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Common and idiosyncratic movements in Latin-American Exchange Rates*

FREDY GAMBOA-ESTRADA♦ JOSE VICENTE ROMERO+

Abstract

We propose a simple theoretical and empirical approach to differentiate between common and idiosyncratic exchange rate movements in 5 Latin-American economies: Brazil, Chile, Colombia, Mexico, and Peru. Our approach allows us to distinguish the effects on exchange rates of a regional exchange rate common factor and macroeconomic fundamentals differentials. The methodology and estimation strategy are suitable for both low and high frequency settings. We provide evidence that the regional common factor has a significant effect on the dynamics of the Latin-American exchange rates. In our estimations the relation between exchange rates and the common factor is contemporaneous and stable during the studied period.

JEL Classification Numbers: F31, F37, G17.

Keywords: Exchange rate, exchange rate in Latin-American countries, factor model, forecasting and simulation.

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Movimientos comunes e idiosincráticos en las tasas de cambio de América Latina

FREDY GAMBOA-ESTRADA JOSE VICENTE ROMERO

Resumen

En este artículo proponemos una aproximación teórica y empírica simple para diferenciar los movimientos comunes e idiosincráticos de las tasas de cambio de cinco economías latinoamericanas: Brasil, Chile, Colombia, México y Perú. Nuestra aproximación permite distinguir los efectos resultantes de un factor común regional y los diferenciales de los fundamentales macroeconómicos sobre las tasas de cambio de la región. Esta metodología y estrategia de estimación es aplicable tanto para datos de alta como de baja frecuencia. Se presenta evidencia que el factor común regional tiene un impacto significativo en la dinámica de las tasas de cambio seleccionadas. En nuestras estimaciones, la relación entre las tasas de cambio y el factor común es contemporánea y estable durante el periodo de estudio analizado.

Clasificación JEL: F31, F37, G17.

Palabras clave: Tasas de cambio, tasas de cambio en Latinoamérica, modelos factoriales, pronósticos y simulación.

I. Introduction

Exchange rates in Latin-America display an important level of comovement. This phenomenon may be related to investors' appetite and portfolio inflows to the region, despite the differences that may exists between these countries. Even though practitioners and academics have pointed out that the comovement in Latin-American exchange rates may be linked to the existence of underlying factors - *related to global financial cycles or commodity prices* - there is not a consensus regarding this phenomenon. Thus, in this paper, we set out to explore the capability of a regional common factor to explain the dynamics of Latin-American exchange rates.

Our paper enlarges the literature on analyzing the determinants of exchange rates and its contribution is twofold. On one hand, this is the first paper we are aware of that documents the determinants of bilateral exchange rates in Latin America, including the recent period of the Covid-19 pandemic, using a simple theoretical and empirical approach that allows to differentiate between regional and idiosyncratic movements in exchange rates. On the other, this method permits us to examine if there is evidence of structural changes in the factors that explain comovements of exchange rates in the region. We show that the regional common factor has been an important and stable driver of exchange rates in the region and we provide evidence that models that include such factor perform well in both low and high frequency settings.

This article consists of six sections aside from the introduction. The second section briefly reviews the literature on common currency factors driving exchange rates. The third section describes a simple theoretical approach that allows to differentiate the regional factor from idiosyncratic fundamentals. Section four discusses the main stylized facts about the performance of exchange rates in Brazil, Chile, Colombia, Peru and Mexico (henceforth LATAM) and its relationship with the regional common factor. The fifth section presents and analyzes the results. The last section summarizes the main findings and discusses policy implications.

II. Literature review

Different econometric methods have been extensively used to study the main determinants of bilateral exchange rate movements. Nevertheless, the literature on common currency factors driving exchange rates is not that abundant for emerging economies. The most influential research we are aware of are Cayen et al. (2010), Lustig, Roussanov, and Verdelhan (2011), , Greenaway-McGrevy et al. (2018), Aloosh and Bekaert (2019), and Baku (2019)..

Cayen et al. (2010) present a novel approach to identify economic factors that drive bilateral exchange rates in the long run. The authors identify two common factors using a dynamic factor model for a panel of six developed economies over the 1980-2007 period. The first factor is driven by U.S shocks and linked to the U.S. fiscal policy, and the second factor is driven by commodity prices. These factors can explain between 36 and 96 per cent of each of the U.S. bilateral real exchanges included in the analysis.

Lustig, Roussanov, and Verdelhan (2011) identify common risk factors in average excess returns between high and lows interest rate currencies, namely, the returns on the currency carry trade. The analysis is made from the U.S. investor perspective using monthly portfolios for high and low interest rates. Using a model of interest rates and exchange rates and a principal component analysis, they find two factors that explain the variation in foreign currency excess returns: i) the dollar risk factor, and ii) the "slope factor" or carry trade risk factor. The authors find evidence that the "slope factor" identified in exchange rates is related to equity market volatility at the global level. This factor accounts for most of the cross-sectional variation in exchange rates.

Greenaway-McGrevy et al. (2018) perform an empirical factor identification. They find that exchange rate returns from 1999 to 2015 in a sample of 27 currencies are driven by global factors. They identify two stochastic discount factors, a dollar factor and a euro factor. These factors are linked to geographical and risk-based dimensions. The authors estimate multilateral models for bilateral exchange rates based on the identified factors. These models outperform the random walk and purchasing power parity based fundamental models for out-of-sample forecasting.

Aloosh and Bekaert (2019) explain which factors determine the comovements of exchange rates in G10-countries. The authors find that a factor model including a clustering factor, a commodity currency factor, and a world or market factor, explains much better currency variation than other models based on other factors such as currency-value, carry, and global FX volatility. In their analysis, they include the concept of currency basket defined as an equally weighted average appreciation of one currency relative to the basket of G10 currencies. The advantage of this approach is that currency changes can be explained from the dollar perspective and from other based currencies. Their model performs quite well in emerging market currencies.

Baku (2019) predicts currency returns for Brazil, Chile, Colombia, Mexico, and Peru between 2001 and 2016. The author uses a two-step procedure. First, she estimates a cointegration equation. Second, she estimates an error-correction equation. The results indicate that the Global Exchange Rate Factor derived from a factor model approach is an important determinant of exchange rate movements. In addition, commodity prices, domestic risk premium, and equity prices are fundamental drivers of exchange rates.

III. Theoretical approach

We propose a simple theoretical model to provide a broad perspective on the possible drivers of spot exchange rates in LATAM. This approach is suitable for small open economies. We begin with some definitions. We denote s_t as the log spot exchange rate of any country within the region defined as the domestic price of the US dollar.

We assume that the risk-neutral efficient market hypothesis does not hold due to the failure of the risk neutrality condition and the rational expectations condition. Therefore, if market participants are risk averse and the rational expectations condition holds ($s_{t+1} = E_t s_{t+1} + \eta_{t+1}$) where η_{t+1} is the rational expectations forecast error, the uncovered interest rate parity (UIP) may be distorted by a risk premium. Thus, the modified UIP is:

$$i_t - i_t^* = \Delta s_{t+1} + \rho_t \tag{1}$$

Where Δs_{t+1} are the exchange rate returns, ρ_t is the time-varying risk premium composed by a constant term and a time-varying term equal to the standard deviation of the rational expectations forecast error η_{t+1} (Domowitz and Hakkio, 1985), i_t and i_t^* are the domestic and the US interest rates, respectively.

