COMMON FACTORS AND THE EXCHANGE RATE: RESULTS FROM THE BRAZILIAN CASE

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ABSTRACT
This paper studies the usefulness of factors models in explaining the dynamics of the exchange rate Real / Dollar from January 1999 to August 2011. The paper verifies that the inclusion of factors embedded on the common movements of exchange rates of a set of countries significantly improves the in-sample and out-of-sample predictive power of the models comprising only macroeconomic fundamentals commonly used in the literature to forecast the exchange rate. The paper also links the information contained in the factors to global shocks as the demand for "dollars" – a dollar effect, volatility, and liquidity of global financial markets.

Keywords: Exchange rates; Factor models; forecasting.

RESUMO
O trabalho estuda o papel de fatores comuns na dinâmica da taxa de câmbio Real / Dólar norte-americano no período de Janeiro de 1999 a Agosto de 2011. O trabalho verifica que a inclusão de fatores extraídos a partir dos movimentos comuns das taxas de câmbio de um conjunto de países melhora significantemente o poder preditivo dentro e fora da amostra dos tradicionais modelos macroeconômicos comumente usados para prever a taxa de câmbio. O trabalho também liga a informação contida nos fatores a choques globais tais como a demanda por "dólares" – Efeito dólar, volatilidade e liquidez dos mercados financeiros.

Palavras-Chave: Taxa de Câmbio; Modelos fatoriais; Previsão.

JEL Classification: F31; F47.

Área 8 - Microeconomia, Métodos Quantitativos e Finanças

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1. Introduction

Following the collapse of Bretton Woods in the beginning of the 1970s and the adoption of floating exchange rate regimes by most developed countries, the behavior of exchange rates has been a frequent topic of analysis, as this variable exerts a significant impact on countries' trade balance, price levels, and output. Given the important role of the exchange rate on the economy, being able to forecast is of great relevance. Unfortunately, the body of research dedicated to analyzing the predictive power of exchange rate determination models has reached limited success in forecasting the exchange rate, especially for short term predictions. This difficulty is considered one of the major weaknesses of international macroeconomics (Bacchetta and Wincoop, 2006).

Meese and Rogoff (1983), in their very influential work, verified the lack of predictive power of theoretical exchange rate models. They argued that little or no information about the future movement of exchange rates over short horizons can be extracted from macroeconomic variables such as monetary aggregates, price levels, output gap, or interest rates. They found that no model was able to forecast significantly better than a simple random walk model. After more than 20 years, Cheung, Chinn, and Pascual (2005) performed a similar exercise incorporating models developed during the 1990s and applying new econometric techniques. The authors concluded that some models perform well for certain projections or specific exchange rates; however, their results do not identify a model that is broadly consistent.[2] Faust et. al. (2003) also noted that most of the works that find that macroeconomic models outperform the random walk model are sensitive to the choice of horizons and sample periods.[3]

In the last years the literature has been discussing different reasons to explain this instability on the forecasting of the exchange rate. From a theoretical point of view, one possible explanation for this fragility in forecasting the exchange rate would be the way the exchange rate is determined. If the exchange rate is the expected present discounted value of current and future fundamentals it is possible that the evolution of the exchange rate is affected not only by the dynamics of observables fundamentals like monetary aggregates, price level, or output, but also by unobservable variables such as risk premium or noise trading. As discussed by Engle, Mark, and West (2008), if these unobservable factors have little correlation with the observable, it reduces the predictive power of the models, leading to the weak results found in the literature.[4] Consistent with this role of unobservable variables in explaining movements of the exchange rate, Bachetta and Wincoop (2004, 2011) developed the scapegoat theory. The theory asserts that if the dynamics of the exchange rate is partially given by unobservable variables, changes in the expectations of the agents with respect to the structural parameters of the economy generated by shocks on these unobservable variables will generate this instability on the relationship between the exchange rate and fundamentals.

The question brought by the literature then is how we can capture these unobservable movements that have an impact in the dynamics of the exchange rate in order to deal with the issue of this instability in forecasting the exchange rate. Evans and Lyons (2002, 2005, 2008) and Chinn and Moore (2010) adopt a microstructure approach to the traditional macroeconomic models with the objective of answering the question. In these papers, the inclusion of order flow variables would solve the problem of the

[2] The Brazilian experience mirrors the international experience. Muinhos, Alves, and Riella (2003) found that models incorporating uncovered interest rate parity outperformed the random walk model when describing the behavior of the Brazilian exchange rate from May 1999 to December 2001. Yet, Moura, Lima, and Mendonça (2008), using data from January 1999 to December 2007, conclude that only models that incorporate the Taylor rule outperformed the random walk model.

[3] The use of panel techniques to forecast exchange rates has been reaching relative success. Applying various techniques, Mark and Sul (2001) and Groen (2005) used panels from various countries to determine the co-integration relationship between exchange rates and monetary fundamentals and used this relationship to successfully forecast the exchange rate over long horizons. Similarly, Galimberti and Moura (2013) show in a panel of emerging economies that a Taylor rule exchange rate model has out-of-sample exchange rate predictability.

[4] Another explanation supplied by Engel and West (2005) is that if the exchange rate is determined by the present value deducted by future fundamentals and if at least one of the fundamentals possesses a unit root and the discount factor is near 1, the exchange rate will behave similarly to the random walk. They argue that within this framework, it would be very difficult for macroeconomic models to beat a random walk in forecasting the exchange rate.

conventional models because these variables would account for shocks that lead to instability in the relationship between the exchange rate and fundamentals.[5]

This paper goes in a direction different from the microstructure approach. We use common factors that are extracted directly from the dynamics of the exchange rate of a set of 18 countries in order to identify the unobservable component of the exchange rate dynamics. Two conditions are needed for the use of factor models to be helpful in forecasting the exchange rate. The first one is that the information embedded in the common movements of the exchange rates of various countries is related to the unobservable variables and the second one is that these variables play a significant role in the dynamics of the exchange rate. The paper analyzes whether these conditions are satisfied by studying the dynamics of the exchange rate Brazilian Real to the U.S. dollar after the adoption of the floating exchange rate regime in Brazil.

The advantage of factor models compared to the microstructure approach is that they might improve the predictive power of the models without losing their tractability. This is the case since factor models allow the information set to be condensed into a small number of factors, the data needed for implementing the methodology are easily obtained, and it is more straightforward to establish a link between the estimated factors and *proxies* for different global shocks and this would improve our knowledge about the role played by different unobservable shocks in the dynamics of the exchange rate.[6]

Factor models are widely used to forecast macroeconomic variables (see Forni and Reichlin (1998), Forni et al. (2000), Stock and Watson (2002) and Bai (2004)), but they are rarely used in the case of exchange rates. Groen (2006) uses a dynamic factors model to identify the "exchange rate level dictated by fundamentals" and used the difference between this value and the exchange rate to successfully forecast the exchange rate over a two-year horizon. Engel, Mark, and West (2008) constructed factors derived from the exchange rates of 17 countries and used these factors to forecast the exchange rate over a two-to-four-year horizon. The authors obtained satisfactory results for the period between 1999 and 2007.

