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Country Department for Central America, Mexico, Panama and the Dominican Republic

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Remittances payments through central banks: an application to Central American countries exchange rates

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ABSTRACT

This paper analyzes the potential effect on the level and volatility of the Central American countries' exchange rates of transferring remittances through central banks. To do so, we estimate the determinants of the level and volatility of the exchange rate in these countries. Given the importance of remittances for these economies, transferring a percentage of remittances through central banks diminishes the supply of dollars in the local currency market. This reduces the volatility and depreciates slightly the exchange rate, along with the need of the central bank to intervene in the currency market.

JEL Codes: *E42, E58, F24, F31.*

Keywords: *Remittances, payment systems, Federal Reserve, central banks, exchange rate, Dutch disease, Central America.*

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1. Introduction

Several countries in the Central America and Dominican Republic (CARD) region, receive a substantial amount of remittances. In 2018, remittances in Guatemala, Honduras, Nicaragua, and the Dominican Republic, amounted to 12, 19, 10, and 8 percent of their respective GDP.

The large amount of remittances is a challenge to local currency markets. As a result, several central banks in the region take an active role in the foreign exchange market. For example, the central bank of Guatemala has intervened in the exchange market selling dollars for 2,500 million in 2017, and 1,500 in 2018. The central bank of Honduras intervenes daily to maintain the exchange rate into the exchange rate band. Their interventions (direct or through rules) attempt to mitigate short-term exchange movements and volatility that restrict the well-functioning of the currency market.

Absorbing remittances, when its size is large in relation to economic activity, is also a major challenge to an economy as is a source of Dutch disease (Acosta et al., 2009; and Amuedo, 2004). Large amount of remittances would appreciate the real exchange rate, resulting in a loss of competitiveness of the export sector. This is particularly relevant when remittances are volatile, can be reduced abruptly from changes in foreign migration policies, or will diminish over time as workers settle in the destination country.

The literature analyzing the effects of large amounts of remittances on the exchange rate (level and volatility) is scarce and mechanisms to mitigate these effects null. In this paper we analyze both.

Using the case of Central America is particularly useful for this analysis because; (i) countries in the region receive large amounts of remittances with respect to the size of their economies, (ii) we can analyze the effect on a bilateral exchange rate -local currency por dollar- as the US is the main origin of remittances and most important trade and investment partner to this region, and (iii) migration policies in the US and the transit countries are changing. For example, the Temporary Protection Status (TPS) was eliminated by the U.S. federal government, restricting its asylum policy and tightened its border. Also, Mexico and Guatemala have started receiving US asylum seekers.

In concrete, we analyze the potential effects on the exchange rate's level and volatility of transferring (a proportion of) remittances through central banks. A payment system between the Federal Reserve and other central banks (or similar institutions) already exists, it is called FedGlobal ACH Payments5. In the region, it works with Mexico (with the commercial name “Directo a México”) and Panama. The cycle of payment begins with a financial institution in the US that receives the remittance (in dollars). Then, it is transferred to the Federal Reserve, which charges a small fee (in the case of a transfer to Mexico 0.67 dollars per transaction). The Federal Reserve transfers to the local central bank (or a similar institution in countries where there is no a central bank), which changes the payment to local currency for a fee (the central bank of Mexico charges 0.21% and offers the interbank exchange rate) and transfers it to the beneficiary's local account. Remittances payed through this system do not enter directly to the local currency market, reducing short-run instability in the market. In the case of Mexico, remittances that the central bank receives by “Directo a México” is very small with respect to the total, only around 3%. The amount received is usually sold at the market exchange rate to a public development bank to pay its foreign currency debt.

In the next sections, we present estimates of the determinants of the exchange rate level and volatility, and perform some exercises to evaluate the potential effects of the implementation of the payment system described above.

The document is divided in four sections. Section 2 presents the modeling strategies divided in (i) panel data with cross sectional dependence evidence, and (ii) transfer-realized volatility model with GARCH effects. Section 3 shows the empirical results, and section 4 concludes. There are 3 additional appendices where we include descriptive statistics of the variables used in the analysis as well as unit root evidence, and extended econometric results.

[5] https://www.frbservices.org/financial-services/ach/fedglobal/index.html

2. Econometric strategy

We aim to model the exchange rate – remittances relationship. The underlying hypothesis is that the former (remittances) affects both level and volatility of the exchange rate. Our strategy is therefore twofold: on the one hand, a panel data strategy is used to estimate the relationship within an expanded set of Latin American economies. In this regard, it is worth noting that many Latin American countries, in addition to those in Central America, have been included in the sample. The interrelation between Central American economies with their counterparts both north and south can be a fundamental factor in understanding the region dynamics. On the other hand, we apply a second strategy that primarily focus on the realized volatility of the exchange rate using individual samples (this is, a separate model for each Central American economy). The hypothesis is that remittances also affect the realized volatility of the exchange rate. We thus estimate a transfer model with conditional heteroskedasticity autoregressive effects (GARCH models, to be precise) defining the realized volatility of the exchange rate as a dependent variable. Our specification includes several economic variables (remittances, external debt, etc.) helping to quantify the effect of remittances in the realized volatility of the exchange rate.

2.1 Panel data analysis

Panel data models have been widely used in economics and finance in recent years. These models have been used to analyze complex phenomena due to the ease with which it is possible to control and even exploit the heterogeneity presented between cross-section units. Such models allow to identify various effects that are simply not detected in pure cross-sectional or time series econometric models.

When analyzing economic phenomena, it is observed that cross-section units may be exposed to the influence of statistical structures that end up creating interdependence between them, which is called cross sectional dependence. Such a dependence gave rise to a wide literature because the respective statistical inference is considerably more difficult. It is important to note that neglecting the cross sectional dependence may generate spurious results, and, therefore, nonsense inference. When the cross-sectional dimension (N) is not large enough, but the time-series dimension (T) is large, a simple linear estimate, such as Generalized Minimum Squares, (GLS) of

the Seemingly Unrelated Regression Equation system models (SURE) may be an adequate option. However, such an approach is not longer valid in most of macroeconomic panel data. This is due to the fact that, in general, when both dimensions, N and T, are large, a correlation between errors and the regressors is typically found. The type of econometric models that have been used to analyze these data structures are called "large data panels with cross-dependence."[6]

As aforementioned, the growing popularity of multivariate macroeconomic analysis through panel data with several countries, made researches (both, theoretical and empirical) focus on the study and treatment of panels with cross sectional dependence. Chudik et al. (2011) define the concepts of weak and strong dependences, based on the asymptotic behavior of the higher eigenvalue of the associated covariance matrix of the variables under study. A strong dependence can be generated by a process of common factors, while a weak one can have its origin in spatial processes (see Bailey et al., 2012).

In this study, we assume that a common factor structure drives the cross sectional dependence between the countries analyzed. Such factors may be originated by geographical or economic reasons. The approach followed in this paper does not demand to identify these reasons, but only to take into account to control for such cross sectional dependence in the estimation procedure.

Consider the following heterogeneous panel data model:

$$y_{it} = \boldsymbol{\alpha}_i' \boldsymbol{d}_t + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + e_{it}, \qquad (1)$$

where d_t is a $N \times 1$ vector that represents common observable effects (these may include deterministic factors), $\boldsymbol{x}_{it}$ is a $k \times 1$ vector of individual observed regressors specific to the i-th cross-section unit in period t, and e_{it} represent the random shocks that have the following common factor structure:

$$e_{it} = \gamma_{i1} f_{1t} + \cdots + \gamma_{im} f_{mt} + \epsilon_{it} \equiv \boldsymbol{\Gamma}_{\boldsymbol{i}}' \boldsymbol{F}_{\boldsymbol{t}} + \epsilon_{it}, \qquad (2)$$

where $\boldsymbol{F}_{\boldsymbol{t}} = (f_{1t}, \ldots, f_{mt})'$ is an m-dimensional vector that includes non-observed common factors, and $\boldsymbol{\Gamma}_{\boldsymbol{i}} = (\gamma_{i1}, \ldots, \gamma_{im})'$ is the $m \times 1$ vector that includes the associated factor loadings.