To derive the pattern of spot exchange rates, we specify the monetary policy rules followed by the domestic and foreign monetary authorities as follows:

$$i_t = \gamma_\pi \pi_t + \gamma_y y_t + \gamma_q q_t + \delta i_{t-1} + v_t \tag{2}$$

$$i_t^* = \gamma_\pi \pi_t^* + \gamma_y y_t^* + \delta i_{t-1}^* + v_t^* \tag{3}$$

where π_t is the inflation rate, y_t is the output gap, and q_t is the real exchange rate. * denotes foreign variables. $\gamma_\pi, \gamma_y, \gamma_q$ are non-negative and $0 \leq \delta < 1$.

Using the two Taylor rules above with the modified UIP (1) we get the following equations:

$$i_t - i_t^* = \gamma_\pi(\pi_t - \pi_t^*) + \gamma_y(y_t - y_t^*) + \delta(i_{t-1} - i_{t-1}^*) + \gamma_q q_t + (v_t - v_t^*) \tag{4}$$

$$\Delta s_{t+1} + \rho_t = \gamma_\pi(\pi_t - \pi_t^*) + \gamma_y(y_t - y_t^*) + \delta(i_{t-1} - i_{t-1}^*) + \gamma_q q_t + (v_t - v_t^*) \tag{5}$$

$$\Delta s_{t+1} = \gamma_\pi(\pi_t - \pi_t^*) + \gamma_y(y_t - y_t^*) + \delta(i_{t-1} - i_{t-1}^*) + \gamma_q q_t + (v_t - v_t^* - \rho_t) \tag{6}$$

If the output gap is a function of the terms of trade, and there is not any explicit reaction of the domestic economy to the real exchange rate ($q_t = 0$), we get the following expression for the spot exchange rate returns:

$$\Delta s_{t+1} = \gamma_\pi(\pi_t - \pi_t^*) + \gamma_y(T_t - T_t^*) + \delta(i_{t-1} - i_{t-1}^*) + \psi_t \tag{7}$$

where T_t and T_t^* are measures of the terms of trade for the domestic and foreign economy, respectively, and ψ_t measures country risk and is approximately equal to $(v_t - v_t^* - \rho_t)$. As a proxy for ψ_t we use credit default swaps (CDS) for each country in our estimations.

In this paper we describe the pattern of the spot exchange rate for each country as a function of the common exchange rate factor of LATAM region. Thus, if we have two countries A and B, we have the following set of equations:

$$\Delta s_{t+1}^{A} = \gamma_{\pi}(\pi_t^A - \pi_t^*) + \gamma_y(T_t^A - T_t^*) + \delta(i_{t-1}^A - i_{t-1}^*) + \psi_t^A \quad (8)$$

$$\Delta s_{t+1}^{B} = \gamma_{\pi}(\pi_t^B - \pi_t^*) + \gamma_y(T_t^B - T_t^*) + \delta(i_{t-1}^B - i_{t-1}^*) + \psi_t^B \quad (9)$$

Therefore, in relative terms, variables for the US denoted by * cancel out in the equation as follows:

$$\Delta s_{t+1}^{A} = \Delta s_{t+1}^{B} + \gamma_{\pi}(\pi_t^A - \pi_t^B) + \gamma_y(T_t^A - T_t^B) + \delta(i_{t-1}^A - i_{t-1}^B)$$

$$+(\psi_t^A - \psi_t^B) \quad (10)$$

Then, the depreciation rate of country A relative to the average depreciation rate of the region must be equal to:

$$\Delta s_{t+1}^{A} = F_t + \gamma_{\pi}(\pi_t^A - \pi_t^{LATAM}) + \gamma_y(T_t^A - T_t^{LATAM})$$

$$+\delta(i_{t-1}^A - i_{t-1}^{LATAM}) + (\psi_t^A - \psi_t^{LATAM}) \quad (11)$$

where F_t is the common exchange rate factor for LATAM economies excluding country A. π_t^{LATAM}, T_t^{LATAM}, i_{t-1}^{LATAM}, ψ_t^{LATAM} are the simple average of the corresponding variables for LATAM economies excluding country A.

Finally, we transform equation (11) into this form:

$$\Delta s_{t+1}^{A} = F_t + \gamma_{\pi}\left(\frac{\pi_t^A}{\pi_t^{LATAM}}\right) + \gamma_y\left(\frac{T_t^A}{T_t^{LATAM}}\right)$$

$$+\delta(i_{t-1}^A - i_{t-1}^{LATAM}) + (\psi_t^A - \psi_t^{LATAM}) \quad (12)$$

For our empirical approach, we estimate the common factor in LATAM currencies using a dynamic factor model.

IV. Stylized facts of LATAM currencies and the regional common factor

In this section, we analyze the main stylized facts about the performance of exchange rates in Brazil, Chile, Colombia, Peru, and Mexico. Throughout the nineties, central banks in LATAM economies switched to a system of flexible or managed exchange rates. After floating their currencies, central banks in these economies adopted an inflation targeting monetary framework. These characteristics make them very suitable for studying the pattern of their currencies and their main determinants. Figure 1 displays the dynamics of exchange rates in LATAM between 2003 and 2020. It is evident the co-movement between currencies in the region which increased during three episodes: i) the global financial crisis of 2008-2009; ii) the sharp decline in commodity prices between mid-2014 and early 2016; and iii) the recent global crisis caused by the COVID-19 pandemic (Figure 1).

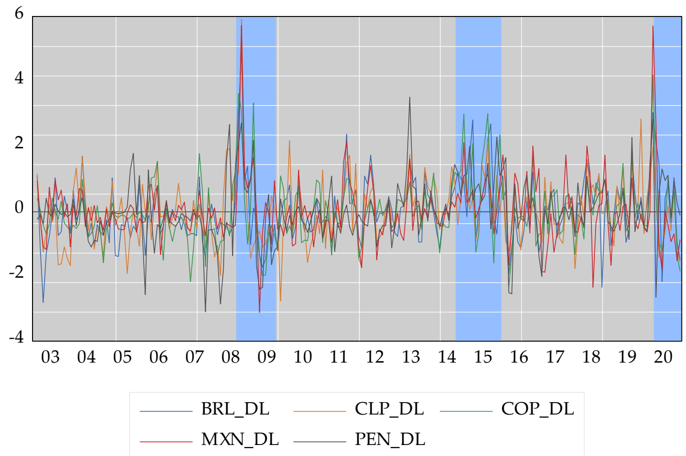

FIGURE 1. LATIN-AMERICAN EXCHANGE RATE MONTHLY CHANGES (LOG-DIFFERENCES)

Source: Bloomberg and authors calculations. *Notes:* The series correspond to the log differences of the nominal exchange rate indices of the Brazilian Real (BRL_DL), the Chilean Peso (CLP_DL), the Colombian Peso (CLP_DL), the Mexican Peso (MXN_DL) and the Peruvian Sol (PEN_DL). The blue-shaded areas correspond to the 2008/2009 Global Financial Crisis, the 2014/2016 Commodities price shock, and the Covid-19 Recession.

