Exchange Rates Predictability In Emerging Markets[*]

Elisa Baku

Amundi Asset Management,
University Paris 1 Pantheon Sorbonne
& Paris School of Economics
Elisa.Baku@etu.univ-paris1.fr

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Abstract

This paper uses financial and macroeconomic variables to predict currency returns, by using a two-step procedure. The first step consists of a cointegration equation that explains the exchange rate level as a function of global and domestic financial factors. The second step estimates an error-correction equation, for modeling the expected returns. This approach is a factor model analysis, where a Lasso derived technic is used for variable selection. This paper will focus on the main Latin American currencies, Brazil(BRL), Chile (CLP), Colombia (COL), Mexico (MXN) and Peru (PEN), during the time horizon from December 2001 until February 2016. The first finding is that Global Exchange Rate Factor offers information about the exchange rate movements. In addition, this paper shows that commodity, equity prices and domestic risk premium are important variables for explaining exchange rates. Moreover, confirm the existing results for the carry and slope variables.

Keywords: Exchange Rates, Latin America Emerging Markets, Lasso, Error-Correction, Factor Model.

JEL classification: F31, C3, E44.

1 Introduction

The relationship between exchange rates and financial, macroeconomic fundamentals remains a research question, even though there exist extensive literature on the subject, dating at least since in the early 1970s. Nowadays, the direction of the research is toward a new methodology called 'factor model'. In their paper, Engel *et al.* (2010) state:

> [...] *"exchange rates themselves have information that is hard to extract from observable fundamentals. This information might be hard to extract because standard measures of fundamentals (e.g. money supply and output) are error ridden, or because we simply lack any direct measures of non-standard fundamentals such as risk premia or noise trading"*.

They propose a principal component decomposition of exchange rates and use the components to predict bilateral exchange rate. But some economist argue that by using principal component methodology one fails to report the share of common variation of each currency pair. While Verdelhan (2013) focuses on two risk factors - carry and dollar - to provide a natural interpretation in any no-arbitrage model.

Empirical studies analyzing the evolution of exchange rates in emerging countries have been relatively limited. The paper of Caporale *et al.* (2016) is among the few one that studies the effects of exchange rates on the emerging markets, the authors used a VAR-GARCH(1,1) model to analyze mean and volatility spillovers between macro news (in the form of newspaper headlines) and the exchange rates vis-a-vis both the US dollar and the euro of the currencies of a group of emerging countries. They find a dynamic linkages between the first moments compared to the second moments, causality-in-variance being found in a number of cases. The conditional correlations also provide evidence of co-movement. Further, Caporale *et al.* (2014), studied the linkage between stock market prices and exchange rates in advanced economies. They found that the dependence between the two variables has increased during the recent crisis, which implies limited opportunities for investors to diversify their assets during this period. Finally, the recent global financial crisis appears to have had a significant impact. Moreover, some single-country studies have been made such as Sifunjo(2011) to examine chaos and nonlinear dynamical approaches for predicting exchange rates in Kenya.

Knowing that the difficulty in predicting the logarithm of exchange rates has been a longstanding problem in international economics, the present paper tries to predict exchange rate in the context of a two-step error correction model. The same methodology to predict Exchange Rates was also used by Lustig *et al.* (2011) and Irigoyen and Aguirre (2014). The difference between the focus of this paper and what the previous authors have done, is the importance we give to the variables that might not be significant but have predictive power (see Lo *et al.* (2014)). Previous studies have only included the variables that are significant.

First, we estimate a cointegration equation to explain the exchange rate level as a function of global and domestic financial factors. Second, to model expected

returns, we estimate an error-correction (predictive) equation, where the change in the exchange rate is regressed on the lagged residual from the first step plus additional financial variables, also lagged and in differences. Our model is a factor model, as it uses other market variables to properly price exchange rates and predict currency returns. The main factor variable is constructed from the exchange rates following Engel *et al.* (2010). The dataset consist of a time series of five main Latin American countries from December 2001 until February 2016.

The choice of the variables to be included in the analysis is very crucial to have a good model. A spectrum of feature selection approaches exists. The so called Lasso was first introduced by Tibshirani (1995) in order to improve the prediction accuracy and interpretability of regression models by altering the model fitting process to select only a subset of the provided covariates for use in the final model rather than using all of them. Before Lasso approach, there were two widely used methods. The first one was the stepwise selection that was used for choosing which covariates to include, but it only improves prediction accuracy in certain cases, such as when only a few covariates have a strong relationship with the outcome. The second method was ridge regression, which improves prediction error by shrinking large regression coefficients in order to reduce over fitting, but it does not perform covariate selection. The benefit of Lasso is achieving both, variable selection and shrinkage, by forcing the sum of the absolute value of the regression coefficients to be less than a fixed value, thereby forcing certain coefficients to be set to zero and, effectively choosing a simpler model that does not include those coefficients. For the purpose of our research, we used elastic net extends lasso method for variable selection, which was introduced by Zou and Hastie (2005). They addressed several shortcoming of Lasso, claiming that when $p > n$ (the number of covariates is greater than the sample size) Lasso can select only n covariates (even when more are associated with the outcome) and it tends to select only one covariate from any set of highly correlated covariates. Additionally, even when $n > p$, the covariates are strong correlated, ridge regression tends to perform better. In other words, this method work by just adding another penalty to the main Lasso.

This paper provides additional evidence that Global Exchange Rate Factor offers information about exchange rates own movement. In addition, we show that commodity prices and equity market are important variables when it comes to explaining the exchange rates, where higher commodity prices lead to stronger exchange rate through an improvement in the terms-of-trade and higher stock prices signal higher expected economic growth. Furthermore, for Brazil, Peru and Mexico, measures of domestic risk premium were shown to significant, and high levels of risk premia being associated with lower valuations and higher expected returns. Moreover, the findings for carry and slope variables are in line with the existing literature, where higher carry leads to home currency appreciation in the next period due to its higher yield and a higher slope leads to home currency appreciation by signaling monetary policy tightening in the near term. This paper provides evidence that a higher risk aversion level, measured by the VIX index, leads to home currency appreciation in the next period by lowering the exchange rate level today and increasing its expected

return. Global Financial Crisis (2008) was included in the analysis and it was shown that the crisis had an effect on the exchange rates returns for the main Latin America countries. Lastly, inflation is more likely to have a significant negative effect, rather than a significant positive effect on the exchange rates. Furthermore, impulse response function (IRF) was implemented.

The reminder of the paper is as follows. Section two describes our empirical model. Section three presents the data based on the methodology used for variable selection. The empirical results will be provided in Section four. Lastly, Section five will conclude.

2 Empirical Model

2.1 Introducing the Global Factor

Engel *et al.* (2010) find evidence that exchange rates themselves offer information about common trends that are difficult to extract from observable fundamentals. Following their finding and methodology, we estimate the global variable as follows:

$$F_{i,t} = \omega_{1,t}f_{1,t} + \omega_{2,t}f_{2,t} + \omega_{3,t}f_{3,t} \tag{1}$$

where $f_{1,t}$, $f_{2,t}$ and $f_{3,t}$ are respectively the first, the second and the third factor, and ω_i is the respective weight.

To extract the components with the highest explanatory power, principal components analysis (PCA) was used, employing monthly observations of the 30 most actively traded global exchange rates according to the 2013 Triennial Central Bank Survey from the Bank for International Settlements (BIS). The log of the nominal exchange rate levels was taken before estimation. The graphical representation in Figure (3) in Appendix shows that the first three principal components explain 86% of the total variability across the 30 exchange rates, where the first component accounts for 56%, the second 16% and the third 14%. The first principal component can be interpreted as a dollar factor that has a correlation coefficient with the DXY index[1] of 0.9, and the second principal component can be interpreted as a carry factor that has a correlation coefficient of 0.68 with Deutsche Bank's G10 FX Carry Index [2], as shown in Figure (1). We could interpret the third principal component as volatility factor, even its correlation with JPMorgan's Global FX Volatility Index is 0.4, which is not as strong as it was for the first two principal components. Figure (4) in Appendix, shows that the three factors are uncorrelated.

