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Abstract

This thesis studies the connection between the forward premium and volatility. In the first part a SDF framework is used to perform an empirical test on the relationship between the forward premium and global FX volatility. The estimation is done using GMM. I found a negative relationship between currencies which offer a high carry relative to the USD and global FX volatility. The second part test the currency trading strategy of Corte, Ramadorai, and Sarno (2016) which uses the volatility risk premium to select currencies. This strategy sells currencies which are expensive to insure and buys currencies which are cheap to insure. I show that the strategy does not yield a significant positive return. Moreover the strategy does not provide any valuable information about spot price movements.

Keywords: Forward premium puzzle, carry, volatility risk premium, currency predictability.

1. Introduction

The concept of a currency carry trade is around for a very long time. It simply means one borrows in a low interest rate currency and lends in a high interest currency. The trader then seeks to capture the interest rate differential. Nevertheless, the concept of Uncovered Interest Parity (UIP) states that the exchange rate should move in a way such that this trade does not yield any profits. It has, however, been shown by several empirical studies, the most prominent is probably Fama (1984), that UIP does not hold. Because UIP fails to hold, the currency carry trade is a profitable investment strategy on average (see Brunnermeier, Nagel, and Pedersen (2008)). This violation of the UIP is called the forward premium puzzle. It is actually quiet astonishing that such a strategy can be profitable for such a long time in the FX market. This market is generally known as being highly liquid and having low transaction costs. Moreover, the presence of speculators in that market, which is reported by Brunnermeier, Nagel, and Pedersen (2008), should have led to no profitable carry trades in this market.

Engel (1984) and Fama (1984) explain the findings with the concept of time-varying risk premia. This means their theory states that investments in high interest currencies are highly risky and thus particularly exposed to market turbulences. Because of this risk risk averse investors reward these currencies with a higher risk premium. In the last 10 years several studies showed that there is empirical support for that theory. Brunnermeier, Nagel, and Pedersen (2008), as well as Menkhoff et al. (2012) found empirical evidence. Both studies showed that risk measured by volatility is able to explain the forward premium puzzle. Their findings confirmed that high interest currencies are more exposed to a crash in bad times than low interest currencies. Therefore, high interest currencies yield a risk premium above low interest currencies to encounter investors for this higher risk.

The study of Corte, Ramadorai, and Sarno (2016), builds on those findings and introduces a trading strategy which exploits this risk premium. They sort currencies into portfolios according to their volatility risk premium. They short sell currencies with a low premium and go long currencies with a high risk premium. The study demonstrates that this is not only a profitable strategy, the returns from this strategy are also uncorrelated to returns from other FX strategies such as momentum, carry, and value.

All in all, in the last 10 years a lot of progress has been made towards understanding the forward risk premium. This thesis will builds on the findings of Menkhoff et al. (2012) and will show that volatility risk can explain parts of the forward premium puzzle. If that can be shown it might be possible using that information to forecast the spot movement in the exchange rates, as Corte, Ramadorai, and Sarno (2016)

demonstrated. I will set up an investment strategy which exploits this volatility risk premium and investigate whether this yields any excess return. Moreover, I will also test if that is really a new strategy or if those returns can be explained by any other already well known investment strategy.

The central theme of this master thesis is to test whether the volatility can be used to predict spot price movements in order to obtain a return in excess of UIP. This thesis is structured in the following way. I start with chapter two where I introduce the forward premium puzzle and give and overview over the literature. The third chapter covers the theoretical asset pricing setup as well as the empirical estimation. The fourth chapter presents a trading strategy based on FX volatility. Chapter five concludes over the findings.

2. Motivation and Literature Overview

The Forward Premium has been studied for decades. In principle it is a violation of the UIP which is essentially a no arbitrage condition. Suppose the interest rate in Europe is $\mathrm{I_{EUR}}$ and the interest rate in the U.S. is $\mathrm{I_{USD}}$. In addition, let us assume that the U.S. interest rate is lower. A U.S. investor could borrow money in the U.S. and lend it in Europe. By doing so he would make a profit since $I_{EUR} - I_{USD} > 0$. However, this trade only pays off if the exchange rate would stay unchanged. If all U.S. investors want to lend their money which they borrowed in US Dollar in Euro they have to exchange their US Dollars into Euros. When their investment is completed, hence the European borrower repaid the loan, they have to exchange their Euros back into U.S. Dollars to repay their loan. If the U.S. Dollar appreciated during the trade up to a certain value the trade would not have been profitable. In fact, the U.S. Dollar should appreciate to a value which reduces the profits of the trade to exactly zero, otherwise an arbitrage opportunity would exist. Generally, the low interest rate currency is referred as the funding currency while the high interest currency is referred as the investment currency. Let me show this relationship more formally:

Let S_t be the spot rate of the Euro Dollar exchange rate in period t, hence S_t denotes the price of foreign currency in terms of domestic currency. Then UIP states that:

$$\frac{\mathrm{E(S_{t+1})}}{\mathrm{S_t}}(1 + \mathrm{I_{EUR}}) = (1 + \mathrm{I_{USD}}) \qquad (1)$$

Let from now on the natural logarithms of a variable be denoted by a small letter, hence $s_t = \log S_t$. By taking the natural logarithm of equation 1 one obtains:

$$E(s_{t+1}) - s_t = i_{USD} - i_{EUR} \quad (2)$$

This is the most famous representation of the UIP. If we replace the expected spot rate by the forward rate we get the covered interest rate parity (CIP):

$$f_t - s_t = i_{USD} - i_{EUR} \quad (3)$$

Notice that the natural logarithm of the forward rate f is not in expectations since it is known in period t. Covered interest parity usually holds close in the data (see Akram, Rime, and Sarno (2008)). However, UIP does not hold empirically. The difference between the forward rate and the spot rate in period t is known as the carry.

With the interest rates different, CIP implies a depreciation of the investment currency. Hence, the forward rate is bigger than the spot rate. In order for UIP to hold the forward rate in period t must be equal to the spot rate in period t+1. In other words, the investment currency should depreciate to the forward rate. If, however, UIP does not hold the return on a carry trade is positive. As mentioned before it has already been shown long time ago that the UIP and hence the simple market efficiency hypothesis does not hold in the currency market (see Hansen and Hodrick (1980)). The average excess return one gets by being long the high interest currency is on average positive over time. This finding is consistent over decades. Therefore, the phenomena cannot simply be described as a sort of behavioral finance abnormality which occurred for a short time and was gone as soon as it was discovered. The fact that this excess return is consistent indicates that it might not be a free lunch, it should actually be a reward for taking a risk. As mentioned in the introduction the most prominent explanation of the forward premium puzzle is the theory of time varying risk premia. The task is to identify factors which explain that premium. Actually, a case can be made for a variety of factors (see Brunnermeier, Nagel, and Pedersen (2008), Menkhoff et al. (2012), as well as Lustig, Roussanouv, and Verdelhan (2011)). This thesis will focus on the factor volatility. It is, however, worthwhile to mention that that factor is definitely not the only factor which explains a part of the puzzle. The forward premium is caused by different sources of risk. I will also show that political risk (idiosyncratic risk) has a connection to the forward premium to support the finding that volatility can only explain a part of the forward premium.

Brunnermeier, Nagel, and Pedersen (2008) where among the first to show that currencies which offer a higher carry are more exposed to crash risk. This means the higher the carry the more negative skewed is

the distribution of returns. Although these currencies deliver on average a positive carry trade return one is more likely to face extreme devaluations with such currencies than with currencies which yield on average a smaller carry return. The theory is the following, for every carry trader there must be another investor who is willing to accept a negative carry. Those investors can be risk averse agents who want to be insured against currency devaluations, hence they are willing to pay a premium (the negative carry for the insurance). The more likely a crash is the more expensive is the insurance. The study of Lustig, Roussanouv, and Verdelhan (2011) identifies two risk factors which drive the excess returns of carry trades. The first is the so called Dollar Risk Factor (DOL), this factor is the average of all forward risk premia relative to the dollar. The factor identifies the part of the risk premia which an investor obtains for investing outside of the United States. The second factor is the High minus Low factor (HML). This factor is constructed by being long high interest rate currencies and short low interest rate currencies. It can be interpreted as the slope and is essentially a zero cost strategy. Their approach is the same used here. They use a stochastic discount factor model (SDF) to price the excess returns of five different portfolios which are constructed by sorting currencies according to their carry. The advantage of their approach is that it can be shown that the HML factor is a common risk factor to which all currencies are exposed in a similar way. This means that risk factor is systemic and cannot be fully diversified away at no costs. Menkhoff et al. (2012) use the same methodology, but identify a new common risk factor: global FX volatility innovations (VOL). This risk factor captures developments in the global volatility of the FX market. They could show that currencies with a higher carry take losses during times of high volatility while currencies with a low forward premium serve as a hedge against an increase in volatility. Therefore, the excess return over UIP, which high interest rate currencies generate, is at least partially a reward for being exposed to volatility developments. Again, the concept of insurance with risk averse agents explains their findings. Volatility increases as market turbulences increases, since low interest rate currencies insure against that risk their return will be lower. Menkhoff et al. (2012) also show that sorting currencies according to their beta with volatility is similar to sorting by the carry. Moreover, in their study they also show that their volatility factor is correlated with common measures of global market liquidity such as the TED spread. However, in any asset pricing test they did the volatility factor always dominated the liquidity factor meaning the volatility factor is the stronger force.

The study of Corte, Ramadori, and Sarno (2016) presents a currency carry trading strategy which uses FX volatility to predict the movements in the spot rate. They calculated implied volatility according to Britten-Jones and Neuberger (2000). They then estimated the volatility risk premia as realized volatility minus implied volatility. Afterwards, they constructed portfolios where currencies are sorted according

to their volatility risk premium. Portfolio 5 contains the 20% of currencies which are cheapest to insure (highest volatility risk premium), while portfolio 1 contains the currencies which are most expensive to insure. They then calculated the average excess return (in excess to UIP) within the portfolios, as well as the return from a strategy which is long portfolio 5 and short portfolio 1. The intuition behind the strategy is rather simple: the realized volatility is usually below implied volatility. Whenever the opposite is true, this is usually caused by a selloff. Since volatility is mean reverting the volatility level is expected to decrease to lower levels right after the selloff. The strategy selects currencies which suffered a huge selloff, and bets on a reversal. Note that the strategy presented in Corte, Ramadori, and Sarno (2016) uses developments in the individual volatility of a currency (idiosyncratic and systemic risk) while Menkhoff et al. (2012) use global volatility innovations (systemic risk).

