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Por: Juan Manuel Julio-Roman

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Juan Manuel Julio-Roman†

Abstract

Together with a set of not commonly reported ones, the most widely known stylized facts of high frequency Nominal Exchange Rates in Brazil, Chile, Colombia, Mexico, and Peru with respect to the US Dollar are studied and interpreted to the light of recent literature in this paper. Among many other results, findings include (i) the tails of ordinary and absolute returns distributions follow inverse power laws, a family of widely occurring empirical regularities which seem to arise from Central Limit Theorem assumption violations and which may be interpreted through the "universality principle"; (ii) the smooth sinusoidal long-run trend and short-term noise dynamics of our nominal exchange rates are dominated by a ragged short to long-term non-symmetric cyclic component in Chile, Colombia and Brazil, while the opposite happens in the remaining two countries; and (iii) time domain component correlation between countries suggest the existence of common factors explaining these rates that may be related to carry trade and time-varying risk related to the appetite for risk of international investors.

Keywords: Nominal Exchange Rate, Stylized Facts, Latam
JEL: F31, F41, G17.

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†Senior Researcher, Research Unit, Technical Presidency, BANCO DE LA REPÚBLICA DE COLOMBIA and Associate Professor, Department of Statistics, Universidad Nacional de Colombia. Bogotá D. C., Colombia. e-mail:jjulioro@banrep.gov.co.

Sobre los Hechos Estilizados de las Tasas Nominales de Cambio en Brazil, Chile, Colombia, México y Perú[§]

Juan Manuel Julio-Roman[¶].

Resumen

A la luz de literatura reciente en este escrito se interpretan los hechos estilizados más comunes de las tasas de cambio nominales en Chile, Colombia, México y Perú con respecto al Dólar Norteamericano, y se explora un conjunto no muy conocido de estos hechos. Entre muchos otros hallazgos se encontró que: (i) las colas de la distribución de los retornos ordinarios y absolutos obedecen leyes de potencia inversa, "inverse power laws", un conjunto de regularidades empíricas que ocurren con frecuencia y que parecen surgir de violaciones a los supuestos del Teorema del Límite Central y que se puede interpretar a travź del "principio de universalidad"; (ii) la suave tendencia sinusoidal de muy largo plazo y el ruido de corto plazo de estas tasas están dominados por un componente cíclico no simétrico con cambios repentinos de dirección en Brazil, Chile y Colombia, pero lo opuesto ocurre en los dos países restantes; y (iii) la correlación entre los componentes en el dominio del tiempo de distintos países sugiere la existencia de factores comunes que esplican estas tasas y que pueden estar relacionados con "carry trade" y riesgos tiempo dependientes relacionados con el apetito por riesgo de los inversionistas internacionales.

JEL: F31, F41, G17.
Palabras Clave: Tasa de Cambio Nominal, Hechos Estilizados, Latam.

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[¶]Investigador Principal, Unidad de Investigaciones, Gerencia Técnica, BANCO DE LA REPUBLICA DE COLOMBIA y Profesor Asociado, Departamento de Estadística, Universidad Nacional de Colombia. Bogotá D. C., Colombia. e-mail:`jjulioro@banrep.gov.co`.

1 Introduction

The most widely known stylized facts of the nominal exchange rates (NERs), of Brazilian (BRL), Chilean (CLP), Colombian (COP), Mexican (MXN) and Peruvian (PEN), currencies with respect to the US Dollar, USD, are studied in this paper. In addition to the commonly studied features of the conditional and unconditional distributions of NERs ordinary and absolute returns, this study addresses other dimensions such as the time series properties of NER levels, the relationship among them, the relationship (or lack of) with selected economic indicators, and their spectral properties.

These stylized facts provide the dynamic features that economic models should account for in order to identify the impact of foreign shocks on the local economy, an important task for central bankers in small open economies, portfolio managers, and academics as well.

A variety of descriptive statistic and time-series techniques are brought together to characterize the dynamic properties of NERs, which are interpreted, in turn, in the light of recent literature. For instance, the spectral decomposition of NER levels reveals that cycles dominate the smooth sinusoidal NER long-run trend, seasonality and noise in a group of countries, but trend fluctuations dominate in the remaining ones. More interestingly, the NERs' smooth sinusoidal long-term trends of different countries are strongly related between them, but log-NERs are not co-integrated. Furthermore, the long-term cycles of different NERs show an important degree of association, but a moderate one arises among short-term cycles. Finally, the association between seasonal and noise components between countries is the weakest among the components.

Interesting interpretations might arise from these facts. Along with the existence of time varying risk premium and the effect of carry trade on our NERs, these results suggest the existence of dominating cyclical common dynamic factors which may be related to international investors appetite for risk and to interest rate differentials with respect to the US, i.e. some form of extended UIP. These common factors may supply an important input for NER modelling through Dynamic Factor models or Factor Augmented VARs for inflation targeting small open economies, specially. However, an important component, perhaps idiosyncratic, of NER variations is still unexplained.

In order to reap the benefits that such statistical procedures and interpretations bring about, we chose a set of sufficiently similar countries to enable the discovery of a common NER stylized facts. However, this set of countries is sufficiently diverse to imprint our results with robustness and to allow discovering idiosyncratic facts as well. In fact, our five countries follow inflation targeting regimes, perform different sorts of FOREX (sterilized) interventions, and belong to the Latam risk class. But on the other hand, these countries differ sharply in their size (Brazil and Mexico as opposite to Chile, Colombia and Peru), exchange rate policy (Peru in comparison to the rest), geographical closeness to major economies (Mexico in contrast to the other countries), among many others.

This paper is distributed in three sections aside from this introduction. The second describes the dataset and previous treatment of the variables under analysis. Section three summarizes the stylized facts. And the fourth and last, concludes.

2 Data

The data set under analysis, its source, code names and frequency are summarized in Table A.1. Daily nominal exchange rates records, i.e. the price in local currencies of one US dollar, were obtained from Antweiler (2014)[1]. These records are complemented with daily country risk measures, i.e. JP Morgan's EMBI spreads, monetary policy rates for the five countries in the sample and the US, and the appetite for risk of international investors measured as the spread between Moodie's corporate BAA bonds and US treasuries rates. Finally, the dataset contains also quarterly output gap measures of the countries involved in the exchange.

3 Stylized facts

Under free float, nominal exchange rate returns and levels have a widely known set of stylized facts, yet another set not usually studied is also explored in this section. We start by studying the unconditional distribution of returns in subsection 3.1. Subsection 3.2 contains the stylized facts of the unconditional distribution of absolute returns, i.e. risk. The conditional distribution of returns and absolute returns is explored in subsection 3.3, while the time series properties of NERs are analysed in subsection 3.4. Finally, the relationship between nominal exchange rates and other macro and financial variables are summarized in subsection 3.5.

3.1 The unconditional distribution of returns

Stylized Fact 1**: The unconditional distribution of returns has thick tails which follow near inverse cubic laws with important differences among the tail decays of some of the five NERs**.

[1] Antweiler (2014) points out that these NERs correspond to spot noon rates, when available, and to official ones otherwise. Differences should largely be irrelevant for this study.

P-values< 0.01 in Table A.2 show the presence of considerable and very significant excess return kurtosis with respect to the Gaussian distribution for each of the five currencies in the sample. These coefficients range widely from 4.80 for CLP/USD returns to 78.83 for PEN/USD ones, suggesting important differences between the tails of NER returns.

However, the interpretation of kurtosis coefficient has been challenged and improved measures based on tail thickness have been proposed. In fact, excess kurtosis is viewed as a measure of high density concentration around the mode, a beneficial feature, and thicker than normal distribution tails, a very troublesome one, as it relates to the non-existence of return moments when unbounded returns are assumed. However, this measure may be misleading as it depends on the number of crossing between the density and the Gaussian and, therefore, does not necessarily describe the distribution features of interest. As a result, more useful measures focus directly on the return distributions thickness. See Finucan (1964), for instance.

The most common measure of tail thickness is the decay of the probability of extreme returns, $P[|Y_t - E(Y_t)| > k\sigma_y]$, with respect to the decay of a normal density, $\sqrt{\frac{2}{\pi}}e^{-k^2/2}$, as k increases. Slower decaying tails than Gaussian are deemed thick, while faster decaying ones are denominated thin. Results in Table A.3, show that the estimated frequencies of extreme returns, $\widehat{P}[|Y_t - \widehat{E}(Y_t)| > k\widehat{\sigma}_y]$, decay very slowly with respect to the Gaussian for all currencies under analysis. Three important cases stand out in this Table; beyond three standard deviations, the tail decay of CLP/USD return distribution is the fastest among the NERs considered, while PEN/USD and BRL/USD returns tails are among the slowest. Therefore, strong evidence in favour of thick tails arise and important differences among these rates of decay are also present.

These slowly decaying tails suggest the existence of *Inverse Power Laws*, IPLs. The tails of a random variable Y_t are said to follow an IPL if

$$P[|Y_t - E[Y_t]| > k\sigma_y] = \kappa\sigma^{-\alpha} \times k^{-\alpha} = C \times k^{-\alpha} \tag{1}$$

as k increases, for a (not very important) $C > 0$ and *Tail Index*, $\alpha > 0$. From this equation α can be estimated by OLS by taking logs on both sides

$$\log\left(P[|Y_t - E[Y_t]| > k\sigma_y]\right) = \log(C) - \alpha\log(k)$$

which yields estimated tail indexes $\hat{\alpha}$ close to 3 for the five currencies, a very slow polynomial tail decay when compared to the faster than exponential decay of the normal tail[2].

[2] More generally a random variable has an IPL tail if $P[S > x] = C \times x^{-\alpha}$ which corresponds to the following probability density function at the tails

$$f(x) = (C\alpha) \times x^{-\alpha-1} \tag{2}$$

from which further properties may be deduced. For instance, it is widely known that if an unbounded

In order to explore this matter further, we compare our previous results with Hill (1975) tail index estimates. Figure B.1 displays the Hill's tail index estimate for absolute (left panels), right tail (center panels) and left tail returns (right panels), across the currencies under analysis. On each panel, Hill's α estimate (bold line) and its 95% confidence intervals (dashed lines) are shown along the order statistics whose numbers lie on the lower horizontal axis.

Several important conclusions may be drawn from figure B.1. First, there is ample evidence of thick tails, IPLs with exponent less than or equal to 3[3]. Second, CLP/USD returns seem to have thinner tails than all the remaining distributions. And Third, PEN/USD returns seem to have thicker tails than any other return distribution in the sample.

The latest finding is important as it emphasizes the distinctive NER dynamics under different exchange rate regimes. This result relates to the physics PLs *universality principle* which states that thermodynamic processes with similar tail indexes share the same fundamental dynamics. This interpretation fits nicely the difference between the left tail index of PEN/USD returns and the tails of the remaining return distributions. Furthermore, this result also relates tail index estimates of NERs returns under fixed NERs, $\hat{\alpha} \leq 2$, and free float, $\hat{\alpha} \approx 3$, reported in Haas and Pigorsch (2011). Therefore, the degree of floating seems to determine the dynamic properties of NERs.

IPLs are widely known *empirical regularities* that arise in many in many physical, biological and human endeavours[4]. See James, Marsh, and Sarno (2012, Ch. 4), Gabaix (2009) and Haldane (2012) for more examples and a detailed discussion on PLs in economics and finance.

The source of PL behaviour is still a work in progress. According to Gabaix (2009) the explanation of widely occurring PL's regularities should be "robust", i.e. independent of the particular details and parameter fine tuning of the process under analysis[5]. As a result, it is widely believed that return distributions arise from a self organized system

random variable follows a PL distribution with tail index α, all moments higher than or equal to $\alpha - 1$ do not exist. Furthermore, it is also known that the family of PL distributions is closed under addition, multiplication, polynomial transformations, minimization and maximization, under the rule that "when combining two PL's, the fattest dominates". See Gabaix (2009).

[3]When returns are assumed to be bounded this fact might is not important. Under these circumstances all return moments exist and extreme values are also bounded.

[4]An interesting case in point is the Zipf's law, which describes the distribution of the population size of cities, or any other geographical unit. This PL states that the probability that a city's population, X, is greater than some x is proportional to $1/x$, i.e. the tail index assumes a value of 1 and no other. This PL is, in turn, a particular case of the income distribution proposed by Pareto (1906) in which the tail index may also assume any other value different from one. Another important example in point is the highly documented inverse cubic law in the distribution of stock market returns, a key fact in understanding stock market crashes according to Gabaix (2009) and Haldane (2012)

[5]For instance, Zipf's law arises as a limiting case of Gibrat's law that postulates the independence between the growth rate and the size of a geographical unit (city).

much like the dynamics of a uniformly and continuously fed pile of sand. See the references in Haldane (2012), for instance.

Following this lead, Haldane (2012) highlights that the key to explain IPLs in financial market returns lies on the violation of "critical assumptions" of the Central Limit Theorem. According to this author, NER returns result from a dynamic system (i.e. the market) having *strong interactions* between its units, a violation of the limited interaction assumption for Central Limit convergence. More precisely, Haldane (2012) stresses that these interactions may take the form of (i) non-linear dynamics and chaos; (ii) critically self organized systems, which seems to explain the formation of stock market crashes; (iii) preferential attachment, which leads to multiple equilibria; and (iv) highly optimized tolerance that would yield high risk states "due to well-meant, but imperfect, regulation". As a result, this author argues that the sub-prime crises might have been the result of well-meaning, albeit imperfect, financial oversight, that arose from the lack of proper means to deal with PL's.

As a result, no satisfactory models for high tails are available. Although the relationship between the tail index and other conditional return moments is well understood and may account, in part, for IPLs, fat-tailed innovations distributions are still needed to account for the empirical features of return tails. In fact, it is widely known that GARCH models under Gaussian innovations, which include relationships between higher moments and fat tails, fail to account for the slow tail decay observed in financial returns. Therefore, it is common practice to assume fat tailed innovation distributions in GARCH modelling[6]. That is, a share of the tail's fat is left unexplained when normality is assumed. See Engle (1982). Therefore, high tailed innovations in ordinary and integrated GARCH models might explain some of the features of NERs returns.

Furthermore, even the introduction of dynamic complexity, i.e. non-linearities and/or multiple equilibria, which may also play a role in explaining the low coefficients of return determination of linear NER return models, fails to account for observed high-tailedness. Evidence of its presence in our currencies follows the BDS linearity tests results in Table A.6. According to Hansen (2011) exchange rate Threshold Auto Regressions, TAR, and Self Exiting TAR, SETAR models have modestly improved the fit and forecasts of NER returns with respect to naive forecasts when modelling deviations from UIP, asymmetric transaction costs, etc. In addition, Taylor (2000) and Sarno, Taylor, and Chowdhury (2004) justify the use of TAR modelling as a departure from linear dynamic mean reversion towards the Law Of One Price, LOOP, and/or Purchasing Power Parity, PPP. The appeal of TAR/SETAR and Hamilton (1989) Markov Switching models, in which the innovation process is assumed Gaussian, is that the unconditional distribution of returns is a Gaussian Mixture and thus heavy tailed. However, the tails of the unconditional dis-

[6] Mikosch and Starica (2000) established the conditions under which the unconditional return distribution in a GARCH(1,1) model decay asymptotically on a PL fashion.

tribution of Gaussian mixtures eventually decay in a Gaussian fashion, and therefore this approach might represent more realistically the return processes when assembled with high tail innovations. See Haas and Pigorsch (2011), for instance.

Finally, time-varying volatility and higher moment autocorrelation seem to play a role in explaining unconditional return non-normality according to Haas and Pigorsch (2011). For instance, the observed dependence of time varying second order moments, also known as "volatility clustering", emerges in finite Gaussian mixtures as in TAR/SETAR modelling. Thus, multiple Gaussian return equilibria leads to volatility clustering. Moreover, Sheikh and Qiao (2009) and Lin, Rosen, and Mergenthaler (2012) mention that time-varying correlation with other assets may also play a role in explaining non-normality, i.e. leptokurtosis, skewness and the non-existence of higher moments.

Summarizing, two important results were found regarding the kurtosis of NERs returns. First, the excess return kurtosis found is related to inverse cubic laws, i.e. IPLs with tail indexes $\hat{\alpha} \leq 3$. This behaviour is a *empirical regularity* whose explanation must be "robust" to the parameters and details of the market according to Gabaix (2009), and arises form the violation of the central limit theorem limited dependence assumption according to Haldane (2012). As a result, these return processes look chaotic and non-linear, i.e. similar to a self-organized system, much like the formation of a pile of sand. Although the auto-correlation of higher return moments (which leads to the popularity of integrated and ordinary GARCH modelling) and Gaussian mixtures (derived from TAR, SETAR and Hidden Markov Models) may explain some of the height of the tails, it is still required to assume high-tail innovation distributions to mimic the observed NER returns tail height, i.e. some of the return tail height is left unexplained. According to Haldane (2012) the lack of proper understanding of the causes of this behaviour led supervisors to become tolerant to high-risk states, and issue highly optimized and well-meant but imperfect regulations that led to the 2007 global financial crises. And second, important differences among the tail decays of the five NERs were found. The more important is the very high left PEN/USD tail, $\alpha \approx 2$ in contrast to the remaining returns tails. This result fits nicely the findings of Haas and Pigorsch (2011) who report that under free float $\alpha \approx 3$, and under fixed exchange rates $\alpha \leq 2$. These differences might also be interpreted through the "universality principle" which states that thermodynamic systems with different tail indexes have very distinctive dynamics, and thus, different types of dynamic models and properties.

***Stylized Fact 2*: The unconditional distributions of returns are skewed. This seems to reflect the existence of both, carry trade with respect to the US currency and time-varying risk premium**.

There is evidence in favour of very significant unconditional return distribution skewness for the five NERs under examination. Lack of return symmetry tests results in Table A.2 show positive and very significant skewness for all NERs but BRL/USD, which displays a significantly negative one. This Table shows also a high skewness coefficient, 2.13, for PEN/USD returns with respect to the remaining NREs whose absolute values are below one.

A more detailed view of the frequency of signed returns in Table A.3 indicates that skewness is not necessarily a tail-related matter. In fact, the negative return skewness observed in Chile, Mexico and Peru is at odds with the excess frequency of positive returns beyond two to eight standard deviations when compared to the frequency of negative ones. As a result, skewness has to do with returns within two standard deviations in these countries. In contrast, in Brazil and Colombia negative/positive skewness may relate to a higher frequency of negative/positive returns beyond five and seven standard deviations, respectively. Therefore, excess return frequencies up to two standard deviations seem to play an important role in determining unconditional kurtosis, with some role of the far tails in particular cases.

A popular explanation to NER return skewness is the effect of carry trade on high yield currencies. Nirei and Sushko (2011) show evidence in favour of the fact that "asymmetry [of JPY/USD returns] is magnified and power-law tails are more elongated during times of higher interest rate differential between U.S. and Japan and higher VIX level, indicating that carry trade may be the driver".

This fact also seems to arise in the currencies under study in this paper. The diagonal panels in Figure B.3 show that ex-post future rates of devaluation against USD relate directly to policy rate differentials against US rates[7]. Furthermore, the off-diagonal panels indicate that ex-post cross-Latam currencies depreciation over six months does not relate as strongly with cross-country policy rate differentials with a few exceptions. Therefore, devaluation tends to offset shifts in policy rate differentials against the US, but not necessarily against other Latam countries.