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[1]The US Dollar Index (USDX, DXY) is an index (or measure) of the value of the United States dollar relative to a basket of foreign currencies (Euro (EUR), Japanese yen (JPY), Pound sterling (GBP), Canadian dollar (CAD), Swedish krona (SEK), Swiss franc (CHF)) often referred to as basket of US trade partners' currencies.

[2]Their strategy is to use the 3-month interest rate to rank G10 currencies each quarter. They then buy the top-3 yielding currencies and sell the bottom-3 currencies. In this way, they are regularly invested in the 3 largest carry trades in the G10 world.

Figure 1: First and second PCA factors

2.2 Model selection

The methodology used in this paper is a two step-error correction model, where the first step consists on estimating a cointegration equation for the nominal exchange rate, where the exchange rate logarithmic level is explained as a function of global and domestic financial factors. In the second step an error-correction equation is estimated, where the change in exchange rate is regressed on the lagged residual from the first step plus additional variables lagged and in differences.

2.2.1 The cointegrating equation

which uncovers a long-run relationship between exchange rates and other variables, is estimated by the following equation:

$$s_{i,t} = \delta_i F_{i,t} + X_{i,t}^\top \beta_i + \varepsilon_{i,t} \tag{2}$$

where the depended variable $s_{i,t}$ is the logarithm of exchange rate, the vector $X_{i,t}$ includes all the observable variables that were found to have an explanatory power, $F_{i,t}$ is the global variable defined in Equation (1), and $\varepsilon_{i,t}$ represents an idiosyncratic error.

The first-step equation was estimated by the dynamic ordinary least squares (DOLS). But since it is estimated in levels and the variables are most likely non-stationary, it might be the case that we will have spurious regression. In order to address this issue, we first check whether the variables are cointegrated; that is, if a linear combination of the variables is stationary, then the equation can be estimated in levels and the regression estimates will be valid. To test the cointegration among the variables a two-step Engle-Granger cointegration test[3] was performed.

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[3]The Engle-Granger two-step procedure involves estimating the level equation with OLS and then

2.2.2 The error-correction model

It consists on estimating the following equation:

$$ds_{i,t} = c + \theta_i \varepsilon_{i,t-1} + Z_{i,t-1}^{\top} \gamma_i + u_{i,t} \tag{3}$$

where the dependent variable is the exchange rates changes for every country or the currency returns; $\varepsilon_{i,t-1}$, is the lagged residuals from the first step regression and Z is the set of additional explanatory variables and c is a constant. The lagged residuals is the most important feature, it assumes exchange rate deviations from their fundamental value are expected to mean revert fast enough. Having said so, we are expecting to have a negative and significant coefficient. Ordinary Least Squared methodology is used to estimate the second step.

2.3 Variable selection

At this stage we go further from the existing literature on the exchange rates by using a specific methodology for variable selection, called elastic net. Elastic net method is a comination of lasso and ridge regression. In principle, both lasso and ridge regression can be interpreted as minimizing the same objective function:

$$min_{\beta_0,\beta}\{\frac{1}{N}||y - \beta_0 - X\beta||_2^2\} \tag{4}$$

but with respect to different constraints:

- $||\beta||_1 \leq \tau$ for the lasso approach;

- $||\beta||_2^2 \leq \tau$ for the ridge approach.

From Figure (2), you can see that the constraint region defined by the ℓ^1 norm is a square rotated so that its corners lie on the axes, while the region defined by the ℓ^2 norm is a circle (in general an n-sphere) which is rotationally invariant and, therefore has no corners. As seen in the figure, convex object that lies tangent to the boundary, such as the line shown, is likely to encounter a corner (or in higher dimensions an edge or higher–dimensional equivalent) or a hypercube, for which some components of β are identically zero, while in the case of an n–sphere, the points on the boundary for which some of the components of β are zero are not distinguished from the others and the convex object is no more likely to contact a point at which some components of β are zero than one for which none of them are (see Zou and Hastie, 2005)).

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running a stationary test on the estimated residuals. Engle-Granger (1987) suggest a cointegration test, which consists of estimating the cointegration regression by OLS, obtaining the residuals $\hat{u}_t$ and applying unit root test for $\hat{u}_t$. To test an equilibrium assertion, they propose testing the null that $\hat{u}_t$ has a unit root against the alternative that it has a root less than unity. Only if a cointegration relationship exist, if one wants to derive more information about the dynamic behavior of the variables, he will have to apply an error-correction model. Engle and Weib (1983) demonstrated that if a set of cointegration variables exist, they can be regarded as being generated by an error-correction model, which is called the Granger representation theorem.

Figure 2: Lasso vs ridge regression
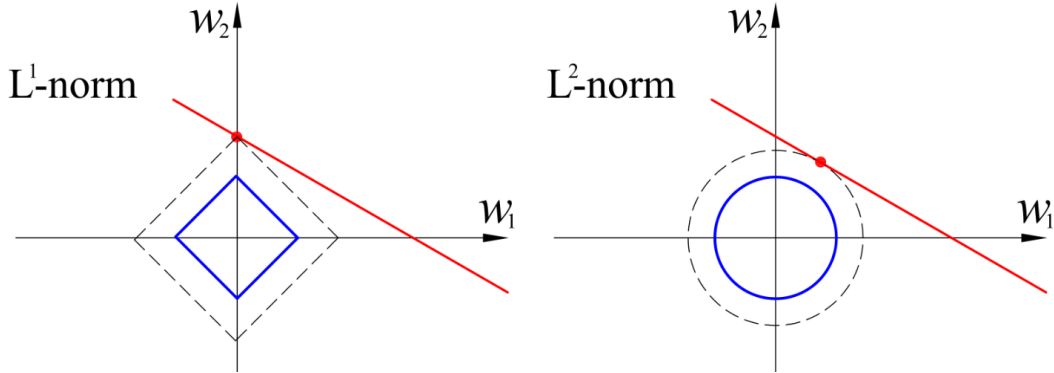
On the other hand the elastic net method, uses both penalties in order to make the shrinkage and the variable selection. The regularization path is computed for the lasso or elasticnet penalty at a grid of values for the regularization parameter lambda.. The algorithm is extremely fast, and can exploit sparsity in the input matrix x. The following is the elastic net extends lasso by adding an additional l^2 penalty term (see Zou and Hastie (2005)):

$$min_{\beta_0,\beta}\{||y - X\beta||_2^2 + \lambda_1||\beta||_1 + \lambda_2||\beta||_2^2\} \tag{5}$$

Equation (5) can be written in a different way

$$min_{\beta_0,\beta}\frac{1}{N}\sum_{i=1}^{N}\omega_i l(y_i, \beta_0 + \beta^T x_i) + \lambda[(1-\alpha)||\beta||_2^2]/2 + \alpha||\beta||_1] \tag{6}$$

Over a grid of values of λ covering the entire range. Here $l(y,\eta)$ is the negative log-likelihood contribution for observation i. The elastic–net penalty is controlled by α, and bridges the gap between lasso ($\alpha = 1$) and ridge ($\alpha = 0$). The tuning parameter λ controls the overall strength of the penalty. It automatically selects the variables that have an impact on the dependent variable. To estimate it, we used glmnet instead of lars. Hastie (2013) well established the benefits of using glmnet instead of lars such as: its speed; ability to handle large variables; variety of models; and above all elastic net includes both the ridge and lasso hybrids in between. [4]

3 Data and summary statistics

We would like data on as many countries as possible, the binding constraint is the availability of comparable data. Having said so, the data used in our analysis consist of time series of main Latin America countries (Brazil (BRL), Colombia

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[4]The name of R packages are glmnet and LARS.