3. Pricing the Risk Factor Global FX Volatility

3.1. Data

The sample covers 38 countries, the earliest observation starts on 21.12.1983. The sample is not balanced, this means for some countries data is available at a longer horizon than for others. A list of these countries and the length of their data streams can be found in the appendix. All exchange rates are relative two the U.S. Dollar. I collected the exchange rates on a daily frequency. Although the analysis will be done on a monthly frequency I need the daily exchange rate data to construct the volatility proxy. That process will be described in more detail later. In addition, I also collected data on the forward points of the 1 month forwards. I then calculated the forward rate using the forward points and the spot rate together. If no data on the forward points was available I used the outright instead. For the spot as well as the forward points I collected data for bid, ask, and mid quote. If only two of these three where available I calculated the third using the following relationship:

$$Mid = \frac{Bid + Ask}{2}$$

That was, however, only necessary for two observations. I took the political risk score from the Economist Intelligence Unit (EIU) as a measure of political risk. The data is available on a monthly basis.

All data was collected from Bloomberg. The statistical calculations are all done using the software package “R”.

3.2. Constructing Portfolios

I construct five different portfolios where the currencies are sorted according to their forward discount $f - s$. This means portfolio 1 contains the currencies with the highest positive forward discount and portfolio 5 contains the currencies with the highest negative forward discount. In effect, the currencies in portfolio 5 are the funding currencies. I followed the studies of Lustig, Roussanouv, and Verdelhan (2011) as well as Menkhoff et al. (2012) and adjusted portfolio 1 to 4 for transaction costs which occur with long positions and portfolio 5 with transaction costs which occur with short positions. To calculate the forward discount both the mid quote for the forward rate and the spot rate are used. Since Covered Interest Parity (CIP) usually holds closely in the data, sorting according to the forward discount is equivalent to sorting according to the interest rate differential (Menkhoff et al. (2012), 688). I started the Portfolio selection in April 1997. At this point in time I had data on 16 different currencies. If possible, currencies are sorted such that all portfolios contain an equal number of currencies. This means after the exercise there are five portfolios where portfolio number 1 contains the 20% of currencies with the highest forward discount and portfolio 5 contains the 20% of currencies with the lowest forward discount. I follow Lustig, Roussanouv, and Verdelhan (2011) and Menkhoff et al. (2012) and use equally weighted portfolios. If the number of currencies divided by five does not yield an integer number, the additional currencies are first allocated to the portfolios with the lower forward discount. This means if there is data on 17 currencies, portfolio 1-3 contains 3 currencies each and portfolio 4 and 5 contains 4 currencies each. The portfolios are rebalanced every month. I follow Lustig, Roussanouv, and Verdelhan (2011) as well as Menkhoff et al. (2012) and built the portfolios such that I assume investors are long all currencies in portfolio 1-4 and are short all currencies in portfolio 5. The return of a currency which exits the portfolio at t+1 and entered the portfolio at time t is $rx^l_{i,t+1} = f^b_t - s^a_{t+1}$ for a long position and $rx^s_{i,t+1} = -f^a_t + s^b_{t+1}$ for a short position. If the currency stays in the portfolio the return is $rx^l_{i,t+1} = f^b_t - s_{t+1}$for a long position and $rx^s_{i,t+1} = -f^a_t + s_{t+1}$for a short position. For currencies which have been in the portfolio before period t the return is: $rx^l_{t+1} = f_t - s^a_{t+1}$ for a long position and $rx^s_{t+1} = -f_t + s^b_{t+1}$ for a short position. The return for currencies which have been in the portfolio before period t and stay in the portfolio after period t+1 is: $rx^l_{t+1} = f_t - s_{t+1}$ for a long position and $rx^s_{t+1} = -f_t + s_{t+1}$ for a short position. In the first period all currencies enter a portfolio and in the last period all currencies exit a portfolio. All returns are calculated as log returns.

Portfolio	1	2	3	4	5	Avg.	H/L
Mean	5.74%***	1.11%	0.28%	-0.81%	-2.09%**	0.84%	7.99%***
Median	7.55%	3.46%	1.55%	-1.20%	-2.93%	0.94%	11.85%
Std. dev	8.99%	7.28%	6.57%	5.82%	4.40%	6.61%	11.02%
Skewness	-0.91	-0.72	-0.95	0.10	0.60	-0.38	-1.25
Kurtosis	3.83	2.74	3.57	0.99	3.23	2.87	6.43
Sharpe Ratio	0.21	-0.37	-0.54	-0.79	-1.34	-0.57	0.38

Table 1: Portfolio Overview: Portfolio 1-4 contain long trades, while portfolio 5 contains short trades only. Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. The significance level of the returns is calculated using a simple t test. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

Table 1 shows the results of this portfolio construction. The returns of the portfolios is decreasing as moving from portfolio 1 to 5. This is in line with findings of Lustig, Roussanouv, and Verdelhan (2011) and Menkhoff et al. (2012) the return of portfolio 5 is the negative of the short position return. Hence, in shorting all currencies in portfolio 5 would yield a positive return. This picture is also robust to the choice of the length of the sample. If one would also use short positions in portfolio 4 the return would increase and become positive. This suggests that the majority of forward discounts are negative, but small in absolute terms in that portfolio. Since this is a priori unknown I decided using long positions in portfolio 4 to be in line with Lustig, Roussanouv, and Verdelhan (2011) and Menkhoff et al. (2012) and to avoid data mining problems. The column H/L is a portfolio which is long portfolio 1 and short portfolio 5. Most important here is that the structure found by the two previous studies does also hold here for the mean, the median, the skewness, and the Sharpe ratio. Only the kurtosis does not show any pattern. Menkhoff et al. (2012) found a decreasing kurtosis as one moves from portfolio 1 to portfolio 5. The magnitude of the return is also comparable to findings of Menkhoff et al. (2012). Histograms of the portfolio excess returns can be found in the appendix. The table motivates the forward premium puzzle and shows that there is considerable evidence against UIP in the short run.

The column Avg. presents the average return over all 5 portfolios, which is exactly the Dollar Risk factor used in the two papers mentioned earlier in this paragraph. This factor represents the benefit one gets by investing outside the United States. I will call that factor form now on DOL. The returns that this factor delivers can be seen as a reward for leaving the safe heaven currency USD and taking foreign country risk.

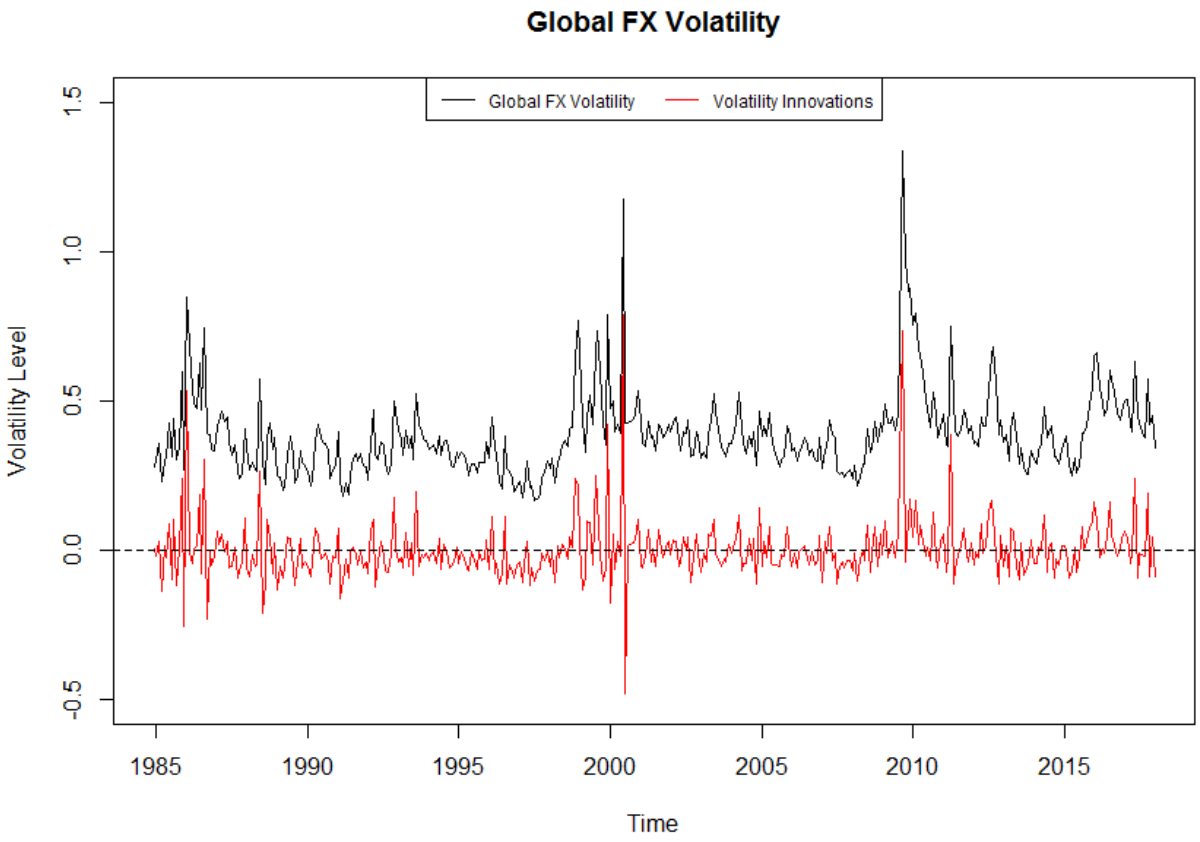
3.3. Measuring Volatility Innovations

I measure volatility innovations in a similar way as Menkhoff et al. (2012). I start by calculating the absolute daily log return for every currency k on day τ in the sample: $\left|r_{\tau}^{k}\right|$. The daily sample starts on the

21.12.1983 and goes until the 28.02.2017. I then calculate the monthly global FX volatility according to the following formula:

$$\sigma_t^{FX} = \frac{1}{T_t}\sum_{\tau \in T_t}[\sum_{k \in K_t}(\frac{|r_\tau^k|}{K_\tau})] \quad (4)$$

Where T_t denotes the number of trading days in a month and K_τ denotes the number of currencies for which data is available at day τ. This gives a global volatility observation σ_t^{FX} for each month. Note that the currencies here are equally weighted and not weighted according to shares in international trade. Menkhoff et al. (2012) provide robustness checks for that in their study and show that this does not make much of a difference. For the analysis of the connection between the forward premium and volatility innovations I need the change in volatility rather than the absolute level. These changes are, however, significantly autocorrelated. Therefore, I follow Menkhoff et al. (2012) and use the residuals from an estimated AR(1) model of the global volatility proxy as the volatility innovations. The estimation is done over the full sample exactly as Menkhoff et al. (2012) did it in their study. Graph 1 depicts both the global volatility proxy as well as the volatility innovations obtained from the AR(1) process.



Graph 1 This graph depicts the Global FX Volatility as estimate by equation (4) and the residuals of an AR(1) model of the Global FX Volatility. Both time series shown in this graph are multiplied by the factor 100.