The results in the paper confirm the usefulness of using factor models. The paper shows that the estimated factors are related to unobservable shocks, providing an economic meaning for the factors. The paper links the estimated factors with observable variables usually used as proxies for several global shocks. The paper shows that the information contained in the factors is related to common global shocks as the global demand for "dollars" – a dollar effect, volatility, and liquidity of global financial markets.

Besides giving an economic interpretation for the factors, the paper shows that the inclusion of the factors systematically increases the in-sample and out-of-sample predictive power of the models that contain only the macroeconomic variables, traditionally used to forecast the exchange rate. The results indicate that the factors carry useful information for forecasting the exchange rate and are crucial to understanding the dynamics of the exchange rate.

The present study is organized as follows: the following section shows the data used in the paper. Section 3 describes the exchange rate model used in the paper and the estimation of the common factors. Section 4 studies the links between the common factors and different global shocks. Section 5 presents the results of the in-sample and out-of-sample exercises. Section 6 concludes.

[5] One possibility discussed by the microstructure approach literature is that order flow variables carry private information that becomes embedded in the exchange rate.

[6] It is worth noting that the microstructure approach and factor models are not competing methodologies. It is possible that two approaches capture similar features of the data. Depending on the availability of the data and their periodicity it might be the case that one has an advantage compared to the other. In this sense, these are complementary approaches with the intention to capture useful information to understand the dynamics of the exchange rate that is not contained in the macroeconomic fundamentals.

2. Data

We use monthly data from January 1999 to August 2011. The data starts in January 1999, since this was the date when Brazil adopted a floating exchange rate regime. The exchange rates used to construct the factors are from countries with *de facto* floating exchange rate regimes and independent monetary policies, according to the International Monetary Fund classification. The following countries and economic alliances met the selection criteria: Australia, Canada, Chile, South Korea, Philippines, England, Iceland, Israel, Japan, Mexico, New Zealand, Norway, Poland, South Africa, Sweden, Switzerland, Turkey, and the Euro Zone. We used exchange rates from the end of the month. All exchange rates are relative to the U.S. dollar and follow the convention of local currency quantity per unit of foreign currency.

The choice of the macroeconomic fundamentals included in the estimations is made according to the extensive body of literature related to the prediction of exchange rates using macroeconomic fundamentals. The monetary model links the exchange rate with money supply and output differentials. The Taylor rule models view the interest rates, and not monetary aggregates, as the instruments used for conducting monetary policy.[7] Hence, we also include inflation differential and the output gap in our estimations. The purchasing power parity is also viewed as a model for the determination of the exchange rate. Therefore, the dynamics of price level differences are also included as a macroeconomic fundamental in the estimations. In all specifications, macroeconomic fundamentals are measures with respect to differences relative to U.S. fundamentals.

The Brazilian economic data are obtained from the Brazilian Central Bank (Banco Central do Brasil) and the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística [IBGE]) database. Data for the U.S. are acquired from the Federal Reserve and the Bureau of Labor Statistics indicator databases.

The accumulated inflation over 12 months is used and is based on the Brazilian national consumer price index (Índice Nacional de Preços ao Consumidor [IPCA]) and the Consumer Price Index (CPI) for urban consumers in the U.S. Both indices are seasonally adjusted. Price levels are given by the accumulation of the monthly inflation for these same indices, with a base of 100 in January 1990. Regarding the currency, the monthly M1 is used for both the U.S. and Brazil.

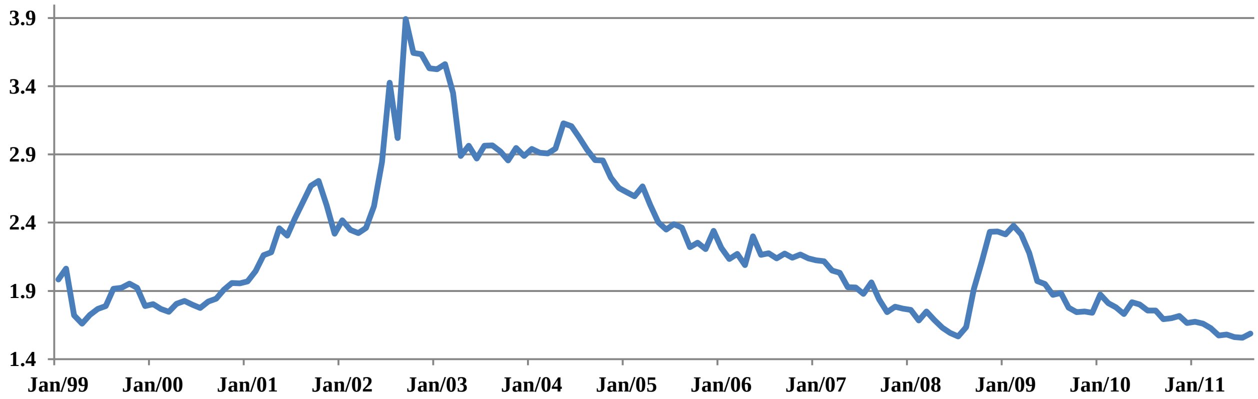
The seasonally adjusted monthly industrial production is used as a proxy for the output, and the output gap is estimated using the Hodrick-Prescott filter. Although the use of industrial production as a proxy for GDP represents only a portion of the total economic activity, this approximation is necessary because the low frequency of the GDP data (quarterly) would significantly reduce the sample size. Given the relatively short history of floating exchange rates in Brazil, the use of monthly data is appropriate. Except when it is mentioned, all variables are in logarithms.

Figure 1 shows the evolution of the exchange rate of the Brazilian Real to the U.S. Dollar in the period of interest. The trajectory of the exchange rate can be divided into two different periods. From January 1999 to 2003, when after a speculative attack Brazil abandoned a crawling-peg exchange rate regime and adopted a floating exchange rate regime. During this period, the domestic currency depreciated, markedly suffering from several episodes of large devaluation with brief periods of tranquility. Beginning in 2003, there was more stability in the evolution of the exchange rate with a continuous trend of appreciation of the domestic currency, only interrupted by the global financial crisis of 2008 that resulted in a rapid and acute devaluation of the Brazilian currency, a movement that was reversed throughout 2009 and 2010.

[7] More details on this model can be found in Mark (2008) and Engel and West (2006).

Figure 1 – Evolution of the Exchange rate Brazilian Real / US$ from 1999 to 2011

Figure 1 shows the trajectory of the exchange rate Real / US$ from January 1999 to August 2011.



3. Exchange Rate Model

The following exchange rate determination model is considered as our baseline specification:

$$\Delta S_t = \alpha + \beta . F_t + \gamma . Z_t + u_t \tag{1}$$

Where ΔS_t are changes in the (log-)nominal exchange rate, F_t is the set of common global factors, which are estimated in order to capture the dynamics of the unobservable variables, and Z_t is the set of macroeconomic fundamentals (all variables in log-differences).