(COL), Chile (CLN), Mexico (MXN) and Peru (PEN)). Data were collected at a monthly frequency from Bloomberg. Our sample begins in December 2001 and ends in February 2016. It represents 171 months in total and includes the worst months of the global 2007 - 2009 financial crisis. Exchange rates are at the end of month values of US Dollar versus the currencies of five main Latin America countries. The analysis in done in country by country basis. We initially started with a large number of variables without making the distinction for every country and then we implemented the methodology for variable selection explained in Session 3. Based on it Table (3) in Appendix provides the variables that were chosen to be used for the two-step regression.

3.1 For the cointegrating equation

For every country the Global Exchange Rate Factor was selected to be included in the regression; this variable captures the idea that exchange rates themselves offer information about their own movement. Secondly, commodity prices were included for some countries. The intuition behind it, is that higher commodity prices are expected to lead to stronger exchange rate through an improvement in the terms-of-trade. Moreover, a variable measuring the equity market for each country was selected, behind the choice there is an economic intuition that claims that higher stock prices signal higher expected economic growth. Furthermore, for Brazil and Peru, a measure of domestic risk premium-5 year (5y) Credit Default Swap (CDS) spreads were included in the regression, while for Mexico, 1 month (1m) FX option-implied volatility was included. High levels of risk premia are usually associated with lower valuations and higher expected returns. In the end, SPX Index, Eurostoxx and Equity China were included in the analysis. The idea behind this selection could be given by the trade relationship that the Latin American countries have with USA, Europe and China.

3.2 For error correction equation

After the residuals of the first step, carry is the second variable incuded in the second step of the regression. Carry is the interest rate level differential between the home country and the US as a measure of carry, using a three month (3m) implied yields. The intuition behind the use of this variable is that higher carry is expected to lead to home currency appreciation in the next period due to its higher yield. Secondly, interest rate slope differential using one month-one year (1m1y) slopes, as it contains relevant information about the future of monetary policy. A higher slope is expected to lead to home currency appreciation by signaling monetary policy tightening in the near term. Moreover, the so called VIX index is added in the analysis as an index of the global risk aversion. Intuitively, a higher risk aversion level may lead to home currency appreciation in the next period by lowering the exchange rate level today and increasing its expected return. Of course, this result depends on the persistence of the process driving the VIX index. Since the recent global financial crisis is within the time horizon of our study, we included a dummy to capture

the effect that crisis has on the exchange rates returns for the main Latin America countries. Lastly, inflation was also included in the regression. Inflation is more likely to have a significant negative effect, rather than a significant positive effect on the exchange rates.

Some basic features of data to help guide our empirical design are provided in Table (4) and Table (5) in Appendix. They provide reports means and sample ranges of the variables used for the first and the second step, respectively. There is no significant difference in mean returns. The bottom panel of Table 2 shows the skewness and kurtosis for the exchange rates. The skewness is positive and different from 0 for all countries except for Peru, that has a negative skewness. In our case the values of the skewness are all between $-\frac{1}{2}$ and $+\frac{1}{2}$, which indicates that the distribution is approximately symmetric.

On the other hand, kurtosis is lower than 3 for all the countries. A value of kurtosis equal to 3 is considered to be the value for a normal distribution, this distribution is called platykurtic. Compared to a normal distribution, its tails are shorter and thinner, and often its central peak is lower and broader. We proceed by performing the Jarque-Bera normality test. By the results obtained, we reject the normality hypothesis of the test for all the countries. So, we conclude that exchange rate changes are non-Gaussian for most countries and hence are not jointly and normally distributed. This might indicate that the information on higher-order moments of exchange rate changes should be helpful in factor construction.

3.3 Impulse response function (IRF)

We use the IRF to investigate the interactions between some of the variables and the Exchange Rates. In esence the impulse response function is based upon the world moving average representation of a VAR(p)-process. The $(i, j)th$ coefficients of the matrices Φ_s are thereby interpreted as the expected response of variable $y_{i,t+h}$ to a unit change in variable $y_{j,t}$. These effects can be cumulated through time $h = 1,2,...$, and hence one would obtain the cumulated impact of a unit change in variable j on the variable i at time h. Rather than these impulse response coefficients, it is often conceivable to use orthogonal impulse responses as an alternative. This is the case if the underlying shocks are less likely to occur in isolation but rather contemporaneous correlation between the components of the error process u_t exists; i.e., the off-diagonal elements of Σ_u are non-zero. The orthogonal impulse responses are derived from the Choleski decomposition of the error variance–covariance matrix $\Sigma_u = PP^\top$, with P being lower triangular. The moving average representation can then be transformed to:

$$y_t = \mu + \Psi_0\varepsilon_t + \Psi_1\varepsilon_{t-1} + ... + \Psi_q\varepsilon_{t-q} \tag{7}$$

with $\varepsilon_t = P^{-1}u_t$ and $\Psi_i = \Phi_i P$ for i = 0,1,2,... and $\Psi_0 = P$ (see Gentmen et $al.$ (2008)). Incidentally, because the matrix P is lower triangular, it follows that only a shock in the first variable of a VAR(p)-process exerts an infuence on all te remaining ones and that the second and following variables cannot have a direct

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impact on $y_{1,t}$. We assume we have one standard deviation shock on some of the significant variables (based on the results) and see the impact they have on the depended variables (exchange rates of the Latin America Countries).

4 Results

In order to validate our two-step modelling framework, the variables should be cointegrated. If that won't be the case then we might be estimating a spurious regression, which will lead to not consistent estimates. Table (6) in Appendix, provides the Engle-Granger cointegration test results. The variables are not stationary in levels but stationary in first difference, so they are I(1). Moreover in the case of Engle and Granger Cointegration we test whether the residuals we obtain from the cointegrating relationship are stationary, so the the critical values are different. For all cases we reject the null hypothesis [5], we interpret this as evidence that the residuals are stationary and the series cointegrated. Having said so we validate our two-step modelling framework and can continue with the interpretations of the results of the methodology used.

4.1 For the cointegrating equation

The results of the First-step regression are provided in Table (7) and Table (8) in Appendix. A measure of domestic risk was found to be important for Brazilian Real (BRL), Mexican Peso (MXN) and Peruvian Sol (PEN), five year Credit Default Swaps (CDS) for the first two and one month FX-implied volatility for the last one. Higher 5 year Credit Default Swaps (CDS) spreads are associated with a weaker BRL and weaker PEN. Higher 1 month FX-implied volatility is associated with a weaker MXN.

The R-squared is above 0.80 in all cases, with the exception of Colombia. The global exchange rate factor enters with a statistically significant effect in all cases, except for Peru. Commodity prices were found to be important for our Latin America Emerging countries. For Mexican and Colombian Peso, oil prices enter with a statistically significant negative coefficient. Moreover, for Chilean Peso (CLP), copper prices have negative significant effect. For Peru, based on the variable selection methodology, three were the commodity prices that were found to have an impact on Peruvian Sol; copper, gold and oil prices. At first, we used copper, but by doing so the residuals of the first step equation were not stationary anymore. This was the case when gold was used as well. We then tried the oil price as a proxy for the comodity prices for Peru, after having passed all the tests. Moreover, oil price has a statistically significant negative impact over the sample period.The negative coefficient is as expected; an increase in commodity prices is associated with a strong

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[5]The critical values in Engle and Yoo (1987) are given in absolute value; the null hypothesis is rejected when the test statistic is negative and the magnitude is smaller than the table values (see table 2 at Engle and Yoo (1987))

domestic exchange rate(lower USD/EMFX), while Brazil is the only country where the comodity index enters positively but it is not statistically significant.

Equity markets are important in Brazil. A stronger BOVESPA is associated with a stronger Brazilian real (the negative sign is due to the fact that the exchange rate is expressed USD/local), while a higher SP500 is associated with a weaker exchange rate due to dollar strengthening. Moreover, Eurostoxx has a significant negative effect on the exchange rate of Brazil, while the effect of Equity China is positive but not significant. Therefore, a stronger Eurostoxx strengthen Brazilian real, while a stronger Equity China will have a stronger effect on the dollar. On the contrary, a higher SP500 is associated with a stronger Mexican peso; the strong links between the US and Mexican business cycles make MXN a higher-beta play of the USD. While the impact of Eurostoxx and Equity China, are not significant in Mexico, which once again verifies the strong link between Mexico and USA. For Colombia none of equity markets are significant, while for Chile only Equity China has a statistical positive effect. For Peru, SP500 and Equity China have a negative effect, while Eurostoxx has a positive effect.