One can see that several crises are covered by the volatility proxy. These are the 1987 crash, the internet bubble as well as the financial crisis of 2008. Hence, this volatility proxy seems to capture times of market turbulences quite well.

3.4. Asset Pricing Tests

3.4.1. Pricing the Risk Factors

The model used here to test the explanatory power of volatility innovations is a simply stochastic discount factor model (SDF). The approach is similar to the one presented in Cochrane (2001). Additionally, the approach was also used by Menkhoff et al. (2012) as well as Lustig, Roussanouv, and Verdelhan (2011). Let m_{t+1} be the discount factor. Then the expected discounted excess return is equal to zero.

$$E\left[m_{t+1} rx_{t+1}^{i}\right] = 0 \tag{5}$$

If the discount factor is linear one can set up a beta pricing model of the form $E\left[rx_{t+1}^{i}\right] = \lambda'\beta_i$, where both λ (the factor price) and β (the quantity of the factor) are vectors. This can easily be shown. Let $m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{VOL}VOL_{t+1}$ be the SDF. Where b is a coefficient, DOL_{t+1} and VOL_{t+1} are the Dollar risk factor and the volatility innovations. The letter μ denote the mean of a factor. Note that μ_{VOL} must be equal to zero, because VOL_{t+1} are the residuals of an AR(1) process. Since $cov\left(m_{t+1}, rx_{t+1}^{i}\right) = E\left[m_{t+1}rx_{t+1}^{i}\right] - E[m_{t+1}]E\left[rx_{t+1}^{i}\right]$ equation 5 can be written as:

$$0 = E[m_{t+1}]E\left[rx_{t+1}^{i}\right] + cov\left(m_{t+1}, rx_{t+1}^{i}\right) \tag{6}$$

The expected value of the discount factor equals one:

$$E[m_{t+1}] = E[1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{VOL}VOL_{t+1}] =$$

$$= 1 - b_{DOL}(E[DOL_{t+1}] - \mu_{DOL}) - b_{VOL}E[VOL_{t+1}] = 1$$

Note that $E[DOL_{t+1}] = \mu_{DOL}$ and $E[VOL_{t+1}] = 0$

Therefore, equation 6 can be simplified:

$$0 = E\left[rx_{t+1}^{i}\right] + cov\left(m_{t+1}, rx_{t+1}^{i}\right)$$

By substituting for the SDF one obtains:

$$E\left[rx_{t+1}^{i}\right] = b_{DOL}cov\left(DOL_{t+1}, rx_{t+1}^{i}\right) + b_{VOL}cov\left(VOL_{t+1}, rx_{t+1}^{i}\right)$$

Dividing and multiplying by the variance of the risk factors yields:

$$E\left[rx_{t+1}^{i}\right] = b_{DOL}\frac{cov\left(DOL_{t+1}, rx_{t+1}^{i}\right)}{Var(DOL)}Var(DOL) + b_{VOL}\frac{cov\left(VOL_{t+1}, rx_{t+1}^{i}\right)}{Var(VOL)}Var(VOL) \tag{7}$$

This can be simplified to:

$$E\left[rx_{t+1}^{i}\right] = \lambda_{DOL}\beta_{DOL}^{i} + \lambda_{VOL}\beta_{VOL}^{i} \tag{8}$$

Where $\lambda_{DOL} = b_{DOL}Var(DOL)$ and $\beta_{VOL}^{i} = \frac{cov\left(DOL_{t+1}, rx_{t+1}^{i}\right)}{Var(DOL)}$, the coefficients for the volatility risk factor are of similar style. Note that the price of risk is the same for all assets, while the quantity of risk varies from asset to asset. Moreover, form equation 7 it can be seen that $\lambda_{DOL} = var(DOL)b_{DOL}$ (similar for the other risk factor). Hence, by estimating the variance of the risk factor as well as the coefficient in the SDF one can estimate the price of the risk factor.

I will empirically estimate β as well as λ. The quantity of risk can easily be obtained by running an OLS regression of the two risk factors on the excess returns of the portfolio. Estimation of the price of risk is also not too complicated. In principle, the literature offers two options. The first one is the so called Fama and MacBeth (1973) (FMB) methodology. This method builds on the OLS methodology. The second option, Generalized Methods of Moments (GMM), is a more modern approach. The advantages of GMM are simply that no distribution has to be specified, it allows for heterogeneity of unknown form, and parameters can be estimated even if the model cannot be solved analytically (Verbeek (2004), p. 169). I consider GMM to be superior to the traditional FMB approach for the reasons mentioned and decided to use the GMM approach. Studies like Lustig, Roussanouv, and Verdelhan (2011) and Menkhoff et al. (2012) which used both approaches showed that both methodologies deliver similar results.

3.4.2. An Introduction to Generalized Methods of Moments

I will explain the GMM approach in an asset pricing environment, in principle, the approach can also be applied to different kind models. This chapter only provides a very brief overview over the methodology, more detailed information about GMM can be found in Hall (2005) and Cochrane (2001). GMM is actually a very straightforward and intuitive approach. The standard SDF approach delivers the equation:

$$E[m(b)rx_{t+1}] = 0$$

where b is a vector of parameters. In this equation the SDF consists of data and parameters. The goal is to estimate the parameters in order to calculate the SDF. The most simple and natural way to do so is to choose the parameters in order that the equation holds. The equation should hold for every asset. Those conditions are the so called moment conditions. Let $u_{t+1}(parameters)$ be the error term:

$$u_{t+1}(b) = E[m(b)rx_{t+1}]$$

Such an error term exists for every asset tested. The goal of GMM is to find the parameters in order that the model best fits the data, i.e. the error term is as close to zero as possible. Let me define the sample mean of the error term as:

$$g_T(b) = \frac{1}{T}\sum_{t=1}^{T} u_t = E_T[u_t(b)]$$

To find the parameters which minimize the error term the following optimization must be solved:

$$\min_b g_T(b)\,'W g_T(b)$$

This will yield an estimate of b which I call $\hat{b}_1$. W denotes a matrix. This matrix W is a weighting matrix which weights the different moment conditions. By the choice of W one can put more or less weight on specific moment conditions, with the identity matrix all moments are weighted equally. That matrix can be any arbitrary matrix. Usually the identity matrix is chosen. It is possible to stop the estimation here. This estimation would then be called a first stage GMM.

However, one can also continue and use the estimate $\hat{b}_1$ obtained from the first step to estimate another matrix:

$$S = \sum_{j=-\infty}^{\infty} E[\, u_t(\hat{b}_1) u_{t-j}(\hat{b}_1)']$$

This matrix can then be used to estimate $\hat{b}_2$:

$$\hat{b}_2 = argmin_b g_T(b)' \hat{S}^{-1} g_T(b)$$

The estimate $\hat{b}_2$ is consistent, asymptotically normal, and efficient (Cochrane (2001), p. 189-191). The estimation will deliver $\hat{b}_2$ such that the expected discounted return is as close to zero as possible.

3.4.3. Results

I start with the GMM estimation. I use the SDF as presented in chapter 3.4.1., the average return among all five portfolios where used as the DOL factor and the residuals form the AR(1) process of the volatility innovations estimated according to Chapter 3.3. were used as the VOL factor. In contrast to previous studies I estimated the model using only the central moment condition. I did that because I could not identify any benefit from estimating the mean and the variance of the factors within the GMM, rather than estimating them separately. Therefore, I decided to make the GMM as simple as possible and only used one moment condition:

$$g(z_t, \theta) = [1 - b'(h_t - \mu)] r x_t$$

Here z_t stands for the data input (h_t, rx_t) and θ stands for the parameters of the model (b, μ). The letter h_t stands for a vector containing the two factors. I used a two stage approach with W equal to the identity matrix. The factor prices were estimated afterwards using the relationship form equation 8. Table 2 shows the results from the GMM estimation.

GMM Estimation	DOL	VOL	J Test
b	-0.14	-9.02	3.09
p-value	0.15	0.02	0.38
λ	-0.25	-0.11	

Table 2: I followed Menkhoff, Sarno, and Schmeling (2012) and estimated the standard errors according to Newey-West (1987). The number of lags which was used in the Bartlett Kernel was determined according to Andrews (1991).

The parameter of main interest is the factor price of volatility. As one would expect it is significant and negative. This means that volatility and excess returns from currency carry trades comove. Therefore, to be less exposed to volatility developments one needs to give up return. In other words, portfolios with a negative correlation to volatility demand a risk premium. The DOL factor is not statistically significant. That is in line with the findings of Menkhoff et al. (2012). The J Test cannot reject the null hypothesis that the models moment conditions are valid. This means the model is statistically not rejected by the data.

As a next step I estimated the factor betas using an OLS regression. To do so, I first checked if all the inputs to the regression are stationary. The regression equation used is the following:

$$rx_t = \alpha + \beta_1 DOL_t + \beta_2 VOL_t$$

To test for stationary I used an Augmented Dickey Fuller Test (see Verbeek (2012), 294-269). The test showed that all inputs into the regression are stationary. Therefore an ordinary OLS regression can be estimated. Table 3 presents the results.

Portfolio	alpha	DOL	VOL	R Squared
1	0.00	1.49	-2.74	0.71
p-value	0.00	0.00	0.00	
2	0.00	1.34	-0.13	0.78
p-value	0.95	0.00	0.83	
3	0.00	1.13	-1.13	0.71
p-value	0.54	0.00	0.07	
4	0.00	1.06	1.87	0.71
p-value	0.01	0.00	0.00	
5	0.00	-0.02	2.14	0.04
p-value	0.00	0.78	0.01	

Table 3: OLS regressions results. All regression in this table where estimated using standard errors corrected for heteroskedasticity. The coefficients are percentage values.

The regression output shows the expected picture. Portfolios which earn a higher excess return have a negative beta while portfolios which earn a lower excess return have a positive beta with volatility. The

Beta is increasing by moving from portfolio 1 to portfolio 5 (except portfolio 2 which does not fit the pattern). The interpretation of the VOL beta is simple, as the volatility increases the excess return of portfolio 1 decreases. All volatility betas are significantly different form zero except the one form portfolio 2. Note that portfolio 5 is the only portfolio which has an insignificant DOL beta. This is somewhat intuitive. Since the currencies in portfolio 5 are all low interest currencies and usually also referred to as safe heaven currencies. Therefore, these currencies should not earn a premium for investing outside the U.S. and leaving the stability of the U.S. financial system. Moreover, one can see that the R^2 is generally above 70%, only portfolio number 5 has an R^2 of only 4%. That is the only portfolio with an insignificant DOL factor. Therefore, it could be that it is actually the DOL factor which is responsible for the relatively high R^2 and not the VOL factor. This would mean that the VOL factor only explains little of the variations in the excess returns. A second regression without the DOL factor confirmed that this factor explains most of the variations in excess returns. Leaving out the DOL factor results in an R^2 lower than 10% for all portfolios. That means although the VOL factor is a significant component when pricing excess returns, as the GMM estimation and the OLS estimation showed. It does, however, not account for much of the variation in the excess returns.