Based on equations (1) and (2), there are some relevant characteristics to consider.

[6] See Chudik, A & Pesaran, H (2015) for an excellent literature review.

1. Microeconomic panels generally assume that the relationship between the regressors and the dependent variable does not vary with the cross-sectional variable. In that sense, an assumption of homogeneous coefficients ($\beta_i = \beta \; \forall i$) may be useful and a pooled estimate can be followed. However, this assumption is inappropriate when working with macroeconomic panels, as is our case. The above may be due to the heterogeneity of causal relationships between various countries, for instance. We therefore assume, in equation (1), heterogeneous coefficients.
2. It is also interesting to obtain an estimate of the expected value of the heterogeneous parameters, i.e. $\beta = E(\beta_i)$ to draw global inference. In this sense, Pesaran & Smith (1995) propose to estimate β through the average of heterogeneous parameters, labelled "group average estimators or mean group estimators, MGE).[7] The estimation strategy is detailed below.
3. The number of unobservable factors (m) that drive the cross sectional dependence is assumed fixed with respect to N, and in particular it is assumed that it is much smaller, so that m≪N.

It is known that when the regressors, x_{it}, in equation (1), are strictly exogenous, the panel model can be consistently and efficiently estimated via GLS based on the factor structure of equation (2). However, when working with macroeconomic panels it is very possible that the factor structure is correlated with the observable factors d_{it}, as well as with the x_{it} regressors. Because of this, the following specification is adopted, which allows the model to be even more general:

$$\boldsymbol{x}_{it} = \boldsymbol{A}_i^{'}\boldsymbol{d}_t + \boldsymbol{\Gamma}_{\mathrm{i}}^{'}\boldsymbol{F}_t + \boldsymbol{\nu}_{it}, \qquad (3)$$

where $\boldsymbol{A}_i$ and $\boldsymbol{\Gamma}_{\mathrm{i}}$ are $N \times k$ and $m \times k$ loading matrices of observed and non-observed factors, and $\boldsymbol{\nu}_{it}$ is the idiosyncratic component of $\boldsymbol{x}_{it}$; the latter are independently distributed from the common factors $\boldsymbol{F}_{t'}$ and from the error term $\epsilon_{jt'}$ for all i, j, t and t'.

In this work, we follow the methodology proposed by Pesaran (2006) that treat cross sectional averages of the observed variables as proxies of the common unobserved factors. The estimation method is called correlated common effects (CCE) and has been widely used in the empirical literature due to the ease of the estimation procedure, primarily because it does not require

[7] These estimates do not contemplate the existence of cross sectional dependence, so the MGE could also be inconsistent.

knowledge of the number of common factors. The CCE method has been studied in the literature to allow unit root processes (Kapetanios et al., 2011) and long memory processes (Ergemen and Velasco, 2017), whose procedures are used in this study due to the potential persistence shown by some macroeconomic variables.

2.2 Volatility model.

Remittances may also be related to the dynamics of the exchange rate (NER); they could affect its realized volatility (RV). As previously stated, an appropriate vehicle to test this hypothesis is a type-RV-GARCH model. The latter allows the practitioner to specify the conditional second moment as an autoregressive process plus explanatory variables. To be more specific, the second moment is precisely defined as the realized volatility. If the model fits properly and the parameters are statistically significant, we then obtain evidence that the realized volatility of the exchange rate depends, at least partially, of these explanatory variables. We naturally focus our attention a specific variable: Remittances.

The Realized Volatility is simply the variation in "log-returns" for the NER. It is computed via the historical log-returns within a month. It is commonly measured through the standard deviation of the NER. We first define the RV of the NER:

$$RV_t = \sqrt{\sum_{i=1}^{T}(p_t - p_{t-1})^2}, \qquad (4)$$

where $p_t - p_{t-1}$ is the log-return over the time interval. In this model, we estimate the determinants of the RV, taking into account that the RV itself often exhibits volatility, usually referred to as Volatility of Volatility (Vol of Vol, or VoV hereafter). VoV may reflect deep uncertainty about the structural robustness of the Exchange rate to economic shifts.

Due to the main interest in this work, and to data availability, we focus on the following Central American countries: Costa Rica, El Salvador, Guatemala, Honduras, and Nicaragua. Although Mexico is not part of Central America (it is rather part of North America), however, we include it in the sample because it receives large amounts of remittances.

We aim to model the RV of the NER (RV_t). In the first part of the model, we assume that its behavior can be explained with the dynamics of the following variables:

- R_t Remmitances,
- I_t Interventions (proxied with Central Bank Reserves),
- D_t External Debt.

The model itself is:

$$RV_t = \beta_0 + \beta_1 \, ln(R_t) + \beta_2 \, ln(I_t) + \beta_3 \, ln(D_t) + \emptyset_1 RV_{t-1} + \emptyset_2 RV_{t-2} + \varepsilon_t, \quad (5)$$

where parameters β_i, $\emptyset_1$, and $\emptyset_2$ with $i = 0,1,2,3$ are the parameters, and ε_t is the error term. Note the two autoregressive terms, $\emptyset_1 RV_{t-1}$ and $\emptyset_2 RV_{t-2}$ in the specification. Such a model is a transfer one. It is important to emphasize that RV_t is, by itself, a measure of the volatility of the NER, this is, an estimation of the second moment. The second part of the model, as previously mentioned, specifies the volatility of the volatility, the VoV through a GARCH (Generalized Autoregressive Conditionally Heteroskedasticity) specification, this is, through a pure time-series specification of ε_t. The later term behaves as white noise, except that, when squared, its conditional expectation is as follows:

$$\varepsilon_t = v_t \sqrt{h_t}, \qquad (6)$$

$$h_t = \xi + \alpha \varepsilon_{t-1}^2 + \gamma h_{t-1}, \qquad (7)$$

where v_t is an *iid* N(0,1) term, and $\xi,\ \alpha,\ and\ \gamma$ are the second moment (VoV) parameters. In this sense, h_t is specified as a GARCH(1,1) model.

3. Empirical results

Our data set includes annual data from the following North, Central and South American Countries: Bolivia, Brazil, Colombia, Costa Rica, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, and United States. On the one hand, all these countries where employed to estimate the panel data model whilst, on the other hand, only Central American ones (plus Mexico) where used to estimate individual volatility models (Costa Rica, el Salvador, Guatemala, Honduras and Nicaragua).

The sample size spans the period 1980-2018, although not all the series are complete.[8] The variables are: real exchange rate (Figure 1), remittances (Figure 2) (net remittances in models), external debt (Figure 3), international reserves (as a proxy for exchange rate-market interventions) (Figure 4), and GDP per capita[9] (as a proxy of productivity) (Figure 5). Realized volatilities are built through the yearly sum of the daily exchange rate as defined in equation (4) and is displayed in Figure 6.

In the panel analysis, we use deflated net remittances, deflated external debt, and deflated international reserves as a proportion of the GDP of the respective country. This is to homogenize variables due to some differences in their magnitudes across countries. Our specifications are a bit sensitive with respect to high variability in our sample, we avoid incorporating a type of GARCH specifications in our panel modeling to focus on our main interest which is to understand the underlying mechanism in the region. Furthermore, GDP per capita is treated as a proportion of the GDP per capita of the US. In this sense, we are following the theoretical economic basis pointed out in López-Marmolejo and Ventosa-Santaulària (2019).

