MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master's Thesis

„Volatility Risk Premium in Foreign Exchange Markets"

verfasst von / submitted by

Verena Baumann, BSc (WU), BA

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2019 / Vienna 2019

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	A 066 974
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Banking and Finance
Betreut von / Supervisor:	Univ.-Prof. Dipl.-Vw. Thomas Gehrig, PhD

Abstract

We test volatility risk premium as a new predictive variable for a currency prediction model. Volatility risk premium is the difference between the expected realized exchange rate volatility and options implied volatility. From the perspective of an investor, it is the insurance cost against currency volatility fluctuations. Our analysis shows that volatility risk premium is complementary to commonly used indicators such as interest rate parity, value, real effective exchange rate and order flows. It does not show significant correlation with already known risk factors and contains new information to determine future currency movements. Our data comprises twenty currencies denominated against the USD from developed and emerging countries from 2006 to 2018. Our intention is to predict one-month, six-month and one-year currency returns. To do so, we use the indicators to test several currency trading strategies and to conduct numerous regression analysis. To test currency trading strategies, we use the relative values of the indicators to estimate the currencies' likeliness to appreciate or depreciate to generate several long and long-short portfolios. The regressions served to construct currency models to generated ex-post and ex-ante predictions. Although the out-of-sample results are rather weak, the in-sample regression results and the returns of the portfolio strategies show very promising results. All in all, volatility risk premium is a valuable indicator that perfectly complements covered interest rate parity, value, real effective exchange rate and order flows in a currency prediction model.

Content

1. Introduction and Research Question

There is a comprehensive amount of research that attempts to explain and predict currency movements. Examples include economic fundamental-based models, general asset pricing, and factor-based approaches. The consensus in this line of research is that it is nearly impossible to predict exchange rate movements, especially over short horizons. Even if there are good models, they are usually not very robust. We derive eight predictors from this vast currency literature and try to develop our own prediction model. Four of them, covered interest rate parity, value, real effective exchange rate and order flows, are already well-known and strong indicators. Momentum, Purchasing Managers' Index and the USD factor are complementary indicators. The last parameter, volatility risk premium (VRP), is rather new. It is a popular concept in other asset classes, but it is not part of classical currency models. Our research efforts focus on this indicator and analyse whether it is a valuable addition to the already well-established parameters. To be more specific, our research question is:

"Is volatility risk premium an empirical and economical valuable indicator to predict currency movements and a suitable completion to the already well-established interest rate parity, value, real effective exchange rate and order flow predictors?"

To answer this question, we follow two different approaches. First, we use the parameters to implement numerous currency trading strategies and secondly, we conduct several regression analyses. For both we compare our results to a random walk benchmark without a drift. We use twenty currencies denominated against the USD from developed and emerging countries; due to data limitations we only analyse the period from 2006 to 2018. The analysed parameters are F.VRP, F.CIRP, F.Value, F.REER, F.FXFuture, F.MOM, F.USD and F.PMI. To distinguish our calculated currency indicators from well-known concepts, such as real effective exchange rate, we call them factors and put an "F" in front of these abbreviations. This should emphasize that while, these factors stem from well-known concepts, they are specifically calculated indicators.

As explained earlier, we have derived these eight predictors from the exchange rate literature to create our own currency model. The first one is F.VRP, which is the difference between the expected realized exchange rate volatility and the implied volatility from currency options. The notion is that currencies with a higher F.VRP are more likely to appreciate. Secondly, F.CIRP takes advantage of the well-known covered interest rate parity and goes long currencies with a low interest rate and short ones with a high interest rate. F.Value considers the change in the relative purchasing power parity of each country, where a decreasing value should lead to a stronger currency. F.REER compares the real effective exchange rate to its historical average to determine whether a currency is over- or undervalued. F.MOM is the well-known momentum strategy, which bets on the continuance of an existing market trend. Similar to this factor is F.USD, but instead of historical individual currency movements, it considers cross-sectional ones. F.FXFuture is our proxy for order flows and is the non-commercial FX Future positions of several major currencies against the USD. If the volume increases, the respective currency should also increase. Finally, F.PMI uses the Purchasing Managers' Index to estimate future economic growth and the subsequent strength of the currency. The two latter factors always receive special treatment due to data limitations.

Our first approach to answer the research question is to create two portfolios for each factor. For the first one, we apply only a long strategy and for the second a long-short one. They are reallocated either on a monthly, biannually or yearly basis. At each allocation moment, the factors are used to evaluate the attractiveness of the 20 currencies and to order them from most likely to appreciate to most likely to depreciate. Subsequently, the currencies are divided into quartiles and allocated to four different currency baskets. The currencies from the best basket are chosen to go long against the USD. Thus, in this portfolio we are always short the USD. For the long-short portfolios, the same approach was chosen, but additionally we also go short the worst currency basket. This way we always have an equal number of currencies short or long against the USD. Furthermore, we also use combined factors. For those we created portfolios where we considered several factors at the same time to determine the currency attractiveness. Overall, we generated very promising results. F.VRP, F.CIRP, V.REER and F.Value generate very high returns per annum and have no difficulties to beat the benchmark at any point in time. The results for F.MOM and F.USD are rather modest, although they are usually able to beat the random walk. F.FXFuture and F.PMI yield quite promising results, but they are not entirely conclusive due to data limitations.

Our regression analysis and the generated prediction models yield similar results. We regress one-month and six-month future currency log returns on our calculated factors. By doing so we apply ordinary least squares (OLS) and heteroscedastic and autocorrelation consistent estimators (HAC). The latter one is necessary to resolve an overlapping data issue. In a second step, we apply the developed models to generate ex-ante and ex-post predictions. These are evaluated with the root mean squared error (RMSE), symmetric mean absolute percentage error (SMAPE), Theil's uncertainty coefficient (U_2) and a direction of change criteria. In general, F.VRP, F.CIRP, F.REER and F.Value continue to be the best factors, although F.USD, F.MOM and F.FXFuture generate some additional benefits. Unfortunately, like all other research efforts we only generate very weak out-of-sample results, although the in-sample ones were very promising. The best evaluation tests seem to be SMAPE and the direction of change criteria, as they are not affected by the scale of the individual variables and therefore more useful for the comparison of different data sets.

In summary, all results indicate that F.VRP is a valuable new factor, complementary to the already well-established indicators of covered interest rate parity, value, real effective exchange rate and order flow parameters. It shows low correlation with these and other risk indicators and contains new information to determine future currency movements.

1.2 Currency Models

The following section gives a short overview of foreign exchange markets, the existing literature on currency models and the popular random walk benchmark. By doing so we emphasize that none of the models yields robust out-of-sample results especially for short-term periods. Still, many of the models and research approaches served as an inspiration for the development of our own currency model.

The main place for currency trading is the foreign exchange market or Forex (FX). In terms of trading volume, it is the most liquid and biggest financial marketplace worldwide. Forex is an over-the-counter market where convertible currencies can be exchanged 24 hours a day, excluding weekends. (Wang 2009) Forex is characterized by huge transaction volumes with low transaction costs; there are no short-selling constraints and it has a variety of FX specific quoting conventions. Usually, the main actors at Forex markets are sophisticated professional investors, such as investment banks. All in all, it is a highly dynamic and challenging market with a vast number of market participants. (Menkhoff et al. 2012)

A comprehensive amount of literature attempts to explain FX markets and predict currency movements. Examples include economic fundamental-based models, general asset pricing, and factor-based approaches. The consensus in this line of research is that it is nearly impossible to predict exchange rate movements, especially over short horizons. The reason for this is that exchange rates closely follow a random walk and are influenced by unobservable shocks. Thus, even if there are decent models, they are usually not very robust. (Ahmed, Liu, and Valente 2016; also Engel et al. 2007; also Engel and West 2005) Indeed, Engel and West (2005) show that under specific circumstances, exchange rates theoretically behave like a random walk. They illustrate their point with a general asset pricing model with discount factors, which is highlighted below. It states that currency movements are determined by the present value of expected future fundamentals such as interest rates, money supply or income. It can be summarized as

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i\, E_t(f_{1,t+1} + z_{1,t+i}) + b\sum_{i=0}^{\infty} b^i\, E_t(f_{2,t+1} + z_{2,t+i}),$$

where b is the discount factor, f are observable economic fundamentals, z are unobservable fundamentals or shocks and s_t is the spot rate at time t. If the discount factor is close to one, the change in the FX rate will only be explained by the error term z and thus, behaves like a random walk. Engel and West (2005) conclude that currencies show this behaviour if at least one variable has a unit autoregressive root and the discount factor is close to one. This entails that currency changes at time t are uncorrelated with the information from $t-1$ and that FX rates are non-integrated with observable fundamentals. Furthermore, if the discount factor is close to one, variables far into the future become more relevant. This way, current economic fundamentals have relatively little weight compared to expectations of future fundamentals. (Engel and West 2005) It also explains why random walk models are a very difficult benchmarks to beat. Although they have very low predictive power in other research fields, they describe the underlying currency dynamics quite well. To account for this, one needs alternative evaluation methods for currency prediction models such as the criterion for direction of change. (Engel et al. 2007)

Some of the most important economic concepts regarding foreign exchange rates are the international parity conditions. They are purchasing power parity (PPP), covered interest rate parity (CIRP), uncovered interest rate parity (UIRP) and the international Fisher effect (IFE).

The first one, purchasing power parity (PPP), is the theory that nominal exchange rates are determined by the law of one price. This fundamental economic concept states that if transport costs are relatively small, the price of an internationally traded commodity must be the same in different regions. Indeed, if adjusted for the exchange rate, each currency requires the same purchasing power. If the purchasing powers differed, everyone would just demand the cheaper product until prices would converge. Hence, the nominal exchange rate is the necessary link to ensure the law of one price. (Wang 2009) A further implication of this concept is that the currency strength between two countries reflects the difference in their inflation rates. Although PPP is useful to predict long-term changes of the nominal exchange, it is less useful to predict short-term changes. Additionally, it also does not always apply. The more non-tradable goods and services a nation has, and the higher transportation costs are, the less precise PPP becomes. (Wang 2009)

The second important international parity concept is interest rate parity (IRP), which ensures another no-arbitrage condition in exchange markets. It represents an equilibrium state under which investors are indifferent regarding the interest rates of two nations. It implies that the expected return on domestic assets will equal the expected return on foreign assets if the exchange rate is considered. (Wang 2009) The important preconditions for this equilibrium are capital mobility and perfect substitutability of domestic and foreign assets. There are two forms of interest rate parity, the uncovered interest rate parity (UIRP) and the covered interest rate parity (CIRP). UIRP states that the difference in interest rates between two countries will equal the relative change of FX rates over the same period. By contrast, the covered interest rate parity states that to prevent arbitrage, the forward premium must be equal to the two countries' interest rate differential. (Wang 2009) Hence, if the interest rate in a foreign country increases compared to the domestic country and UCIRP holds true, the exchange rate has to weaken by the same amount. This is illustrated in the below example where Canada has a five percent higher return on the issued bond than the USA and therefore, its exchange rate is expected to depreciate by five percent against the USD. Thus, a forward contract with the same maturity would incorporate this expected depreciation and would be quoted at the expected lower exchange rate.

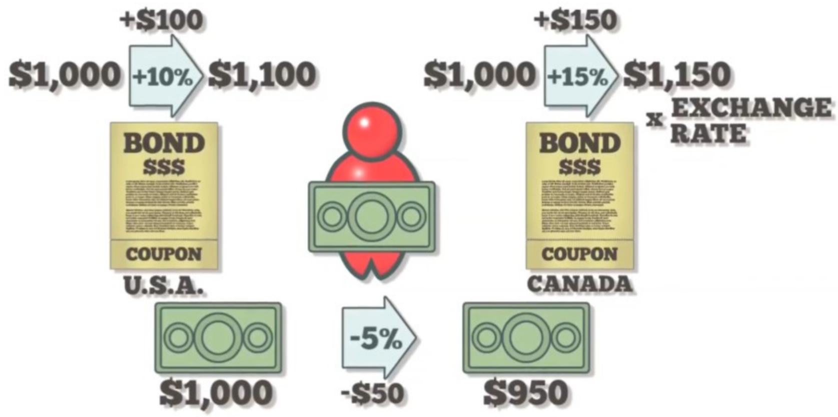


Figure 1: Covered Interest Rate Parity, Source: (Investopedia 2019)

Closely related to the CIRP is the International Fisher Effect (IFE). Before we go into the details of IFE, we will revise the Fisher Effect itself. It states that the nominal interest rate is the sum of the real interest rate and the inflation expectations of the same period. Therefore, real interest rates fall as inflation increases, unless nominal rates increase at the same rate as inflation. The International Fisher Theorem is an extension of this concept and is applied for several nations. It combines the individual Fisher Effects of each country, PPP and exchange rate expectations. (Wang 2009) It states that real interest rates is equal across countries. It suggests that the expected change in exchange rates are equal to the interest rate differential between two countries. This is nearly the same proposition as UIRP, but it is caused by different mechanisms. IFE also considers expected inflation, as it can cause a change in the monetary policy of central banks and consequently, in interest rates. This can lead to a changed purchasing power parity and subsequently different exchange rates. (Wang 2009) The following chart summarizes the explained macroeconomic principles and highlights their interconnectedness.

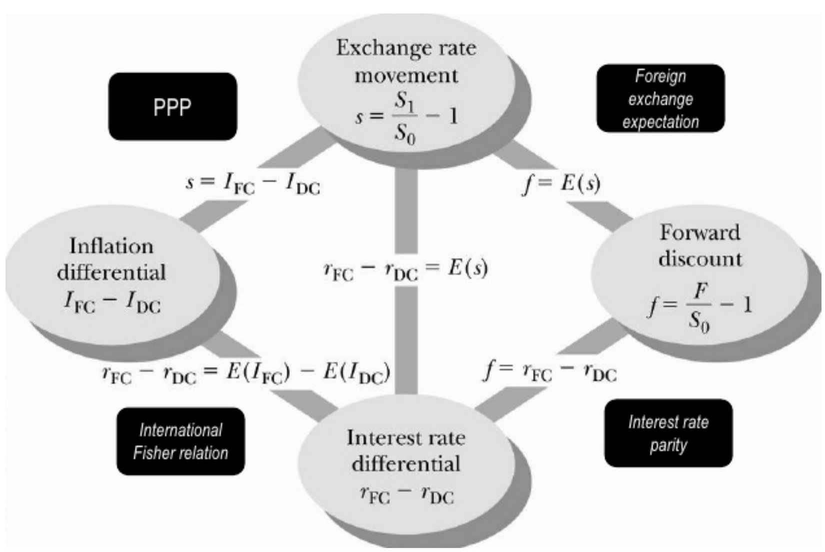


Figure 2: International Parity Conditions, Source: (IPC 2019)

Most studies attempt to predict and explain currency movements focus on bilateral exchange rates versus the USD and OECD countries. These research efforts have shown that the forecasting horizon is important, as models' predictive ability might depend on them. They range from intraday to yearly periods and comprise different time intervals. Usually, they are compared to the random walk model without a drift, although this model is difficult to beat. (Rossi 2013) The regressors used were sometimes forecasted, lagged or simply the realized fundamentals were applied. There is no consensus amongst scholars on which of these methods is the best, although they do agree that regressors play a more important role. The most popular predictors are purchasing power parity, the monetary model, uncovered interest rate parity, portfolio balance models (trade balance, current account etc.), Taylor rule and net foreign asset models. The most promising out-of-sample result confirmed Taylor rule and the net foreign asset model. (Rossi 2013) Additionally, the monetary model works somewhat for very long prediction horizons and the uncovered interest parity for some countries and time intervals. PPP is not typically significant for short horizons, but it can outperform the benchmark for forecasting periods longer than 2-3 years. Unfortunately, most models and predictors are not robust. Just because they possessed a predictive power for a certain data set does not mean that they are significant for other periods or countries. (Rossi 2013) Concerning the models themselves, researchers have found that linear models are better than non-linear ones, especially when prediction is the intention. The single-equation error correction model (ECM) and the panel ECM achieved promising results. By contrast, the results for the multi equation vector error correction model were mixed and VAR-models did not seem to improve the forecasting capabilities. Typically, for the evaluation of the out-of-sample prediction models, the rolling window forecasting scheme or the recursive scheme were used. The applied tests were root mean squared error (RMSE), mean squared error (MSE) and the direction of change criteria. (Rossi 2013)

Since robust or comparable research results are lacking, Cheung et al. (2019) conducted a comprehensive and standardized performance analysis of well-established currency models. They analysed uncovered interest rate parity, relative purchasing power parity, sticky price monetary model, behavioural equilibrium exchange rate (BEER) model, Taylor rule fundamentals, real interest differential and the yield curve slope. Each of them was modelled in an error correction and first-difference specification and compared to a random walk without a drift. The forecasting horizons comprised one, four and twenty quarters and were evaluated with the mean squared error, direction of change and a consistency test. (Cheung et al. 2019) The direction of change criteria is particularly useful, as it measures whether the model correctly predicts if the currency appreciates or depreciates. The out-of-sample forecasts were estimated from rolling regressions where the actual realized values of the right-hand side variables were used. Cheung et al. (2019) conclude that no model generally performs well over all currencies or periods. They do not consistently outperform a random walk by a mean squared error measure, but many of them do well with the direction of change criteria. PPP was the best performing factor, but interest rate parity also achieved decent results. The Taylor rule model usually outperformed the benchmark, but the values were not significant. (Cheung et al. 2019) Many of these models and the performance analysis method of Cheung et al. serves as an inspiration for the development of our own currency model.

2. Factors

Our chosen indicators for the development of a currency model are F.VRP, F.CIRP, F.Value, F.REER, F.FXFuture, F.MOM, F.USD, $F.PMI_{Rel}$ and $F.PMI_{Chg}$. For each parameter, we will give a short theoretical introduction, briefly highlighting former empirical results and explaining the computation. To distinguish our currency indicators from well-known concepts, we call them factors and put an "F" in front of their abbreviation. This should emphasize that while these factors stem from well-known concepts, they are specifically calculated indicators.

Abbreviation	Meaning
t	Time
j	Indicator for specific currency e.g. CAD
n	Number of observations
r	Return, usually log return
ln	LOG
V	Volume
$F.$	Factor or regressor
μ	Mean
σ	Standard deviation
$s_{j,t}$	Bilateral exchange rate of currency j per USD at time t
FX	Foreign exchange

F.VRP:

Volatility risk premium (VRP) is the compensation for speculators to provide volatility insurance. It is the difference between options-implied volatility and expected realized volatility. Della Corte, Ramadorai and Sarno (2016) calculate this VRP and use it to implement a trading strategy in their paper *"Volatility risk premia and exchange rate predictability"*. For Forex markets, VRP is the difference between the expected realized volatility and the price of a currency variance swap. From the perspective of an investor, it reflects the costs of insurance against currency volatility fluctuations. Thus, when VRP is high, insurance is relatively cheap. A large amount of literature analysing VRP in different asset classes has shown that on average, VRP is negative. (Della Corte, Ramadorai, and Sarno 2016) This means that insurance buyers are willing to accept a negative average excess return to hedge market volatility. (Carr and Wu 2009)

VRP = Expected Realized Volatility - Implied Volatility from Currency Otions

VRP = Historical FX Volatility - Price of FX Variance Swap

$$F.VRP_{j_{t,\tau}} = E_t^{\mathbb{P}}[RV_{j_{t,\tau}}] - E_t^{\mathbb{Q}}[RV_{j_{t,\tau}}]$$

Della Corte, Ramadorai and Sarno (2016) propose that VRP can be used to predict exchange rate movements. They suggest selling high insurance-cost currencies and buying low cost ones. They posit that, the higher VRP is, the more likely the currency will appreciate. For our own VRP calculations we stuck very closely to Della Corte, Ramadorai and Sarnos' approach, which will be explained in more detail in Section 3.

$$\boldsymbol{FX} \uparrow = \boldsymbol{Real.Vol} \uparrow - \boldsymbol{Impl.Vol} \downarrow$$

Della Corte, Ramadorai and Sarno do not propose a theoretical model explaining why this investment strategy works, but they do show empirically that VRP cannot be explained by traditional risk factors such as carry or momentum. Hence, VRP as a trading strategy is not only profitable, it is also complementary to other risk factors. (Della Corte, Ramadorai, and Sarno 2016) One explanation as to why this factor works could be limited arbitrage opportunities. If they are restricted, it affects the interaction between hedgers and speculators and subsequently prices. Indeed, Della Corte et al. (2016) observed that when the demand for volatility protection is higher (e.g. a spike in the VIX) and funding liquidity is lower (e.g. an increase in the TED spread), there is an increase in volatility insurance costs across currencies. Additionally, one can observe that risk-averse investors are reluctant to take or hold positions in currencies that are expensive to insure. (Della Corte, Ramadorai, and Sarno 2016)

F.CIRP:

Our F.CIRP factor takes advantage of the previously described covered interest rate parity (CIRP). It is based on the theoretical concept of interest rate parity (IRP) and the no-arbitrage condition in exchange markets. IRP is based on the idea that the nominal exchange rate ensures that the expected return on domestic assets will equal the expected return on foreign assets. Hence, if the interest rate in a foreign country increases relative to the domestic one and IRP holds true, the currency of the foreign country has to weaken by the same amount. (Wang 2009) Similarly, CIRP determines the relationship between interest rates and the spot and forward currency values of two countries to ensure an arbitrage-free equilibrium. To prevent arbitrage, the forward premium must be equal to the two countries' interest rate differential. This is expressed in the formula below where the Forward F is calculated with the spot rate S and the foreign i_f and domestic i_d interest rates.

$$F = S * \frac{1 + r_d}{1 + r_f}$$

Using insights from CIRP, we calculate our F.CIRP factor, which is essentially the interest rate differential between the USA and the twenty other nations in this analysis. The idea is that the higher the interest rate differential, the more likely the currency with the higher interest rate will depreciate.

$$F.CIRP_{j,t} = \frac{F_{j,t}}{S_{j,t}} - 1$$

F.Value:

F.Value is calculated from purchasing power parity (PPP), which is a well-known and widely analysed determinant of exchange rates. It is based on the law of one price and states that an internationally traded good must have the same price in different regions when adjusted for the exchange rate. If the purchasing power in one country increases relative to that of other nations, its exchange rate would need to increase to maintain the equilibrium. (Wang 2009) Hence, PPP is a useful variable to predict FX movements over long horizons, but unfortunately it is less useful for short ones. (Cheung et al. 2019) For our own analysis we used the relative purchasing power parity indicator, which measures the relative PPP strength against the United States. The lower this value, the higher the purchasing power, and the more likely an increase in the exchange rate. For our analysis we used the monthly log returns from PPP of currency j to calculate our value factor.

$$F.Value_{j,t} = ln\left(\frac{PPP_{j,t}}{PPP_{j,t-1}}\right)$$

F.REER:

Closely related to the economic concept of purchasing power parity is the real exchange rate (RER). RER is the nominal exchange rate adjusted by the ratio of prices of two observed countries. In this case, ‘prices’ is synonymous with the average price of the same goods basket of two nations. If absolute PPP holds, the real exchange rate is one and the currencies are not over- or undervalued. (Wang 2009) Balduzzi and Chiang (2019) conducted an extensive analysis of the predictive power of RER in Forex markets and concluded that it is a valuable indicator. However, it is quite volatile, as it captures information about currency risk premiums, which changes over time. These researchers also state that RER has more predictive power for long-term currency movements than for short-term fluctuations. (Balduzzi and Chiang 2019) For the calculation of our F.REER factor, we follow a similar approach to Barroso and Santa-Clara (2015). We use the RER to predict currency movements, but instead of standardizing it cross-sectionally, we put it in relation to its own historical value. Additionally, instead of using the real exchange rate, we use the real effective exchange rate (REER). The REER exclusively considers the average of the bilateral and trade weighted RERs between one country and its trading partners. To create our factor, we first calculate the seven-year simple moving average of REER for country j:

$$\mu_{j,t}^{n} = \frac{1}{n}\sum_{i=0}^{n-1} R\,EER_{j,t-i}$$

Secondly, we use the REER of currency j at period t, subtract the historical five-year REER average and divide it by the same value.

$$F.REER_{j,t} = \frac{REER_{j,t} - \mu_{j,t}^{n}}{\mu_{j,t}^{n}}$$

By constructing F.REER this way, we can see that the currency is undervalued compared to its own historical value if the factor is negative. Conversely, it is overvalued if the average five-year REER is lower than the REER at time t.