4.2   For the error–correction equation

Table (9) in Appendix shows the results of the second step regression, error-correction equations. As expected, the regressions have low R-squared coefficient: the dependent variables are exchange rate returns and the independent variables all lag one period. The error-correction term enters with a statistically significant negative coefficient in all cases. This is evidence of mean reversion in deviations from fundamental values. Coefficients range from -0.079 to -0.213 and imply a half-life of 1-2 months.

The carry factor is statistically significant in all cases, except Colombia. In Brazil, Mexico and Peru the sign is negative: a higher local yield relative to the US leads to home currency appreciation. In Mexico, the carry factor enters in differences. Oddly, the sign is positive in Chile. It is negative in Colombia, but not significant at the 10%. The slope factor is statistically significant in Colombia, Chile and Peru, but not in Brazil and Mexico. Negative signs in Colombia and Peru imply a steepening in local yields relative to the US leads to home currency appreciation by signaling a tightening in domestic monetary policy in the following months.

The VIX index enters with a negative significant coefficient in Brazil, Mexico, Colombia, Chile, Peru. As stated before, a negative coefficient may signal that higher risk aversion levels lead to home currency appreciation in the next period by lowering the exchange rate level today and increasing its expected return. This result will depend on the persistence of the process driving the VIX index.

The dummy variable enters with a significant positive effect in Brazil, Mexico, Colombia, Chile, while its effect in Peru is positive but not statistically significant. Finally, the effect of inflation on exchange rates is consistent with the existing literature on this field. An increase in inflation is expected to negatively affect the exchange rate, so it will depreciate the currency of the country. We find this to be

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the case for Brazil, Colombia, Chile and Peru. While for Mexico this is not the case. The effect of inflation in the Mexican Peso is negative but not significant.

4.3 For the impulse response function

Figure (5) shows the response of Brazilian Real (BRL) if there will be a shock on Sovereign Credit Deafaut Swaps (CDS), IBOVESPA or Eurostoxx. A shock in Brazilian CDS and Eurostoxx will depreciate the Brazilian Real, while a shock in IBOVESPA will appreciate the BRL. Moreover, Figure (6) shows that when there is a shock on the Oil Prices the Mexican Peso (MXN) will appreciate; if the shock will be on the SPX or on one month FX-implied volatility (MXN FX) the MXN will depreciate. Figure (7) shows the appreciation of the Colombian Peso (CLP) in the case of a shock on the Oil Prices; while the Chilean Peso (CLP) will appreciate, Figure Figure (8), if there is a shock on the Copper Price and depreciate in the case of a shock on Equity China. Figure (9) shows the depreciation of the Peruvian Sol (PEN) when there is a shock to Eurostoxx or SPX and appreciate if there will be a shock on the Oil Prices. While the effect of a shock on Peruvian CDS on PEN, changes over the time horizon.

5 Backtesting

To evaluate the model we conduct a backtesting, the model is estimated at every month-end. The sample is from December 2001 to February 2016. For in-sample estimation five years, December 2001 to December 2005, were used and the remaining observations were used for out-of-sample forecasting. Each following month, new observations to the datastr were added, re-estimated the model and calculated new forecasts. We did recursive rather than rolling estimations, adding new observations each month without dropping observations from initial periods.

Table (1) shows the results of the backtesting exercise. The first panel shows the models the results, and the last one provide the momentum strategy. We included the main times that characterize the frequency distribution of returns. Expected returns and volatility estimates are calculated monthly and annualized. We also include the sharpe ratio. From the results we see that our model performs better than the momentum strategy. What is important to mention is that our model has impresive results when we create a equaly weighted portfolio of all the currencies, with a sharpe ratio of 1 and the anual return of 7,81%.

The results are encouraging, the model provides a Sharpe ratio of 1, while a common strategy for the momentum provides a sharpe ratio of 0,45. Moreover, we run a simple regression of the momentum strategy over the model strategy, the idea behind this regression is that a significant and positive intercept β_0 (also known as the alha, model mispricing and risk-adjusted return depending on the setting) implies that investors that already have the momentum strategy in their portfolio, can improve their risk adjusted performance if thay add this model strategy on the margin to their portfolio. In other words, it shows that the strategy is independent

from momentum and can add value to investors that are already invested in momentum, which, as shown in Table 2, is true for all the currency returns except for Peru, where the constant is positive but not significant.

Moreover, Figure 10 in the Appendix provides the currency correlations, as shown the currencies are not strongly correlated with one another, suggesting that model returns are also not strongly correlated across currencies. In Figure 11, are shown all the cumulative returns for all the currencies, as well as the cumulative return for the common strategy, while Figure 12 shows the cumulative returns of the model for each currency and those of the momentum strategy.

Table 1: Backtesting Results

Currencies	BRL	MXN	COL	PEN	CLP	All
Model						
Returns (yearly)	4,41%	9,81%	6,09%	2,03%	14,13%	7,81%
Volatility	16,21%	11,05%	14,51%	5,52%	11,83%	7,85%
Sharpe Ratio	0,27	0,89	0,42	0,37	1,19	1,00
Momentum						
Returns (yearly)	1,12%	4,63%	1,75%	2,70%	3,10%	4,04%
Volatility	10,62%	10,39%	12,85%	4,78%	10,80%	8,92 %
Sharpe Ratio	0,36	0,44	0,13	0,56	0,28	0,45

6 Conclusion

This paper finds that exchange rate themselves offer information about common trends that are difficult to extract from observable fundamentals. This is an important finding, because it implies the need for global currency risk management. If changes in exchange rates were independent and random, then buying assets in many different currencies would offer a simple diversification mechanism of currency risk. Therefore, there is a clear need to hedge the currency exposures. We find a strong link between currency carry and the exchange rate return as well as slope factor and currency returns. Further, we document that currency returns are pos-

itively correlated with increases in implied stock market volatility VIX. Moreover, exchange rate returns depend from the crisis and the inflation rate.

An extension of the current framework to the major Eastern Europe, Middle East, and Africa (EEMEA) and Asian currencies, will be necessary to have a more complete view of exchange rate movements in emerging markets. It is desirable for us, to compare our findings to other kinds of methodologies. Lastly, it will be interesting to show that a significant variable is not automatically a good predictive variable, while a not significant one could be.

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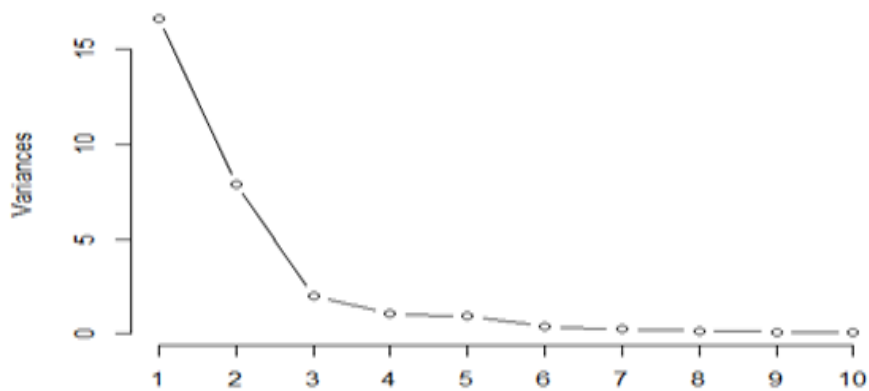
A Appendix