A closer look at the relationship between ex-post depreciation and policy rate differentials reveals that some form of UIP may be present. Under rational expectations the simplest UIP can be written as:

$$s_{t+k} - s_t = R_{t,t+k} - R^*_{t,t+k} \tag{3}$$

where s_t is the log-NER at time t, $R_{t,t+k}$ and $R^*_{t,t+k}$ are the local and foreign nominal interest rates for a zero coupon deal with maturity k. Figure B.3 show the relationship between these variables in two different ways; the left hand side panels depict the scatter plots, OLS fit lines and their corresponding estimated parameters, while those on the the

[7]Under the expectations hypothesis of interest rates, policy rate differentials proxy interest rate differentials on longer maturities. Furthermore, since the mode of daily returns is nearly time-invariant and close to zero, half a year devaluation shifts approximate mean daily return shifts and, therefore, indicates daily returns skewness shifts as well.

right-hand side show the evolution of these variables along time[8]. Several conclusions may be drawn from this Figure. First, remarkably high and positive interest rate differential slopes were found in all countries but Brazil, which range widely between 0.71 and 0.84 for PEN/USD and CLP/USD depreciation rates, respectively[9]. Second, the slopes and intercepts suggest that unconditional UIP ($\beta_0 = 0$ and $\beta_1 = 1$) is not satisfied in several countries in the sample, but conditional UIP might hold. And third, the slope seems to increase in times of crises (high depreciation rates accompanied by high interest rate differentials) in Chile, Colombia and Peru. Similar results were also found by Flood and Rose (2001).

The non-satisfaction of the unconditional UIP suggests the existence of risk aversion. Under risk aversion the UIP can be written as

$$s_{t+k} - s_t = R_{t,t+k} - \rho_{t,t+k} - R^*_{t,t+k} \tag{4}$$

where $\rho_{t,t+k}$ is the risk spread, which we proxy with country risk, i.e. the Emerging Markets Bond Index, EMBI spread. Therefore, $(1 - B^k)s_{t+k} + \rho_{t,t+k} = R_{t,t+k} - R^*_{t,t+k}$, implies a direct relationship between nominal interest rate differentials and country risk, see Flood and Rose (2001, pp. 3). The left hand side panels and two top-most panels to the right hand side of Figure B.4 show a very close relationship between country risk and policy rate differential in Mexico, a slightly more loose one in Colombia, some detachment of these indicators since 2011 in Chile and Peru, and not a good one in Brazil. Additional evidence of risk aversion arises from the fact that simple UIP deviations $R_{t,t+k} - R^*_{t,t+k} - (1 - B^k)s_{t+k}$ tend to be positive, with medians $6.4, 1.6, 2.4, 2.7$ and 1.3 for Brazil, Chile, Colombia, Mexico and Peru respectively. Negative deviations from simple UIP arise in crisis periods, mostly, i.e. high interest rate differentials accompanied by high ex-post devaluations, which may suggest that the relationship between ex-post devaluations and policy rate differentials shifts in times of crises. In fact, Flood and Rose (2001) finds that simple UIP holds during crises.

Furthermore, the appetite for risk of international investors, i.e. the spread between BAA corporate bonds and US treasuries, is an important exogenous determinant of country risk in small open economies. As a matter of fact, the bottom-right panel of Figure B.4, which depicts the evolution of this appetite, shows a strong correlation between this appetite for risk and EMBI spreads in all countries but Brazil. These results agree with the findings of Nirei and Sushko (2011) since VIX and this appetite are closely related.

Therefore, a direct relationship between the exogenous appetite for risk of international investors and policy rate differentials arises. Figure B.5 summarizes the relationship between these indicators through the cross correlation function (left hand side panels), the

[8] Under strong assumptions OLS is a consistent estimate of the slope. However, we take these results are indicative.

[9] The estimated equation $s_{t+k} - s_t = \beta_0 + \beta_1(R_{t,t+k} - R^*_{t,t+k})$

spectral densities (center panels), and squared coherences (right panels). An important empirical fact arises from this figure: lagged and current appetite for risk correlates positively and significantly with current policy rate differentials. These correlations are not only significant and positive, but also moderate to large (between 0.4 and 0.8), for Chile, Colombia and Peru, and small but statistically significant in the biggest countries, Brazil and Mexico. Furthermore, the similarity between the spectral densities of interest rate differentials and risk appetite (panels in the middle of Figure B.5) show that the distribution of the unconditional variance along frequencies is similar between the exogenous appetite for risk of international investors and policy rate differentials. And finally, the fact that the contemporary square coherences (right hand side panels of Figure B.5) looks flat, imply that these correlations spread evenly across frequencies. Therefore, a positive, significant, and evenly distributed correlation among frequencies between the exogenous appetite for risk of international investors and policy rate differentials arises only for the small open economies in our sample.

Summarizing, the NER return distributions under study are skewed, which seems to be explained by carry trade from high yield currencies as reported by Nirei and Sushko (2011) for the case of Japan. This implies, in turn, a close relationship between interest rate differentials and future depreciation rates, which is also observed in our sample. Thus, our NERs obey some form of UIP. On the other hand, the existence of risk premium implies a close co-movement between interest rate differentials and EMBI spreads, which is also observed in our countries. Since small open economies country risk depends on the exogenous international investors appetite for risk, this finally implies that shifts in this appetite lead to NER return skewness. Therefore, our results point out to carry trade and risk aversion as the source of skewness shifts and, thus, to the presence of unconditional return skewness.

***Stylized Fact 3*: Unconditional return distributions tend to have non-positive medians and the corresponding NER return processes display a negative non-significant drift**.

Median returns in Table A.2 range from -1.96% for MXN/USD to zero for CLP/USD, but the median PEN/USD return is the only one statistically different from zero. Mean returns, in contrast, are greater than or equal to zero for all NREs but PEN/USD. This result is consistent with the degree of skewness found above for all countries but Brazil, and suggests that NER drift are small. In fact, the estimated drift parameter of EGARCH$(1, 1)$ processes on NER returns in Table A.2 are significant, although negative and small. More specifically, Brazil's NER model reports the highest absolute drift, 2.4, and Colombia the lowest, 0.54, which seems to be consistent with the appreciation trend observed in our NERs. Therefore, this non-zero drift is likely sample dependent, implying that the long-term drift of the NERs processes is zero, a result consistent with Moosa and Bhatti (2010, pp. 7).

Therefore, if our NERs were drift-less random walks, they would be dominated by long-run swings, from appreciation to depreciation, of random duration and amplitude, which contrast sharply with the ones observed in trending crawling pegs or bands. See Moosa and Bhatti (2010) and Jondeau, Poon, and Rockinger (2007, Ch. 2), for instance.

In brief, despite the fact that median returns tend to be non-significant and negative, the estimated drift return parameters are significantly negative but small. However, the sign and size of these drifts arise from a sample that covers a single appreciation run. Thus, our NERs might likely be drift-less processes. As a result, were our NER processes behave as random walks, they would follow the efficient market hypothesis, and they would be dominated by long-term swings, from appreciation to depreciation, of random duration and amplitude, which agrees with the results of Moosa and Bhatti (2010, pp. 7) for NERs in developed countries.

3.2 The unconditional distribution of absolute returns

***Stylized Fact 4*: The unconditional distributions of absolute returns, i.e. the unconditional volatility distributions, follow inverse cubic laws that may be related to non-stationarities in the volatility process**.

This fact follows from the following observations.

Fist, the return volatility process has thick tails. As a matter of fact, absolute return tails decay slowly for all currencies in the sample but CLP/USD, whose tail decay is the fastest, as can be observed in Table A.3. Furthermore, Hill estimates on the left hand side panels of Figure B.1 show that IPL tail indexes do not seem to be statistically different from three, with slight variations among them, specially for CLP/USD. Therefore, return volatility processes follow near inverse cubic laws.

This stylized fact relates to the first one above and its source is thus similar. In fact, higher return moments correlation, especially volatility clustering, explains at least partially the occurrence of high return tails according to Haas and Pigorsch (2011, pp. 35), Sheikh and Qiao (2009) and Lin et al. (2012). Thus, the source of thick return and absolute return tails is closely related.

Third, according to Mikosch and Starica (2004), this fact relates with two common features of absolute and square returns that have to do with a type of non-stationarity related to unconditional variance shifts, which may imply the existence of long-range volatility dependence and IGARCH effects. We will explore these issues below.

3.3 The conditional distribution of returns and absolute returns

***Stylized Fact 5*: As far as (linear) autocorrelation goes, and regardless of the**

sampling frequency (daily, weekly, monthly or quarterly), NER returns behave as white noise, which support the existence of a "weak" form of the "efficient markets hypothesis". Furthermore, long-range return dependence does not seem to be important.

The (linear) autocorrelation and partial autocorrelation functions of NER returns display the features of "white noise" processes regardless of the measurement frequency. Under the assumption that the process driving returns is linear, i.e. can be approximated arbitrarily well by a member of the ARIMA family, Auto Correlation and Partial Auto Correlation Functions, ACF and PACF, identify the polynomial orders of these processes. The diagonal panels of Figures B.6 to B.9 and the corresponding panels in Figures B.10 to B.13 depict the sample ACF and PACF functions of NER returns. The diagonal panels in the first set of these Figures show that return autocorrelation is small and not significant, suggesting that no linear dynamics seems to be present in return processes regardless of the measurement frequency. This result is confirmed in the diagonal panels in the second set of Figures, which show non-significant and small partial autocorrelations also. Therefore, regardless of the sampling frequency NER returns show the dynamic features of white noise.

This finding supports the existence of a "weak" form of the efficient markets hypothesis (i.e. best linear forecast based on past return information), and the dominance of long-range random appreciation and depreciation cycles. As a matter of fact, this result amounts to say that any linear non-stationarity present in log NERs reduces by differencing, and thus the best linear log NER forecast is the last observed corrected by its drift. As a result, past return information conveys no information gain over naive forecasts and supports the random walk hypothesis of NERs. And therefore, NERs variation along the time is dominated by appreciation-depreciation swigs of random amplitude and length when the drift parameter is zero. See Moosa and Bhatti (2010), for instance.

Furthermore, these NERs seem to show evidence of anti-persistence. To explore this issue we estimate the Hurst (1951) and Hurst (1955), H exponent, a measure of long-range dependence. Contrary to short-term dependence, where autocorrelations decay exponentially fast, under long-range dependence, observations far apart may be correlated. A value $0.5 < H < 1$ indicates the existence of long-range dependence and implies that a large time series value will likely be followed by similarly large values, and that large values of the same sign will be observed into the future. However, if $0 < H < 0.5$ the process is deemed anti-persistent and implies that large values are likely followed by large negative ones, and this switching pattern is long lasting. Therefore, these processes fluctuate intensely. Finally, the case $H = 0.5$ is consistent with a exponentially decaying autocorrelation function, i.e. a short memory process. See Maldelbrot (2002).

We estimate the Hurst exponent H through the process' fractal dimension, D, Maldelbrot (1967), being the latter a measure of time series roughness. Furthermore, as these quantities relate through the equation $H = 2 - D$, they convey the same information. Figure B.14 shows the estimated "madograms" (Gneiting, Sevcikova, and Percival (2012)), and their corresponding fractal dimensions for our five NER return series. The estimated dimensions range from 1.95 for Chile to 1.98 for Peru, with slight variations among NERs. These estimates are slightly below but close to 2, which result in Hurst exponent estimates ranging from 0.02 to 0.05. These results strongly suggest the existence of anti-persistence and nicely match the findings of Barkoulas, Baum, Caglayan, and Chakraborty (2004) regarding the lack of long-range dependence of NER returns in eighteen developed countries.

Therefore, these results along with those about the ordinary and partial autocorrelation functions imply the existence of some form of weak foreign exchange market efficiency in our currencies. As a result, adjusting ARFIMA type of models may not necessarily yield return forecast improvements. However, these results along with the excess return volatility and return tails may have self-similarity implications.

***Stylized Fact 6*: There does not seem to be evidence in favour of long-range absolute return dependence and some evidence in favour of IGARCH effects**.

The diagonal panels of Figure B.15 display the sample ordinary autocorrelation of absolute daily NER returns for the five countries under analysis. These panels reveal a moderate short lag correlation below 0.5 with extremely slowly decaying tails which suggest long-range NER return volatility persistence.

The diagonal panels in Figure B.16 display the sample partial autocorrelation of absolute daily NER returns for the five countries in the sample. Partial autocorrelations decay very fast to become borderline significant after just a few lags, which seems to be consistent with long-range dependence.

However, these results might be misleading as Mikosch and Starica (2000) showed that under IGARCH effects, estimated autocorrelation functions are unreliable and, therefore, evidence on long-range dependence should be addressed by other methods. In fact, long-range dependence, according to Cont (2005), has to do with the existence of a PL, i.e. a polynomially decaying ACF of absolute returns. For instance, a GARCH$(1,1)$ model of the form

$$\begin{aligned} Y_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha\sigma_{t-1}^2 + b\epsilon^2 \quad 0 < a + b \leq 1 \end{aligned} \tag{5}$$

leads to positive autocorrelation in the volatility process σ_t and a ACF decay to depend on $a+b$. The closer $a+b$ is to one the slower the autocorrelation decay. For instance, when $a + b < 1$ a stationary solution to this equation exists, whereas when $a + b = 1$ integrated volatility arises.

Unit root test results in Table **??** provides some evidence in favour of absolute returns having a unit root. As a matter of fact, KPSS test results show that the null of absolute return stationarity is rejected in favour of the presence of a unit root in all our currencies at any level below 0.05, but the null of stationarity is not rejected in any country either. However, the unit root null in Phillips-Perron test is strongly rejected in both cases. Therefore, the volatility process of our five currencies seem to be integrated of order one, but this evidence is not strong as KPSS and Phillips-Perron tests results do not agree.

Evidence from absolute returns spectral functions also indicates the presence of a unit root. As a matter of fact, absolute returns spectra (diagonal panels) in Figure B.17 at frequency zero are extremely high, which is consistent with the process having an infinite very-long-run variance, i.e. a unit root. Therefore, this evidence supports the existence of IGARCH effects.

However, the volatility processes underlying our five NERs seem to be anti-persistent, which discards any evidence in favour of long-range dependence. As a matter of fact, although the Hill tail index estimates of the left hand side panels in Figure B.1 could suggest the existence of long-range dependence, the madograms in figure B.18 show that their estimated fractal dimension, D, is very close to 2. This, according to our discussion above, leads to very small Husrt exponent estimates which suggest, on the contrary, anti-persistence. This result seem to agree (with the caveats on estimated auto-correlations mentioned above) with absolute return auto-correlations that are small (and positive) at small lags, slowly decaying and very small at long lags. In fact, Hurst estimates strongly suggest that the volatility processes shift intensely from low to high volatility runs, and that these runs are therefore short lived.

Summarizing, absolute returns ordinary sample autocorrelations are moderate at small lags and decay slowly thereafter, while their sample partial autocorrelations decay very fast to become borderline significant at long lags. These results might convey some evidence in favour of long-range absolute return dependence. However, since Mikosch and Starica (2000) showed that autocorrelations estimates are unreliable under IGARCH, we explore absolute returns unit root tests and spectral density estimates. Unit root tests seem to suggests that NERs volatility processes are integrated, but this evidence is not strong as the results of different tests disagree. Estimated absolute return spectra are, in turn, extremely high at frequency zero, i.e. the variance share of very-long-run periodic fluctuations of absolute returns is infinite, which amounts to absolute return unit root and, therefore, to the existence of IGARCH effects. However, Hurst exponent estimates suggest that the volatility processes underlying our NERs shift intensely from low to high volatility runs, and that these runs are thus short lived. Therefore, IGARCH models might be suitable empirical alternatives to model this kind of volatility dependence, thus improving return volatility forecasts.

Stylized Fact 7**: There is high cross contemporary correlation among returns**

of different countries.

The off-diagonal panels of Figure B.15 display the cross-correlation functions of absolute daily NER returns in the five countries under analysis. The cross correlation functions peak around lag 0, with correlations below 0.5, which suggest an immediate or very fast transmission of volatility shocks among currencies. However, these cross-correlations are remarkably moderate. Furthermore, the highest cross correlation, which is slightly greater than 0.5 happens between the biggest countries, Brazil and Mexico, followed by the correlation between Chile and Mexico, Brazil and Chile, and Colombia and Mexico.

In turn, the off-diagonal panels in Figure B.16 display the sample partial cross-correlation functions of absolute daily NER returns for the five countries in the sample. Sample partial cross-correlations become borderline significant or non-significant for long lags.

However, these results are easily challenged, as above, because of Mikosch and Starica (2000) findings, and thus the spectral function might shed light on the co-dependence nature of the processes involved. Evidence on the coherence of absolute returns suggests the existence of contemporary relationships that spread along all the range of frequencies. In fact, sample coherence functions in Figure B.17, do not reveal systematic coherence accumulation around specific frequencies. Therefore correlation between absolute returns spread evenly along all frequencies.

Summarizing, cross ACF and PACFs of absolute returns are consistent with moderate contemporary volatility co-variation. These co-movements spread evenly along the frequency dimension, i.e. along all the range of periodic movements. Furthermore, risk transmission is stronger between big countries and weaker between small ones, and risk events in big countries, Brazil and Mexico, seem to transmit to smaller ones, being Peru and Colombia the last countries to respond, in this order. Therefore, our results constitute evidence in favour of stronger risk transmission from big to small countries than otherwise.

3.4 Time series properties

***Stylized Fact 8*: There is strong evidence in favour of NER unit root behaviour and return stationarity**.

Even though unit root test results have important power drawbacks, there is strong evidence in favour of log NERs having a unit root, more specifically, they are likely driftless random walks. In Table A.7 a combination of KPSS and Dickey-Fuller type of tests, as suggested in time series literature, unanimously supports the existence of a unit root in log NERs and the stationarity of returns. KPSS test for stationarity of log NER are rejected and Phillips-Perron unit root hypothesis are not rejected at a 5% level. In addition, the results of these tests on log differences show the non-rejection of the KPSS stationarity null and the rejection of the unit root under Phillips-Perron. Therefore, our statistical evidence suggests the existence of unit a root in log NERs and return stationarity.

Moreover, forecast performance evaluation of structural models and economic intuition supports these findings, more specifically that floating NERs follow drift-less random walks. In fact, it is widely known that forecasts derived from structural models do not outperform naive forecasts obtained from a random walk: $\log(NER_{t|t-1}) = \log(NER_{t-1}) + \mu$, where the drift parameter μ is usually 0. Thus, the unit root property of nominal exchange rates supports the efficient markets hypothesis. As a result, daily returns comprise the unanticipated components of the NER at time t, i.e. returns are driven by news surprises. Therefore, the Foreign Exchange market, FX, is viewed by many authors as a "fair game", making the random walk hypothesis a no arbitrage condition. See James et al. (2012, Ch. 4), for instance.

An important consequence of the unit root property of NER is that the response of $\log(NER_t)$ to a one time surprise is permanent (i.e. a step function) regardless of any (usually very small) return autocorrelation remaining. Therefore, surprises have long-term effect on $\log(NER_t)$, i.e. step functions[10].

A second important implication of the drift-less unit root property of our NERs is that their long-term trend is composed of appreciation and depreciation swings of random amplitude and length. As pointed out above, this contrast sharply with the behaviour of nominal exchange rates under trending crawling pegs or bands, or from the increasing long-term trend of other macro variables with unit roots such as GDP or CPI.

***Stylized Fact 9*: However, these very long-term appreciation and depreciation swings are dominated by cycles (i.e. periodic movements beyond 1 year but shorter than the long-term trend), in Brazil, Chile and Colombia, while the opposite happens in Mexico and Peru. Moreover, very short-term fluctuations have a rather limited effect on the non-stationary component of our NERs and, therefore, they might not be of interest to macro-economists and medium to long-term-portfolio managers as they are related to the short-term volatility process**.