F.USD:

As previously discussed, exchange rates are very hard to predict since they behave like a random walk with unobservable shocks. Engel, Mark and West (2014) believe that currencies themselves may contain low frequency information that can solve this issue. This incorporated data may explain common currency trends that are hard to extract from other observable fundamentals. They propose that a weighted average of log levels of exchange rates represents a central tendency of the analysed currencies. The assumption is that the deviation of the spot rate from this central tendency can help to predict currency movements. (Engel, Mark, and West 2014) Nelson and Donggyu (2018) reached similar conclusions and created their own currency factor. They observed that exchange rates have substantial cross-sectional correlation and are driven by two main underlying variables, the EUR and the USD factor. They calculate these parameters from panel data with several macroeconomic techniques. (Mark and Sul 2018) For our own currency factor, we follow an approach similar to that of Alloosh and Bekaert (2019). We simply use the average log return across all analysed currencies at time t.

$$F.USD_{j,t} = \frac{1}{19} * \sum_{i}^{19} ln\left(\frac{s_{i,t}}{s_{i,t-1}}\right)$$

To be more specific, the USD factor for currency j is the cross-country average over all FX log returns, except for currency j itself. For instance, $F.USD_{EUR,t}$ is the average exchange rate change of all other 19 currencies against the USD except for the EUR. (Fourel et al. 2015)

F.MOM:

The momentum strategy belongs to the best known and most widely used trading strategies across all asset classes. It simply involves buying assets with high historical returns and selling those with low ones. Profits from the momentum factor cannot be understood with traditional risk factors, but researchers have proposed explanations based on behavioural or transaction costs concepts. One behavioural explanation may be that investors tend to under- and overreact to financial markets and are tempted to move with the market sentiment. (Menkhoff et al. 2012) To test these assumptions and the profitability of the strategy, Menkhoff et al. (2012) created long-short momentum portfolios over a large set of currencies. They, like many others, find significant cross-sectional returns between past winner and loser currencies. Their results indicate that the returns for currencies with a high volatility and from countries with a high-risk rating are larger in general. Additionally, the portfolio returns are sensitive towards transaction costs and they decrease significantly if adjusted for bid–ask spreads. (Menkhoff et al. 2012) For the purpose of our own analysis, we calculate the momentum factor in an identical manner to Barroso and Pedro Santa-Clara (2015). First, we compute the FX log return of currency j.

$$r_{j,t} = ln(s_{j,t}) - ln(s_{j,t-1})$$

$ln(s_{j,t})$ denotes the bilateral log exchange rate of the foreign currency j per USD at time t. Secondly, the seven-year simple moving average and standard deviation is calculated.

$$\mu_{j,t}^{n} = \frac{1}{n}\sum_{i=0}^{n-1} r_{j,t-i}$$

$$\sigma(r_{j,t}^{n}) = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n-1}(r_{j,t-i} - \mu_{j,t}^{n})^2}$$

$$F.MOMj,t = \frac{[ln(s_{j,t}) - ln(s_{j,t-3})] - \mu_{j,t}^{n}}{\sigma(r_{j,t}^{n})}$$

Thirdly, to compute our momentum factor, we use the three-month FX log return of currency j and standardize it. To do this we subtract the five-year moving average and divide it by the five-year moving standard deviation of currency j.

F.FXFuture:

Several researchers have found that order flows have a great explanatory power for asset prices and for exchange rates in particular. They have proven to be a strong and robust predictive indicators across different currencies and time periods. This holds true particularly for short forecasting intervals ranging from 30 seconds to one month. However, their predictive power decreases the longer the forecasting horizon extends. (Fourel et al. 2015) Order flows are such a valuable predictor because they aggregate information on macroeconomic fundamentals that are not observable in real time. This stems from small entities such as households and businesses that have not yet been captured in major macroeconomic fundamentals. Order flows also seem to hold information about (shocks to) liquidity and risk-aversion. (Fourel et al. 2015) Unfortunately, order flow data is extremely difficult to obtain as currencies are traded over the counter and information about them is hardly published. As we were not able to receive any data, we used order flows from future contracts as a proxy. This information has been sourced from Bloomberg and is provided by the U.S. Commodity Futures Trading Commission (CFTC). This data is only available on a monthly basis for the EUR, GBP, CHF, CAD, AUD, NZD, JPY, BRL, MXN and RUB. Our F.FXFuture factor was calculated with the following equation

$$F.FXFuture_{j,t} = ln\left(\frac{V_{j,t}}{V_{j,t-1}}\right)$$

In this equation $V_{j,t}$ is the monthly volume of the non-commercial FX Future positions against the USD for currency j. The non-commercial FX Future is the position of the speculator.

F.PMI:

Much research has shown that economic growth is a very important factor to determine future exchange rate movements. This has been directly and indirectly incorporated in many currency prediction models, such as the Taylor rule or the monetary model. Indeed, there is a strong economic link between currency returns and the relative strength of the business cycle. Economies that experience strong growth usually have an upwards pressure on their currency and vice versa. This can be used to generate significant excess returns in Forex markets. The profits stem primarily from the spot exchange rate predictability and cannot be understood by using traditional risk factors. (Colacito, Riddiough, and Sarno 2018) One very important indicator for (future) economic growth is the Purchasing Managers' Index (PMI), which has become quite popular in financial markets. The PMI is calculated from a monthly survey about business conditions and is polled from companies that represent the makeup of specific industries. (Koenig and others 2002) One benefit of the PMI is the frequency of its publication. It is also not subject to large revisions, which makes it easier to use "real-time-vintage" right-hand side data in currency models. However, one disadvantage is that the PMI is a diffusion index, meaning that it is not good at measuring the intensity with which economic conditions are changing. It is also unsuccessful in capturing if business conditions in a small but important industry are strongly deteriorating. A positive PMI simply means that there are more positive poll results than negative ones. (Koenig and others 2002) Unfortunately, historical PMI data is difficult to obtain, and we only received sufficient data for the following currencies: DKK, NOK, SEK, CHF, CAD, NZD, HUF, ZAR, CNY. In our research, we calculated two different PMI factors and used them for our portfolio analysis.

$$F.PMI_{Chg_{j,t}} = ln\left(\frac{PMI_{j,t}}{PMI_{j,t-1}}\right)$$

$$F.PMI_{Rel_{j,t}} = \frac{PMI_{j,t} - PMI_{USA,t}}{PMI_{j,t}}$$

$PMI_{Chg_{j,t}}$ is the monthly change of the PMI index of country j and reflects the well-being of the national economy. $PMI_{Rel_{j,t}}$ measures the PMI of country j relative to the US PMI. Thus, the relative economy strength is used to predict the currency strength against the USD.

2.1 Sourced Data

All data was temporarily sourced from Bloomberg on a monthly basis to calculate our factors from 2005 to 2019. This time span was chosen due to data limitations, especially for the implied currency volatilities. Every chosen economic and financial indicator was downloaded for the United States, Euro Zone, Great Britain, Canada, Australia, New Zealand, Japan, South Korea, Taiwan, Poland, Mexico, Thailand, Norway, Sweden, Hungary, Brazil, Turkey, South-Africa, India, Russia and Indonesia. We downloaded the exchange rate, forward outright, overnight deposit rate, REER, PPP, the implied currency volatilities, PMI, CPI and the FX future volume for each country. In doing so we always chose the last price of the business day, and if applicable the mid-prices of the indicators. Before providing a more detailed summary on the acquired data, we will clarify two important Bloomberg price sources, BGN and CMPN. The former stands for Bloomberg generic price, Bloomberg's own calculated market price that intends to reflect a market consensus price. Similarly, CMPN is the Bloomberg composite rate and represents the "best market" calculation for bank indications for bid and ask rates for the New York time frame.

- **Exchange Rate:** The EUR, GBP, CAD, AUD, NZD, JPY, KRW, TWD, PLN, MXN, THB, NOK, SEK, HUF, BRL, TRY, ZAR, INR, RUB and IDR spot exchange rates were sourced on a daily basis. All twenty currencies are denominated against the USD e.g. ZAR/USD is 0.7 USD per one ZAR.
- **Forward Points:** The twelve-month BGN forward outrights were sourced and used to calculate the forward rates according to the individual quoting conventions.
- **Overnight Deposit Rate:** is the annualized interest rate that a bank will charge or pay for lending or borrowing a currency for a specific tenor. In this case, the Bloomberg Generic Price was sourced.
- **Implied Volatilities:** is the market expected future volatility of a currency exchange rate for a given time. The BGN implied volatilities for the at-the-money, 25D risk reversal, 25D butterfly, 10D risk reversal and 10D butterfly delta (D) were sourced for the maturity of one-year.
- **Real broad effective exchange rate (REER):** is based on the producer price index and is published by J.P. Morgan.
- **Purchasing power parity (PPP):** We downloaded the yearly OECD PPP data from Bloomberg for the full country set. From FactSet we retrieved quarterly PPP data for a large number of nations. We calculated the monthly PPP by adjusting the quarterly or yearly PPP with the ratio of the cumulative inflation rate of country j and the USA at that time.
  $$PPP_{j,t} = PPP_{j,t-n} * \frac{CPI_{j,t}}{CPI_{USA,t}}$$
- **Consumer Price Index (CPI):** was published by the IMF and sourced from Bloomberg on a monthly basis.
- **Purchasing Managers' Index (PMI):** The PMI data was only available for a selected number of countries and was published by domestic research institutions.
- **Currency Future Volume:** The actually traded volume of currency futures is published by the U.S. Commodity Futures Trading Commission (CFTC) on a monthly basis for specific currencies. By law, traders must report their future position if they reach a certain reporting

level. For our purposes, the non-commercial FX future volumes were downloaded, which are the positions of the speculator.

- **VIX Index and TED Spread:** We sourced two VIX indices and the TED spread from Bloomberg. The TED Spread is the 3M LIBOR (London Inter-bank Offered Rate) minus the US generic government 3-month yield. The first VIX index is the Chicago Board Options Exchange (CBOE) Volatility Index, which reflects the market estimate of future market volatility of the S&P 500. The second sourced VIX index is the CBOE Emerging Markets ETF Volatility Index. These indices are used to better analyse the underlying dynamics of the F.VRP factor.

3. Calculation of the Volatility Risk Premium (VRP)

In the following section, we will discuss how we calculated the volatility risk premium. In doing so, we closely follow the approach of Della Corte, Ramadorai and Sarno (2016) put forth in their paper *"Volatility risk premia and exchange rate predictability"*. VRP is the difference between the historical realized exchange rate volatility and the price of a currency volatility swap. To derive it, we first calculate the FX volatility smile from currency options with a maturity of one year. Secondly, for each implied volatility, we compute the option prices with the Garman and Kohlhagen modified Black-Scholes model. Thirdly, the integration of the volatility smile and the option prices yield the variance swap price. Finally, the difference between the historical currency volatility and the variance swap price is the VRP.

Overview Notation:

Abbreviation	Meaning
VRP	Volatility Risk Premium
t	Specific point in time
τ	Specific point in time, in our case $t \mp 252$ days
T	Time in years, in our case one year
F	Forward
X	Strike
S	Spot rate
r	Currency log return
C	Call
P	Put
D or Δ	Delta
σ	Implied volatility
RV	Realized volatility of the underlying
N(.)	Cumulative normal distribution function
f	Foreign
d	Domestic
i_d	Domestic risk-free rate, in our case US risk-free rate
i_f	Foreign risk-free rate

3.1 Introduction

As previously discussed, VRP is the difference between the expected realized volatility and the implied volatility from option prices. For Forex markets, this is the difference between the historical realized exchange rate volatility and the price of a currency volatility swap. Hence, VRP reflects the costs of insuring against currency volatility fluctuations. Della Corte, Ramadorai and Sarno (2016) propose using this information as a trading strategy, where the investor sells high insurance-cost currencies and buys low-cost ones.

$VRP_{t,\tau} = E_t^{\mathbb{P}}[RV_{t,\tau}] - E_t^{\mathbb{Q}}[RV_{t,\tau}]$

VRP = Historical FX Volatility - Price of FX Variance Swap

As currency variance swaps are traded over-the-counter, their traded prices are not made publicly available and have to be synthesized via European plain vanilla currency options. In Forex markets, options are generally quoted in terms of Garman and Kohlhagen implied volatilities at fixed deltas (D), which can be used to calculate the option prices. (Della Corte, Ramadorai, and Sarno 2016) Unfortunately, there are many quotation conventions for the implied volatility delta in currency markets, which makes it difficult to calculate the variance swap price correctly. The four main ones are domestic per foreign (d/f), percentage foreign ($\%f$), percentage domestic ($\%d$) and foreign per domestic (f/d). Additionally, the sensitivities can be quoted with respect to changes in the spot or the forward. (Clark 2011) For our own research, one of the biggest challenges was to determine the correct quoting conventions used by Bloomberg, our main data provider. This is especially important as they can vary between different currencies or periods. Thus, we stuck closely to the Bloomberg data and compared our results to Bloomberg's own currency option pricing model.

For our calculations, we sourced the implied volatilities for five levels of delta on a monthly basis with a maturity of one year. As is typical for market conventions, we were able to download the at-the-money, 25D risk reversal, 25D butterfly, 10D risk reversal and 10D butterfly implied volatilities. With this data it is possible to calculate the corresponding strike prices of the currency options. In a further step, we inter- and extrapolated the volatilities to calculate the implied volatility smile. The price of the currency options is derived with the Garman and Kohlhagen modified Black-Scholes model for each generated data point. By integrating the volatility smile and option price data, we receive the variance swap price. Finally, the difference between the historical currency volatility and the volatility swap price yields the VRP. This process was followed for all twenty analysed currencies and will be explained in more detail in the following section.

3.2 Calculate the Implied Volatility or the Currency Variance Swap Price

Calculate the Implied Volatilities for 25D Call, Put and 10D Call, Put

In a first step, the at-the-money (ATM), 25D risk reversal (RR), 25D butterfly (BF), 10D risk reversal and 10D butterfly implied volatilities are sourced from Bloomberg. They are used to calculate the 25D Call, 25D Put, 10D Call and 10D Put implied volatilities. This is achieved by rearranging the following formulas: (Clark 2011)

$$RR25 = 25DCall - 25DPut$$

$$BF25 = \frac{25DCall + 25DPut}{2} - ATM$$

The same formulas are used to calculate the 10D put and call implied volatilities. (Clark 2011)

Convert the Implied Volatilities into Strikes

In a second step, the implied volatilities are used to derive the strike prices. To do this, we need to rearrange the formula of the currency delta for the proper quoting convention. Bloomberg quotes them in forwards and pips with no premium and uses the formula stated below. (Clark 2011)

$$\Delta_{F,pips} = \omega N(\omega d_1)$$

$$d_{1,2} = \frac{ln\left(\frac{F_{t,\tau}}{K}\right) \pm \frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}$$

In this formula, K is the strike price, T is one year, F is the forward price with the maturity τ. $-N^{-1}(.)$ is the inverted cumulative normal distribution function and σ is the implied volatility for the given delta. In general, delta or $\Delta_{F,pips}$ is the rate of change of the option price with respect to the price of the underlying asset. (Clark 2011; also Haug 2007) Rearranging of the delta formula results in:

$$K_{Call} = F * e^{(-N^{-1}(\Delta)*\sigma\sqrt{T}+\frac{1}{2}\sigma^2 T)}$$

$$K_{Put} = F * e^{(N^{-1}(-\Delta)*\sigma\sqrt{T}+\frac{1}{2}\sigma^2 T)}$$

Calculate the Volatility Smile

With the five deltas, the volatility smile can be calculated via inter- and extrapolation. For the former one, a cubic spline with the Forsythe, Malcolm and Moler method is applied between the minimum and maximum available implied volatilities. The advantage of this is that the implied volatility smile is smooth between the maximum and minimum available strikes, as an exact cubic is fitted through the five points at each end of the data. For the extrapolation, the implied volatility is assumed to be constant beyond the maximum and minimum strike prices. (Della Corte, Ramadorai, and Sarno 2016; also Jiang and Tian 2005) The following chart illustrates the calculated volatility smile.

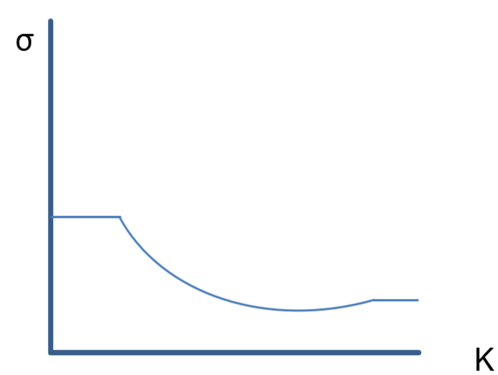


Figure 3: Volatility Smile

Calculate Option Prices: Black-Scholes-Merton Model

In a next step, the plain vanilla European currency option prices are calculated for all several hundred generated strikes and implied volatilities at time t. To do this, we use the Garman and Kohlhagen modified Black-Scholes model stated below. (Haug 2007) The abbreviations c and p denote the call and put prices respectively at strike X and i refers to the risk-free rate. The latter one is supposed to be the continuously compounded yield on the government bond of country j of maturity closest to the option. However, due to data limitations, we used the annualized overnight deposit rate instead. To be more specific, the domestic risk-free rate i_d is the annualized overnight US deposit rate and i_f is the foreign deposit rate, i.e. the risk-free rate of the other 20 analysed countries.

$$c = Se^{-i_f T}N(d_1) - Xe^{-i_d T}N(d_2)$$

$$p = Xe^{-i_d T}N(-d_2) - Se^{-i_f T}N(-d_1)$$

$$d_1 = \frac{ln\left(\frac{S}{X}\right) + \left(i_d - i_f + \frac{\sigma^2}{2}\right) * T}{\sigma * \sqrt{T}}$$

$$d_2 = \frac{ln\left(\frac{S}{X}\right) + \left(i_d - i_f - \frac{\sigma^2}{2}\right) * T}{\sigma * \sqrt{T}} = d_1 - \sigma\sqrt{T}$$

Calculate the Variance Swap Prices:

The following equation delivers the price of the variance swap or the implied currency option volatility $E_t^{\mathbb{Q}}[RV_{t,\tau}^2]$. In this context $P_{t,\tau}(X)$ and $C_{t,\tau}(X)$ are the put and call prices respectively at maturity date $t+\tau$ and $F_{t,\tau}$ is the forward price matching the option maturity date. S_t is the price of the underlying, and $i_{d_{t,\tau}}$ is the τ -period domestic risk-free rate. (Della Corte, Ramadorai, and Sarno 2016)

$$E_t^{\mathbb{Q}}[RV_{t,\tau}^2] = \kappa\left(\int_0^{F_{t,\tau}} \frac{1}{X^2} P_{t,\tau}(X)dX + \int_{F_{t,\tau}}^{\infty} \frac{1}{X^2} C_{t,\tau}(X)dX\right), \ \ where \qquad \kappa = 2 * e^{i_{d_{t,\tau}} * T}$$

To solve this equation, trapezoidal integration was used, which is a technique for approximating the definite integral. It breaks the integral area into many trapezoids, whose areas are subsequently more easily computable. (Della Corte, Ramadorai, and Sarno 2016)

Calculate the Model-Free Implied Volatility:

Finally, the model-free implied volatility can be calculated. (Della Corte, Ramadorai, and Sarno 2016)

$$E_t^{\mathbb{Q}}[RV_{t,\tau}^2] = \sqrt{E_t^{\mathbb{Q}}[RV_{t,\tau}]}$$

3.3 Calculate Expected Realized Volatility or Ex-post Realized Volatility

The expected realized volatility is proxied via the lagged realized volatility. (Della Corte, Ramadorai, and Sarno 2016) In this context τ is 252 days and r is the daily log return of the underlying security.

$$E_t^{\mathbb{P}}\left[RV_{t,\tau}\right] = RV_{t-\tau,\tau} = \sqrt{\frac{252}{\tau}\sum_{i=0}^{\tau} r_{t-i}^2}$$

3.4 Calculate Volatility Risk Premium

Finally, the volatility risk premia can be calculated.

$$VRP_{t,\tau} = E_t^{\mathbb{P}}\left[RV_{t,\tau}\right] - E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right]$$

Hence, at time t we measure the volatility risk premium over the $[t, t+\tau]$ time interval. Where the ex-post realized volatility $E_t^{\mathbb{P}}\left[RV_{t,\tau}\right]$ is measured over the $[t-\tau, t]$ interval and the implied volatility $E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right]$ over the $[t, t+\tau]$ interval. (Della Corte, Ramadorai, and Sarno 2016) For instance, if we want to calculate the VRP for January 1st 2018, we use the ex-post realized volatility from 2017-01-01 until 2018-01-01 and the ex-ante implied volatility from 2018-01-01 until 2019-01-01.