3.4.4. Is the Puzzle solved?

Having found that the volatility explains only a fraction of excess returns it is natural to ask which other factors play a role. It is worthwhile to mention here explicitly that volatility does not solve the forward premium puzzle. It has been shown above that it explains only a little part of the forward premium puzzle. However, there are numerous other factors which are relevant in fully explaining those excess returns. Especially when it comes to emerging markets currencies. These countries are generally very heterogeneous, with often very unstable governments. Therefore, I think when it comes to such kind of countries the excess return is also a premium for the willingness to insure investor against political risk in such countries. To highlight that point I also calculated the monthly political risk of every portfolio using the EIU Index. I found that the political risk is constantly decreasing as one moves from portfolio 1 to portfolio 5. Table 4 shows these results. This indicates that the higher excess returns are compensation for taking higher political risk. It is kind of natural that one demands a premium for investing in a currency where the political situation is relatively unstable and unpredictable. This also shows that currencies which offer a higher carry are probably exposed to higher political risk. I also calculated the average political risk score over all five portfolios. I then calculated the correlation between the political

risk factor and the other two risk factors. Both correlations are very low, this indicates the political risk is probably not captured by the other two factors.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
EIU Political Risk Score	44.72	33.70	28.81	24.06	20.01
	Avg.				
Correlation with DOL Factor	-0.09				
Correlation with VOL Factor	0.11				

Table 4: The political risk factor is calculated by taking the average over the individual political risk scores of the countries within a portfolio.

Since this thesis is about the connection between volatility and the currency carry I do not investigate the political risk factor further. The message form this paragraph is that volatility only explains a fraction of the forward premium puzzle. Hence, the puzzle is not solved. A topic for further research is to investigate on how important the political risk is when pricing excess returns of currency carry trades.

4. An FX trading Strategy based on the Volatility Risk Premium

4.1. Introduction

The second part of this thesis covers a trading strategy based on the paper of Corte, Ramadorai, and Sarno (2016). The basic idea of this strategy is very simple. One is long currencies which are cheap to insure and is short currencies which are expensive to insure. The price of the insurance is determined by the volatility risk premium. The volatility risk premium is the difference between realized volatility and implied volatility. Realized volatility is measured by using the historic volatility over a given period. Measuring implied volatility is a little bit more complicated. I will discuss that in more detail later. The idea of the volatility risk premium is rather simple. Implied volatility is a forward looking measure, as it effectively shows the expectations of market participants about the future volatility in a given period. If implied volatility is above realized volatility market participants expect the volatility to increase above the historic level for a given period. This is on average the case in the FX market as the results of this study and the results of Corte, Ramadorai, and Sarno (2016) show. The reason for this difference in implied and realized volatility can be explained by the concept of risk aversion. If people are risk averse they dislike risk. A put option can be used as a hedge to reduce risk as it can hedge the downside of an investment. People are willing to pay for this reduction in risk, i.e. the implied volatility reflects how much they are willing to pay for the insurance. If the price of insurance is high implied volatility will be high. As explained before high implied volatility means that market participants expect higher volatility levels in the future, hence risk averse agents are willing to pay more for insurance to reduce the risk. The difference in implied volatility and realized volatility does therefore indicate the degree of risk aversion of people. If people are on average risk averse implied volatility will be on average above realized volatility. If there is an unexpected period of market turbulences, like an unexpected depreciation of a currency realized volatility will increase. Because volatility is mean reverting agents expect the volatility to decrease to lower levels in the future, implied volatility will be below realized volatility in this situation. If realized volatility is above implied volatility the asset is said to be cheap to insure, because the implied volatility is low compared to realized volatility. In the case where implied volatility is above realized volatility the currency is expensive to insure.

The strategy of Corte, Ramadorai, and Sarno (2016) exploits the volatility risk premium in the FX market. The investor invests into currencies which are cheap to insure. Realized volatility is usually above implied volatility in a period of market turbulences. This means the currencies the investor buys have come under pressure in the last periods and suffered unexpected depreciations. Corte, Ramadorai, and Sarno (2016) implement their strategy using forward contracts. The agent who has the other side of the

contract can be seen as someone who demands insurance against further depreciation, i.e. by being long a currency which is cheap to insure the investor is actually providing insurance against further depreciation. Therefore, the investor is betting on a mean reversion of volatility. On the other hand, the investor is also short currencies which are expensive to insure. For these currencies the market expects an increase in the volatility. In this case the investor is demanding insurance and the agent on the other side of the contract is providing insurance. The strategy effectively bets on a depreciation of currencies where the implied volatility is extremely high. The claim of Corte, Ramadorai, and Sarno (2016) is that the majority of the returns obtained from this strategy are derived by movements in the spot rate and not by the interest rate differential. This means that currencies which are cheap to insure tend to appreciate while currencies which are expensive to insure tend to depreciate. If this result is true this would mean that the volatility risk premium provides information which can be used to forecast the spot rates. Moreover, Corte, Ramadorai, and Sarno (2016) also claim that the predictability of the spot rate is stronger than from any of the other currency strategies they considered.

In general it is widely accepted that the forecasting of short run movements in the spot exchange rate is a nearly impossible task. Studies of Meese and Rogoff (1983) and Neely and Sarno (2002) show that the forecasting power of traditional macroeconomic models is essentially zero. More recent research could produce models which can beat at least the random walk, examples are Engel, Mark, and West (2007) and Molodtsova and Papell (2009). However, all of these tests are estimated without considering transaction costs. Therefore, it remains questionable if their forecasts are useful to build a profitable trading strategy. The evidence from these studies is clear, currencies do in general not behave like a random walk as it was widely assumed until the turn of the century. It is, however, unclear if the information obtained from currency forecasting models is strong enough to obtain a profitable trading strategy.

Corte, Ramadorai, and Sarno (2016) split their sample into two parts a developed country sample and a full sample including also developing countries. They found evidence for their strategy and the predictability of spot returns with both samples. According to their finding the strategy works better in the sample including only developed countries. This seems somewhat strange to me. The strategy effectively takes advantage of mispricing of forwards. One would expect that mispricing's are more likely in emerging markets since these currencies tend to be a lot less liquid than developed market currencies. The sample I use can be seen as an extension to the Corte, Ramadorai, and Sarno (2016) sample. My sample covers all countries they have in their sample, except Turkey, plus 19 additional countries. In addition, my sample covers a longer horizon. Therefore, my results can be seen as a more general test of

the strategy Corte, Ramadorai, and Sarno (2016) propose. I follow their methodology and also compare the volatility risk premium strategy (VRP) against other commonly used currency trading strategies such as carry, momentum, and value. I did not compare it to a risk reversal strategy because there was not enough data available to test this strategy. I will also show what the exchange rate return of the strategies is to answer the question if the volatility risk premium delivers valuable information about spot price movements.

4.2. Measuring the Volatility Risk Premium

4.2.1. Realized Volatility

The volatility risk premium as it is defined in Corte, Ramadorai, and Sarno (2016) is the difference between realized and implied volatility.

$$\mathrm{VRP}_t = \mathrm{RV}_t - \mathrm{IV}_t$$

To measure realized volatility I follow Corte, Ramadorai, and Sarno (2016) and simply calculate the daily volatility over the last year exactly as they did it:

$$\mathrm{RV}_{t-\tau,t} = \sqrt{\frac{252}{\tau}\sum_{i=0}^{\tau} r_{t-i}^2}$$

Where r_t is the daily log return, and τ represents the number of observations within a year. I calculate this measure of realized volatility for every currency in the sample.

4.2.2. Implied Volatility

Measuring implied volatility is more complex. Corte, Ramadorai, and Sarno (2016) calculated a swap rate of a volatility swap. In theory this would be the ideal solution. However, calculating this swap rate is practically impossible, only an approximation can be calculated. The swap rate represents the expected volatility over a given period. The difference between realized volatility and the swap rate would then be the volatility risk premium. Constructing this swap rate is not easy as the descriptions of Corte, Ramadorai, and Sarno (2016) show. Because at the money (ATM) implied volatility is directly observable and the results of the strategy using this measure are similar to that using the swap rate, as Corte, Ramadorai, and Sarno (2016) point out, I decided to use ATM implied volatility as a measure of implied volatility. For better understanding of the work of Corte, Ramadorai, and Sarno (2016) I will briefly describe here how the swap rate can be obtained. The approach builds on Britten-Jones and Neuberger (2000). They calculate a risk neutral expectation of the return variance over the next year. This can be done by calculating the integral over option prices which expire at the end and at the beginning of the

year over an infinite range of strike prices. The problem with this approach is that options are not quoted for a continuum of strike prices. In the FX market options are usually quoted at fixed deltas. Moreover, Corte, Ramadorai, and Sarno (2016) did not directly observe the delta of single options. They only observed combinations of options such as straddles, risk reversals, and butterfly spreads. From this combination the implied volatility of the single options must be extracted. Having done this one needs to interpolate between these fixed deltas to get a continuum. By doing so one obtains the volatility smile. With this information the risk neutral expectation of the return variance for the next year can be calculated. Obviously this method delivers only an approximation, hence the result comes with errors. One error comes from the interpolation the other one form the numerical integration. Although Corte, Ramadorai, and Sarno (2016) claim that the errors are small the swap rate still cannot be exactly calculated. Given that the results using the swap rate and ATM implied volatility are similar I see the ATM implied volatility an adequate approximation, in addition calculating the swap rate demands an enormous effort and huge dataset on currency options.

4.2.3. The Volatility Risk Premium

Having calculated both the realized volatility and the implied volatility one can calculate the volatility risk premium. I follow Corte, Ramadorai, and Sarno (2016) and calculate the VRP for a one year horizon. The VRP is updated on a monthly frequency. Realized volatility is calculated as described in 4.2.1.. I use one year ATM implied volatility as a proxy for implied volatility.

$$VRP_{t,t+\tau} = RV_{t-\tau,t} - IV_{t,t+\tau}$$

This VRP will be calculated for every currency in the sample. If the VRP is high the currency is cheap to insure, since the price the hedger pays (implied volatility) is lower than the variable he hedges against (realized volatility). If the VRP is low the opposite is true.

4.3. Data

The data on forward rates and currency spot rates is the same as used in the first part of this study. I used data on 38 different currencies. The sample for 1Y ATM implied volatility starts at 26.02.1999 and ends on 28.02.2017. The data is available on a monthly frequency. The sample is not balanced, this means for some currencies data is only available after February 1999. There is no data for Ghana, Zambia and Egypt. I also collect data on Purchasing Power Parity (PPP) to construct value portfolios. I used the PPP rate from the OECD this rate was also used by Corte, Ramadorai, and Sarno (2016), if this rate was not available I switched to the PPP rate from the IMF. The PPP rates are available on a monthly base

from 26.02.1999 to 28.02.2017. Again the sample is not balanced. A table which shows which data is available since what date for what country can be found in the Appendix.