The global financial crisis of 2008-2009 reduced capital inflows in LATAM economies which depreciated their currencies (Villar, Romero, & Pabón, 2015). Mexico was one of the most negatively affected economies in the region due to its bilateral trade relationship with the United States. From 2009 to 2012, there was a rapid surge in capital flows to Emerging Economies mainly determined by quantitative easing in the United States (Barroso, 2016). Central banks in the region resumed their programs of reserves accumulation as exchange rates were appreciating which ended by the tapering tantrum. Additionally, a decrease in commodity prices negatively affected the terms of trade depreciating exchange rates in the region. In addition, central banks adopted different mechanisms of foreign exchange intervention to face these effects along with the adverse consequences of the tapering. Finally, the pattern of oil prices during the first quarter of 2020 jointly with the strength of the US dollar, the effects of the Covid-19, and local idiosyncratic factors had significant effects on LATAM currencies. For instance, during that quarter, the Mexican Peso depreciated 25%, the Chilean Peso 13.6%, the Peruvian Sol 3.5%, the Colombian Peso 23.7%, and the Brazilian Real 29.4%. Table 1 shows ordinary Pearson correlations between LATAM exchange rates returns. We see that all the correlations are positive, and significantly different from zero. Currencies in Chile, Colombia and Mexico are highly correlated with the Brazilian Real, while the Peruvian Sol is highly correlated with the Colombian Peso.

Table 1—Correlations between monthly changes of Latin-American Exchange Rates

Correlation [t-Statistic]	BRL_DL	CLP_DL	COP_DL	MXN_DL	PEN_DL
BRL_DL	1.00				

CLP_DL	0.60***	1.00			
	[11.20]	-----			
COP_DL	0.64***	0.51***	1.00		
	[12.00]	[8.69]	-----		
MXN_DL	0.61***	0.48***	0.590***	1.00	
	[11.36]	[8.19]	[10.94]	-----	
PEN_DL	0.42***	0.40***	0.52***	0.41***	1.00
	[6.84]	[6.38]	[8.87]	[6.61]	-----

Source: Authors' calculations. *Notes:* The series correspond to the log differences of the nominal exchange rate indices of the Brazilian Real (BRL_DL), the Chilean Peso (CLP_DL), the Colombian Peso (CLP_DL), the Mexican Peso (MXN_DL) and the Peruvian Sol (PEN_DL). [] t-stat. * p< 0.1 ; ** p<0.05 ; *** p<0.01. These correlations are computed from 2003:01 to 2020:12.

For our empirical approach, we estimate the common factor in LATAM currencies using a dynamic factor model following the methodology proposed by Solberger and Spånberg (2019) (See Appendix 1)[1].

Figure 2 shows the estimated regional common factor. In the first graph we show the common factor using the five currencies. The rest of the graphs shows the common factor used in the estimation of equation (12), which is computed only with four currencies.

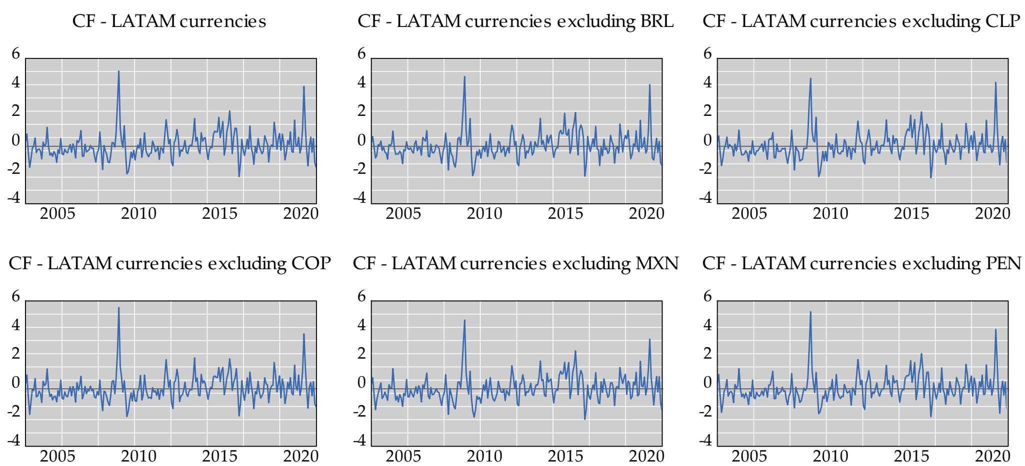

FIGURE 2. LATAM CURRENCY COMMON FACTOR

Source: Authors' calculations. Note: All series represent monthly returns.

In Figure 3 we plot the relationship between each currency and the common factor constructed with the remaining LATAM currencies. There is evidence of a positive relationship between exchange rate returns and the common factor of exchange rates in the region. This relationship seems to be stronger for Brazil and Colombia.

[1] Similar results were obtained using principal component analysis.

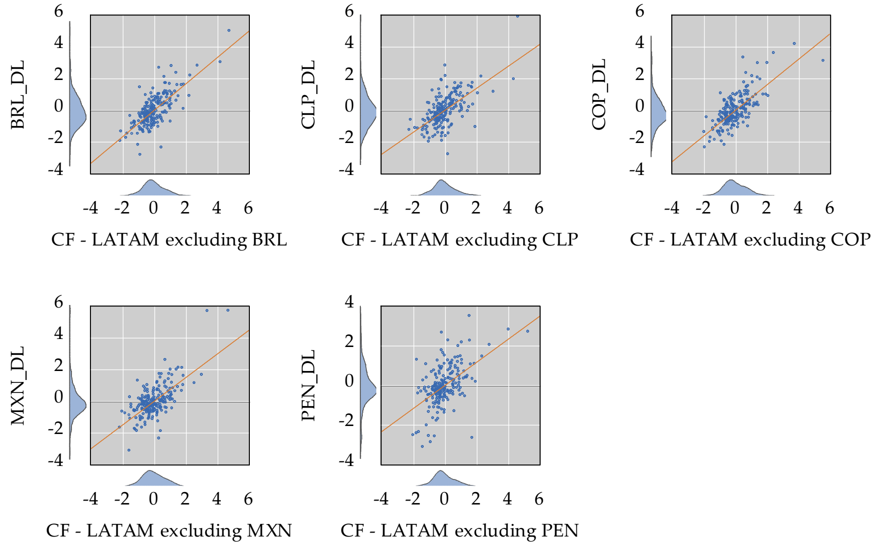

FIGURE 3. LATIN-AMERICAN EXCHANGE RATE MONTHLY CHANGES AND THE REGIONAL COMMON FACTOR (LOG-DIFFERENCES)

Source: Authors' calculations. *Notes:* For the graphs the common factor plotted against each exchange rate is computed as the dynamic factor of the other four currencies. The CF – LATAM represents monthly returns.

But how this relationship has evolved over time? Figure 4 displays the correlation between each exchange rate and the common exchange rate factor between 2003 and 2020. The correlation between exchange rate returns and the common factor is stronger and positive during turbulent periods such as the financial crisis of 2008-2009, the drop of commodity prices between mid-2014 and early 2016, and the recent crisis caused by the COVID-19 pandemic.

