Model with the real interest rate		Model with the nominal interest rate	
	CUSUM	CUSUMSQ	CUSUM	CUSUMSQ
Bangladesh	Stable	Unstable	Stable	Unstable
China	Stable	Unstable	Stable	Unstable
Dominica	Unstable	Unstable	Unstable	Stable
Egypt	Stable	Stable	Stable	Stable
El Salvador	Stable	Unstable	Stable	Unstable
Ghana	Stable	Stable	Stable	Stable
Guatemala	Stable	Stable	Stable	Unstable
Honduras	Stable	Unstable	Unstable	Unstable
India	Stable	Stable	Stable	Stable
Indonesia	Unstable	Stable	Stable	Stable
Jamaica	Stable	Unstable	Stable	Stable
Lesotho	Stable	Stable	Stable	Stable
Mexico	Stable	Stable	Stable	Unstable
Morocco	Stable	Unstable	Stable	Stable
Nigeria	Stable	Stable	Stable	Unstable
Pakistan	Stable	Stable	Stable	Unstable
Philippines	Stable	Unstable	Stable	Unstable
Senegal	Stable	Stable	Stable	Unstable
Thailand	Stable	Stable	Stable	Unstable
Togo	Stable	Stable	Stable	Stable
Tonga	Stable	Stable	Stable	Unstable

3.2. Panel Estimations

The empirical model for one-way cross-section fixed effect is specified by using the same variables included in Equation (1).

$$\ln REMSR_{it} = a + b\ln REX_{it} + cINTR_{it} + d\ln PCIR_{it} + e\ln M2SR_{it} + u_{it}, \qquad (3)$$

where $u_{it} = a_i + \varepsilon_{it}$ and $E(X_{it}\, a_i) \neq 0$.

The Estimated Generalized Least Squares (EGLS) were used to estimate the model with the cross-sectional fixed effects by considering the weights for the potential heteroscedasticity across the cross-sectional data. Two different weight methods were used for the fixed effect model: PCSE (Panel Corrected Standard Errors) and CSUR (Cross-section Seemingly Unrelated Regression). The PCSE assumes the presence of cross-sectional heteroscedasticity in the data and corrects the heteroscedasticity by replacing the residuals with moment estimators. The CSUR estimates the model by correcting for both cross-section heteroscedasticity and contemporaneous correlation in the pooled data through cross-section clustering (Beck and Katz, 1995).

Three different samples were used based on the groups of remittance receiving countries (RRC) for the period of 1982-2017. They are (1) a full sample of 20 remittance receiving countries, (2) top 10 countries in largest dollar ($) remittance, and (3) top 10 counties with the largest remittance share (%) among their GDP. In order to balance the panel, a country (El Salvador) was dropped from the sample due to the lack of real interest rate data in early 1980s. All variables used in the model were logged in the estimations except the real interest rate variable.

Table 5A presents the estimation results from the EGLS with the one-way cross-sectional fixed and random effects and we found that the results were quite consistent with our hypotheses. The signs of coefficients for $\ln REX$ in two fixed effect models were all negative and mostly significant at the 1% level in full sample estimations. The result supports the existing evidence on the inverse relationship between the real exchange rate and the remittance flow; a country would receive more remittance when the country's currency gets weaker and vice versa. Only exception was that the coefficient for $\ln REX$ was insignificant in the estimation with the sample of 10 countries with largest remittance share.

Both fixed effect models also produced expected negative coefficients for $\ln PCIR$, the relative per capita income of RRC, and they were all significant in all three samples. As per capita income of remittance receiving countries decrease, more remittance is expected to flow into the countries, which supports the traditional altruism hypothesis.

The last variable, $\ln M2R$, represent the relative level of financial market development in RRC and the coefficient for the variable also showed expected signs and they were significant in all three samples. As the financial markets deepens and broadens, it would be easier for the RRC to receive remittance from other countries.

The relative real interest rates, INTR, was the only exception; the coefficient for the variable was insignificant in all samples with an exception of cross-section fixed SUR estimation with full sample. The insignificant coefficient for real interest rate differential is consistent with the findings of Straubhaar (1986) and implies that the remittance flows are not affected by the real interest rate differentials. Table 5B presents the estimation results of the same model but with the logged relative nominal interest rates ($\ln INTN$) in the model, which produced quite different results for the variable. The coefficients of $\ln INTN$ were all positive and significant at the 1% level in 5 samples out of six, which clearly supports the findings of Castillo-Ponce et al. (2011) and Peters and Kamau

(2015). As discussed earlier, the positive relationship between the widening nominal interest rate spread and the size of remittances can be the result of both altruism and long-term investment flow.