4.4. Constructing Portfolios

All four strategies are constructed exactly as they were described in the paper of Corte, Ramadorai, and Sarno (2016). I refused from changing the strategies to make the results comparable. For every strategy five portfolios were constructed. I sorted the currencies into the portfolios such that every portfolio contains an equal number of currencies. If the number of currencies available divided by five was not an integer number I preceded in the same way as in the previous part. The currencies within a portfolio are all equally weighted. Therefore, the portfolio excess return is simply the average excess return across the currencies within a portfolio. Portfolios 1 to 4 are always adjusted for transaction costs occurring with long positions while portfolio 5 is always adjusted for transaction costs occurring with short positions. For all strategies I also calculated the returns of a zero cost strategy. This is a strategy which is long Portfolio 1 and short portfolio 5. All portfolios start in March 1999 and run until February 2017. At the beginning of the sample all positions were opened and at the end of the sample all positions were closed.

4.4.1. VRP Portfolios

These portfolios represent the volatility risk premium strategy described earlier. Currencies are sorted into the portfolios according to their volatility risk premium. Portfolio 1 contains the 20% of currencies which are cheapest to insure, while portfolio 5 contains the 20% of currencies which are most expensive to insure. The volatility risk premium which is used for the decision in period t only contains information which is available at the end of period t-1. The long/short strategy is denoted as VRP.

4.4.2. Carry Portfolios

The Carry portfolios are identical to the carry portfolios used in the first part of this thesis. The only difference is that the portfolios start in March 1999, the rest is identical. The long/short strategy is denoted as CAR.

4.4.3. Momentum Portfolios

The momentum strategy is a strategy which bets on the continuation of a price trend. In effect, the strategy invests in currencies which performed relatively well over a given period and sells currencies which showed a relatively bad performance over a given period. To calculate the momentum portfolios I

first calculated the exchange rate return over the last three months. The 3 months exchange rate return used for the decision in period t was calculated for the months t-1 to t-3, hence only past information was used. Afterwards, the currencies where assigned to the portfolios. Portfolio 1 contains the 20% of currencies with the highest exchange rate return over the last three months while portfolio 5 contains the 20% of currencies with the lowest exchange rate return over the last three months. The long/short strategy is denoted as MOM.

4.4.4. Value Portfolios

Value is a strategy which invests in undervalued securities and short sells overvalued securities. To estimate the value of a currency PPP was used to calculate the real effective exchange rate, i.e. I divided the spot rate through the PPP rate. The 20% of currencies with the lowest real effective exchange rate where assigned to portfolio 1, while the 20% of currencies with the highest real effective exchange rate where assigned to portfolio 5. This is exactly the opposite way than Corte, Ramadorai, and Sarno (2016) describe it in their paper. However, their description does not yield a meaningful value strategy. Therefore, I suspect that they made a typo in their description and set up the value strategy here such that it follows the classic definition of a value strategy. The long/short strategy is denoted as VAL.

4.4.5. Measuring the Return

In total I tested 4 different strategies. All strategies are implemented using one month currency forwards, exactly like it was done in the first part of this thesis. All returns where measured as the natural logarithm of the variable. I measured two types of returns. First, I measured the excess return of the strategy over UIP. This was done exactly as it is described in section 3.2.. These returns are adjusted for transaction costs. Moreover, I also measured the exchange rate return. This is the part of the return which comes from the movement of the spot rate. I also used returns adjusted for transaction costs here. If a trader enters a long position at the beginning of period t and closes it at the end of period t the log exchange rate return will be $r^l_{i,t+1} = s^b_t - s^a_{t+1}$. Note that an increase in the spot yields a negative return since this represents a depreciation of the currency. For a short position the exchange rate return is: $r^s_{i,t+1} = -s^a_t + s^b_{t+1}$. If a trader sells a position in period t which was already in the portfolio in period t-1 his exchange rate return is: $r^l_{i,t+1} = s_t - s^a_{t+1}$. For a short position the exchange rate return in this case is: $r^s_{i,t+1} = -s_t + s^b_{t+1}$. If the position is opened in period t and not closed at the end of the period the period t exchange rate return is: $r^l_{i,t+1} = s^b_t - s_{t+1}$. For a short position the corresponding exchange rate return is: $r^s_{i,t+1} = -s^a_t + s_{t+1}$. If a position was already in the portfolio before period t and is not

closed at the end of period t the period t exchange rate return is: $r^l_{i,t+1} = s_t - s_{t+1}$. For a short position the exchange rate return in this case is: $r^s_{i,t+1} = -s^a_t + s_{t+1}$.

4.5. Empirical Results

4.5.1. The Volatility Risk Premium

I started by estimation the VRP as described in the sections 4.2.1.-4.2.3.. Table 5 presents the summary statistics on the average implied volatility, the average realized volatility, and the average volatility risk premium. First, I calculated a cross sectional average for every period and then calculated another average across the whole sample period.

	VRP	ATM 1Y Implied Volatility	1Y Realized Volatility
Mean	-0.33	10.66	10.33
St.dev	4.69	2.17	5.11
Skew	3.19	1.79	2.71
Kurt	10.13	5.51	7.43

Table 5: Summary statistics for the average volatility risk premium. The sample period reaches from March 1999 to February 2017.

The data shows that on average the implied volatility (10.66%) is above the realized volatility (10.33%). The negative average volatility risk premium is what hedgers on average have to pay to insure themselves against increases in volatility. The negative sign is what one would expect to see here, since a positive VRP would mean that hedgers would on average earn money for being insured. This result is in line with the theoretical motivation of section 4.1. as well as the results of Corte, Ramadorai, and Sarno (2016). Moreover, also the magnitude of the mean is relatively close to the results of Corte, Ramadorai, and Sarno (2016). Therefore, I conclude that the calculation of the VRP is valid and comparable to the estimates of Corte, Ramadorai, and Sarno (2016).

4.5.2. Portfolio Statistics

This section provides an overview over the different strategies. I will provide summary statistics on all portfolios. All tables show the currency excess return as well as the exchange rate return. I also tested whether the returns are statistically significantly different from zero or not using a simple t-test.

Table 6 shows the summary statistics of the VRP portfolio.

Portfolio	1	2	3	4	5	Avg.	VRP
				Excess Returns			
Mean	3.12%*	0.51%	-0.25%	0.11%	1.94%	1.09%	1.15%
Median	2.64%	1.18%	-0.39%	0.19%	4.07%	0.04%	2.20%
Std. dev	7.33%	4.51%	5.53%	5.92%	5.06%	5.67%	6.94%
Skewness	-0.81	0.17	-1.03	-0.27	-0.48	-0.48	-0.57
Kurtosis	3.53	1.49	4.87	1.74	1.00	2.53	2.38
Sharpe Ratio	-0.09	-0.73	-0.73	-0.63	-0.37	-0.51	-0.38
				Exchange Rate Returns			
Mean	-2.25%	-1.77%	-0.81%	-1.18%	-1.81%	-1.57%	-0.45%
Median	-0.09%	-1.13%	-0.46%	-0.78%	0.63%	-0.07%	1.12%
Std. dev	7.64%	5.34%	5.63%	5.96%	6.13%	6.14%	7.35%
Skewness	-1.51	-0.86	-1.32	-0.31	-0.95	-0.99	-1.25
Kurtosis	6.60	3.34	6.16	1.75	2.66	4.10	5.79
Sharpe Ratio	-0.79	-1.05	-0.82	-0.84	-0.92	-0.88	-0.58

Table 6: Summary statistics of the five volatility risk portfolios. Portfolio 1-4 contain long trades, while portfolio 5 contains short trades only. Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

To start with there is no strict pattern in the returns or for any statistical measure considered here when moving from portfolio 1 to portfolio 5. These findings are in line with the results of Corte, Ramadorai, and Sarno (2016). Although the VRP strategy is estimated exactly as described in Corte, Ramadorai, and Sarno (2016) the return of the VRP strategy is considerably lower compared to Corte, Ramadorai, and Sarno (2016) and not statistically significant. Moreover, there is no evidence for the predictability of the spot rate using the VRP strategy. None of the exchange rate returns is statistically significantly different from zero. I also estimated the portfolios using the same period as Corte, Ramadorai, and Sarno (2016) to see if the returns of the VRP strategy are dependent on the sample period. This did not yield a much different picture. It was in fact the case that returns of the VRP strategy where negative, although not significant. Another main difference of the sample used here and the one used by Corte, Ramadorai, and Sarno (2016) is the number of countries. Although the sample used by Corte, Ramadorai, and Sarno (2016) is almost a subsample of the sample used here the results are different. Therefore, it could be that the different results can be explained by the additional countries of the sample used here. To also test this I replicated the sample of Corte, Ramadorai, and Sarno (2016). I also collected data on Turkey for this case to have an identical set of countries. There is, nevertheless, still one difference between the replicated sample and the original. My sample starts in February 1999 and not in January 1998 as the original sample does. In my opinion this is only a small differences and the results should be similar. However, my calculations did not yield similar results. In fact the return of the VRP strategy using the replicated Corte, Ramadorai, and Sarno (2016) sample was negative. The summary table of the VRP

strategy estimated with the replicated sample can be found in the Appendix. I also used the replicated sample to calculate all the other strategies. I did this to check if the calculations are correct. I got similar results for the ranking of the CAR, VAL, and MOM return. However, the magnitude of the returns was different. This difference is in my opinion too big to be attributed to the slightly different sample. The momentum portfolio 1 and 5 deliver almost identical returns (portfolio 1 performs slightly better) until 2011. Afterwards portfolio 5 outperforms portfolio 1. Since my sample starts a bit latter this last part of the sample weights heavier on the overall return. That explains the negative MOM return and the difference to Ramadorai, and Sarno (2016) for this strategy. A full overview over the returns of the strategies using the replicated sample as well as a graph showing the momentum portfolio 1 and 5 can be found in the appendix. A last difference between my study and the work of Corte, Ramadorai, and Sarno (2016) could be the construction of the portfolios. It is nowhere mentioned in the work of Corte, Ramadorai, and Sarno (2016) how they select currencies into portfolios when an equal distribution was not possible. Given their small number of currencies such a detail can lead to large differences in the results. If this is the case this wo uld mean the strategy is highly sensitive to the construction method and not robust.

I will provide several reasons for the validity of the result presented here. First, the estimation of the volatility risk premium yielded values which are in line with Corte, Ramadorai, and Sarno (2016). Second, the methodology of calculating the returns is identical with the one of Menkhoff et al. (2012). Moreover, the returns calculated in the first part of the thesis were close to the one of Menkhoff et al. (2012). Therefore, I conclude that the calculation of the returns is correct, since there is evidence for the correct calculation of the returns and the correct measurement of the volatility risk premium. I conclude that the results I present here are correct.