Figures B.19 to B.23 display the spectral decomposition of log NERs (left-hand side panels), their cumulative spectral decomposition (middle panels), and the cumulative spectral decomposition of absolute returns (right-hand side panels), for each country in the sample. From top to bottom the left-hand side panels depict (a) the "long-term trend", (b) long-term "cycles" with a period higher than 5 years, (c) short-term "cycles" with a

[10] In practice, slight return autocorrelation may remain due to operational factors or trading costs. This autocorrelation is otherwise unimportant for modelling or trading as it induces as very low coefficients of low order AR or MA polynomials, thus negligibly affecting the response of $\log(NER_t)$ to unexpected shocks.

period between 1 and 5 years, (d) and the remaining very short-term "seasonal and noise" component, i.e. cycles between two days and one year. The panels to the center of each figure display the cumulative spectral decomposition so that the bottom center panel is the corresponding NER. Finally, the right hand side panels show the cumulative spectral decomposition of absolute daily returns and thus, the bottom right panel portrays the absolute return dynamics. The following results can be derived from these figures.

The long-term NER trend is dominated by cycles in Brazil, Chile and Colombia, while the opposite happens in Mexico and Peru. As a matter of fact, the left-hand side panels of these figures show that the range of the long-term trend in Brazil and Chile is about half the combined ranges of short and long-term cycles, while the latter is 20% higher than the former in Colombia. Thus, there seems to be a clear dominance of cycles over long-term trends in these countries. In Mexico and Peru, however, the long-term trend dominates the combined cyclic movements by a factor bigger than 10. Thus, there is marked difference between the two sets of countries regarding the components that dominance NER fluctuations.

By definition, very short-term seasonal and noise fluctuations play a very limited role in explaining the non-stationary component of our NERs, and are related to short-term volatility. In fact, the range of periodic fluctuations less than one year long is extremely small when compared to the combined range of short to long-term cycles in all countries. As a result, these fluctuations might be of little importance for macro-economists and medium to long-term portfolio managers, but are important for risk managers.

On the whole, the range of combined cyclical movements in Brazil, Chile and Colombia is bigger than the range of their long-term trends establishing a dominance of the former over the latter. However, the opposite happens in Mexico and Peru. This result shows a clear difference between the two sets of countries. Furthermore, seasonal and noise fluctuations might not be of interest to portfolio managers on medium to long-term portfolio tranches or to macro-economists.

***Stylized Fact 10*: The corresponding components of different NERs show co-movement whose degree increases as their associated frequencies reduce. These results may suggest the existence of common factors explaining the long-term trend and cycles of our NERs**.

A high degree of co-movement is observed between the corresponding components of our NERs, especially in trend differences. Contemporary correlations between NERs trend differences in the top panel of Table A.8 range between an absolute minimum of -0.19 for COP/USD and MXN/USD and a maximum of $0.9977 \propto 1$, between CLP/USD and PEN/USD[11]. Remarkably, MXN/USD trend difference correlates negatively with the remaining trend differences, and these correlations tend to be smaller than the ones observed

[11] A preliminary co-integration analysis shows no long-run trend co-movement among our NERs and thus

among the rest of NERs, more particularly, those related with BRL/USD. As a result, the smaller countries seem to be detached (at least trend-wise) from Mexico, while they seem to be more attached to Brazil.

Furthermore, high contemporary correlations are observed among long-term cycles. In fact, BRL/USD and COP/USD long-term cycle correlation reaches 0.98, followed closely by the correlation between CLP/USD and COP/USD and between BRL/USD and CLP/USD, 0.84 and 0.78, respectively. However, the correlation between MXN/USD and PEN/USD and with the remaining NERs reach a moderate maximum of just 0.64 between COP/USD and MXN/USD long-term cycles.

Additionally, moderate and more uniform correlation among the short-term cycles of our NERs are also observed; the highest arises between COP/USD and PEN/USD short-term cycles 0.71, and the lowest 0.52 for PEN/USD with BRL/USD and MXN/USD short-term cycles.

Finally, small correlations arise between the seasonal and short-run noise component of the NERs in our sample ranging from 0.29 to 0.59.

Therefore, contemporary component correlations tend to increase as the components frequencies reduce, and two groups of countries with different behaviour seem to arise. As a result, there seems to be some evidence in favour of the existence of strong medium to long-term NER co-movement likely derived from a common external source. By combining these results with the second stylized fact, the common source of NER fluctuations should involve the risk appetite of international investors and the US monetary policy with respect to the local one. Therefore, our results suggest not only the existence of common cyclical factors in the explanation of NER fluctuations.

Stylized Fact 11**: Our NERs follow a pattern of busts, i.e. sudden local currency depreciations, followed by slow recoveries associated to cycles, i.e. non-symmetric cycles**.

The most important share of stationary NER fluctuations has to do with cycles, particularly short-term ones, which become a key source of NER raggedness and uncertainty. The left-hand and center panels of Figures B.19 to B.23 show that short-term cycle fluctuations are amplified when (co) related to the ups and downs of long-term ones, leading to sudden depreciations and slow recoveries. In other words, the interplay of short and long-term cycles, and to some extent the trend, induces NER cycle asymmetry. Similar results reported by Haas and Pigorsch (2011) suggest that non-symmetric cycles are widespread in NERs.

trend differences are utilized in the top panel of Table A.8. However, an equally preliminary impulse response analysis indicates that Granger causality goes from Brazil and Mexico towards the smaller countries. Further work will shed more light on this issue.

In brief, an important share of our NER fluctuations has to do with short to log-term cycles, being the former a key source of NER raggedness and uncertainty. Additionally, the NREs in our sample display a pattern of busts and slow recoveries related to the cyclic components, which induces cycle non-symmetry, a stylized fact of the NERs in free floating developed countries.

3.5 Relationship between NER's and selected financial and macroeconomic indicators

***Stylized Fact 12*: The cycles of our NERs are not clearly related to the output gap of the countries involved in the exchange**.

Each panel in Figure B.24 displays the quarterly NER cycle component (continuous black line with scale on the left vertical axis), and the US and local country GDP gaps (blue and red dashed lines, respectively, with scale on the vertical axis to the right). In this Figure the NER gap is the deviation of the log NER from a Hodrick-Prescott filter[12].

Contrary to stock market cycles, NER ones do not seem to relate strongly with the business cycle of the countries involved in the exchange. As a matter of fact, Figure B.24 and Table A.9 show that correlations are moderate, at most, between output and NER gaps. The correlation between the NER gap and US output gap is negative, with a moderate absolute maximum of 0.41 for Chile, and below 0.25 in absolute value otherwise. The correlation between NER gaps and local GDP gaps are negative with surprising moderately high absolute values of 0.62 and 0.65 for Brazil and Chile, respectively, and below 0.23 otherwise. Therefore, nominal exchange rate gaps do not seem to relate in a simple manner to local or US business cycles. However, the surprisingly high correlation between de Chilean and Brazilian NER gaps with their corresponding output gaps is noteworthy.

However, as pointed in the second stylized fact, there seems to be a relationship between our NERs with policy rate differentials with respect to the US and the appetite for risk of international investors.

4 Conclusion

In this paper we set out to explore the stylized facts of the NERs in five LATAM countries and to interpret those to the light of more recent literature. A second set of not commonly explored facts was also studied. The dataset under analysis comprises daily NERs

[12]The smoothness parameter was $\lambda_f = s^4\lambda_q$, where $\lambda_q = 1600$ is the parameter for quarterly series and $s = 1$ is the sampling frequency in a quarter, as recommended by Ravn and Uhlig (2002). For the different sampling frequencies, with adequate values for s, the estimated components are almost identical.

measures, various macro financial indicators such as policy rates and risk measurements, as well quarterly GDP gap measures for a period of time when these countries pursued some form of inflation targeting with differing degrees of discretionary FOREX market intervention. The countries include in this analysis are sufficiently similar to ensure that common stylized facts arise, and different enough to guarantee both, the robustness of our results and idiosyncratic facts to emerge.

The main conclusions can be summarized as follows:

1. One of the most important and less understood facts of NER returns is excess kurtosis. Two important insights are worth mentioning regarding return kurtosis. Firstly, excess return kurtosis relates to the existence of inverse power laws on return distribution tails with *tail indexes* near or below three. These laws are widely occurring *empirical regularities* of (return) distributions, and for this reason their explanation is required to be "robust" to the parameters and details of the system (market) they arise from. In the case of financial markets, for instance, it has been proposed that they result from the violation of the limited dependence assumption underlying the central limit theorem, and as a result, financial prices and returns look chaotic and non-linear, similar to a self organized system such as the formation of a pile of sand. Although higher return moment auto-correlation (a celebrated feature of GARCH models) and Gaussian mixtures (derived from TAR, SETAR and Hidden Markov Models) may explain some of the returns tails height, it is still required to assume high tail innovation distributions for models to reproduce the observed tail return heights. According to Haldane (2012) the lack of understanding of the causes of this behaviour in the stock market led supervisors to become tolerant to high risk states and issue "well-meant but imperfect regulations", which led to the 2007 global financial crises.

   And secondly, important differences among the tail decays of the five NERs were found. The most important is the very high left PEN/USD tail, $\alpha \approx 2$. This result fits nicely the findings of Haas and Pigorsch (2011) who report that under free float $\alpha \approx 3$, and under fixed exchange rates $\alpha \leq 2$. These differences are, in turn, explained by the physics "universality principle" which states that thermodynamic systems with different tail indexes have very distinctive dynamics. Therefore, different types of models might be required for PEN/USD returns in contrast to the returns other countries.

2. NER return skewness seems to be explained by carry trade and by international investors risk aversion. Similar results were reported by Nirei and Sushko (2011) for the case of Japan. In our countries, a close relationship between policy rate differentials and future rates of devaluation were observed, which implies that they obey some form of UIP. On the other hand, the existence of risk premium implies

both, a close co-movement between interest rate differentials and EMBI spreads, which is also observed in our countries, and positive UIP deviations, which also arise in our analysis. Furthermore, since the country risk of the small economies under consideration relates to the exogenous appetite for risk of international investors, shifts in this appetite lead to NER return skewness. Therefore, some form of extended UIP underlie our NERs, which transmit through return skewness and kurtosis shifts.

3. While median returns tend to be negative and non-significant, estimated drift return parameters are significantly negative but small. However, the sign and size of these drifts are likely the result of the sample period, and thus our NERs might be drift-less processes. If these NER processes were random walks, they would not only follow the efficient market hypothesis, but also their very long-term trend components would be dominated by very long-term swings, from appreciation to depreciation, of random duration and amplitude. These results agree with the findings in Moosa and Bhatti (2010, pp. 7) for NERs in developed countries.

4. The unconditional distributions of absolute returns, i.e. the unconditional volatility distributions, follow inverse cubic laws. The explanation to this behaviour is the same as in stylized fact one. Furthermore, according to Mikosch and Starica (2004), this fact relates to two common features of absolute and square returns that have to do with a type of non-stationarity related to unconditional variance shifts. These shifts give rise to Long-Range volatility dependence and IGARCH effects.

5. As far as (linear) autocorrelation goes, and regardless of the measurement frequency (daily, weekly, monthly or quarterly), NER returns behave as white noise, which support the existence of a "weak" form of the "efficient markets hypothesis", in the sense of the best linear forecast based on past information. Furthermore, long-range return dependence does not seem to be an issue. As a result, adjusting ARFIMA type of models may not necessarily yield return forecast improvements. However, returns show important signs of anti-persistence (large negative returns are followed by large positive returns, and this pattern repeats over very log horizons), which leads returns to shift signs frantically. This makes NER returns behave differently from ordinary linear drift-less random walks. As a result, these results together with excess return volatility and long return tails may have self similarity implications.

6. Risk transmission is stronger between big countries and weaker between small ones, and risk events in big countries, Brazil and Mexico, seem to transmit to smaller ones, being the last countries to respond Peru and Colombia in this order. Therefore, our results above constitute evidence in favour of stronger risk transmission from big to small countries than otherwise.

7. There is strong evidence in favour of NER unit root behaviour and return stationarity. An important consequence of the unit root property of NER is that the response of

$\log(NER_t)$ to a one time surprise is permanent (i.e. a step function) regardless of any (usually very small) return autocorrelation remaining. Therefore, surprises have long-term effect on $\log(NER_t)$, i.e. the response is a step function. A second implication of the drift-less unit root property of our NERs is that they follow a very long-term trend composed of appreciation and depreciation swings of random amplitude and length. This behaviour stands as opposite to nominal exchange rate regimes such as trending crawling pegs or bands.

8. Unit root tests and spectral density estimates suggest that NERs volatility processes are integrated. However, Hurst exponent estimates are consistent with intensely shifting volatility (i.e volatility anti-persistence) from low to high volatility runs, and that these runs are short lived as a result. Therefore, IGARCH models might be suitable empirical alternatives to model this kind of volatility dependence, which may improve return volatility forecasts.

9. However, these very long-term appreciation and depreciation swings are dominated by ragged cycles, i.e. periodic movements beyond 1 year and shorter than the long-term trend, in Brazil, Chile and Colombia, while the opposite happens in Mexico and Peru. This result shows a clear difference between the two sets of countries. As a result, short-term noise and seasonal might not be of interest to portfolio managers on medium to long-term portfolio tranches or to macro-economists, but are key to risk managers.

10. Contemporary NERs component correlations between countries tend to increase as the component frequencies reduce, and two groups of countries with different behaviour seem to arise. This constitutes evidence in favour of the existence of strong medium to long-term NER co-movement and the existence of common cyclical external sources of NER fluctuations. Adding these results to the second stylized fact, may imply that the common source (factor) of NER fluctuations should involve the risk appetite of international investors and local monetary policy with respect to the US policy.

11. Our NERs follow a pattern of busts, i.e. sudden local currency depreciations, followed by slow recoveries associated to cycles. In other words, when short and long-term cycles are combined (sometimes including thye trend as well) a pattern of sudden depreciations arises, which are generally followed by slow recoveries inducing cycle asymmetry. Short-term cycles, in particular, are a key source of NER raggedness and uncertainty. Similar results reported by Haas and Pigorsch (2011) suggest that non-symmetric cycles are widespread in NERs.

12. Nominal exchange rate gaps do not seem to relate in a simple manner to local or US business cycles. However, a surprising correlation arises in Brazil and Chile with local GDP gaps. However, as pointed in the second stylized fact, there seems to be a

relationship between our NERs with policy rate differentials with respect to the US and the appetite for risk of international investors.

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Appendices

A Tables

Table A.1: Data description, code and source

Name	Code	Source	Start	End	Freq.
Brazilian Reals per USD	BRL/USD	Antweiler (2014)	2000-01-04	2014-04-30	Daily
Chilean Pesos per USD	CLP/USD	Antweiler (2014)	2000-01-04	2014-04-30	Daily
Colombian Pesos per USD	COP/USD	Antweiler (2014)	2000-01-04	2014-04-30	Daily
Mexican Pesos per USD	MXN/USD	Antweiler (2014)	2000-01-04	2014-04-30	Daily
Peruvian New Sols per USD	PEN/USD	Antweiler (2014)	2000-01-04	2014-04-30	Daily
EMBI Brazil	EMBI Brazil	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
EMBI Chile	EMBI Chile	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
EMBI Colombia	EMBI Colombia	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
EMBI Mexico	EMBI Mexico	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
EMBI Peru	EMBI Peru	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
Policy Rate Brazil	SELIC	`http://www.bcb.gov.br`	2000-01-04	2014-04-30	Daily
Policy Rate Chile	TPM	Bloomberg L. P.	2000-01-04	2014-04-30	Daily
Policy Rate Colombia	TPM	`http://www.banrep.gov.co`	2000-01-04	2014-04-30	Daily
Policy Rate Mexico	TFB	`http://www.banxico.org.mx`	2000-01-04	2014-04-30	Daily
Policy Rate Peru	TPM	`http://www.bcrp.gob.pe`	2000-01-04	2014-04-30	Daily
Policy Rate US	Federal Funds Rate	FRED Saint Louis FED	2000-01-04	2014-04-30	Daily
Moodie's BAA Corporate Bonds	DBAA	FRED Saint Louis FED	2000-01-04	2014-04-30	Daily
20Y Treasury Rate	Federal Funds Rate	FRED Saint Louis FED	2000-01-04	2014-04-30	Daily
Real GDP Gap Brazil	H-P Filter	GDP from FRED Saint Louis FED	2000-Q1	2014-Q1	Quarterly
Real GDP Gap Chile	H-P Filter	GDP from FRED Saint Louis FED	2000-Q1	2014-Q1	Quarterly
Real GDP Gap Colombia	Filter	BANCO DE LA REPUBLICA	2000-Q1	2014-Q1	Quarterly
Real GDP Gap Mexico	H-P Filter	GDP from FRED Saint Louis FED	2000-Q1	2014-Q1	Quarterly
Real GDP Gap Peru	H-P Filter	GDP from `http://www.bcrp.gob.pe`	2000-Q1	2014-Q1	Quarterly

Source: Complied by the Author.

Table A.2: Unconditional distribution of daily nominal exchange rate returns.

	Exchange Rate				
Satatistic	BRL/USD	CLP/USD	COP/USD	MXN/USD	PEN/USD
Minimum	-1015.57	-343.91	-621.13	-613.11	-415.11
1 Quartile	-48.00	-34.23	-28.08	-33.67	-9.98
Median[1]	-1.70	0.00	-1.28	-1.96	-0.89***
3 Quartile	47.97	32.58	26.96	31.59	7.53
Maximum	761.32	468.38	496.06	825.57	669.66
Mean[2]	0.54	0.18	0.04	0.90	-0.63
Sd. Deviation	102.64	64.59	66.42	65.33	30.95
Skew[2]	-0.12***	0.53***	0.22***	0.71***	2.13***
Ex. Kurtosis[2]	10.94***	4.80***	9.61***	15.36***	78.83***
Drift[3]	-2.40**	-0.54**	-0.98**	-1.70**	-0.86**
Sample size	3593	3593	3593	3593	3593

(***) (**) (*) Denotes statistical significance at 1%, 5% and 10% level.
[1] Zero location Wilcoxon's signed rank test.
[2] T test.
[3] Intercept of an EGARCH(1,1) returns process with Generalized Error Distribution innovations.
Source: author's calculations.

Table A.3: Estimated probability (%) of extreme daily returns for each currency: $P\left(|Y_t - E[Y_t]| > k\sigma_y\right)$

	k						
	2	3	4	5	6	7	8
BRL/USD	4.286	1.642	0.835	0.390	0.167	0.139	0.056
CLP/USD	4.815	1.280	0.501	0.278	0.111	0.028	0.000
COP/USD	5.344	1.753	0.751	0.390	0.195	0.111	0.028
MXN/USD	4.258	1.392	0.696	0.417	0.167	0.139	0.056
PEN/USD	4.676	1.781	0.724	0.390	0.223	0.139	0.111
z	4.550	0.270	0.006	0.000	0.000	0.000	0.000

Source: Author's calculations.

Table A.4: Unit root test for daily absolute returns and their differences.