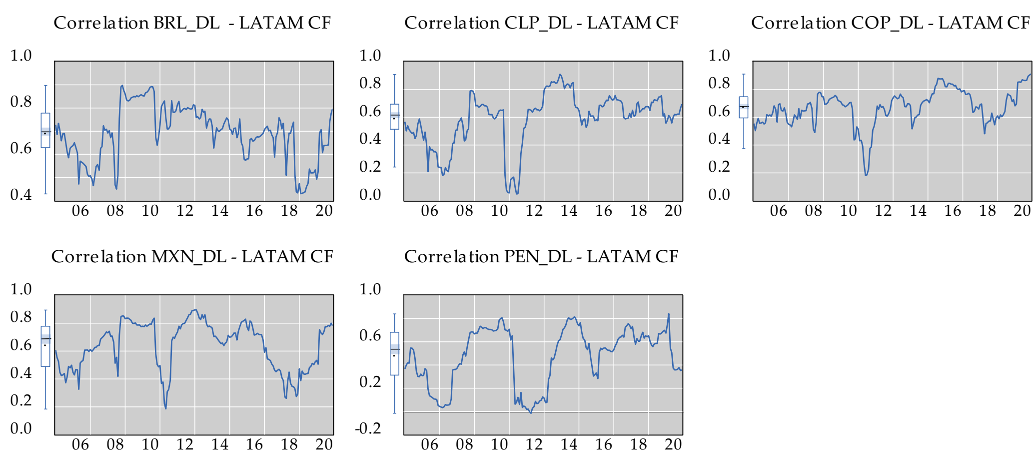

FIGURE 4. CORRELATION BETWEEN LATIN-AMERICAN EXCHANGE RATE MONTHLY CHANGES AND THE REGIONAL COMMON FACTOR (LOG-DIFFERENCES)

Source: Authors' calculations. *Notes:* The series correspond to the log differences of the nominal exchange rate indices of the Brazilian Real (BRL_DL), the Chilean Peso (CLP_DL), the Colombian Peso (CLP_DL), the Mexican Peso (MXN_DL) and the Peruvian Sol (PEN_DL). For the moving correlations, the common factor plotted against each exchange rate is computed as the dynamic factor of the other four currencies. The correlations are computed using a 24-month rolling window. In the box-plot, the box portion represents the first and third quartiles (middle 50 percent of the data). The mean is represented by the black dots, the black line stands for the median and the blue shaded areas are the median 95% confidence interval.

V. Including the Latin-American currency factor in exchange rate models

Equation (12) shows a simple way to divide exchange rate changes into a common factor and idiosyncratic elements. We use this basic specification to test our model in both low (monthly) and high (daily) frequencies. We do not include the relative inflation between each country and the average inflation of the region as this variable does not result significant. For the monthly models we also include an FX intervention index[2]. It is important to note that for each model we computed a specific factor. For example, in the case of the Brazil Real, the estimated models use a LATAM common factor that includes Chilean peso, Colombian Peso, Mexican Peso and Peruvian Sol. Table 2 presents the main results for the monthly frequencies using both OLS and GMM between January 2003 and December 2020. The results are robust if the estimation sample excludes the COVID-19 shock period.

Our results show evidence of the relevance of this regional common factor to explain the individual exchange rates. Table 2 shows that the common factor is significant in all estimations, and that the adjustment of the models seems to be higher than is usually found in exchange rate models. The parameter associated with the common factor in our OLS estimations ranging from 0.23 in the case of Peru to 1.2 in the case of Brazil.

As a robustness check, we also compute model (12) using GMM. Although it is possible to defend that the common factor computed is exogenous, we estimate the model using GMM and instrumented the LATAM factor using a broad emerging market currency index with similar results. The estimates in the GMM estimations are higher than in the OLS estimations confirming that the performance of exchange rates in EMEs is a good proxy for the common factor of LATAM currencies.

Our estimations show that the Brazilian Real and the Mexican Peso are more sensitive to the regional common currency factor during the period analyzed compared to other LATAM economies. While the currencies of Colombia and Chile respond in a similar way to the common factor, the Peruvian Sol is the least sensitive in the region.

An important result in these exercises is that adding the common currency factor intensely increases the adjusted R-squared in each estimation. For instance, the explanatory power of this variable increases the adjusted R-squared in GMM estimations from 0.24 to 0.58 in Brazil, from 0.16 to 0.38 in Chile, from 0.16 to 0.55 in Colombia, from 0.01 to 0.50 in Mexico, and from 0.17 to 0.37 in Peru. Although relative commodity prices, interest rate differentials and risk premium differentials are important variables for explaining the dynamics of exchange rates in the region, the estimates related to these factors are not significant for each specification. Additionally, the FX intervention index is only significant for Peru.

[2] The intervention index uses the information provided in Adler et al (2021). The intervention index includes information of both spot and forward intervention. The series are normalized with mean equal to 0 and variance set to 1.

Table 2—OLS and GMM estimations based on equation (12)

Variable	BRAZIL (DLOG(BRL))		CHILE (DLOG(CLP))		COLOMBIA (DLOG(COP))	
	OLS	GMM	OLS	GMM	OLS	GMM
	DLOG(BRL)	DLOG(BRL)	DLOG(CLP)	DLOG(CLP)	DLOG(COP)	DLOG(COP)
DLOG(Latam common factor ex_)	1.247 ***	1.643 ***	0.699 ***	1.001 ***	0.979 ***	1.089 ***
	[0.11]	[0.11]	[0.09]	[0.08]	[0.07]	[0.08]
D(Commodities ratio)	-0.006	-0.035	-0.033 ***	-0.031 ***	-0.060 **	-0.056 **
	[0.03]	[0.04]	[0.00]	[0.00]	[0.02]	[0.03]
D(CDS spread ex_)	0.000 ***	0.000 ***	0.000	0.000	0.000 **	0.000 **
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
D(Interest rate spread ex_)	-0.009 **	-0.010 **	-0.006	-0.009	0.003	0.003
	[0.04]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Intervention index	-0.002 *	0.000	0.001	0.001	0.001	0.000
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Adjusted R-squared	0.616	0.577	0.431	0.379	0.558	0.553
Durbin-Watson stat	1.727	1.700	1.634	1.580	1.731	1.737
BG Serial Correlation LM Test (up to lag 36):	0.923	-	1.568	-	1.422	-
BG No Serial Correlation P-value:	0.598	-	0.031	-	0.072	-

Variable	MEXICO (DLOG(MXN))		PERU (DLOG(PEN))	
	OLS	GMM	OLS	GMM
	DLOG(MXN)	DLOG(MXN)	DLOG(PEN)	DLOG(PEN)
DLOG(Latam common factor ex_)	0.975 ***	1.207 ***	0.230 ***	0.231 ***
	[0.10]	[0.09]	[0.03]	[0.03]
D(Commodities ratio)	-0.062 *	-0.060 *	0.000	0.000
	[0.03]	[0.03]	[0.00]	[0.00]
D(CDS spread ex_)	0.001 ***	0.001 ***	0.000 **	0.000 **
	[0.00]	[0.00]	[0.00]	[0.00]
D(Interest rate spread ex_)	0.010 **	0.010 **	-0.006	-0.006
	[0.00]	[0.00]	[0.00]	[0.00]
Intervention index	-0.001	-0.001	-0.002 ***	-0.002 ***
	[0.00]	[0.00]	[0.00]	[0.00]
Adjusted R-squared	0.530	0.501	0.372	0.372
Durbin-Watson stat	1.547	1.441	1.638	1.637
BG Serial Correlation LM Test (up to lag 36):	1.288	-	0.905	-
BG No Serial Correlation P-value:	0.145	-	0.626	-

[ ] Std. Error. HAC standard errors & covariance.
* p<0,10; ** p<0,05; *** p<0,01

Source: Authors' calculations. Sample: 2003M01-2020M12.