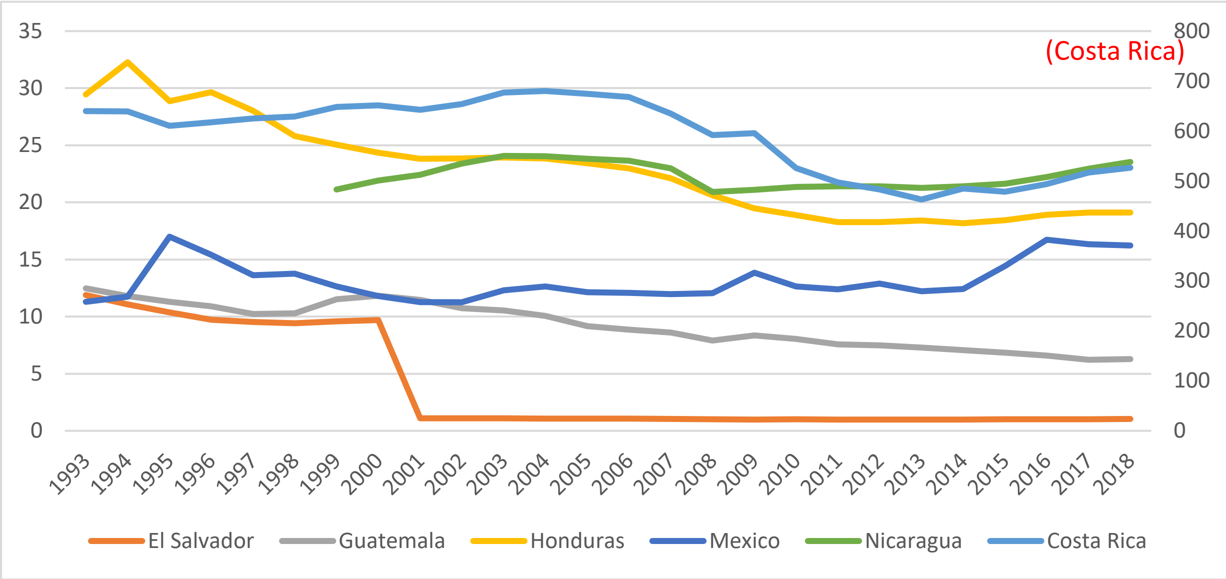
In the volatility analysis, our variables are not deflated neither defined as a proportion of GDP. In this sense, we prefer to work with rough variables because its high volatility is now incorporated by itself in our specification.

The respective standard descriptive statistics can be found in appendix A. We obtained overwhelming evidence of nonstationarity of all these variables through two testing procedures: (i) the Augmented Dickey-Fuller test, and; (ii) the Phillips-Perron test. Both were employed using three different deterministic control settings, no constant, constant and constant plus trend. Results can be found in appendix B.

[8] Source: World Bank. https://data.worldbank.org/indicator

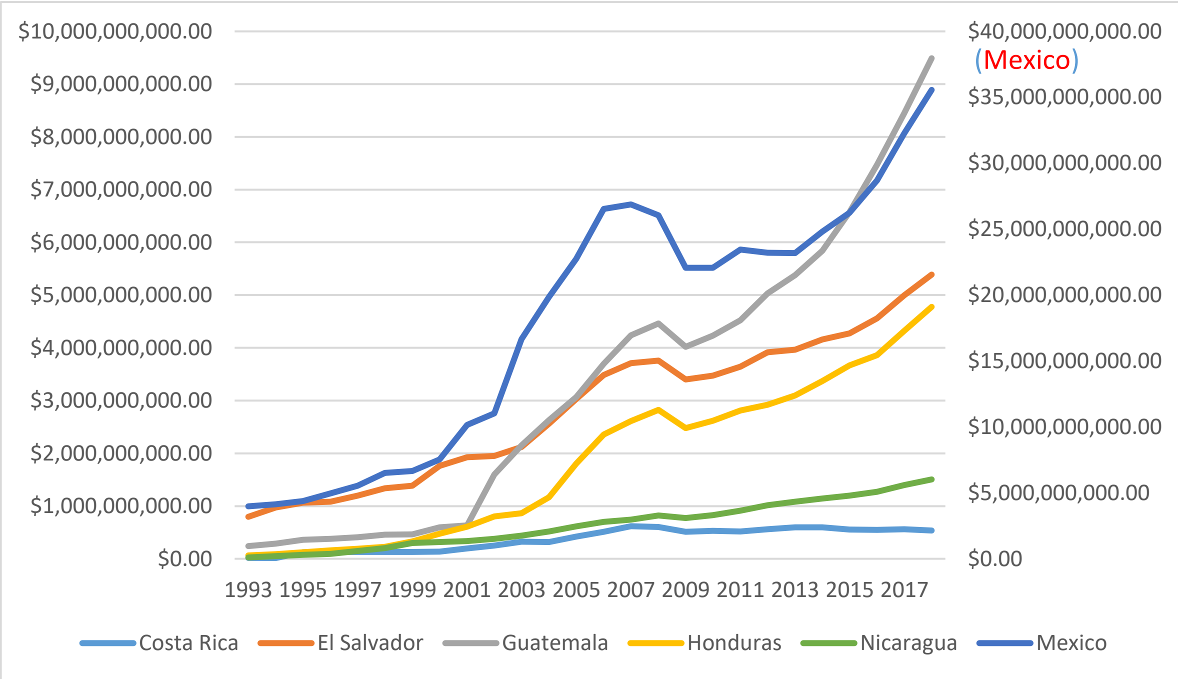
[9] The US data is used to build real exchange rate series (the NER of the US) and the productivity proxy (GDP per capita of a Latin American country relative to the US GDP per capita).

Figure 1: Real Exchange Rate. Central America



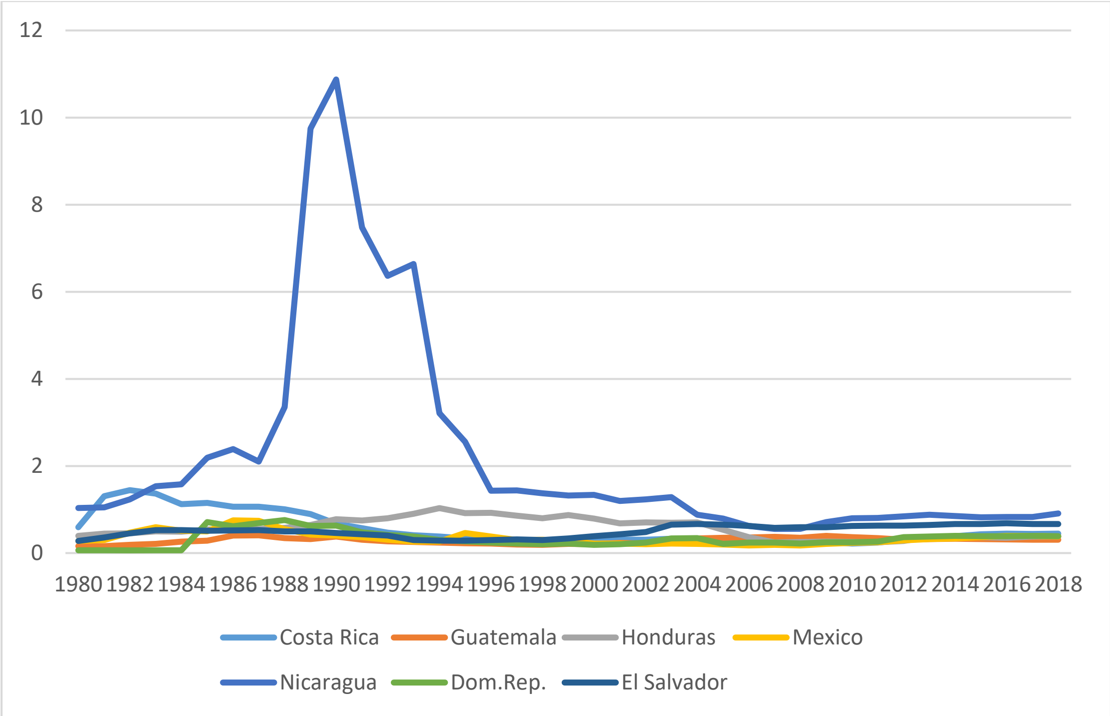
Source: World Development Indicators, The World Bank.