A.1 Additional figures

Figure 3: Principal component factor selection

Table 2: Model vs momentum strategy

	(BRL)	(MXN)	(COL)	(PEN)	(CLP)
Constant	0.03*	0.06**	0.01*	0.014	0.10***
	(0.033)	(0.002)	(0.03)	(0.0014)	(0.0022)
Observations	123	123	123	123	123
Adjusted R^2	0.10	0.11	0.027	0.047	0.15
Note:			*p<0.1; **p<0.05; ***p<0.01		

A.2 List of variables

Correlation	Factor 1	Factor 2	Factor 3
Factor 1	1,00		
Factor 2	-0,08	1,00	
Factor 3	0,37	-0,10	1,00

Figure 4: Factors correlations

Table 3: The selected variables

Included variables	BRL	MXN	COP	CLP	PEN
Cointegration equation					
Global Factor	√	√	√	√	√
CRB Index	√				
Oil prices		√	√		
Copper prices				√	√
Gold prices					√
IBOVESPA Index	√				
CDS	√				√
FX option volatility		√			
SPX Index	√	√	√	√	
Equity China	√	√	√	√	√
Eurostoxx	√	√	√	√	√
Error correction Equation					
Carry differential	√	√	√	√	√
Slope differential	√	√	√	√	√
VIX	√	√	√	√	√
Crisis dummy	√	√	√	√	√
Inflation	√	√	√	√	√

A.3   Additional results

Table 4: Summary statistic for the first step

Statistic	N	Mean	St. Dev.	Min	Max
MXN	171	2.49	0.14	2.20	2.90
BRL	171	0.82	0.24	0.44	1.39
CLP	171	6.33	0.13	6.08	6.62
COP	171	7.70	0.17	7.47	8.10
PEN	171	1.12	0.10	0.94	1.29
Global Factor	171	6.95	0.15	6.76	7.38
CRB Index	171	5.61	0.23	4.98	6.14
Oil prices	171	4.14	0.46	2.97	4.94
Copper prices	171	8.52	0.56	7.27	9.20
Gold prices	171	6.69	0.56	5.62	7.50
IBOVESPA Index	171	10.57	0.56	9.06	11.19
Peru CDS	171	5.44	0.46	4.61	6.78
Brazil CDS	171	5.76	0.61	4.94	7.79
FX option volatility	171	2.31	0.38	1.69	3.68
SPX Index	171	7.17	0.25	6.60	7.65
Equity China	171	7.69	0.39	6.97	8.69
Eurostoxx	171	8.01	0.19	7.59	8.41
Exchange Rates	Skewness	Kurtosis	JB		
MXN	0.53	0.07	8.26		
BRL	0.51	−0.56	9.49		
CLP	0.44	−0.88	10.83		
COP	0.44	−0.94	11.61		
PEN	−0.07	−1.32	12.17		

Table 5: Summary statistics for the second step

Statistic	N	Mean	St. Dev.	Min	Max
Carry Brazil	171	11.93	4.51	5.53	26.14
Slope Brazil	171	0.02	1.94	-3.47	10.71
Carry Mexico	171	4.36	1.80	1.701	12.70
Slope Mexico	171	0.11	0.94	-2.04	4.79
Carry Colombia	171	4.43	1.81	0.54	8.94
Slope Colombia	171	0.94	2.60	-7.34	13.85
Carry Chile	171	2.09	2.05	-3.09	6.74
Slope Chile	171	-0.30	1.07	-3.87	2.16
Carry Peru	171	2.00	2.58	-5.56	12.10
Slope Peru	171	-0.14	1.81	-8.31	6.69
VIX	171	20.20	8.45	10.42	59.89
Crisis	171	0.05	0.21	0.00	1.00
Inflation Brazil	171	6.74	2.83	2.96	17.24
Inflation Mexico	171	4.16	0.87	2.13	6.53
Inflation Colombia	171	4.64	1.78	1.76	7.94
Inflation Chile	171	3.27	2.20	-2.28	9.85
Inflation Peru	171	2.65	1.28	0.20	5.78

A.4 Estimated parameters

Table 6: Engle Granger two-step test

| | First step results | | | |
| | In level | | | In difference |
	Dickey Fuller	p-value	Dickey Fuller	p-value
BRL	-0.71	0.96	-4.95	0.01
MXN	-2.40	0.41	-5.82	0.01
COP	-0.52	0.98	-5.82	0.01
CLP	-1.23	0.90	-4.84	0.01
PEN	0.14	0.99	-4.09	0.01
Global Factor	-1.80	0.66	-5.74	0.01
CRB	-1.90	0.62	-5.02	0.01
SPX	-2.55	0.35	-5.12	0.01
IBOVESPA	-1.19	0.91	-5.99	0.01
Europe	-2.60	0.33	-4.59	0.01
China	-2.97	0.17	-4.34	0.01
Brazil CDS	-1.35	0.85	-6.55	0.01
Oil	-1.08	0.92	-5.72	0.01
MXN FX	-3.38	0.06	-6.11	0.01
Copper	-1.56	0.76	-5.81	0.01
Peru CDS	-2.66	0.30	-6.10	0.01
Gold	-0.17	0.99	-4.76	0.01
	Second step results			
	Test statistic			
Residuals for Brazil	-3.60			
Residuals for Mexico	-3.35			
Residuals for Colombia	-3.20			
Residuals for Chile	-3.25			
Residuals for Peru	-3.50			

Table 7: *First step results*

	Dependent variable		
	BRL	MXN	COP
	(1)	(2)	(3)
F	0.573***	0.041***	0.258***
	(0.109)	(0.004)	(0.067)
CRB Index	0.013		
	(0.067)		
Oil prices		−0.121***	−0.304***
		(0.012)	(0.019)
SPX Index	0.374***	−0.122**	0.016
	(0.057)	(0.051)	(0.049)
IBOVESPA Index	−0.306***		
	(0.066)		
MXN_FX		0.064***	
		(0.017)	
Eurostoxx	−0.230***	0.044	0.021
	(0.057)	(0.039)	(0.043)
Equity China	0.041	−0.007	−0.031
	(0.039)	(0.014)	(0.021)
Brazil CDS	0.119**		
	(0.049)		
Constant	−1.841**	3.130***	7.122***
	(0.883)	(0.318)	(0.438)
Observations	171	171	171
Adjusted R^2	0.836	0.894	0.736

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: *First step results*

	Dependent variable:	
	CLP	PEN
	(1)	(2)
F	0.313***	0.033***
	(0.039)	(0.028)
Peru CDS		0.053***
		(0.012)
Copper prices	−0.242***	
	(0.010)	
Oil prices		−0.127***
		(0.010)
SPX Index	0.041	−0.045*
	(0.029)	(0.022)
Eurostoxx	−0.038	0.225***
	(0.025)	(0.018)
Equity China	0.056***	−0.040***
	(0.013)	(0.008)
Constant	5.788***	−0.044
	(0.256)	(0.233)
Observations	171	171
Adjusted R^2	0.857	0.873

Note: In brakets are shown the standard errors *p<0.1; **p<0.05; ***p<0.01

Table 9: Results for the second step

	Dependent variable				
	returns				
	(1)	(2)	(3)	(4)	(5)
Error Correction	−0.154***	−0.213***	−0.095**	−0.031**	−0.079**
	(0.041)	(0.049)	(0.038)	(0.053)	(0.035)
Carry Factor	−0.003	−0.002	0.001	0.006***	0.001**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Slope Factor	0.005*	0.003	−0.001	0.011***	0.0002
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
VIX Index	−0.002**	−0.001**	−0.001**	−0.001***	−0.0004**
	(0.001)	(0.0003)	(0.0005)	(0.0004)	(0.0002)
Dummy	0.080**	0.055***	0.047*	0.050***	0.005
	(0.024)	(0.013)	(0.017)	(0.016)	(0.007)
Inflation	0.004*	−0.016	0.016*	0.002	0.005**
	(0.003)	(0.007)	(0.009)	(0.005)	(0.002)
Constant	0.036*	0.028***	0.018*	0.010	0.005
	(0.015)	(0.009)	(0.010)	(0.008)	(0.003)
Observations	170	169	169	169	169
Adjusted R^2	0.108	0.188	0.060	0.096	0.073