Overall this is strong evidence against the VRP strategy. Additionally, the strategy did not yield a positive Sharpe ratio for any of the portfolios. Apart from failing to predict the spot return the strategy was also not profitable during the tested period.

Table 7 shows the summery statistics of the carry portfolios.

Portfolio	1	2	3	4	5	Avg. (DOL)	CAR
				Excess Returns			
Mean	5.72%***	1.15%	-0.16%	-0.27%	-2.35%**	0.82%	8.25%***
Median	8.23%	3.46%	1.06%	0.43%	-3.07%	-0.25%	12.21%
Std. dev	8.67%	7.28%	6.69%	5.70%	4.41%	6.55%	4.42%
Skewness	-1.21	-0.85	-0.95	0.01	0.64	-0.47	-1.51
Kurtosis	4.87	2.91	3.58	1.23	3.64	3.24	7.73
Sharpe Ratio	0.24	-0.34	-0.57	-0.69	-1.36	-0.54	1.04
				Exchange Rate Returns			
Mean	-5.36%**	1.30%	-0.76%	-0.06%	-1.02%	-1.18%	-4.38%*
Median	-1.06%	-0.66%	0.53%	1.25%	-2.29%	-0.19%	-1.82%
Std. dev	8.99%	6.47%	6.72%	5.70%	4.45%	6.47%	10.67%
Skewness	-1.57	0.92	-0.96	0.03	0.68	-0.18	-1.77
Kurtosis	5.17	3.22	3.47	1.39	3.18	3.28	7.77
Sharpe Ratio	-1.02	-0.39	-0.68	-0.68	-1.09	-0.77	-0.77

Table 7: Summary statistics of the five carry portfolios. Portfolio 1-4 contain long trades, while portfolio 5 contains short trades only. Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

The results of the carry strategy, although the sample is now shorter are not meaningfully different to the results of the carry strategy in section 3.2.. Moreover, it can be seen that the return of the carry strategy is derived solely by the carry and not by movements in the exchange rate. It is in fact the case that for the CAR strategy the exchange rate return is negative and statistically significantly different from zero, although only at the 10% level. The return of the CAR strategy is much higher than the one Corte, Ramadorai, and Sarno (2016) found. This can be explained by the different samples. As I showed in the first part the excess return of the carry strategy depends on the carry. Because the sample here includes more emerging and frontier market currencies than the sample of Corte, Ramadorai, and Sarno (2016), the CAR strategy delivers a higher return here. Corte, Ramadorai, and Sarno (2016) also found the return of the CAR strategy increasing when adding emerging market currencies to the sample.

Table 8 shows the summery statistics of the momentum portfolios.

Portfolio	1	2	3	4	5	Avg.	MOM
				Excess Returns			
Mean	3.09%*	0.22%	0.90%	-2.38%	7.30%***	1.83%	-3.94%
Median	3.92%	0.71%	1.30%	1.21%	5.75%	0.10%	-3.44%
Std. dev	7.54%	6.32%	5.64%	6.99%	6.39%	6.58%	10.70%
Skewness	-0.23	-1.03	-0.32	-1.83	0.85	-0.51	-0.17
Kurtosis	2.64	6.13	3.88	6.77	4.63	4.81	1.90
Sharpe Ratio	-0.10	-0.57	-0.52	-0.89	0.55	-0.30	-0.72
				Exchange Rate Returns			
Mean	0.78%	-1.64%	-0.91%	-4.25%**	3.11%*	-0.58%	-2.26%
Median	1.98%	-0.40%	-0.31%	-0.26%	3.54%	-0.02%	-0.19%
Std. dev	7.52%	6.59%	5.73%	7.15%	7.85%	6.97%	9.83%
Skewness	-0.25	-1.65	-0.46	-2.03	0.19	-0.84	-0.61
Kurtosis	2.77	10.11	3.87	7.64	3.64	5.61	3.36
Sharpe Ratio	-0.40	-0.83	-0.82	-1.13	-0.09	-0.65	-0.62

Table 8: Summary statistics of the five momentum portfolios. Portfolio 1-4 contain long trades, while portfolio 5 contains short trades only. Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

There is no clear pattern to see with the momentum portfolios. It is interesting to observe that all five momentum portfolios have a negative exchange rate return, while the excess return is positive for four portfolios. This means the return does not come from movements in the spot rate it comes from the interest difference. That is in contrast to the classic momentum strategies used in the stock market where the momentum return is almost exclusively the return from price movements. Also worthwhile to mention is the result that portfolio 5 delivered the highest return. This indicates that the momentum horizon may be too long. It seems to be that portfolio 5 captures a reversion after periods of negative momentum. To stay in line with the work of Corte, Ramadorai, and Sarno (2016) I did not change the momentum horizons. This would also result in a datamining problem since it is a priori not known what the optimal momentum horizon should be. Also Corte, Ramadorai, and Sarno (2016) could not find predictability of the spot rate using a momentum strategy. Moreover, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) found the performance of currency momentum strategies declining drastically over the last decade. Hence, the poor performance I found here is not an unusual result.

Table 9 presents the summery statistic of the value portfolios.

Portfolio	1	2	3	4	5	Avg.	VAL
				Excess Returns			
Mean	3,90%***	0,92%	1,60%	0,10%	-2,06%**	0,89%	6,07%***
Median	3,84%	3,87%	2,78%	1,82%	-0,99%	0,16%	5,48%
Std. dev	6,16%	6,61%	7,82%	5,41%	4,18%	6,04%	6,78%
Skewness	-0,80	-0,88	-0,64	-1,12	-0,04	-0,70	-0,42
Kurtosis	5,62	2,36	2,19	3,92	-0,19	2,78	1,75
Sharpe Ratio	0,01	-0,44	-0,28	-0,69	-1,40	-0,56	0,33
				Exchange Rate Returns			
Mean	-2,40%	-2,18%	-0,80%	-1,33%	-0,82%	-1,51%	-1,60%
Median	0,85%	1,19%	1,33%	0,81%	-0,36%	0,08%	0,05%
Std. dev	6,41%	6,68%	7,85%	5,43%	4,12%	6,10%	6,91%
Skewness	-2,22	-0,98	-0,66	-1,12	-0,07	-1,01	-1,49
Kurtosis	12,63	2,56	2,16	3,90	-0,02	4,25	7,49
Sharpe Ratio	-0,97	-0,90	-0,59	-0,95	-1,12	-0,91	-0,78

Table 9: Summary statistics of the five value portfolios. Portfolio 1-4 contain long trades, while portfolio 5 contains short trades only. Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

The value portfolio shows the expected pattern. Portfolio 1, the most undervalued portfolio delivers the highest return while portfolio 5 which is the most overvalued portfolio delivers the lowest return. There is no evidence for the predictability of the spot rate using the value factor.

Overall the results, except the results for the volatility risk premium portfolios, do not differ in an implausible way to Corte,Ramadorai, and Sarno (2016). CAR outperforms both VAL and MOM. In contrast to Corte, Ramadorai, and Sarno (2016) I found significant returns for CAR and VAL. In my opinion this is due to the bigger sample which includes more emerging and frontier markets.

4.5.3. Comparing VRP with the other Strategies

As a next step I compared the VRP strategy to the other three strategies. Although the previous section already showed that the VRP strategy does not deliver a positive Sharpe ratio it could be that it is a useful strategy in combination with other strategies. I therefore also calculated the correlation among the strategies. Table 10 shows the results.

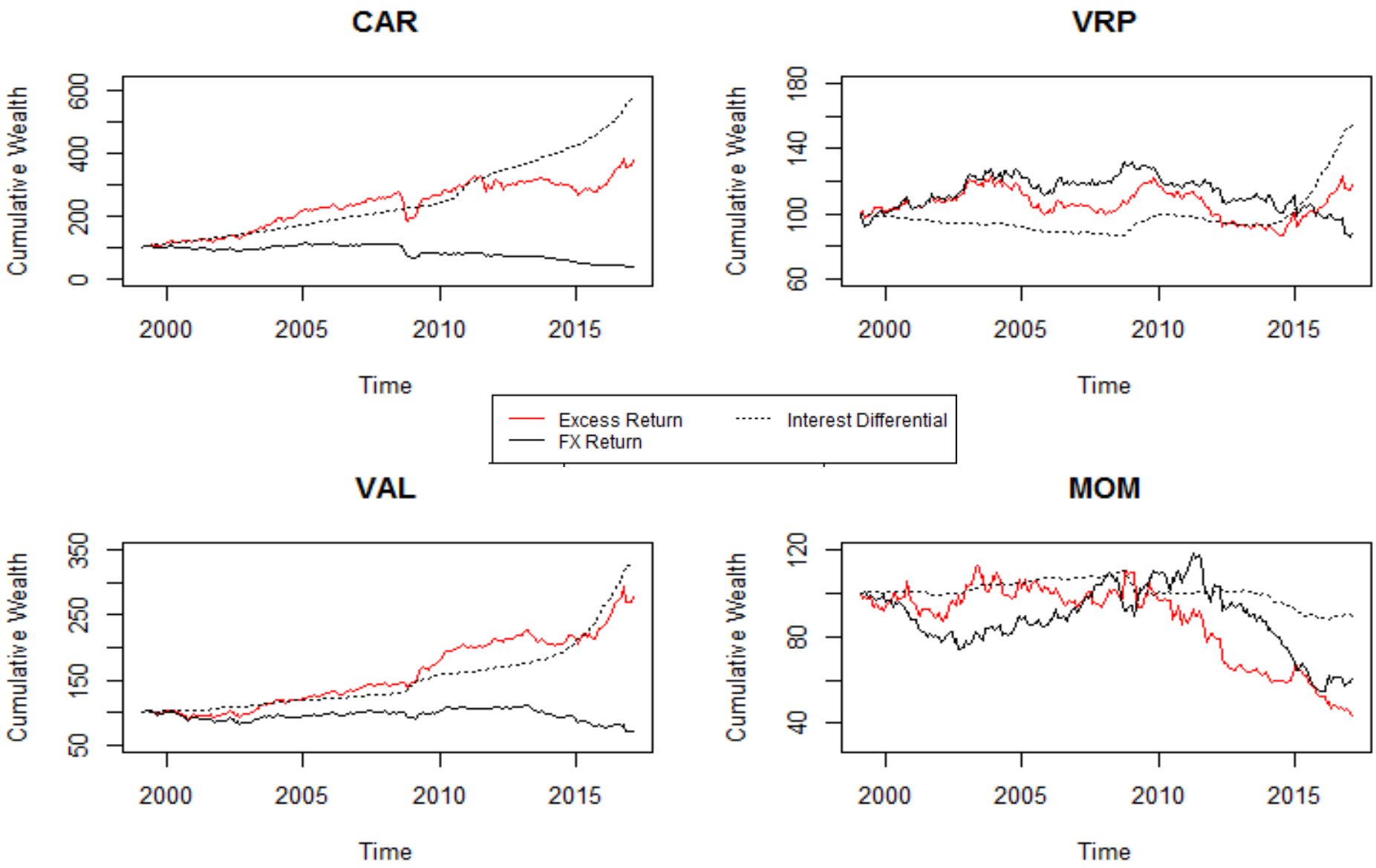
Portfolio	VRP	VAL	MOM	CAR
		Excess Returns		
Mean	1,15%	6,07%***	-3,94%	8,25%***
Median	2,20%	5,48%	-3,44%	12,21%
Std. dev	6,94%	6,78%	10,70%	4,42%
Skewness	-0,57	-0,42	-0,17	-1,51
Kurtosis	2,38	1,75	1,90	7,73
Sharpe Ratio	-0,38	0,33	-0,72	1,04
		Exchange Rate Returns		
Mean	-0,45%	-1,60%	-2,26%	-4,38%*
Median	1,12%	0,05%	-0,19%	-1,82%
Std. dev	7,35%	6,91%	9,83%	10,67%
Skewness	-1,25	-1,49	-0,61	-1,77
Kurtosis	5,79	7,49	3,36	7,77
Sharpe Ratio	-0,58	-0,78	-0,62	-0,77
		Correlations		
VRP	1,00	0,06	0,10	0,23
VAL	0,06	1,00	-0,19	0,51
MOM	0,10	-0,19	1,00	-0,02
CAR	0,23	0,51	-0,02	1,00