Figure 2: Remittances inflows in Central America



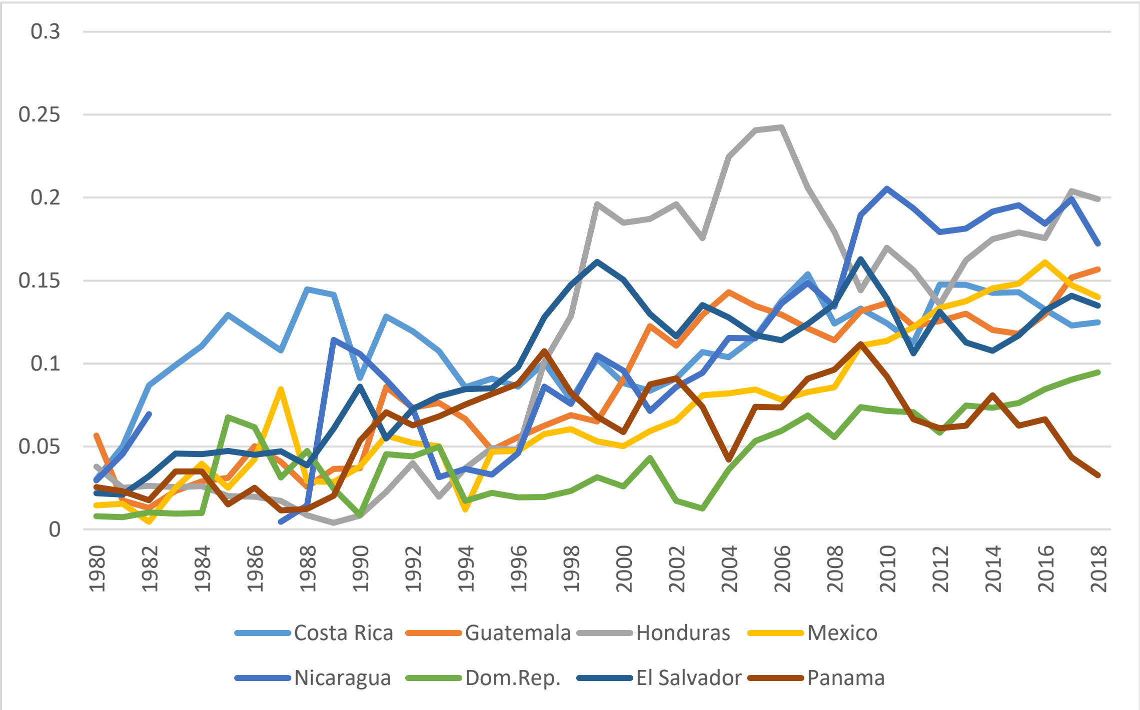
Source: World Development Indicators, The World Bank.

Figure 3: External debt, relative to GDP



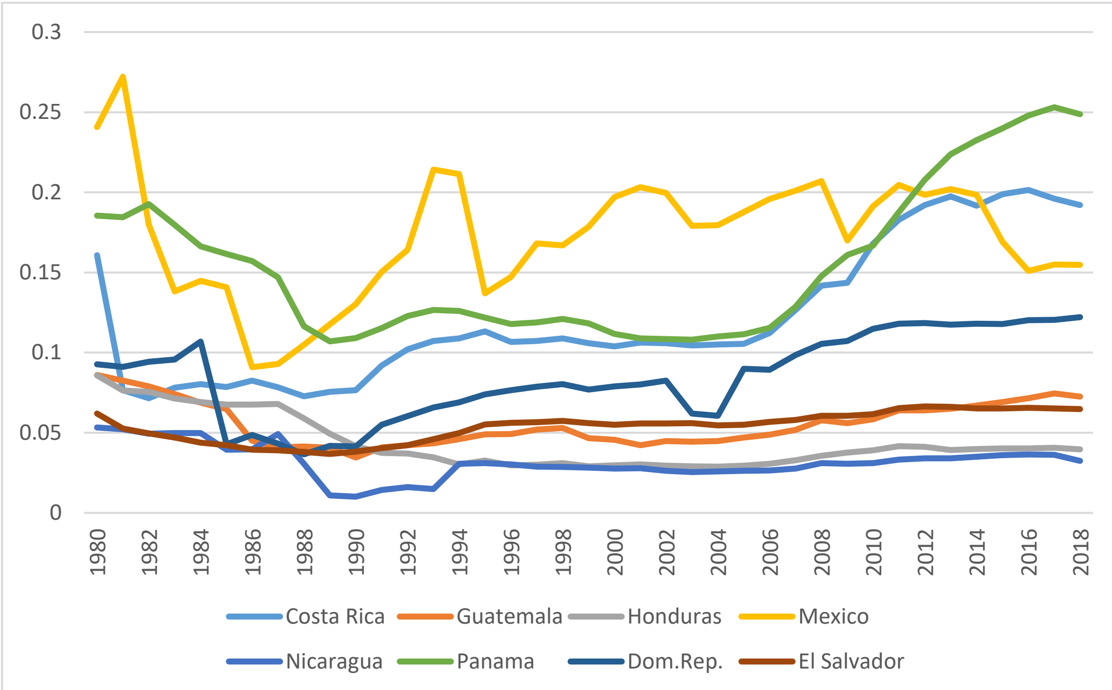
Source: World Development Indicators, The World Bank.

Figure 4: Reserves, relative to GDP



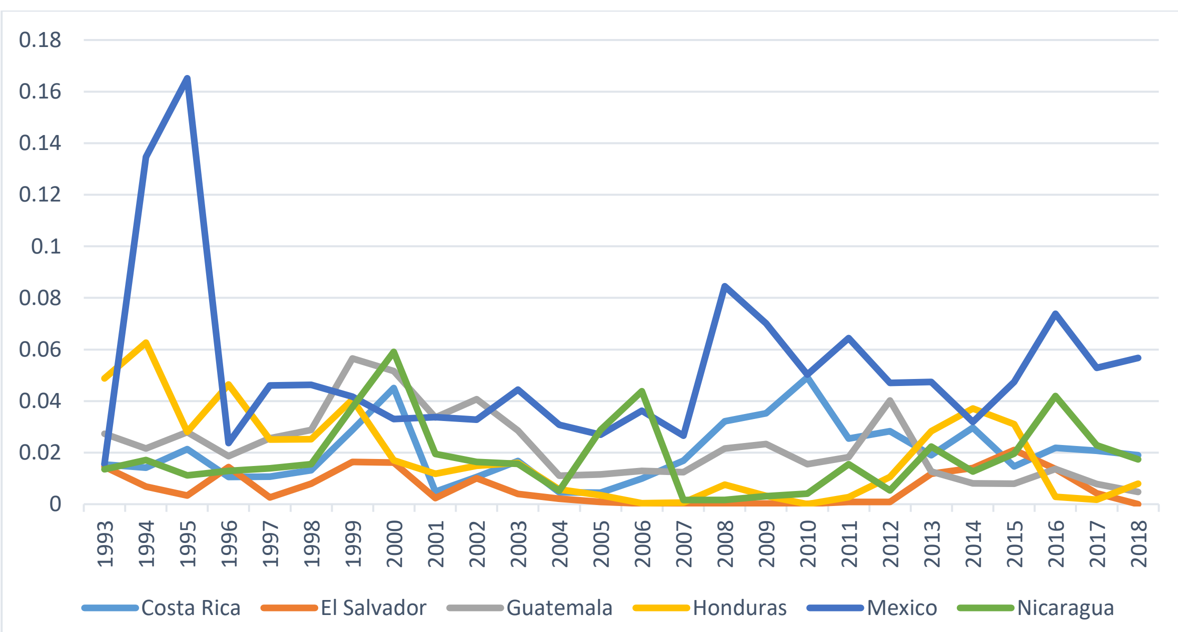
Source: World Development Indicators, The World Bank.

