Universidade de Brasília
Faculdade de Economia, Administração e Contabilidade
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Fatores Comuns e Variáveis não Observáveis na Dinâmica das Taxas de Câmbio

Victor Candido de Oliveira

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Dissertação apresentada ao Programa de Mestrado em Economia da Universidade de Brasília como requisito à obtenção do título de Mestre em Ciências Econômicas.

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Abstract

This paper studies non-observable variables in the exchange rate dynamics using factor models in order to extract a common dynamic from more than 20 exchange rates. The main contribution is the use of supervised machine learning techniques in order to identify the underlining variables that drive the non-observable dynamics of a panel made with 26 exchange rates using a rigorous lasso model. Most of the results are correlated with macroeconomic and financial theory.

Keywords: exchange rate,exchange rate, factor analysis, robust estimation.

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1 Introduction

This paper combines traditional econometric approach (factor analysis) with supervised machine learning techniques (Rigorous Lasso) to analyze and identify the effects of the non-observable variables in the cross section of a panel made with 26 exchange rates.

The process of identification of these unobservable variables is important since it can provide a macroeconomic and financial interpretation for them. In order to make the non-observable variables visible we extract the factors using the n-orthogonal estimation method from a sample of 26 exchange rates, in a daily frequency. After the factor extraction we apply a rigorous lasso regression in order to identify the underlining fundamentals (and their correlated variables) that are linked with each one of the factors, in order to explain these unobservable dynamics.

The results shows that that the dollar effect, interest rate differentials, carry trade returns, risk aversion and real interest rates in a global scale, are the principal drivers of the factors movements. Other variables such as volatility indexes, economic surprise indexes, interest rates spreads, swap prices in different currencies, among others also play an important role with the cross section dynamics of the exchange rates.

All the finds are correlated with findings from various theoretical works in macroeconomic and finance, and some results are strongly linked to stylized facts, such as carry trade, uncovered interest rate parity, risk premia, yield curves movements etc.

2 Literature review

Since the collapse of Bretton Woods in the beginning of the 1970s and the adoption of floating exchange rate regimes by most developed countries, make the behavior of exchange rates become a frequent topic of analysis, as this variable exerts a significant impact on countries trade balance, price levels, and output. Economists and investors had trying for decades to develop models to explain and forecast the exchange rate dynamics.

In this work, different form the others, we incorporated financial assets into our samples, since investors and practioners have, in their way, successful making forecasts and models that explain exchange rate dynamics, since financial assets can incorporate real-time information about the economy and impact the exchange rate dynamic as noted by Andersen (2007). Melvin (2013) noted that the goal of an investor in foreign exchange market is different to that of much of the academic literature. While the gold standard for academic has been to produce accurate point forecasts for the future of levels of bilateral exchange rates, the investor has an easier task. One only need to be concerned with the actual cross-section of realized relative returns. Errors in forecast can be averaged out over a large cross-section of currencies, and the rank order of forecasts matters more than their size.

Beyond the macroeconomic affect there is a prolific financial market around the globe for exchange rate and related instruments, such as spot currency, future contracts, swaps, over the counter taylor-made derivatives, among others, all this instruments have a strong link with economic fundamentals. Unfortunately, the body of research dedicated to analyzing the predictive power of exchange rate determination models has reached a very limited success in forecasting or even fitting models in order to explain this variable. This difficulty is considered one of the major weaknesses of international macroeconomics as noted by (Bacchetta and van Wincoop, 2006), B. Rossi (2013) and the seminal work of Meese and Rogoff (1983).

There is a great number of models that focus in forecasting and making inference about price factors in exchange rates, but most of the them had limited capacity or just work under very strict horizons and selected variables, as we discuss next. The literature shows that it is very difficult to find a model framework which can work in a generic way for a variety of countries and for different time frames and data frequency, as noted by B. Rossi (2013). The work of B. Rossi is important since it provides a detailed road map of all the models and their failures and relative success in order to try to fit and forecast exchange rates.

Meese and Rogoff (1983), verify the lack of predictive power of theoretical exchange rate models. They argue 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 is able to explain significantly better than a simple random walk model, even in frameworks that only try to fit the variables in sample.

Macroeconomic variables has a very poor performance in fully explain the variations in the exchange rate. Cheung et al. (2005) performs a similar exercise incorporating models developed during the 1990s and applies new econometric techniques. The authors conclude that some models perform well for certain projections or specific exchange rates, however, their results do not identify a model that is broadly consistent. Faust et al. (2003) also noted that most of the work that find macroeconomic models outperform the random walk model are sensitive to the choice of horizons and sample periods. B. Rossi (2013) also found that much of the models cannot have good results in a generic way, their success only occurs under some specific time frames and frequencies.

As discussed by Rossi (2014), one of the best explanations, from a theoretical point of view, on the fragility in explaining the exchange rate would be the way the rate itself is determined. If the exchange rate is the expected present discounted value of current and future fundamentals of an economy, it's possible that the dynamics is affected not only by the observables macroeconomic fundamentals, but also by unobservable variables such as risk premium, noise trading, or any another factor that can create short term distortions on the expectations of the economic agents about the future of a given economy. Engel (2012 and 2013), McGrevy (2018) also discuss the importance of taking the unobservable in account when dealing with exchange rate dynamics, both authors use the factor extraction method in panels made from exchange rates.

Since the price discovery - which is a process through which information is timely incorporated in prices in the search for a new equilibrium - for exchanges rates happens in financial markets with very liquid instruments and the market for exchange rates is global, and it is relative without borders, which gives the investor the possibility to make trades around the world, making arbitrages or hedges operations using different currencies, sometimes the price action happens regardless of the underlining economic fundamentals of these economies. Now all the trades are done in an electronic environment, which reduces the possibility to make arbitrages between currencies, with more information, the market is always near an competitive equilibrium, LeRoy (2014).

Investors have several different motivations to make trades in the exchange rate markets, since making directional just for speculative motives trades betting in a devaluation of a specific currency or to make a complex derivative structure to hedge a commercial operation, regardless the motive all the movement in the markets immediately affects the price of a specific currency.

Some countries have the price discovery of the exchange rate given by the price of the future market and not in the spot market. This happens with s ecurities and underlining assets which have a fragmented market where these similar assets are traded in multiple venues. And information flows through these different markets affecting prices, as discussed by (Caporale and Girardi, 2013, Fernandes and Scherrer, 2013, among others). We can use Brazil as an example, as stated by Garcia et. Al (2015): "Brazil has a long history of exchange rate crises that have originated different forms of capitals controls. This process created an atypical FX market structure where, contrary to common international practice, most of the liquidity is concentrated in the first-to-mature futures contract." This kind of "noise" affects the capacity of the traditional models to capture the underlining dynamics in the exchange rate movement.

If these unobservable factors have little or no correlation with the observable ones, this reduce the predictive power of the model. Leading to the weak results found in the literature, such as discussed by Mark (2008), Rossi (2014) and Engel (2012).

In order to resolve the problems discussed earlier, Bacchetta and Van Wincoop (2004), Bacchetta (2014) develop the scapegoat theory, which is consistent with this role of the unobservable variables in explaining movements of the exchange rate. This theory asserts that if the dynamics of the exchange rate is partially given by unobservable variables, changes in the agents' expectations 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 bought by literature is how to capture and identify 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.

Such as in Rossi (2014) common factors are extracted directly from the dynamics of the exchange rate in a set of 26 countries. Two conditions are needed for the use of factor models to be helpful in forecasting the exchange rate:

1. The information embedded in the common movements of the exchange rate of various countries is related to the unobservable variables;

2. These variables play a role in the countries exchange rate.

Factor models are widely used to forecast macroeconomic variables, but they are rarely used in the case of the exchange rates as noted by Rossi (2014). Groen (2006) uses a dynamic factors model to identify the exchange rate level dictated by fundamentals and uses the difference between this value and the exchange rate to successfully forecast the exchange rate over a two-year period. Engel (2008) construct factors derived from the exchange rate of 17 countries and uses these factors to also forecast the exchange rate with satisfactory results. Also Engel (2012 and 2013) uses factor models to apply yield curve effects and carry trades into the cross-section of a panel made from various currencies. McGrevy (2018) uses a factor model in panel made from 27 exchange rates and uses econometric identification methods in order to explain the unobservable dynamic.