Table 10: Mean, median, and the standard deviation are annualized. The Sharpe ratio is computed using a generic US 10Y government bond yield. * stands for the 1% significance level, ** stands for the 5% significance level, *stands for the 10% significance level.**

The comparison clearly shows that carry delivers the highest Sharpe ratio among these strategies. The VRP strategy cannot deliver returns which are statistically significant different form zero. Only CAR and VAL are able to produce positive Sharpe ratios and statistically significant positive returns. Moreover, there is almost no evidence for the predictability of exchange rates using any of these four strategies. There is only weak evidence that a high carry predicts a low exchange rate return. This finding is in line with the prediction of UIP. My findings do not support the findings of Corte, Ramadorai, and Sarno (2016). There is no evidence for the VRP strategy proposed by Corte, Ramadorai, and Sarno (2016) to be a profitable strategy or to be able to predict movements in the spot price. The strategy does not deliver a positive Sharpe ratio and its return is considerably lower than the return of a carry or value strategy. In addition the VRP strategy does not provide any information on movements of the spot rate. Moreover, since Corte, Ramadorai, and Sarno (2016) cannot really provide a theoretical explanation for their results it is likely that the results they found were incorrect.

The correlation matrix shows an expected picture. First MOM and VAL are negatively correlated. This result is what one would expect since currencies with a high momentum are less likely to be undervalued than currencies with a very low momentum. Moreover the VRP strategy shows only weak correlations with the other strategies, a result which also the study of Corte, Ramadorai, and Sarno (2016) found. One can also see a negative correlation between CAR and MOM as well as a relatively high correlation between CAR and VAL. Also this finding is in line with the results of Corte, Ramadorai, and Sarno (2016).

Graph two shows another analysis of the strategies. I plotted the excess return, the exchange rate return and the interest differential for all the zero cost strategies. One can clearly see that the return of the CAR strategy is driven by the interest rate difference. There was, however, a period when the movements in the sport rate delivered positive returns. This period can be identified as the period where the red line (excess return) is above the dotted black line (interest rate differential). The sharp increase of the interest differential during the end of the sample is explained by counties like Zambia, Ghana, and Egypt which enter the portfolios towards the end of the sample (2013) and by a general increase in the carry of emerging and frontier market currencies. These countries deliver a relatively high carry and hence push up the interest differential. For the VRP strategy it is not so clear which component delivers the return. In the first part of the sample the interest difference is negative and the return is driven by the exchange rate return. Towards the end of the sample this reverts as the interest difference in the sample increases. It cannot really be identified which component is the main driver of the return. The VAL strategy is similar to the CAR strategy. It is, however, the case that the exchange rate component delivers a higher return compared to the CAR strategy. Again as the frontier markets mentioned before enter the sample the interest differential increases. The sharp increase in the excess return towards the end of the sample also shows that the interest rate differential increases by more than the exchange rate return decreases. As expected for the MOM strategy the exchange rate return is the main driver, the interest rate differential, however, softens the movements in the exchange rate return which leads to considerable differences in the exchange rate return and the excess return. Comparing all strategies one can see that none of these strategies is exclusively driven by the exchange return. Moreover, the two strategies which deliver significantly positive excess return are also the two strategies with a constantly positive interest differential.



Graph 2: This graph shows the excess return interest differential and the exchange rate return for all four strategies. The time series are initialized at 100. Therefore, the cumulative wealth shows what one would have got with the different returns if he would have invested 100 at the beginning of the sample.

5. Conclusion

Within the first part of this thesis I could show that there is a connection between volatility and the forward premium. I found support for the results of Menkhoff et al. (2012). Currencies which offer a high carry are more exposed to spikes in global FX volatility. However, the forward premium puzzle remains a puzzle. The results show that global FX volatility can only explain a small fraction of the forward premium puzzle. I could show that other sources of risk like political stability also affect the forward premium. In particular the problem of explaining the forward premium is a problem of measuring risk. There is simply no measure of risk which captures all source and factors of risk. Therefore, every risk factor only explains a fraction of the puzzle. Nevertheless, the results support an important point. The forward premium is not a free lunch, it is a risk premium which can be explained. Investors which are long high interest rate currencies and short low interest rate currencies obtain a premium for insuring other agents against potential depreciations in the high interest currencies. This risk that high interest rate currencies inherit is, however, far more complex as that the simple measure of global FX volatility used in this thesis could capture it as a whole. In fact global FX volatility measures the global risk in the FX market, but not the individual risk a currency faces, like political risks. It is therefore vital for the understanding of the forward premium puzzle to also take into account other sources of risk which measure the risk a singular currency pair faces. I showed towards the end of the first part that there is evidence for a connection between the FX carry and political risk within a country.

In the second part of this thesis I looked at strategy proposed by Corte, Ramadorai, and Sarno (2016). I could not find evidence for the profitability of this strategy. Out of the four strategies only the carry and the value strategy delivered significant positive excess returns. In addition, there is no one which can predict movements in the spot price of a currency using the volatility risk premium. There is also not much evidence for predicting movements in the spot price using any other of the tested strategies. The return of the two successful strategies carry and value comes mainly from the interest difference. I can therefore conclude that the volatility risk premium does not contain any information about future spot price movements on a one-month horizon. In addition, the volatility risk premium can in general not be used to form a trading strategy as Corte, Ramadorai, and Sarno (2016) proposed. Comparing my results with Corte, Ramadorai, and Sarno (2016) the strategy seems to be highly sensible to the choice of the sample and the way portfolios are constructed. Moreover, the absence of a theoretical model which could explain the returns of the VRP strategy is another argument against the robustness of the strategy.

To sum up, the forward premium puzzle remains a puzzle I could, however, show that parts of it can be explained by movements in global FX volatility and identify political risk as a variable which could be responsible for another part of this puzzle. Moreover, I could show that the VRP strategy does in general not generate any excess returns nor does it yield information about future spot price movements. The results here are strong evidence against robustness of the results of Corte, Ramadorai, and Sarno (2016).

6. Appendix

6.1. Data Overview

Country	FX Spot	Forward Rate	first Portfolio entry	Country	FX Spot	Forward Rate	first Portfolio entry
Australia	20.12.1983	Forward Points	30.05.1997	Kuwait	11.12.1995	Forward Points	30.05.1997
Brazil	04.02.1992	Forward Points	30.06.1999	Malaysia	20.12.1983	Forward Points	31.05.1999
Bulgaria	10.06.1993	Forward Points	30.09.2004	Mexico	20.12.1983	Forward Points	31.03.1998
Canada	20.12.1983	Forward Points	30.05.1997	New Zealand	05.04.1985	Forward Points	30.05.1997
Chile	20.12.1983	Forward Points	31.08.1998	Norway	20.12.1983	Forward Points	30.05.1997
Colombia	19.08.1992	Forward Points	31.12.2001	Philippines	28.11.1991	Forward Points	30.04.1999
Croatia	11.12.1996	Forward Points	31.07.2002	Poland	21.06.1993	Forward Points	30.11.1998
Czech Republic	11.12.1995	Forward Points	30.05.1997	Romania	12.12.1995	Forward Points	30.06.2005
Denmark	20.12.1983	Forward Points	30.05.1997	Russia	28.10.1993	Forward Points	29.07.2005
Egypt	11.12.1995	Forward Points	31.05.2013	Saudi Arabia	11.12.1995	Forward Points	30.05.1997
Euro Area	01.01.1999	Forward Points	30.04.1999	Singapore	20.12.1983	Forward Points	30.05.1997
Ghana	29.03.1994	Forward Points	30.04.2013	Sweden	20.12.1983	Forward Points	30.05.1997
Hong Kong	20.12.1983	Forward Points	30.05.1997	Switzerland	20.12.1983	Forward Points	30.05.1997
Hungary	18.06.1993	Forward Points	30.11.1998	South Africa	20.12.1983	Forward Points	30.05.1997
India	20.12.1983	Forward Points	30.06.1999	Taiwan	20.12.1983	Forward Points	30.04.1999
Indonesia	28.11.1991	Forward Points	30.06.2004	Thailand	20.12.1983	Forward Points	30.05.1997
Israel	23.07.1984	Forward Points	30.11.1998	Ukraine	11.12.1995	Outright	30.06.2005
Japan	20.12.1983	Forward Points	30.05.1997	United Kingdom	20.12.1983	Forward Points	30.05.1997
Korea	20.12.1983	Forward Points	29.10.2004	Zambia	11.12.1995	Outright	31.05.2013

Table 11: Overview of the Sample. The Column FX Spot shows from which date on daily data on the FX Spot is available. The Column first Portfolio entry show the date a currency entered the Portfolio for the first time.