Figures 5 and 6 show the CUSUM and the parameter stability tests for the OLS estimations. In all specifications there is evidence of coefficients stability according to the CUSUM stability test (Figure 5). In addition, the response of exchange rates to the common currency factor has been stable after de 2008-2009 financial crises (Figure 6). The proposed empirical specification also shows a reasonable in sample forecasting performance. Using traditional forecasting evaluation metrics, we find that in most cases the estimated models beat a random walk model. Detailed results regarding forecasting evaluation are shown in Appendix 2.

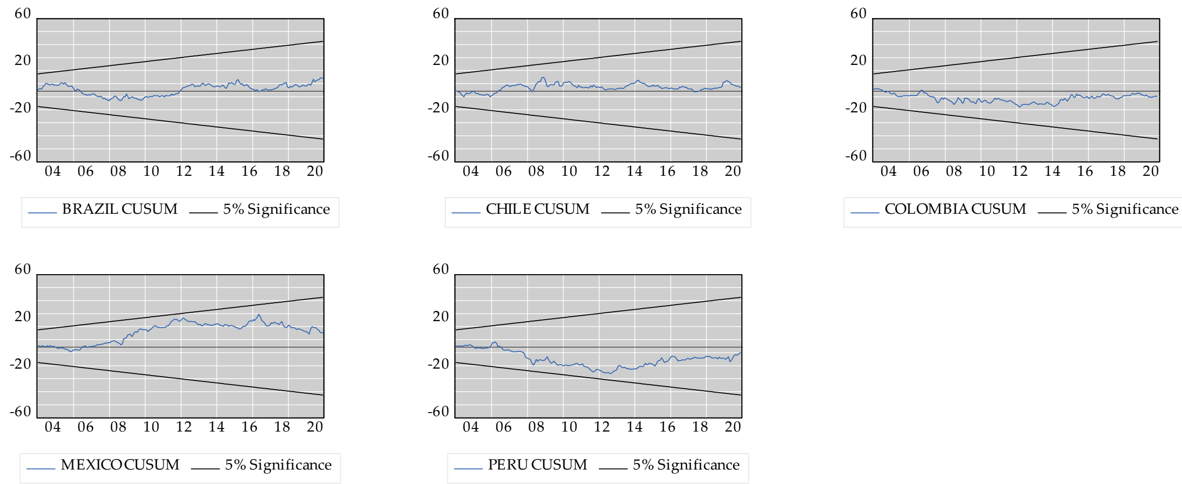

FIGURE 5. CUSUM TEST FOR THE OLS ESTIMATES OF EQUATION (12)

Source: Authors' calculations. *Notes:* 5% confidence bands.

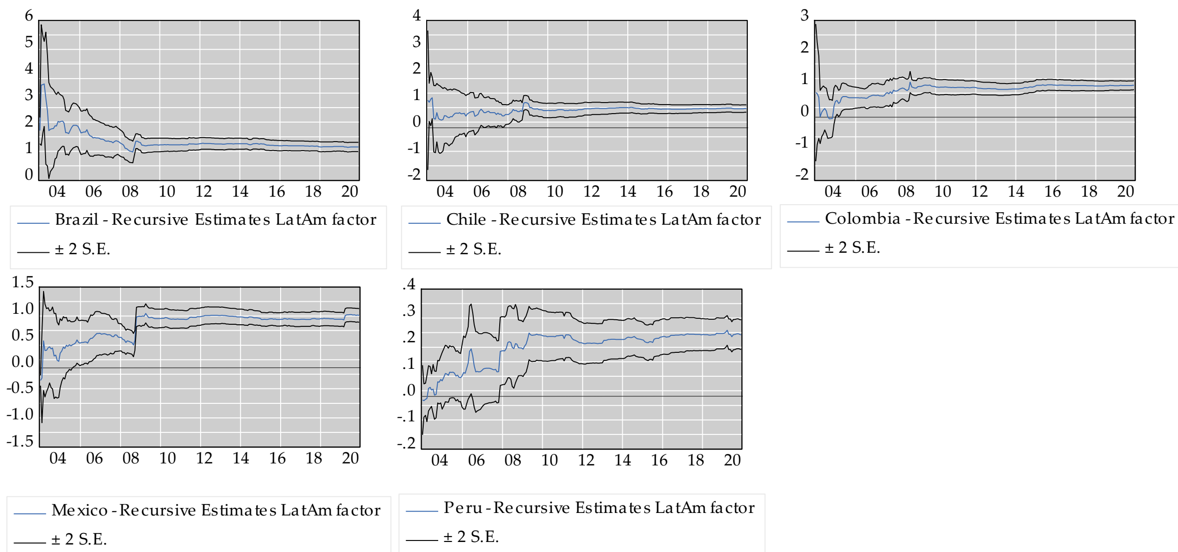

FIGURE 6. PARAMETER STABILITY. RECURSIVE OLS ESTIMATES OF EQUATION (12)

Source: Authors' calculations.

In order to assess the dynamic properties of our specifications, we compute the local projections impulse response functions using the OLS estimation. According to the impulse response derived from local projections (Figure 7), the sensitivity of LATAM exchange rates to a shock in their common factor is positive and significant, with the total effect completed after two months.

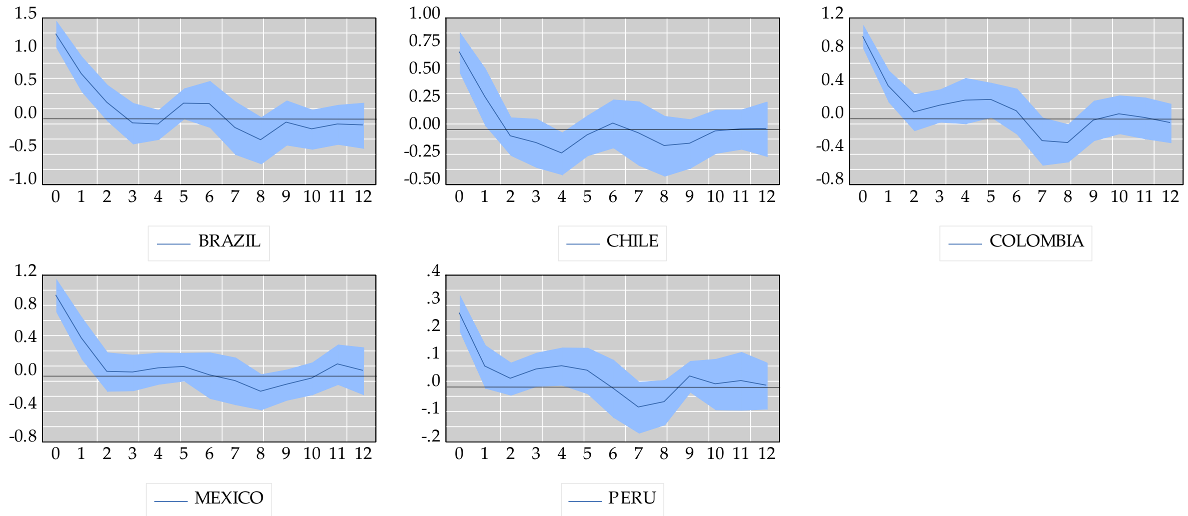

FIGURE 7. LOCAL PROJECTIONS
SENSITIVITY OF LATAM EXCHANGE RATES TO THEIR RESPECTIVE COMMON FACTOR

Source: Authors' calculations. Notes: Blue-shaded areas represents ± 1 standard deviation.