Tables 5C and 5D reports the panel data estimation results by using error component models, which were quite similar to the findings reported in 5A and 5B. Again, with an exception of relative real interest rate variable, all three estimation methods produced correct signs for the variables in the model and they were mostly significant. The results become even stronger when the model included the relative nominal interest rate instead. Da Silva method, for example, produced significant coefficients for all variables in the model with the correct signs, which supported the existing evidence in the literature.

4. CONCLUDING REMARKS

When it comes to external funding of development, remittances have grown both in size and importance. Known for their relative stability, counter cyclicality, and lower risks associated with informational asymmetries, they are unique flows of scarce foreign exchange that many LMICs want to tap into and have made a policy priority. To guide such policy, this paper looks at the macroeconomic determinants of these flows to some of the major destinations, in both absolute and relative terms using time-series as well as panel methods.

While the empirical literature on the topic employing panel methods is quite rich, most existing studies based on panel or cross-sectional data tend to generalize the macroeconomic determinants and, thus, potentially ignoring a country's specific characteristics related to remittance flow. Possibly due to data limitations, the literature is quite sparse when it comes time-series studies of individual countries; this study addresses that void. Specifically, we employ the bounds-testing approach to cointegration and error-correction modeling (Pesaran et al., 2001) since the short-run dynamics can be different from the underlying long-run relationships. We also run the traditional panel methods and compare the results.

Remittance behavior is governed by both altruism and investment considerations - "tempered-altruism" or "enlightened self-interest". Identifying the relative importance of these factors can help developing countries design appropriate policies boosting remittance inflows. Our results based on both bounds-testing and panel methods suggest that financial development and innovations would facilitate these flows. However, there were some notable differences. For example, in most cases under the panel methods, the coefficient estimate of real interest is positive and insignificant whereas its time-series counterpart is mostly negative, and significant for Ghana, Lesotho, Mexico, and Togo (Table 3A). The coefficient-estimate of nominal interest rate, likewise, is positive and significant in almost all cases under the panel methods but not so under the time-series estimation (Table 3B) - barring Nigeria and Tonga, the coefficient is negative and insignificant in most cases. Thus, it appears that country-specific time-series studies incorporating both short- and long-run dynamics, in contrast to the traditional panel data analyses, might help design more effective policies - policies tailored to individual countries' needs.

APPENDIX

Data, Definitions, and Sources

Annual data are used to carry out the empirical work. The sample comprises of Bangladesh (1980-2017), China (1980-2016), Dominica (1981-2017), Egypt (1982-2017), El Salvador (1980-2017), Ghana (1980-2017), Guatemala (1980-2017), Honduras (1982-2016) (1980-2017), India (1980-2016), Indonesia (1986-2017), Jamaica (1980-2017), Lesotho (1980-2016), Mexico (1980-2016), Morocco (1980-2017), Nigeria (1980-2016), Pakistan (1980-2017), Philippines (1980-2017), Senegal (1980-2017), Thailand (1980-2017), Togo (1980-2017), and Tonga (1980-2017). The data come from the World Development Indicators (World Bank), May 2019.

REM = Remittance inflows, expressed as % of GDP.

REX = the Real exchange rate, defined as $P_j/(E_j.P_{US})$; where P_j stands for CPI in country *j*, Pus is the United States CPI, and E_j is the number of *j*'s currency per US $ (the nominal exchange rate). Thus, an increase in RER implies a real appreciation of the domestic currency.

$INTR = R_j/R_{US}$, where R_j (R_{US}) is real interest rate in country j (US);

Real interest rate = Lending interest rate and inflation rate (based on CPI). In case of missing data, other interest rates (e.g., money market rate, deposit interest rates, etc.) were used as a proxy for lending interest rate. Consistency was maintained throughout.

$GDPR = GDP_j/GDP_{US}$ = Country *j*'s real GDP relative to US real GDP.

$PCIR = PCI_j/PCI_{US}$ = Country j's real per capita income relative to US real per capita income.

$M2SR$ = Broad money (M2) as a % of GDP.

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