Test	BRL/USD	CLP/USD	COP/USD	MXN/USD	PEN/USD
Abs. returns $\lvert y_t \rvert$					
KPSS	0.59^{**}	1.07^{***}	2.84^{***}	2.45^{***}	1.12^{***}
Phillips-Perron	$-3{,}432.96^{***}$	$-4{,}571.64^{***}$	$-3{,}901.70^{***}$	$-3{,}682.28^{***}$	$-3{,}041.48^{***}$
Diff. $(\lvert y_t \rvert - \lvert y_{t-1} \rvert)$					
KPSS	0.00	0.00	0.00	0.00	0.00
Phillips-Perron	$-4{,}213.69^{***}$	$-4{,}377.31^{***}$	$-4{,}234.24^{***}$	$-4{,}330.92^{***}$	$-4{,}310.99^{***}$

$^{(***)}$ $^{(**)}$ $^{(*)}$ Denotes rejection of the null hypothesis at the 1%, 5% and 10% significance level.

Source: Author's calculations.

Table A.5: Estimated probability (%) of extreme signed daily returns for each currency: $P\left[(Y_t - E[Y_t]) > k\sigma_y\right]$ and $P\left[(Y_t - E[Y_t]) < -k\sigma_y\right]$

		k						
		2	3	4	5	6	7	8
BRL/USD	+	2.394	0.835	0.473	0.195	0.083	0.056	0.000
	−	1.893	0.807	0.362	0.195	0.083	0.083	0.056
CLP/USD	+	2.728	0.835	0.362	0.195	0.111	0.028	0.000
	−	2.087	0.445	0.139	0.083	0.000	0.000	0.000
COP/USD	+	2.728	1.030	0.501	0.223	0.139	0.056	0.000
	−	2.616	0.724	0.250	0.167	0.056	0.056	0.028
MXN/USD	+	2.421	0.724	0.445	0.223	0.111	0.083	0.028
	−	1.837	0.668	0.250	0.195	0.056	0.056	0.028
PEN/USD	+	2.588	0.974	0.334	0.167	0.111	0.083	0.056
	−	2.087	0.807	0.390	0.223	0.111	0.056	0.056
z	±	2.275	0.135	0.003	0.000	0.000	0.000	0.000

Source: Author's calculations.

Table A.6: Daily returns non linearity BDS-test results.

	m		
ϵ	3	5	7
BRL/USD			
$\hat{\sigma}_y$	22.40*	31.32*	40.99*
$2\hat{\sigma}_y$	23.20*	26.79*	28.62*
CLP/USD			
$\hat{\sigma}_y$	14.90*	21.04*	28.45*
$2\hat{\sigma}_y$	15.77*	19.06*	20.95*
COP/USD			
$\hat{\sigma}_y$	23.81*	32.12*	41.94*
$2\hat{\sigma}_y$	22.31*	25.38*	27.57*
MXN/USD			
$\hat{\sigma}_y$	16.57*	23.51*	29.83*
$2\hat{\sigma}_y$	18.21*	21.97*	23.75*
PEN/USD			
$\hat{\sigma}_y$	27.59*	34.79*	42.29*
$2\hat{\sigma}_y$	19.02*	21.72*	23.38*

(*) Denotes rejection of the null hypothesis at the 1% significance level.

Source: Author's calculations.

Table A.7: Unit root test results for daily exchange rates and returns.

Test	BRL/USD	CLP/USD	COP/USD	MXN/USD	PEN/USD
$s_t = \log(S_t)$					
KPSS	12.43***	18.54***	20.77***	27.68***	33.61***
KPSS (Trend)	3.08***	1.65***	2.99***	0.94***	2.18***
Phillips-Perron	-1.51	-1.66	-1.43	-1.66	-0.98
P-P (Trend)	-1.90	-2.30	-2.86	-3.12	-2.36
Returns ($y_t = s_t - s_{t-1}$)					
KPSS	0.18	0.11	0.22	0.03	0.08
Phillips-Perron	-60.86***	-55.54***	-58.18***	-60.50***	-63.92***

(***) (**) (*) Denotes rejection of the null hypothesis at the 1%, 5% and 10% significance level.

Source: Author's calculations.

Table A.8: Contemporary Correlations of NERs Components

		CLP/USD	COP/USD	MXN/USD	PEN/USD
Trend diff.	BRL/USD	0.97	0.88	-0.63	0.97
	CLP/USD		0.75	-0.79	1.00
	COP/USD			-0.19	0.73
	MXN/USD				-0.80
>5 years	BRL/USD	0.78	0.98	0.55	0.53
	CLP/USD		0.84	0.51	0.45
	COP/USD			0.64	0.59
	MXN/USD				0.30
1-5 years	BRL/USD	0.68	0.64	0.56	0.52
	CLP/USD		0.58	0.55	0.56
	COP/USD			0.68	0.71
	MXN/USD				0.52
< 1 year	BRL/USD	0.59	0.43	0.53	0.30
	CLP/USD		0.32	0.42	0.25
	COP/USD			0.47	0.29
	MXN/USD				0.29

Source: Author's calculations.

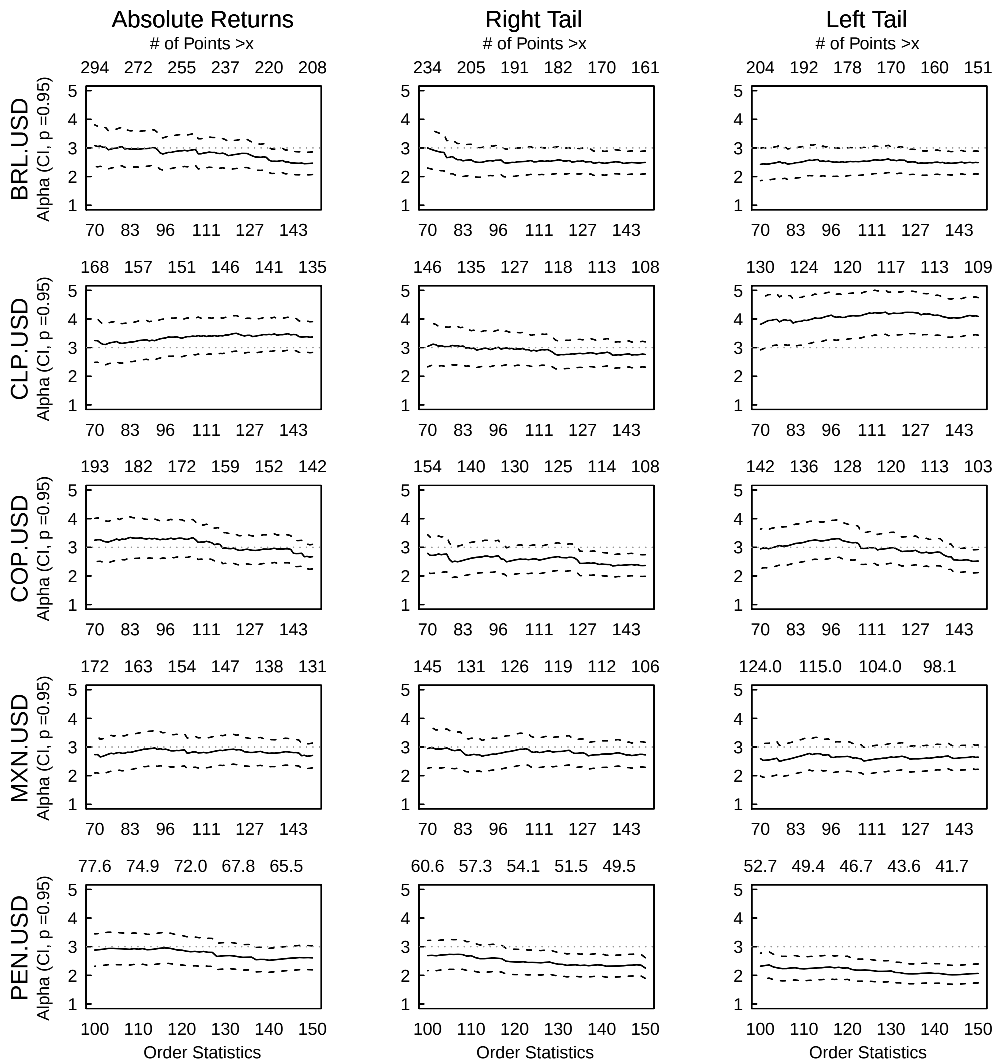
Table A.9: Comtemporary correlations between the NER Gap, Local GDP Gap and US Gap

		Local GDP Gap	Gap NER
Brazil	US GDP Gap	0.16	-0.25
	Local GDP Gap		-0.62
Chile	US GDP Gap	0.37	-0.41
	Local GDP Gap		-0.55
Colombia	US GDP Gap	-0.21	-0.25
	Local GDP Gap		-0.10
Mexico	US GDP Gap	0.16	-0.23
	Local GDP Gap		-0.24
Peru	US GDP Gap	-0.02	-0.01
	Local GDP Gap		-0.31

Source: Author's calculations.

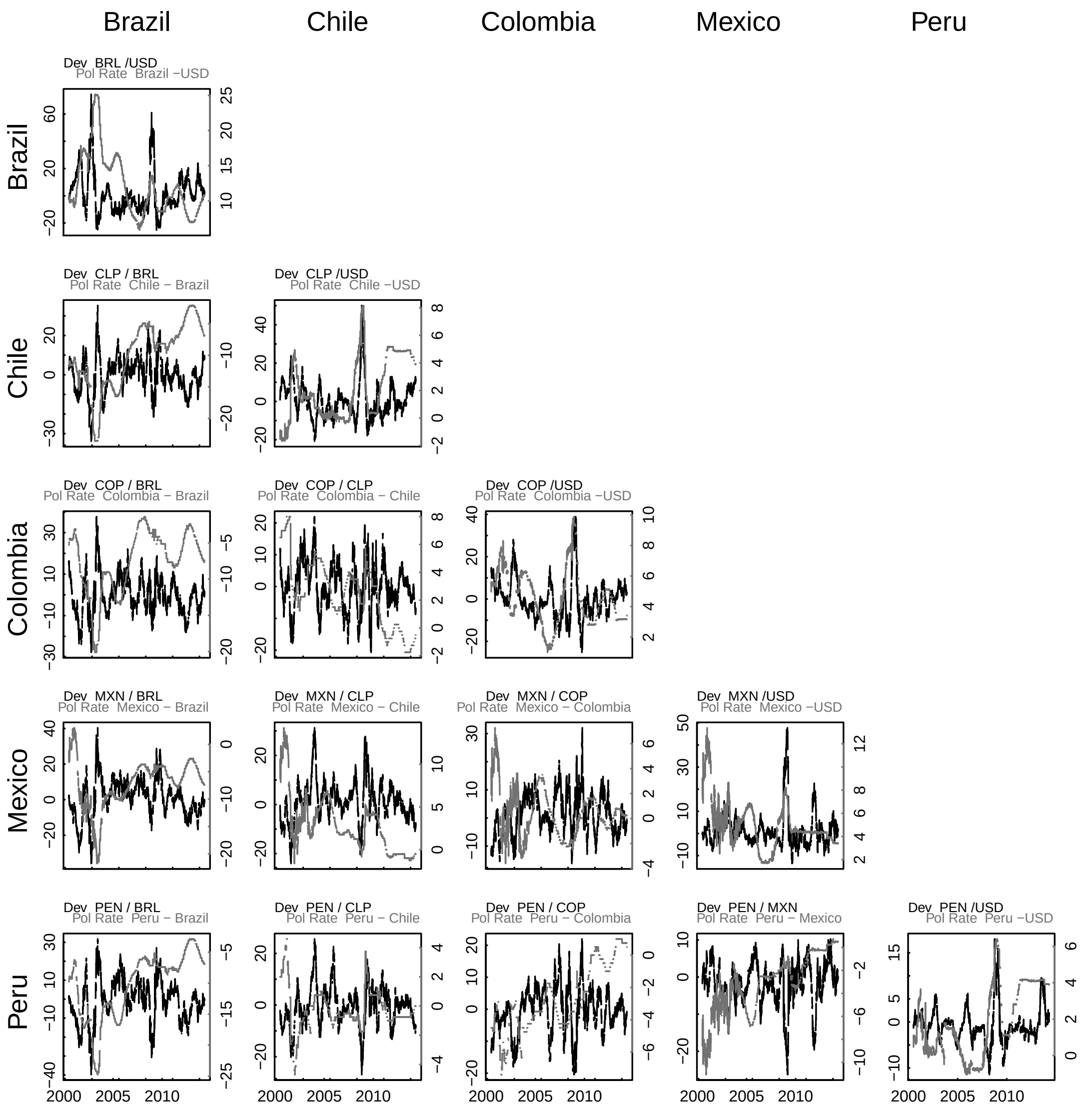
B Figures

Figure B.1: Absolute, Negative and Positive Return Hill Tail Index (α) Estimates



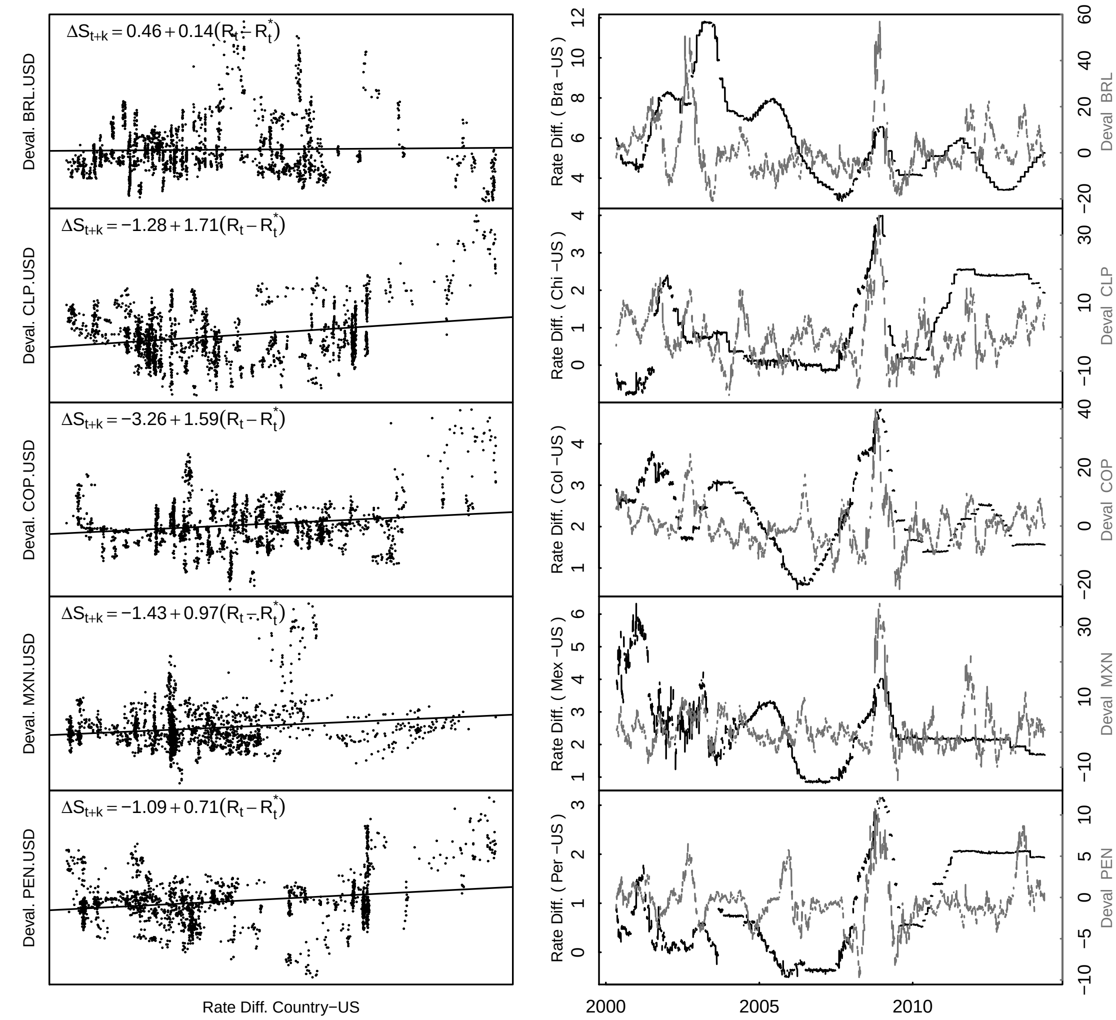
Source: Author's calculations.

Figure B.2: Cross Nominal Exchange Rates Devaluations Over 6 months and Policy Rate Differential



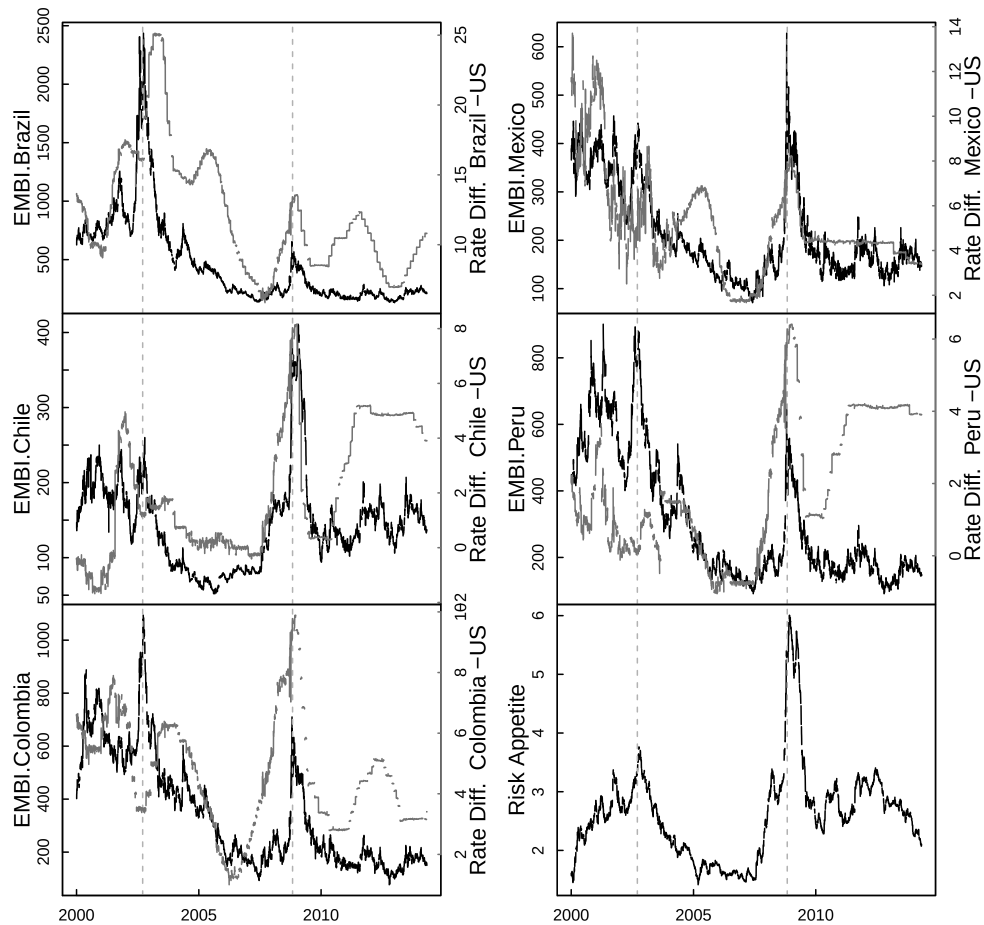
Source: Author's calculations.