The literature discusses several details with respect to the estimation of exchange rate models that led us to focus in models like (1) to analyze the usefulness of the factors. First, since conventional tests usually do not reject the presence of unit root in the variables, one could use a model in levels instead of differences (error-correction models). Ferraro, Rogoff and Rossi (2012) argue that error-correction models supply more gains for lower than for higher frequencies. Given that exchange rate forecast is more difficult for higher frequencies we rather use models like in (1). In addition, Chen, Rogoff and Rossi (2010) argue that models like (1) are more appropriate than error-correction models when one is not testing any specific model but only the predictive power of a variable, exactly the case here with respect to the estimated common factors.[8] Finally, a specification like in (1) is consistent with the view that the exchange rate is given by the present value of future fundamentals as demonstrated by Engel and West (2005) and Bacchetta and Wincoop (2011).[9]

3.1 Extracting the Common Factors

3.1.1 Baseline Framework

The common factors are extracted from a panel of 18 exchange rates. Some econometric issues arise for the estimation of the factors. Cayen et. al. (2010) analyze two main methodologies to identify the comovements among the exchange rates: factor analysis and state-space modeling. The authors discuss the advantages and disadvantages of each methodology. They show that the results are identical regardless of the method used for the identification of the factors, with no one methodology having a clear advantage compared to the other. In order to keep the simplicity and the focus of the paper in the usefulness of the factors we perform a factor-analysis estimation where an *n*-orthogonal factor model is estimated.

The determination of the number of factors is done using two different criteria: the Kaiser-Guttman and Bai and Ng (2002). In the first criterion, we consider only factors whose associated eigenvalues are larger than 1. In the Bai and Ng (2002) criterion the number of factors is chosen to minimize a loss function based on mean square deviations of the changes of the exchange rate and the

[8] Chen and Rogoff (2003) discuss the difficulties in using error-correction models in order to test exchange rate models.

[9] Note that unlike Fratscher, Sarno and Zinna (2012), we consider that the coefficients are not time-varying. The idea is to analyze whether the inclusion of the common factors per se is able to impose a more stable relationship between the exchange rate and the fundamentals.

estimated factors. Results show that both criteria indicate that N=3 factors are driving the dynamics of the exchange rate in our sample.[10] Figure 2 shows the trajectory of the estimated factors.

Figure 2 – Evolution of the Common Factors

Figure 2 refers to the evolution of the estimated factors. For each country i we have $\Delta s_{it} = \sum_{j=1}^{n} \delta_{ij} F_{jt} + v_{it}$. The factors shown are cumulated from first differences. The estimates follow the standard case for this study using 152 monthly samples and 18 exchange rates, and the factors are estimated by maximum likelihood.

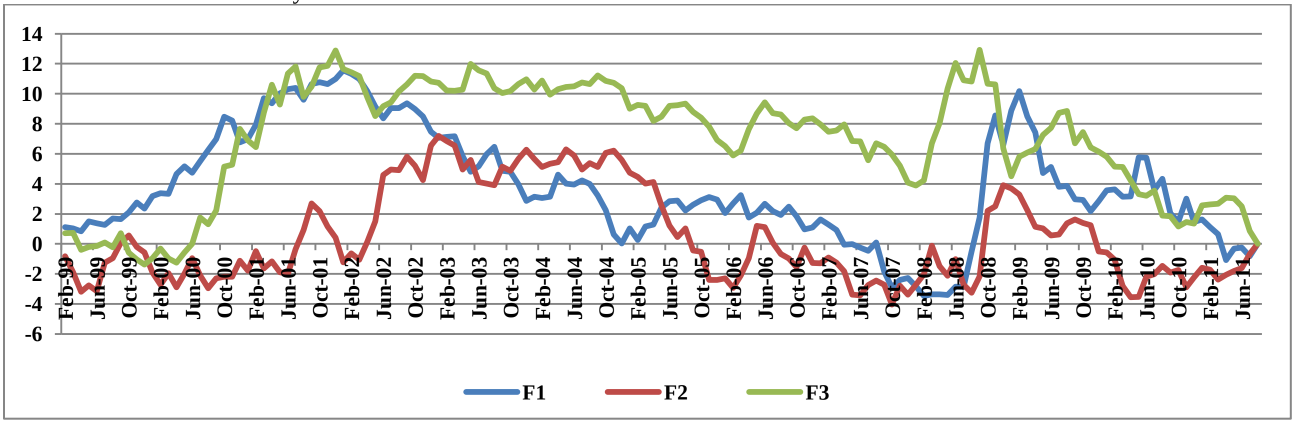
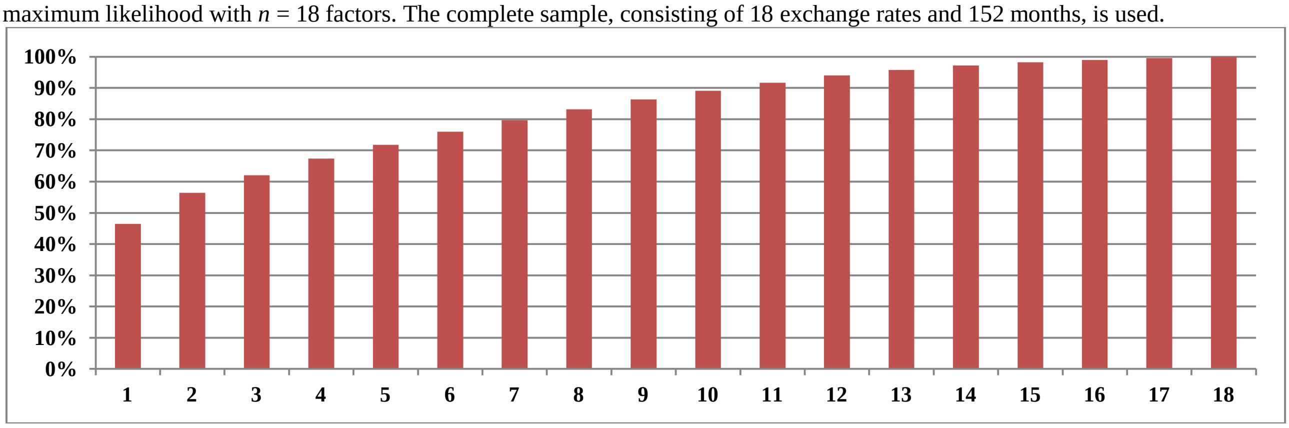


Figure 3 shows the percentage of the variance of the exchange rate that is cumulative explained by the first *n* estimated factors for the complete sample (1999–2011). The figure indicates that the first three factors jointly explain approximately 62% of the variability in the data with the three factors explaining, respectively, 46%, 10% and 6% of the variability in the data.

Figure 3 – Analysis of the factors

Figure 3 shows cumulative variance explained by the first *n* factors for the complete sample (1999–2011). Factors are estimated by maximum likelihood with *n* = 18 factors. The complete sample, consisting of 18 exchange rates and 152 months, is used.



4. Identification of the common factors

One of the main criticisms of factor models is that in most cases the estimated factors lack an economic interpretation. This identification is important since it can help in improving the theoretical macroeconomic models that are traditionally used to study the exchange rate determination.