4. Data and Data Analysis

4.1 Correlation of Currencies and Cluster Analysis

The following chart analyses the one-month log returns of all currencies and illustrates their correlations and clusters. Naturally, all exchange rates are positively correlated, as they are denominated against the USD. Interestingly, one can see that not only the European currencies are strongly correlated, but also the EUR and the CAD, AUD, NZD. There is quite a big cluster of currencies in the lower part of the chart, starting from the GBP and ending with the INR. They all show a correlation level between 0.5 and 0.8. Only JPY, IDR, RUB, BRL and TRY seem not to be that strongly correlated with their peers.

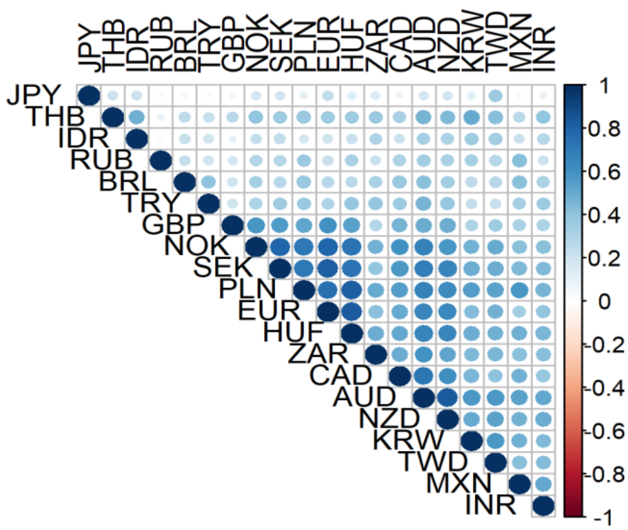


Chart 1: Correlation Analysis Monthly Currency LOG Returns

4.2 Principal Component Analysis of Exchange Rates

In a second step, we conducted a principal component analysis (PCA) of the monthly FX log returns of all analysed currencies. Surprisingly, PC 1 has a very high explanatory power for the exchange rates with a proportion of variance of 42%. This principal component is highly correlated with individual FX rates such as the EUR/USD or the CAD/USD. It reflects the strong correlation between the currencies and the firm cluster among them. Hence, if one manages to predict the general strength or weakness of the USD, one would have a very strong explanatory variable for a currency prediction model. Unfortunately, neither PC 1 nor any individual exchange rate has a significant explanatory power for the future exchange rates. Nevertheless, we try to extract this information with the F.USD factor.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	0.108	0.058	0.054	0.046	0.042	0.036	0.030
Proportion of Variance	0.416	0.118	0.102	0.074	0.061	0.047	0.032
Cumulative Proportion	0.416	0.534	0.636	0.710	0.771	0.818	0.850

Table 1: Principal Component Analysis Monthly Currency Log Returns

4.3 Correlation of Factors

For each currency *j* and their individual factors, correlation analyses were conducted. Table 2 summarizes the findings and shows the correlation average across all currencies for each factor. Additionally, the correlation to the future, one-month FX log returns are summarized under "RSpot". The table shows that the benchmark (F.BM) and the F.USD factor are strongly positively correlated. This is unsurprising, as the F.BM is a random walk model of exchange rates and the F.USD is the average of the lagged currency log returns. F.VRP, F.USD, F.MOM and F.BM also show a rather strong correlation, indicating that they measure similar things such as FX volatility. Most interesting is the last row of the table. It indicates the correlations of the factors with the future FX log returns. The results support past findings in literature and logical intuition that F.REER, F.CIRP and F.FXFuture are negatively correlated with "RSpot"; all others have a positive correlation. Yet there is one exception. The F.Value factor should also have a negative sign. Still, as the factor is negatively correlated with all other factors, the core intuition seems to hold true. In summary, none of the factors seem to have a particularly high correlation with "RSpot", indicating that a prediction will be difficult.

Factors	F.BM	F.VRP	F.CIRP	F.REER	F.Value	F.USD	F.MOM	F.PMI_Ch	F.PMI_Rel	F.FXFutur	RSpot
F.BM	1.000	0.303	-0.058	0.224	-0.081	0.718	0.580	0.077	0.032	0.213	0.037
F.VRP	0.303	1.000	-0.132	0.171	0.028	0.343	0.440	0.109	-0.091	0.066	0.077
F.CIRP	-0.058	-0.132	1.000	0.012	0.024	-0.070	-0.116	-0.044	-0.101	0.160	-0.038
F.REER	0.224	0.171	0.012	1.000	-0.007	0.149	0.232	-0.005	0.119	0.159	-0.050
F.Value	-0.081	0.028	0.024	-0.007	1.000	-0.070	-0.084	-0.029	-0.028	-0.041	0.037
F.USD	0.718	0.343	-0.070	0.149	-0.070	1.000	0.443	0.061	0.005	0.170	0.054
F.MOM	0.580	0.440	-0.116	0.232	-0.084	0.443	1.000	0.122	-0.003	0.222	0.081
F.PMI_Ch	0.077	0.109	-0.044	-0.005	-0.029	0.061	0.122	1.000	0.362	0.028	0.011
F.PMI_Rel	0.032	-0.091	-0.101	0.119	-0.028	0.005	-0.003	0.362	1.000	0.185	0.067
F.FXFutur	0.213	0.066	0.160	0.159	-0.041	0.170	0.222	0.028	0.185	1.000	-0.023
RSpot	**0.037**	**0.077**	**-0.038**	**-0.050**	**0.037**	**0.054**	**0.081**	**0.011**	**0.067**	**-0.023**	**1.000**

Table 2: Correlation of Factors and Lagged One-Month Currency Log Returns

4.4 Period of Strong USD

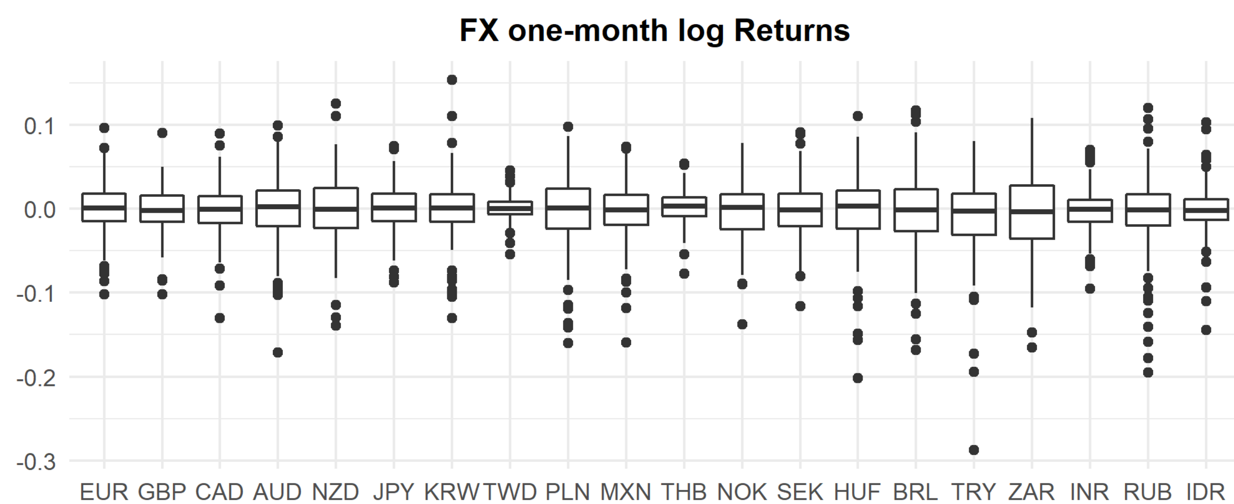


Chart 2: Box Plot Monthly Currency LOG Returns

During the observation period from 2006 to 2018, there was quite a strong USD. This affects our results and in particular the investment strategies detailed in Chapter 5. To better understand this fact along with the bilateral currency movements, we analyse this issue in more detail. The box plots above show all monthly currency log returns against the USD. The distribution of the returns is quite similar except for the TWD, THB, INR and IDR, whose small variance might point towards foreign exchange interventions. It is also striking that there are quite a lot of negative outliers in particular for TRY and RUB. To make the negative skew more obvious. Table 3 summarises the mean and median for the monthly log returns, as well as the difference between the two. All of them have a negative mean except for the TWD, JPY, THB and most of them have a negative skew.

Value	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Mean	-0.021	-0.193	-0.103	-0.025	-0.011	0.046	-0.063	0.045	-0.091	-0.394
Median	0.057	-0.231	-0.099	0.248	-0.041	0.119	0.094	0.005	0.090	-0.148
Diff	-0.078	0.038	-0.004	-0.273	0.030	-0.073	-0.157	0.041	-0.181	-0.245

Value	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Mean	0.153	-0.159	-0.134	-0.175	-0.325	-0.875	-0.525	-0.279	-0.563	-0.245
Median	0.296	0.175	-0.154	0.339	-0.108	-0.267	-0.382	-0.044	-0.139	-0.222
Diff	-0.143	-0.334	0.020	-0.514	-0.217	-0.608	-0.142	-0.235	-0.424	-0.023

Table 3: Mean, Median of Monthly Currency Log Returns

The below Chart 3 of selected cumulative spot rates highlights the strength of the USD during the observation period. It clearly shows the sharp devaluation of the currencies during the financial crisis in 2008 and a more prolonged downward trend from 2012 to 2017.

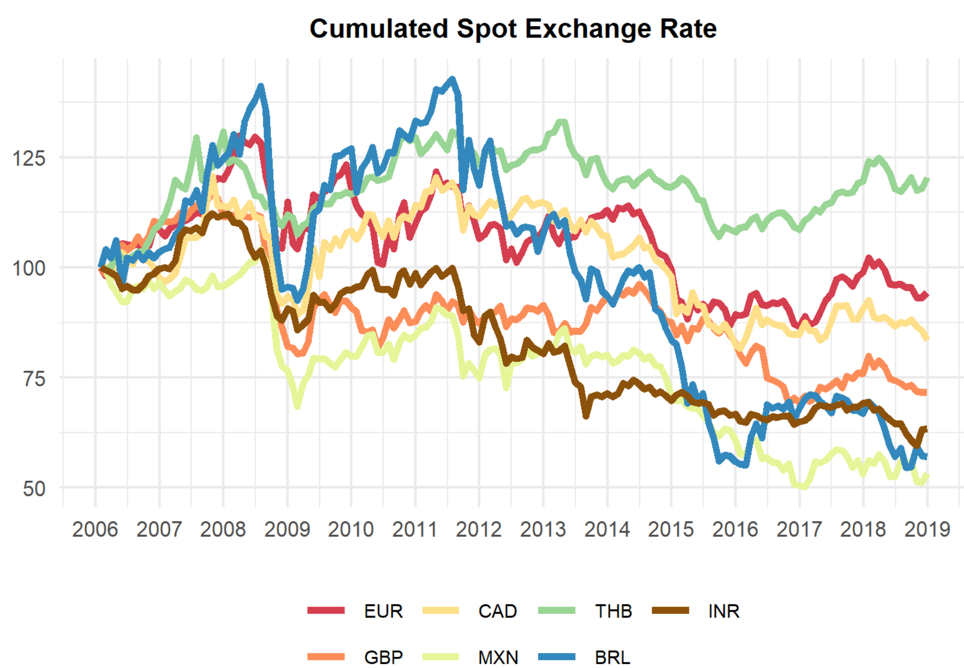


Chart 3: Cumulative Spot Rates Denominated Against the USD

5. Portfolios

In Chapter 5, the calculated factors are used to implement currency trading strategies to see if they have predictive power over exchange rates. Each factor is used to evaluate 20 currencies, including each one's likeliness to appreciate or depreciate, and to sort them into long and long-short currency baskets. With these baskets, we then create portfolios that are reallocated on a monthly, six-month or yearly basis from 2006 until 2018. This process is repeated for the portfolios where several factors, rather than only one, are simultaneously considered to determine the currency attractiveness. All in all, the trading strategies generated very promising results, especially for F.CIRP, F.VRP, F.REER and F.Value. In this chapter, we begin by providing a detailed explanation of the applied methodology. Afterwards, we discuss the performance of the individual portfolios and the currency selection patterns of the factors. Finally, all performance results are summarized in overview tables in Section 5.4.

5.1 Introduction Portfolios

We take our factors to implement currency trading strategies to determine if they have predictive power over exchange rates. We use twenty currencies denominated against the USD and try to generate profits by trading them. For each factor, two individual portfolios are created, one with only a long strategy and one with a long-short one. They are reallocated either on a monthly, six-month or yearly basis from 2006 until 2018. At each moment of allocation, the factors are used to evaluate the attractiveness of the 20 currencies and to order them from most likely to appreciate to most likely to depreciate. Afterwards, the currencies are divided into quartiles and allocated to four different currency baskets. The best basket containing 25% of the currencies is considered for the long positions and, if applicable, the bottom 25% for the short positions. Thus, in the portfolio with the long only strategy, we go long the 25% currencies that are most likely to appreciate and short the USD. By contrast, we do the same for the portfolio with the long-short strategy, but we also go short the currencies of the bottom 25% bucket and long the USD. Finally, the actual returns from the trading activities are considered for the cumulative performance of the investment strategies. Whether the 20 currencies are ordered in an ascending or descending manner depends on the individual factor values and theoretical intuition regarding how the indicators are related to bilateral currency movements. Hence, the values based on the F.BM, F.VRP, F.USD, F.MOM, $F.PMI_{Chg}$ and $F.PMI_{Rel}$ were ordered decreasingly and the values of F.CIRP, F.REER, F.Value and FX.Future increasingly.

In a second step, we repeated this process for an extended factor set that also includes F.PMI and F.FXFuture. Due to the data limitations of these two indicators, all currencies are divided into only two currency baskets. Table 4 gives an overview of the available data and the used currencies for each factor. As always, all currencies are denominated against the USD.

Factors	Available Currencies
F.VRP, F.CIRP, F.Value,	EUR, GBP, CAD, AUD, NZD, JPY, KRW,
F.FX.Future	EUR, GBP, CHF, CAD, AUD, NZD, JPY,
F.PMI_Chg, F.PMI_Rel	DKK, NOK, SEK, CHF, CAD, NZD, HUF,

Table 4: Overview Data Availability

Thirdly, additional portfolios are created where several factor combinations of F.VRP, F.CIRP, F.REER and F.Value are tested for the investment strategy. At each reallocation moment, all chosen factors are considered simultaneously in making the investment decision. Each time, the currencies get a ranking that ranges from one to twenty for all selected factors. The average ranking decides the overall order of the currencies before they are divided into quartiles. In summary, the portfolios generate very promising results, as they beat the benchmark almost every time.

5.2 Portfolio Performance

The following charts show the cumulative returns of the monthly and yearly rebalanced portfolios. On the left-hand side are the portfolios with the long only strategy; on the right-hand side are the ones with the long-short positions. Additionally, in Appendix 9.3 one can find additional charts analysing the individual performance of each factor. They illustrate the cumulative return of all four portfolio baskets created upon sorting the currencies and dividing them into quartiles.

Cumulative Returns from Monthly Reallocated Portfolios

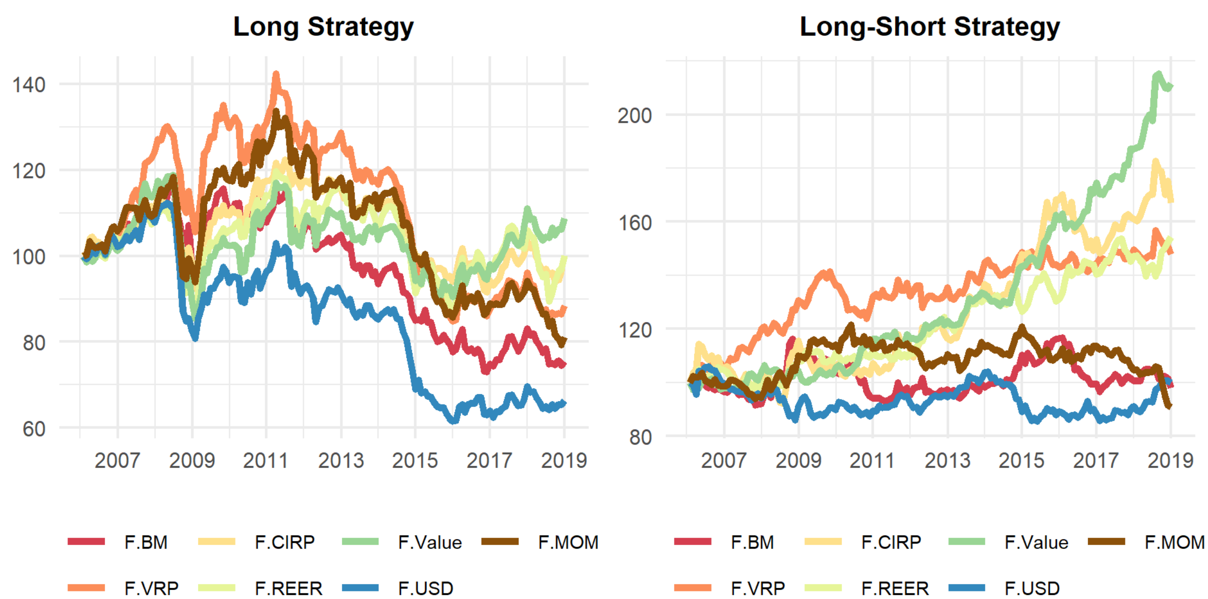


Chart 4: Cumulative Returns from Monthly Reallocated Portfolios (All Factors)

Chart 4 illustrates the very good performance of F.VRP, F.REER, F.CIRP and F.Value compared to their peers and the benchmark. F.VRP in particular has high returns during the financial crisis of 2008 and the years thereafter. The same holds true for the performance of the individual currency baskets of the factors in Appendix 9.3. They show that the indicators do an excellent job ordering the currencies and allocating them to the correct basket. They have a clear hierarchical pattern, as the top 25% currencies always perform significantly better than the bottom 25% ones. By contrast, F.USD and F.MOM seem to have more difficulties in correctly allocating the currencies to the right quartiles. In Appendix 9.3 one can observe that the performance of the portfolio with the top 25% currencies lies too close to the performance of the portfolio with the bottom 25% ones. This is also reflected in Chart 4 where the portfolios with the long-short position perform poorly compared to their peers. The benchmark has similar issues; it does not seem to be able to rank the currencies correctly. Moreover, it is striking that the portfolios with the long only strategies hardly generate positive returns. This relates to the fact that they are always short the USD and that this period is characterized by a strong USD.

Cumulative Returns from Yearly Reallocated Portfolios

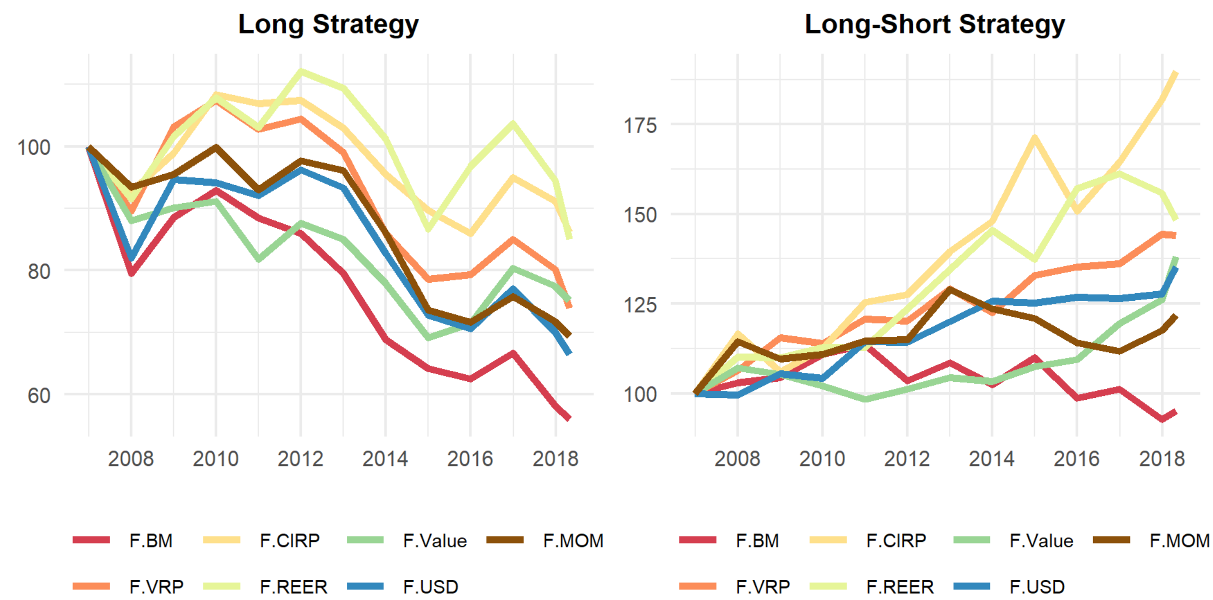


Chart 5: Cumulative Returns from Yearly Reallocated Portfolios (All Factors)

The performance of the yearly reallocated portfolios (Chart 5) is also very satisfactory. F.VRP, F.REER and F.CIRP still do a very fine job allocating the currencies to the right quartiles. Although F.Value has some issues, it still belongs to the best performing factors. Compared to Chart 4, the performance of the F.USD factor has improved significantly, but F.MOM continues to be rather weak.