Figure 5: GDP per capita as proportion of GDP per capita of the US.



Source: World Development Indicators, The World Bank.

Figure 6: Realized volatility. Selected countries



Source: Bloomberg.

3.1 Panel data analysis

To study the dynamics of the real exchange rate (RER), we begin with the panel data analysis by estimating simplified panel data models with only one regressor, GDP per capita relative to US GDP per capita as a proxy for productivity.

We estimate three different models to analyze the performance of our estimates, first, neglecting that countries are cross-correlated with mean group MG) and demeaned mean groups (DMG) estimators, and second, considering a possible cross sectional dependence in the panel with the common correlated effect mean groups estimators (CCEMG). The basic idea is to understand if the sign and magnitude of the parameters change when considering or neglecting that a unobserved factor structure drives a cross sectional dependence between Latin American countries. In addition, we include a constant term, and a deterministic trend (only in the CCEMG variant).

Table 1: Panel estimation with one variable

Variable	Dependent variable: log(RER)			
	MG	DMG	CCEMG	CCEMG+T
log(GDP per capita relative to the US)	-0.743*** (0.273)	-0.647*** (0.226)	-0.635*** (0.034)	-0.644*** (0.032)
Trend				0.002
Constant	1.617	-0.134	0.88	0.509
Observations	644	644	644	644
Pesaran CD stat	-1.1413	5.6455***	0.1975	-0.5636
CIPS stat	-1.7697**	-2.0158***	-2.5928***	-3.0394***

Notes: (1) *p<0.1; **p<0.05; ***p<0.01; (2) H0 in Pesaran CD stat is no cross-sectional dependence; (3) H0 in CIPS is not stationarity; (4) MG means "Mean Group Estimators"; DMG means "Demeaned MG estimators"; CCEMG means "Common Correlated Effects MG estimators";

As shown in Table 1, in all models, our productivity measure significantly affects the real exchange rate. This is an expected result. All the countries in the sample have suffered a productivity loss with respect to the US. Such a loss is a driving force that eventually depreciates the local currency in dollar terms. It is, in short, the opposite of a Balassa-Samuelson effect. As long as these economies keep lagging behind the US in terms of productivity gains, their exchange rate

should eventually depreciate. See López-Marmolejo and Ventosa-Santaulària (2019), for further details. Note that the deterministic trend in the CCEMG model is not statistically significant. This, again, is rather intuitive. In the PPP literature, a deterministic trend is usually included to consider the Balassa-Samuelson effect. The latter, as previously said, occurs because of a differential of productivities among (commercial and non-commercial sectors of) the country and its trade partners. By including the GDP per capita, the deterministic trend becomes irrelevant. Note that neglecting the cross-sectional dependence provokes a small negative bias that is controlled by CCEMG estimators. Finally, that we fail to reject the null hypothesis of no-cross sectional dependence in the panel model estimated with CCEMG. Cointegration is also supported in the CCEMG model, which is also relevant due to our variables follow unit root processes as shown in Appendix B.

The following set of models incorporate, in addition of GDP per capita relative to the US, the remaining economic variables: remittances, reserves, and external debt (relative to the corresponding GDP). Results are shown in Table 2.

Table 2 shows the results of the extended models. Model 1 is the simplified one previously described; we include it as a benchmark. Model 2 includes remittances. Note that its effect is negative, and significant. This implies that increases in remittances tend to appreciate the exchange rate, as hypothesized in this work. Model 3 includes Central Bank interventions (proxied with reserves), Model 4 adds external debt, and Model 5 adds both, reserves and debt [10].

Overall, International Reserves and External Debt have the expected effect on the real exchange rate: An increase of reserves (possibly an intervention of the Central Bank) implies buying dollars and selling the local currency. This should depreciate the value of the local currency.

An increase of external debt also implies receiving foreign currency and thus a depreciation of the local currency.

In sum, the panel data model(s) provides evidence that Latin (Central) American exchange rates are related to productivity (relative to the US), remittances, central bank interventions and debt. Signs are correct and parameters are significant.

[10] Model 5 allows for heterogeneous (this is, country-specific) results, the latter are shown in appendix C. Note that some countries present important biases, which may be controlled by including more specific variables in a country-specific analysis. We are analyzing some particular cases using ARDL methodology, but the analysis is out of the scope of this paper.

It is important to see how the bias presented in some coefficient is corrected after controlling for a specific effect. For instance, the impact of GDP per capita relative to the US is higher until we control for debt. This indicates that neglecting debt in the specification may provoke a positive bias. Furthermore, a strong positive bias is found when reserves are not considered in a specification with remittances and debt, see model 4. Model 5 corrects for this positive bias in remittances after incorporating reserves.

As in the previous table, trend is not significant but it helps to maintain the right signs. Note that in model 5 (our main finding) we do not find cross-sectional dependence in the residuals of the panel model. Furthermore, all residuals through models 1-5 are stationary indicating cointegration, this means that we have long-run relationship in our specifications.

Table 2: Panel estimation with all the variables

Dependent Variable: log (RER)					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
log(GDP per capita relative to the US)	-.644***	-0.631***	-0.621***	-0.882***	-0.902***
	(0.032)	(0.034)	(0.037)	(0.035)	(0.037)
Remittances/GDP		-5.947***	-9.373***	0.032	-3.531***
		(0.548)	(0.494)	(0.734)	(0.603)
log(Reserves/GDP)			0.025		0.067***
			(0.014)		(0.012)
log(Debt/GDP)				-0.182***	-0.162***
				(0.023)	(0.024)
Trend	0.002	-0.004	-0.004	0.003	-0.0001
Constant	0.509	2.301***	2.509***	1.394	1.403
Observations	644	605	605	514	514
Pesaran CD stat	-0.5636	2.2622**	3.248***	-0.0134	1.495
CIPS stat	-3.0394**	-3.2631***	-3.5461***	-3.0394***	-3.6513***

Notes: (1) *p<0.1; **p<0.05; ***p<0.01; (2) H0 in Pesaran CD stat is no cross-sectional dependence; (3) H0 in CIPS is not stationarity; (4) All models are estimated by Common Correlated Effects Mean Groups estimators.

The implementation of a payment system as the one described here, would prevent part of the incoming flows from entering directly into the exchange market. According to the coefficients estimated (Table 2 Model 5), if such a payment system captures, for example, 1.0% of GDP in remittances, thus preventing an increase in central bank´s interventions (*proxied* by reserves accumulation) by 10% (for example, if reserves go from 10% to 11% of GDP), the real exchange rate would be 0.7% more depreciated. To this effect, an additional depreciation resulting from competitive pressure (better exchange rate for the beneficiaries) should be added. This effect is not estimated in this exercise, but Mexico's experience could be useful as a benchmark (López-Marmolejo and Ventosa-Santaulària, 2020).

3.2 Volatility analysis

We commented in the previous section that remittances could affect both the level and the volatility of the exchange rate. The panel data model provided evidence that remittances indeed affect the real exchange rate. In this section we turn our attention to the volatility using the transfer-GARCH model.

We now employ the nominal exchange rate as it is a more natural vehicle to study the volatility. Furthermore, for the same reasons, remittances interventions and debt are in real terms but not relative to the US. Results are shown in Table 4.

Table 4: Transfer-Garch estimations

Model	Estimate	Costa Rica	Guatemala	Honduras	Mexico	Nicaragua
Variance (level)	Constant	---	0.415*	-0.261	-0.351***	0.028***
	Remmitances	0.002***	0.005***	0.004***	0.021***	0.004***
	Interventions	---	---	-0.012**	-0.036**	-0.013***
	Debt	---	-0.019***	0.022***	0.038***	0.009***
	AR(1)	0.318**	-	0.230*	-0.199	0.252*
	AR(2)	---	-	0.307	---	---
VoV (variance)	Constant	---	$1.00\text{x}10^{-5}$*	---	---	---
	e^2_{t-1}	0.198	-0.13***	-0.519*	0.740***	-0.206
	h_{t-1}	0.801***	1.054***	1.519***	0.259**	1.206***

***Significative at 1%, ** at 5%, * at 10%.

It is important to emphasize that we estimate a different model for each country. Interventions and debt are not included in every case. We opted only for those that help to obtain a coherent specification and, preferably, are associated to significant parameter estimates.