According to the forecast decomposition (Figure 8), we find evidence that the common exchange rate factor is an important driver for LATAM exchange rates, especially during the financial crisis of 2008-2009, the commodity price shock in the middle of the las decade, and during the recent Covid-19 pandemic (see Appendix 3 for detailed results).

Finally, the previous results are consistent with the high frequency estimations presented in Table 3 as there is evidence that the common currency factor in LATAM economies is an important driver of daily exchange rates returns. In addition, the conditional volatility derived from GARCH models was higher during the financial crisis of 2008-2009 than during the recent Covid-19 crisis. This result may be related to the nature of these shocks and the way they changed the structure or functioning of each economy (Figure 9).

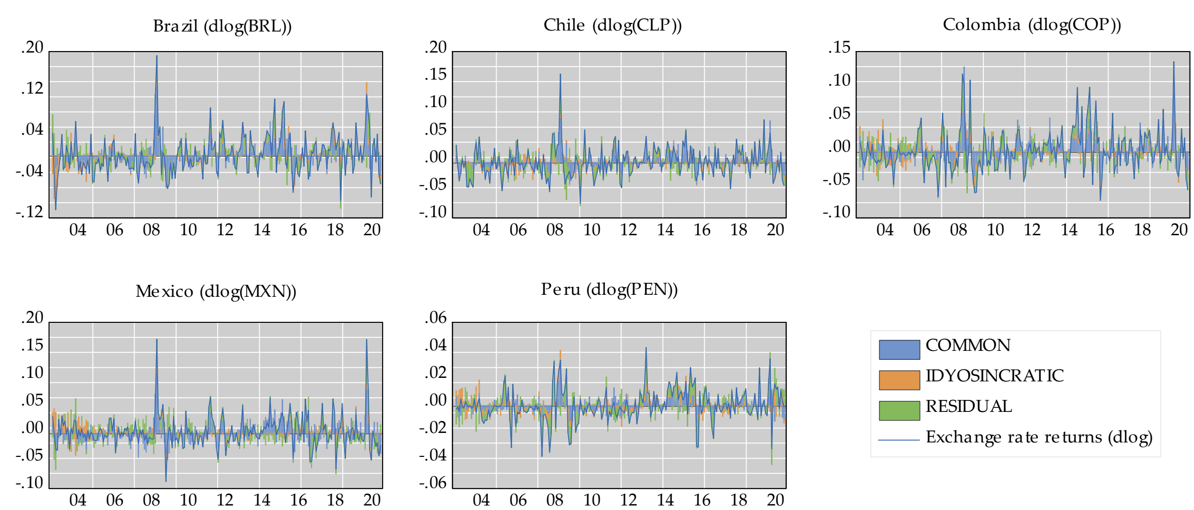

FIGURE 8. EXCHANGE RATE CONTRIBUTIONS USING EQUATION (12)– COMPLETE SAMPLE

Source: Authors' calculations.

Table 3—GARCH estimations based on equation (12)

	DLOG(BRL)	DLOG(CLP)	DLOG(COP)	DLOG(MXN)	DLOG(PEN)
DLOG(Latam common factor ex_)	0.9645 ***	0.5621 ***	0.6348 ***	0.6850 ***	0.1280 ***
	[0.021]	[0.013]	[0.014]	[0.012]	[0.002]
DLOG(Commodities ratio)	-0.0030	-0.0123 ***	-0.0142 ***	0.0103 **	-0.0001
	[0.005]	[0.001]	[0.002]	[0.004]	[0.000]
D(CDS spread ex_)	0.0004 ***	-0.0001 ***	0.0001 ***	0.0001 ***	0.0000 **
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
D(Interest rate spread ex_)	-0.0017 *	-0.0013 *	0.0001	0.0000	0.0004
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Variance equation					
Constant	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
α1	0.0950 ***	0.0551 ***	0.1012 ***	0.1003 ***	0.2173 ***
	[0.006]	[0.003]	[0.005]	[0.004]	[0.006]
α2	0.8891 ***	0.9384 ***	0.8914 ***	0.8926 ***	0.8079 ***
	[0.007]	[0.002]	[0.005]	[0.005]	[0.004]
Adjusted R-squared	0.346	0.251	0.301	0.300	0.138
Durbin-Watson stat	2.292	1.958	1.970	2.170	1.987
Log likelihood	15449.320	16955.940	16739.520	16826.660	21057.190

[ ] t- Statistic. HAC standard errors & covariance.

* p<0,10; ** p<0,05; *** p<0,01

Source: Authors' calculations.

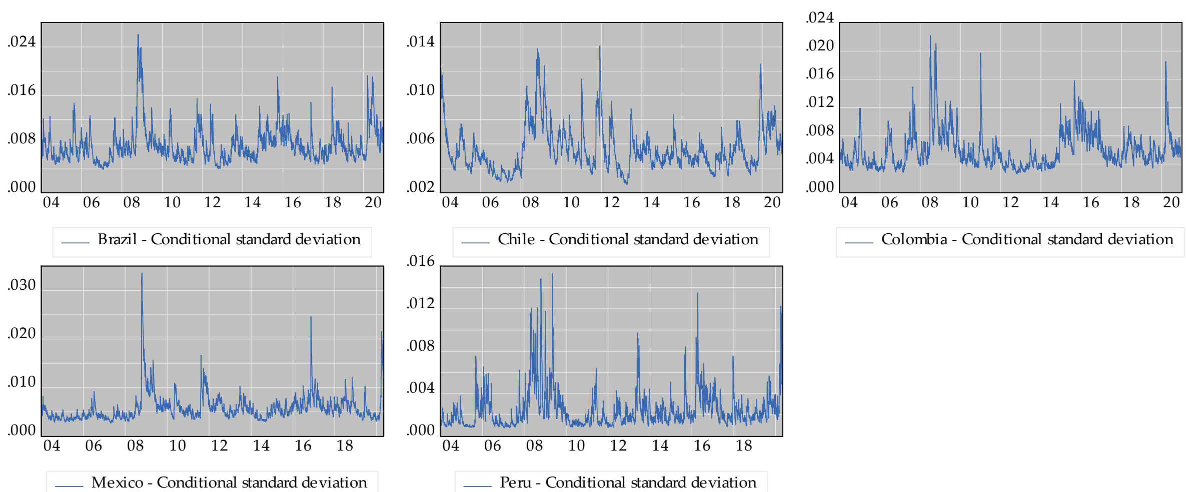

FIGURE 9. CONDITIONAL STANDARD DEVIATION FROM A GARCH (1,1) ESTIMATION BASED ON EQUATION (12)

Source: Authors' calculations.