Figure B.3: Ex-post Nominal Exchange Rate Devaluations agains USD Over 6 months and Policy Rate Differential



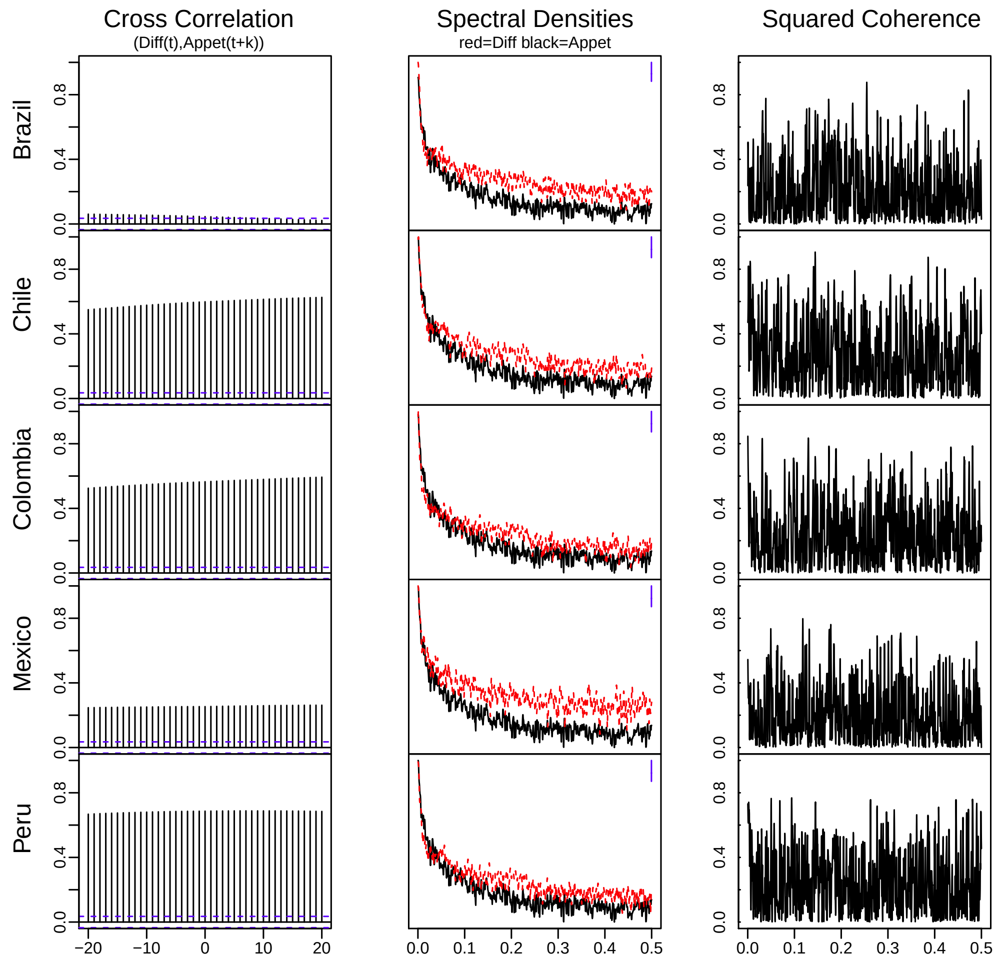
Source: Author's calculations.

Figure B.4: Country Emerging Markets Bond Indexes EMBI, Policy Ratte Differential and Risk Appetite



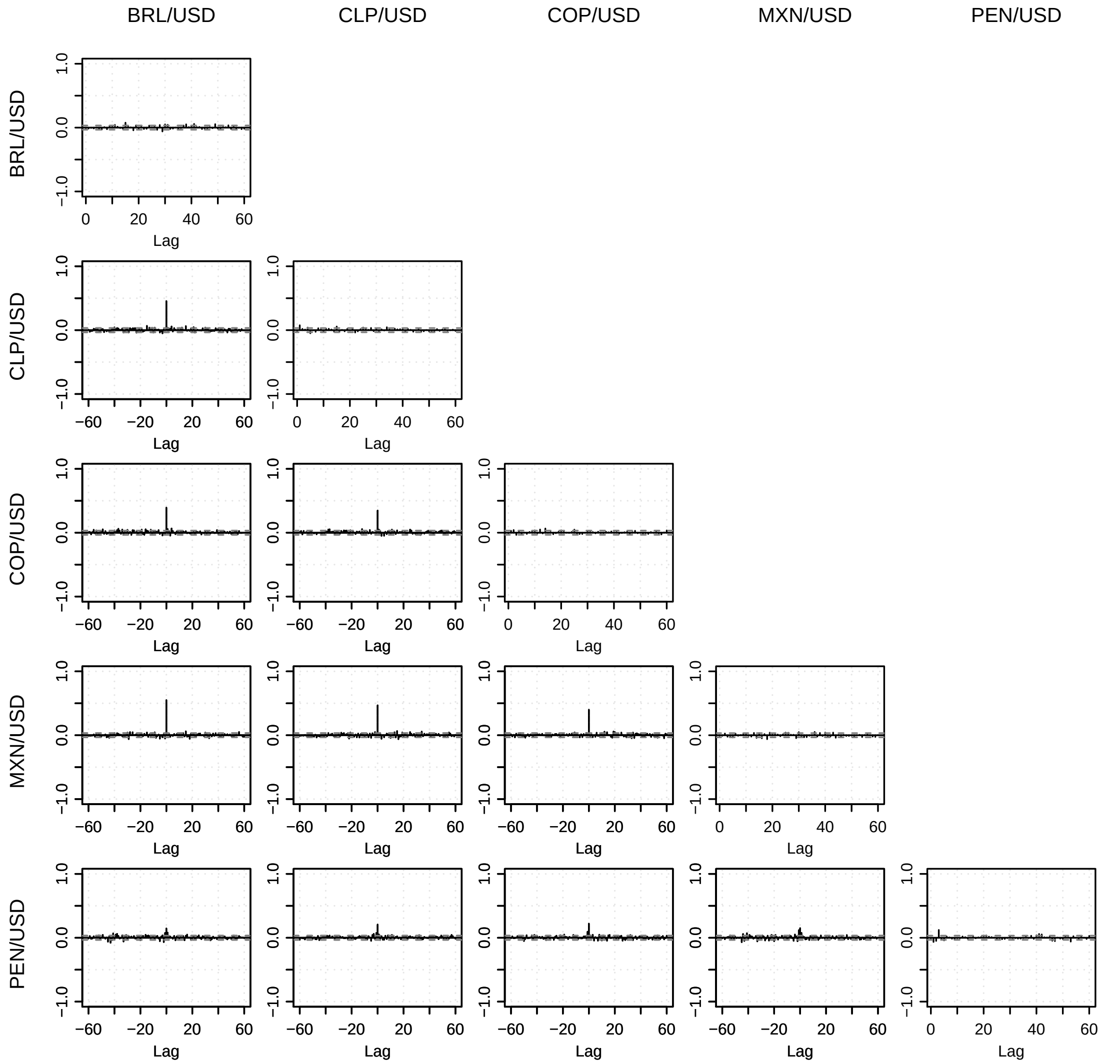
Source: Author's calculations.

Figure B.5: Cross Correlation, Spectral Densities and Coherence of Policy Rate Differentials and Appetite for Risk of International Investors



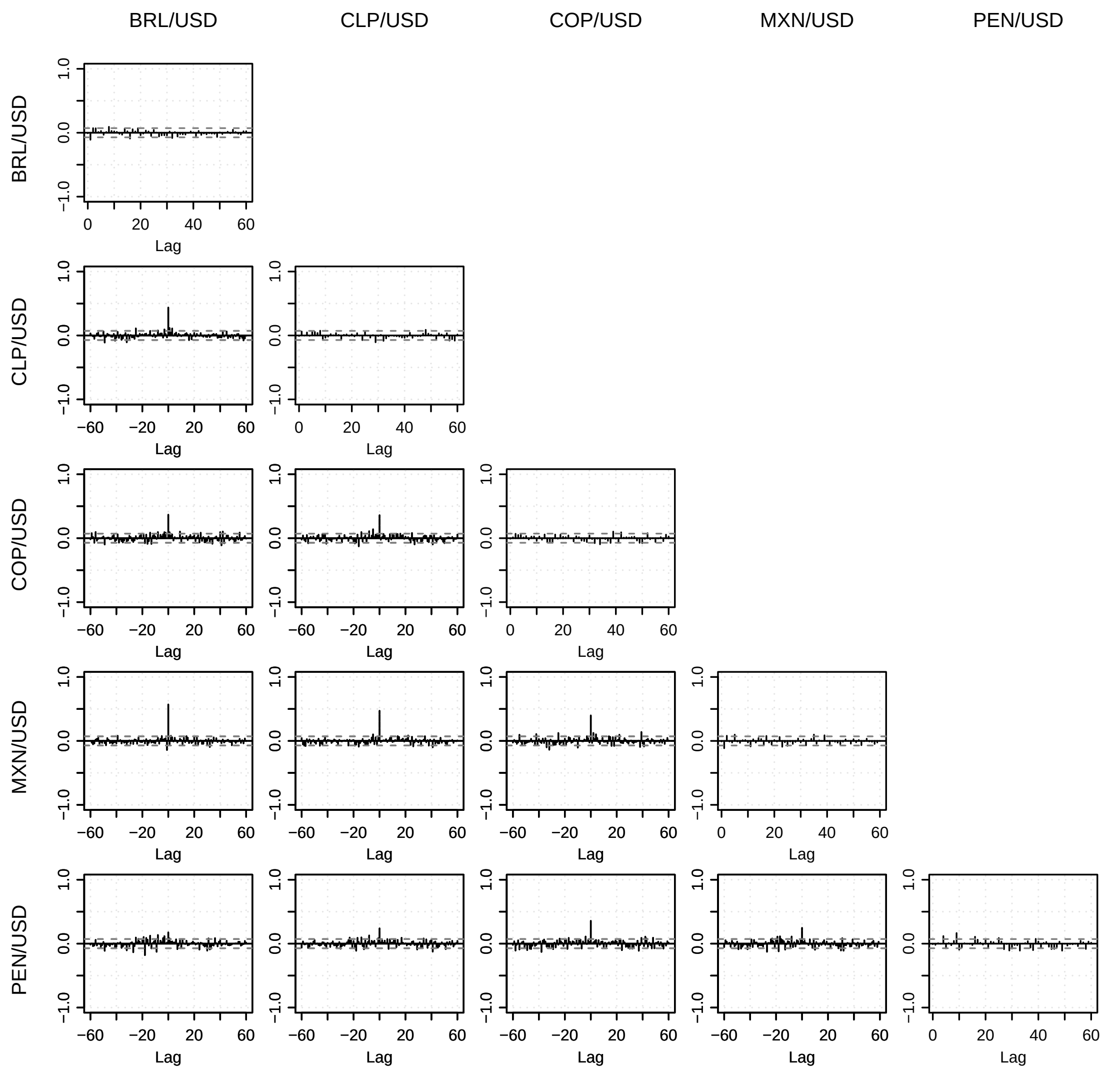
Source: Author's calculations.

Figure B.6: Sample Autocorrelation (diagonal) and Cross correlations (off diagonal) of Daily NER returns



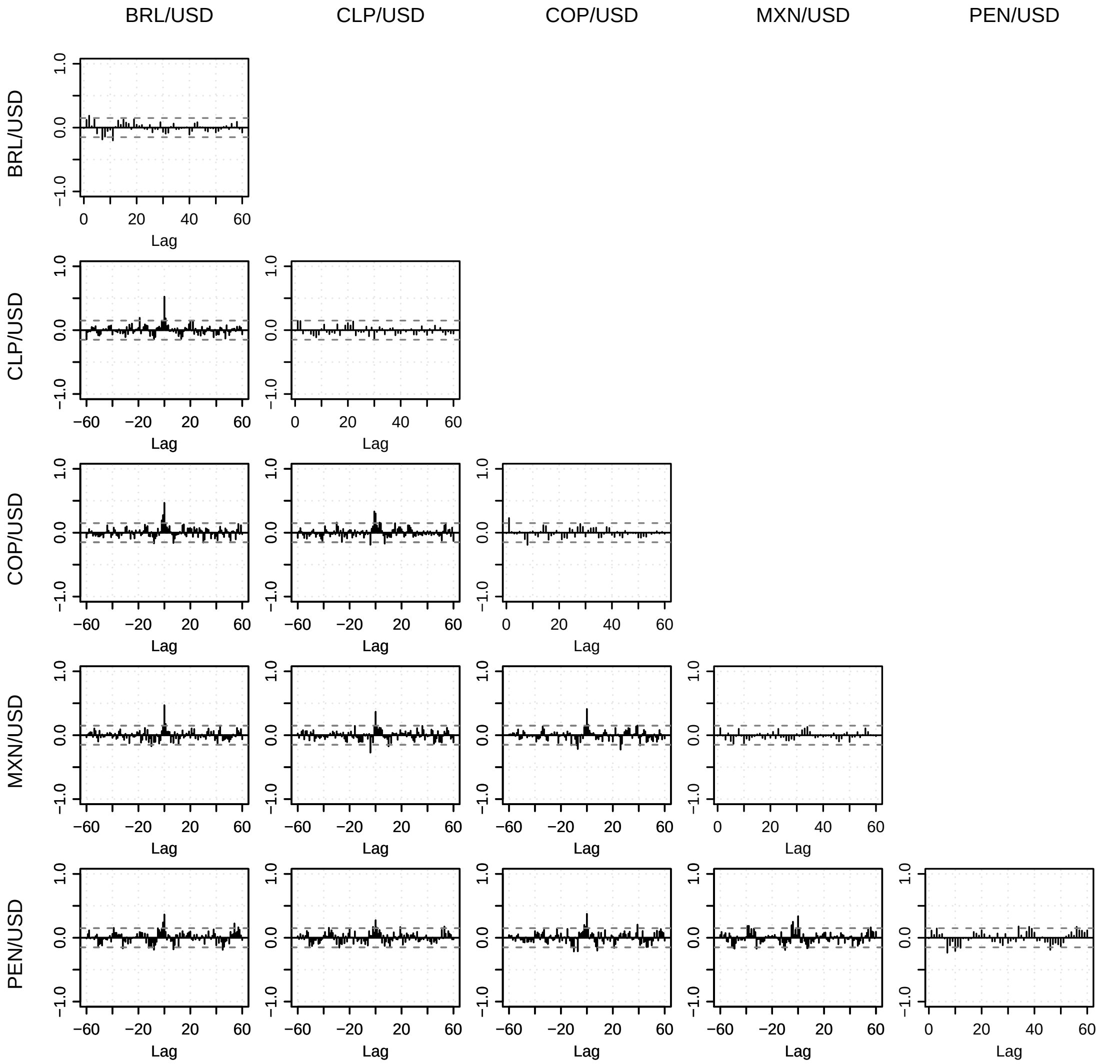
Source: Author's calculations.

Figure B.7: Sample Autocorrelation (diagonal) and Cross correlations (off diagonal) of Weekly NER returns



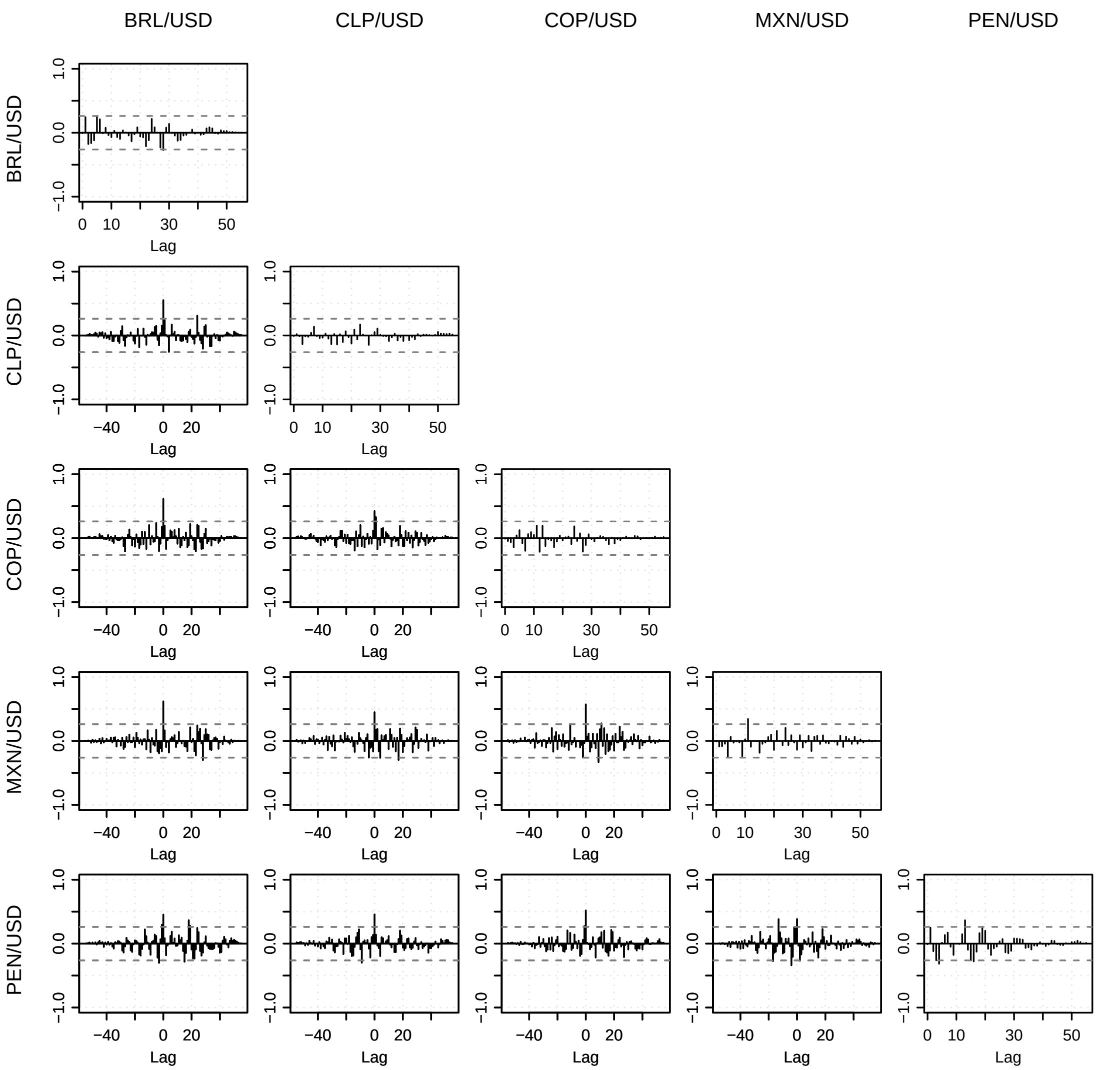
Source: Author's calculations.