Nonetheless, it is important to note that, in all cases, an increase in remittances augments the realized volatility. Moreover, it is also revealing that in many cases interventions (proxied with reserves), decrease the RV of the NER. This seems to be true for Honduras, Mexico and Nicaragua. For the remaining countries, it does not play a significant role. The impact of debt is less clear. It is positive for Honduras, Mexico and Nicaragua, but negative for Guatemala. It seems that debt does not play a significant role as a determinant of RV for Costa Rica.

In all cases, there is evidence of Volatility of Realized Volatity, “VoV” in the form of conditional heteroskedasticity. This implies that RV is itself clustered and suffers episodes of high uncertainty.

4. Concluding remarks

We aimed at studying the dynamics of the (real and nominal) exchange rate in Central American countries. To be precise, we paid particular attention to the impact of remittances in the exchange rate. Countries of Central America receive rather significant amounts of remittances from abroad. Such inflows should probably tend to appreciate the local currency, a phenomenon that has many potential negative effects on the economy. Our strategy to obtain evidence on this matter is twofold:

on the one hand, we estimated the impact of remittances in the level of the real exchange rate. We found a significant and negative effect of remittances in the real exchange rate. An increase in remittances appreciates the exchange rate. We also found evidence that losses of productivity (relative to the US) depreciate the exchange rate, whilst interventions and increases of external debt depreciate it.

On the other hand, we estimated the effect on exchange rate volatility due to remittances, and found, once again, evidence that the latter also tends to increase it (the volatility of the exchange rate). In sum, despite the many positive effects that remittances may have in the economy, this paper also shows some non-desirable consequences in the exchange rate. It is worth emphasizing that central bank interventions (*proxied* by the change in reserves), at least in Honduras, Mexico and Nicaragua, seem to reduce the volatility of the exchange rate.

The evidence so far gathered represents a solid argument in favor of payment systems such as "Directo a México". As remittances appreciate the exchange rate and increase its volatility, a system in which remittances are transferred through central banks would prevent part of the incoming flows from entering directly into the exchange market, thus alleviating short-term appreciation and volatility of the exchange rate. The exercises performed here contribute to analyze to what extent.

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Appendix

Appendix A: descriptive statistics

Table A1: descriptive stats. RER

		Bolivia	Brazil	Colombia	Costa Rica	Dom.Rep	El Salvador	Guatemala	Haiti	Honduras	Jamaica	Mexico	Nicaragua	Panama	Paraguay	Peru
Real Exchange Rate	NaNs	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0
	Min	3.60	1.62	1585.84	369.17	6.22	38.07	15.55	70.43	10.23	20.91	0.66	2206.54	2.59	36.23	0.98
	Max	9.92	4.09	3389.91	754.71	14.72	111.64	32.27	148.37	19.89	24.07	1.11	8463.31	11.59	67.13	16.76
	Range	6.32	2.47	1804.07	385.54	8.50	73.57	16.72	77.93	9.65	3.16	0.45	6256.77	8.99	30.90	15.77
	Median	7.00	2.41	2499.96	637.35	9.17	64.62	19.46	99.61	12.88	22.07	0.94	4716.23	3.29	40.92	9.52
	Mean	6.85	2.57	2428.29	606.61	9.60	64.11	21.64	102.36	13.78	22.33	0.92	4863.73	4.25	44.34	7.16
	Var	2.53	0.50	265533.73	6711.23	4.89	412.26	21.68	384.27	5.48	1.24	0.02	2340597.97	5.24	70.25	36.14
	Std.Dev.	1.59	0.70	515.30	81.92	2.21	20.30	4.66	19.60	2.34	1.11	0.13	1529.90	2.29	8.38	6.01
	Skewness	0.19	0.64	0.00	-0.88	0.26	0.33	0.51	0.41	0.85	0.29	-0.50	0.56	1.63	1.31	0.10
	Kurtosis	-0.44	-0.79	-1.18	0.21	-1.10	-0.79	-1.03	-0.46	0.01	-1.62	-0.84	0.11	1.47	0.68	-1.74

Table A2: descriptive stats. Remittances

		Bolivia	Brazil	Colombia	Costa Rica	Dom.Rep	El Salvador	Guatemala	Haiti	Honduras	Jamaica	Mexico	Nicaragua	Panama	Paraguay	Peru
Remmitances / GDP	NaNs	0	0	0	0	0	8	0	0	0	8	0	0	5	0	0
	Min	-0.001	0.000	0.000	0.000	-0.001	0.022	0.000	0.013	0.005	-0.002	-0.006	0.003	-0.003	0.018	0.011
	Max	0.074	0.005	0.032	0.013	0.124	0.309	0.217	0.156	0.028	0.115	0.014	0.032	0.021	0.109	0.216
	Range	0.075	0.005	0.032	0.013	0.125	0.287	0.217	0.143	0.024	0.116	0.019	0.029	0.024	0.091	0.205
	Median	0.009	0.001	0.011	0.003	0.024	0.175	0.051	0.086	0.013	0.082	0.004	0.015	0.011	0.062	0.127
	Mean	0.017	0.001	0.013	0.004	0.053	0.145	0.085	0.085	0.016	0.063	0.004	0.017	0.010	0.059	0.128
	Var	0.000	0.000	0.000	0.000	0.002	0.009	0.006	0.002	0.000	0.002	0.000	0.000	0.000	0.000	0.004
	Std.Dev.	0.020	0.001	0.008	0.004	0.048	0.093	0.080	0.047	0.007	0.040	0.006	0.009	0.007	0.022	0.065
	Skewness	1.021	0.741	0.318	0.860	0.236	-0.097	0.316	-0.085	0.326	-0.492	-0.100	0.275	-0.490	0.023	-0.343
	Kurtosis	0.098	-0.544	-0.427	-0.455	-1.794	-1.425	-1.662	-1.548	-1.309	-1.467	-1.246	-1.241	-0.878	-0.278	-1.327

Table A3: descriptive stats. Debt

		Bolivia	Brazil	Colombia	Costa Rica	Dom.Rep	El Salvador	Guatemala	Haiti	Honduras	Jamaica	Mexico	Nicaragua	Panama	Paraguay	Peru
Debt / GDP	NaNs	0	0	0	0	0	0	0	0	0	0	0	0		0.000	0
	Min	0.245	0.154	0.194	0.219	0.159	0.103	0.244	0.451	0.175	0.554	0.222	0.262		0.062	0.279
	Max	1.432	0.499	0.474	1.445	0.408	0.461	1.032	1.976	0.751	10.874	0.884	1.190		0.758	0.685
	Range	1.188	0.345	0.280	1.226	0.249	0.358	0.788	1.525	0.576	10.320	0.662	0.928		0.695	0.406
	Median	0.671	0.290	0.303	0.381	0.305	0.312	0.541	0.912	0.304	1.233	0.410	0.519		0.273	0.518
	Mean	0.639	0.295	0.320	0.548	0.288	0.307	0.565	0.912	0.344	2.196	0.442	0.526		0.327	0.504
	Var	0.081	0.010	0.006	0.130	0.005	0.007	0.052	0.110	0.021	6.332	0.029	0.044		0.034	0.019
	Std.Dev.	0.285	0.101	0.078	0.361	0.071	0.083	0.229	0.332	0.144	2.516	0.172	0.211		0.183	0.137
	Skewness	0.675	0.344	0.187	1.209	-0.118	-0.340	0.237	0.984	1.151	2.157	0.659	1.019		0.671	-0.301
	Kurtosis	0.491	-1.026	-1.231	-0.035	-1.234	-0.196	-1.238	1.083	0.884	3.693	-0.430	0.882		-0.214	-1.358