Country	ATM 1Y IV	PPP	PPP Source	Country	FX Spot	PPP	PPP Source
Australia	26.02.1999	26.02.1999	OECD	Kuwait	30.06.2008	26.02.1999	IMF
Brazil	31.10.2003	26.02.1999	OECD	Malaysia	31.05.1999	26.02.1999	IMF
Bulgaria	no data	26.02.1999	IMF	Mexico	26.02.1999	26.02.1999	OECD
Canada	26.02.1999	26.02.1999	OECD	New Zealand	26.02.1999	26.02.1999	OECD
Chile	26.02.1999	26.02.1999	OECD	Norway	26.02.1999	26.02.1999	OECD
Colombia	29.11.2002	26.02.1999	OECD	Philippines	31.03.1999	26.02.1999	IMF
Croatia	30.06.2008	26.02.1999	IMF	Poland	30.09.1999	26.02.1999	OECD
Czech Republic	31.03.1999	26.02.1999	OECD	Romania	30.06.2008	26.02.1999	IMF
Denmark	28.02.2001	26.02.1999	IMF	Russia	31.03.2005	26.02.1999	OECD
Egypt	no data	26.02.1999	IMF	Saudi Arabia	30.06.2008	26.02.1999	OECD
Euro Area	26.02.1999	26.02.1999	OECD	Singapore	29.12.2000	26.02.1999	IMF
Ghana	no data	26.02.1999	IMF	Sweden	26.02.1999	26.02.1999	OECD
Hong Kong	26.02.1999	26.02.1999	IMF	Switzerland	26.02.1999	26.02.1999	OECD
Hungary	31.03.2005	26.02.1999	OECD	South Africa	26.02.1999	26.02.1999	OECD
India	31.03.1999	26.02.1999	OECD	Taiwan	26.02.1999	26.02.1999	IMF
Indonesia	26.02.1999	26.02.1999	OECD	Thailand	26.02.1999	26.02.1999	IMF
Israel	26.02.1999	26.02.1999	IMF	Ukraine	30.06.2008	26.02.1999	IMF
Japan	26.02.1999	26.02.1999	OECD	United Kingdom	26.02.1999	26.02.1999	OECD
Korea	26.02.1999	26.02.1999	OECD	Zambia	no data	26.02.1999	IMF

Table 12: Overview of the sample and the availability of data.

6.2. Histograms of the Portfolios

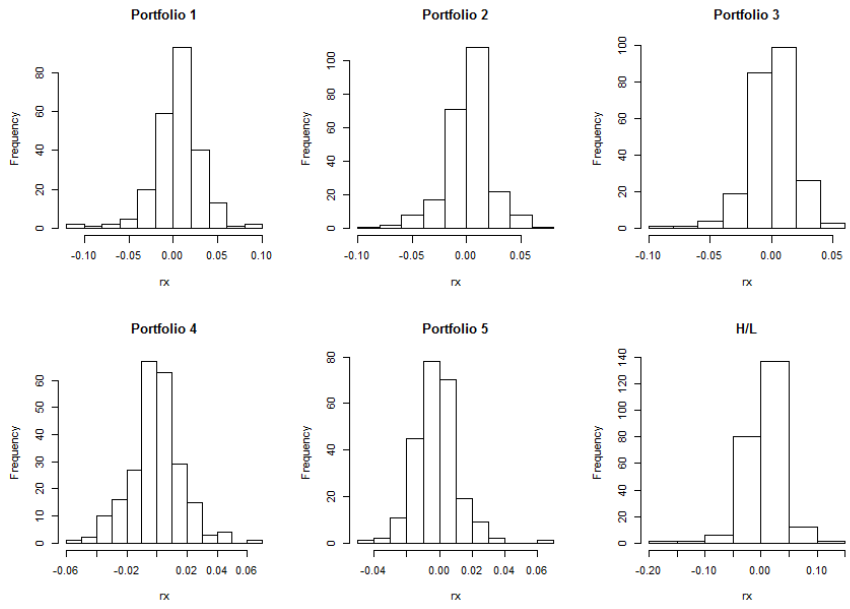


Figure 1: Histograms of the excess returns of the five portfolios

6.3. Results from the replicated Corte, Ramadorai, and Sarno (2016) Sample

6.3.1. VRP Strategy

Portfolio	1	2	3	4	5	Avg.	VRP
Mean	2,40%	1,69%	-0,75%	0,08%	3,54%*	1,39%	-1,10%
Median	2,96%	0,77%	1,20%	-0,06%	1,67%	-0,05%	1,77%
Std. dev	8,38%	6,36%	7,00%	6,35%	7,13%	7,04%	9,22%
Skewness	-1,03	0,54	-1,34	0,14	-0,19	-0,38	-0,62
Kurtosis	3,79	1,85	6,73	2,24	1,49	3,22	1,96
Sharpe Ratio	-0,24	-0,42	-0,73	-0,68	-0,12	-0,44	-0,59

Table 13: This table shows the excess return of the VRP strategy for the replicated sample. Turkey enters the sample in February 2004.

6.3.2. CAR Strategy

Portfolio	1	2	3	4	5	Avg. (DOL)	CAR
Mean	8,49%***	-3,31%*	1,98%	-0,07%	-2,34%*	0,95%	11,06%***
Median	10,27%	-2,96%	2,39%	0,17%	-3,23%	0,80%	10,01%
Std. dev	11,15%	7,52%	8,50%	5,55%	4,75%	7,49%	12,14%
Skewness	-1,08	0,71	-0,39	-1,36	0,67	-0,29	-0,70
Kurtosis	4,15	3,93	2,08	7,96	3,03	4,23	2,20
Sharpe Ratio	0,42	-0,95	-0,22	-0,70	-1,30	-0,55	-0,74

Table 14: This table shows the excess return of the CAR strategy for the replicated sample. Turkey enters the sample in February 1999.

6.3.3. MOM Strategy

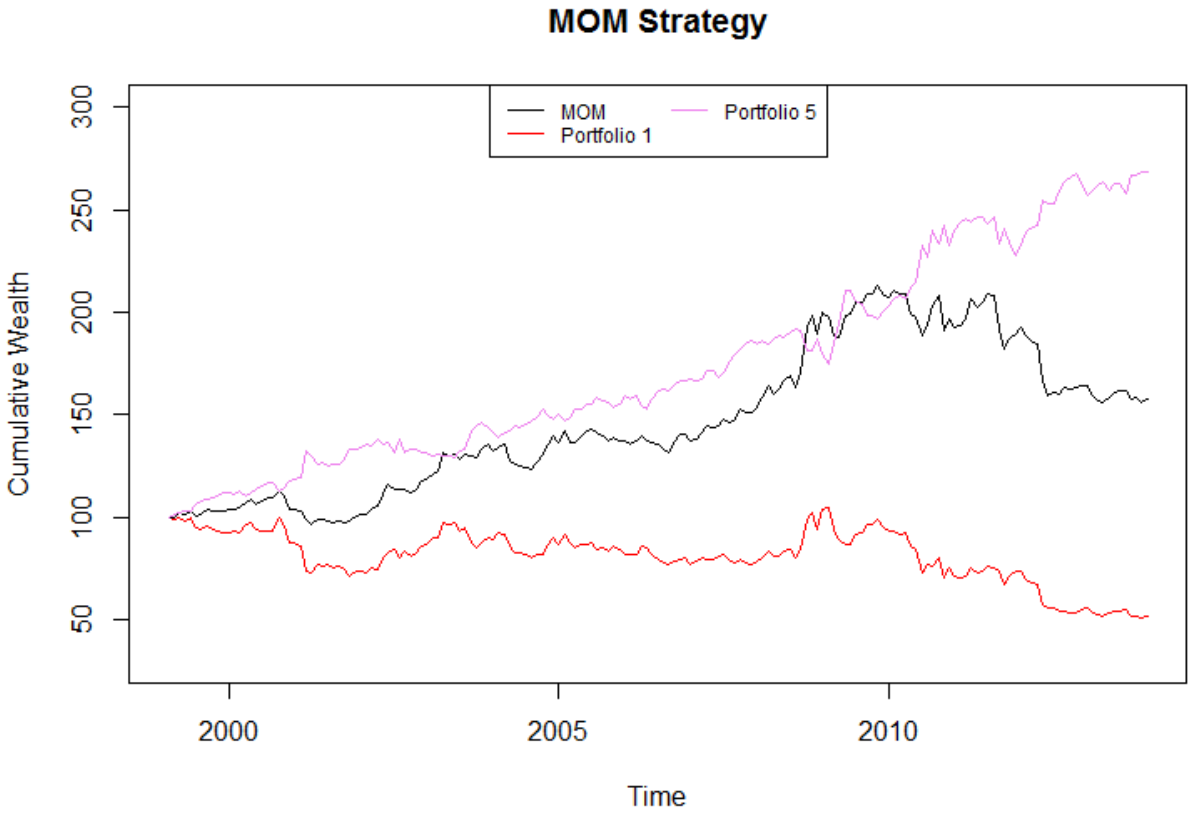
Portfolio	1	2	3	4	5	Avg.	MOM
Mean	3,58%	3,37%	0,99%*	0,13%	7,21%***	3,06%	-3,40%
Median	3,96%	0,55%	2,29%	0,48%	9,01%	-0,07%	-3,39%
Std. dev	9,44%	8,05%	8,23%	8,83%	8,01%	8,51%	14,33%
Skewness	-0,06	0,19	-1,29	-1,31	0,76	-0,34	-0,22
Kurtosis	3,48	1,82	5,92	4,95	3,00	3,83	3,24
Sharpe Ratio	-0,08	-0,12	-0,41	-0,48	0,35	-0,15	-0,54

Table 15: This table shows the excess return of the CAR strategy for the replicated sample. Turkey enters the sample in February 1999.

6.3.4. VAL Strategy

Portfolio	1	2	3	4	5	Avg.	VAL
Mean	5,04%*	2,39%	0,61%	2,36%	-0,38%	2,00%	5,45%**
Median	5,10%	5,87%	2,70%	0,34%	0,60%	-0,05%	3,86%
Std. dev	9,19%	10,66%	5,96%	7,26%	4,88%	7,59%	10,53%
Skewness	-1,28	-1,20	-2,09	0,09	-0,01	-0,90	-0,79
Kurtosis	8,03	3,12	8,46	0,87	0,08	4,11	5,11
Sharpe Ratio	0,07	-0,19	-0,63	-0,28	-0,97	-0,40	0,10

Table 16: This table shows the excess return of the CAR strategy for the replicated sample. Turkey enters the sample in February 1999.



Graph 3: This graph shows the performance of the MOM strategy and its two components the momentum portfolio 1 and 5.

6.4. German Abstract

Diese Arbeit befasst sich mit dem Zusammenhang zwischen dem Forward Premium Puzzle und der Volatilität. Im ersten Teil wird ein SDF Ansatz verwendet um den Zusammenhang zwischen dem Forward Premium und globaler FX Volatilität zu untersuchen. Die Berechnungen wurden mit Hilfe der Methode der GMM durchgeführt. Ein negativer Zusammenhang zwischen Währungen mit einem hohen Carry

relativ zum USD und globaler FX Volatilität wurde gefunden. Im zweite Teil wird die Handelsstrategie von Corte, Ramadorai, and Sarno (2016) welche Währungen anhand des Volatilitätspremiums auswählt untersucht. Diese Strategie verkauft Währungen welche teuer zu versichern sind und investiert in Währungen welche günstig zu versichern sind. Es wird gezeigt das die Strategie keine signifikant positive Rendite liefert. Außerdem liefert die Strategie keine Information über Bewegungen des Spotpreises.

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