Figure B.8: Sample Autocorrelation (diagonal) and Cross correlations (off diagonal) of Monthly NER returns



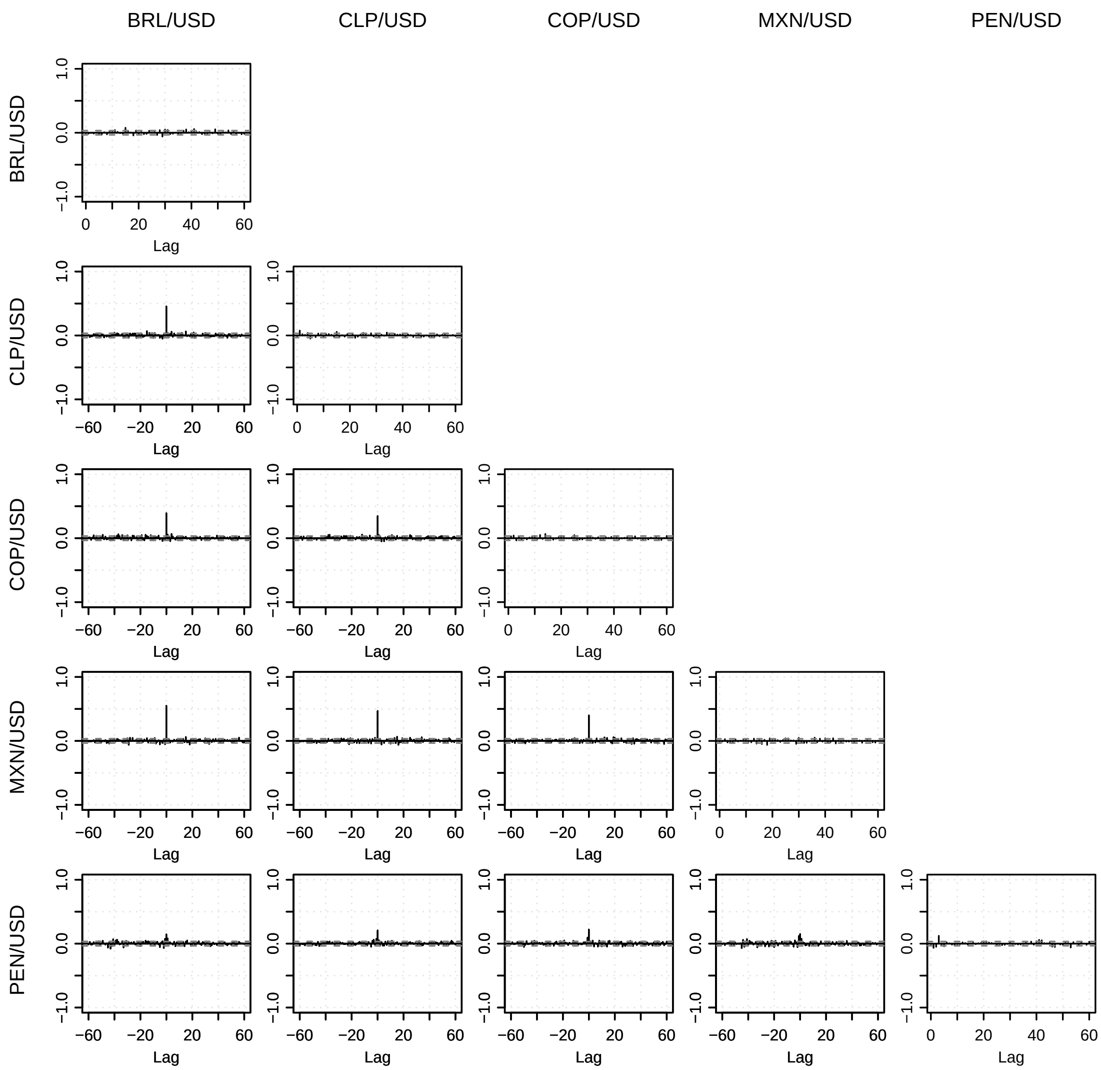
Source: Author's calculations.

Figure B.9: Sample Autocorrelation (diagonal) and Cross correlations (off diagonal) of Quarterly NER returns



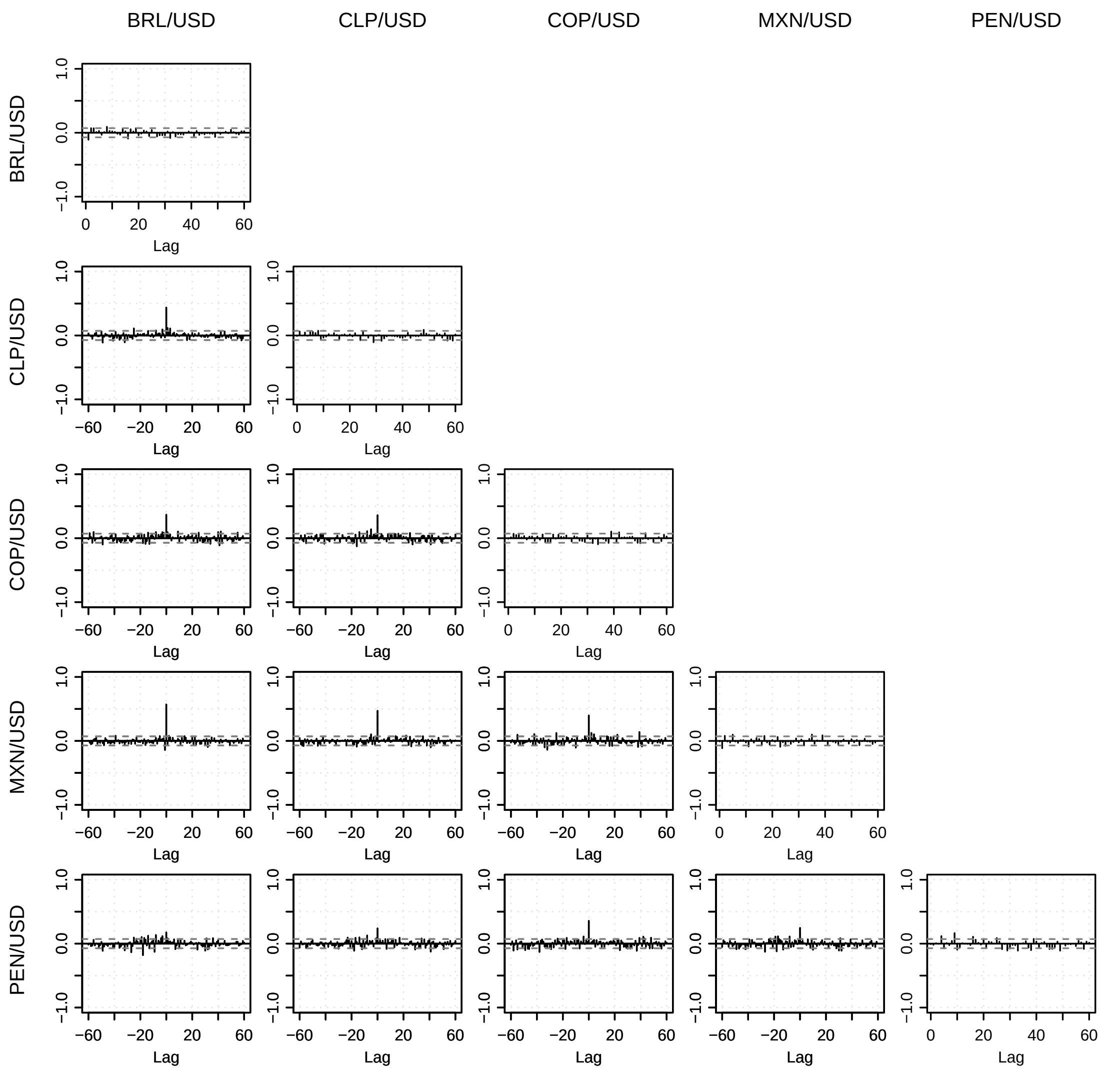
Source: Author's calculations.

Figure B.10: Partial Sample Autocorrelation (diagonal) and Partial Cross correlations (off diagonal) of Daily NER returns



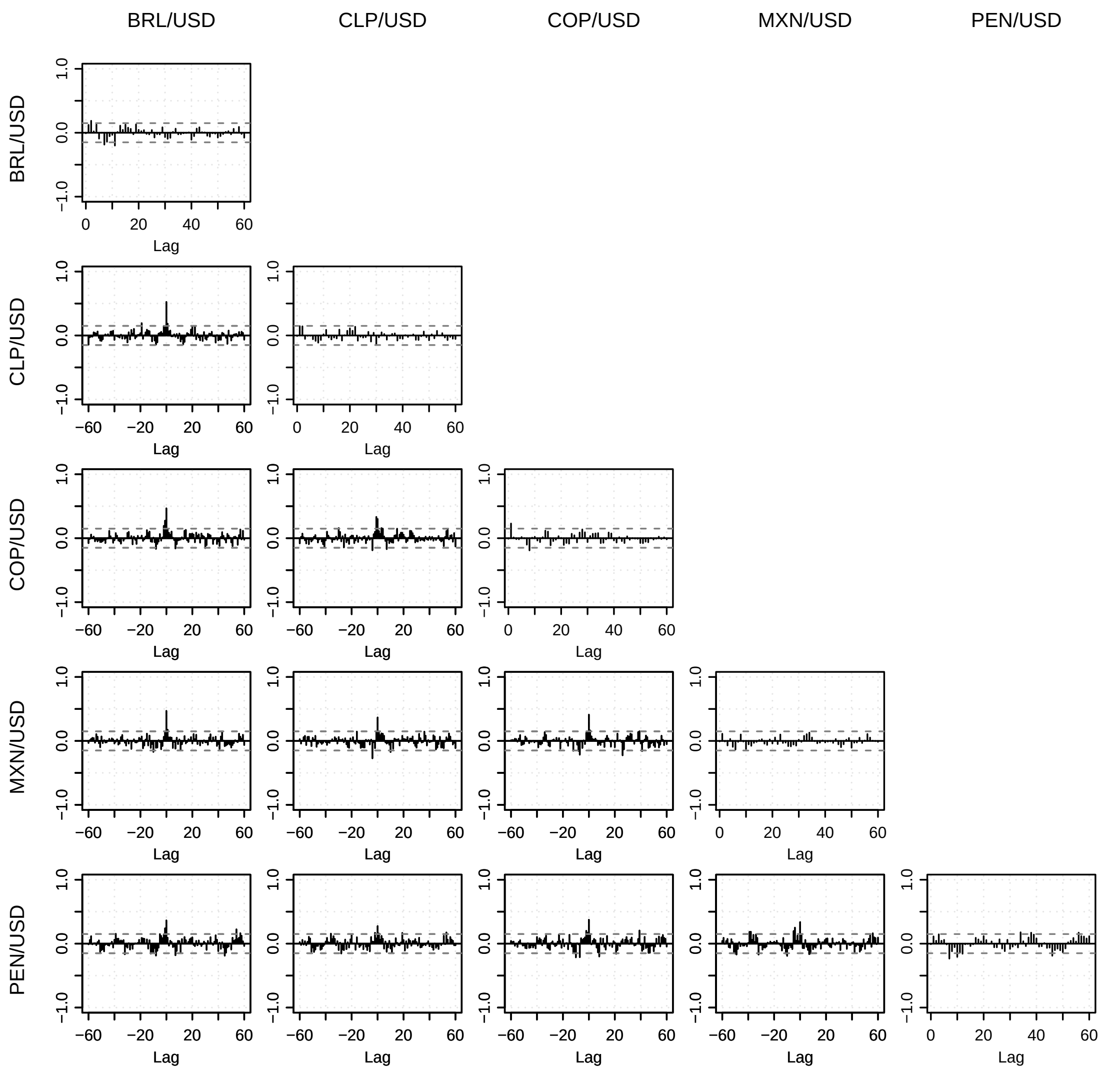
Source: Author's calculations.

Figure B.11: Partial Sample Autocorrelation (diagonal) and Partial Cross correlations (off diagonal) of Weekly NER returns



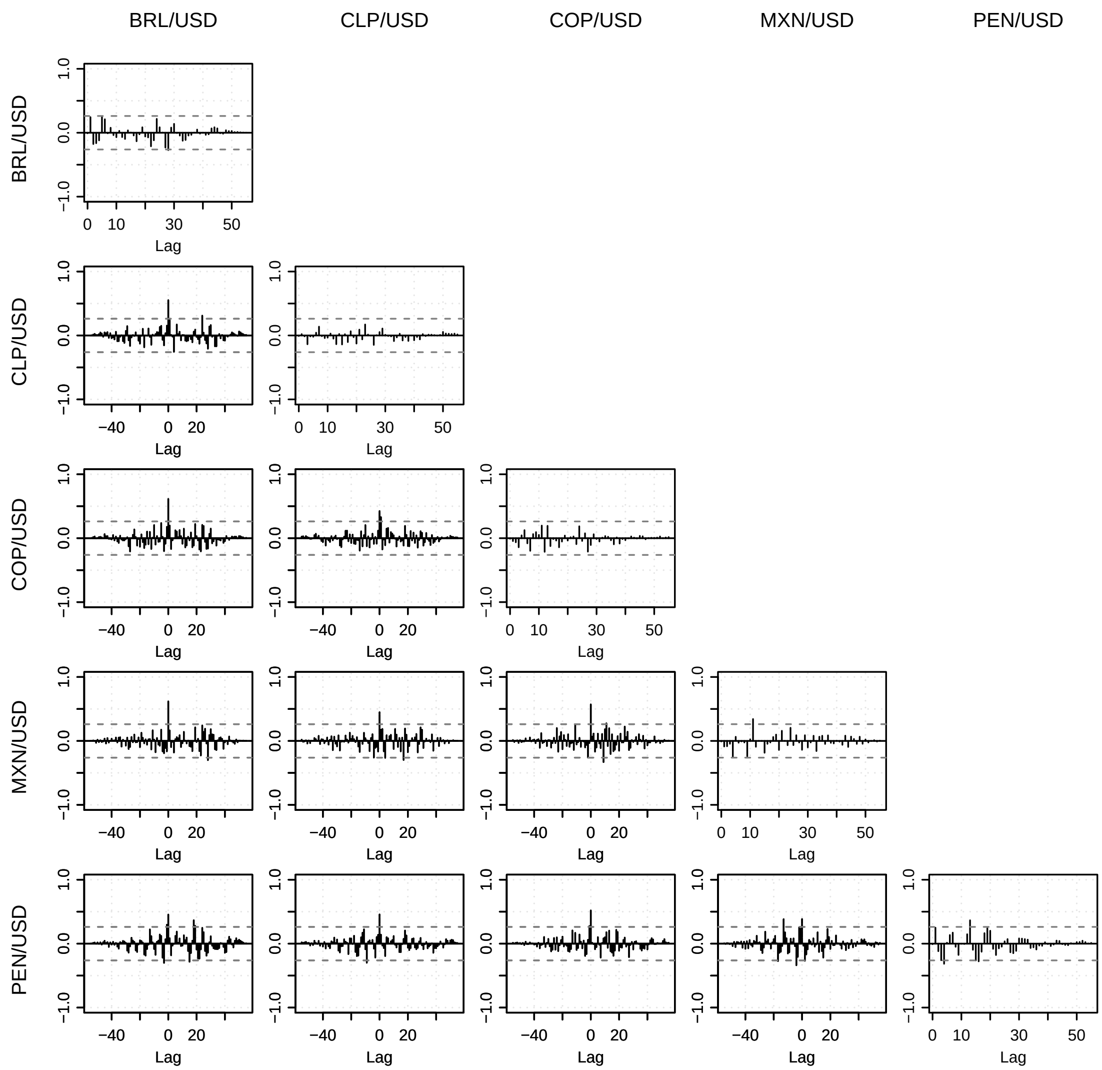
Source: Author's calculations.

Figure B.12: Partial Sample Autocorrelation (diagonal) and Partial Cross correlations (off diagonal) of Monthly NER returns



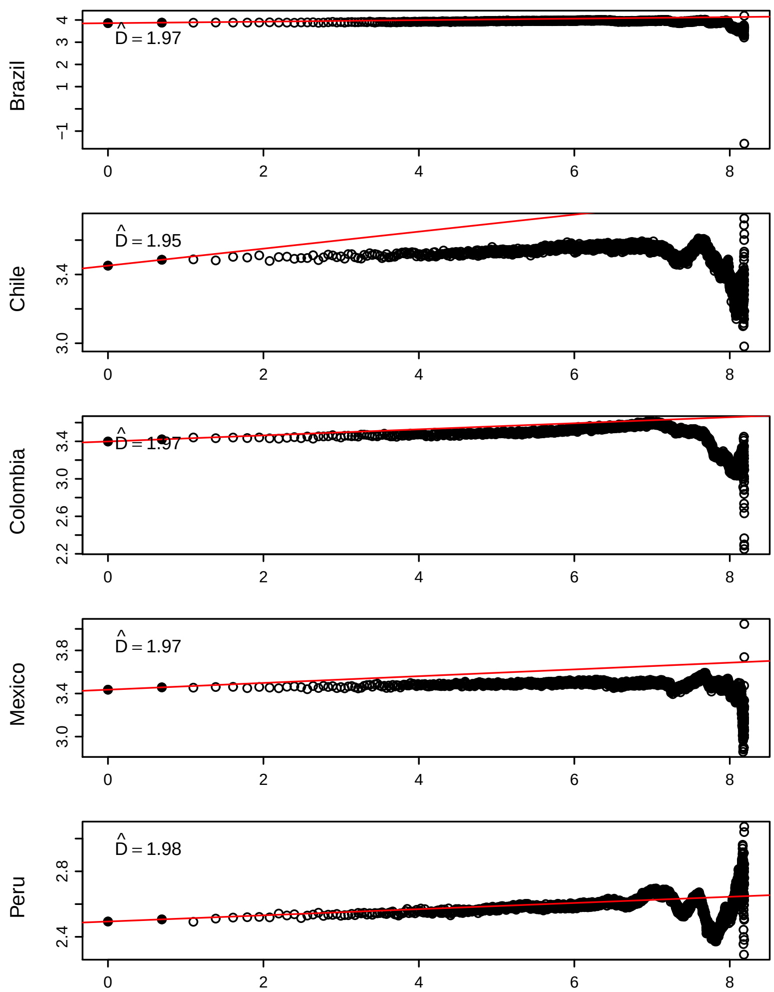
Source: Author's calculations.

Figure B.13: Partial Sample Autocorrelation (diagonal) and Partial Cross correlations (off diagonal) of Quarterly NER returns



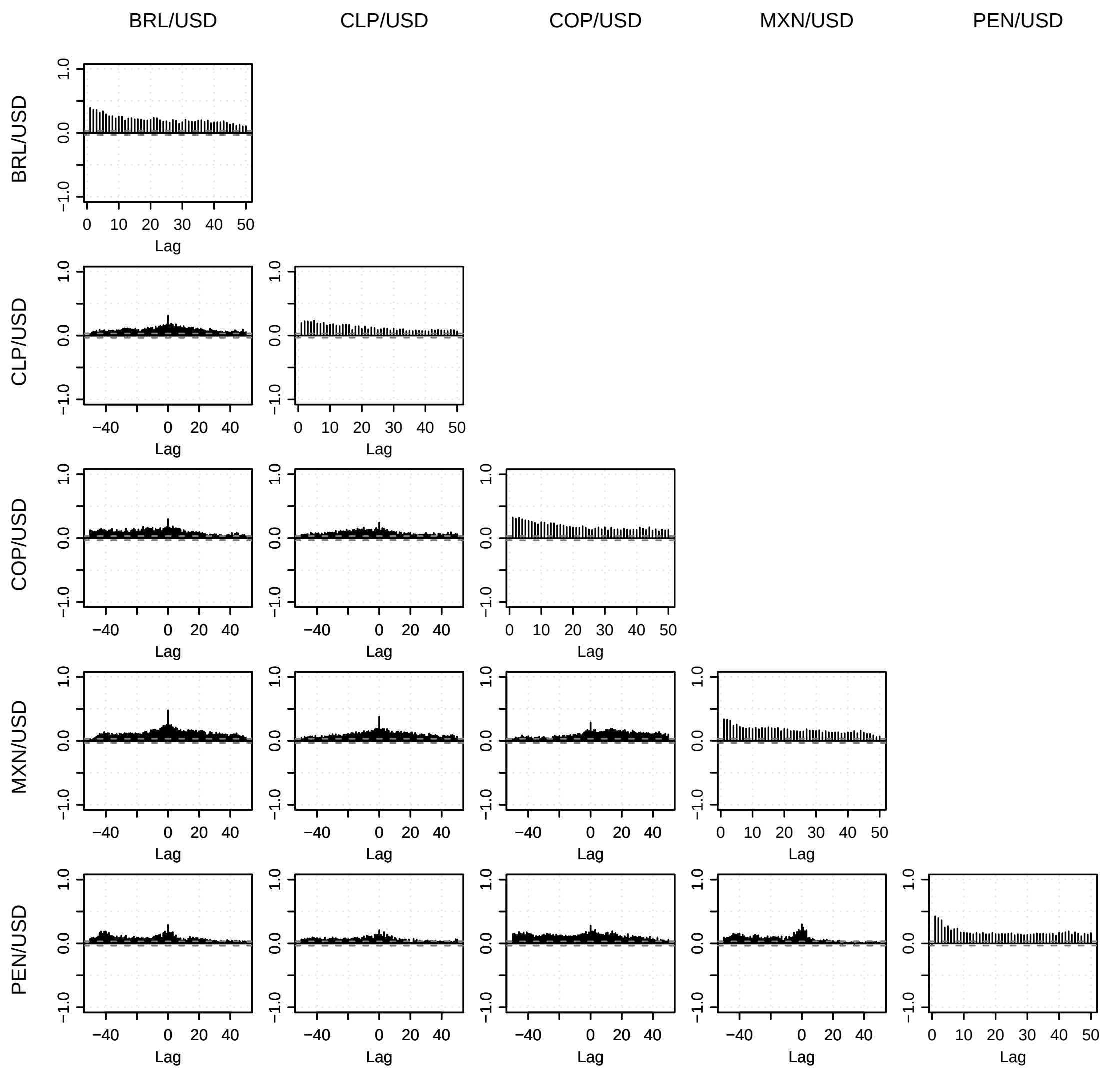
Source: Author's calculations.