Table A4: descriptive stats. Reserves

		Bolivia	Brazil	Colombia	Costa Rica	Dom.Rep	El Salvador	Guatemala	Haiti	Honduras	Jamaica	Mexico	Nicaragua	Panama	Paraguay	Peru
Reserves / GDP	NaNs	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
	Min	0.017	0.014	0.036	0.030	0.013	0.001	0.004	0.017	0.005	0.005	0.011	0.076	0.031	0.007	0.021
	Max	0.437	0.202	0.163	0.154	0.157	0.290	0.242	0.256	0.161	0.205	0.112	0.193	0.323	0.095	0.163
	Range	0.420	0.188	0.127	0.124	0.144	0.289	0.239	0.238	0.156	0.201	0.100	0.117	0.292	0.087	0.142
	Median	0.109	0.065	0.099	0.113	0.086	0.051	0.136	0.119	0.059	0.105	0.066	0.126	0.170	0.044	0.113
	Mean	0.160	0.081	0.104	0.111	0.087	0.089	0.113	0.117	0.072	0.110	0.060	0.128	0.172	0.043	0.098
	Var	0.022	0.003	0.001	0.001	0.002	0.010	0.007	0.005	0.002	0.004	0.001	0.001	0.009	0.001	0.002
	Std.Dev.	0.148	0.056	0.028	0.027	0.044	0.100	0.082	0.069	0.044	0.061	0.028	0.031	0.094	0.027	0.042
	Skewness	0.826	0.724	-0.093	-0.729	-0.119	0.958	-0.019	0.187	0.483	0.074	-0.221	0.125	0.136	0.185	-0.362
	Kurtosis	-0.931	-0.667	0.312	0.525	-1.504	-0.733	-1.724	-1.253	-0.959	-1.303	-1.080	-0.892	-1.279	-1.333	-1.234

Table A5: descriptive stats. GDP per capita relative to the US

		Bolivia	Brazil	Colombia	Costa Rica	Dom.Rep	El Salvador	Guatemala	Haiti	Honduras	Jamaica	Mexico	Nicaragua	Panama	Paraguay	Peru
GDP PER CAPITA / GDP PER CAPITA USA	NaNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Min	0.023	0.074	0.053	0.072	0.035	0.008	0.029	0.049	0.091	0.010	0.107	0.034	0.034	0.037	0.037
	Max	0.074	0.266	0.156	0.201	0.086	0.020	0.086	0.103	0.272	0.053	0.253	0.123	0.127	0.122	0.066
	Range	0.051	0.191	0.103	0.130	0.051	0.011	0.057	0.054	0.181	0.043	0.146	0.089	0.093	0.086	0.030
	Median	0.033	0.142	0.083	0.107	0.052	0.014	0.039	0.092	0.178	0.031	0.129	0.063	0.068	0.082	0.056
	Mean	0.040	0.143	0.089	0.122	0.056	0.014	0.044	0.087	0.173	0.032	0.154	0.072	0.075	0.084	0.054
	Var	0.000	0.002	0.001	0.002	0.000	0.000	0.000	0.000	0.001	0.000	0.002	0.001	0.001	0.001	0.000
	Std.Dev.	0.014	0.048	0.029	0.043	0.014	0.003	0.016	0.014	0.038	0.011	0.047	0.026	0.026	0.027	0.009
	Skewness	0.687	0.716	0.900	0.700	0.542	0.062	1.115	-1.040	-0.061	0.145	0.789	0.393	0.590	-0.182	-0.403
	Kurtosis	-0.894	-0.242	-0.102	-0.993	-0.958	-0.946	-0.167	0.263	0.065	-0.151	-0.748	-1.234	-0.893	-1.201	-1.116

Table A6: descriptive stats. RV

		Costa Rica	El Salvador	Guatemala	Honduras	Mexico	Nicaragua
REALIZED VOLATILITY	Obs	26	26	26	26	26	26
	Min	0.004	0.000	0.005	0.000	0.016	0.002
	Max	0.049	0.021	0.057	0.063	0.165	0.059
	Range	0.045	0.021	0.052	0.063	0.150	0.057
	Mediana	0.018	0.004	0.020	0.013	0.046	0.016
	Mean	0.020	0.006	0.022	0.018	0.052	0.018
	Var	0.000	0.000	0.000	0.000	0.001	0.000
	Std.Dev.	0.012	0.007	0.014	0.018	0.033	0.014
	Skewness	0.893	0.689	1.010	0.932	2.230	1.322
	Kurtosis	0.573	-0.952	0.591	0.050	5.521	1.802

Appendix B: Unit root tests

Table B1: descriptive stats. RER

	ADF-GLS			Phillips-Perron		
	driftless	with drift	drift + trend	driftless	with drift	drift + trend
Bolivia	-0.018	-0.956	-1.520	-0.020	-0.654	-1.268
Brazil	-0.529	-2.822	-2.617	-0.490	-2.163	-2.051
Chile	0.309	-2.463	-2.455	0.742	-2.115	-2.386
Colombia	0.361	-2.522	-2.630	0.489	-1.733	-1.842
Costa Rica	0.385	-3.325	-3.1173**	0.391	-2.977	-2.9636**
Ecuador	-1.286	-2.051	-0.817	-1.297	-2.086	-0.833
Guatemala	-0.431	-1.490	-0.870	-0.459	-1.349	-0.784
Haiti	-0.975	-2.897	-1.403	-0.934	-2.540	-0.976
Honduras	-0.051	-1.407	-1.510	-0.027	-1.470	-1.577
Jamaica	0.106	-2.473	-2.486	0.445	-2.731	-2.803
Mexico	0.101	-3.125	-3.1508**	0.017	-2.745	-2.814
Nicaragua	0.271	-1.790	-1.931	0.659	-1.658	-1.598
Panama	-2.0027**	-1.322	-1.801	-3.9612**	-0.317	-2.9385**
Paraguay	0.446	-1.331	-1.527	0.398	-1.476	-1.564
Peru	-1.742	-1.490	-1.782	-1.321	-1.434	-1.250
Rep. Dom.	-0.503	-3.071	-2.202	-0.408	-2.863	-2.012
Salvador	-1.554	-2.037	-0.841	-1.582	-2.116	-0.864
Uruguay	-0.407	-3.081	-2.728	-0.500	-2.080	-1.828

Notes: This table shows ADF and Phillips-Perron test results. The number of lags in the nonparametric estimation of the autocorrelation factor in both tests is done through the ad hoc rule [12(T/100)1/4]. *, **, and *** denote rejection of the null hypothesis (unit root) at the 10%, 5%, and 1%, respectively.

Table B2: descriptive stats. Remittances

	ADF-GLS			Phillips-Perron		
	driftless	with drift	drift + trend	driftless	with drift	drift + trend
Bolivia	1.887	-2.061	-0.596	2.064	-2.077	-0.576
Brazil	0.690	-1.966	-1.142	1.094	-1.517	-1.292
Chile	-	-	-	-	-	-
Colombia	1.847	-2.667	-1.312	1.995	-2.454	-1.125
Costa Rica	2.371	-0.940	-1.258	2.484	-1.267	-1.403
Ecuador	1.523	-1.607	-2.596	1.520	-1.519	-2.269
Guatemala	0.841	-2.536	-0.901	0.853	-2.632	-1.032
Haiti	2.428	-4.0137**	-1.410	5.671	-4.5845**	-2.823
Honduras	2.384	-1.416	-1.298	2.699	-1.493	-1.261
Jamaica	2.756	-1.275	-1.181	2.763	-1.606	-0.856
Mexico	4.717	-0.899	-0.951	2.670	-5.9548**	-3.3534**
Nicaragua	2.026	-1.683	-2.707	2.941	-1.113	-2.303
Panama	0.714	-1.951	-0.662	0.723	-2.039	-0.865
Paraguay	1.157	-2.866	-0.519	1.657	-2.293	-0.946
Peru	1.398	-2.495	-1.832	3.196	-3.431	-4.195**
Rep. Dom.	2.705	-2.029	-2.579	2.435	-1.680	-1.652
Salvador	3.498	-0.783	-1.660	3.995	-1.065	-1.745
Uruguay	0.883	-2.051	-2.354	0.572	-37.427**	-40.9963**

Notes: This table shows ADF and Phillips-Perron test results. The number of lags in the nonparametric estimation of the autocorrelation factor in both tests is done through the ad hoc rule [12(T/100)1/4]. *, **, and *** denote rejection of the null hypothesis (unit root) at the 10%, 5%, and 1%, respectively.