Cumulative Returns from Monthly Reallocated Portfolios: F.PMI & F.FXFuture

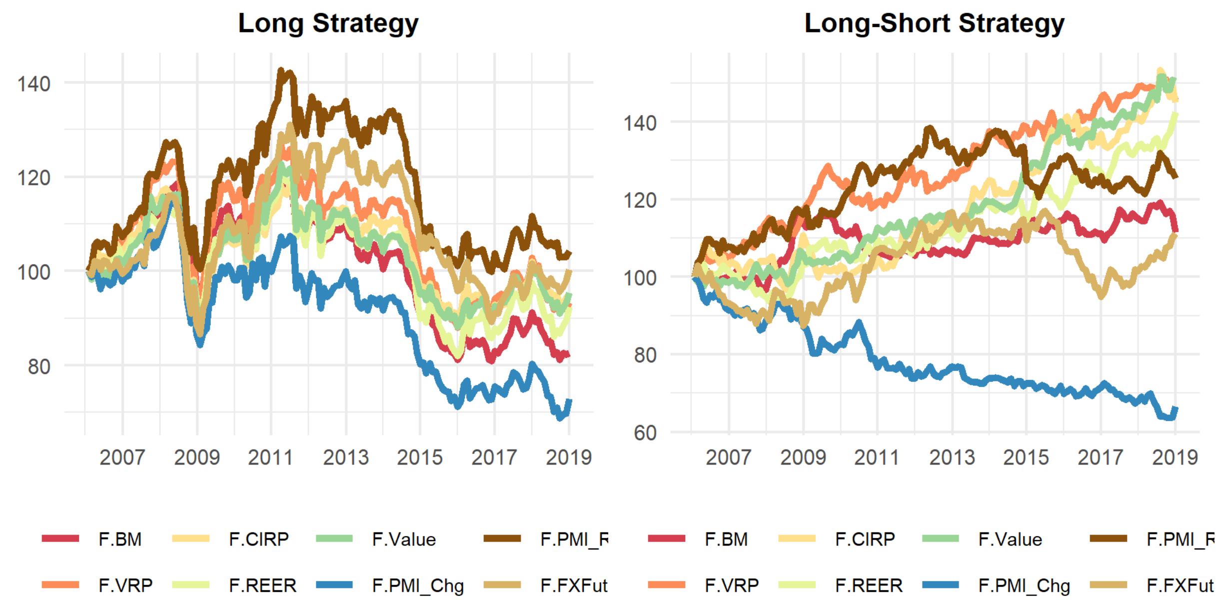


Chart 6: Cumulative Returns from Monthly Reallocated Portfolios (Extended Factors)

In this section, a special focus is placed on the F.PMI and F.FXFuture factors. Due to data limitations, they have a smaller pool of currencies in their data set; thus, it would not make sense to divide them into quartiles. Accordingly, all currencies are only divided by the median into two subgroups, the ones that are more likely to appreciate or depreciate. As the overall number of currencies is not the same for all factors, the performance comparison has to be done carefully. Chart 6 illustrates the factors' performance for the monthly reallocated portfolios. It shows that $F.PMI_{Rel}$ has a particularly good performance and F.FXFuture also does fine. Surprisingly, this cannot be said about $F.PMI_{Chg}$, which does not seem to be able to correctly sort the currencies into the upper and lower 50% portfolios.

Cumulative Returns from Yearly Reallocated Portfolios: F.PMI & F.FXFuture

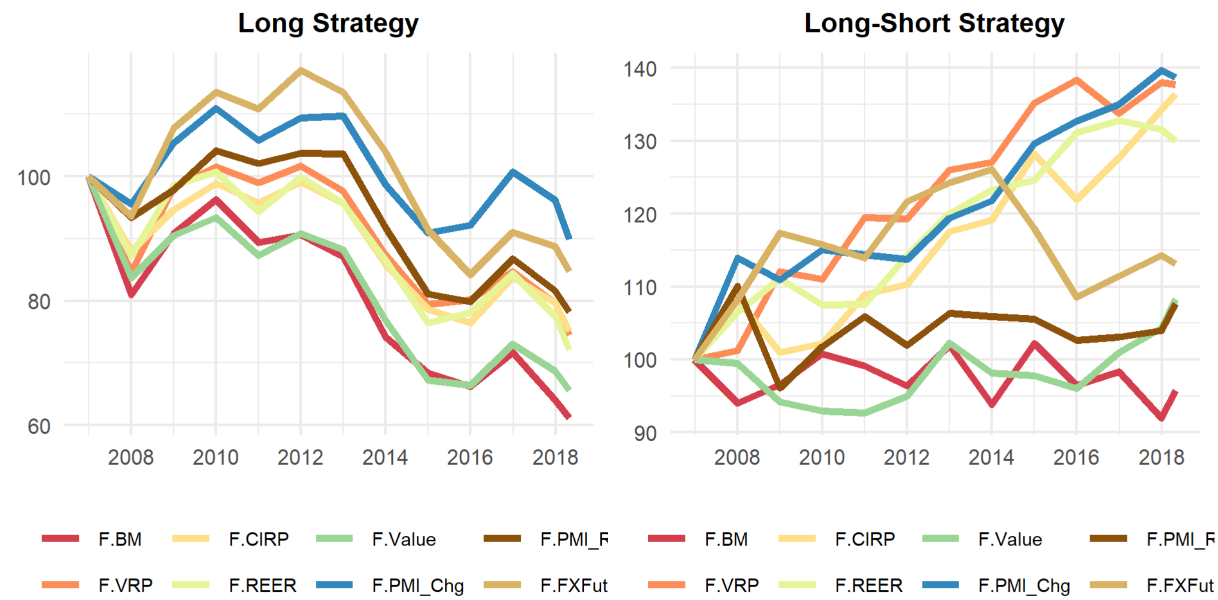


Chart 7: Cumulative Returns from Yearly Reallocated Portfolios (Extended Factors)

Interestingly, for the yearly reallocation (Chart 7), the situation between $F.PMI_{Chg}$ and $F.PMI_{Rel}$ changes completely. This time $F.PMI_{Chg}$ has an excellent performance but $F.PMI_{Rel}$ does not do so well. Thus, it seems that the relative PMI performance of county j to the USA is more relevant for the prediction of currency movements over short horizons. For longer forecasts, the country's individual PMI and its change over time is more important. F.FXFuture also improved as compared to Chart 6, although the overall performance did not change much.

Cumulative Returns from Monthly Reallocated Portfolios: Combined Factor Portfolios

For the combined portfolios, several factors simultaneously are considered to divide all 20 currencies into quartiles. In this section, only the best factors - F.CIRP, F.VRP, F.REER and F.Value - are used. Only the best performing combinations are shown in the charts below. Table 5 provides information on the combinations that are illustrated:

Combination	Factors
Comb 1	F.Value, F.VRP, F.CIRP, F.REER
Comb 3	F.Value, F.CIRP, F.REER
Comb 5	F.VRP, F.CIRP, F.REER
Comb 7	F.Value, F.CIRP
Comb 8	F.Value, F.REER
Comb 11	F.CIRP, F.REER

Table 5: Overview Factor Combinations

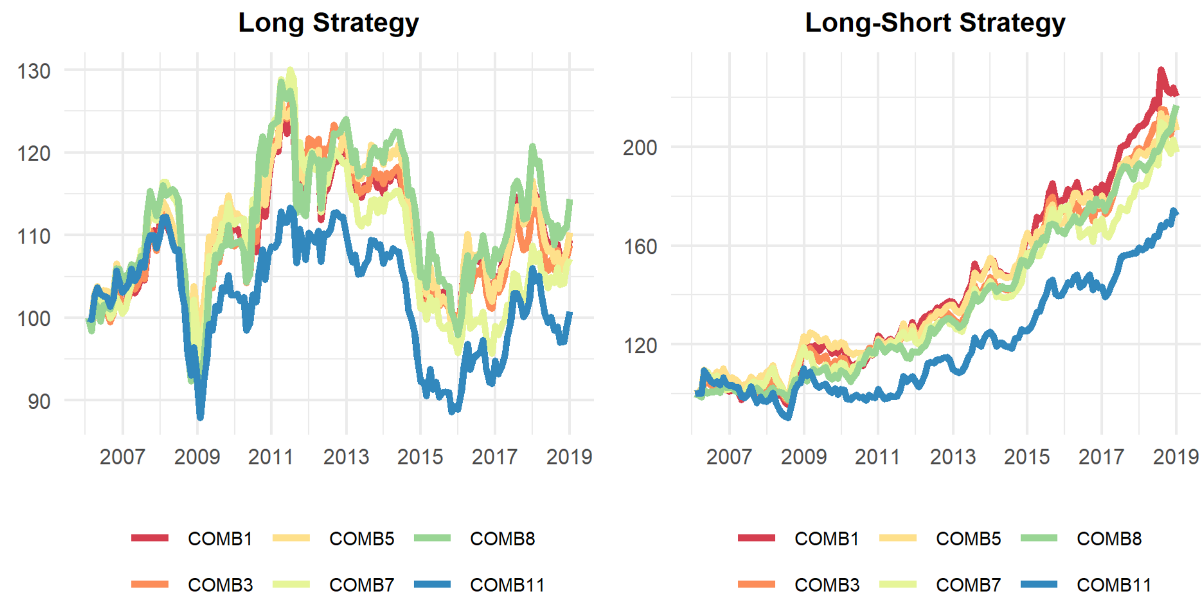


Chart 8: Cumulative Returns from Monthly Reallocated Portfolios (Combined Factor Portfolios)

At first glance, one can see that the overall performance of the combined portfolios is much better than that of the individual strategies (Chart 8). Most of them even have positive annual returns from the long only portfolios and they beat nearly all individual factor strategies. Additionally, in Appendix 9.3, one can observe that all combinations do a stellar job attributing the currencies to their quartile, as there is a clear hierarchical ranking of the currency baskets.

Cumulative Returns from Yearly Reallocated Portfolios: Combined Factor Portfolios

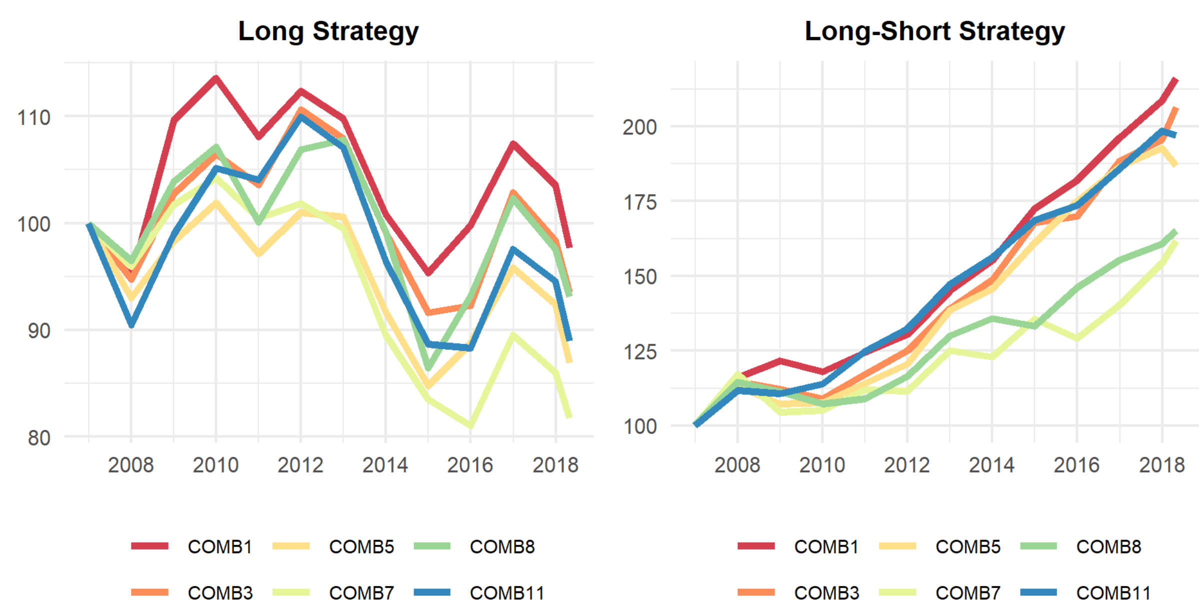


Chart 9: Cumulative Returns from Yearly Reallocated Portfolios (Combined Factor Portfolios)

The performance of the yearly reallocated portfolios (Chart 9) is similar to the previous one. Although the overall performance is slightly weaker, the combined factors continue to do an excellent job allocating the currencies to their quartile. Over all holding periods, combination one is the best performing combination, closely followed by combination three and combination eight. Hence, F.VRP is an excellent addition to already well-established risk factors.

5.3 Chosen Currencies

Chart 10 highlights for each factor the chosen currencies for the top 25% (long position) and the bottom 25% (short position) currency baskets across all portfolio allocation decisions. The larger the circle, the more often the currency was selected for the long or short basket. From this chart, we can see that F.BM, F.MOM, F.USD and F.Value have a uniform distribution over all twenty currencies and the long and short positions. By contrast, the remaining factors show a more distinct allocation pattern. F.CIRP clearly prefers currencies with a low interest rate for the long positions and high interest rates for the short ones. It also has the most focussed allocation over all indicators, as interest rate differentials did not change that drastically over the observation period. F.REER has slightly more allocations in general with currencies from developing countries and shows a clear separation between the long an short portfolio. The last factor, F.VRP, favours currencies from developed countries for the long positions. This seems reasonable, as they usually are less volatile, more frequently traded and thus, should have lower hedging costs. Additionally, F.CIRP, F.VRP and F.REER select similar currencies for the long and short positions, although the market timing is not observable from the chart.

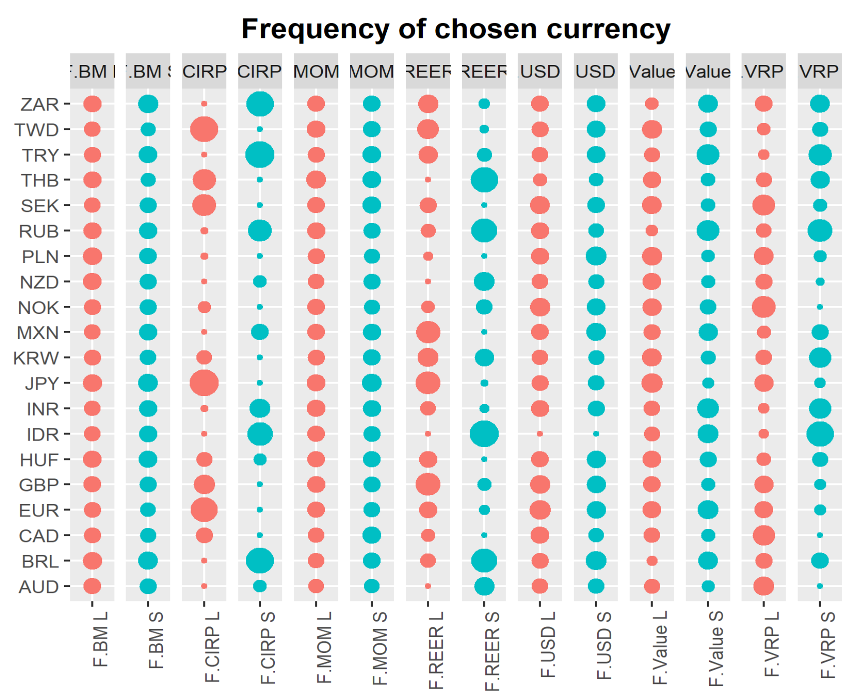


Chart 10: Selected Currencies for the Long Short Currency Basket

5.4 Portfolio Performance per annum

The following tables summarize the annualized returns for all strategies. Any portfolio that outperformed the benchmark and belongs to the top three performing factors of its class is highlighted in green. Table 6 shows all portfolios that used four currency baskets; Table 7 shows only the ones with two baskets. With the latter table, one needs to keep in mind that different currency pools were used for F.PMI and F.FXFuture than for the other factors. Generally, one can see that F.CIRP, F.REER and F.Value are always among the top performing factors, but F.VRP also does fairly well.

Portfolio	Reallocation	F.BM	F.VRP	F.CIRP	F.REER	F.Value	F.USD	F.MOM
long	1M	-2.157	-0.952	-0.287	0.006	0.651	-3.127	-1.606
long	6M	-4.200	-2.816	-0.371	-0.030	-0.766	-0.781	-3.947
long	1Y	-4.991	-2.633	-1.306	-1.426	-2.491	-3.549	-3.174
long-short	1M	-0.166	3.069	4.051	3.420	5.974	-0.013	-0.737
long-short	6M	-1.334	1.474	4.500	3.269	5.515	3.065	-2.351
long-short	1Y	-0.442	3.272	5.813	3.539	2.886	2.703	1.758

Table 6: Performance per Annum All Factors

Portfolio	Reallocation	F.BM	F.VRP	F.CIRP	F.REER	F.Value	F.PMI_Ch	F.PMI_Rel	F.FXFutur
long	1M	-1.463	-0.532	-0.385	-0.609	-0.367	-2.419	0.327	0.024
long	6M	-2.673	-1.811	-0.972	-1.453	-1.455	-0.682	-0.454	-0.645
long	1Y	-4.245	-2.572	-2.490	-2.841	-3.654	-0.942	-2.151	-1.453
long-short	1M	0.850	2.943	2.919	2.782	3.219	-3.113	1.774	0.820
long-short	6M	-0.021	1.574	2.874	2.171	2.043	1.121	1.484	0.509
long-short	1Y	-0.384	2.865	2.775	2.339	0.706	2.927	0.657	1.093

Table 7: Performance per Annum Extended Factor Set

The next two tables give an overview of the combined factor portfolios and their annualized performance. The top four performing combinations for each allocation interval are highlighted in green. In general, all combinations have a strong performance, but combinations one, three and eight are particularly good.

Combination	Factor 1	Factor 2	Factor 3	Factor 4
Comb 1	F.Value	F.VRP	F.CIRP	F.REER
Comb 2	F.Value	F.VRP	F.CIRP	
Comb 3	F.Value	F.CIRP	F.REER	
Comb 4	F.Value	F.VRP	F.REER	
Comb 5	F.VRP	F.CIRP	F.REER	
Comb 6	F.Value	F.VRP		
Comb 7	F.Value	F.CIRP		
Comb 8	F.Value	F.REER		
Comb 9	F.VRP	F.CIRP		
Comb 10	F.VRP	F.REER		
Comb 11	F.CIRP	F.REER		

Table 8: Overview Combined Factor Portfolio

Portfolio	Reallo-cation	COMB1	COMB2	COMB3	COMB4	COMB5	COMB6	COMB7	COMB8	COMB9	COMB10	COMB11
long	1M	0.695	0.286	0.651	0.857	0.766	-0.158	0.536	1.048	-0.703	-0.666	0.059
long	6M	0.871	-0.421	0.139	-0.638	-0.497	-0.750	0.566	0.497	-0.622	-1.279	-0.005
long	1Y	-0.205	-1.928	-0.594	-0.905	-1.228	-1.947	-1.758	-0.624	-2.197	-1.690	-1.027
long-short	1M	6.317	5.768	5.804	5.740	5.783	5.578	5.424	6.176	4.488	3.668	4.292
long-short	6M	5.792	4.635	5.506	3.020	4.010	4.078	5.621	4.830	4.943	3.136	4.820
long-short	1Y	7.031	5.059	6.597	4.173	5.666	3.596	4.339	4.525	4.975	4.686	6.164

Table 9: Performance per Annum Combined Factor Portfolios

5.5 Conclusion Portfolios

The portfolio analysis of the factors generates very promising results, especially for F.VRP, F.CIRP, F.REER and F.Value. All four do an excellent job sorting the 20 currencies according to their likeliness to appreciate or depreciate. This is also reflected in a very good annualized performance of the long-short portfolios with the yearly reallocation. In this segment, F.VRP reaches a return of 3.3%, F.CIRP 5.8%, F.REER 3.5% and F.Value 2.9% per annum. As these factors performed the best, they were also used for combined factor portfolios, where several factors simultaneously were considered for the investment decision. All combinations achieve very good annualized returns. The best combination is F.VRP, F.Value, F.CIRP, F.REER, with a return of 7% p.a. for the yearly reallocated long-short portfolio. Thus, F.VRP has proven to be a valuable addition to the already well-established risk factors.

As we have discussed in Section 4.4, our observation period of 2006-2018 is characterized by a strong USD. This negatively affects the performance of the portfolios with the long only strategy, as they are always short the USD. Their cumulative performance shows drawdowns, particularly during the 2008 financial crisis and during 2012-2017, which were periods of a strong USD.

Additionally to the four best factors, a few other financial or macroeconomic indicators were analysed. The supplementary factors F.MOM and F.USD have significant difficulties to correctly predict currency movements. They usually do not sort the currencies correctly and there is no clear hierarchical order between the upper and lower currency baskets. This is also reflected in the annual performance, where only some of the long-short portfolios achieved a positive performance. More promising additions to the factors are F.PMI and F.FXFuture. Unfortunately, the data availability is much more limited for these factors and a smaller currency basket had to be used. For the PMI factor, it seems that the relative performance to the US PMI is more relevant to predict short-term currency movements. For longer predictions, the country's individual PMI and its development over time seem more important. The F.FXFuture factor has mixed results, but it appears to warrant further analysis.

6. Regression Analysis

6.1 Introduction Regression Analysis

Following the very good portfolio results, we use our factors to conduct several regression analyses to test the factors' predictive capabilities. We regress one-month and six-month future FX returns on three developed basic models. The best factors model includes the F.VRP, F.CIRP, F.REER and F.Value factors. The extended model additionally involves F.USD, F.MOM and the third model combines the four base factors with the F.FXFuture factor. The models are estimated with ordinary least squares (OLS) and heteroscedastic and autocorrelation consistent (HAC) estimators. In a second step, we use the models to generate ex-post and ex-ante predictions and to check their forecasting properties with several test statistics. For this step we used the root mean squared error (RMSE), symmetric mean absolute percentage error (SMAPE), Theil's uncertainty coefficient (U_2) and a direction of change criteria.

6.2 Methodology

To further analyse our factors and to test their predictive power, we conduct several ordinary least squares (OLS) and heteroscedastic and autocorrelation consistent (HAC) regressions. In this process, we always regress either lagged one-month or six-month FX log returns on our indicators. One of our primary models is stated below, where we use F.VRP, F.CIRP, F.REER and F.Value as independent variables.

Best Factors Model:

$$ln\left(\frac{s_{j,t}}{s_{j,t-n}}\right) = \alpha + \beta_1 F.VRP_{j,t-n} + \beta_2 F.CIRP_{j,t-n} + \beta_3 F.REER_{j,t-n} + \beta_4 F.Value_{j,t-n}$$

The lagged FX returns are regressed on country j's factors. In this context, $ln(s_{j,t})$ denotes the bilateral log exchange rate of currency j per USD at time t. The abbreviation n is either one or six months to calculate the future log returns. To take into account the n month prediction period and to make the time series stationary, the difference of the independent variables is used for the regressions.

$$ln\left(\frac{s_{j,t}}{s_{j,t-n}}\right) = \alpha + \beta_1 \vartriangle F.VRP_{j,t-n} + \beta_2 \vartriangle F.CIRP_{j,t-n} + \beta_3 \vartriangle F.REER_{j,t-n} + \beta_4 \vartriangle F.Value_{j,t-n}$$

To be more specific, for the regression of monthly returns, the first difference of the independent variables is used, e.g. $\vartriangle VRP_{j,t-1} = VRP_{j,t-1} - VRP_{j,t-2}$. For the six-month period, the six-month difference is used, e.g. $\vartriangle VRP_{j,t-6} = VRP_{j,t-6} - VRP_{j,t-12}$. Moreover, the very short observation period during the years of 2006-2018 and the regression on six-month returns cause another significant issue. Either we use overlapping data or we one only have 26 available observations. The latter option hardly leaves enough information for a proper regression analysis and thus was dismissed. This, however, creates a moving average error; OLS estimates would be inefficient and the hypothesis test biased (Harri and Wade Brorsen 2009). Harri and Brorsen (2009) devoted a paper to this issue and discussed how it is best resolved. They state that the two most popular ways within the research community of tackling this issue are to refrain from using overlapping data and from applying HAC estimators. Although they criticise HAC estimators as potentially inefficient, they admit that they provide asymptotically valid hypothesis tests. After considering Harri and Brorsens' research and their alternative solution concepts, we decided to apply the Newey & West HAC covariance matrix estimator to tackle the overlapping data problem. In addition to the main regression model, we developed two more models with an extended factor set.