VI. Conclusions

We examine a simple factor model, that allows us to differentiate theoretically and empirically the common and idiosyncratic movements in Latin-American exchange rates. This approach helps to explain currency comovements and displays a good fit with the data. Furthermore, the regional common factor seems to be a significant determinant of the Latin-American exchange rates, and we show evidence that its inclusion is suitable in both low and high frequency empirical settings. Also, we find that the regional common factor has been an important driver explaining exchange rates during stress episodes such as the Global Financial Crisis and the recent COVID-19 health crisis.

From a policy perspective, the possibility to distinguish regional and idiosyncratic factors could be a useful tool that allows to explore the underlaying drivers of FX movements, particularly during stressed episodes. In line with this argument, further areas of research should explore the drivers of the regional common factor, the influence of the global financial cycle on regional FX dynamics, and the influence of the regional common factor on FX volatility. Finally, separating common from local drivers could also allow policy makers to make a better assessment of possible relative FX misalignments.

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Appendix 1: Estimation of the common factor for LATAM currencies

In this section we present the approach we followed to estimate the common factor for LATAM currencies. We followed the methodology proposed by Solberger and Spånberg (2019) from which this appendix borrows.

Let $\boldsymbol{s}_t = (x_{1,t}, x_{2,t}, \dots, x_{N,T})'$ be a vector of N exchange rate log returns, each of which is a real-valued stochastic $\{s_{i,t}, t \in \mathbb{Z}\}$. Suppose we observe a finite realization of $\boldsymbol{s}_t$ over some time points $t = 1,2,\dots,T$, and let the empirical information available at time t be condensed into the information set $\mathcal{F}_t = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_t\}$. Thus, the dynamic factor model is specified such that each observable exchange rate $s_{i,t}$ $(i = 1,2,\dots,N)$ is the sum of two independent and unobservable components: a common component $\chi_{i,t}$, which is driven by a small number of factors that are common to all exchange rates, and a remaining idiosyncratic (individual-specific) component $\epsilon_{i,t}$. In panel notation, the model is:

$$s_{i,t} = \chi_{i,t} + \epsilon_{i,t}, \qquad (i = 1,2,\dots,N; t = 1,2,\dots,T)$$

$$\chi_{i,t} = \upsilon_i(L)'\mathbf{z}_t \qquad \text{(A1)}$$

Where $\upsilon_i(L) = \upsilon_{i,0} + \upsilon_{i,1}L + \cdots + \upsilon_{i,\ell}L^{\ell}$ $(\ell < \infty)$ is a vector lag-polynomial of constants loading onto a vector of $\mathcal{K}$ unobservable common factors, $\mathbf{z}_t = (z_{1,t}, z_{2,t}, \dots, z_{\mathcal{K},t})'$. Thus, only the left-hand side of (1) is observed; the right-hand side is unobserved. If the dimension of $\mathbf{z}_t$ is finite $(\mathcal{K} < \infty)$, then there exists for every i an $(\mathcal{R} \le \mathcal{K})$ of constants $\lambda_i = (\lambda_{i,1}, \lambda_{i,2}, \dots, \lambda_{i,\mathcal{R}})'$, such that $\upsilon_i(L)' = \boldsymbol{\lambda}_i' C(L)$, where $\mathbf{C}(L)$ is an $\mathcal{R} \times \mathcal{K}$ matrix lag-polynomial, $\mathbf{C}(L) = \sum_{m=0}^{\infty} \boldsymbol{C}_m L^m$, that is absolutely summable, $\sum_{m=0}^{\infty} \|\boldsymbol{C}_m\| < \infty$. Thus, letting $\mathbf{f}_t = (f_{1,t}, f_{2,t}, \dots, f_{\mathcal{R},t})' = \mathbf{C}(L)\mathbf{z}_t$, the dynamic factor model can be cast in the static representation:

$$s_{i,t} = c_{i,t} + \epsilon_{i,t},$$

$$c_{i,t} = \boldsymbol{\lambda}_i'\mathbf{f}_t, \qquad \text{(A2)}$$

Which, equivalently, can be written in vector notation as

$$\mathbf{s}_t = \mathbf{c}_t + \boldsymbol{\epsilon}_t,$$

$$c_{i,t} = \boldsymbol{\Lambda}\mathbf{f}_t, \qquad \text{(A3)}$$

Where $\mathbf{c}_t = (c_{1,t}, c_{2,t}, \dots, c_{N,t})'$, $\boldsymbol{\epsilon}_t = (\epsilon_{1,t}, \epsilon_{2,t}, \dots, \epsilon_{N,t})'$ and $\boldsymbol{\Lambda} = (\lambda_1', \lambda_2', \dots, \lambda_N')'$. The common factors in $\mathbf{z}_t$ are often referred to as dynamic factors, while the common factors in $\mathbf{f}_t$ are referred to as static factors. The number of static factors, $\mathcal{R}$, cannot be smaller than the number of dynamic factors, and is typically much smaller than the number of cross-sectional individuals, $\mathcal{K} \le \mathcal{R} \ll N$. As with $\chi_{i,t}$, in the dynamic representation of (A1), the scalar process c_i in (A2) or the multivariate process $\mathbf{c}_t$ in (A3) is the common component which we used to represent the LATAM common factor.

Appendix 2: Forecasting evaluation of equation (12)

In this appendix we show the in-sample forecast evaluation of our proposed specification. For each currency we compared the OLS and GMM estimations reported in Table 2 with a naïve random walk model (RW). For each model we compute the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute prediction error (MAPE), and the U-Theil. The shaded cells represent the best model according to each forecast evaluation measure.

Sample: 2003M01 2020M12
Included observations: 216

Forecast	RMSE	MAE	MAPE	U-Theil
Random Walk	0.043070	0.032529	301.3862	1.000000
OLS	0.023374	0.017869	203.4635	0.510226
GMM	0.024507	0.018853	239.1738	0.392982

TABLE A2.1 FORECAST EVALUATION OF BRL ESTIMATIONS OF EQUATION (12).

Source: Authors calculations.

Sample: 2003M01 2020M12
Included observations: 216

Forecast	RMSE	MAE	MAPE	U-Theil
Random Walk	0.032379	0.025198	313.5806	1.000000
OLS	0.020156	0.014456	155.3592	0.725933
GMM	0.021059	0.015059	182.2111	0.700481

TABLE A2.2 FORECAST EVALUATION OF CLP ESTIMATIONS OF EQUATION (12).

Source: Authors calculations.

Sample: 2003M01 2020M12
Included observations: 216

Forecast	RMSE	MAE	MAPE	U-Theil
Random Walk	0.036616	0.026181	252.2429	1.000000
OLS	0.021056	0.016589	178.3127	1.580276
GMM	0.021178	0.016808	192.5298	1.424707

TABLE A2.3 FORECAST EVALUATION OF COP ESTIMATIONS OF EQUATION (12).

Source: Authors calculations.

Sample: 2003M01 2020M12
Included observations: 216

Forecast	RMSE	MAE	MAPE	U-Theil
Random Walk	0.035204	0.025024	346.4360	1.000000
OLS	0.019804	0.015244	186.4113	0.805343
GMM	0.020414	0.016091	220.9546	0.874437

TABLE A2.4 FORECAST EVALUATION OF MXN ESTIMATIONS OF EQUATION (12).