Usually the literature tries to identify the factors through the inspection of the estimated loadings. Initially, we followed this procedure. Results in table 1 indicate that the factor 1 has significant and positive loadings in all of the currencies used. The factor is a weighted mean of all of the exchange rates. This fact allows us to interpret the factor as reflecting the common movements of the currencies with respect to the reference currency. Therefore, factor 1 can be viewed as indicating the strength (weakness) of the dollar against the average of the other currencies – A Dollar effect. The dynamics of this factor, shown in figure 2, corroborates this explanation. From 1999 to 2001, a period when the dollar appreciated

[10] Eigenvalues are 8.357, 1.797 and 1.007.

against almost all currencies, there was an increase in the factor, in opposition, between 2002 and 2008, a period when the dollar depreciated compared to most of currencies in the sample, figure 2 indicates an almost continuous decrease of the factor. Due to the appreciation of the dollar relative to the other currencies during the financial crisis, there was an increase in the factor in 200. Finally, beginning in 2009, when the dollar weakened again compared to the currency of the other countries, a reduction in the value of the factor took place as well.

Table 1 - Identification of the Common Factors

Table 1 shows the loadings of each estimated factor and the results from the estimation of the following equation $\Delta s_{it} = \mu_i + \sum_{j=1}^{3} \delta_{ij} F_{jt} + v_{it}$ for each country i when F_{jt} are the three estimated common factors. *, **and *** represent, respectively, 1%, 5% and 10% levels of significance. t-statistics are in parenthesis.

	Factor Loadings			Regression			
	F1	F2	F3	F1	F2	F3	Adjusted - R^2
Australia	0.3089	0.1155	-0.0082	1.18 (25.63)*	0.441 (3.90)*	-0.031 (-0.29)	0.818
Canada	0.2459	0.2009	-0.0930	0.651 (10.94)*	0.532 (5.48)*	-0.246 (-1.90)**	0.578
Switzerland	0.2489	-0.4130	-0.0039	0.781 (15.51)*	-1.29 (-14.13)*	-0.0125 (-0.09)	0.821
Chile	0.1805	0.2657	0.1223	0.599 (6.54)*	0.881 (3.63)*	0.405 (2.03)*	0.402
Euro	0.2975	-0.2679	-0.1084	0.924 (27.20)*	-0.832 (-14.95)*	-0.337 (-3.39)*	0.878
UK	0.2414	-0.1395	-0.2643	0.617 (10.02)*	-0.356 (-3.12)*	-0.675 (-3.54)*	0.584
Israel	0.1875	0.0489	-0.2172	0.457 (9.22)*	0.119 (0.89)	-0.529 (-2.77)*	0.332
Iceland	0.2006	-0.0157	0.2785	0.890 (5.106)*	-0.070 (-0.26)	1.23 (2.83)*	0.403
Japan	0.0792	-0.4466	0.3898	0.224 (3.12)*	-1.26 (-10.03)*	1.10 (6.47)*	0.555
South Korea	0.2291	0.0618	0.3439	0.775 (6.24)*	0.209 (1.53)	1.16 (4.64)*	0.555
Mexico	0.1862	0.4220	-0.1795	0.491 (8.51)*	1.11 (11.86)*	-0.474 (-4.25)*	0.635
Norway	0.2875	-0.1771	-0.1270	0.937 (13.32)*	-0.577 (-4.12)*	-0.414 (-3.64)*	0.758
New Zealand	0.2850	0.0385	0.0374	1.10 (14.42)*	0.149 (1.19)	0.145 (0.75)	0.676
Phillippines	0.1631	0.1340	0.6006	0.325 (6.87)*	0.267 (4.94)*	1.11 (6.53)*	0.610
Poland	0.2814	0.0038	-0.2274	1.14 (17.42)*	0.0158 (0.10)	-0.928 (-5.54)*	0.708
Sweden	0.3070	-0.1765	-0.1182	1.06 (32.38)*	-0.611 (-9.41)*	-0.409 (-4.52)*	0.855
Turkey	0.1641	0.3475	0.0426	0.872 (6.14)*	1.84 (5.82)*	0.226 (0.799)	0.432
South Africa	0.2068	0.1637	0.1463	1.00 (11.18)*	0.793 (3.71)*	0.709 (2.24)*	0.415

In addition to the loadings, Table 1 also shows the results of the estimation of (1) for each country for a model containing only the estimated factors. Results for factor 1 confirm that this factor represent a "dollar effect". Factor 1 has a positive and statistically significant impact on all currencies. It is interesting to reinforce that factor 1 accounts for almost 50% of the variability of the exchange rates in the sample, as shown in figure 3.

The analysis for factor 2 indicates a division of the impact of common shocks in two different groups of countries: developed and developing countries. Results in table 1 show that developed countries present a negative loading (and statistically significant impact) with Japanese yen and Swiss franc having the highest (negative) impact and the Mexican Peso and Turkish Lira presenting the highest (positive) loadings and estimated coefficients in the regression. These results might indicate that this factor represents a possible "flight to quality" in moments of turmoil when capitals flow between the two groups of countries and we observe a disparity in the movements of the exchange rate.

The analysis of factor 3 is more emblematic with respect to the difficulties in using only the analysis of the loadings for assigning an economic interpretation for the common factors. It is not possible to verify any clear pattern among the loadings or in the coefficients that result from the estimation of (1) for each country. Very dissimilar countries with respect to economic development have similar signs making its interpretation a difficult task.

We turn then to another approach in order to assign an economic interpretation to the factors. We analyze the correlation between the factors and some observable variables usually considered by market participants and scrutinized by the literature as exerting an influence in the path of the exchange rate. These variables are frequently used as proxies for common global shocks as investors' risk aversion, or liquidity shocks, among other possibilities. This methodology, in addition to help in the economic interpretation of the factors, might reinforce a possible advantage of the use of factor models, that is, the concentration of the information set into a small number of factors.

The empirical literature identifies different variables as correlated with common factors that have an impact in the trajectory of the exchange rate. Cayen et. al. (2010), using a similar factor analysis, verify a correlation between commodity prices and common global factors. We use the CRB – Commodity Index in order to analyze this relationship.

McGrevy et. al. (2012) identifies the euro/dollar, yen/dollar, and swiss-franc/dollar as the common factors. They argue that the first two exchange rates are the two highest volume of foreign exchange transactions in the spot markets and the Japanese yen and Swiss franc serve as "safe-haven" currencies in moments of turmoil in the U.S. Considering that anecdotal evidence indicates a correlation between gold prices and moments of turmoil, since gold is also viewed as a safe-haven in moments of turmoil in financial markets, we analyze the correlation between gold-prices and the factors. Market participants use the High-yield spread as a proxy for risk aversion. Higher spreads indicate a lower desire by investor to bear risks. We include then the high yield spread in the analysis.

Lustig et. al. (2011) found that a 'slope' effect account for more of the cross-sectional variation in average excess returns between high and low interest rate currencies. They relate these factors to global equity market volatility. In a similar way, Menkhoff et. al. (2012) found that global foreign exchange volatility risk account for the highest explanation of cross-sectional excess returns of carry trade portfolios and that liquidity risk also play a role in the explanation of their foreign exchange expected returns. By constructing a measure of FX global liquidity, Banti et. al. (2012) show that there is a link between liquidity across currencies and that liquidity risk is priced in the cross section of currency returns.