Note: *p<0.1; **p<0.05; ***p<0.01

A.5 Impulse response functions
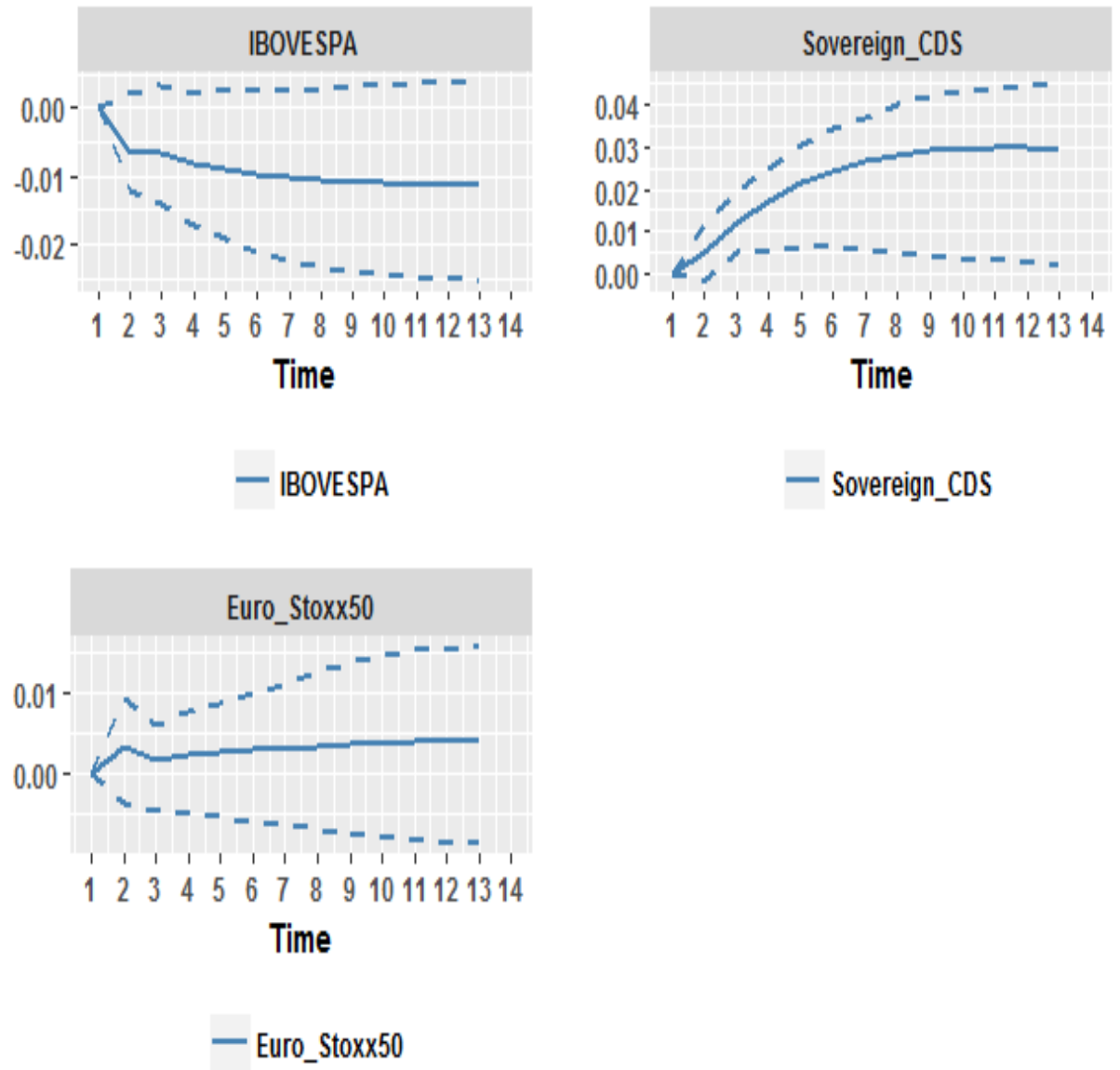
Figure 5: Impulse response function for Brazil
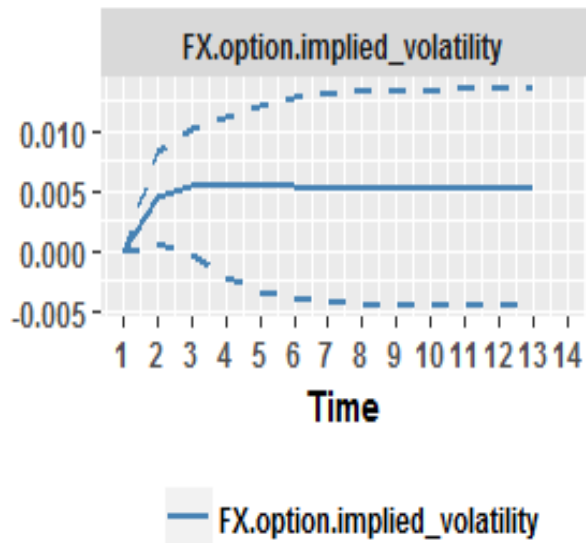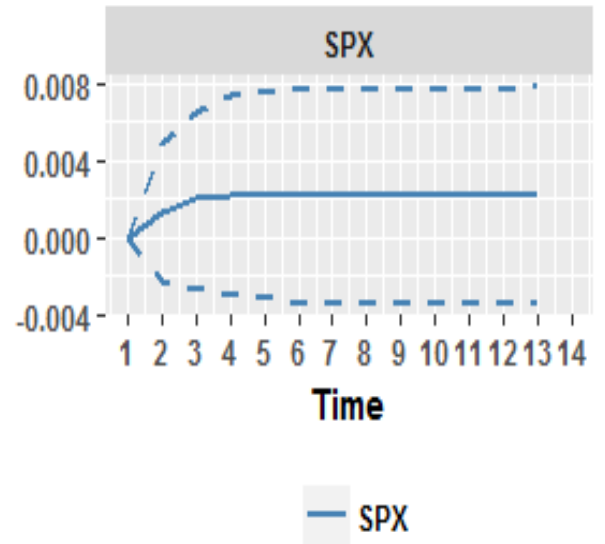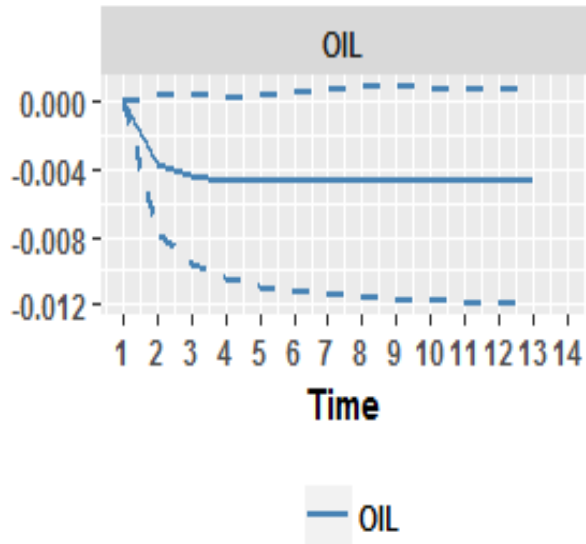
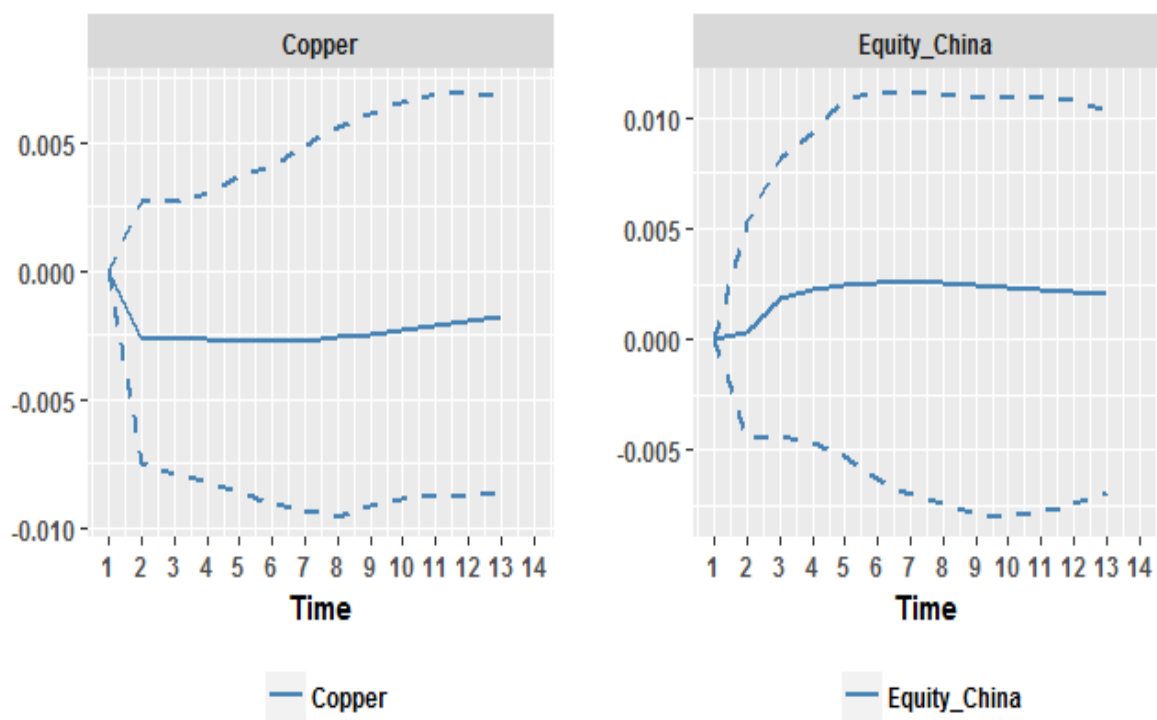Figure 6: Impulse response function for Mexico
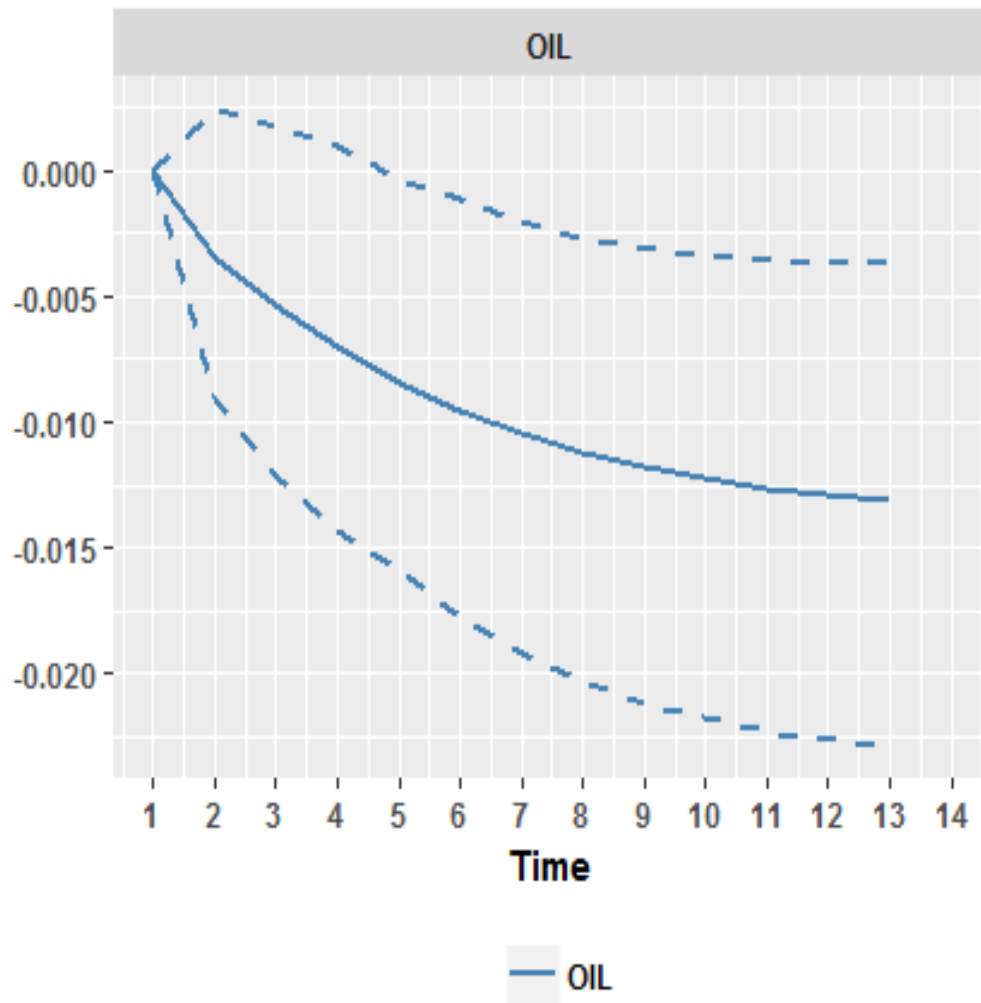
Figure 7: Impulse response function for Colombia
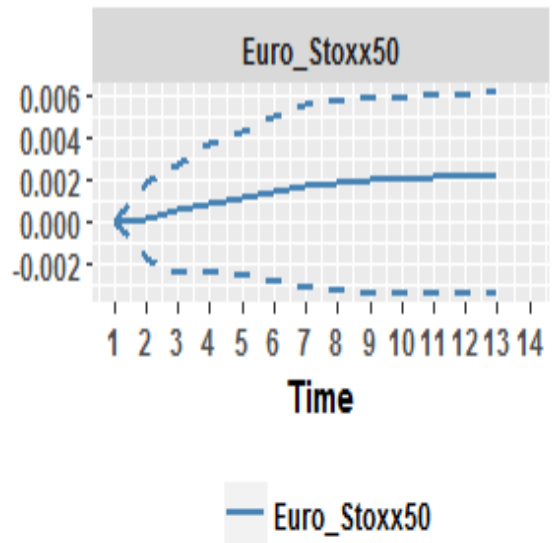
Figure 8: Impulse response function for Chile
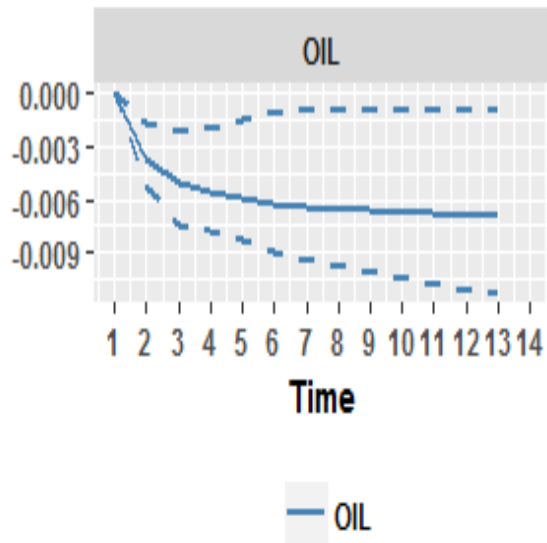
Figure 9: Impulse response function for Peru
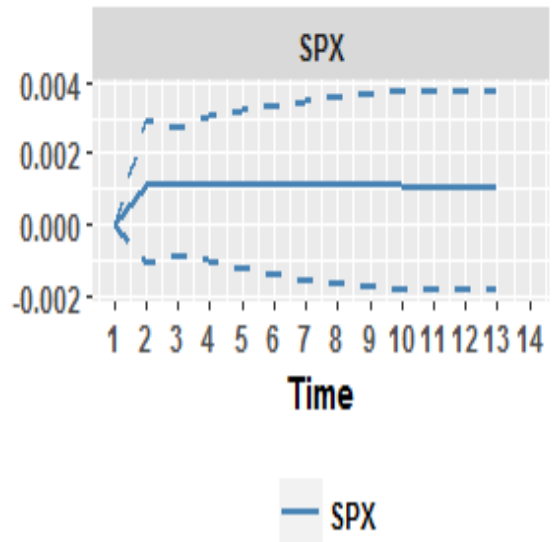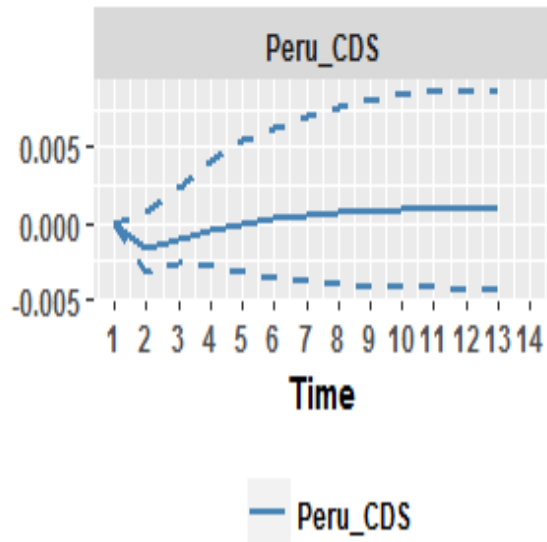
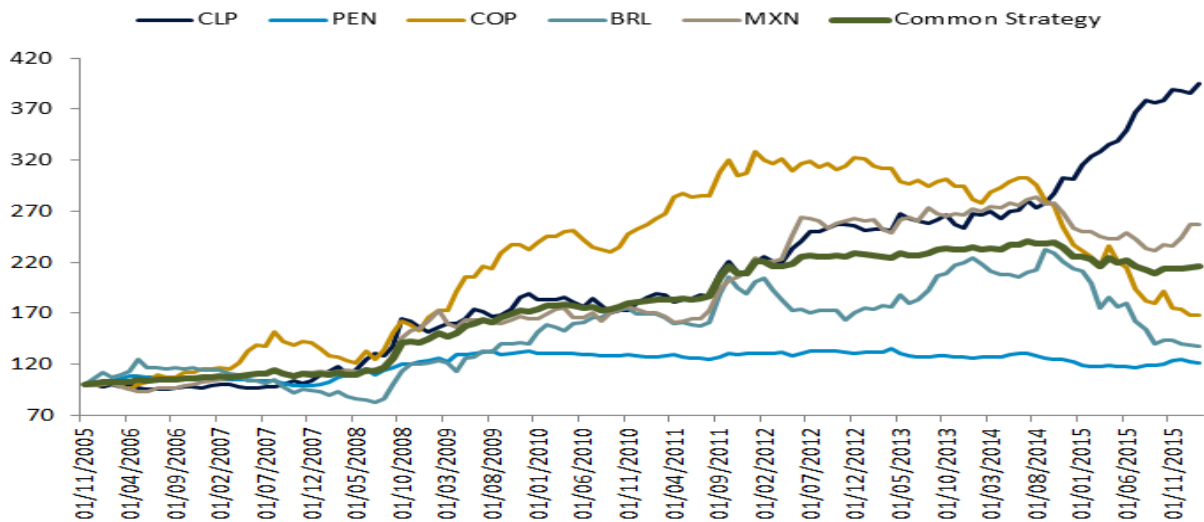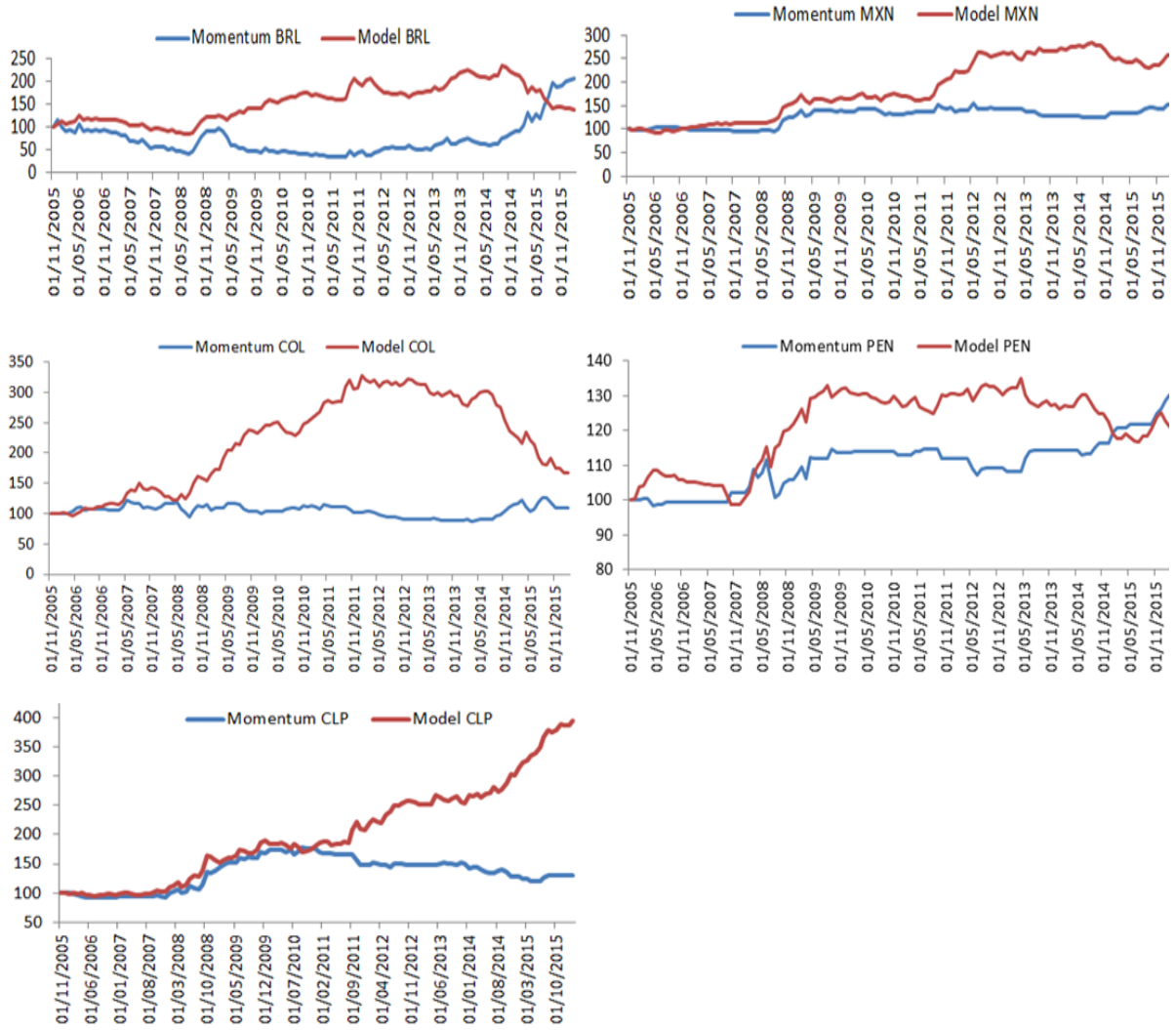| Correlation	Brazil	Mexico	Columbia	Peru	Chile
Brazil	1,00				
Mexico	0,31	1,00			
Columbia	0,39	0,29	1,00		
Peru	0,16	0,11	0,34	1,00	
Chile	0,24	0,39	0,08	0,07	1,00

Figure 10: Correlations of the currency returns

Figure 11: Cumulative returns

Figure 12: Cumulative returns