Source: Authors calculations.

Sample: 2003M01 2020M12
Included observations: 216

Forecast	RMSE	MAE	MAPE	U-Theil
Random Walk	0.014316	0.009594	382.5134	1.000000
OLS	0.009362	0.006988	226.5614	0.981504
GMM	0.009362	0.006991	227.0610	0.983544

TABLE A2.5 FORECAST EVALUATION OF PEN ESTIMATIONS OF EQUATION (12).

Source: Authors calculations.

Appendix 3: Exchange rate decomposition during the Global Financial Crisis and the COVID-19 shock

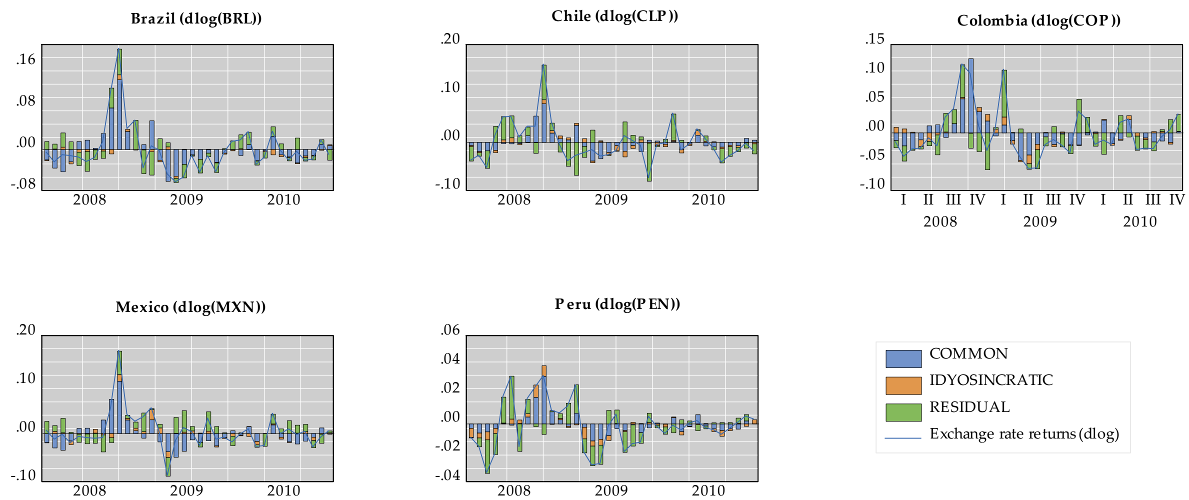

FIGURE A3.1 FORECAST DECOMPOSITION OF LATAM EXCHANGE RATES DURING THE GLOBAL FINANCIAL CRISIS. MONTHLY DEPRECIATION

Source: Authors' calculations.

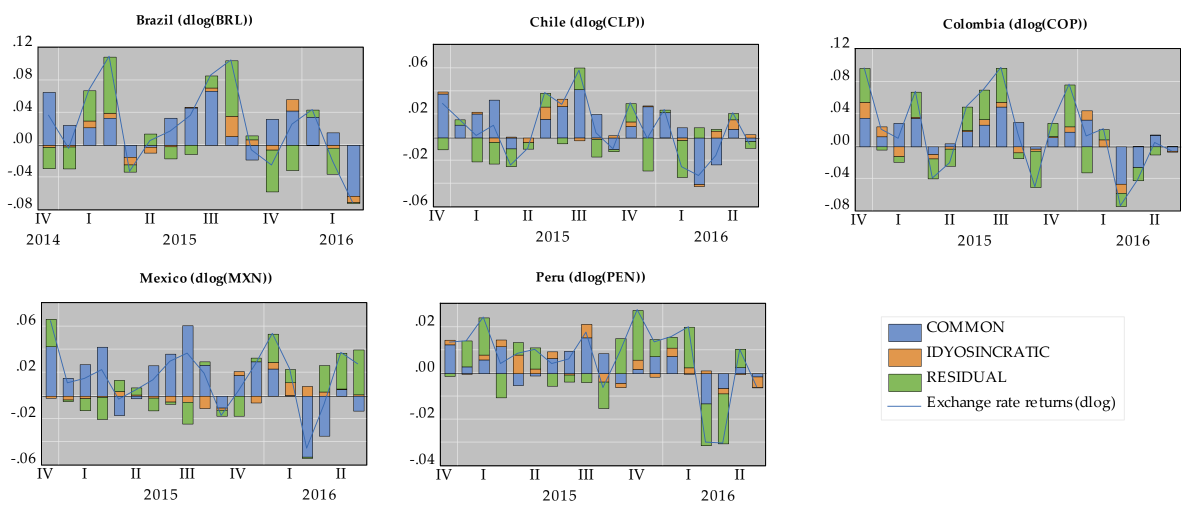

FIGURE A3.2 FORECAST DECOMPOSITION OF LATAM EXCHANGE RATES DURING THE COMMODITY-PRICE SHOCK

Source: Authors' calculations.

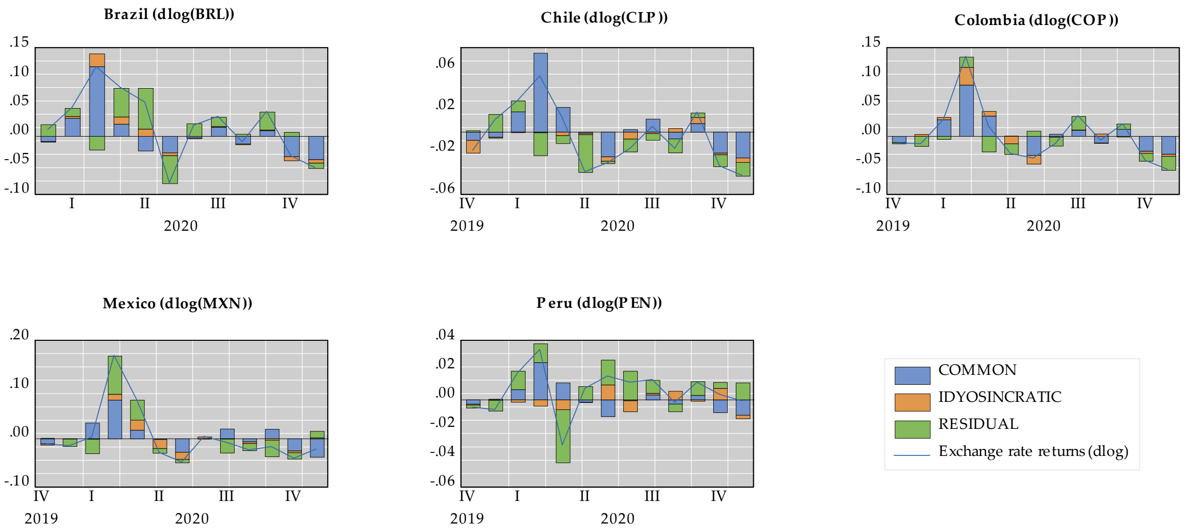

FIGURE A3.3 FORECAST DECOMPOSITION OF LATAM EXCHANGE RATES DURING THE COVID-19 SHOCK. MONTHLY DEPRECIATION.

Source: Authors' calculations.


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