Given the possible role of common volatility and liquidity shocks in the dynamics of the exchange rate we analyze the correlation between the factors and different proxies for these common shocks. The VIX - the Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 index options is used as our proxy for global volatility. For liquidity shocks we use the TED spread and the stock market liquidity measure constructed by Pastor and Stambaugh (2003). Table 2 reports the correlation matrix between the factors and all variables.

Table 2 - Correlation Common Factors and Observable Variables

Table 2 shows the correlation between the estimated common factors and some observable variables proxies for common shocks (all variables in log-differences). CRB is the CRB commodity price index. Gold stands for the spot gold prices. VIX stands for the Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 index options. High Yield Spread is the Merrill Lynch US High Yield Spread. TED Spread is calculated by the difference between the interest rates on interbank loans and on short-term U.S. government debt. Liquidity is the stock market liquidity calculated by Pastor and Stambaugh (2003). * represents 5% level of significance.

	F1	F2	F3	CRB	Gold	VIX	High Yield Spread	TED Spread	Liquidity
F1	1.000								
F2	0.000	1.000							
F3	0.000	0.000	1.000						
CRB	-0.570*	-0.104	0.072	1.000					
Gold	-0.341*	0.055	-0.152*	0.250*	1.000				
VIX	0.379*	0.440*	-0.028	-0.254*	0.042	1.000			

HighYield Spread	0.437*	0.436*	0.017	-0.359*	0.051	0.568*	1.000		
TED Spread	0.098	-0.088	0.003	-0.068	-0.008	0.093	0.068	1.00	
Liquidity	0.024	-0.232*	0.068*	0.100	0.027	-0.141	-0.141	-0.24*	1.00

Results in table 2 show that factors are correlated with several variables, corroborating the idea that the factors are able to condense information from a set of observable variables that is frequently argued by market players and the international literature as playing a role in the exchange rate dynamics. The results in table 2 also highlight significant differences between the factors, especially with respect to their economic interpretation.

The results indicate that factor 1 is highly correlated with the price of commodities. This is in line with the interpretation that factor 1 represents the strength of the reference currency – the American dollar. Since the prices of these commodities are quoted in U.S. dollars, they are tied up with the movements of the dollar compared to other currencies, explaining this high correlation between the factor and the price of commodities.

In contrast, factor 2 has a correlation with the price of the commodities that is lower than factor 1. Corroborating the idea that factor 2 might represent the impact of the investors' perception of the risk in the dynamics of the exchange rate, this factor has higher correlation with the VIX and the high yield spread - the variables that are usually adopted by market participants as measures of risk or investors' risk aversion. Finally, consistent with the previous analysis, unlike the other two factors, factor 3 is not highly correlated with any variable, and the highest correlations are with the price of gold and with the liquidity measure.[11]

Table 3 shows the results of a more formal analysis between the relationship between the factors and the observable variables. The results of two types of estimations are shown in table 3. In Panel A the common factors and the variables are in (log-) differences, yet in panel B we look for the existence of a long-run relationship between the factors and our proxies for common shocks; therefore, in this case we use the variables in levels and perform a dynamic OLS estimation in order to capture this relationship. Results in table 3 confirm that there is a relationship between the first factor and the price of commodities. For all of the specifications there is a significant relationship between the first factor and the CRB Index. It is interesting to note that although the high yield spread and the TED spread play a role in the dynamics of the factor, almost all explanatory power of the observable variables comes from the Commodity index.

Results in table 3 indicate that factor 2 carries information related to volatility and liquidity shocks. In both specifications, the VIX, the high yield spread, the TED spread and the liquidity variable present a robust and statistically significant relationship with the factor – although the liquidity shows a different sign depending on the specification. When we analyze the separate impact of each variable we get that the high yield spread accounts for the bulk of the variability of the factor.

When we observe the R^2 of each specification we verify that the variables used in the specifications account for a significant proportion of the variability of the factors in the case of factors 1 and 2, but this is not the case for factor 3. Corroborating previous results, the identification of factor 3 is a more complex task. Results show that the factor is correlated with the gold prices, the VIX, and the proxies for liquidity, but none of the results are robust. In addition, the specifications for the factor present the lowest R^2 among all specifications.

In summary, the results indicate that the three estimated factors are able to condense information embedded in several variables related to different global shocks and which are advocated by the literature as playing a role in the dynamics of the exchange rate but that are not direct observable by market participants. Therefore, the condition that the information embedded in the common movements of the

[11] One limitation for assigning the significance of the factors using this methodology is that one variable might proxy different common shocks. Bekaert et. al. (2010) show, for example, that the VIX might be decomposed into two components: a proxy for risk aversion and expected stock market volatility (uncertainty). This is also true for other proxies. Yet, the analysis allows us to establish the usefulness of the factor in condensing the information carried by a set of observable variables.

exchange rates of various countries is related to the unobservable variables is satisfied by the estimated factor. In the next section, we verify the predictive power of the factors.

Table 3 – Results for the Identification of the Common Factors

Table 3 shows the results for the identification of the common factors. CRB is the CRB commodity price index. Gold stands for the spot gold prices. VIX stands for the Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 index options High Yield Spread is the Merrill Lynch US High Yield Spread. TED Spread calculated by the difference between the interest rates on interbank loans and on short-term U.S. government debt. Liquidity is the liquidity proxy calculated by Pastor and Stambaugh (2003). In panel A all variables are in (log-) differences. Panel B performs the analysis in a cointegration framework performing the estimation by dynamic OLS with a inclusion of 1(one) lag. Cointegration stands for the Engle-Granger cointegration test. *,** and *** represent, respectively, 1%, 5% and 10% level of significance. t-statistics in parenthesis.

	(A)			**(B)**		
Variable/ Factor	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
CRB	-33.29 (-4.71)*	2.00 (0.37)	4.10 (1.11)	-7.92 (-3.02)*	-4.75 (-2.54)*	-2.08 (-0.54)
Gold	-18.83 (-5.26)*	2.70 (1.15)	-3.01 (-1.77)***	-1.32 (-0.99)	3.56 (3.77)*	1.09 (0.569)
VIX	2.95 (1.94)***	2.22 (3.59)*	-0.23 (-0.34)	-0.948 (-0.82)	0.116 (4.12)*	-4.29 (-2.58)**
HighYield Spread	6.12 (2.80)*	3.52 (3.05)*	0.918 (0.967)	2.62 (2.71)*	3.03 (4.41)*	1.69 (1.20)
TED Spread	0.178 (1.84)***	-0.212 (-4.45)*	0.021 (0.319)	0.472 (2.25)**	-0.600 (-4.02)*	-0.859 (-2.83)*
Liquidity	3.58 (1.46)	-2.35 (-2.97)*	0.637 (0.573)	4.399 (1.12)	6.93 (2.48)*	-16.18 (-2.85)*
Constant	0.405 (2.43)**	-0.05 (-0.47)	0.013 (0.134)	53.83 (6.74)	1.72 (0.302)	17.75 (1.53)
$\boldsymbol{R^2}$	0.5133	0.313	0.0327	0.941	0.902	0.486
Adjusted-$\boldsymbol{R^2}$	0.4930	0.285	0.007	0.929	0.883	0.387
Cointegration				Yes	Yes	Yes

5. Exchange Rate Predictability and the Common Factors

In order to test the predictability of exchange rate models the usually literature performs two types of tests: in-sample and out-of-sample tests. As discussed in Chen, Rogoff, and Rossi (2010), the two sets of tests not rarely produce different results. These results will depend on several aspects like the stability of the parameters, sample size, among others. The authors discuss that in-sample exercises have the advantage of make use of the full sample size, present higher power if the parameters are constant, and are more likely to detect predictability, but these exercises are more prone to overfitting and sometimes fail to present out-of-sample predictability. In opposition, out-of-sample exercises would be more realistic, more robust to time variation and misspecification problems. Considering these facts, in this section, we perform the two types of exercises with the objective to analyze the usefulness of the common factors in explaining the dynamics of the exchange rate.

5.1 In-sample Predictability

Table 4 shows the result of a set of in-sample tests.[12] Results in table 4 indicate that the inclusion of the factors significantly improve the exchange rate model that contains only macroeconomic fundamentals. The R^2 of the model containing only the macroeconomic variables is 4.14%. This value increases to 40.28% when the three common factors are included in the model. It is worth noting that the model containing only the estimated factors explains a greater proportion of the changes in the exchange rate than the macro-fundamentals model. The R^2 of the factor-model is 36.45%, which is substantially higher than the R^2 of the model enclosing only the macro-fundamentals. A similar picture emerges when

[12] Initially, we perform exercises similar to those in Fratzscher et. al.(2012).

we use the adjusted-R^2 as a measure of comparison among the models. The adjusted-R^2 rises from 1.49% in the model with only the macro variables to 37.33% when we add the estimated common factors.

Table 4 - In-sample Tests

Table 4 shows the results of a set of in-sample tests. Results are from the estimation of (1) including only the estimated common factors (Only Factors), only the macroeconomic fundamentals (Only Macro Fundamentals) and with the two set of variables together (Factors + Macro fundamentals). Log (SSR/T) is the logarithm of the sum of the square of the residuals, AIC is the Akaike information criteria. HR is the percentage of time that the estimated model correctly predicts the realized change in the exchange rate. HM is the result of the Henriksson and Merton (1981) test. *, ** mean, respectively, 1% and 5% level of significance.

	Only Factors	Only Macro Fundamentals	Factors + Macro Fundamentals
R^2	36.45%	4.14%	40.28%
Adjusted R^2	35.15%	1.49%	37.33%
log (SSR/T)	0.252	0.381	0.237
AIC	-3.50	-3.07	-3.50
HR (%)	73.7%	61.8%	76.3%
HM	0.498 (7.86)*	0.221 (2.88)**	0.501 (7.64)*

The results presented in table 4 using the information criteria confirm that the inclusion of the estimated common factors considerably improve the predictive power of the model containing only the macroeconomic fundamentals. Both – the logarithm of the sum of the square of the residuals and the Akaike criteria – present better values for the models that include the factors than for the models that comprise only the macro variables.

Finally, following Fratzscher et. al. (2012) we perform two different tests to analyze the market timing capability of the models. The hit ratio test (HR) show the percentage of time that the estimated model correctly predicts the realized change in the exchange rate. The HM Test is a test proposed by Henriksson and Merton (1981) to test the market timing ability of a model. The test estimates the correlation between the realized and fitted exchange rate returns. A positive coefficient can be interpreted as the market timing ability of the model.

The results of the market timing ability test shown in table 4 confirm the superior performance of the models containing the estimated factors. A model containing only the macroeconomic fundamentals is able to correctly predict the exchange rate change in 61.8% of the time of the sample, in contrast adding the estimated factors we are able to predict correctly in 76.3% of times. In addition, the analysis of the coefficients of the HM model also point out the higher predictive power of the models with the factors. Besides being positive and statistically significant, indicating the market timing ability of the models, the coefficients in the models with the factors are higher compared to the coefficients in the benchmark model containing only the macroeconomic fundamentals.

5.1.1 Granger Causality

The view that the exchange rate is determined by the present value of future fundamentals make the Granger causality test an useful tool in analyzing the predictive power of the estimated factors. If the common global factors have any predictability over the exchange rate movements one should fail to reject that the estimated factor granger cause the exchange rate. A relevant point to note is that, as discussed by Chen, Rogoff and Rossi (2010), Granger- causality tests may be problematic for macroeconomic fundamentals since there might exist a problem of causality between the exchange rate and fundamentals and this would undermine the test. This is not the case here since we do not expect any role for the dynamics of the exchange rate R$ / US$ in the determination of the factors.

Table 5 confirms these facts. Considering 10% as our level of significance the results in table 5 indicate that the hypothesis that the factors do not granger cause the exchange rate is rejected for all three factors. In addition, the results show that the hypothesis that the exchange rate does not Granger cause the factor is not rejected for all three factors. These results confirm the in-sample predictive power of the common global factors.

Table 5 – Granger Causality and Stability Tests

Table 5 show the results (p-value) of the Granger causality tests between the estimated factors and the exchange rate R$ / US$ in the period between January 1999 and August 2011. The test is performed using heteroskedasticity and autocorrelation robust variance estimation (Newey and West, 1987). Table 5 also reports the p-values for the Andrews stability test.

	Granger - Causality Test	**QLR Test**
F1 does not granger cause Exchange Rate	0.0729	0.1725
Exchange rate does not granger cause F1	0.5041	0.4655
F2 does not granger cause Exchange Rate	0.0189	0.1643
Exchange rate does not granger cause F2	0.2779	0.9091
F3 does not granger cause Exchange Rate	0.0619	0.9057
Exchange rate does not granger cause F3	0.3834	0.2103

Several authors (Chen, Rogoff, Rossi (2010), Rossi (2006, 2012) among others) argue that the difficulty in modeling the dynamics of the relationship between the exchange rate and the macroeconomic fundamentals is that for different reasons this relationship is unstable over time. Rossi (2005) discusses that conventional Granger causality test fail in the presence of these instabilities. In order to analyze this problem, table 5 also reports results from Quandt Likelihood Ratio (QLR) instability tests (Andrews, 1993) for the Granger-causality relationship between the factors and the exchange rate. Results indicate that for any of the relationship analyzed the tests reject the presence of instabilities, strengthening the results from the Granger causality tests.

In summary, all in-sample exercises indicate that the inclusion of the estimated common factors improves the predictive power of the traditional macroeconomic models and that, unlike the relationship between the exchange rate and the macroeconomic fundamentals, the role of the common factors in the exchange rate dynamics seem to be more stable. Next section analyzes whether this in-sample improvement is also translated in a better out-of-sample predictability.

5.2 Out-of-sample Predictability

We follow Ferraro, Rogoff and Rossi (2012) and perform a rolling windows "out-of-sample" forecasting exercise using equation (1). Chen, Rogoff and Rossi (2010) argue that the rolling window scheme is more robust with respect to a possible time-variation of the parameters because it adapts more quickly to possible structural changes compared to a recursive scheme. Yet, we include the use of different methodologies, like the recursive scheme, as robustness exercises. The out-of-sample forecast is done for four different forecast horizons (h=1, 3, 6 and 12 months ahead).

The process of out-of-sample forecasting is executed according to the following steps for a sample size T=152 months. Starting in January 1999, for a given window size (N) and a forecast horizon (h), the factors are estimated from the series of the exchange rate of the 18 countries, using the maximum likelihood method, as follows:

$$\Delta S_{it+h} = \widehat{\delta_\iota}\widehat{F_{t+h}} + \varepsilon_{it+h} \qquad (2)$$

In the second step, equation (1) is estimated using the factors estimated in the first step and/or macroeconomic fundamentals using only data until time t. Given the estimation of (1), a h-period ahead forecast is performed. The process is done for all forecast horizons h=1,3,6 and 12 months ahead. Then we advance one-period and the forecasting is performed again. We continue until the end of the sample.

Here a very important remark has to be made. The forecast exercise performed is not a real "out-of-sample" forecast exercise. Note that according to (2), data until t+h is used in order to estimate the factors; therefore, in the forecasting process, realized value for the factors and the macroeconomic fundamentals are used. West (1996) points out that this type of exercise is useful for the evaluation of the predictability of a model given the path of the variables. Ferraro, Rogoff and Rossi (2012) argue that if the goal of the exercise is to demonstrate the usefulness of the addition of a fundamental – in our case, the common factors – this forecasting strategy would be more appropriate. In their case, they advocate this strategy given the difficult in forecasting oil prices – their additional fundamental. They discuss that if past values of oil prices are not good predictors of future oil prices one might reject the predictability of the model due to poor forecast process that past oil prices give for future oil prices and not because the lack of relationship between the exchange rate and the additional fundamental. It is clear that in our case this problem is even more pronounced given that we do not have any formal model to forecast the factors. Given these facts, we use the rolling "out-of-sample" forecast exercise as our baseline strategy and leave the other strategies to be analyzed in the robustness exercises. The out-of-sample forecasting (described above) is then compared with a forecast model that assumes that the exchange rate follows a random walk with and without a drift.

We use the Theil's U statistic as the criterion for judging the performance of each model. The statistic is calculated as ratio between the mean square prediction error (MSPE) of each model and the mean square prediction error of the two different benchmark models: random walk with and without a drift. Values lower than 1 indicate that the model possesses a smaller MSPE than the random walk model. However, even a value higher than 1 can be considered evidence of a superior performance of the model compared to the random walk. As argued in Clark and West (2006, 2007), if the process generating the exchange rate is, in fact, a random walk, the inclusion of other variables should introduce noise in the forecasting process, leading, on average, to a greater mean square prediction error than the random walk (and thus producing statistics with a value greater than 1). We use then the Clark and West (2006) statistic as the evaluation criteria for forecast quality. The Clark and West statistic (2006) is more appropriate for asymptotic tests than the one given by Diebold and Mariano (1995) and West (1996) (DMW) for nested models. As observed by Clark and West (2006), in nested models, the DMW statistics yields a test statistic with a non-normal distribution, which underestimates the quantity of null hypothesis rejections.

5.2.1 Baseline Results

Table 6 confirms the usefulness of the estimated common factors in improving the predictive power of the models containing only macroeconomic fundamentals. When we analyze the predictive power of the models containing only the macroeconomic variables we verify the conventional instability found by the literature. Although the model is able to beat the random walk in several occasions, it does not do this in a robust manner. In all specifications, for example, the model is not able to beat for short-horizon forecasts (1-month ahead). The model containing only macroeconomic fundamentals seems to have more predictive power for medium and long-horizon forecasts, although even for these forecast horizons the model is not able to beat the random walk benchmark in different opportunities.

The results reported in table 6 show that once we use a model containing the macroeconomic fundamentals together with the estimated common factors not only the model is able to beat the random walk in short-horizons forecasts but also there is a significant reduction in the mean square prediction error of the model, confirming that the common factors carry useful information for forecasting the exchange rate. In fact, in almost all forecast horizons and sample size a model containing the macroeconomic fundamentals together with the estimated factors is able to beat the two benchmark models.

The usefulness of the estimated factors for short-term predictions is evident when we analyze the model containing only these fundamentals. The model containing only the factors presents the lowest mean square error predictions for all specifications. It is interesting to note that the model containing only the factors is also able to beat the benchmark models in almost all specifications, assuring the importance of these factors in the dynamics of the exchange rate.

Table 6 - Forecasting Results

Table 6 shows the Theil's U statistic defined as the ratio between the mean square prediction error of a model and that given by two different benchmark models: the random walk with and without a drift. Asterisks represent the result of the Clark and West (2006) test statistic. *, **and *** represent, respectively, p-values for the test lower than 1%, 5% and 10%. The complete sample corresponds to the period from January 1999 to August 2011 and consists of 152 monthly observations. Exercises are performed for different window sizes shown as a fraction of the full sample.

		Forecasting Horizon (h)			
Model	**Reference Model**	**1 mo**	**3 mo**	**6 mo**	**12 mo**
N=1/2					
Only Factors	Random walk without drift	0.9190*	0.8985*	0.9562*	1.002**
	Random walk with drift	0.9188*	0.8952*	0.9377*	0.9558*
Only Macroeconomic Fundamentals	Random walk without drift	1.096	1.011	0.9972**	1.012
	Random walk with drift	1.096	1.0073**	0.9779*	0.9638*
Factors + Macroeconomic Fundamentals	Random walk without drift	0.9954*	0.9062*	0.9285*	0.9901**
	Random walk with drift	0.9953*	0.9029*	0.9105*	0.9439*
N=1/3					
Only Factors	Random walk without drift	0.8638*	0.9249*	0.9573*	0.9903*
	Random walk with drift	0.8648*	0.9258*	0.9547*	0.9838*
Only Macroeconomic Fundamentals	Random walk without drift	1.091	0.9961**	0.9887**	1.027
	Random walk with drift	1.092	0.9970**	0.9860**	1.009***
Factors + Macroeconomic Fundamentals	Random walk without drift	0.9592*	0.9257*	0.9303*	0.9823**
	Random walk with drift	0.9602*	0.9266*	0.9278*	0.9758**
N=1/4					
Only Factors	Random walk without drift	0.8951*	0.9251*	0.9648*	1.005
	Random walk with drift	0.8963*	0.9275*	0.9670*	1.005
Only Macroeconomic Fundamentals	Random walk without drift	1.084	0.9858*	0.9780*	0.9967***
	Random walk with drift	1.086	0.9883*	0.9802**	0.9970***
Factors + Macroeconomic Fundamentals	Random walk without drift	0.9634*	0.9211*	0.9355*	0.9921**
	Random walk with drift	0.9648*	0.9234*	0.9373*	0.9923**
N=1/5					
Only Factors	Random walk without drift	0.9257*	0.9279*	0.9528*	0.9934**
	Random walk with drift	0.9120*	0.9299*	0.9396*	0.9470*
Only Macroeconomic Fundamentals	Random walk without drift	1.115	1.007**	1.002***	1.017
	Random walk with drift	1.098	1.009**	0.9884**	0.9698**
Factors + Macroeconomic Fundamentals	Random walk without drift	1.022	0.9426*	0.9299*	0.9853*
	Random walk with drift	1.007***	0.9447*	0.9170*	0.9393*

5.2.2 Alternative Specifications

Results found in table 6 might be the result of the specification adopted. In order to verify the strength of the results we perform several robustness exercises.

5.2.2.1 Recursive (Sequential) Strategy

In this exercise we follow procedures similar to the baseline framework but now instead of roll the estimation window we add one observation one by one until the end of the sample, each observation is included in the sample such that the sample available for regression estimation and the factors increases. In this case, we start with a sample size of 1/5 of the full sample. The results in table 7 confirm our previous findings with respect to the usefulness of the common factor in predicting the exchange rate. The results in table 7 indicates that the use of both fundamentals – common factors and macroeconomic –

lead to better results. Although all models are able to beat the benchmark models, the combination of the models gives the best result with lower mean square prediction errors for all forecast horizons.

Table 7 – Robustness Exercises

Table 7 shows the Theil's U statistic defined as the ratio between the mean square prediction error of a model and that given by two different benchmark models: the random walk with and without a drift. Asterisks represent the result of the Clark and West (2006) test statistic. *, **and *** represent, respectively, p-values for the test lower than 1%, 5% and 10%. The complete sample corresponds to the period from January 1999 to August 2011 and consists of 152 monthly observations.

		Forecasting Horizon (h)			
Model	**Reference Model**	**1 mo**	**3 mo**	**6 mo**	**12 mo**
Only Factors	Random walk without drift	0.7915*	0.8837*	0.9505*	1.002***
	Random walk with drift	0.7927*	0.8863*	0.9520*	1.003***
Only Macroeconomic Fundamentals	Random walk without drift	0.9364*	0.9783*	0.9846**	1.001***
	Random walk with drift	0.9379*	0.9811*	0.9862**	1.002***
Factors + Macroeconomic Fundamentals	Random walk without drift	0.7436*	0.8609*	0.9206*	0.9858**
	Random walk with drift	0.7448*	0.8634*	0.9221*	0.9868**

5.2.2.1 Lagged

The rolling "out-of-sample" strategy adopted is not a truly out-of-sample exercise since it uses realized fundamentals. This strategy is of limited use to professional forecasters since it makes use of information not available to the forecaster. Now, we consider the following change in equation (1) for any forecast horizon h:

$$\Delta s_t = \alpha + \beta . F_{t-h} + \gamma . Z_{t-h} + u_t \tag{3}$$

Observe that now only the lagged value of the estimated common factors and the macroeconomic fundamentals are used in order to forecast the exchange rate. Following this procedure, the forecast process is performed using only information available at time t. The other procedures are similar to the exercise done for the baseline framework. The results for a sample size N= ½ of total sample is shown in table 8.[13]

Table 8 - Robustness exercises

Table 8 shows the Theil's U statistic defined as the ratio between the mean square prediction error of a model and that given by two different benchmark models: the random walk with and without a drift. Asterisks represent the result of the Clark and West (2006) test statistic. *, **and *** represent, respectively, p-values for the test lower than 1%, 5% and 10%. The complete sample corresponds to the period from January 1999 to August 2011 and consists of 152 monthly observations. Exercise is performed for a window size equals to ½ of the full sample.

		Forecasting Horizon (h)			
Model	**Reference Model**	**1 mo**	**3 mo**	**6 mo**	**12 mo**
N=1/2					
Only Factors	Random Walk without drift	0.9299*	0.9662*	0.9893**	0.9566*
	Random walk with drift	0.9298*	0.9633*	0.9722*	0.9440*
Only Macroeconomic Fundamentals	Random Walk without drift	1.009	0.9772*	1.007***	0.9774*
	Random walk with drift	1.009	0.9743*	1.006***	0.9352*
Factors + Macroeconomic Fundamentals	Random Walk without drift	0.9721*	0.9600*	0.9724*	0.9513*
	Random walk with drift	0.9721*	0.9571*	0.9556*	0.9389*

The results in table 8 confirm the robustness of the previous analysis. Both - the model containing the factors and the macroeconomic variables - are able to beat the two benchmark specifications with the model using only the macroeconomic fundamentals demonstrating more difficulty to beat the benchmarks, especially for short forecast horizon. This problem seems to be solved once we add the

[13] The results are unchanged with respect to the sample size. For saving space they are not shown but they are available upon request.

estimated factors. The model containing the macroeconomic fundamentals and the estimated factors together is able to beat the random walk benchmarks for any forecast horizon assuring that the factors carry useful information for forecasting the exchange rate.

6. Conclusions

This paper studies the usefulness of the use of factors embedded in the common movements of exchange rates in forecasting the exchange rate of the Brazilian Real / US Dollar from January 1999 to August 2011.

The results confirm that the inclusion of the common factor improves the in-sample and out-of-sample predictability of the traditional models for the determination of the exchange rate that includes only macroeconomic fundamentals.

In the case of the out-of-sample exercise, the paper shows that independently of the forecast horizon or window of estimation a model including the estimated common factors and the macroeconomic fundamentals are able to beat any of the benchmark models considered - the random walk with or without a drift. The results are even more pronounced for short term predictions – a recurrent failure of the traditional models.

The paper also tries to link to the factors with observable variables usually considered by market participants and the literature as proxies for common global shocks. The results indicate that the estimated factors condense the information contained in a set of variables. The estimated factors carry information on the demand for dollars – a dollar effect, global volatility and liquidity shocks.

In summary, the results of the paper note that the use of factors is useful to forecast the exchange rate. There are periods when the unobservable variables captured by the estimation of the factors from the common dynamics of exchange rates are crucial for forecasting the exchange rate.

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APPENDIX

Table A.1- Data Description

Table A.1 shows the data used throughout the text. All of the exchange rates used are from countries that have independent monetary policies and a floating exchange rate, according to the International Monetary Fund (IMF) classification: http://www.imf.org/external/np/mfd/er/2008/eng/0408.htm.

Variable	Country	Description	Source
Exchange Rate	Switzerland	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Norway	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Euro Zone	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	New Zealand	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	United Kingdom	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Sweden	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Japan	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Poland	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Canada	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Australia	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Iceland	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	South Korea	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	South Africa	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Israel	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Mexico	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Chile	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Philippines	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Turkey	log (Domestic Currency / Foreign Currency)	Bloomberg
Exchange Rate	Brazil	log (Domestic Currency / Foreign Currency)	Bloomberg
Industrial Production	Brazil	Index Jan 2002=100 with seasonal adjustment	IBGE
Industrial Production	United States	Index Jan 2007=100 with seasonal adjustment	Federal Reserve
Prices	Brazil	IPCA -Index Dec 98=100	IBGE
Prices	United States	CPI - Index Dec 82=100	BLS
Money Supply	Brazil	R$ millions with seasonal adjustment	Central Bank
Money Supply	United States	US$ billions with seasonal adjustment	Federal Reserve