Extended Model:

$$ln\left(\frac{s_{j,t}}{s_{j,t-n}}\right) = \alpha + \beta_1 F.VRP_{j,t-n} + \beta_2 F.CIRP_{j,t-n} + \beta_3 F.REER_{j,t-n} + \beta_4 F.Value_{j,t-n} + \beta_5 F.USD_{j,t-n} + \beta_6 F.MOM_{j,t-n}$$

Best Factors & FX Future Model:

$$ln\left(\frac{s_{j,t}}{s_{j,t-n}}\right) = \alpha + \beta_1 F.VRP_{j,t-n} + \beta_2 F.CIRP_{j,t-n} + \beta_3 F.REER_{j,t-n} + \beta_4 F.Value_{j,t-n} + \beta_5 F.FXFuture_{j,t-n}$$

As before, the first or six-month difference of the independent variables is used for the regression analysis. The only exceptions are the F.USD and F.MOM regressors, which were already stationary for the one-month regression.

To ensure the accuracy of the regression results, several tests of the input variables and the residuals were conducted. All variables were checked for unit root and stationarity with the Phillips-Perron unit root, Kwiatkowski-Phillips-Schmidt-Shin stationarity (KPSS) and several Augmented Dickey-Fuller tests. Additionally, the residuals of the OLS regressions were tested for autocorrelation with the Durbin-Watson, Breusch-Godfrey, Box-Ljung & Ljung-Box test. We also checked for cointegration of the currency spot rates and the respective regressors. As this was negative, we do not apply a vector error correction model (VECM) as originally planned.

6.3 Regressions

The following tables summarize the regression results for all twenty currencies. Each row represents an individual OLS or HAC regression. The second and third columns illustrate the p-value of the F-statistic; they are followed by the intercept's p-value of the T-test. Adjacent are the multiple R-squared and adjusted R-squared values. Finally, the estimated coefficients and their p-values of the T-test are shown. The p-values are represented by stars, dots or empty spaces and the significance codes are: $0\ '***'\ 0.001\ '**'\ 0.01\ '*'\ 0.05\ '.'\ 0.1\ ''\ 1$. Thus, if the p-value is below 0.05 and equal or above 0.01, the significance level is illustrated by one star.

OLS Regression of one-month Future FX log Returns: Best Factors Model

FX	F.Test	F.Sign	Interc	R	Adj.R	F.VRP	F.CIRP	F.REER	F.Value	VRP	CIRP	REER	Value
EUR	0.009	**		0.085	0.061	-0.370	0.250	3.420	-0.030	*		**	
GBP	0.002	**		0.105	0.081	-0.140	0.240	3.780	-0.090			***	
CAD	0.000	***		0.126	0.102	0.300	0.540	1.380	-0.600	*	*		***
AUD	0.015	*		0.079	0.054	-0.350	0.380	2.820	0.140	*		*	
NZD	0.012	*		0.081	0.057	-0.380	0.730	1.510	-0.070	*	*		
JPY	0.686			0.015	-0.011	0.100	0.190	-0.600	0.070				
KRW	0.023	*		0.072	0.048	-0.160	0.080	2.180	-0.250			*	
TWD	0.847			0.009	-0.017	0.100	-0.050	-0.050	0.040				
PLN	0.001	**		0.111	0.088	-0.410	0.420	3.390	0.220	**	.	**	
MXN	0.071	.		0.055	0.030	0.110	0.220	2.070	-0.050			**	
THB	0.609			0.018	-0.008	-0.110	0.180	11.210	0.070				
NOK	0.072	.		0.055	0.030	-0.080	-0.140	3.870	-0.090			**	
SEK	0.164			0.042	0.017	-0.210	0.050	3.010	0.040			*	
HUF	0.000	***		0.265	0.245	0.140	0.640	1.490	-0.680		**	***	**
BRL	0.825			0.010	-0.016	-0.020	0.100	0.670	-0.040				
TRY	0.505		*	0.022	-0.004	0.030	0.110	0.540	0.170				
ZAR	0.882			0.008	-0.019	-0.040	0.180	0.080	-0.100				
INR	0.793			0.011	-0.015	-0.060	0.100	0.230	0.110				
RUB	0.000	***		0.199	0.177	0.020	0.410	0.300	0.270		**		**
IDR	0.003	**		0.112	0.086	-0.200	-0.060	-0.560	0.030			***	

Table 10: OLS Regression of one-month Future FX log Returns, Best regressors Model

As expected for a currency prediction model, the multiple R-squared and adjusted R-squared of the models are not very high. However, given the circumstances, the results are good. Half of the regressions have a significant F-statistic and many of the regressors are significant. The coefficients do not always have the same sign as the theory would suggest, but their values are also not always significant. The next regressions in the extended model (Table 11) yield similar results. The additional two regressors do not really improve the outcome, as the adjusted R-squared decreases rather than increases. The p-values of the T-test are hardly significant and the coefficient sign of F.USD is negative, which was not expected.

OLS Regression of one-month Future FX log Returns: Extended Model

FX	F.Test	F.Sign	Inter	R	Adj.R	F.VRP	F.CIRP	F.REER	F.Value	F.USD	F.MOM	VRP	CIRP	REER	Value	USD	MOM
EUR	0.032	*		0.088	0.051	-0.300	0.310	3.540	-0.070	-0.100	0.000			**			
GBP	0.004	**		0.121	0.086	-0.060	0.190	3.210	-0.210	-0.000	0.000			**			
CAD	0.001	**		0.138	0.103	0.320	0.480	0.610	-0.700	0.110	0.000	*	.		***		
AUD	0.021	*		0.095	0.058	-0.280	0.430	3.220	0.240	-0.330	0.000		.	*			
NZD	0.028	*		0.090	0.053	-0.270	0.730	1.100	-0.180	-0.060	0.010		*				
JPY	0.661			0.027	-0.012	0.220	0.190	-0.690	-0.090	-0.100	0.000						
KRW	0.059	.		0.078	0.040	-0.190	0.060	1.950	-0.260	0.140	-0.000			*			
TWD	0.883			0.016	-0.024	0.080	-0.110	0.020	0.030	0.040	0.000						
PLN	0.006	**		0.113	0.078	-0.330	0.430	3.280	0.130	-0.070	0.000	.	.	**			
MXN	0.068	.		0.075	0.038	0.250	0.160	2.210	-0.290	0.030	0.010			**			
THB	0.449			0.038	-0.001	-0.250	0.210	22.720	0.130	0.130	-0.000	.				.	
NOK	0.177			0.058	0.020	-0.040	-0.120	3.590	-0.150	-0.020	0.000			*			
SEK	0.310			0.046	0.008	-0.150	0.100	2.970	0.020	-0.120	0.000			*			
HUF	0.000	***		0.320	0.293	0.200	0.320	1.740	-0.930	0.210	0.010			***	***		*
BRL	0.234			0.052	0.014	0.010	0.030	0.970	-0.200	0.180	0.010				.		.
TRY	0.707		*	0.025	-0.015	0.060	0.110	0.650	0.130	0.010	0.000						
ZAR	0.929			0.013	-0.027	-0.020	0.150	-0.020	-0.170	0.080	0.000						
INR	0.929			0.013	-0.028	-0.060	0.080	0.250	0.100	0.020	0.000						
RUB	0.000	***	.	0.261	0.230	0.340	0.510	0.240	0.090	-0.710	0.010	*	**			***	*
IDR	0.011	*		0.117	0.076	-0.300	-0.070	-0.550	0.110	0.110	-0.000			***			

Table 11: OLS Regression on one-month Future FX log Returns: Extended Model

The addition of the F.FXFuture factor to the base model (Table 12) seems to improve the model slightly for the EUR, CAD, AUD, NZD and MXN. From these results, it becomes evident that the order flow factor does not hamper the effect of F.VRP or any other factor.

OLS Regression of one-month Future FX log Returns: Best Factors & FX Future Model

FX	F.Test	F.Sign	Interc	R	Adj.R	F.VRP	F.CIRP	F.REER	F.Value	F.FXFut	VRP	CIRP	REER	Value	FX.Future
EUR	0.012	*		0.092	0.062	-0.370	0.290	3.500	-0.070	-0.140	*		**		
GBP	0.005	**		0.107	0.077	-0.130	0.250	3.820	-0.090	0.140			***		
CAD	0.001	**		0.127	0.098	0.280	0.560	1.340	-0.590	-0.150	*	*		***	
AUD	0.009	**		0.097	0.067	-0.290	0.380	2.960	0.110	0.520	.		*		.
NZD	0.008	**		0.099	0.069	-0.360	0.710	1.650	-0.080	0.530	*	*			.
JPY	0.749			0.018	-0.015	0.100	0.180	-0.470	0.070	-0.190					
MXN	0.008	**		0.099	0.068	-0.310	-0.160	2.500	0.390	0.590	*		**	*	

Table 12: OLS Regression of one-month Future FX log Returns: Best regressors & FX Future Model

The subsequent two tables summarize the results of the HAC regressions of the future six-month log returns. As explained in the methodology section, the Newey & West heteroscedastic and autocorrelation consistent (HAC) covariance matrix estimator are used to overcome the overlapping data issue.

HAC Regression of six-month Future FX log Returns: Best Factors Model

FX	F.Test	F.Sign	Interc	F.VRP	F.CIRP	F.REER	F.Value	VRP	CIRP	REER	Value
EUR	0.003	**		0.740	-0.300	-0.010	-0.060	**		*	
GBP	0.168			0.560	-0.460	-0.000	0.120				
CAD	0.538			0.190	-0.400	-0.000	0.010				
AUD	0.087	.		0.890	-0.130	-0.000	-0.420	*			.
NZD	0.000	***		0.810	-0.580	0.000	-0.050	.		*	
JPY	0.291			-0.310	-0.110	-0.000	-0.030			.	
KRW	0.024	*		-0.160	0.140	0.000	0.290			.	
TWD	0.428			-0.090	0.490	0.000	-0.220				
PLN	0.000	***		0.920	-0.130	0.000	-0.850	**		**	**
MXN	0.081	.	*	-0.100	0.290	-0.000	-0.480		.		*
THB	0.117			-0.040	-0.010	-0.080	0.710			.	*
NOK	0.032	*		0.790	-0.230	0.010	-0.380	*			.
SEK	0.003	**		0.670	-0.220	-0.000	0.250	*		*	
HUF	0.000	***		1.010	-0.520	-0.010	-1.070	***	*	**	**
BRL	0.000	***		0.690	-0.290	-0.000	-0.010	.		***	
TRY	0.467		***	-0.150	0.410	0.000	-0.220				
ZAR	0.000	***	.	-0.440	0.420	0.000	-0.010			***	
INR	0.000	***	*	0.150	-0.060	-0.000	0.580			***	**
RUB	0.130		*	0.030	-0.010	0.000	-0.210				.
IDR	0.096	.	*	0.060	0.300	0.010	-0.580				*

Table 13: HAC Regression of six-month Future FX log Returns: Best Regressors Model

Table 13 shows that half of the regressions have a significant F-test as they did before, but interestingly the currencies for which the model works have now changed. For the GBP, CAD, AUD, RUB and IDR the regression no longer yields a significant F-test, but for the NOK, SEK, BRL, ZAR, INR it now does. The T-test values have likewise changed and more intercepts are significant. The coefficient signs also have changed and direct more towards the theoretical intuition we applied for the portfolio analysis. The coefficients for F.REER, F.Value and F.CIRP are negative, whereas F.VRP turned more positive. Similar to the one-month regressions, the extended model does not really improve our regression results.

HAC Regression of six-month Future FX log Returns: Extended Model

FX	F.Test	F.Sign	Interc	F.VRP	F.CIRP	F.REER	F.Value	F.USD	F.MOM	VRP	CIRP	REER	Value	USD	MOM
EUR	0.003	**		0.840	-0.440	-0.010	-0.070	1.480	0.190	**		*		**	
GBP	0.320			0.440	-0.500	-0.000	0.150	-0.320	0.200						
CAD	0.485			0.090	-0.740	-0.010	-0.010	0.760	0.410						.
AUD	0.229			1.040	-0.120	-0.000	-0.430	0.280	-0.200	*			.		
NZD	0.000	***		0.800	-0.600	0.000	-0.060	1.220	0.090	*		.		.	
JPY	0.273			-0.290	-0.350	-0.000	-0.020	0.490	0.320			.			
KRW	0.021	*		-0.070	0.120	0.000	0.310	1.050	-0.020			*			
TWD	0.627			-0.070	0.530	0.000	-0.200	-0.140	-0.040						
PLN	0.002	**		1.160	-0.140	0.000	-0.880	1.310	-0.330	**		*	**		
MXN	0.145		*	-0.210	0.280	-0.000	-0.450	-0.170	0.140		.		*		
THB	0.190			-0.010	0.010	-0.070	0.650	0.570	0.000				*		
NOK	0.057	.		0.660	-0.270	0.010	-0.360	0.010	0.200	.			.		
SEK	0.012	*		0.720	-0.220	-0.000	0.250	0.240	-0.070	*		*			
HUF	0.000	***		0.910	-0.470	-0.010	-1.050	0.550	0.160	***	.	**	**		
BRL	0.000	***		0.610	-0.330	-0.000	-0.000	-0.830	0.200	.		***			
TRY	0.484		***	-0.360	0.340	0.000	-0.180	-0.290	0.420						
ZAR	0.000	***	.	-0.630	0.360	0.000	0.010	-0.140	0.430	.		***			
INR	0.000	***	*	-0.090	-0.070	-0.000	0.620	-0.300	0.200			***	**		
RUB	0.017	*	*	-0.280	-0.080	0.000	-0.150	0.250	0.840						*
IDR	0.090	.	*	-0.070	0.300	0.010	-0.550	-0.480	0.110				*		

Table 14: HAC Regression of six-month Future FX log Returns: Extended Model

6.4 Ex-post and Ex-ante Prediction Evaluation

In this section, we evaluate the regression results with an ex-post and ex-ante prediction model and several performance tests. Ex-post means that the previously calculated regression equations are used to predict $\hat{y}_t$, the lagged FX log returns. Afterwards, $\hat{y}_t$ is compared to the actual realized FX log returns y_t. This is done with the same data and for the same time period from which the model was developed. (Hackl 2013) Conversely, the ex-post prediction model uses a completely different data set for model development and its application to predict $\hat{y}_t$. As we had insufficient data for rolling regressions, we applied a recursive scheme, i.e. a continuously expanding time interval. We started with a data set of 8.5 years for the first out-of-sample estimation. Each time we produced our forecast and moved on to the next prediction, we extended our data set with the new information from that period. This ensured that we always used the full set of historical data to generate out-of-sample predictions. To evaluate our results, we used the root mean square error, symmetric mean absolute percentage error, Theil's uncertainty coefficient and the direction of change criteria. We evaluated all models for the ex-post prediction, but for the ex-ante analysis we used only the best factors model and the extended model.

The results are summarized in the following tables. The first column always indicates the evaluated model and all values are stated in percentages. If the prediction beats the benchmark, it is highlighted in green.

Abbreviation	Model
1M	one month model
6M	six-month model
1M4R	Best Factors model
1M6R	Extended model
1MBM	Benchmark
1MFut	Best Factors & FX Future model

Table 15: Overview Abbreviations

Root Mean Square Error (RMSE)

$RMSE = \sqrt{\frac{1}{n^*}\sum_t (Y_t - \widehat{Y}_t)^2},$ where n^* is the number of observations.

RMSE is the standard deviation of the prediction errors; the lower this value, the better the prediction. Unfortunately, this test is sensitive towards big forecast errors and the scale of the variables. Hence, the RMSE of the one-month models are not directly comparable with that of the six-month models. (Hackl 2013) Surprisingly, all regressions can beat the benchmark when considering the RMSE criteria. Some of the out-of-sample estimates are even better than the ex-post predictions. For the in-sample tests, the extended model is better than the best factors model, but this completely reverses with the ex-ante tests. The best factors & FX future model has relatively good results and can even beat all other models for the EUR, AUD, NZD, and MXN.

Root Mean Square Error (RMSE): Ex-Post Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**4.24**	**3.61**	**4.26**	**5.38**	**5.93**	**3.78**	**5.06**	**2.01**	**5.60**	**4.74**	**2.71**	**4.73**	**4.73**	**6.18**	**6.48**	**6.28**	**6.64**	**3.45**	**5.40**	**3.79**
1M4R	2.81	2.49	2.71	3.74	3.90	2.77	3.35	1.47	3.92	3.35	1.91	3.32	3.29	3.74	4.62	4.62	4.64	2.51	4.17	2.75
1M6R	2.81	2.46	2.69	3.71	3.88	2.76	3.34	1.47	3.91	3.32	1.89	3.32	3.29	3.59	4.52	4.61	4.62	2.51	4.01	2.74
1MFut	2.80	2.48	2.70	3.70	3.86	2.77				3.27										
BM 6M	**10.98**	**11.43**	**10.02**	**15.39**	**15.17**	**10.50**	**11.35**	**5.71**	**18.07**	**13.19**	**6.29**	**13.58**	**13.72**	**17.31**	**18.48**	**16.91**	**16.76**	**8.61**	**19.21**	**11.25**
6M4R	6.96	7.33	6.72	9.80	9.69	7.47	7.66	3.68	10.79	8.33	4.76	8.81	8.67	9.76	12.68	11.11	10.54	5.82	13.04	7.19
6M6R	6.80	7.31	6.60	9.79	9.59	7.38	7.62	3.67	10.70	8.32	4.75	8.79	8.67	9.73	12.64	11.05	10.48	5.77	12.86	7.15
6MFut	6.80	7.33	6.64	9.61	9.33	7.38				8.28										

Table 16: Root Mean Square Error (RMSE): Ex-Post Prediction

Root Mean Square Error (RMSE): Ex-Ante Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**4.24**	**3.61**	**4.26**	**5.38**	**5.93**	**3.78**	**5.06**	**2.01**	**5.60**	**4.74**	**2.71**	**4.73**	**4.73**	**6.18**	**6.48**	**6.28**	**6.64**	**3.45**	**5.40**	**3.79**
1M4R	2.50	2.74	2.55	3.00	3.78	2.80	2.56	1.38	3.08	3.71	1.62	3.01	3.00	2.65	5.18	5.91	4.73	1.74	4.55	2.00
1M6R	2.55	2.77	2.65	3.30	3.83	2.84	2.63	1.38	3.12	3.87	1.69	3.04	3.03	2.76	5.25	6.08	4.77	1.80	4.68	2.07
BM 6M	**10.98**	**11.43**	**10.02**	**15.39**	**15.17**	**10.50**	**11.35**	**5.71**	**18.07**	**13.19**	**6.29**	**13.58**	**13.72**	**17.31**	**18.48**	**16.91**	**16.76**	**8.61**	**19.21**	**11.25**
6M4R	5.15	7.00	4.36	5.10	5.71	6.63	5.17	3.69	7.25	6.93	3.79	6.00	5.67	6.44	120.8	14.02	112.5	3.92	12.91	5.12
6M6R	5.02	7.40	4.53	5.22	5.70	6.46	5.14	3.68	7.36	7.02	3.77	6.01	5.71	6.38	131.5	14.06	118.6	3.78	12.38	5.08

Table 17: Root Mean Square Error (RMSE): Ex-Ante Prediction

Symmetric Mean Absolute Percentage Error (SMAPE)

$$SMAPE = \frac{1}{n^*}\sum_t \left| \frac{Y_t - \widehat{Y}_t}{\frac{(|Y_t| + |\widehat{Y}_t|)}{2}} \right|$$

SMAPE computes the symmetric mean absolute percentage error between the prediction and the observed value. It is not as sensitive to big forecast errors as RMSE and there is no issue with the scale of the variables. It is bound between 1% and 200%. For SMAPE, the lower the value, the better the prediction. (Hackl 2013) Hence, SMAPE seems to be a more suitable test method than RMSE for our purposes. For this test, the one-month and six-month values are comparable; one can see that the six-month forecasts perform much better. This supports the notion that FX movements are easier to predict for longer periods. Unfortunately, with SMAPE, the models have much more difficulties in beating the benchmark, especially for the ex-ante prediction. The in-sample predictions are also clearly better than the out-of-sample results. One cannot see if the best factors model or the extended model is better, although the latter one performs better in sample. The best factors & FX future model has pretty good SMAPE values and can even beat all other models for the EUR, JPY and MXN.