3 Methodology

The challenge we face is to explain the non-observable dynamics. In order to solve this problem, we use a regularized regression, which is a supervised machine learning technique, to identify the model that best fits a pool of 126 candidate variables with the four extracted factors.

Machine learning techniques are better than traditional econometric modelling since it uses algorithms to select the better model, since the algorithm do this process in an automatic way. This auto selection feature is desirable when dealing with a big datasets, which is the case of this work. Consequently, since the model is endogenous selected, the selection bias is minimized, giving another advantage and eliminating data mining by the research which is trying to select the best model.

Traditional regression techniques such as OLS has a very poor performance with a larger number of regressor and does not provide any model selection feature. When the number of regressors is greater than three, OLS starts to lose efficiency (Stein's phenomenon) Ahren et. al (2019). And when the number of regressors is large, forecasting starts to have a poor performance.

The primary purpose of supervised machine learning, like regularized regression algorithms is prediction. This type of regression typically does not yield estimates that can be interpret as causal and statistical inference on theses coefficients can be problematic, as stated by Ahren et. al (2019). While normal regression analysis may select the true model as the sample size increases, this is generally the case under strong assumptions. However, regularized regression can aid causal inference without relying on the strong assumptions required for perfect model selection. The post-double-selection of methodology of Belloni et al. (2014a) and the post-regularization approach of Chernozhukov et al. (2015) can be used to select control variables from a set of factors and, thereby, improving the robustness of estimation of the parameters of interest, Ahrem (2019), all these models had been developed for use in economics and have a very strong theorical ground.

Another reason that we choose to use a regularized regression approach in this work, is the fact that this kind of regression solves the problem of the bias variance trade-off, Tibshirani (1996). The variance of the estimated prediction increases with model complexity, whereas the bias tends to decrease with model complexity, a difficult trade-off. By reducing model complexity and inducing a shrinkage bias, regularized regression methods tend to outperform OLS in terms of out-of-sample prediction performance Ahren et al.(2019). In doing so regularized regression addresses the common problem of overfitting: high in-sample fit (high R) but poor prediction performance on unseen data, Ahren (2019).

This kind of approach can be used to select more parsimonious models for causal inference.

Another advantage, that Ahren et al (2019) presents is that the regularization methods such as lasso (and variants) can produce models with sparse solutions, an important feature to variable identification. High dimensional problems where the number of predictors is large relative to the samples size, imposes a challenge in the model specification, especially when the true model is treated as unknow.

Regularized regression methods rely on tuning parameters that control the degree and type of penalization (variable exclusion). The normal approach in machine learning is to select tuning parameters using cross- validation in order to get an optimal out-of-sample model performance. Cross-validation methods generally perform well for predictions task but are computationally very expensive and presents a poor performance for causal inference in time series models as highlighted by Ahren et al (2019). Another simple approach relies on information criteria such as the Akaike information criteria's (Zou et al, 2007 Zhang et al. 2010). Information criteria are easy to calculate and have attractive theorical properties but are less robust and can have problems like violation of the independence and homoscedasticity as noted by Arlot and Celisse (2010).

In order to solve the problems and uses a machine learning method that can work with good performance on economic problems, Belloin developed the rigorous penalization for the lasso and square-root lasso provides a third option. The approach is valid in the presence of heteroskedastic, non-gaussian and cluster depend errors (Belloin et al. 2012, 2014, 2016), characteristic that are very common to financial variables. The rigorous approach places a high priority on controlling overfitting, thus often producing parsimonious models or less complex models. This strong focus on containing overfitting is of practical and theorical benefit for selection control variables for a structural model, a high desirable feature in macroeconomics.

Since the dataset we use in this work is basically financial and economic time series, the most appropriate method for us to select the tuning parameter is the rigorous lasso. The penalization is chosen to dominate the noise of the data-generating process (represented by the score vector), which allows derivation of theoretical results regarding consistent prediction and parameter estimation. Ahren (2019).

3.1 The Lasso Model

The lasso takes a special position, as it provides the basis for the rigorous penalization approach. The lasso minimizes the mean squared error subject to a penalty as shown by the equation (1).

$$\beta_{lasso}(\lambda) = argmin\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i^{'}\beta)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\psi_i|\beta_j| \tag{3.1}$$

The tuning parameterλ controls the overall penalty level and j are predictor-specific penalty loadings.

Tibshirani (1996) stated that the lasso model have two major advantages over OLS. Given the nature of the 'L1-penalty', the lasso sets some of the coefficient estimates exactly to zero and, which leads to removing some predictors from the model, which is the way the model selection feature happens, shrinking coefficients to zero, consequently, excluding variables from the model.

The lasso coefficient path, which constitutes the trajectory of coefficient estimates as a function of λ is linear with chances in slope where variables enter of leave the active set. The change points are referred as knots. It's simple to see that if $\lambda = 0$, the model, yields the OLS solution and if $\lambda \to \infty$ yields and empty model where all coefficients are zero, because of this dynamics it is very important to choose the better method to choose the λ for each case, since the final model that will be selected is very sensible to λ.

The lasso, unlike OLS, can be affect by linear transformation of the variables, which is why the scale of the variables used matters Ahrem et al. (2019). If the predictors are not of equal variance, the most common approach is to pre-standardize the data such that $\frac{1}{n}\sum_i x_{ij}^2 = 1$ and set $\psi_i = 1 for j = 1, ..., p$

3.2 Rigorous penalization

Following Ahren (2019) and Chernozhukov et al. (2016), the term 'rigorous' is used to emphasize that the framework is constructed with theory. In particular, the penalization parameters are chosen to achieve consistent prediction and parameter estimation. Rigorous penalization is of special interest for us, since it provides the bases for methods to facilitate causal inference in the presence of many instruments and/or many control variables.

Ahren (2019) explains that are three main conditions required to guarantee that the lasso is consistent in terms of prediction and parameter estimation. The first condition relates to sparsity. Sparsity is important when we have a large set of potentially relevant regressors, or consider several models specifications, but assume that only one true model exists and such model only includes a small number of regressors. The lasso method relies in the exact sparsity condition, but this assumption is stronger than we need, Ahren et al.(2019). For example, some true coefficient may be non-zero, but small in absolute size, the traditional lasso will rule them out of the model, for this reason the approximate sparsity is desirable.

Another condition that is different in the rigorous penalization is the regularization event, which concerns the choice of the penalty level λ and the predictor-specific loadings ψ_j . The idea is to select he penalty parameters to control the random part of the problem in the sense that

$$\frac{\lambda}{n} \geq c \max_{1\leq j\leq p} |\psi_j^{-1} S_j| \quad where \quad S_j = \frac{2}{n}\sum_{i=1}^{n} x_{ij}\varepsilon_i \tag{3.2}$$

With high probability here, $c > 1$ is a constant slack parameter and S_j is the jth element of the score vector $S = \Delta\hat{Q}(\beta)$, the gradient of $\hat{Q}$ at the true value β . The score vector summarizes the noise associate with the estimation problem.Ahren (2019).

Denote by $\Lambda = nmax|\psi_j^{-1} S_j|$ the maximal element of the score vector scaled by n and ψ_j , and denote by $q\Lambda(.)$ the quantile function for Λ. In the rigorous lass, we choose the penalty parameters λ and ψ_j and the confidence level γ so that $\lambda \geq cq_{\Lambda}(1-\gamma)$.