Table B3: descriptive stats. External debt

	ADF-GLS			Phillips-Perron		
	driftless	with drift	drift + trend	driftless	with drift	drift + trend
Bolivia	1.876	-1.977	-0.663	2.714	-2.211	-1.256
Brazil	2.087	-2.701	-0.826	3.909	-2.788	-1.726
Chile	-	-	-	-	-	-
Colombia	3.064	-3.077	-1.300	6.120	-1.972	-0.892
Costa Rica	1.852	-1.368	-0.086	3.513	-1.057	-0.266
Ecuador	2.116	-1.930	-0.832	3.003	-3.447	-2.587
Guatemala	2.464	-2.084	-0.662	4.835	-1.814	-1.079
Haiti	1.289	-3.7973**	-2.140	1.959	-3.095	-2.315
Honduras	1.509	-2.680	-2.151	2.601	-2.724	-2.788
Jamaica	2.729	-2.375	-1.984	3.062	-1.621	-1.071
Mexico	2.180	-3.188	-1.601	3.612	-2.764	-1.874
Nicaragua	1.180	-2.370	-2.598	1.827	-2.154	-2.635
Panama	-	-	-	-	-	-
Paraguay	2.027	-2.108	-1.036	3.039	-1.917	-1.398
Peru	2.923	-1.890	-0.483	3.765	-1.813	-0.479
Rep. Dom.	2.197	-2.451	-1.794	2.567	-2.269	-1.732
Salvador	2.836	-1.992	-0.471	4.767	-1.662	-0.878
Uruguay	-	-	-	-	-	-

Notes: This table shows ADF and Phillips-Perron test results. The number of lags in the nonparametric estimation of the autocorrelation factor in both tests is done through the ad hoc rule [12(T/100)1/4]. *, **, and *** denote rejection of the null hypothesis (unit root) at the 10%, 5%, and 1%, respectively.

Table B4: descriptive stats. International reserves

	ADF-GLS			Phillips-Perron		
	driftless	with drift	drift + trend	driftless	with drift	drift + trend
Bolivia	1.220	-2.607	-0.716	1.457	-2.457	-0.358
Brazil	1.358	-3.6951**	-0.262	1.818	-2.567	-0.393
Chile	1.649	-2.504	-1.376	2.469	-3.7496**	-2.9733**
Colombia	1.025	-4.559**	-0.905	2.015	-2.480	-0.824
Costa Rica	2.966	-2.517	-0.660	3.017	-2.941	-0.607
Ecuador	0.439	-3.122	-1.859	0.414	-3.495	-2.103
Guatemala	1.131	-4.4344**	-0.156	1.345	-3.281	-0.023
Haiti	1.218	-2.821	-0.224	1.094	-2.996	-0.456
Honduras	1.065	-2.501	-0.493	1.241	-2.232	-0.357
Jamaica	2.347	-2.097	-1.058	2.211	-2.818	-1.178
Mexico	1.971	-4.5326**	-1.224	1.743	-5.6666**	-1.290
Nicaragua	2.030	-3.7034**	-2.071	2.338	-4.181**	-2.718
Panama	1.145	-2.648	-1.016	1.364	-2.740	-1.493
Paraguay	1.560	-1.846	-0.170	2.040	-1.728	-0.561
Peru	1.575	-3.103	-1.395	2.027	-2.483	-1.264
Rep. Dom.	1.685	-3.8786**	-1.069	1.643	-4.0925**	-1.124
Salvador	1.252	-3.139	-0.484	1.627	-2.360	-0.505
Uruguay	1.774	-3.287	-0.187	1.636	-3.6135**	-0.368

Notes: This table shows ADF and Phillips-Perron test results. The number of lags in the nonparametric estimation of the autocorrelation factor in both tests is done through the ad hoc rule [12(T/100)1/4]. *, **, and *** denote rejection of the null hypothesis (unit root) at the 10%, 5%, and 1%, respectively.

Table B5: descriptive stats. GDP per capita

	ADF-GLS			Phillips-Perron		
	driftless	with drift	drift + trend	driftless	with drift	drift + trend
Bolivia	1.824	-1.162	0.484	2.519	-0.861	0.564
Brazil	1.068	-2.523	-1.086	1.343	-2.214	-1.080
Chile	1.279	-3.7633**	-0.930	2.293	-2.235	-0.816
Colombia	1.673	-2.550	-0.796	2.540	-1.953	-0.990
Costa Rica	2.240	-3.388	0.115	2.653	-2.809	0.050
Ecuador	1.050	-2.087	-0.720	1.601	-1.496	-0.298
Guatemala	2.363	-1.705	0.322	3.072	-1.482	0.352
Haiti	1.421	-3.5307**	-1.483	1.643	-2.850	-1.310
Honduras	1.794	-1.046	0.574	2.040	-2.412	-1.992
Jamaica	1.492	-2.887	-0.908	1.313	-3.127	-0.558
Mexico	1.131	-3.299	-1.671	1.507	-2.767	-1.899
Nicaragua	0.498	-2.893	-1.370	0.518	-2.619	-1.191
Panama	1.870	-1.905	0.149	4.714	-0.939	0.264
Paraguay	1.139	-2.418	-0.912	1.862	-1.804	-0.857
Peru	2.638	-1.914	-0.252	2.445	-2.413	0.012
Rep. Dom.	2.091	-2.235	-0.496	2.048	-2.561	-0.511
Salvador	2.235	-2.518	-0.249	5.586	-1.652	0.041
Uruguay	0.875	-3.7641**	-1.317	1.645	-2.272	-1.071

Notes: This table shows ADF and Phillips-Perron test results. The number of lags in the nonparametric estimation of the autocorrelation factor in both tests is done through the ad hoc rule [12(T/100)1/4]. *, **, and *** denote rejection of the null hypothesis (unit root) at the 10%, 5%, and 1%, respectively.

Appendix C: Panel results of model 5. Heterogeneous estimates.

	Heterogenous parameters in Model 5					
	(Intercept)	log(GDPCvsUSA)	RemmPIB	log(ResPIB)	log(DebtPIB)	trend
Bolivia	0.810	-0.780	-1.438	0.044	-0.154	-0.015
Brasil	5.156	-0.469	-28.137	-0.049	0.371	-0.034
Colombia	4.829	-1.134	1.999	0.110	-0.526	0.033
CostaRica	4.123	-0.892	-5.569	0.000	-0.032	0.006
Guatemala	-2.002	-1.008	-1.525	0.012	-0.077	0.006
Haiti	2.104	-0.214	2.006	0.005	0.022	-0.005
Honduras	1.012	-0.961	-0.200	-0.011	-0.031	-0.022
Jamaica	-3.143	-0.390	6.482	-0.030	0.196	0.008
Mexico	0.655	-0.530	-0.812	-0.057	0.340	-0.003
Nicaragua	0.831	-0.266	1.683	0.007	-0.010	0.019
Paraguay	3.783	-1.114	-8.830	0.145	-0.162	0.039
Peru	9.670	-1.689	-10.133	0.316	-0.723	-0.043
RepDom	3.737	-0.349	5.024	0.055	-0.207	-0.001
Salvador	-11.926	-2.829	-9.986	0.396	-1.279	0.009