Symmetric Mean Absolute Percentage Error (SMAPE): Ex-Post Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**152.2**	**150.8**	**154.2**	**149.3**	**152.6**	**146.0**	**145.8**	**139.2**	**145.0**	**148.1**	**138.3**	**147.0**		**143.0**	**146.5**	**142.9**	**153.1**	**149.7**	**133.4**	**145.1**
1M4R	148.9	153.8	143.2	151.7	151.9	169.7	162.1	171.1	147.9	154.7	161.9	160.7	160.2	146.6	166.2	147.7	160.5	161.0	142.9	161.5
1M6R	149.3	150.3	140.3	148.5	151.3	166.0	162.6	166.9	148.6	153.2	155.3	160.7	159.1	141.1	155.5	148.3	161.2	160.7	141.2	161.6
1MFut	148.5	151.5	142.8	150.5	153.6	165.5				149.3										
BM 6M	**139.1**	**143.4**	**147.1**	**135.6**	**147.1**	**149.0**	**146.2**	**154.3**	**143.2**	**145.0**	**131.3**	**144.1**	**149.9**	**147.8**	**133.4**	**139.8**	**134.0**	**144.8**	**137.1**	**136.7**
6M4R	152.9	141.3	157.3	151.6	147.6	160.5	163.9	148.6	147.6	139.6	146.2	141.2	141.8	134.2	149.4	116.2	140.9	129.0	135.0	141.6
6M6R	139.8	141.5	153.5	154.5	145.0	151.4	158.0	148.9	143.1	141.4	145.3	140.8	141.0	134.9	148.4	116.7	140.2	132.2	135.2	138.6
6MFut	138.7	140.7	150.9	151.7	146.1	150.4				139.3										

Table 18: Symmetric Mean Absolute Percentage Error (SMAPE): Ex-Post Prediction

Symmetric Mean Absolute Percentage Error (SMAPE): Ex-Ante Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**152.2**	**150.8**	**154.2**	**149.3**	**152.6**	**146.0**	**145.8**	**139.2**	**145.0**	**148.1**	**138.3**	**147.0**		**143.0**	**146.5**	**142.9**	**153.1**	**149.7**	**133.4**	**145.1**
1M4R	156.5	166.0	144.3	162.1	172.1	178.9	155.1	174.4	154.7	161.2	173.0	152.3	167.7	162.6	153.7	157.6	163.3	154.7	146.5	165.1
1M6R	163.4	160.0	141.1	155.2	171.8	172.6	163.0	180.9	162.8	149.9	179.4	163.2	169.2	146.7	160.8	159.5	163.6	159.8	150.7	156.4
BM 6M	**139.1**	**143.4**	**147.1**	**135.6**	**147.1**	**149.0**	**146.2**	**154.3**	**143.2**	**145.0**	**131.3**	**144.1**	**149.9**	**147.8**	**133.4**	**139.8**	**134.0**	**144.8**	**137.1**	**136.7**
6M4R	154.5	146.8	146.3	149.2	148.0	150.5	170.7	152.1	158.1	130.4	149.0	128.0	130.2	126.2	141.8	117.1	155.2	120.0	154.2	171.3
6M6R	140.0	152.6	140.4	153.7	150.4	146.0	169.4	149.2	157.1	137.9	148.8	127.7	132.5	125.7	141.7	120.0	159.2	120.4	152.5	167.0

Table 19: Symmetric Mean Absolute Percentage Error (SMAPE): Ex-Ante Prediction

Theil's Uncertainty Coefficient

$$U_2 = \frac{\sqrt{\frac{1}{n^*}\sum_t (\widehat{Y}_t - Y_t)^2}}{\sqrt{\frac{1}{n^*}\sum_t Y_t^2}}$$

Theil's uncertainty coefficient (Theil 1996) is a measure of forecast quality. It can be interpreted as the RMSE divided by the RMSE of a no-change model. Values lower than 100 show an improvement over the simple no-change forecast whereas values higher than 100 are a deterioration. It is independent from the scale of the variables and therefore easier to compare across different data sets. (Theil 1996; also Hackl 2013) Similar to the SMAPE test, one can observe that the six-month forecasts are generally better than the one-month predictions. We can also see that the extended model is almost always better than the best factors model. The best factors & FX future model again does pretty well, as it is the best model for EUR, AUD, NZD and MXN. Unfortunately, the ex-ante prediction performs particularly poorly in this test.

Theil's Uncertainty Coefficient: Ex-Post Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**144.2**	**137.2**	**148.4**	**138.4**	**145.8**	**135.6**	**145.0**	**134.8**	**134.9**	**137.1**	**139.1**	**138.8**	**141.1**	**141.9**	**139.6**	**132.6**	**143.3**	**136.5**	**117.7**	**132.9**
1M4R	95.6	94.4	93.5	96.0	95.8	99.2	96.3	99.5	94.2	96.6	98.8	97.1	97.8	85.7	99.2	97.2	99.1	98.7	88.8	93.7
1M6R	95.5	93.5	92.8	95.1	95.4	98.6	96.0	99.2	94.1	95.6	97.8	97.0	97.6	82.4	97.1	97.0	98.8	98.7	85.3	93.5
1MFut	95.3	94.3	93.4	95.0	94.9	99.1				94.3										
BM 6M	**148.7**	**148.4**	**147.2**	**150.1**	**149.4**	**140.9**	**140.6**	**151.8**	**154.3**	**150.7**	**123.8**	**147.6**	**151.1**	**159.9**	**141.9**	**137.7**	**147.7**	**133.2**	**142.7**	**144.5**
6M4R	93.8	95.0	98.0	94.0	96.3	98.8	94.6	97.7	91.0	93.7	96.0	94.8	93.7	89.3	95.9	89.2	95.1	88.3	93.5	88.5
6M6R	91.7	94.6	96.2	93.8	95.4	97.6	94.2	97.4	90.1	93.5	95.7	94.7	93.7	89.0	95.6	88.7	94.6	87.6	92.2	88.0
6MFut	91.6	94.9	96.8	92.2	92.8	97.7				93.1										

Table 20: Theil's Uncertainty Coefficient: Ex-Post Prediction

Theil's Uncertainty Coefficient: Ex-Ante Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M	**144.2**	**137.2**	**148.4**	**138.4**	**145.8**	**135.6**	**145.0**	**134.8**	**134.9**	**137.1**	**139.1**	**138.8**	**141.1**	**141.9**	**139.6**	**132.6**	**143.3**	**136.5**	**117.7**	**132.9**
1M4R	357.1	341.2	327.7	396.7	293.5	652.5	333.5	964.0	365.5	427.0	788.5	453.6	459.3	316.0	649.1	540.0	540.4	496.2	213.2	429.4
1M6R	359.9	306.8	265.0	274.8	287.4	367.7	303.4	857.9	375.4	304.7	616.5	436.7	455.9	200.2	373.3	411.1	468.0	499.7	193.8	327.0
BM 6M	**148.7**	**148.4**	**147.2**	**150.1**	**149.4**	**140.9**	**140.6**	**151.8**	**154.3**	**150.7**	**123.8**	**147.6**	**151.1**	**159.9**	**141.9**	**137.7**	**147.7**	**133.2**	**142.7**	**144.5**
6M4R	327.1	156.9	331.9	240.1	206.8	588.6	140.0	299.3	263.0	206.6	387.3	187.3	221.8	179.7	102.9	343.0	99.7	140.6	139.8	232.1
6M6R	246.3	146.7	221.4	228.7	202.4	646.5	137.6	311.4	234.4	204.9	399.4	185.4	222.7	182.1	102.7	340.4	99.7	136.1	145.7	223.4

Table 21: Theil's Uncertainty Coefficient: Ex-Ante Prediction

Direction of Change

This indicator considers whether or not the analysed model correctly predicts the direction of change of currency j. If the prediction has the same sign as the observed value, 1 is assigned to d; otherwise it is 0. Afterwards, the T-test is conducted to determine if the value is significant. (Cheung et al. 2019) If the model correctly predicts the direction of change by more than 50% (Direct), its value is highlighted in dark green. If the T-test is significant (p-val), its value is highlighted in light green.

Average Direction of Change:

$$\bar{d} = \frac{1}{n^*} \sum d$$

P-Value Direction of Change:

$$\frac{\bar{d} - 0.5}{\frac{SD}{\sqrt{n*}}}$$

SD is the sample standard deviation

From the highlighted values, it becomes clear that the six-month predictions are better than the one-month forecasts. The ex-post prediction almost always outperforms the benchmark, but the ex-ante prediction has much more difficulties in achieving positive results. From the comparison of the best factors model and the extended model, no clear superior model emerges.

Direction of Change Criteria: Ex-Post Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M p-Val	68.38	97.28	73.82	89.94	83.09	62.50	83.09	13.18	50.00	16.91	2.72	62.50	21.25	62.50	73.82	16.91	83.09	56.33	10.06	26.18
BM 1M	48.08	42.31	47.44	44.87	46.15	48.72	46.15	54.49	50.00	53.85	57.69	48.72	53.21	48.72	47.44	53.85	46.15	49.36	55.13	52.56
1M4R p-Val	3.23	4.59	0.13	18.93	18.93	40.52	53.19	18.93	6.37	11.47	3.23	11.47	14.89	28.78	28.78	8.64	0.97	13.03	31.29	24.89
1M4R Direct	57.42	56.77	61.94	53.55	53.55	50.97	49.68	53.55	56.13	54.84	57.42	54.84	54.19	52.26	52.26	55.48	59.35	54.55	52.00	52.90
1M6R p-Val	0.97	3.23	0.23	40.52	8.64	11.47	46.81	34.47	8.64	8.64	4.59	8.64	3.23	3.23	18.93	8.64	3.23	7.38	25.77	56.72
1M6R Direct	59.35	57.42	61.29	50.97	55.48	54.84	50.32	51.61	55.48	55.48	56.77	55.48	57.42	57.42	53.55	55.48	57.42	55.84	52.67	49.28
1MFut p-Val	0.62	4.59	0.23	18.93	3.23	11.47				6.37										
1MFut Direct	60.00	56.77	61.29	53.55	57.42	54.84				56.13										
BM 6M p-Val	26.05	62.58	50.00	0.47	73.95	50.00	37.42	68.49	56.37	78.89	1.18	73.95	73.95	62.58	7.38	26.05	5.36	26.05	1.79	0.76
BM 6M	52.60	48.70	50.00	60.39	47.40	50.00	51.30	48.05	49.35	46.75	59.09	47.40	47.40	48.70	55.84	52.60	56.49	52.60	58.44	59.74
6M4R p-Val	0.40	1.04	1.04	5.02	20.65	12.56	68.82	2.41	43.50	0.14	0.66	0.24	5.02	0.01	1.04	0.00	1.04	0.10	5.62	1.42
6M4R Direct	60.81	59.46	59.46	56.76	53.38	54.73	47.97	58.11	50.68	62.16	60.14	61.49	56.76	64.86	59.46	66.22	59.46	62.59	56.64	59.54
6M6R p-Val	0.14	1.61	2.41	37.18	3.52	0.66	31.18	3.52	12.56	0.01	1.04	0.40	3.52	0.02	1.04	0.00	0.66	0.06	5.62	2.20
6M6R Direct	62.16	58.78	58.11	51.35	57.43	60.14	52.03	57.43	54.73	64.86	59.46	60.81	57.43	64.19	59.46	67.57	60.14	63.27	56.64	58.78
6MFut p-Val	0.04	0.66	12.56	37.18	6.98	0.66				2.41										
6MFut Direct	63.51	60.14	54.73	51.35	56.08	60.14				58.11										

Table 22: Direction of Change Criteria: Ex-Post Prediction

Direction of Change Criteria: Ex-Ante Prediction

Model	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
BM 1M p-Val	68.38	97.28	73.82	89.94	83.09	62.50	83.09	13.18	50.00	16.91	2.72	62.50	21.25	62.50	73.82	16.91	83.09	56.33	10.06	26.18
BM 1M	48.08	42.31	47.44	44.87	46.15	48.72	46.15	54.49	50.00	53.85	57.69	48.72	53.21	48.72	47.44	53.85	46.15	49.36	55.13	52.56
1M4R p-Val	79.92	92.03	4.49	92.03	97.67	95.51	60.98	50.00	50.00	28.84	79.92	20.08	79.92	71.16	20.08	20.08	13.10	33.64	67.01	56.75
1M4R Direct	44.00	40.00	62.00	40.00	36.00	38.00	48.00	50.00	50.00	54.00	44.00	56.00	44.00	46.00	56.00	56.00	58.00	53.06	46.67	48.48
1M6R p-Val	71.16	79.92	2.33	95.51	79.92	79.92	71.16	60.98	79.92	13.10	99.82	71.16	71.16	39.02	28.84	20.08	20.08	66.36	44.17	43.25
1M6R Direct	46.00	44.00	64.00	38.00	44.00	44.00	46.00	48.00	44.00	58.00	30.00	46.00	46.00	52.00	54.00	56.00	56.00	46.94	51.11	51.52
BM 6M p-Val	26.05	62.58	50.00	0.47	73.95	50.00	37.42	68.49	56.37	78.89	1.18	73.95	73.95	62.58	7.38	26.05	5.36	26.05	1.79	0.76
BM 6M	52.60	48.70	50.00	60.39	47.40	50.00	51.30	48.05	49.35	46.75	59.09	47.40	47.40	48.70	55.84	52.60	56.49	52.60	58.44	59.74
6M4R p-Val	32.64	32.64	14.55	8.64	85.45	22.61	67.36	14.55	77.39	1.02	14.55	8.64	4.69	22.61	14.55	0.01	44.04	3.16	90.09	94.08
6M4R Direct	53.49	53.49	58.14	60.47	41.86	55.81	46.51	58.14	44.19	67.44	58.14	60.47	62.79	55.81	58.14	76.74	51.16	64.29	39.47	34.62
6M6R p-Val	8.64	32.64	14.55	14.55	91.36	1.02	67.36	14.55	91.36	1.02	14.55	8.64	4.69	22.61	14.55	0.00	22.61	6.21	94.72	94.08
6M6R Direct	60.47	53.49	58.14	58.14	39.53	67.44	46.51	58.14	39.53	67.44	58.14	60.47	62.79	55.81	58.14	79.07	55.81	61.90	36.84	34.62

Table 23: Direction of Change Criteria: Ex-Ante Prediction

6.5 Conclusion Regression analysis and Prediction Evaluation

In summary, the regressions of the one-month and six-month future FX returns yielded good results. F.REER, F.Value, F.VRP and F.CIRP have proven to be very valuable regressors which are independently important determinants of future currency strength. Although the coefficient sign of F.VRP is not that stable, it is a important addition to the already well-established factors, since it captures new information. FX.Future, F.MOM and F.USD are interesting supplements to the base model, but they are not able to generate a noticeable improvement. The RMSE, SMAPE, Theil's U and the direction of change tests of the ex-ante and ex-post predictions support these findings. The ex-ante forecasts almost always beat a random walk and although the test statistics are pretty high, they are good for a currency model. However, the results for the ex-ante predictions were rather weak. Like all other research efforts, we were generally unable to outperform a random walk out-of-sample. Overall, the SMAPE and the direction of change criteria seemed to be the best test statistics to compare the performance of our models. These clearly showed that the six-month predictions are more accurate than the short-term forecasts. Sometimes, they also detected a slight outperformance of the extended model compared to the best factors model, but the results were ambiguous.

7. F.VRP Analysis

From the previous chapters, we have seen that F.VRP is a good indicator for future currency movements. It generates high returns with the portfolio strategy and is a significant parameter in the regression analyses, irrespective of other explanatory variables. In Section 4.3, we have learned that F.VRP has a low correlation with most factors. The only higher correlations are with F.BM, F.USD and F.MOM, as they are also based on past currency volatilities. Additionally, Chapter 5.3 has shown that F.VRP tends to predict that currencies from developed countries are more likely to appreciate than those form emerging countries. This seems to be due to a lower volatility, more liquidity and subsequent smaller hedging costs for developed countries' currencies. To understand this new factor even better, we will take a closer look at its principal components, correlations and its additional value for our currency model.

As mentioned earlier, Della Corte, Ramadorai and Sarno (2016) do not propose a theoretical model to explain why the VRP indicator works. One explanation they suggest is limited arbitrage opportunities. If they are restricted, it affects the interaction between hedgers and speculators and subsequently prices. Indeed, Della Corte et al. (2016) observed that when the demand for volatility protection is higher (e.g. a spike in the VIX) and funding liquidity is lower (e.g. an increase in the TED spread), an increase in volatility insurance costs occurs across currencies. To analyse this aspect, we conducted a principal component analysis across all F.VRP indicators and looked at correlations to several VIX indices and the TED spread.

Principal Component Analysis (PCA) F.VRP

	PC1	PC2	PC3	PC4	PC5
Standard deviation	0.110	0.071	0.039	0.028	0.027
Proportion of Variance	0.546	0.229	0.069	0.036	0.033
Cumulative Proportion	0.546	0.774	0.843	0.879	0.911

Table 24: Principal Component Analysis F.VRP

The principal component analysis (PCA) of F.VRP yields a very strong PC 1 and PC 2, with a cumulative proportion of 77%. The first component explains 55% of the combined F.VRP variance whereas the second component explains 23% of it. The next table highlights the correlation of PC 1 and PC 2 to the TED Spread and two VIX indices of the Chicago Board Options Exchange. The VIX indices, in particular the emerging markets VIX, have quite a high correlation with the first principal component. The second one correlates with the TED Spread. This would support Della Corte, Ramadorai and Sarnos' notion of the influence of the lack of arbitrage opportunities on the VRP indicator.

Correlation Analysis F.VRP PCA with VIX Indices & TED Spread

VIX SP 500 & PC 1	VIX Emerging Markets & PC	TED Spread & PC 2
0.12	0.21	0.26

Table 25: Correlation Analysis F.VRP PCA with VIX Indices & TED Spread

To better evaluate the usefulness of F.VRP for our currency models, we will take a closer look at the R^2 of the regression analyses. To do so, we compare the R^2 of two nearly identical regressions, one with F.VRP included as a regressor and one where it is excluded. In general, R^2 is a goodness-of-fit measure for the OLS regression. It measures how much of the variance in the dependent variable can be explained by the independent variables. However, it can be increased by simply adding an additional regressor. To prevent this effect, we compare the adjusted R^2 of the models and not the simple R^2. Adjusted R^2 only increases if the additional indicator leads to a valid improvement of the explanatory power, but it has the disadvantage that it is no longer bounded between zero and 100%. (Hackl 2013) In Chart 11, we illustrate the results for the OLS regressions of Chapter 6.3. For instance, the leftmost image shows the adjusted R^2 results for each regression of the best factor models with F.VRP, F.REER, F.CIRP and F.Value as regressors. The second, darker purple bar illustrates the adjusted R^2 for the same regression, but with only F.REER, F.CIRP and F.Value as explanatory variables. All in all, the comparison shows that F.VRP leads to an improvement of most regressions, as the models achieve a higher adjusted R^2.

F.VRP Adjusted R^2 Comparison

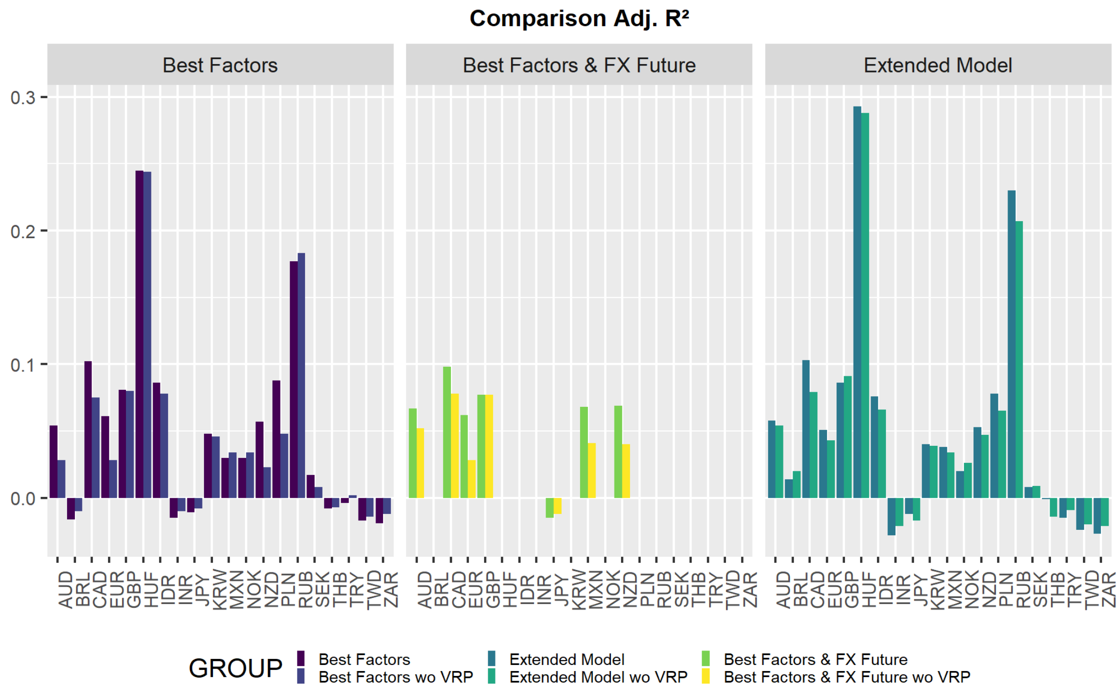


Chart 11: F.VRP Adjusted R^2 Comparison

Finally, we also examine the relative importance of the OLS regressors from Chapter 6.3. We apply the Lindeman, Merenda and Gold (1980) and Kruskall (1987) method to quantify the relative contributions of the regressors to the model's total explanatory value. This method suggests averaging sequential sums of squares over orderings of regressors. The following tables summarize our results. The first row depicts the R^2 for each regression. The second block of values is the relative importance or contribution percentages for each factor. The third block ranks the importance of the factors from 1 untill the maximum number of regressors in the model. The best ranks are highlighted in green and the last column illustrates the average value over all currencies for each factor. From the first table, we can see that all factors do very well. F.REER has the greatest relative importance with an average rank of two, followed by F.VRP and F.Value. The same holds true for the second table.

Unsurprisingly, F.MOM and F.USD yield the lowest relative importance over all factors, which supports our earlier findings. Concerning F.VRP, we can observe that it has a high relative importance over all three models, but in Table 28 it yields the best result with an average rank of 2.4. Additionally, F.VRP seems to have a higher explanatory power for currencies from developed than from emerging countries.