3.3 Rigorous Lasso

Belloni et al. (2012) show using moderate deviation theory of self-normalized sums from Jing et al. (2003)| that the regularization events have asymptotic behavior, i.e:

$$P(\max_{1\leq j\leq p} c|S_j|) \geq \frac{\lambda\psi_j}{n} \to 1 \quad as \quad n\to\infty, \quad \lambda\to 0 \tag{3.3}$$

If the penalty levels and loadings are set to:

- Homoskedascity: $\lambda = 2c\sigma\sqrt{n\Phi^{-1}}(1-\frac{\gamma}{2p})$, where $\psi_j = \sqrt{\frac{1}{n}\sum_i x_{ij}^2}$
- Heteroskedascity: $\lambda = 2c\sqrt{n\Phi^{-1}}(1-\frac{\gamma}{2p})$, where $\psi_j = \sqrt{\frac{1}{n}\sum_i x_{ij}^2\varepsilon_i^2}$

3.4 Post-estimation OLS

Penalized regression methods induce an attenuation bias that can be alleviated by post-estimation OLS, which applies OLS to the variables selected by the firs-stage variable selection method;

$$\beta_{post} = arg\min \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i^{'}\beta)^2 \quad subject \quad to\beta_j = 0 \quad if\tilde{\beta}_j = 0 \tag{3.4}$$

Where $\tilde{\beta}_j$ is a sparse first-step estimator such as the lasso. Thus, post-estimation OLS treats the first-step estimator as a genuine model selection technique. For the case of the lasso, Belloni (2012) and Chernozhukov (2013) have shown that the post-estimation OLS, also referred to as post-lasso, performs as well as the lasso under some additional assumptions if theory-driven penalization is employed. Since we have an interest in the causal effects, be able to run a traditional OLS model that take advantage of the model selection employed by the rigorous lasso, it is very desirable.

4 Data

All the data we use is in a daily frequency from January 2001 to June 2019. All series starts in 2001 since on this data all the countries inside the sample already had adopted the floating exchange rate mechanism. All the selected countries have the facto floating exchange rate regimes and independent monetary policies, all according to the most recent International Monetary Fund classification, IMF (2019).

The following countries and economic alliances met the selection criteria: Switzerland, Norway, Euro Zone, New Zealand, Great Britain, Sweden, Japan, Philippines, Canada, Australia, Iceland, South Korea, South Africa, Israel, Mexico, Colombia, Poland, Turkey, Peru, Paraguay, Uruguay, Hungary, Chile, Indonesia and Thailand. All prices are the end of the day adjusted rate. All exchange rates are relative to the US Dollar and follow the conventional of local currency quantity per unit of foreign currency. The currency exchange dataset is obtained from Bloomberg, a total of 125.814 (4839 points for each country) datapoints only from the currency exchanges series.

For the financial and economic inference of the factors we use 123 variables, all from Bloomberg, divided in six categories: (1) Spreads; (2) Swap rates; (3) Volatility indexes; (4) Prime rate indexes from the principal money markets around the world; (5) The 22 principal stock exchanges indexes and (6) diverse market data, such as short positions in the dollar market, commodities prices (CRB and Gold). The next table show how the variables are divided in categories.The complete description of the data can be found in the appendix.

Categories	*Number of Variables*
Interest Rate Spreads	*16*
Swap Rates	*33*
Votality Indicators	*13*
Referencial Rates	*13*
Stock Index	*18*
Commodities	*4*
Economic Indicators	*6*
Carry Trade Total Return Indicator	*3*
Diverses Market Indicators	*4*
TOTAL	**110**

Figure 1 – Variables categories

4.1 Factor Estimation

We consider the following exchange rate determination model as the baseline specification:

$$\Delta S_T = \alpha + \beta F_t + u_t \tag{4.1}$$

WhereΔS_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 variable.

We run the estimations using a robust OLS specification. Robust regression is an alternative to normal least squares regression when data are contaminated with outliers or influential observations, which is the case in our sample and a very common situation with financial data that are prone to variance cluster, since the sample can be contaminated by noise generated by the financial market movements, as shown by Andersen (2008).

4.2 Extracting the common factors

The common factors we extract from a panel of 26 exchange rates. Some econometric issues arise for the estimation of the factors. Cayen et al. (2010) analyze two different methodologies to identify the co-movements among the exchange rates: factor analysis and state space modeling. The authors discuss the advantages and disadvantages of each method. They show that the results are identical regardless of the method used for the identification process. As Rossi (2014) in this work we use, for simplicity, the n-orthogonal estimation.

4.3 The factor estimation

The factor model assumes that for individual , the observable multivariate vector, (which contains all the 26 exchange rates) is generated by:

$$X_i - \mu = LF_i + e_i \tag{4.2}$$

Where μ is a $p \quad x \quad 1$ vector of variable means, L, is a $p \quad x \quad m$ matrix of coefficients, F_i is a vector of standardized unobserved variables, termed common factors, and e_i is a $p \quad x \quad 1$ vector of errors or unique factors.

The model expresses the p observable variables $(X_i - \mu)$ in terms of m unobservable common factorsF_t and p unobservable unique factors e_t. Note that the number of unobservable exceeds the number of observables.

The factor loading pattern matrix L links the unobserved common factors to the observed data. The i-th row of L represents the loadings of the i-th variable on the common factors. Alternately, the row can be viewed as the coefficients for the common factors for the i-th variable.

The process of factor estimation is performed in two steps:

1. The estimation of the covariance matrix and the factor loadings

2. Create the factor series using the covariance matrix and factor loadings

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, are considered 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 estimated factors. The approach employed is the same that Rossi (2014) uses, which is to use these two tests, which yielded the same number of factors.

Results show that both criteria indicate that N=4 factors are driving the dynamics of the exchange rate the sample. Figure 2 summarizes the results from the factor estimation.

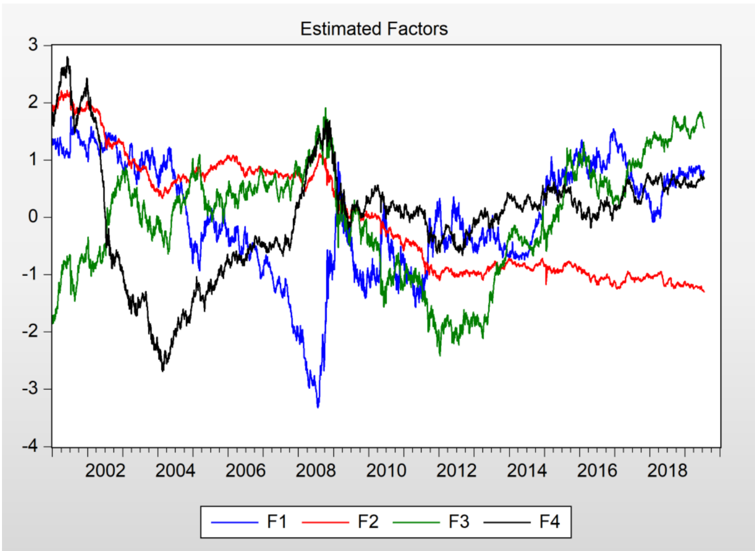

Figure 2 – Trajectory of the four estimated factors

Figure (3) shows the percentage of the variance of the exchange rate that is cumulatively explained by the n=4 factors, for the complete sample. We found that the 4 factors explain approximately 96% of the variability in the data. With the four factors explaining, respectively, 43,92%, 28,96%, 16,27% and 10,85%.

It's clear that a significant portion of the co-movement between the exchange rates are captured by our estimated factors. The challenges, as stated earlier, is to give an economic interpretation for them.

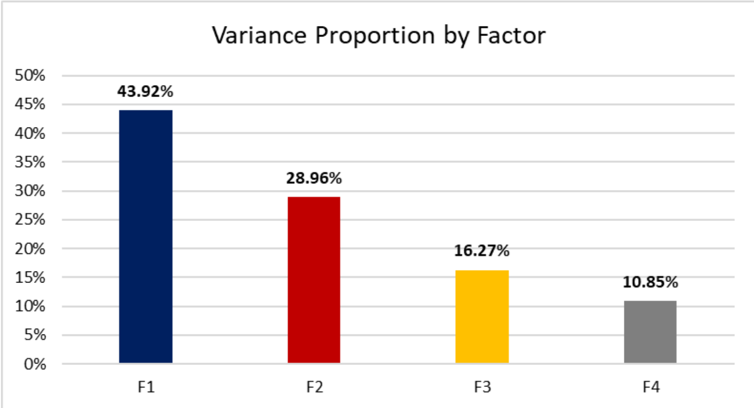

Figure 3 – Variance proportion by factor

4.4 Identification of the common factors

After estimation give an economic interpretation to the factors is crucial. The literature tries to identify the factors trough the inspection of the estimated loadings. Our results in table 1 indicates that the factor 1 has significant and positive loadings in all of the currencies used. The factor is by construction a weighted mean of all of the exchange rates. This fact allows to interpret the factor as reflecting the common movements of the currencies with respect to the reference currency, the same conclusion that Rossi (2014) had achieved. Factor 1 is the dollar effect since it's the reference currency.

	Factor Loadings					
Country	**F1**	**F2**	**F3**	**F4**	**Communality**	**Uniqueness**
Australia	0.69	0.60	0.32	0.20	0.98	0.02
Brazil	0.75	-0.22	0.56	-0.10	93%	7%
Canada	0.83	0.39	0.32	0.13	96%	4%
Swistzerland	0.37	0.91	0.03	0.02	97%	3%
Chile	0.80	0.09	0.49	0.06	88%	12%
Colombia	0.71	-0.08	0.66	-0.11	95%	5%
Euro	0.88	0.30	0.02	0.29	95%	5%
G. Britain	0.65	-0.46	0.04	0.47	85%	15%
Hungary	0.85	-0.28	0.05	0.38	96%	4%
Indonesia	0.38	-0.59	0.47	0.42	89%	11%
Iceland	0.40	0.72	0.00	-0.44	87%	13%
Japan	0.18	-0.66	-0.29	0.48	79%	21%
S. Korea	0.44	0.44	0.54	0.09	69%	31%
Mexico	0.58	0.10	-0.19	0.31	48%	52%
Norway	0.24	-0.85	0.37	0.14	94%	6%
N. Zeland	0.86	0.01	0.33	0.34	97%	3%
Peru	0.58	0.71	0.08	0.29	92%	8%
Philipines	0.66	0.48	0.53	-0.08	95%	5%
PLN	0.52	0.43	0.48	-0.31	79%	21%
Paraguay	1.00	0.00	0.00	0.00	100%	0%
Sweden	0.45	0.05	0.60	-0.55	87%	13%
Thailand	0.84	0.23	0.24	0.37	95%	5%
Turkey	0.51	0.80	0.13	-0.14	94%	6%
Uruguay	0.38	-0.75	0.43	0.19	93%	7%
S. Africa	0.24	-0.46	0.67	-0.49	96%	4%
Thailand	0.49	-0.56	0.34	0.46	88%	12%
Average	0.59	0.05	0.28	0.09	**89%**	**11%**

Figure 4 – Factor loadings

The dynamics of the first factor corroborates the dollar effect theory. Between 2002 and 2008 the dollar have depreciated compared to most of the currencies in the sample, figure 1 indicates a very sharp e continuous movement of decrease in the factor in this period of time. Since 2010 a new regime begins, but in a different direction, now implying that the dollar had strengthen relative to the other currencies. The next graph brings the plot of the DXY index, which is a weighted basket of six currencies against the dollar, the composition is:

1. Euro (EUR), 57.6% weight
2. Japanese yen (JPY) 13.6% weight
3. Pound sterling (GBP), 11.9% weight
4. Canadian dollar (CAD), 9.1% weight
5. Swedish krona (SEK), 4.2% weight
6. Swiss franc (CHF) 3.6% weight

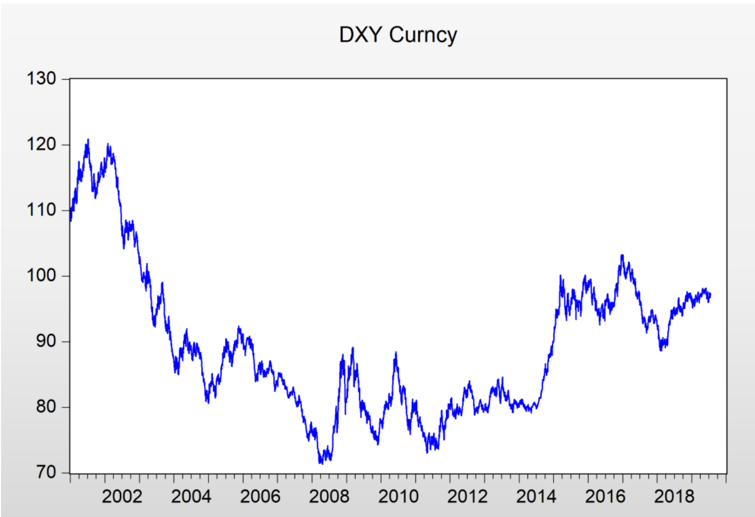

Figure 5 – DXY currency

The DXY basket it is used as the most important us dollar proxy in the financial markets.It's very clear how similar the DXY basket pattern is relative to the first factor. But there's some not accounted difference that is left to be explained by other variables.

The analysis for the remaining factors starts to impose challenges, since the results of the factors loadings and from the regression is not straight forward. To better understand the dynamics and properly identifies the factors, we employ the rigorous lasso methodology discussed early. We show the results with the rigorous lasso selected coefficients and post-ols estimation right on side.

We use the rigorous lasso approach in a pool of 126 variables to identify each of the factors that we extracted. The next table brings the result of the estimation for the first extracted factor. The first factor accounts for almost 44% of the cross-section return

Selected Variables	Variable Category	Rig. Lasso	Post-est OLS
DXY Currency Index	Currency	1.1774031	1.8921605
CBOE 10-Year Treasury Note Volatility Future	Volatility Index	0.0278596	0.0384106
Carry Trade Return 10 EM	Carry Return	0.0067556	0.0092601
Carry Trade Return 8 DE	Carry Return	-0.0114065	-0.017159
6 Month Treasury spread on Federal Funds Rate	Interest Rate Spread	-0.0752819	-0.1465815
ICE Spreads (US$), 7 Year Tenor	Swap rate	-0.2162329	-0.7422078
ICE Spreads (US$) 10 Year Tenor	Swap rate	-0.2569124	0.2774457
6 Month-LIBOR based on Yen	Referencial Rate	-0.2850015	-0.9409356
C	Cosntant	-3.3322797	-1.4723632

Figure 6 – Rigorous Lasso and Post-est OLS for Factor 1

of our panel of currencies. As we stated before, this factor is the dollar effect (by the factor construction), the lasso approach shows us that the cost of funding and interest rate differentials of instruments linked to the us dollar has an important role in the global exchange rate dynamics, since it affects the co-movement of our panel of currencies.

Looking into the results, we can see a significant sensibility to the DXY basket, which explains more than 50% of the dollar movement around the currencies sample and have a negative correlation with interest rate on the US and in other developed economies. Besides the DXY, we found that the interest rate variables play an important role in the principal factor that we extract.

Besides the DXY, we found that the interest rate variables play an important role in the principal factor that we extract, an result also found by Engel (2012), which also uses a factor method and shows that carry trades and interest rates plays a very important role in the cross-section of the returns of a panel of exchange rates.

The negative signal that we find in the interest rate variables is expected, since it's the carry cost of the dollar. For example: the more sensible is the cost of short-term money in dollars, when the cost of borrowing capital in other advanced economies as Japan for example (Libor in Yens). Naturally investors will search for higher yield in other liquid currencies such the US dollar. The same principle holds for to the interest rate spreads (7 year and 10-year tenor) which is an instrument that the investor can use to hedge positions in dollar (higher yield) when he's being funded in another currency, simple the investor can change the interest rate that he is exposed.

With the same direction and less intensity in the relationship, we can see that other variables such as the return of carry trades for different currencies which directly affects the US dollar relative strength, and the volatility (which indicates turbulence in markets) of the 10 year treasuries which is the most liquidity sovereign fixed income instrument in the world and reference for fixed income yields all around the globe.

Selected Variables	Variable Category	Lasso	Post-est OLS
6 Month-LIBOR rate on Yen	Referencial Rate	0.4919312	0.4919312
Spot - LIBOR rate on Yen	Referencial Rate	0.3885568	-0.1327675
Spot - LIBOR rate on Euros	Referencial Rate	0.0793606	0.071413
5 year Treasury spread on Federal Funds Rate	Interest Rate Spread	0.0728888	0.0961247
Moody's Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Interest Rate Spread	0.0728888	0.0961247
1 Week - LIBOR rate on Euro	Referencial Rate	0.0634517	0.1151807
Carry Trade Return 8 DE	Carry trade return	0.0016033	0.0040835
Carry Trade Return 10 EM	Carry trade return	-0.0033538	-0.0056424
5-Year US Breakeven Inflation Rate	Interest Rate Spread	-0.1191193	-0.1607817
DXY Currency	Currency	-0.26146	-0.0595316
Constant	Constant	-0.6047595	-0.6556501

Figure 7 – Rigorous Lasso and Post-Est OLS for Factor 2

Our second factor which captures 29% of the co-movement of our exchange rate panel, appears to be related to the real interest rate dynamic, these correlation if real rates is expected since from an investor point of view, the different levels of real interest rates around the world sets the cost that an investor face to funding positions and trades in different currencies. Melvin (2013) notes that these differentials are in reality the opportunity cost that market agents faces when they decide to be long or short in one determined currency or in a basket of currencies, this relationship are also closely linked to the results founds by Engel (2009) who also applies a factor model in order to study the cross section determinants of 17 exchange rates. Also, this dynamic is grounded in a classical relationship on macroeconomics and international finance, which is the interest rate differential between countries.

The real yields plays another important role, since the moments of an yield curve can be seem as beacon who reveal a great deal of information about the expectations of a certain economy, Chen (2013) construct a yield curve factor based on the methodology of Nelson-Siegel (1987). The yield curve and their related instruments such as swaps and referential rates that we use here in our analysis are important since they embedded information about the investors' expectations about present and future economic dynamic such as monetary policy, output level and inflation, a dynamic that is also found in the work of Andersen (2007). Chen uses the yield curve factor to explain the cross section of returns from a panel of 10 exchange rates. Our results stated below shows how the yield movements in developed countries affects the cross section returns of currencies and which financial instruments appears to better reflect this dynamic into markets.

Two very important variables selected by our model is the libor rate in yens and the libor denominated in euros, followed by the spread between the fiver year treasury and the fed funds, all this measures are directed linked to the opportunity cost to make trades in different currency's when the investor is funded in us dollars. The real component comes in the form of the U.S five-year breakeven rate. The breakeven inflation rate is the inflation expectation that are embed inside fixed income futures and reflects the investors expectation for future inflation in the us economy, affecting the investors expectations of real returns in the future.

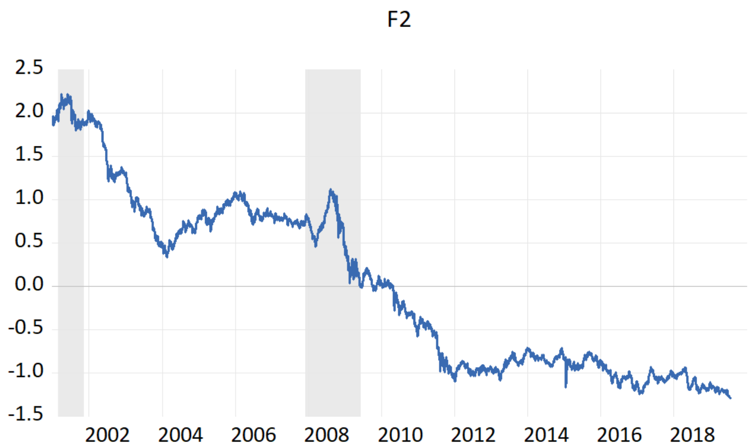

Figure 8 – Second factor after 2008 crises

The graph above shows that after the 2008/2009 crisis, highlighted by the shade, the second factor appears to entry in a new regime, of negative values. This dynamic is very similar to the one presented by the first component of a principal component analysis made from the FED Funds, Libor spot rate in USD and the ECB discount rate, all major referential interest rates that after the crises had been set to zero, yielding negative real rates, which is captured by this factor.

In the same direction, our model shows a negative signal on the carry trade return of the ten most liquid exchange rate of developed economies, the G- 10 group (Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States, with Switzerland), all of them have turn to very loose monetary policy since the 2008 crisis, setting their policy rates to zero or near zero, an important new dynamic noted by Williams (2014). So, our results indicate that when the rates are low the carry return is negative, affecting the return of investing on theses currency's when funded in dollars.

The second factor, also has significant negative interaction with the DXY currency, which is the dollar, this corresponds to reality since the crisis the US as the first country to start to normalize monetary policy. By now the fed funds is around 2,25% and the deposit rate in Europe and Japan stills near or even below zero. This signal in the DXY corroborates the idea of the second factor being like a real yield indicator for currency exchange markets. Williams (2014) and Engel (2013) found similar dynamics that corroborated our findings in way that higher real interest rates tend to strength a currency and Engel (2013) shows that this dynamic is also present in the cross section of the returns of a panel made from 17 exchange rates.

Selected	Variable Category	Lasso	Post-est OL
2-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar	Referencial Rate	0.3595909	0.4731292
10-Year Treasury Constant Maturity Minus 6-Month Treasury Constant Maturity	Interest Rate Spreads	0.1557229	0.0213096
1-Week London Interbank Offered Rate (LIBOR), based on U.S. Dollar	Referencial Rate	0.0501572	-0.0120733
CBOE Emerging Markets ETF Volatility Index	Volatility Index	0.0006961	0.0111941
Citi economic surprise - Europe	Economic Indicators	0.000177	0.0008277
LATAM Countries - FX Carry trade return index	Carry Trade Return	-0.0014965	-0.0033069
CRB - Food commodities Index	Commodities	-0.0016967	-0.0017273
ICE BofAML High Grade Emerging Markets Corporate Plus Sub-Index Option-Adju	Interest Rate Spreads	-0.0269635	-0.2644858
USD ATM 3 - Month - Volatility	Volatility Index	-0.0284622	-0.0471086
CBOE 10-Year Treasury Note Volatility Future	Volatility Index	-0.0302218	-0.0386517
G10 Countries - FX Carry trade return index	Carry Trade Return	-0.0305285	-0.0277037
ICE Spreads, Based on U.S. Dollar, 2 Year Tenor	Swap Rates	-0.519802	-0.6249846
1 Week - LIBOR rate on Euro	Referencial Rate	-0.7193663	-0.2635574
Constant	-	8.0504032	8.1777985

Figure 9 – Rigorous Lasso and Post-Est OLS for Factor 3

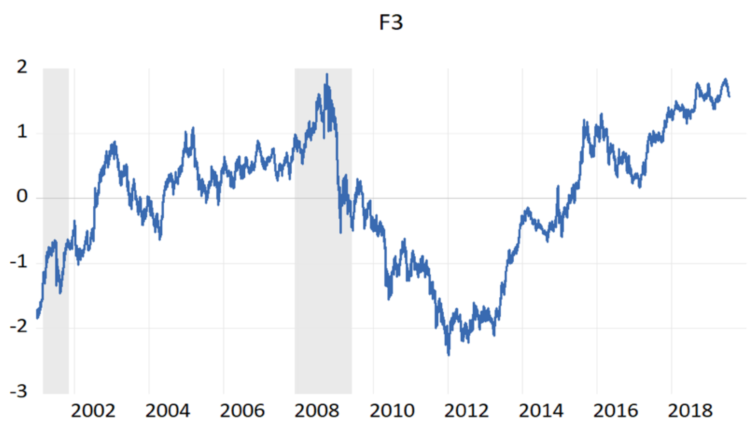

Figure 10 – Rigorous Lasso and Post-Est OLS for Factor 3

The third factor, which accounts for 16% of the exchange rate movements, shows us what appear to be the carry trade or the opportunity cost to be founded on us dollars, an result in line with the fact stated by Engel (2013) of the higher interest rate level of a country tends to strength their currency, and by consequence enhance the carry return of that currency. Since all the currencies are in bilateral form with the us dollar, and the latter is the world principal reserve currency, it is reasonable to point that the carry return of the us dollar have an effect on all the currencies of our sample.

Our model indicates that more than 93% of the third factor is explained by referential rates such as libor, swap rates and interest rate spreads. Note that we have identified the same instrument with different signals, indicating, again, that the currency in which the instrument is funded makes difference, because the opportunity cost (the country interest rate) differs around the globe. All this instruments are commonly used by traders and financial agents to make carry trades using the us dollar.

The graph above shows a improvement in the factor after 2012, exactly the same period when the libor rate in euros and the ICE spreads start to diminish since the EUR and US engaged in more loose monetary policy. Since the ICE Spreads in dollars are the instrument that offshore investors use to hedge positions in dollars when funded in euros as an example.

Selected Variable	Variable Category	Rig. Lasso	Post-est OLS
ICE Spreads, Based on U.S. Dollar, 7 Year Tenor	Swap Rates	1.2564616	1.3413846
1 - Week London Interbank Offered Rate (LIBOR), base on GBP	Referencial Rates	0.0707251	0.2954969
CBOE DJIA Volatility Index	Volatility Index	0.00371	0.0104728
3-Month Treasury Constant Maturity Spread on Federal Funds Rate	Interest Rate Spreads	0.0033759	0.0309263
Citi economic surprise - Europe	Economic Indicators	0.0005618	0.0009476
G10 Countries - FX Carry trade return index	Carry Trade Total Return Indicator	-0.002301	-0.0019687
CBOE Gold ETF Volatility Index (	Votality Indicators	-0.0052776	-0.0034311
ICE BofAML Euro High Yield Index Option-Adjusted Spread	Interest Rate Spreads	-0.0103041	-0.0728533
Moody's Aaa Corporate Bond Minus Federal Funds Rate	Interest Rate Spreads	-0.0180735	-0.0036241
USD ATM 3 - Month - Volatility	Diverses Market Indicators	-0.0282751	-0.0500825
Moody's Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Interest Rate Spreads	-0.0789288	0.0576068
12-Month London Interbank Offered Rate (LIBOR), based on Swiss Franc	Referencial Rates	-0.1573419	-0.2546778
Constant	Constant	1.7424966	1.8179953

Figure 11 – Rigorous Lasso and Post-Est OLS for Factor 4

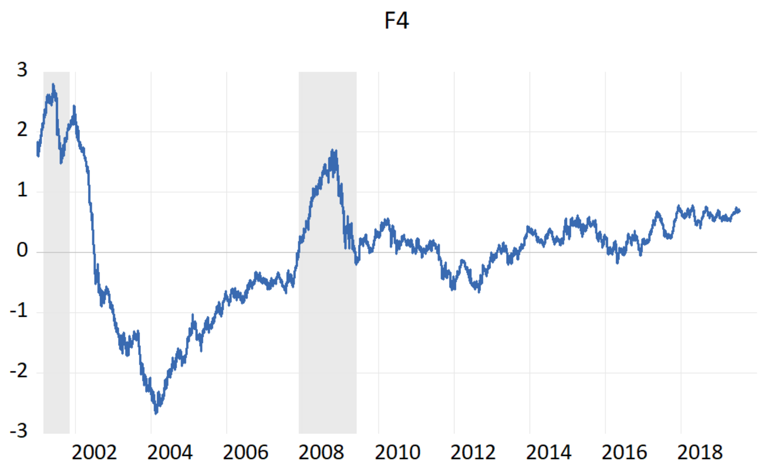

Figure 12 – Rigorous Lasso and Post-Est OLS for Factor 4

The last factor that we estimate, accounts for 10% of the co-movements, this factor is linked to risk movement in the currencies market. Since the two more important variables is the ICE Spreads contract denominated in us dollars with long duration, since it's a since

7 contract and the 1 year forward libor rate in swiss francs, another risk averse position that investors make when markets are in a sell off, facing a turbulence. This risk aversion movement are in line with the findings made by Melvin (2013) which stated that investors are sensitive to turbulence in currency markets and that volatility periods can make them unwind positions and by consequence affecting the return of different exchange rates.

Our model captured some turbulence triggered variables, such as spreads in triple A bonds relative to 10 year treasury bond, the volatility of options linked to the us dollar, gold volatility index, and the VIX volatility index the most important volatility contract in the world and the spread between the 3month with the 10 year treasury note another famous risk indicator that investor uses as gauge of the financial conditions.

5 Conclusions

The exchange rate dynamics is a puzzle for researchers and market practitioners, as we stated earlier there's an extensive body of literature about the price action, fundamentals and forecast of exchange rates. None of them have a "final" theory or a complete model that works in a generic way for all the currencies.

In this work we combined the factor analysis which has been extensively used, with relative success, to explain exchange rate movements, but without giving them economic interpretation, together with supervised machine learning in order to select models from a pool of hundreds of variables to explain the factors.

Our results give the factors, a unobservable variable a link with observed variables. Most of the results are correlated with macroeconomic stylized facts such as interest rate differential and arbitrage, showing that even the unobservable events have a strong correlation with theory and financial markets common knowledge. Since the variables that we use here are in a daily frequency this framework can be real time updated to give a straightforward analysis of the global currency markets.

The great limitation of this work and a future challenge for new research is to continue to address the forecast problem. As shown in the literature review section, this is one of the biggest puzzles in the macroeconomic research and new techniques at least for economic research, such as lasso and even unsupervised machine learning can be employed in this task.

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A Categories of variables

Categorie	Name	Description	Source
Interest Rate Spreads	Moody's Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Series is calculated as the spread between Moody's Seasoned AAA Corporate Bond and 10-Year Treasury Constant Maturity	Moody's
Interest Rate Spreads	Moody's Aaa Corporate Bond Minus Federal Funds Rate	Series is calculated as the spread between Moody's Seasoned AAA Corporate Bond and Effective Federal Funds Rate	Moody's
Interest Rate Spreads	Moody's Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Series is calculated as the spread between Moody's Seasoned Baa Corporate Bond and 10-Year Treasury Constant Maturity	Moody's
Interest Rate Spreads	Moody's Baa Corporate Bond Minus Federal Funds Rate	Series is calculated as the spread between Moody's Seasoned Baa Corporate Bond and Effective Federal Funds Rate	Moody's
Interest Rate Spreads	3-Month Commercial Paper Minus Federal Funds Rate	Series is calculated as the spread between 3-Month AA Financial Commercial Paper and Effective Federal Funds Rate	Federal Reserve Bank of St. Louis
Interest Rate Spreads	10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity	Series is calculated as the spread between 10-Year Treasury Constant Maturity (BC_10YEAR) and 2-Year Treasury Constant Maturity (BC_2YEAR).	Federal Reserve Bank of St. Louis
Interest Rate Spreads	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	Series is calculated as the spread between 10-Year Treasury Constant Maturity (BC_10YEAR) and 3-Month Treasury Constant Maturity (BC_3MONTH).	Federal Reserve Bank of St. Louis
Interest Rate Spreads	10-Year Treasury Constant Maturity Minus 6-Month Treasury Constant Maturity		
Interest Rate Spreads	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	series is calculated as the spread between 10-Year Treasury Constant Maturity (BC_10YEAR) and Effective Federal Funds Rate	Federal Reserve Bank of St. Louis

Figure 13 – Categories of variables

Interest Rate Spreads	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	series is calculated as the spread between 10-Year Treasury Constant Maturity (BC_10YEAR) and Effective Federal Funds Rate	Federal Reserve Bank of St. Louis
Interest Rate Spreads	10-Year Breakeven Inflation Rate	The breakeven inflation rate represents a measure of expected inflation derived from 10-Year Treasury Constant Maturity Securities (BC_10YEAR) and 10-Year Treasury Inflation-Indexed Constant Maturity Securities (TC_10YEAR). The latest value implies what market participants expect inflation to be in the next 10 years, on average.	Federal Reserve Bank of St. Louis
Interest Rate Spreads	5-Year Treasury Constant Maturity Minus Federal Funds Rate		
Interest Rate Spreads	3-Month Treasury Constant Maturity Minus Federal Funds Rate		
Interest Rate Spreads	5-Year Breakeven Inflation Rate	The breakeven inflation rate represents a measure of expected inflation derived from 5-Year Treasury Constant Maturity Securities (BC_5YEAR) and 5-Year Treasury Inflation-Indexed Constant Maturity Securities (TC_5YEAR). The latest value implies what market participants expect inflation to be in the next 5 years, on average.	Federal Reserve Bank of St. Louis

Figure 14 – Categories of variables

Interest Rate Spreads	ICE BofAML Emerging Markets Corporate Plus Index Option-Adjusted Spread	This data represents the Option-Adjusted Spread (OAS) for the ICE BofAML Emerging Markets Corporate Plus Index (https://fred.stlouisfed.org/series/BAMLEMCBPITRIV?cid=32413), which tracks the performance of US dollar (USD) and Euro denominated emerging markets non-sovereign debt publicly issued within the major domestic and Eurobond markets. To qualify for inclusion in the index, the issuer of debt must have risk exposure to countries other than members of the FX G10 (US, Japan, New Zealand, Australia, Canada, Sweden, UK, Switzerland, Norway, and Euro Currency Members), all Western European countries, and territories of the US and Western European countries. Each security must also be denominated in USD or Euro with a time to maturity greater than 1 year and have a fixed coupon. For inclusion in the index, investment grade rated bonds of qualifying issuers must have at least 250 million (Euro or USD) in outstanding face value, and below investment grade rated bonds must have at least 100 million (Euro or USD) in outstanding face value. The index includes corporate and quasi-government debt of qualifying countries, but excludes sovereign and supranational debt.	Intercontinental Exchange, Inc. (ICE)
Interest Rate Spreads	ICE BofAML High Grade Emerging Markets Corporate Plus Sub-Index Option-Adjusted Sprea	This data represents the Option-Adjusted Spread (OAS) for the ICE BofAML High Grade Emerging Markets Corporate Plus Index is the subset of the ICE BofAML Emerging Markets Corporate Plus Index, which includes only securities rated AAA through BBB3. The same inclusion rules apply for this series as those that apply for ICE BofAML Emerging Markets Corporate Plus Index	Intercontinental Exchange, Inc. (ICE)
Interest Rate Spreads	ICE BofAML Euro High Yield Index Option-Adjusted Spread	This data represents the Option-Adjusted Spread (OAS) of the ICE BofAML Euro High Yield Index tracks the performance of Euro denominated below investment grade corporate debt publicly issued in the euro domestic or eurobond markets. Qualifying securities must have a below investment grade rating (based on an average of Moody's, S&P, and Fitch). Qualifying securities must have at least one year remaining term to maturity, a fixed coupon schedule, and a minimum amount outstanding of Euro 100 million. Original issue zero coupon bonds, "global" securities (debt issued simultaneously in the eurobond and euro domestic markets), 144a securities and pay-in-kind securities, including toggle notes, qualify for inclusion in the Index. Callable perpetual securities qualify provided they are at least one year from the first call date. Fixed-to-floating rate securities also qualify provided they are callable within the fixed rate period and are at least one year from the last call prior to the date the bond transitions from a fixed to a floating rate security. Defaulted, warrant-bearing and euro legacy currency securities are excluded from the Index.	Intercontinental Exchange, Inc. (ICE)

Figure 15 – Categories of variables

Votality Indicators	CBOE EuroCurrency ETF Volatility Index	Exchange Traded Funds (ETFs) are shares of	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE Gold ETF Volatility Index (	Exchange Traded Funds (ETFs) are shares of	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE Crude Oil ETF Volatility Index	Exchange Traded Funds (ETFs) are shares of trusts that hold portfolios of stocks designed to closely track the price performance and yield of specific indices. Copyright, 2016, Chicago Board Options Exchange, Inc. Reprinted with permission.	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE DJIA Volatility Index	The CBOE DJIA Volatility Index (VXD) is based on real-time prices of options on DJIA, with an options ticker of DJX, and is designed to reflect investors' consensus view of future (30-day) expected stock market volatility CBOE	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE Emerging Markets ETF Volatility Index	CBOE Emerging Markets ETF Volatility Index. CBOE now applies its proprietary CBOE VIX methodology to create indices that reflect expected volatility for options on select ETFs. VXEEM reflects the implied volatility of the EEM ETF, the iShares MSCI Emerging Markets Index.	Chicago Board of Exchange Options -CBOE

Figure 16 – Categories of variables

Votality Indicators	CBOE 10-Year Treasury Note Volatility Future	** Product specifications link below ** CBOE/CBOT 10-Year Treasury Note Volatility Index Futures Description: The VXTYN is based on real-	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE/COMEX Gold Volatility Index	CBOE/COMEX Gold Volatility Index	Chicago Board of Exchange Options -CBOE
Votality Indicators	JP. Morgan Emerging Market Volatility Index	JPMorgan Volatility index is calculated based on currency 3 month ATMF vols, which are combined with a set of fixed weights to produce the daily result.	JP. Morgan
Votality Indicators	Risk aversal real	The Risk Reversal is a measure of the skew in the demand for out-of-the-money options at high strikes compared to low strikes and can be interpreted as the market view of the most likely direction of the spot movement over the next maturity date. It is defined as the implied volatility for Call Options minus the implied volatility for Put Options on the base currency with the same delta.	JP. Morgan
Votality Indicators	Vol 3M OTM Real	Implied volatility is a measure of the market expected future volatility of a currency exchange rate from now until the maturity date. The future volatility is the single undeterminable variable in the common Black Scholes option pricing model. Bloomberg ATM implied volatilities can be used to obtain the correct Black Scholes price for a delta neutral straddle struck at maturity.	JP. Morgan

Figure 17 – Categories of variables

Votality Indicators	TRADE WHEIGHTED DOLAR		Federal Reserve Bank of St. Louis
Votality Indicators	Vix Volatlity Index	The Chicago Board Options Exchange Volatility Index reflects a market estimate of future volatility, based on the weighted average of the implied volatilities for a wide range of strikes. 1st & 2nd month expirations are used until 8 days from expiration, then the 2nd and 3rd are used.	Chicago Board of Exchange Options -CBOE
Votality Indicators	CBOE Emerging Markets ETF Volatility Index	CBOE Emerging Markets ETF Volatility Index. CBOE now applies its proprietary CBOE VIX methodology to create indices that reflect expected volatility for options on select ETFs. VXEEM reflects the implied volatility of the EEM ETF, the iShares MSCI Emerging Markets Index.	Chicago Board of Exchange Options -CBOE

Figure 18 – Categories of variables

Swap Rates	ICE Swap Rates, Based on Euros, 10 Year Tenor	e principal global benchmark for swap rates	Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates Based on Euros, 12 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 15 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 1 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 20 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 25 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 2 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 30 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 3 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 4 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 5 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 6 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 7 Year Tenor		Intercontinental Exchange, Inc. (ICE)

Figure 19 – Categories of variables

Swap Rates	ICE Swap Rates, Based on Euros, 8 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on Euros, 9 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 10 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 15 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 1 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 20 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 2 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 30 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 3 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 4 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 5 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 6 Year Tenor		Intercontinental Exchange, Inc. (ICE)

Figure 20 – Categories of variables

Swap Rates	ICE Swap Rates, Based on US Dollars, 7 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 8 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Spreads, Based on U.S. Dollar, 10 Year Tenor	ICE Swap Rate, formerly known as ISDAFIX, is recognised as the principal global benchmark for swap rates and spreads for interest rate swaps. It represents the mid-price for interest rate swaps (the fixed leg), at particular times of the day, in three	Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Spreads, Based on U.S. Dollar, 2 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Spreads, Based on U.S. Dollar, 3 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Spreads, Based on U.S. Dollar, 5 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Spreads, Based on U.S. Dollar, 7 Year Tenor		Intercontinental Exchange, Inc. (ICE)
Swap Rates	ICE Swap Rates, Based on US Dollars, 9 Year Tenor		Intercontinental Exchange, Inc. (ICE)

Figure 21 – Categories of variables

Referencial Rates	12-Month London Interbank Offered Rate (LIBOR), based on Swiss Franc		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	3-Month London Interbank Offered Rate (LIBOR), based on Swiss Franc		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	1-Week London Interbank Offered Rate (LIBOR), based on Euro		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	12-Month London Interbank Offered Rate (LIBOR), BGBP		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	1 - Week London Interbank Offered Rate (LIBOR), base on GBP		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	6-Month London Interbank Offered Rate (LIBOR), based on British Pound		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	1-Week London Interbank Offered Rate (LIBOR), based on Japanese Yen		Intercontinental Exchange, Inc. (ICE)

Figure 22 – Categories of variables

Referencial Rates	6-Month London Interbank Offered Rate (LIBOR), based on Japanese Yen		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	Spot Next London Interbank Offered Rate (LIBOR), based on Japanese Yen		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	12-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	1-Week London Interbank Offered Rate (LIBOR), based on U.S. Dollar		Intercontinental Exchange, Inc. (ICE)
Referencial Rates	2-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar	London Interbank Offered Rate is the average interest rate at which leading banks borrow funds of a sizeable amount from other banks in the London market. Libor is the most widely used "benchmark" or reference rate for short term interest rates	Intercontinental Exchange, Inc. (ICE)
Referencial Rates	6-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar		Intercontinental Exchange, Inc. (ICE)

Figure 23 – Categories of variables

Stock Index	ASX 200	The S&P/ASX 200 measures the performance of the 200 largest index-eligible stocks listed on the ASX by float-adjusted market capitalization. Representative liquid and tradable, it is widely considered Australia's preeminent benchmark index. The index is float-adjusted. The index was launched in April 2000.	Bloomberg
Stock Index	CAC 40 Index	The CAC 40® is a free float market capitalization weighted index that reflects the performance of the 40 largest and most actively traded shares listed on Euronext Paris, and is the most widely used indicator of the Paris stock market. The index serves as an underlying for structured products, funds, exchange traded funds, options and futures. It is operated by Euronext, the pan-European exchange.	Bloomberg
Stock Index	Nasdaq Composite Index	The NASDAQ Composite Index is a broad-based capitalization-weighted index of stocks in all three NASDAQ tiers: Global Select, Global Market and Capital Market. The index was developed with a base level of 100 as of February 5, 1971.	Bloomberg
Stock Index	Deutsche Boerse (DAX) Index	The German Stock Index is a total return index of 30 selected German blue chip stocks traded on the Frankfurt Stock Exchange. The equities use free float shares in the index calculation. The DAX has a base value of 1,000 as of December 31, 1987. As of June 18, 1999 only XETRA equity prices are used to calculate all DAX indices.	Bloomberg

Figure 24 – Categories of variables

Stock Index	Dow Jones Industrial Average	The Dow Jones Industrial Average was compiled by Dow Jones as a way to gauge the performance of the industrial component of America's stock markets. It is the oldest continuing U.S market index. To see a complete list of the members, please type INDU <Index> DES <go>.	Bloomberg
Stock Index	Milan Stock Exchange Index	The Index consists of the 40 most liquid and capitalized stocks listed on the Borsa Italiana. In the FTSE MIB Index foreign shares are eligible for inclusion. Secondary lines are not eligible for inclusion. The calculation and methodology is unchanged from S&P MIB Index.	Bloomberg
Stock Index	Hong Kong Hang Seng Index	The Hang Seng Index is a free-float capitalization-weighted index of a selection of companies from the Stock Exchange of Hong Kong. The components of the index are divided into four subindices: Commerce and Industry, Finance, Utilities, and Properties. The index was developed with a base level of 100 as of July 31, 1964. HSI does not have official ISIN registered.	Bloomberg
Stock Index	IBEX 35 Stock Exchange Index	The IBEX 35 is the official index of the Spanish Continuous Exchange. The index is comprised of the 35 most liquid stocks traded on the Continuous market. It is calculated, supervised and published by the Sociedad de Bolsas. The equities use free float shares in the index calculation. The index was created with a base level of 3000 as of December 29, 1989. For options please run IDA Index OMON.	Bloomberg

Figure 25 – Categories of variables

Stock Index	Sao Paulo Stock Exchange Index	It is a gross total return index weighted by free float market cap & is comprised of the most liquid stocks traded on the Sao Paulo Stock Exchange. It has been divided 10 times by a factor of 10 since Jan 1, 1985:12/02/85, 08/29/88, 04/14/89, 01/12/90, 05/28/91, 01/21/92, 01/26/93, 08/27/93, 02/10/94, and 03/03/97. See IBOVHIST <INDEX> for additional history 1968-1989. Shares scaled by 10000000.	Bloomberg
Stock Index	Santiago Stock Exchange Index	S&P/CLX IPSA (CLP) TR	Bloomberg
Stock Index	Korea Stock Exchange Index	The KOSPI Index is a capitalization-weighted index of all common shares on the KRX main board. The Index was developed with a base value of 100 as of January 4, 1980. Note: The preferred shares are excluded in calculating the KOSPI Index from June 14, 2002. Volume on quote line is in 000's. See PEKS index DES<GO> for KOSPI2 P/E from Korea Stock Exchange including negative earnings.	Bloomberg
Stock Index	Merval Argentina Stock Index	Merval Argentina Index	Bloomberg
Stock Index	Nikkei 225	The Nikkei-225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange. The Nikkei Stock Average was first published on May 16, 1949, where the average price was ¥176.21 with a divisor of 225. *We are using official divisor for this index	Bloomberg

Figure 26 – Categories of variables

Stock Index	Shangai Composite Index	The Shanghai Stock Exchange Composite Index is a capitalization-weighted index. The index tracks the daily price performance of all A-shares and B-shares listed on the Shanghai Stock Exchange. The index was developed on December 19, 1990 with a base value of 100. Index trade volume on Q is scaled down by a factor of 1000.	Bloomberg
Stock Index	S&P 500	The S&P 500® is widely regarded as the best single gauge of large-cap U.S. equities and serves as the foundation for a wide range of investment products. The index includes 500 leading companies and captures approximately 80% coverage of available market capitalization.	Bloomberg
Stock Index	Stoxx 600	The STOXX Europe 600 Index is derived from the STOXX Europe Total Market Index (TMI) and is a subset of the STOXX Global 1800 Index. With a fixed number of 600 components, the STOXX Europe 600 Index represents large, mid and small capitalization companies across 17 countries of the European region.	Bloomberg
Stock Index	Tawain Stock Exchange Index	The TWSE, or TAIEX, Index is capitalization-weighted index of all listed common shares traded on the Taiwan Stock Exchange. The index has a base value of 100 based on its 1966 level. The index is also known as the TSEC Index.	Bloomberg
Stock Index	FTSE 100 Index	The FTSE 100 Index is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange. The equities use an investibility weighting in the index calculation. The index was developed with a base level of 1000 as of December 30, 1983. * Please see UKEDA100 Index and FTPTP100 Index for the official FTSE 100 Index Dividend Yield and P/E Ratio*	Bloomberg

Figure 27 – Categories of variables

Commodities	CRB - Commodities Index		The Commodity Research Bureau (CRB)
Commodities	CRB - Food commodities Index		The Commodity Research Bureau (CRB)
Commodities	CRB - Metal commodities Index		The Commodity Research Bureau (CRB)
Commodities	Gold Spot Prices	The Gold Spot price is quoted as US Dollars per Troy Ounce. Gold Cross rates are available using XAU followed by 3-character ISO code of the cross currency.	Bloomberg
Economic Indicators	Citi economic surprise - Emerging Markets	The Citi Economic Surprise Indices measure data surprises relative to market expectations. A positive reading means that data releases have been stronger than expected and a negative reading means that data releases have been worse than expected. For more information please	Bloomberg
Economic Indicators	Citi economic surprise - Europe		Bloomberg
Economic Indicators	Citi economic surprise - G10		Bloomberg
Economic Indicators	Citi economic surprise - Global		Bloomberg
Economic Indicators	Citi economic surprise - United States		Bloomberg
Economic Indicators	Citi economic surprise - China		Bloomberg
Carry Trade Total Return Indicator	Emerging Countries - FX Carry trade return index	The EM-8 Carry Trade Index measures the cumulative total return of a buy-and-hold	Bloomberg
Carry Trade Total Return Indicator	G10 Countries - FX Carry trade return index	The G10 Carry Trade Index measures the cumulative total return of a buy-and-hold	Bloomberg
Carry Trade Total Return Indicator	LATAM Countries - FX Carry trade return index	The Latin American Carry Trade Index measures the cumulative total return of a	Bloomberg
Diverses Market Indicators	DXY Net contract positions ATM		Bloomberg
Diverses Market Indicators	TED - Spread		Bloomberg
Diverses Market Indicators	USD ATM 3 - Month - Volatility		Bloomberg
Diverses Market Indicators	Dollar Index Currency Basket		Bloomberg
			Bloomberg

Figure 28 – Categories of variable