Figure B.14: Madogram and Fractal (or Hausdorff) Dimension Estimation of Nominal Exchange Rate returns



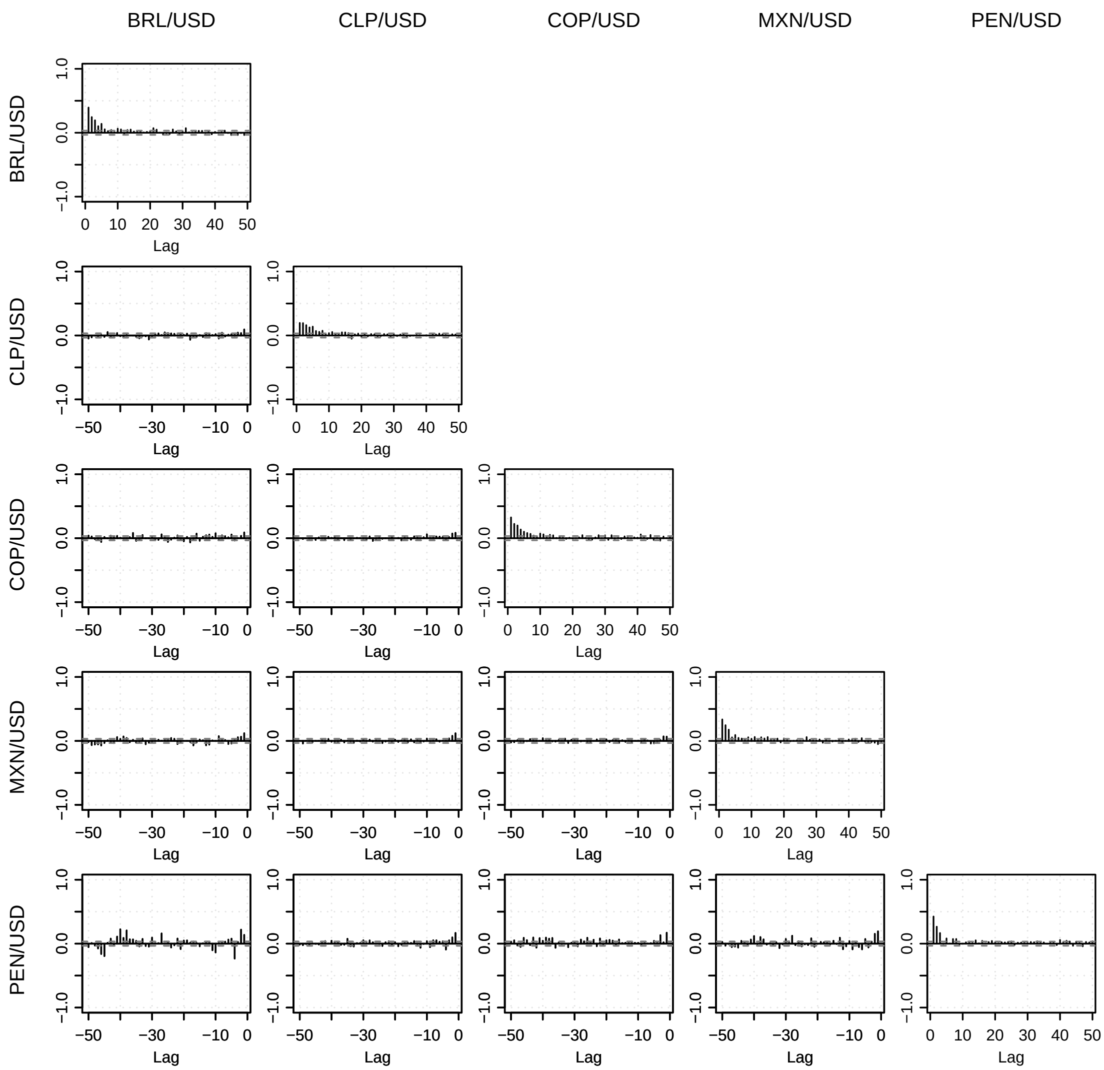
Source: Author's calculations.

Figure B.15: Sample Ordinary Autocorrelation (diagonal panels) and Cross-correlation Functions (off-diagonal panels) of Absolute Exchange Rate returns



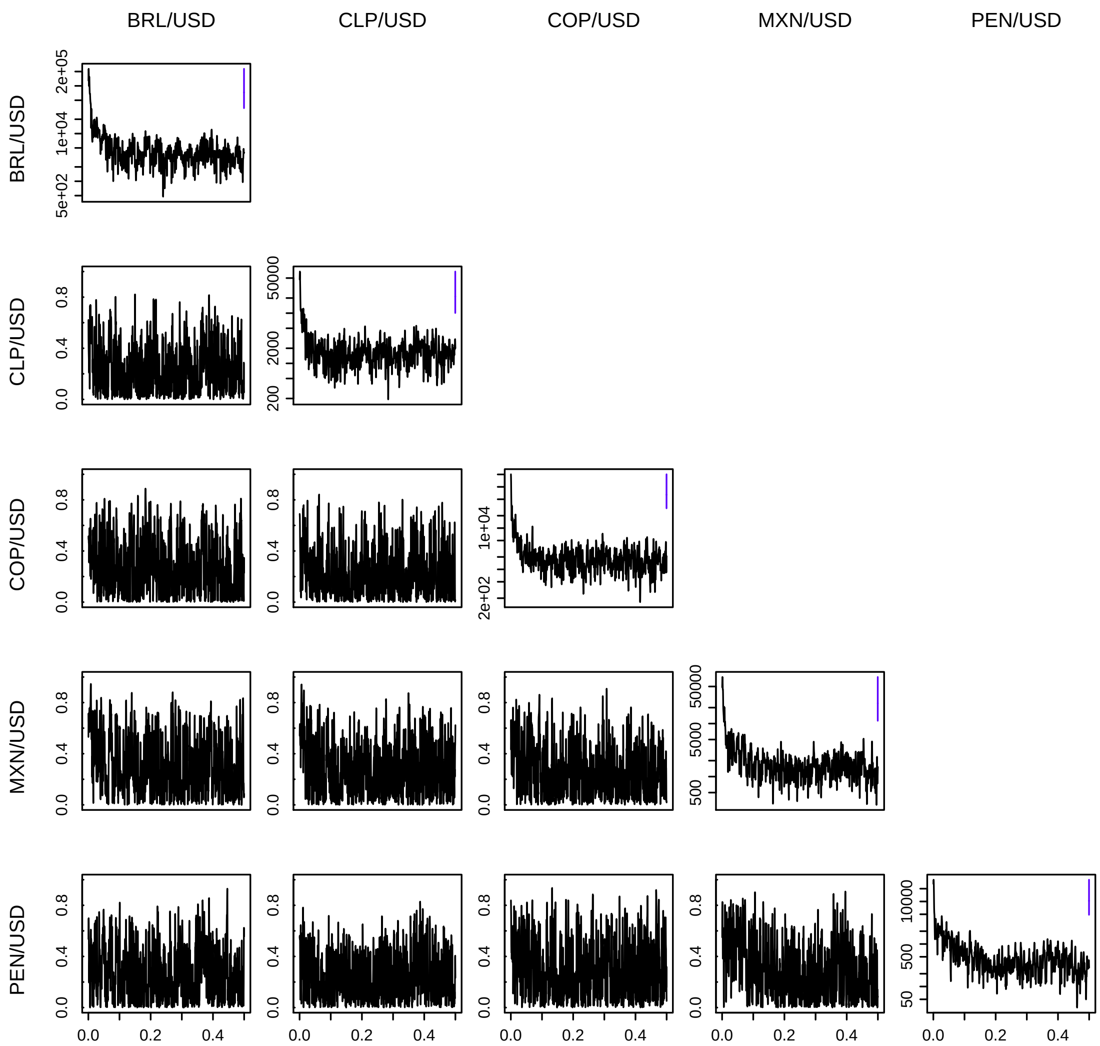
Source: Author's calculations.

Figure B.16: Sample Partial Autocorrelation (diagonal panels) and Partial Cross-correlation Functions (off-diagonal panels) of Absolute Exchange Rate returns



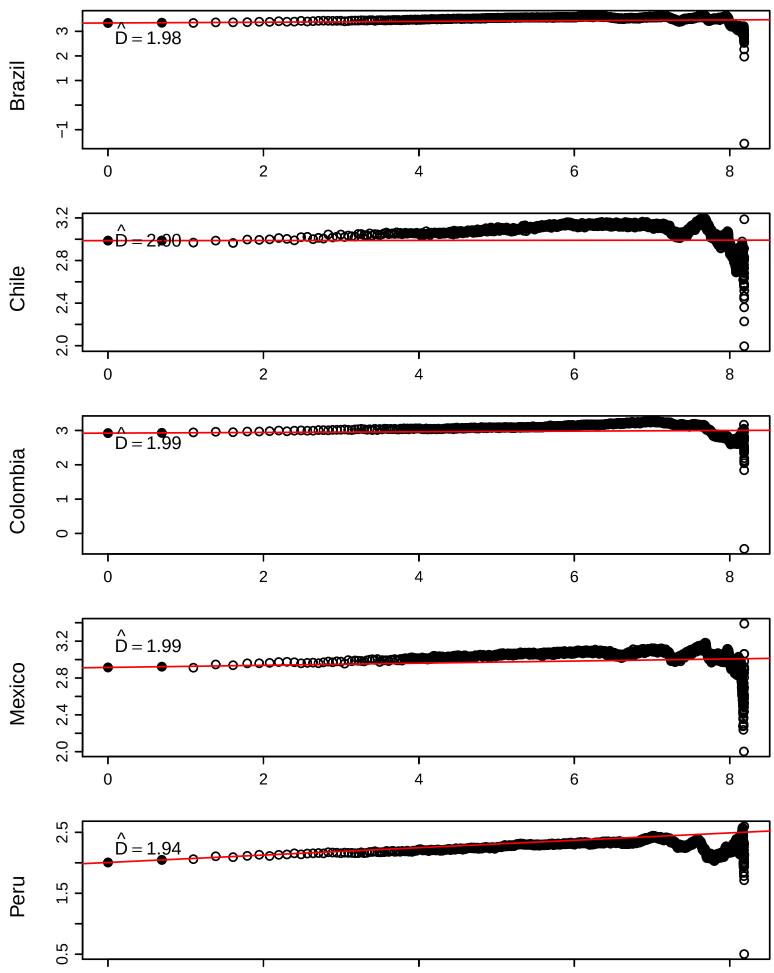
Source: Author's calculations.

Figure B.17: Sample Spectrum (diagonal panels) and Sample Cross Coherence Functions (off-diagonal panels) of Absolute Exchange Rate returns



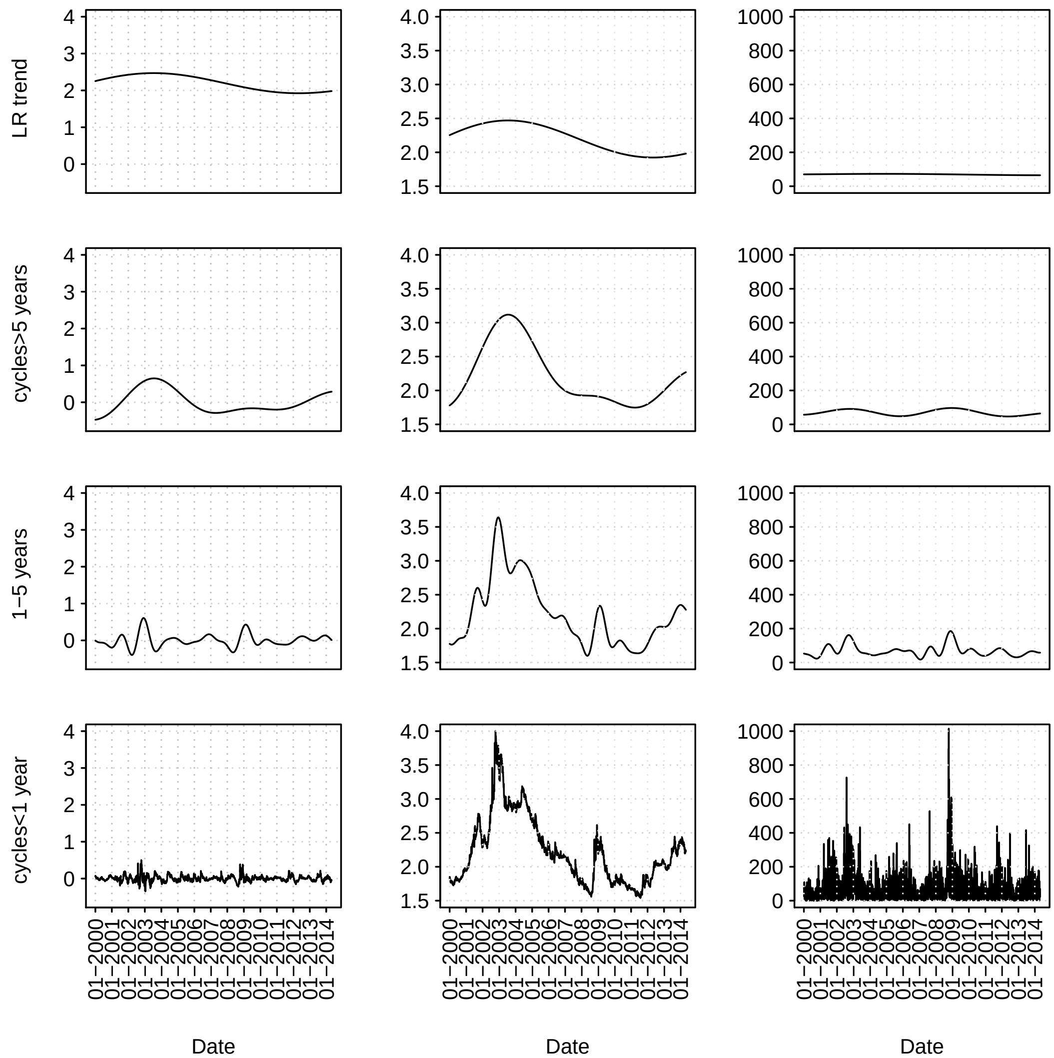
Source: Author's calculations.

Figure B.18: Madogram and Fractal (or Hausdorff) Dimension Estimation of Absolute Nominal Exchange Rate Returns



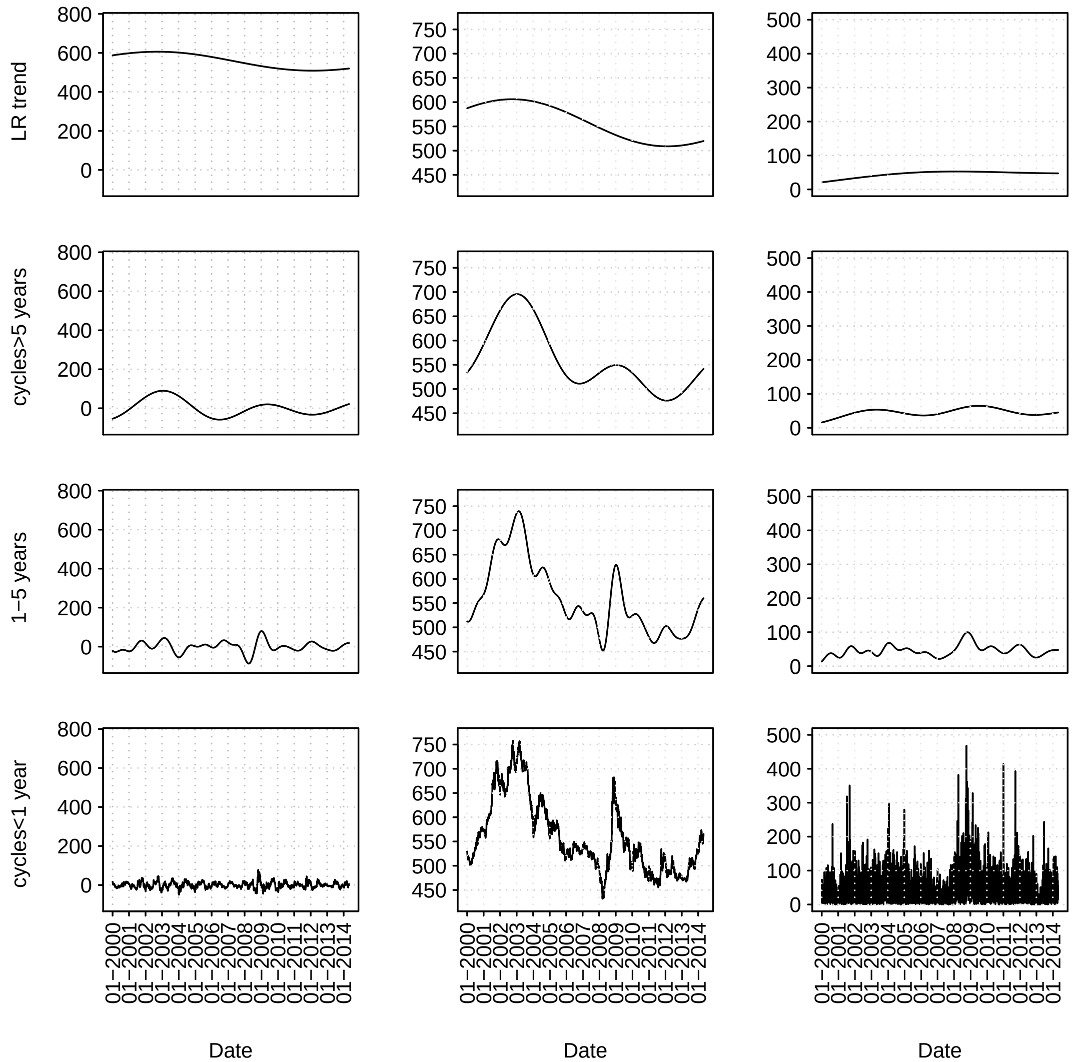
Source: Author's calculations.

Figure B.19: Spectral decomposition of BRL/USD NER and its absolute daily returns. Left panels: BRL/USD components from lower to higher frequency. Middle panels: cumulative components. Right panels: cummulative components of absolute returns.



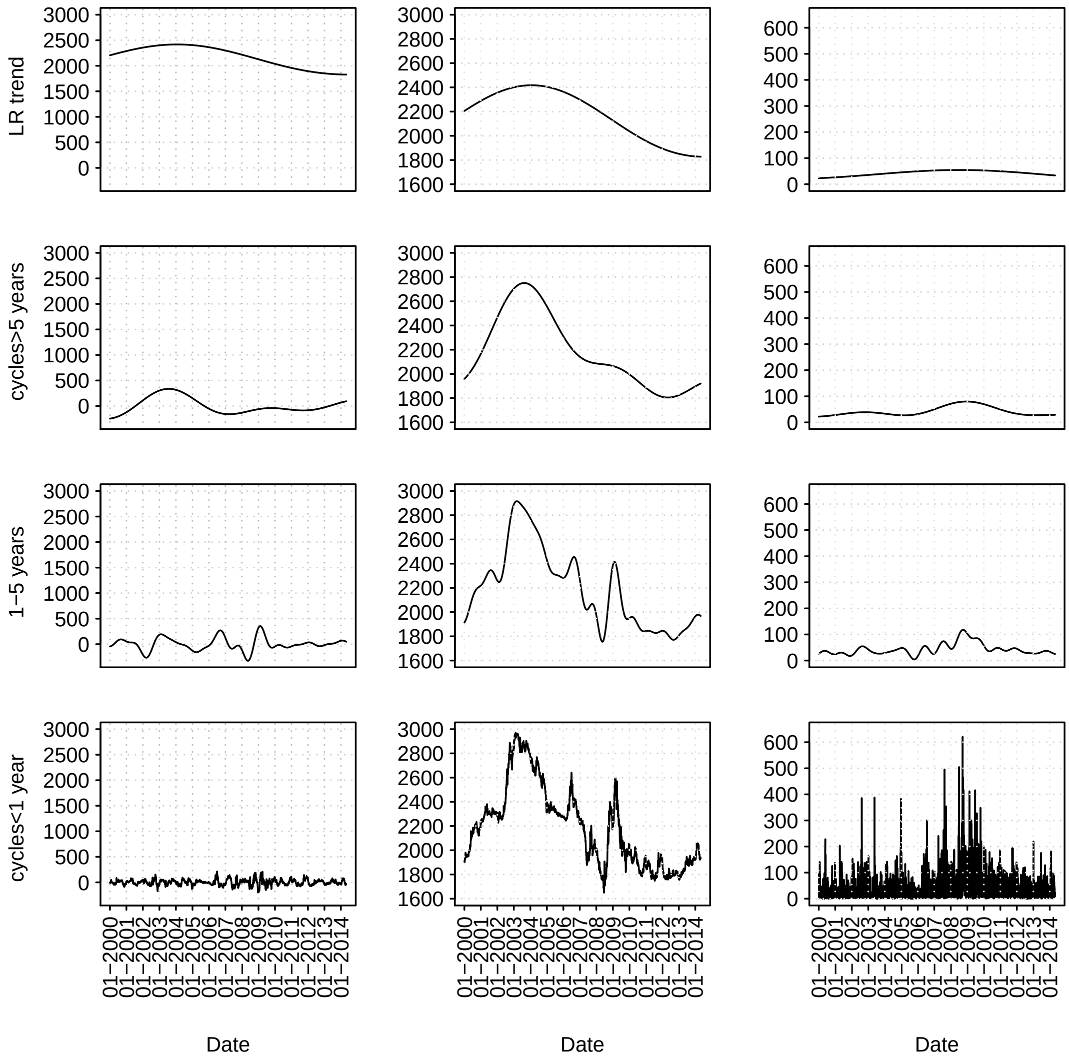
Source: Author's calculations.

Figure B.20: Spectral decomposition of CLP/USD NER and its absolute daily returns. Left panels: CLP/USD components from lower to higher frequency. Middle panels: cumulative components. Right panels: cummulative components of absolute returns.



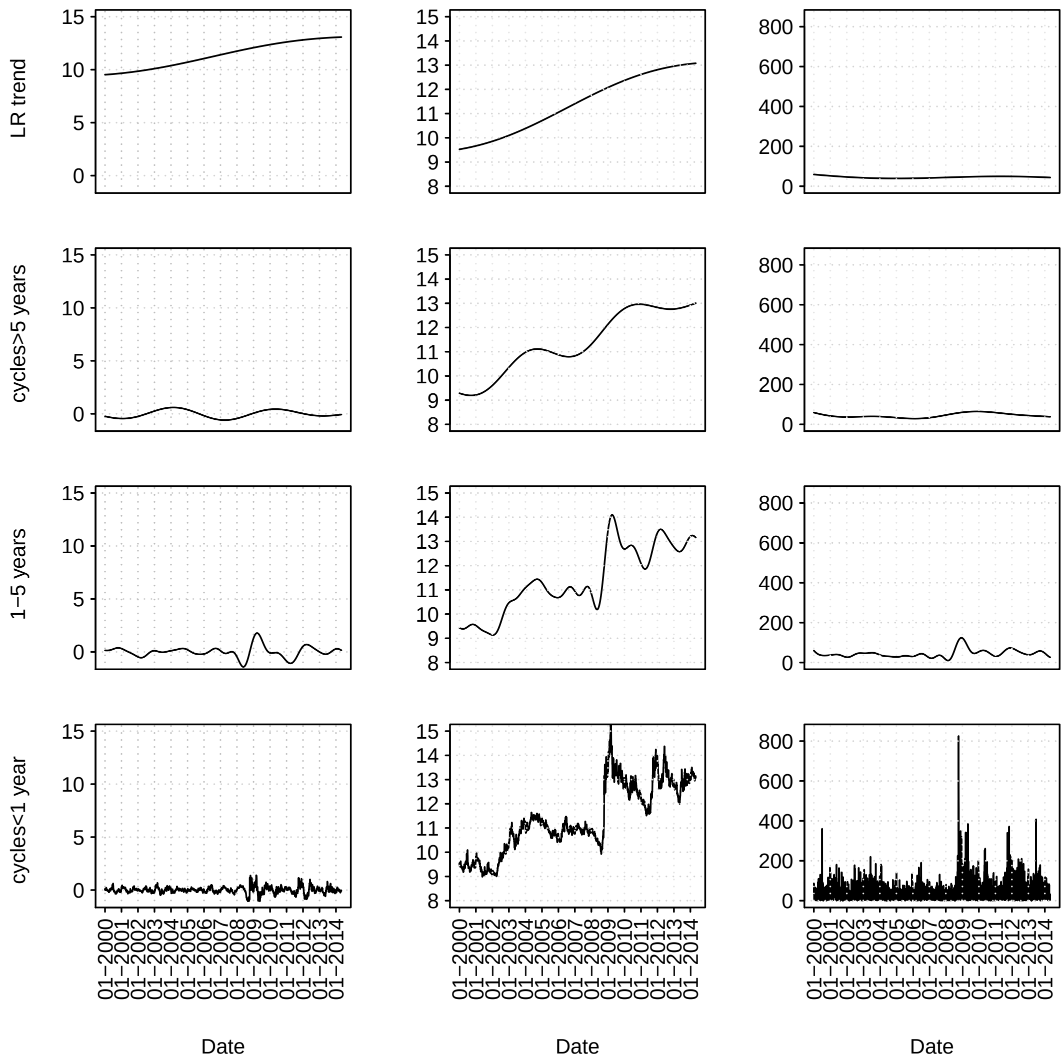
Source: Author's calculations.

Figure B.21: Spectral decomposition of COP/USD NER and its absolute daily returns. Left panels: COP/USD components from lower to higher frequency. Middle panels: cumulative components. Right panels: cummulative components of absolute returns.



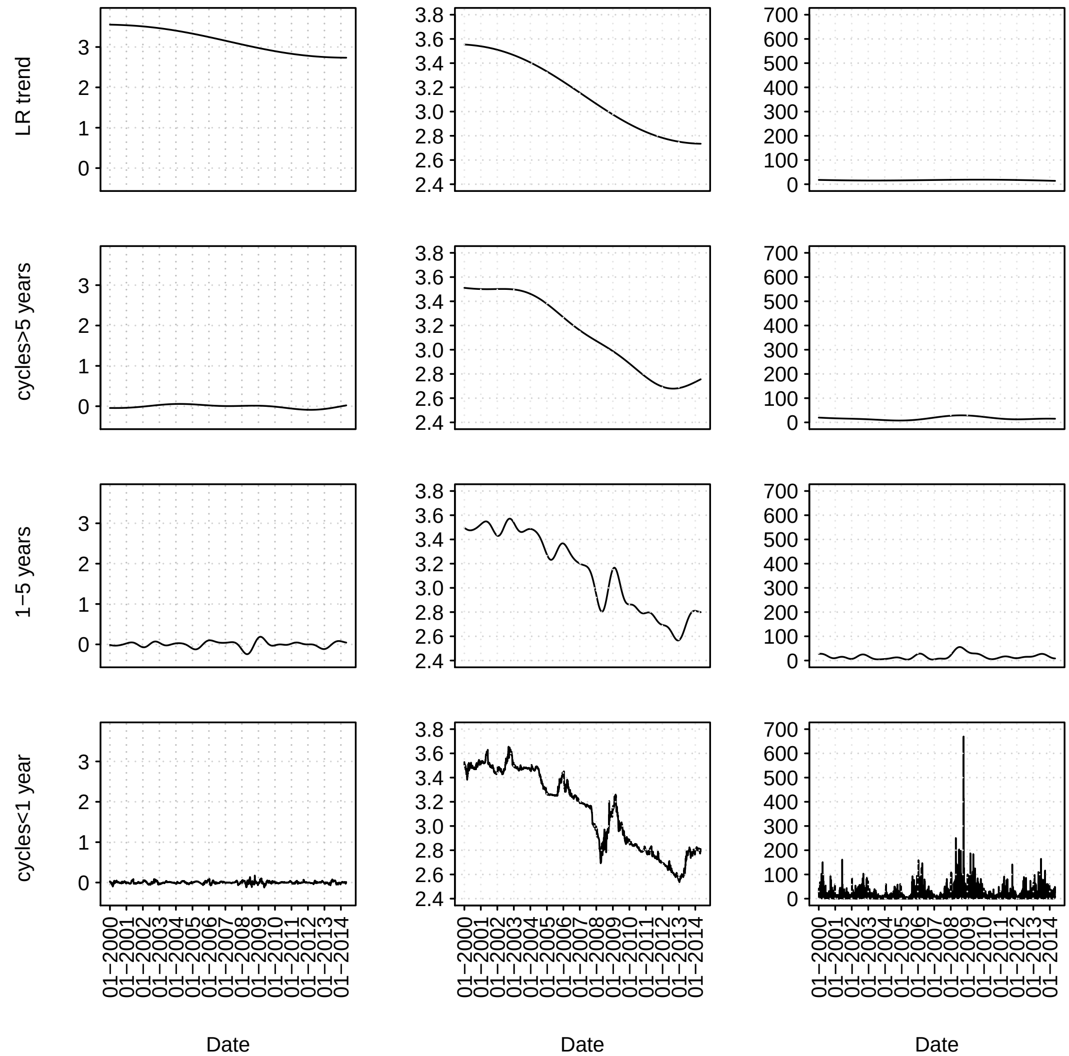
Source: Author's calculations.

Figure B.22: Spectral decomposition of MXN/USD NER and its absolute daily returns. Left panels: MXN/USD components from lower to higher frequency. Middle panels: cumulative components. Right panels: cummulative components of absolute returns.



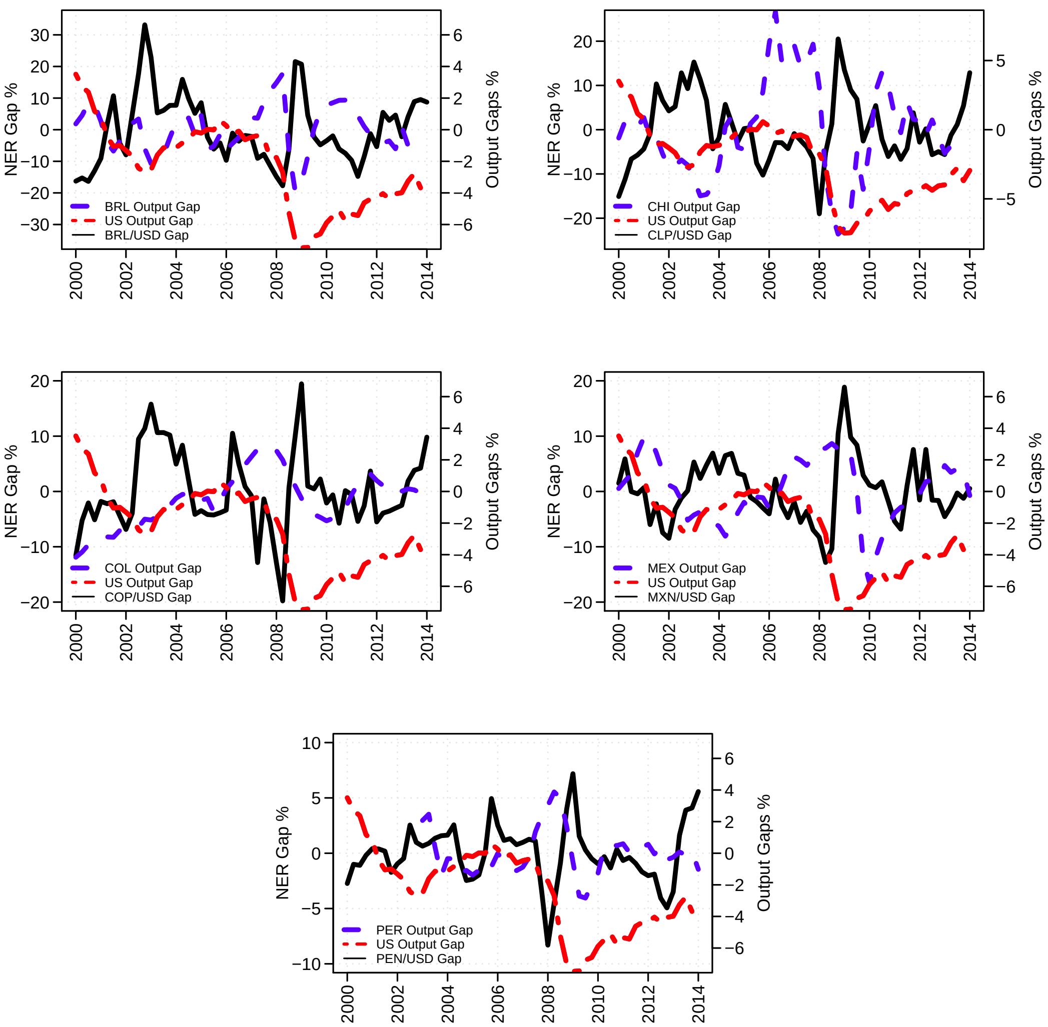
Source: Author's calculations.

Figure B.23: Spectral decomposition of PEN/USD NER and its absolute daily returns. Left panels: PEN/USD components from lower to higher frequency. Middle panels: cumulative components. Right panels: cummulative components of absolute returns.

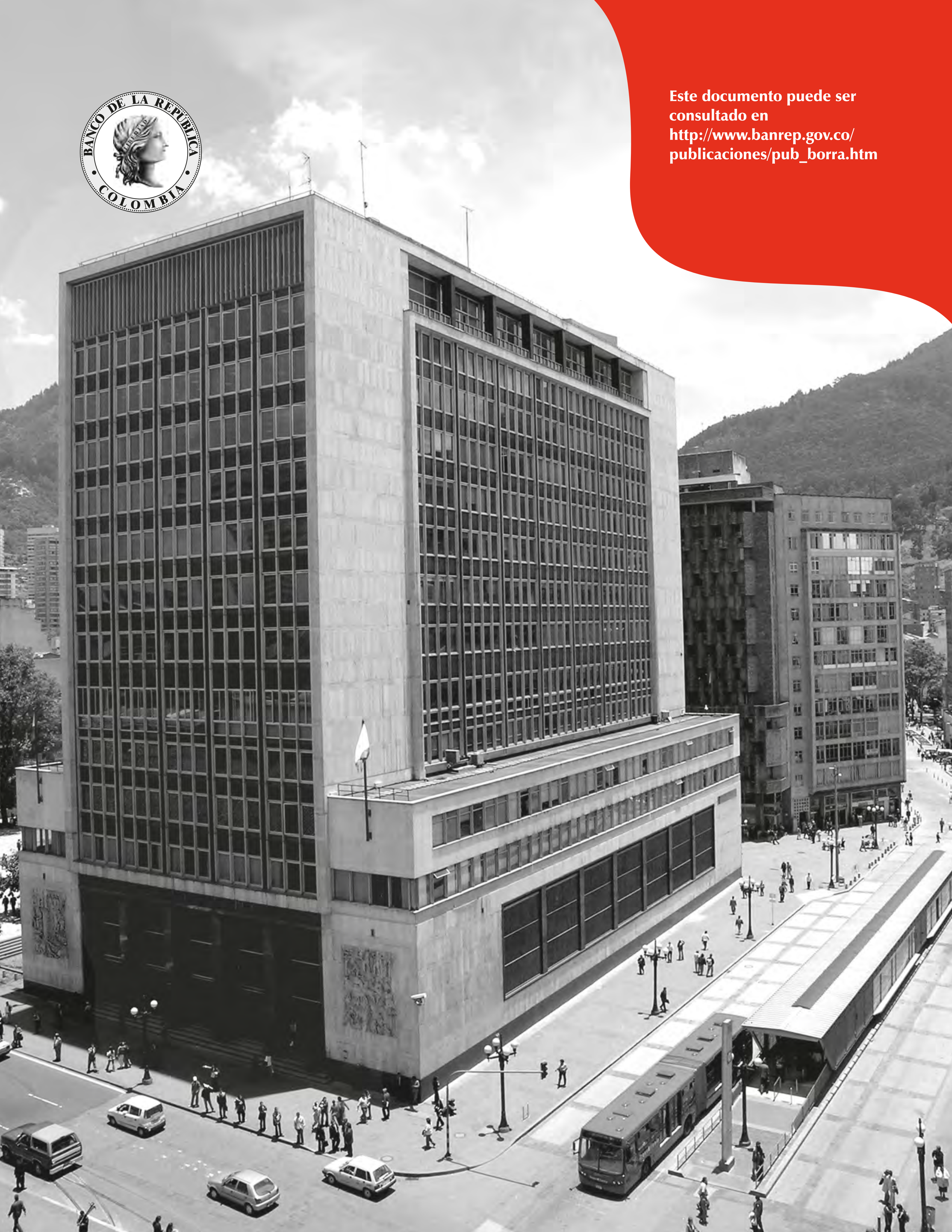


Source: Author's calculations.

Figure B.24: Nominal Exchange Rate Gap, Local Country Output Gap and U.S. GDP Output Gap



Source: Author's calculations.



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