Factors Relative Importance: Best Factors Model

	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR	Ø
R²	8.5	10.5	12.6	7.9	8.1	1.5	7.2	0.9	11.1	5.5	1.8	5.5	4.2	26.5	1.0	2.2	0.8	1.1	19.9	11.2	7.4
F.VRP	38.2	4.0	13.6	28.0	49.8	42.4	22.9	61.9	24.0	8.6	20.0	4.2	23.0	2.9	2.3	9.0	22.5	6.0	12.8	9.8	20.3
F.CIRP	9.2	10.8	15.7	18.4	31.6	18.6	6.0	2.8	20.1	16.2	46.9	2.4	2.1	16.8	10.1	11.6	25.2	25.0	34.2	6.6	16.5
F.REE	46.2	79.7	3.6	43.3	4.2	9.0	43.1	27.8	49.4	73.4	7.8	89.9	72.4	62.5	81.9	44.6	4.3	30.8	5.2	82.8	43.1
F.Valu	6.4	5.6	67.1	10.3	14.3	30.0	28.1	7.4	6.4	1.7	25.3	3.5	2.5	17.8	5.6	34.7	48.0	38.2	47.7	0.9	20.1
VRP	2.0	4.0	3.0	2.0	1.0	1.0	3.0	1.0	2.0	3.0	3.0	2.0	2.0	4.0	4.0	4.0	3.0	4.0	3.0	2.0	2.6
CIRP	3.0	2.0	2.0	3.0	2.0	3.0	4.0	4.0	3.0	2.0	1.0	4.0	4.0	3.0	2.0	3.0	2.0	3.0	2.0	3.0	2.8
REER	1.0	1.0	4.0	1.0	4.0	4.0	1.0	2.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	1.0	4.0	2.0	4.0	1.0	2.0
Value	4.0	3.0	1.0	4.0	3.0	2.0	2.0	3.0	4.0	4.0	2.0	3.0	3.0	2.0	3.0	2.0	1.0	1.0	1.0	4.0	2.6

Table 26: Factors Relative Importance: Best Factors Model

Factors Relative Importance: Extended Model

	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR	Ø
R²	8.8	12.1	13.8	9.5	9.0	2.7	7.8	1.6	11.3	7.5	3.8	5.8	4.6	32.0	5.2	2.5	1.3	1.3	26.1	11.7	8.9
F.VRP	27.8	3.5	11.4	14.7	36.5	32.3	23.4	27.9	16.1	8.1	21.9	3.1	14.5	3.2	1.4	8.2	15.8	4.5	14.7	9.1	14.9
F.CIRP	10.1	5.8	11.6	17.6	25.3	11.4	4.1	8.2	18.2	7.5	22.1	2.1	2.1	8.3	0.8	8.7	11.3	16.9	28.0	4.8	11.3
F.REE	45.2	55.2	2.2	39.4	2.4	6.7	34.6	10.9	44.9	57.8	7.3	71.5	60.0	57.7	22.4	44.6	2.7	32.6	3.5	73.0	33.7
F.Valu	6.2	8.5	63.2	10.5	17.8	11.8	28.3	3.0	3.8	6.4	16.4	5.7	1.6	20.5	17.5	24.8	46.5	25.3	29.6	1.4	17.4
F.USD	4.8	9.6	6.7	11.8	3.6	11.2	7.9	33.2	2.7	10.0	27.3	4.2	5.9	4.8	18.2	7.1	9.3	4.0	11.9	10.3	10.2
F.MOM	5.8	17.5	4.9	6.0	14.4	26.4	1.7	16.8	14.4	10.1	5.1	13.3	15.9	5.5	39.6	6.6	14.4	16.8	12.3	1.5	12.4
VRP	2.0	6.0	3.0	3.0	1.0	1.0	3.0	2.0	3.0	4.0	3.0	5.0	3.0	6.0	5.0	4.0	2.0	5.0	3.0	3.0	3.4
CIRP	3.0	5.0	2.0	2.0	2.0	4.0	5.0	5.0	2.0	5.0	2.0	6.0	5.0	3.0	6.0	3.0	4.0	3.0	2.0	4.0	3.6
REER	1.0	1.0	6.0	1.0	6.0	6.0	1.0	4.0	1.0	1.0	5.0	1.0	1.0	1.0	2.0	1.0	6.0	1.0	6.0	1.0	2.6
Value	4.0	4.0	1.0	5.0	3.0	3.0	2.0	6.0	5.0	6.0	4.0	3.0	6.0	2.0	4.0	2.0	1.0	2.0	1.0	6.0	3.5
USD	6.0	3.0	4.0	4.0	5.0	5.0	4.0	1.0	6.0	3.0	1.0	4.0	4.0	5.0	3.0	5.0	5.0	6.0	5.0	2.0	4.0
MOM	5.0	2.0	5.0	6.0	4.0	2.0	6.0	3.0	4.0	2.0	6.0	2.0	2.0	4.0	1.0	6.0	3.0	4.0	4.0	5.0	3.8

Table 27: Factors Relative Importance: Extended Model

Factors Relative Importance: Best Factors and F.FXFuture

	EUR	GBP	CAD	AUD	NZD	JPY	MXN	Ø
R²	9.2	10.7	12.7	9.7	9.9	1.8	9.9	9.1
F.VRP	36.3	3.7	11.6	17.5	38.6	35.4	19.2	23.2
F.CIRP	9.4	10.9	16.6	15.0	25.4	14.6	3.8	13.7
F.REE	43.4	78.8	3.4	36.9	3.9	5.7	41.7	30.5
F.Valu	6.6	5.5	64.3	7.8	11.7	26.0	20.5	20.3
F.FXFu	4.3	1.0	4.0	22.9	20.4	18.3	14.8	12.2
VRP	2.0	4.0	3.0	3.0	1.0	1.0	3.0	2.4
CIRP	3.0	2.0	2.0	4.0	2.0	4.0	5.0	3.1
REER	1.0	1.0	5.0	1.0	5.0	5.0	1.0	2.7
Value	4.0	3.0	1.0	5.0	4.0	2.0	2.0	3.0
FXFutu	5.0	5.0	4.0	2.0	3.0	3.0	4.0	3.7

Table 28: Factors Relative Importance: Best Factors and

8. Conclusion

Our research generated very promising results, especially for F.VRP, F.CIRP, F.REER and F.Value. For the portfolio analysis, all four indicators do an excellent job of sorting the 20 currencies according to their likeliness to appreciate or depreciate. This is reflected in their high returns of the long-short portfolios per annum. F.VRP, F.CIRP, F.REER and F.Value are also used for combined factor portfolios, which considers several indicators simultaneously to make an investment decision. All combinations achieve very good returns, but the one which performs the best is the combination of all four parameters with a return of 7% p.a. for the long-short portfolio with yearly reallocation. Conversely, F.MOM and F.USD have significant difficulties. They are generally not able to correctly allocate the currencies to the long-short portfolios and their returns are rather disappointing. More promising additions to the indicators are the F.PMI and F.FXFuture factors. If the data availability were less restrictive, they would be valuable additions to the currency model.

The regressions of the one-month and six-month future FX returns yield very similar results. F.REER, F.Value, F.VRP and F.CIRP prove to be significant regressors that are important determinants of future currency strength. FX.Future, F.MOM and F.USD are interesting additions to the base model, but they are not able to generate a noticeable improvement of the forecast. The developed models are used to conduct ex-ante and ex-post predictions, which are evaluated with several test statistics. Although the in-sample results are pretty good, the results for the ex-ante predictions are rather weak. Like all other research efforts, we are generally unable to outperform a random walk out-of-sample. This means that further efforts will have to work towards developing a currency prediction model. Nevertheless, our results have shown that F.VRP, F.CIRP, F.REER and F.Value are the best predictors to determine future currency movements.

Finally, volatility risk premium is a valuable indicator that is complementary to covered interest rate parity, value, real effective exchange rate and order flows in a currency prediction model. It does not show significant correlation with previously known risk factors and contains new information to determine future currency movements of developed and emerging countries.

9. Appendix

9.1 List of Abbreviations

Abbreviation	Meaning
t	Time or specific point in time
τ	Specific point in time, in our case $t \mp 252$ days
T	Time in years, in our case one year
j	Indicator for specific currency e.g. CAD
n	Number of observations
r	Currency log return
ln	LOG
V	Volume
F	Forward
X	Strike
S	Spot rate
C	Call
P	Put
f	Foreign
d	Domestic
i_d	Domestic risk-free rate, in our case US risk-free rate
i_f	Foreign risk-free rate
μ	Mean
σ	Standard deviation
$s_{j,t}$	Bilateral exchange rate of currency j per USD at time t
D or Δ	Delta
σ	Implied volatility
RV	Realized volatility of the underlying
N(.)	Cumulative normal distribution function
FX	Foreign Exchange
$F.$	Factor or regressor
BM	Benchmark
VRP	Volatility Risk Premium
$REER$	Real effective exchange rate
$FXFuture$	Volume change of non-commercial FX Future positions
MOM	Momentum
PMI	Purchasing Managers' Index

Abbreviation	Currency
USD	United States Dollar
EUR	Euro
GBP	Great Britain Pound
CAD	Euro
AUD	Australian Dollar
NZD	New Zealand Dollar
JPY	Japan Yen
KRW	South Korean Won
TWD	New Taiwan Dollar
PLN	Polish złoty
MXN	Mexico Peso
THB	Thai Baht
NOK	Norwegian Krone
SEK	Swedish Krona
HUF	Hungarian Forint
BRL	Brazilian Real
TRY	Turkish Lira
ZAR	South African Rand
INR	Indian Rupee
RUB	Russian Ruble
IDR	Indonesian Rupiah

9.2 General Data Analysis

Spot Rates

FX Spot	EUR	GBP	NOK	SEK	CAD	AUD	NZD	JPY	KRW	TWD
Observations	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000
Minimum	-0.102	-0.102	-0.138	-0.116	-0.130	-0.171	-0.139	-0.088	-0.130	-0.054
Quartile 1	-0.015	-0.016	-0.022	-0.018	-0.014	-0.020	-0.021	-0.017	-0.014	-0.007
Median	0.000	-0.001	0.002	0.000	0.000	0.002	0.002	-0.000	0.002	-0.000
Arithmetic Mean	0.000	-0.001	-0.000	-0.001	0.000	0.000	0.000	0.000	0.001	0.000
Geometric Mean	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000	0.000	0.001	0.000
Quartile 3	0.017	0.016	0.018	0.016	0.016	0.024	0.024	0.019	0.017	0.008
Maximum	0.096	0.090	0.078	0.091	0.089	0.099	0.125	0.163	0.166	0.059
Variance	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Stdev	0.028	0.024	0.032	0.031	0.026	0.036	0.037	0.030	0.034	0.014
Skewness	-0.141	-0.364	-0.218	-0.022	-0.504	-0.505	-0.327	0.453	0.296	0.214
Kurtosis	1.133	1.718	1.055	1.128	2.987	1.885	1.206	2.970	4.869	1.744

FX Spot	HUF	PLN	BRL	MXN	TRY	ZAR	INR	RUB	THB	IDR
Observations	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000	254.000
Minimum	-0.202	-0.160	-0.529	-0.159	-0.359	-0.166	-0.095	-0.477	-0.077	-0.358
Quartile 1	-0.022	-0.022	-0.027	-0.017	-0.035	-0.033	-0.011	-0.013	-0.010	-0.017
Median	0.003	0.001	-0.003	-0.001	-0.007	-0.002	-0.001	-0.002	0.002	-0.001
Arithmetic Mean	-0.001	-0.000	-0.005	-0.003	-0.013	-0.004	-0.002	-0.009	0.001	-0.002
Geometric Mean	-0.002	-0.001	-0.007	-0.004	-0.014	-0.005	-0.002	-0.011	0.001	-0.003
Quartile 3	0.020	0.023	0.022	0.015	0.015	0.028	0.007	0.011	0.012	0.014
Maximum	0.110	0.098	0.170	0.074	0.097	0.108	0.070	0.120	0.104	0.343
Variance	0.002	0.002	0.004	0.001	0.002	0.002	0.000	0.003	0.000	0.003
Stdev	0.039	0.038	0.059	0.030	0.050	0.048	0.021	0.056	0.022	0.054
Skewness	-1.034	-0.770	-2.981	-1.004	-2.101	-0.453	-0.386	-4.652	0.245	-0.022
Kurtosis	4.005	2.061	24.384	3.657	11.577	0.552	3.261	33.751	2.859	16.110

F.VRP

F.VRP	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.088	-0.090	-0.064	-0.094	-0.083	-0.050	-0.201	-0.091	-0.130	-0.228
Quartile 1	-0.026	-0.029	-0.016	-0.020	-0.022	-0.027	-0.047	-0.032	-0.028	-0.038
Median	-0.013	-0.015	-0.007	-0.012	-0.012	-0.014	-0.031	-0.023	-0.014	-0.026
Arithmetic Mean	-0.016	-0.014	-0.009	-0.008	-0.013	-0.013	-0.028	-0.026	-0.017	-0.027
Geometric Mean	-0.016	-0.015	-0.009	-0.008	-0.013	-0.013	-0.029	-0.026	-0.017	-0.027
Quartile 3	-0.004	-0.001	-0.002	-0.001	-0.003	0.001	-0.010	-0.014	-0.003	-0.009
Maximum	0.031	0.050	0.035	0.125	0.065	0.030	0.159	-0.001	0.095	0.069
Variance	0.000	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.001	0.001
Stdev	0.019	0.024	0.014	0.030	0.021	0.018	0.045	0.017	0.031	0.037
Skewness	-0.797	-0.060	-0.468	2.151	0.306	0.167	0.610	-1.367	-0.058	-1.725
Kurtosis	1.658	0.924	2.865	7.732	2.601	-0.711	5.323	2.671	3.290	7.697

F.VRP	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	155.000	151.000	139.000
Minimum	-0.089	-0.056	-0.112	-0.111	-0.171	-0.105	-0.117	-0.272	-0.326	-0.323
Quartile 1	-0.039	-0.016	-0.023	-0.037	-0.039	-0.050	-0.045	-0.045	-0.052	-0.074
Median	-0.031	-0.008	-0.011	-0.020	-0.022	-0.034	-0.028	-0.033	-0.036	-0.055
Arithmetic Mean	-0.024	-0.008	-0.016	-0.023	-0.022	-0.033	-0.025	-0.040	-0.046	-0.063
Geometric Mean	-0.025	-0.008	-0.016	-0.023	-0.023	-0.034	-0.026	-0.041	-0.048	-0.064
Quartile 3	-0.019	0.001	-0.004	-0.011	-0.007	-0.020	-0.005	-0.025	-0.026	-0.034
Maximum	0.072	0.068	0.076	0.079	0.101	0.076	0.105	0.012	0.090	0.018
Variance	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.004	0.002
Stdev	0.031	0.019	0.029	0.028	0.037	0.028	0.034	0.037	0.063	0.049
Skewness	1.352	0.954	-0.767	-0.166	0.055	0.827	0.984	-3.849	-2.263	-2.317
Kurtosis	1.908	3.713	3.592	2.401	3.626	1.917	3.137	18.847	7.691	7.914

F.CIRP

F.CIRP	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.033	-0.019	-0.011	-0.007	-0.007	-0.048	-0.027	-0.050	-0.012	0.020
Quartile 1	-0.015	-0.003	-0.004	0.011	0.019	-0.022	-0.007	-0.028	0.001	0.029
Median	-0.004	0.001	0.001	0.023	0.025	-0.009	0.004	-0.016	0.012	0.036
Arithmetic Mean	-0.007	0.000	0.001	0.022	0.024	-0.016	0.002	-0.018	0.013	0.040
Geometric Mean	-0.007	0.000	0.001	0.022	0.024	-0.016	0.002	-0.018	0.013	0.039
Quartile 3	0.000	0.004	0.008	0.034	0.031	-0.005	0.012	-0.010	0.025	0.052
Maximum	0.019	0.029	0.011	0.055	0.064	-0.003	0.020	0.010	0.038	0.083
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.012	0.009	0.007	0.016	0.013	0.014	0.012	0.012	0.015	0.014
Skewness	-0.256	0.414	-0.130	0.134	-0.035	-1.019	-0.302	-0.080	-0.076	0.660
Kurtosis	-0.234	1.494	-1.324	-0.900	0.855	-0.233	-0.910	-0.863	-1.296	-0.496

F.CIRP	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	155.000	156.000	155.000
Minimum	-0.000	-0.022	-0.032	-0.026	0.028	0.041	0.020	0.006	-0.008	0.014
Quartile 1	0.000	-0.003	-0.018	0.002	0.056	0.072	0.050	0.031	0.038	0.044
Median	0.000	0.009	-0.002	0.025	0.080	0.093	0.059	0.047	0.058	0.055
Arithmetic Mean	0.000	0.006	-0.004	0.021	0.078	0.099	0.060	0.046	0.062	0.062
Geometric Mean	0.000	0.006	-0.004	0.021	0.077	0.099	0.060	0.046	0.061	0.062
Quartile 3	0.000	0.015	0.008	0.040	0.096	0.115	0.068	0.061	0.083	0.073
Maximum	0.000	0.036	0.024	0.150	0.127	0.262	0.104	0.104	0.267	0.230
Variance	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.000	0.002	0.001
Stdev	0.000	0.014	0.016	0.027	0.024	0.038	0.015	0.020	0.047	0.032
Skewness	-0.073	-0.166	-0.091	0.401	-0.193	1.443	0.131	-0.050	1.404	2.203
Kurtosis	-0.174	-0.655	-1.116	1.984	-0.842	3.300	1.017	-0.553	3.570	7.908

F.Value

F.Value	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.050	-0.020	-0.049	-0.030	-0.034	-0.018	-0.012	-0.091	-0.028	-0.068
Quartile 1	-0.007	-0.003	-0.002	-0.003	-0.003	-0.005	-0.003	-0.005	-0.003	-0.003
Median	0.002	0.000	0.000	0.000	-0.000	-0.002	0.000	-0.000	0.000	0.002
Arithmetic Mean	-0.001	-0.000	0.000	0.000	-0.000	-0.002	0.000	-0.002	-0.000	0.002
Geometric Mean	-0.001	-0.000	0.000	0.000	-0.000	-0.002	0.000	-0.002	-0.000	0.002
Quartile 3	0.006	0.003	0.002	0.003	0.002	0.001	0.003	0.004	0.003	0.007
Maximum	0.026	0.020	0.020	0.023	0.020	0.019	0.022	0.024	0.027	0.029
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.011	0.006	0.006	0.007	0.007	0.006	0.005	0.012	0.007	0.010
Skewness	-0.992	0.335	-3.071	-0.506	-0.982	0.605	0.908	-3.391	-0.452	-1.551
Kurtosis	2.010	2.125	28.370	3.787	5.484	2.206	2.248	20.136	3.580	11.515

F.Value	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.025	-0.022	-0.015	-0.034	-0.020	-0.060	-0.020	-0.058	-0.122	-0.026
Quartile 1	-0.002	-0.003	-0.003	-0.003	0.000	-0.000	-0.000	-0.003	0.000	-0.001
Median	0.000	0.000	-0.000	0.001	0.003	0.004	0.002	0.003	0.005	0.003
Arithmetic Mean	0.000	0.001	-0.000	0.000	0.004	0.004	0.004	0.003	0.005	0.004
Geometric Mean	0.000	0.001	-0.000	0.000	0.004	0.004	0.004	0.003	0.005	0.004
Quartile 3	0.002	0.005	0.002	0.004	0.007	0.012	0.007	0.010	0.011	0.007
Maximum	0.041	0.028	0.020	0.038	0.031	0.036	0.027	0.046	0.048	0.050
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.006	0.007	0.006	0.009	0.007	0.013	0.007	0.012	0.017	0.010
Skewness	2.235	0.370	0.214	-0.702	0.954	-1.261	0.378	-0.512	-3.385	1.192
Kurtosis	17.944	1.001	1.050	4.505	3.191	4.473	1.059	3.677	22.345	3.993

F.REER

F.REER	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.126	-0.271	-0.111	-0.084	-0.117	-0.264	-0.309	-0.155	-0.087	-0.206
Quartile 1	-0.062	-0.163	-0.048	-0.015	0.053	-0.162	-0.114	-0.069	-0.047	-0.103
Median	-0.024	-0.074	0.017	0.097	0.082	-0.096	-0.002	-0.056	-0.022	-0.069
Arithmetic Mean	-0.011	-0.089	0.007	0.077	0.080	-0.089	-0.027	-0.057	-0.006	-0.072
Geometric Mean	-0.013	-0.092	0.005	0.073	0.079	-0.093	-0.033	-0.058	-0.007	-0.073
Quartile 3	0.058	-0.037	0.055	0.167	0.123	-0.011	0.068	-0.045	0.014	-0.033
Maximum	0.121	0.102	0.158	0.270	0.196	0.083	0.120	0.027	0.182	0.064
Variance	0.004	0.007	0.004	0.010	0.003	0.008	0.010	0.001	0.004	0.002
Stdev	0.061	0.083	0.065	0.098	0.053	0.090	0.101	0.032	0.059	0.050
Skewness	0.389	0.121	0.125	0.066	-0.657	0.177	-0.470	-0.405	1.107	-0.074
Kurtosis	-1.082	-0.689	-1.121	-1.457	1.276	-1.024	-0.749	1.194	0.528	-0.140

F.REER	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	0.035	-0.131	-0.129	-0.122	-0.246	-0.345	-0.182	-0.124	-0.336	0.012
Quartile 1	0.068	-0.034	-0.048	-0.070	0.008	-0.077	-0.101	-0.038	0.014	0.130
Median	0.125	0.085	-0.033	-0.036	0.184	-0.017	-0.020	-0.011	0.202	0.196
Arithmetic Mean	0.132	0.058	-0.034	-0.026	0.172	0.008	-0.025	-0.011	0.187	0.189
Geometric Mean	0.130	0.054	-0.034	-0.027	0.154	-0.001	-0.028	-0.012	0.164	0.186
Quartile 3	0.180	0.137	-0.018	0.021	0.351	0.113	0.039	0.015	0.329	0.244
Maximum	0.331	0.195	0.033	0.079	0.538	0.281	0.146	0.081	0.768	0.362
Variance	0.005	0.008	0.001	0.002	0.041	0.016	0.007	0.002	0.054	0.006
Stdev	0.070	0.090	0.025	0.050	0.202	0.128	0.082	0.040	0.232	0.077
Skewness	0.549	-0.397	-0.148	0.384	-0.091	0.176	-0.081	0.117	0.091	-0.069
Kurtosis	-0.507	-1.295	0.783	-1.107	-1.158	-0.668	-0.955	-0.171	-0.416	-0.692

F.MOM

F.MOM	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-3.916	-4.163	-3.483	-4.589	-3.409	-2.445	-4.808	-2.491	-4.170	-5.565
Quartile 1	-0.507	-0.448	-0.666	-0.513	-0.764	-0.659	-0.662	-0.654	-0.488	-0.534
Median	-0.009	-0.039	-0.165	-0.080	-0.054	0.029	0.016	0.078	0.013	0.070
Arithmetic Mean	-0.042	-0.124	-0.123	-0.071	-0.137	0.034	-0.129	0.006	-0.020	-0.055
Geometric Mean										
Quartile 3	0.544	0.465	0.440	0.499	0.508	0.589	0.492	0.618	0.586	0.646
Maximum	2.152	2.592	3.178	3.179	3.571	3.240	3.192	2.798	2.176	2.764
Variance	0.922	1.086	1.129	1.000	1.062	1.105	1.127	0.984	1.019	1.348
Stdev	0.960	1.042	1.063	1.000	1.030	1.051	1.061	0.992	1.010	1.161
Skewness	-0.608	-0.764	0.044	-0.793	-0.244	0.371	-0.957	0.010	-0.872	-1.089
Kurtosis	1.480	1.826	1.326	3.522	1.081	0.509	3.120	0.031	1.893	3.947

F.MOM	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-2.243	-4.192	-4.724	-4.100	-4.488	-3.771	-3.107	-3.571	-4.866	-4.481
Quartile 1	-0.624	-0.567	-0.637	-0.599	-0.653	-0.730	-0.620	-0.567	-0.470	-0.423
Median	0.116	-0.045	-0.103	-0.026	0.017	-0.043	-0.066	0.051	0.102	-0.024
Arithmetic Mean	0.024	-0.065	-0.115	-0.020	-0.112	-0.166	-0.050	-0.046	-0.093	-0.025
Geometric Mean										
Quartile 3	0.716	0.550	0.483	0.542	0.474	0.487	0.435	0.644	0.600	0.476
Maximum	2.364	2.121	3.213	2.703	2.683	3.581	3.463	3.008	3.583	2.732
Variance	1.001	1.037	1.256	1.066	1.103	1.222	1.092	1.191	1.776	0.840
Stdev	1.001	1.018	1.121	1.032	1.050	1.106	1.045	1.091	1.333	0.916
Skewness	-0.195	-0.757	-0.515	-0.394	-0.884	-0.439	0.391	-0.434	-1.263	-0.969
Kurtosis	-0.436	1.875	2.329	1.423	2.882	1.030	1.331	0.598	2.640	4.684

F.USD

F.USD	EUR	GBP	CAD	AUD	NZD	JPY	KRW	TWD	PLN	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.111	-0.111	-0.108	-0.105	-0.103	-0.112	-0.112	-0.116	-0.113	-0.110
Quartile 1	-0.017	-0.017	-0.016	-0.016	-0.016	-0.016	-0.016	-0.017	-0.017	-0.016
Median	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000	-0.000
Arithmetic Mean	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003
Geometric Mean	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
Quartile 3	0.013	0.013	0.013	0.013	0.013	0.014	0.014	0.015	0.014	0.014
Maximum	0.062	0.060	0.060	0.058	0.054	0.055	0.057	0.059	0.058	0.056
Variance	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Stdev	0.026	0.026	0.026	0.026	0.026	0.027	0.027	0.027	0.027	0.026
Skewness	-0.734	-0.732	-0.770	-0.786	-0.801	-0.873	-0.874	-0.885	-0.840	-0.818
Kurtosis	2.062	1.962	1.910	1.857	1.816	2.136	2.072	2.109	1.919	1.803

F.USD	THB	NOK	SEK	HUF	BRL	TRY	ZAR	INR	RUB	IDR
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.111	-0.110	-0.109	-0.114	-0.112	-0.105	-0.102	-0.104	-0.107	-0.109
Quartile 1	-0.016	-0.016	-0.016	-0.018	-0.016	-0.016	-0.015	-0.016	-0.015	-0.016
Median	0.001	0.001	0.001	0.001	0.000	-0.000	-0.000	0.000	0.001	0.001
Arithmetic Mean	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.002	-0.002	-0.002	-0.002
Geometric Mean	-0.003	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
Quartile 3	0.013	0.013	0.013	0.015	0.013	0.014	0.013	0.013	0.013	0.014
Maximum	0.056	0.061	0.061	0.057	0.055	0.056	0.056	0.055	0.054	0.057
Variance	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Stdev	0.026	0.026	0.026	0.027	0.026	0.026	0.025	0.025	0.025	0.026
Skewness	-0.833	-0.742	-0.754	-0.858	-0.863	-0.776	-0.786	-0.809	-0.818	-0.812
Kurtosis	2.069	1.971	1.976	1.968	1.980	1.710	1.703	1.796	1.984	1.948

F.PMI Chg

F.PMI Chg	DKK	NOK	SEK	CHF	CAD	NZD	HUF	ZAR	CNY
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.452	-0.240	-0.123	-0.221	-0.253	-0.368	-0.199	-0.166	-0.138
Quartile 1	-0.055	-0.049	-0.025	-0.025	-0.077	-0.045	-0.040	-0.030	-0.009
Median	0.003	0.002	-0.003	0.003	-0.002	0.000	0.006	-0.001	0.000
Arithmetic Mean	0.000	-0.000	-0.001	0.000	0.000	0.001	-0.000	-0.000	-0.001
Geometric Mean	-0.006	-0.003	-0.002	-0.001	-0.007	-0.003	-0.002	-0.002	-0.001
Quartile 3	0.062	0.039	0.024	0.023	0.077	0.053	0.038	0.034	0.010
Maximum	0.353	0.249	0.140	0.119	0.414	0.290	0.141	0.195	0.092
Variance	0.011	0.006	0.002	0.002	0.014	0.007	0.003	0.003	0.001
Stdev	0.106	0.078	0.041	0.043	0.118	0.085	0.057	0.055	0.031
Skewness	-0.699	0.086	0.122	-0.672	0.155	-0.316	-0.241	0.110	-0.724
Kurtosis	2.951	0.814	0.484	3.928	0.175	2.191	0.363	1.319	4.862

F.PMI Rel

F.PMI Rel	DKK	NOK	SEK	CHF	CAD	NZD	HUF	ZAR	CNY
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-0.408	-0.279	-0.140	-0.148	-0.263	-0.291	-0.176	-0.356	-0.207
Quartile 1	-0.036	-0.056	-0.043	-0.034	-0.003	-0.058	-0.053	-0.120	-0.090
Median	0.042	-0.010	0.022	0.028	0.065	0.019	-0.006	-0.066	-0.036
Arithmetic Mean	0.028	-0.001	0.022	0.028	0.061	0.006	-0.008	-0.070	-0.026
Geometric Mean	0.022	-0.005	0.019	0.024	0.056	0.001	-0.011	-0.076	-0.030
Quartile 3	0.106	0.053	0.086	0.081	0.130	0.073	0.035	-0.002	0.015
Maximum	0.269	0.239	0.204	0.240	0.289	0.226	0.152	0.155	0.290
Variance	0.013	0.008	0.006	0.008	0.010	0.009	0.004	0.012	0.008
Stdev	0.116	0.091	0.077	0.089	0.100	0.093	0.067	0.108	0.087
Skewness	-0.736	-0.017	-0.004	0.199	-0.405	-0.446	-0.133	-0.436	0.922
Kurtosis	0.864	0.443	-0.817	-0.517	0.365	-0.190	-0.457	0.089	1.456

F.FXFuture

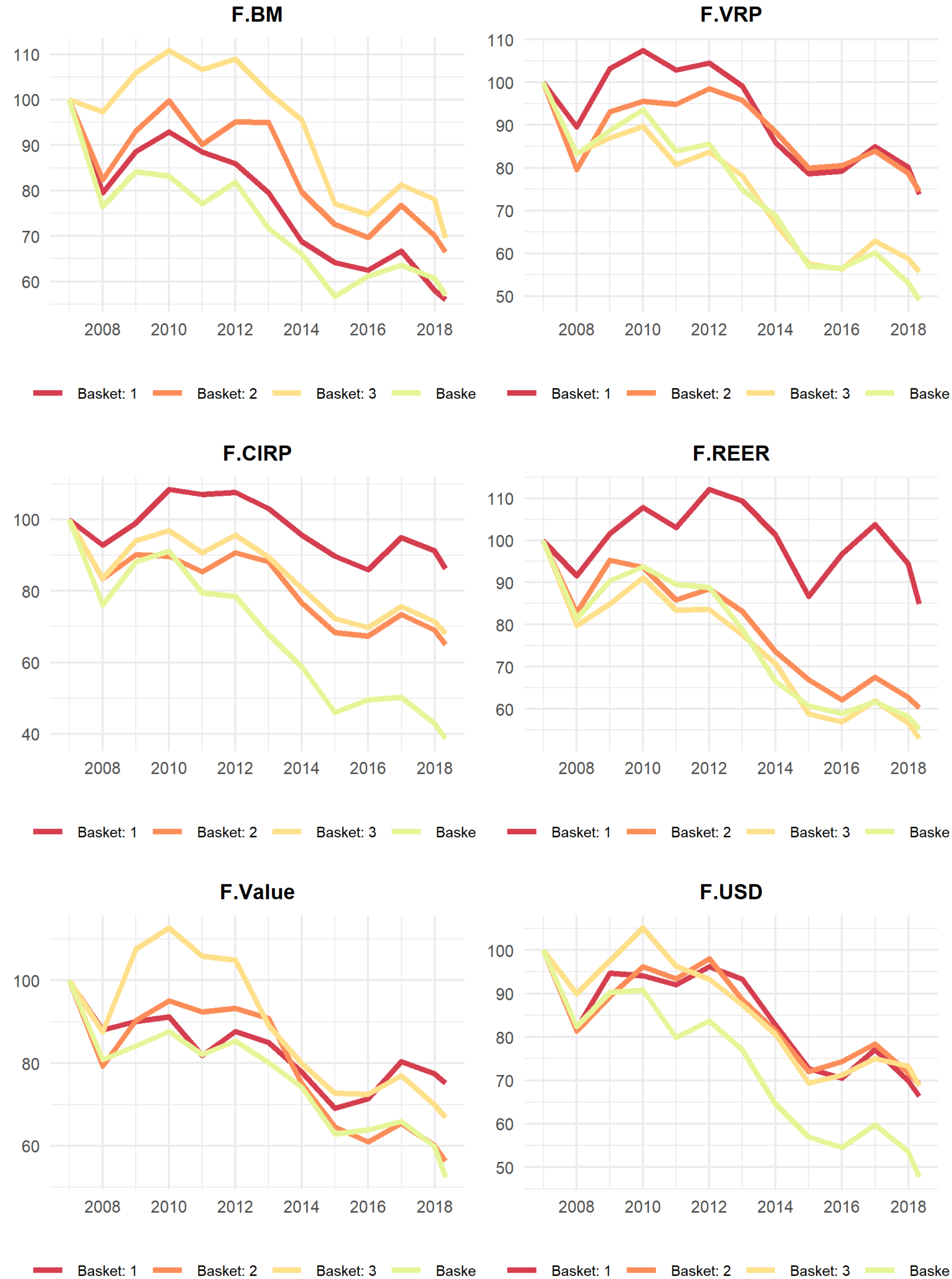
F.FXFuture	EUR	GBP	CHF	CAD	AUD	NZD	JPY	MXN
Observations	156.000	156.000	156.000	156.000	156.000	156.000	156.000	156.000
Minimum	-1.134	-3.881	-4.274	-2.487	-3.058	-5.220	-3.402	-4.057
Quartile 1	-0.576	-1.461	-0.469	-0.953	-0.536	-0.619	-0.510	-0.743
Median	-0.432	-0.473	-0.078	-0.410	-0.041	-0.143	-0.021	-0.480
Arithmetic Mean	-0.218	-0.070	-0.035	-0.176	-0.234	-0.219	-0.507	-0.366
Geometric Mean								
Quartile 3	0.137	1.691	0.650	0.324	0.173	0.480	-0.002	0.197
Maximum	2.073	4.065	4.434	2.159	3.477	3.870	2.579	2.969
Variance	0.206	2.363	2.590	1.167	1.172	2.621	1.779	1.013
Stdev	0.454	1.537	1.609	1.081	1.083	1.619	1.334	1.006
Skewness	1.261	0.521	-0.348	0.713	-0.808	-1.074	-1.190	0.139
Kurtosis	3.012	-0.465	0.880	-0.238	2.158	2.604	0.842	1.999

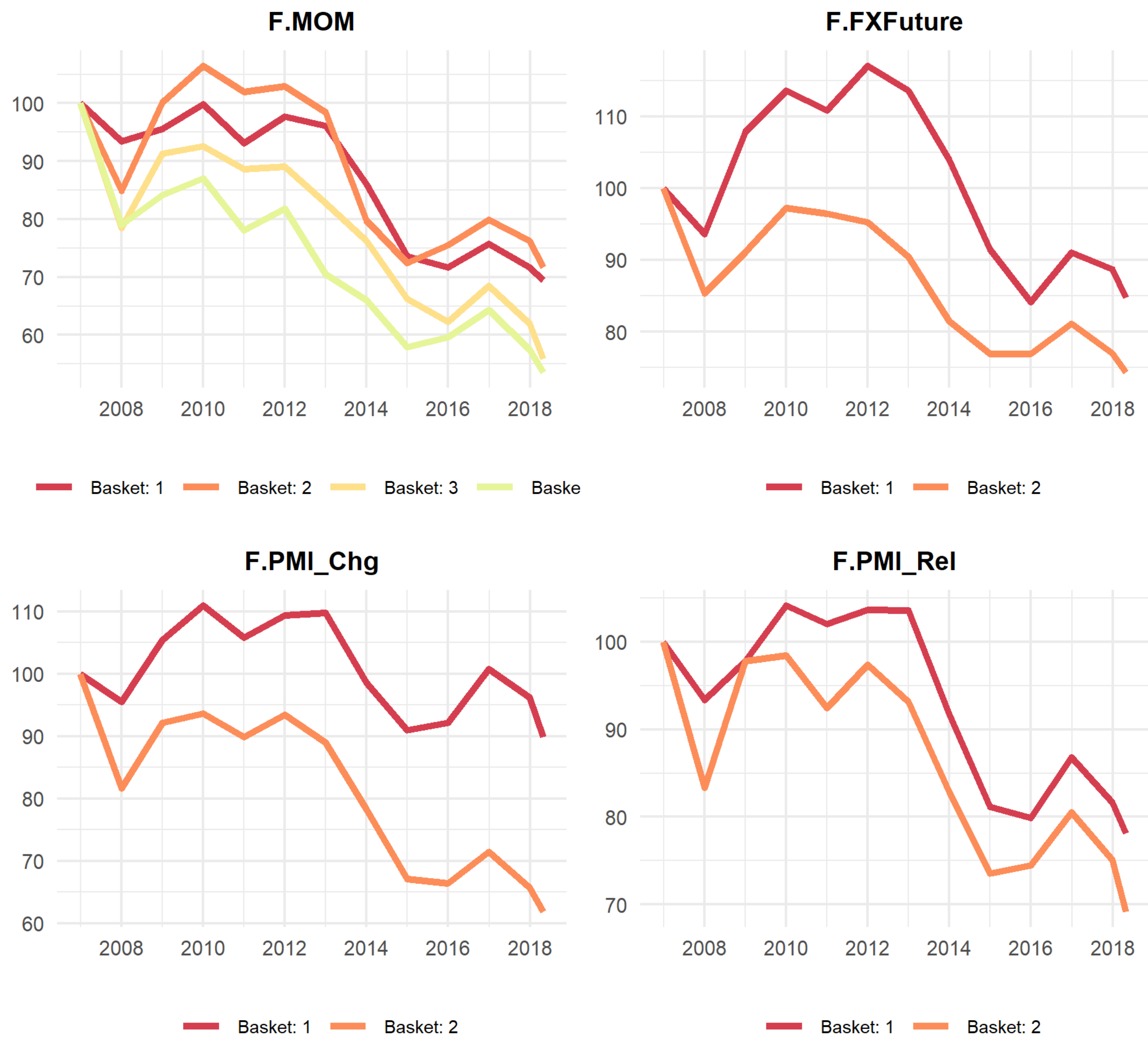
9.3 Individual Portfolio Performance

Currency Basket Performance for each Factor with Monthly Reallocation


F.Value
120
100
80
60
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2
Basket: 3
Baske
F.USD
120
100
80
60
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2
Basket: 3
Baske
F.MOM
120
100
80
60
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2
Basket: 3
Baske
F.FXFuture
130
120
110
100
90
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2
F.PMI_Chg
140
120
100
80
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2
F.PMI_Rel
130
110
90
2007
2009
2011
2013
2015
2017
2019
Basket: 1
Basket: 2

Currency Basket Performance for each Factor with Yearly Reallocation




F.MOM
100
90
80
70
60
2008
2010
2012
2014
2016
2018
Basket: 1
Basket: 2
Basket: 3
Baske
F.FXFuture
110
100
90
80
2008
2010
2012
2014
2016
2018
Basket: 1
Basket: 2
F.PMI_Chg
110
100
90
80
70
60
2008
2010
2012
2014
2016
2018
Basket: 1
Basket: 2
F.PMI_Rel
100
90
80
70
2008
2010
2012
2014
2016
2018
Basket: 1
Basket: 2

9.4 Abstracts

Abstract English

We test volatility risk premium as a new predictive variable for a currency prediction model. Volatility risk premium is the difference between the expected realized exchange rate volatility and options implied volatility. From the perspective of an investor, it is the insurance cost against currency volatility fluctuations. Our analysis shows that volatility risk premium is complementary to commonly used indicators such as interest rate parity, value, real effective exchange rate and order flows. It does not show significant correlation with already known risk factors and contains new information to determine future currency movements. Our data comprises twenty currencies denominated against the USD from developed and emerging countries from 2006 to 2018. Our intention is to predict one-month, six-month and one-year currency returns. To do so, we use the indicators to test several currency trading strategies and to conduct numerous regression analysis. All in all, volatility risk premium is a valuable indicator that perfectly complements covered interest rate parity, value, real effective exchange rate and order flows in a currency prediction model.

Abstract Deutsch

Wir testen Volatilitätsrisiko Prämie als neuen prädiktiven Indikator für ein Währungsprognose-modell. Dies ist die Differenz zwischen der erwarteten realisierten Wechselkursvolatilität und der impliziten Volatilität von Währungsoptionen. Aus der Sicht eines Investors stellt es die Versicherungskosten gegen Währungsschwankungen dar. Unsere Analyse zeigt, dass die Volatilitätsrisiko Prämie eine gute Ergänzung zu häufig verwendeten Währungsindikatoren wie Zinsparität, Kaufkraftparität, Realer Wechselkurs und Auftragsflüsse von Währungsgeschäften ist. Sie zeigt keine signifikante Korrelation mit bereits bekannten Risikofaktoren und enthält neue Informationen zur Bestimmung zukünftiger Währungsbewegungen. Unsere Daten umfassen zwanzig Währungen aus Industrie- und Schwellenländern gegenüber dem USD von 2006 bis 2018. Wir beabsichtigen die Währungsrenditen für einen Monat, sechs Monate und einem Jahr vorherzusagen. Dazu verwenden wir Indikatoren um mehrere Handelsstrategien zu testen und führen zahlreiche Regressionsanalysen durch. Alles in allem ist die Volatilitätsrisiko Prämie ein wertvoller Indikator um Zinssatzparität, Kaufkraftparität, Realer Wechselkurs und Auftragsflüsse von Währungsgeschäften in einem Währungsprognosemodell zu ergänzen.

10. References

Ahmed, Shamim, Xiaoquan Liu, and Giorgio Valente. 2016. "Can Currency-Based Risk Factors Help Forecast Exchange Rates?" *International Journal of Forecasting* 32 (1): 75–97.

Aloosh, Arash, and Geert Bekaert. 2019. "Currency Factors." Cambridge, Mass., USA: National Bureau of Economic Research. http://www.nber.org/papers/w25449.pdf.

Balduzzi, Pierluigi, and I-Hsuan Ethan Chiang. 2019. "Real Exchange Rates and Currency Risk Premiums." *The Review of Asset Pricing Studies*.

Barroso, Pedro, and Pedro Santa-Clara. 2015. "Beyond the Carry Trade: Optimal Currency Portfolios" 50 (5): 1037–56.

Carr, Peter, and Liuren Wu. 2009. "Variance Risk Premiums." *The Review of Financial Studies* 22 (3): 1311–41.

Cheung, Yin-Wong, Menzie D. Chinn, Antonio Garcia Pascual, and Yi Zhang. 2019. "Exchange Rate Prediction Redux: New Models, New Data, New Currencies." *Journal of International Money and Finance* 95: 332–62.

Clark, Iain J. 2011. *Foreign Exchange Option Pricing : : A Practitioner's Guide*. Wiley Finance Series. Chichester, West Sussex, U.K. : Wiley,

Colacito, Riccardo, Steven J. Riddiough, and Lucio Sarno. 2018. "Business Cycles and Currency Returns." *SSRN Electronic Journal*, December, 1–55. https://doi.org/10.2139/ssrn.2906600.

Della Corte, Pasquale, Tarun Ramadorai, and Lucio Sarno. 2016. "Volatility Risk Premia and Exchange Rate Predictability." *Journal of Financial Economics* 120 (1): 21–40.

Engel, Charles, Nelson C. Mark, and Kenneth D. West. 2014. "Factor Model Forecasts of Exchange Rates." *Econometric Reviews* 34 (1-2).

Engel, Charles, Nelson C. Mark, Kenneth D. West, Kenneth Rogoff, and Barbara Rossi. 2007. "Exchange Rate Models Are Not as Bad as You Think [with Comments and Discussion]." *NBER Macroeconomics Annual* 22: 381–473.

Engel, Charles, and Kenneth D. West. 2005. "Exchange Rates and Fundamentals." *Journal of Political Economy* 113 (3).

Fourel, Valere, Dagfinn Rime, Lucio Sarno, Maik Schmeling, and Adrien Verdelhan. 2015. "Common Factors, Order Flows, and Exchange Rate Dynamics." *SSRN Electronic Journal*, no. 1: 1–24.

Hackl, Peter. 2013. *Einführung in Die ökonometrie*. 2., aktualisierte Aufl.. Wi, Wirtschaft 4156. München [u.a.]: Pearson.

Harri, Ardian, and B Wade Brorsen. 2009. "The Overlapping Data Problem." *SSRN Electronic Journal* 3 (January): 78–115. https://doi.org/10.2139/ssrn.76460.

Haug, E.G. 2007. *The Complete Guide to Option Pricing Formulas*. McGraw-Hill. https://books.google.at/books?id=tuoJAQAAMAAJ.

Investopedia. 2019. "Uncovered Interest Rate Parity." https://www.investopedia.com/terms/u/uncoveredinterestrateparity.asp. 2019.

IPC. 2019. "International Parity Conditions." https://www.slideshare.net/buscxc/international-investment-2. 2019.

Jiang, George J., and Yisong S. Tian. 2005. "The Model-Free Implied Volatility and Its Information Content." *The Review of Financial Studies* 18 (4): 1305–42.

Koenig, Evan F, and others. 2002. “Using the Purchasing Managers’ Index to Assess the Economy’s Strength and the Likely Direction of Monetary Policy.” *Federal Reserve Bank of Dallas Economic and Financial Policy Review* 1 (6): 1–14.

Kruskal, William. 1987. “Relative Importance by Averaging over Orderings.” *The American Statistician* 41 (1): 6–10.

Lindeman, Richard H., Peter F Merenda, and Ruth Z. Gold. 1980. *Relative Importance by Averaging over Orderings*. 1. Glenview (Ill.) : Scott, Foresman, 1980.

Mark, Nelson, and Donggyu Sul. 2018. “IDENTIFYING Exchange Rate Common Factors.” *International Economic Review* 59 (4): 2193–2218. http://search.proquest.com/docview/2132310049/.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf. 2012. “Currency Momentum Strategies.” *Journal of Financial Economics* 106 (3): 660–84.

Rossi, Barbara. 2013. “Exchange Rate Predictability †.” *Journal of Economic Literature* 51 (4): 1063–1119.

Theil, Henri. 1996. *Applied Economic Forecasting*. North-Holland Pub. Co.

Wang, Peijie. 2009. *The Economics of Foreign Exchange and Global Finance*. Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg.