A Treatise on Currency Risk and Portfolio Strategies

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„Wollt Ihr mein Geheimnis wissen?“, fragte er seine Zuhörer. „Dies ist mein Geheimnis: Ich habe nichts, gegen das, was geschieht!“– *Jiddu Krishnamurti.*

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Chapter 1

General Introduction

General Introduction

Under the Bretton Woods system, the US-dollar (USD) acted as the reserve currency for many member countries around the world, where the foreign country was required to peg their currency on the USD in a narrow range; a fixed foreign exchange rate regime has been established. After the breakdown of the Bretton Woods system, which was unilaterally triggered by the United States (US) on the 15th of August, 1971, through the termination of the USD convertibility into gold, the investors were confronted with an abrupt regime change in which foreign exchange rates began to free-float. This situation was relatively new after centuries of gold-backed and/or fixed-rate episodes. The most important questions at the time were: what is the fundamental value of a currency? And, what factors sufficiently forecast foreign exchange rate returns?

The first question was answered by the building of monetary exchange rate models that tried to anchor the nominal exchange rate to economic fundamental values, such as money supply differentials, real income differentials, short-term interest rate differentials, and/or inflation differentials (see Bilson, 1978; Dornbusch, 1976; Frankel, 1979; Frenkel, 1976; Hooper and Morton, 1978). These monetary model approaches provide economists with a first long-term view of the respective exchange rate dynamics. With regard to the second question, exchange rate forecasting as such has been identified as a very challenging task. In fact, a seminal study by Meese and Rogoff (1983) found that the forecasting performance of exchange rate models based on fundamentals does not perform better than the naïve random walk model. This empirical fact has not yet been convincingly rejected yet, leading to the term *exchange rate disconnect puzzle*.

To overcome these difficulties in direct exchange rate forecasting, this study concentrates on the following questions: (i) what is the general underlying risk of foreign exchange baskets? And (ii) how can the investor use these risk structures to enhance portfolio efficiency in his foreign exchange exposure? Previous studies by Lustig et al. (2011) and Menkhoff et al. (2012a) investigated the cross-sectional risk dynamics of currency portfolio baskets that are sorted regarding their interest rate differentials. With regard to the summary statistics of the respective baskets, they found specific differences, especially between low-yielding currencies (funding currencies) and high-yielding currencies (investment currencies). While the latter currency group return statistics can be characterized as highly volatile with significant negative skewness and high positive returns, the first group’s returns are less volatile and more Gaussian distributed with on average negative returns for the representative US-investor. Furthermore, Lustig et al. (2011) found in a principal component analysis that all currency basket returns can be explained by two major risk sources: (i) the dollar risk factor (DOL), which basically mirrors the value of the US-dollar (USD) relative to all other foreign currencies, and (ii) the carry trade risk factor (CT), which is the portfolio return of being long investment currencies and short funding currencies. In a standard asset pricing test (based on Ross, 1976), they showed that the DOL risk factor loaded constantly loaded on any portfolio basket, while the CT risk factor was identified as a slope factor that loads negatively on funding currencies and positively on investment currencies, which monotonically increases from basket to basket. With R^2 values reaching over 90%, one can state that they explained nearly all cross-sectional variations of currency portfolio returns sorted by their interest differentials. Especially, the carry trade risk factor was highly significant, therefore, plays a major role in explaining these return variations.

Taking these facts as a basis, Chapter 2 deals with the following important questions: What is the carry trade risk characteristic, or put differently, what drives carry trade returns? Since the carry trade is one of the most famous investment strategy in currency markets, its significant excess returns over the past four decades are well documented (e.g. Burnside et al., 2011b) and have been heavily debated in the recent past. This debate is primarily due to the fact that systematical excess returns over a long period is at odds with the uncovered interest rate parity (UIP). It postulates that the advantage of the interest rate differential by investing into a high-yielding currency, which is subsequently funded by a low-yielding currency, should vanish on average through a depreciation of the investment currency, appreciation of the funding currency, or both. One can formulize the UIP as follows:

$$\mathbb{E}_t[S_T] - F_{t,T} = 0 \tag{1}$$

where $\mathbb{E}_t[S_T]$ denotes the current expectation over the future spot rate in *T*, whereas the current forward rate with maturity *T* is denoted as $F_{t,T}$. The exchange rates are expressed as the price of one foreign currency unit in USD, where an appreciation translates into a depreciation of the USD. Given that the covered interest rate parity holds, the relationship of the current forward to the current spot rate is as follows:

$$F_{t,T} = S_t e^{(i-i^f)\tau} \tag{2}$$

where the annualized domestic USD-rate is denoted as *i* and the corresponding foreign LIBOR as i^f and where τ is just the difference between the maturity date *T* and the current date *t*. If we now reformulate both equations into log-format and substitute (2) into (1), we get

$$\mathbb{E}_t[s_T] - s_t + (i - i^f)\tau = 0 \tag{3}$$

where the lower case letter *s* denotes the respective log spot price. The first term corresponds to the expected spot return and the second term to the deterministic interest rate differential (IRD). A frequently used econometric equation to test the UIP ex post, can be performed as

$$\mathbb{E}_t[s_{t+1}] - s_t = \alpha + \beta(i^f - i)\tau + \varepsilon_{t+1} \tag{4}$$

Given that the UIP holds, one would expect that α is equal to zero and β equal to 1, but the great majority of studies were able to reject this joint hypothesis (see Bilson, 1981; Fama, 1984; Hansen and Hodrick, 1980) and even found significantly negative β coefficients. These results have led financial institutions to establish a strategy to exploit the empirical failure of the UIP, known as the currency carry trade. With regard to the empirical evidence from Lustig et al. (2011), it can be concluded that knowing more about the source of risk to the carry trade would ultimately lead to a better understanding of the currency risk in the cross-section.

After a comprehensive analysis of the underlying risk of the carry trade, the second part of the question becomes important: How can the representative investor use this information to improve the returns of carry trade investments? Chapter 3 provides a sophisticated investment model for exchange rates that uses not only economic fundamentals as state variables, but also the information inherent in exchange rate options. This portfolio selection model, which goes back to the pioneering work of Brandt et al. (2009), models optimal portfolio weights as a function of the underlying risk characteristics. This means that instead of following the traditional mean-variance approach of Markowitz (1952), the model uses any kind of background risk factor that is supposed to have forecasting ability for the underlying risk at hand. Laborda et al. (2014) operationalized this idea to fit the needs for the currency carry trade portfolio, by installing six currency risks related state variables: (i) the average interest rate differential,[1] (ii) the first lag of the carry trade return, (iii) the US-TED spread, (iv) a commodity index return, (v) the US equity-based volatility index VIX, and (vi) a global monetary policy indicator.

While most of these variables have been proven to be statistically significant for future carry trade returns, the results for my sample are more disappointing than those in the original work. Therefore, this study improves the results of the model by implementing risk factors that are naturally forward-looking, namely the FX option-implied variance risk. Using option-implied moment risk variables has been primarily encouraged by the studies by Della Corte et al. (2016), Farhi et al. (2015), Huang and Macdonald (2015), and Jurek (2014), who find a close connection between exchange rate returns and the moment risks traded in the FX option market. However, extracting information from the option market is far more complex. Farhi et al. (2015) for instance, decouple the "disaster risk" exposure, or disaster premium, from out-of-the-money (OTM) put prices of each exchange rate in the sample. As a result, the average disaster risk

[1] To be more specific, Laborda et al. (2014) use the average of the forward discount values, which is the difference between the current forward and spot rate in log prices. One can see this by rearranging equation (2), in which the forward discount rate is equal to the interest rate differential.

exposure explains more than a third of the carry trade excess returns. Jurek (2014) constructed a crash-neutral carry trade portfolio, where he uses at-the-money (ATM) and OTM put options to hedge the downside risk. The difference between the hedged and unhedged portfolio versions have been justified as variance or skewness risk premium. He also concludes that also about one-third of the excess returns to the carry trade are connected to the crash risk.

This study uses a direct way to measure option-implied moment risk that goes back to the theory of contingent claim pricing proposed by Breeden and Litzenberger (1978). Using this approach, Neuberger (2012) developed a realized and option-implied measure for variance and skewness risk that can be used to directly derive moment risk premia. In particular, Neuberger (2012) constructed a realized skewness that perfectly matches the moment of its option-implied counterpart, which can be regarded as novel in the existing literature.

Having this approach in mind, Chapter 4 investigates into the third moment risk premium in currency markets. Given the empirical findings from Brunnermeier et al. (2009) and Jurek (2014), who observed an unusual disconnection between the realized and implied skewness risk between several exchange rates in their sample, a comprehensive analysis for a wide range of exchange rate becomes obligatory. Ruf (2012), for instance, observed a similar picture in the commodity market. After determining the empirical disconnection in the third moment risk premium among 25 different commodities, he provides evidence that the disconnection is primarily due to limits-to-arbitrage effects coming from trade activity in the commodity option market triggered by speculators. Therefore, it is interesting to see whether the skewness risk premium in currency markets is similarly affected as in commodity markets.

Chapter 2

The Carry Trade and Implied Moment Risk

THE CARRY TRADE AND IMPLIED MOMENT RISK

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Abstract

The carry trade is a zero net investment strategy that borrows in low yielding currencies and subsequently invests in high yielding currencies. It has been identified as highly profitable FX strategy delivering significantly excess returns with high Sharpe ratios. This paper shows that these excess returns are especially compensation for bearing FX variance and negative skewness risk. Additionally, factor risks that affect foreign money changes, foreign inflation changes, as well as changes to a newly developed *Carry Trade Activity Index* and the VIX index, as a proxy for global risk aversion, make up the carry trade risk anatomy. These findings are not exclusively important for *carry traders*, but also contribute to the understanding of currency risk in the cross-section. This is directly linked to asset pricing tests from Lustig et al. (2011), which have shown that currency baskets sorted on their interest rate differentials are all exposed to carry trade returns as a risk factor. Furthermore, this paper finds evidence that a decreased level of funding liquidity potentially leads to carry trade unwindings, controlling for equity and FX implied variance and skewness effects, which supports the theoretical model of liquidity spirals developed by Brunnermeier and Pedersen (2009).

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1 Introduction

This paper studies the risk anatomy of the carry trade (CT) foreign exchange rate (FX) strategy. This highly profitable zero net investment strategy uses funding gathered from low yielding currencies, also called funding currencies, and subsequently invests the proceeds into high yielding currencies, or investment currencies. This popular trading strategy has delivered significant returns over at least the past four decades (e.g. Burnside et al., 2011b), which violates the properties of the uncovered interest rate (UIP) parity. The UIP assumes that the current FX forward price is equal to the expected future spot price, or to put it differently, the future currency spot level will remove the advantage or disadvantage of the interest rate differential. Many empirical investigations about the UIP, dating back to at least Hansen and Hodrick (1980), Bilson (1981), or Fama (1984), have shown that there is no supportive evidence that FX forward prices are unbiased predictors of future spot prices. This is known in the literature as the forward premium puzzle.

Guided by the insights of Lustig et al. (2011), who showed using the Arbitrage Pricing Theory (APT) of Ross (1976), we understand that FX cross-sectional portfolios are primarily driven by two risk factors. This is (i) a dollar-based risk, which loads constantly onto all portfolios and (ii) the carry trade risk itself, which increases monotonically from funding to investment currencies. Identifying the carry trade as a significant "slope" factor with respect to the cross-sectional currency portfolios that are sorted by interest differential, means that these portfolios are exposed differently to the carry trade. This leads to the following conclusion: A more profound understanding of the risks inherent in the carry trade helps to understand cross-sectional currency risk. In this respect, any evidence found here is not only important for investors engaged in the carry trade, but is also important to those making any foreign currency investment.

The purpose of this paper is to convincingly identify risk factors, which underlines the reality that the return to the carry trade is a compensation for risk bearing. It provides a comprehensive empirical investigation to literature, which collects several economically important risk factors together in order to get a clearer view of the risk anatomy of the carry trade. This will be achieved in a multifactor model using time series regressions. Most of the risk factors are converted into mimicking FX portfolios to capture risk factors as returns, which can be also used as hedging instruments. Additionally, it will be shown that a newly constructed *Carry Trade Activity Index* (CTI), built on information of aggregated FX future contract positions, is significantly related to CT returns. Moreover, while liquidity risk does not directly exhibit sufficient effects on CT returns, it will be shown that it contributes significantly to CT unwindings, controlling for variance and skewness risks, which supports the thesis of liquidity spirals proposed by Brunnermeier and Pedersen (2009) in the foreign exchange market.

Furthermore, the empirical investigation shows that significant CT returns are mostly due to global FX option-implied variance and skewness risk. These two risk factors, which characterize investors future perceptions about FX return fluctuation and FX crash risk, appear to be uncorrelated to each other and describe more than 70% of the return variation. Other risks like (i) foreign real money growth, (ii) foreign CPI growth, (iii) changes to the CTI, and (iv) changes to the VIX index, complete the risk profile and describe almost 80% of CT return variation.

2 Related Literature

In addition to the pioneering work of Lustig et al. (2011), there are several variations made to describe the risks of cross-sectional FX portfolio returns. Rafferty (2012) uses global FX realized skewness as a substitute for CT returns. He argues that the time series of CT returns is prone to negative skewness and therefore can mimic the risk inherent in the CT strategy. Menkhoff et al. (2012a) investigated global FX volatility innovations, which stand for unexpected volatility changes that drives cross-sectional returns. Huang and Macdonald (2015) instead use returns of a mimicking portfolio of sovereign Credit Default Swaps (CDS) as the representative risk for global liquidity imbalances and sovereign default risk. All of them find evidence that these “FX moment risks” well describe the cross-section of FX returns. In a different study, Farhi et al. (2015) extract information about exposure to global disaster risk out of FX option prices. In this they find a close connection to the observed interest rate differentials. As a result, they justify the high excess return from the CT as a compensation for bearing high world disaster risk. Brunnermeier et al. (2009) offer another interesting perspective regarding liquidity risk. They argue that CT returns are dependent on the supply of speculative risk capital. They claim that when liquidity dries up, it can lead to reductions in CT positions and ultimately, negatively skewed returns. Clare et al. (2015) build up a capital asset pricing model (CAPM) that’s augmented by liquidity risk factors to show that the covariance term of market risk and lagging liquidity risk contributes to the explanation of CT returns, but CT returns continue to be significant. Furthermore, they find little support of the proposed equity downside CAPM model (DR-CAPM) by Lettau et al. (2014). This model relates negative equity market returns to the cross-section of currency portfolios. In a related paper, Christiansen et al. (2011) built a regime-dependent asset pricing model for explaining CT excess returns, where regimes are best described using FX volatility and TED spread levels. They concluded that CT returns are exposed to equity market risks during both periods and to FX market risk in turmoil periods, while the risk adjusted return remains significant. Another link between equity market risk and currency risk was investigated by Aloosh (2014). He found evidence that global equity variance risk premium (VRP^{EQ}) has predictive power to explain CT and equity returns. Also, Bakshi and Panayotov (2013) investigate the time series predictability of CT returns using changes of a commodity index, realized FX volatility and a liquidity risk indicator. They find evidence of the predictability of in-sample as well as out-of-sample CT returns. These contributions have in common that they mostly link FX returns to sources of financial market realized moment risks. They make use of various statistical techniques in order to empirically describe the risk environment of FX returns or to justifying high CT excess returns that are at odds with the theoretical foundations of the UIP.

This paper comprehensively merges FX option-implied variance and skewness risk, foreign macroeconomic fundamental risks, "global investors risk aversion" in the form of the VIX index, as well as risks related to the FX market microstructure. This is the primary source for reliably explaining CT excess returns as compensation for risk bearing.

The remainder of this paper is organized as follows: Section three describes the data and risk variables used in the analysis and the methodology of transforming these risks into factor mimicking portfolios. Section four presents empirical evidence to exemplify the risk profile of the carry trade. Section 5 concludes.

3 Data and Methodology

The foreign exchange data primarily consists of daily bid/ask spot and one-month (1m) and three-month (3m) forward rate data from WM/Reuters fixings. There are three currency samples used for the econometric analysis, one major and two sub-samples. The first one, *Sample I* consists of all 32 foreign currencies, quoted against the US-dollar (USD), covering the sample period from September 2003 at the earliest to June 2015.[1] The first subgroup of *Sample I* is the so called *G-10* currencies from Australia (AUD), Canada (CAD), Denmark (DKK), Europe (EUR), Great Britain (GBP), Japan (JPY) New Zealand (NZD), Norway (NOK), Sweden (SEK) and Switzerland (CHF). *Sample I* also contains FX prices of 22 emerging countries: Brazil (BRL), Chile (CLP), Colombia (COP), Czech Republic (CZK), Hungary (HUF), India (INR), Indonesia (IDR), Israel (ILS), Malaysia (MYR), Mexico

[1] Table A. 1 provides an overview of the various start and end dates of any currency in the coverage.

(MXN), Peru (PEN), Philippines (PHP), Poland (PLN), Romania (RON), Russia (RUB), Singapore (SGP), Slovakia (SKK), South Africa (ZAR), South Korea (KRW), Taiwan (TWD), Thailand (THB), and Turkey (TRY). The second sub-group, *Sample TFF,* deals with up to nine currencies that are listed on the Chicago Mercantile Exchange (CME), where FX future contracts are traded. This sample includes AUD, CAD, CHF, EUR, GBP, JPY, MXN, all starting in September of 2003, while future contracts on NZD and RUB start in November of 2005 and February of 2009, respectively. This paper collects the last month future-only reports as a proxy for end-of-month data points.

The interest rate data is comprised of daily 1m and 3m maturity London interbank offered rates (LIBOR) for all currencies and the USD. In cases where LIBOR is unavailable, implied rates are computed, using the covered interest rate parity (CIP) definition.[2]

Additionally, 10-year (10y) government rates are used for all currencies except for PEN and RON, and 3m government rates are used for all G-10 currencies. The 10y and 3m government yields for the EUR are approximated with the *Euro Benchmark Bond* definition according to Datastream. The 3m CHF government bond rate is approximated with the 1-year rate because of non-availability. The US 4-week T-Bill rate serves as the risk free rate for the US investor.

Also, monthly foreign macroeconomic data for the money stock (M3), consumer price index (CPI), industrial production, and foreign equity index data[3] is collected for *Sample I* currencies. All data is obtained using Datastream except for FX future contract data that is obtained from the *U.S. Commodity Futures Trading Commission's* (*CFTC*) website.

Currency returns, parities and portfolios

It is assumed that the foreign exchange (FX) market is arbitrage-free and without friction. Currency excess returns will be computed using currencies from 1m-forward and spot prices, expressed in terms of the viewpoint of a US-investor. An appreciation of the current exchange rate S_t translates into a depreciation of the USD. Forward prices are denoted as $\mathrm{F}_{t,T}$, subscripted with *t* as the current state of time and *T* as the maturity date. The respective lower-

[2] CIP assumes that the log forward price is equal to the log spot price and the interest rate differential. CIP-implied foreign rates have been computed for the 1m KRW rate from September 2003-July 2004, the 1m TRY rate from November 2005-June 2006, the 1m CLP rate from January 2014-June 2015 and for 1m and 3m SKK rates from January 2009-June 2015 and October 2013-June 2015, respectively.

[3] The local stock index data is taken from the MSCI-Barra website and log returns are computed using "Net Standard Large+Mid Cap" index time-series.

case letters will be used to indicate log prices and *t:T* means the time interval between *t* and *T*. The log currency excess return[4] $rx_{t:T}$ can then be defined as:

$$rx_{t:T} = s_T - f_{t,T} \approx \Delta s_{t:T} - (i_{t,T} - i_{t,T}^{f}) \qquad (1)$$

It can be viewed as buying foreign currency units in the forward market at time *t* and closing the position at maturity *T* by selling foreign currency units in the spot market. If it is assumed that CIP holds, then the excess return can also be approximated as the interest rate differential (*IRD*) minus the change in the spot market ($\Delta s_{t:T} = s_T - s_t$), where $i_{t,T}^{f}$ denotes the foreign LIBOR and $i_{t,T}$ the US-LIBOR. When rearranging formula (1), one will get the forward discount value of the exchange rate, which is then equal to the *IRD:*

$$fd_{t,T} = f_{t,T} - s_t = i_{t,T} - i_{t,T}^{f} \qquad (2)$$

Hence, $fd_{t,\mathrm{T}}$ is negative for investment currencies and usually positive for funding currencies. Another interesting relationship is the uncovered interest rate parity (UIP), as has been briefly mentioned in the introduction. It assumes that the forward price should equal the expected future spot price:

$$F_{t,T} = \mathbb{E}_t\ [S_T] \qquad (3)$$

It is well known in the literature that this relation rarely holds true empirically, so that the forward price can be viewed as a biased predictor for future spot prices. As a result, investment currencies do not depreciate enough or funding currencies do not appreciate enough, on average, to equalize the advantage of the *IRD*. Therefore, the carry trade strategy exploits the failure of the UIP, leading to highly significant returns. Furthermore, in this paper it is not automatically assumed that CIP holds true, so all time frames of high CIP violations are excluded.[5] This step ensures that effects leading to CIP violations do not cause a bias regarding the CT return distribution and forthcoming econometric results.

As it is the case in numerous studies, this paper sorts currencies according to their *IRD*, forming six currency baskets. This is because numerous studies find evidence that these currency groups are different in their risk profiles (see Lustig et al., 2011; Menkhoff et al., 2012a). P-1 denotes the return of the low yielding currency basket and ends with P-6, which contains the returns on investment currencies. The CT return itself is then the difference of P-6 and P-1. Table 1 provides a statistical summary of the return time-series of these currency baskets.

[4] All return series are expressed in logarithmic format throughout the paper.
[5] Table A. 2 provides an overview of excluded time frames according to large CIP violations for all currencies, respectively.

[*Insert Table 1 about here*.]

The first row monotonically increases in average returns when moving from P-1 to CT. Despite the financial crisis in September 2008, the CT return series is the only one that is significantly different from zero at the 10% level. In row three and four, you will find the average interest rate differential in terms of the foreign rate ($IRD^f = i^f - i$) and average spot returns ($\Delta spot$). According to UIP, these values should sum to zero on average. Nevertheless, we see that P-1 currencies earn a negative carry of 139 basis points (bps) annually, while appreciating by only 64 bps. On the other hand, P-6 currencies earn an average of 708 bps but depreciate only by an average of 365 bps. The difference between $\Delta spot$ and IRD^f monotonically increases from P-1 to P-6, which aligns with the findings by Lustig et al. (2011). A similar monotonically increasing pattern arises for the standard deviation for P-1 to P-6, pointing to a less stable return series of investment currencies compared to funding currencies. This is not the case for portfolio skewness and excess kurtosis. Here, the monotonic pattern is only evident for P-1 to P-5 for skewness and P-1 to P-4 for kurtosis. Average transaction cost adjusted currency portfolio returns are provided in the row *Mean (ba).* It is assumed that the costs are primarily driven by trading bid and ask prices in the respective forward and spot market at initiation and end-of-month dates. The costs also rise monotonically from low yielding (98bps) to high yielding currencies (173bps), leading to average transaction costs of 117bps per year. Furthermore, there is no evidence of significant return autocorrelation of investment currency baskets or the CT portfolio, as it is found in Menkhoff et al. (2012a). The Sharpe ratio also rises monotonically from P-1 to CT, which points to the fact that the advantage of rising IRD^f's are not burdened by higher risk. Also, the *Higher Moment Sharpe ratio* (SR^{HM}), a Sharpe ratio that accounts also for the third and fourth moment risk,[6] increases in the same manner as the original *SR* but on a lower basis.

Currency Risk Factors

We have seen that FX portfolios sorted on their IRD values are differently exposed to higher moment risk, which often increases or decreases monotonically with higher interest rate levels. The CT strategy merges both extreme IRD portfolios, earning a significantly positive return over time, with higher Sharpe ratios. The forthcoming analysis will use several different risk factors to uncover the risk anatomy of the CT. It will show that the CT excess return is a compensation for (i) the global 2nd and 3rd FX moment risk, (ii) to foreign money

[6] The Higher Moment Sharpe ratio (SR^{HM}) is according to the definitions in Broll (2016b) that is introduced in Appendix A.

stock and inflation growth rates, (iii) changes to the VIX index, and (iv) to changes of a *Carry Trade Activity Index* that tracks the position changes of currency futures.

In the following analysis, all risk variables used in the empirical section will be introduced, accompanied by the respective underlying theory and the econometric model.

Implied Volatility Smile Procedure

In order to recover FX option prices, this paper makes use of an option implied volatility smile interpolation model developed by Reiswich and Wystup (2012). The resulting volatility smiles are comparable to other smile procedures used in practice; e.g. the vanna-volga method from Castagna and Mercurio (2007). It uses the input parameters 25-delta butterfly, 25-delta risk reversal, at-the-money (ATM) volatility mid quotes, and the respective LIBOR interest rates for 1m and 3m maturities, respectively. The volatility smile gives you information on the current volatility level of different strike prices from a single option maturity. This offers the opportunity to recover option prices and use them to compute implied moment risks. The implied volatility data is taken from Bloomberg via Datastream.

Higher moment risks

The computation of the second- and third-moment risk is based on the theoretical foundation derived from Neuberger (2012). While the variance risk gives information about the degree of price fluctuation for a given time period, the third-moment risk, or skew risk, defines the asymmetry of a return distribution. A negative skew is often referred to as the crash intensity of an underlying asset. In order to place a bet on a specific moment risk of an underlying asset, one can trade a moment swap, where the option-implied moment is swapped against the realized moment risk. This is practically done with building an option portfolio that resembles that moment risk and is subsequently hedged to neutralize asset price fluctuations. Also, the difference between realized and implied moments is usually used to detect risk premiums for any higher risk moment.

While realized moment risk is computed out of an observed return distribution at time frame $t{:}T$, implied moment risk follows from risk-neutral expectation embedded in option prices at t with maturity date T. The advantage of the definition by Neuberger (2012) is that the realized and implied variance and the realized and implied skew risk perfectly aggregate to each other. This Aggregation Property of realized and implied moment risk ensures that both measures are equal in expectation – regardless of the computation frequency used. It is assumed that the price process of exchange rates is martingale.

Neuberger (2012) defines variance through the function $g^V(r) \equiv 2(R - r)$, where R means the discrete return and r the log return of an asset. This variance definition of g^V differs from the more conventional formula of $g^{Var}(r) \equiv r^2$. However, Jiang and Tian (2005) have shown that using squared log returns in a standard variance swap yield an imperfect aggregation of the realized and implied leg.

Therefore, it follows from g^V that the realized variance from log returns is defined as:

$$Rvar_{t,T} = \sum_{t=0}^{T}\left[2\left(\frac{F_{t+1,T} - F_{t,T}}{F_{t,T}} - ln\frac{F_{t+1,T}}{F_{t,T}}\right)\right] \approx \sum_{t=0}^{T}\left[2\left(\frac{S_{t+1} - S_t}{S_t} - ln\frac{S_{t+1}}{S_t}\right)\right] \quad (4)$$

Due to data limitations, this paper uses the spot rate S_t as a forward equivalent in order to compute the realized variance (*Rvar*). According to the function g^V, the implied variance (*Ivar*) that perfectly aggregates to *Rvar* can be priced with a continuum of options, using the spanning approach of Bakshi and Madan (2000):

$$Ivar_{t,T} = \frac{2}{B_{t,T}}\left(\int_0^{F_{t,T}}\frac{P_{t,T}(K)}{K^2}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)}{K^2}dK\right) \approx \frac{2}{B_{t,T}}\left(\sum_{K_j \le F_{t,T}}\frac{P_{t,T}(K_j)}{K_j^2}\Delta J(K_j) + \sum_{K_j > F_{t,T}}\frac{C_{t,T}(K_j)}{K_j^2}\Delta J(K_j)\right) \quad (5)$$

The implied variance *Ivar* is comprised of a portfolio of out of the money (OTM) call and put options. The second RHS term (5) characterizes the discrete approximation, where $\Delta J(K_j)$ defines the difference between strike prices, which is computed as follows:[7]

$$\Delta J(K_j) \equiv \begin{cases} K_{j+1} - K_{j-1}, for\ 0 \le j \le N\ (with\ K_{-1} \equiv 2K_0 - K_1, K_{N+1} \equiv 2K_N - K_{N-1}) \\ 0, \quad otherwise. \end{cases} \quad (6)$$

We will turn now to the definition of the third-moment risk, which is more complicated than the variance risk. Neuberger (2012) defined a g-function g^{ThM}, that approximates the skew risk of log returns. It can be expressed as follows:

$$g^{ThM}(\Delta Ivar^E, r) \equiv 3R\ \Delta Ivar^E + 6(r + (1 + R)r - 2R) \quad (7)$$

The term $\Delta Ivar^E$ means the first difference of the implied variance of the *entropy contract* that is somehow related to the definition (5), but still incorporates the intuition of variance

[7] The finite approximation of formula (6) has been used in Kozhan et al. (2013), who investigated in variance and skewness risk premiums for the S&P 500 equity index.

risk.[8] It's clear from g^{ThM} that the realized third-moment risk, which has the desired Aggregation Property, can be expressed as follows:

$$Rthm_{t,T} = \sum_{t=0}^{T}\left[\left\{3\left(\frac{F_{t+1,T}-F_{t,T}}{F_{t,T}}\right)\left(Ivar^{E}_{t+1,T}-Ivar^{E}_{t,T}\right)\right\}+\left\{6\left(ln\frac{F_{t+1,T}}{F_{t,T}}+\frac{F_{t+1,T}}{F_{t,T}}ln\frac{F_{t+1,T}}{F_{t,T}}-2\frac{F_{t+1,T}-F_{t,T}}{F_{t,T}}\right)\right\}\right] \tag{8}$$

While this paper computes realized moments at a daily frequency, Neuberger states that the higher the return frequency, the more efficient the resulting realized moment.[9] The realized skew risk can be divided into two parts. The term within the first curly braces is interpreted as the covariance between the asset return and the change in variance, also known as the leverage effect. Under the second curly braces, an unconventional expression of cubed asset returns is applied. While the latter disappears in the limiting case, only the covariance term survives. This conclusion is essential to appropriately characterize skew risk in financial markets, while other skew definitions fail to incorporate the leverage effect into their calculations (e.g. Schoutens, 2005).

The implied third-moment risk (*Ithm*) can also be expressed as a continuum of options, taking the function g^{ThM} as a basis and using the spanning approach of Bakshi and Madan (2000):[10]

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_{F_{t,T}}^{\infty}\frac{(K-F_{t,T})}{K^2\,F_{t,T}}C_{t,T}(K)dK - \int_{0}^{F_{t,T}}\frac{(F_{t,T}-K)}{K^2\,F_{t,T}}P_{t,T}(K)dK\right) \tag{9}$$

The discrete version using a finite set of options applies as:

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\sum_{K_j>F_{t,T}}\frac{C_{t,T}(K_j)(K_j-F_{t,T})}{K_j^2F_{t,T}}\Delta J(K_j) - \sum_{K_j\leq F_{t,T}}\frac{P_{t,T}(K_j)(F_{t,T}-K_j)}{K_j^2F_{t,T}}\Delta J(K_j)\right) \tag{10}$$

We see that implied skew consists of a portfolio of OTM puts and calls, where calls are held long and puts are held short. Interpreting a positive implied skew in this context would mean that current call options are more expensive than their corresponding put counterparts, and therefore the market expects a more pronounced upward slope return distribution in the future.

For the discrete calculations of the implied variance and skew risk according to (5) and (10), a string of 20 put and call OTM options will be used, respectively. The option strings are equally spaced between the (+/-) 0.10 and (+/-) 0.50 option delta for calls and puts,

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[8] The definition of $Ivar^{E}$ is discussed in Appendix B.
[9] Please be reminded that for the computation of *Rthm,* the spot prices are taken instead of forwards.
[10] A more thorough derivation of the implied third-moment risk is provided in Appendix C.

respectively. Instead of using the third-moment risk, this paper uses its standardized form, that is comparable to the conventional measure of skewness and is more Gaussian distributed as the pure third-moment risk. As a result, realized skewness is defined as $Rskew = Rthm / Rvar^{3/2}$. Implied skewness is simply expressed as $Iskew = Ithm / Ivar^{3/2}$.

Pre- and Post-Crisis FX Moments

Another interesting aspect of the second- and third-moment risk in currency markets can be seen when comparing pre- and post-crisis levels. Table 2 offers an interesting overview of the second- and third-moment risks.

[*Insert Table 2 about here.*]

Panel A gives an overview of the average volatilities, which are simply the square root of the respective variance and skewness figures during the pre-crisis period for P-1 to P-6 currency baskets. Realized volatilities are lowest for funding currencies and highest for investment currencies, and increases monotonically with *forward discounts*, which can also be observed in Table 1. Also, funding currencies, on average, have a positive skewness, while the investment currencies are prone to crash risk (negative skewness). Whether a significant risk premium for volatility and skewness risk is observable has also been tested. The number in brackets shows T-statistics[11], indicating a significant difference between the realized and implied moment risk. Here we see that in the pre-crisis period, there is no existence of a risk premium for volatility and skewness risk, except for P-4 for volatility risk. This means that there is no significant priced premium in FX option prices to be insured against rising volatility or falling skewness risk. This is not the case for post-crisis moment risk. The realized volatility levels are about 20% higher - except for P-6 currencies, and realized skewness is 36 bps lower on average for all currency baskets. The most important difference from the pre-crisis period is that volatility and skewness risk premiums are significant in magnitude for nearly all portfolios - at least at the 5% level. This means that investors are more willing to pay a premium to be insured against high volatility, or crash risk, post-crisis. Another interesting aspect is that realized volatilities almost cut in half after a crisis period, whereas skewness levels are even lower post-crisis compared to mid-crisis levels.

[11] Inference is based on using the bootstrap method with 10,000 draws, in order to estimate standard errors of the implied and realized risk moment differences. The confidence bounds are then approximated using the normal distribution. These bootstrapped inference appears to be more conservative than conventional HAC standard errors.

This discovery is in line with the findings of Farhi et al. (2015), who observed a remarkable difference between pre- and post-crisis risk reversal levels that mirror the skewness risk definition. For 45 G-10 cross-currency pairs, Jurek (2014) reported significant variance and skewness risk premiums for the majority of exchange rates, concluding that variance and crash risk is priced in the currencies cross-section. Caballero and Doyle (2012) find that the CT strategy even produces significantly positive excess returns, when subsequently hedged with FX options. The fact that implied volatilities traded at very low levels in the pre-crisis period supported these results.

Carry Trade Activity Index (CTI)

This paper provides a novel measure of carry trade activity. The most common data source for the FX derivatives market is the weekly *Traders in Financial Futures* (TFF) report provided by the *U.S. Commodity Futures Trading Commission* (CFTC). While future contract data is taken from the CME, which is the biggest FX market exchange, it is still remarkably small compared to the Over-the-Counter (OTC) market. According to statistical data from the *Bank of International Settlement* (BIS), the notional amounts outstanding in FX derivatives for the *exchange traded market* relative to the *OTC market* is only about 0.5% for June 2015. However, the CFTC provides relatively large records of historical data sets that are presented in various settings.

The TFF report offers FX future contract data on long, short, and spread positions; it distinguishes between three different trader groups, *Commercial*, *Non-Commercial,* and *Non-Reportable*. The group of traders that are most likely to take action in CT positions are of primary interest. This paper follows the logic of Brunnermeier et al. (2009), Breedon et al. (2015), who describe the *Non-Commercial* trader group as a group of speculators that are potentially engaged in CT positions. The data will be transformed to capture the size of net future long positions relative to all futures at risk. This can be formulated as follows:

$$SCF_t^k = \frac{long\ futures_t^k - short\ futures_t^k}{long\ futures_t^k + short\ futures_t^k} \tag{11}$$

The ratio SCF_t^k stands for *speculators capital in futures* in the foreign exchange rate *k* at time *t*.[12] It illustrates the degree of speculation to the long or short side of a single foreign

[12] This definition follows from Ruf (2012), who analysed the skewness risk premium in commodity markets, and uses this as a market pressure variable.

currency in the futures market.[13] The *SCF* measure is rather practical, since it always lies between -1 and 1, where a positive realization translates into a net investment in the foreign currency funded by the USD, and *vice versa*. As this can be seen as a carry trade on a two-country level, the extension to a multi-country level or CT strategy is obvious:

$$CTI_t^K = \frac{1}{K}\sum_{k=1}^{K} \max_{IRD} SCF_t^k - \frac{1}{K}\sum_{k=1}^{K} \min_{IRD} SCF_t^k \tag{12}$$

The *Carry Trade Activity Index* (CTI) averages the *SCF* values of *K* high-yield currencies and deducts the average *SCF* values from *K* low yield currencies, using *Sample TFF* currencies. This simple expression should capture on a multi-currency level, the average degree of speculation in CT currencies. While this index is rather limited on up to nine currencies in the relatively small exchange traded future market, it will be seen in the empirical section that CT returns clearly respond to changes of the *CTI*. A practical extension on the *CTI* will be made, enlarging the future universe with future positions of the *Non-Reportable* traders group. This step seems reasonable, since the correlation of position changes to the *Non-Commercial* trader group is fairly high (avg. 0.50).

As the *CTI* seems to be very similar with the procedure used in Brunnermeier, Nagel, and Pedersen (2009) (BNP), the following differences are crucial: (i) the *CTI* is an aggregated measure that uses the respective average investment ratios of funding and investment currencies in a time-series regression, while the *BNP* employs any individual currency ratio in a panel regression framework; (ii) the extended *CTI* has a somehow broader information set, with adding the *Non-Reportable* traders into its scope; and (iii) the *CTI* distinguishes between funding and investment currencies by using the *K* extreme high and low yielding currencies in the sample, whereas the distinction made by the *BNP* relies solely on the sign of the forward discount rate of any FX rate. The latter point, especially, is often inappropriate in small samples with regard to funding currencies. While the forward discount basically mirrors the interest rate differential to the USD, some low yield currencies would be treated misleadingly as investment currencies in times of relatively low USD-rates.

Macroeconomic Risk Factors

Macroeconomic risk variables have got a longstanding presence in exchange rate literature. After the breakdown of the Bretton-Woods system in the 70's, the monetary model was one

[13] A similar ratio has been used in Brunnermeier et al. (2009), where they used the total Open Interest in futures in the denominator.

of the most prominent models for exchange rate determination (e.g. Frenkel, 1976). While these kind of models do not provide sufficiently stable results for the exchange rate (see Cheung et al., 2005; Rossi, 2006), exchange rate returns nevertheless seem to exhibit sensitivities to macroeconomic risks. In the studies of Lustig and Verdelhan (2007), and De Santis and Fornari (2008), evidence is found that foreign currency returns are related to domestic investors consumption growth risk. While funding currencies reduces the risk of consumption growth for the domestic investor, foreign high-yield currency holdings increase consumption growth risk. Therefore, excess returns to the CT strategy have been viewed as a compensation for additional exposure to the domestic consumption growth risk. This became especially visible in the financial crisis in 2008-2009, when CT returns exhibited large losses. While the theoretical model sounds economically appealing, the resulting coefficients often reveal only low or no statistical significance (see also Burnside, 2011). However, this paper will test the impact of *foreign* macroeconomic aggregates on CT risk apart from domestic macroeconomic variables. In this respect, going back to the vein of the monetary model, it is tested whether factor risks on the following three foreign macro variables, do have potential effects on CT returns: (i) the real money stock, (ii) the real income, and (iii) the price level. The macro risks are proxied by log changes to the money aggregate M3, industrial production[14], and the CPI index of the respective foreign country. The variables (i) and (ii) are deflated by their corresponding CPI index level.

Additionally, as another proxy for macroeconomic risk, it will be tested whether foreign stock market returns possibly spill-over to currency markets. Negative stock market returns are interpreted as a precursor of gloomy economic output or uncertainty. These returns are computed in their respective domestic currency, in order to serve as a pure indicator of foreign macroeconomic risk.

Liquidity Risk Factors

Liquidity risk is formally understood as price reaction of underlying assets due to decreased supply of risk capital. There are many ways to proxy for such risks, while the most prominent variables mentioned in currency literature are the currencies bid-ask spread and the US-TED spread (e.g. Menkhoff et al., 2012a). The former is measured as the relative distance

[14] Industrial production usually coincides with consumption growth data and has the advantage of being available at the monthly horizon. For the countries of AUD, NZD, CLP, and CHF there is no industrial production data available. Henceforth, the data on quarterly GDP data will be used instead and will be transformed into monthly observations using the cubic spline method. Also, for the following countries the broadest available money aggregate M2 have been used instead of M3: IDR, RUB, and TWD.

of daily bid and ask spot prices, averaged over the month, in order to mitigate impacts due to holiday or unusual effects. The TED-spread is the difference between 3m US-LIBOR and 3m US-T-Bill rates, where a higher premium is interpreted as lower available risk capital in the interbank money market. Additionally, inspired by Asness et al. (2013) and Bakshi and Panayotov (2013), an aggregated G10-TED spread will be built, which expands the money universe from only the US to the G10-countries money markets.

Other Risk Sources

A risk variable frequently used in currency literature is the VIX index (e.g. Ang and Chen, 2010; Brunnermeier et al., 2009). It represents the implied variance computed out of 1m-option prices on the S&P-500 equity index. The VIX index is often interpreted as a measure of investors risk aversion due to the importance of the US stock market for the global economy. Additionally, this paper checks the impact of the *CBOE SKEW Index* (*SKEW*) that represents the implied skewness risk of the same stock market index.[15] Another factor that is closely related to macroeconomic risk is the index on *Economic Policy Uncertainty* (EPU).[16] It may consist of information from economic variables that has been overlooked. It collects data from newspaper articles related to economic policy uncertainty, US tax provisions, and forecast dispersions for economic aggregates. The use of these uncertainty indexes is motivated by the work of Balcilar et al. (2015), who found evidence of a relationship between EPU index changes and the variance risk of several dollar-based exchange rates. Since CT returns are prone to FX variance risk, it is likely that through these channels CT returns are affected.

Furthermore, encouraged by Asness et al. (2013), who found evidence that momentum and value risk premiums exhibit strong effects globally and within eight different asset classes, this paper uses factor risks on short term FX momentum and FX-value strategies to uncover its effects on CT returns.

Factor Mimicking Portfolio (FMP)

A factor mimicking portfolio (FMP) is a portfolio that consists of underlying assets that represent a background risk factor. It is usually constructed as a *high minus low* (HML) zero investment portfolio, which is often referred to as the portfolio approach. The setup procedure

[15] The data on the VIX and SKEW index is obtained from the historical section on the Chicago Board Options Exchange's (CBOE) website.

[16] Economic Policy Uncertainty data and its corresponding sub-indexes are collected from www.policyuncertainty.com .

can be characterized as follows: The underlying assets (FX rates) are sorted on a single risk factor; for example the variance of month t. Then for any month *t,* it is decided to purchase the fraction of FX rates with the highest variances, and subsequently sell the fraction of FX rates with the lowest variance levels. The return series from this portfolio is supposed to mimic the risk of global FX variance.

The most popular FMP's are the *book-to-market risk factor* (HML) and the small-minus-big *market capitalization risk factor* (SMB) proposed by Fama and French (1993) in their three-factor model. These two factors augment the well-known market covariance risk of the CAPM model (see Sharpe, 1964), which explains equity market returns.[17] When building mimicking portfolios, usually two questions arise: (i) what is an appropriate fraction size, and (ii) what weighting scheme should be applied? While the fraction size is usually determined between 20-40% as a rule of thumb, the weighting schemes applied here are restricted to the two possibilities of an equal weight (EW) or loading weight (LW).

In a comparative study of mimicking portfolio construction, Asgharian (2004) proposes for FMP's following the portfolio approach the LW approach. He argues that this approach generates the best relation between the risk factor and its FMP, when assets are weighted according to their relative risk factor (*rf*) loadings. This is reached using the following weights for the low risk fraction:

$$w_{k,t}^{L} = 1 - \frac{rf_{k,t} - min_k(rf_{k,t})}{max_k(rf_{k,t}) - min_k(rf_{k,t})} \tag{13}$$

For the high risk fraction:

$$w_{k,t}^{H} = 1 - \frac{max_k(rf_{k,t}) - rf_{k,t}}{max_k(rf_{k,t}) - min_k(rf_{k,t})} \tag{14}$$

Here, the weight $w_{k,t}^{L}$ $\left(w_{k,t}^{H}\right)$ represents the weight of currency *k*, taken from the lowest (highest) risk fraction *L* (*H*) at time *t*. The resulting weights are then normalized to sum to one, respectively.

To ensure that the FMP's developed here are not decoupled from the risks at hand, the weighting scheme as well as the fraction size will not be chosen independently of the risks analysed. This is done by comparing the correlation matrix of the FMP return series with the correlation matrix of the underlying risk factor time-series, which serves as benchmark. The

[17] In a new study by Fama and French (2015), the three-factor model was expanded to a 5-factor model to better describe excess returns on stocks. They constructed two new FMP's that sorts stocks on their profitability (robust minus weak) and its investment exposure (conservative minus aggressive).

fraction size and weighting scheme are subsequently changed until these two correlating matrixes are as close as possible to each other, ensuring that the interdependencies among the FMP's and their risk variables are similar. This procedure ascertains that the resulting coefficient estimates are not biased due to misspecification.

In order to construct a reliable benchmark risk time-series, each risk variable needs to be transformed into a global risk factor. This procedure applies for any risk analysed here and can be formulized as follows[18]:

$$rf_t^{Global} = \frac{1}{K}\sum_{k=1}^{K} rf_{k,t} \tag{15}$$

So, rf_t^{Global} represents a global FX risk factor that is aggregated and averaged over all K currencies from the respective sample at time t. After transforming all country-specific risks into their global representatives, the benchmark correlation matrix can be computed.

As a result, the best fit for factor mimicking portfolios according to all macroeconomic risks, FX-Momentum, FX-Value and the risk according to bid-ask spread changes is achieved using the loading weighting scheme and a fraction size of 30%. For all FX realized and implied moment risks and the risk coming from the aggregated G10-TED spread index, the best fit appears using the equal weighting scheme, with 30% fraction size for all moment risks and 40% fraction size for the G10-TED spread.

Econometric Model

This paper concentrates on a time-series analysis using ordinary least squares (OLS) as the primary econometric model. The objective is to uncover the risk profile of monthly carry trade excess returns ($rx_{t:T}^{CT}$) by regressing on contemporaneous monthly risk variables ($x_{i,t:T}$). These risk variables are in the form of monthly returns coming from factor mimicking portfolios (factor risks)[19], as first differences of a risk variable, or as residuals taken from an AR(i)-model. The main econometric framework can be characterized as follows:

$$rx_{t:T}^{CT} = \alpha + \sum_{i=1}^{N} \beta_i x_{i,t:T} + \varepsilon_t \tag{16}$$

[18] One exception is made for the realized and implied skewness risks, which are additionally signed by their interest rate differential *sign(i^f-i),* taking possible "flight-to-quality" affects into account in times of market turmoil. This procedure has been used in Rafferty (2012) for his global FX skewness risk variable.
[19] In the forthcoming analysis, the risk variables that are constructed out of factor mimicking portfolios will be superscripted with *FMP* and are referred to as *factor risks*.

Inference is based on a heteroscedasticity and autocorrelation corrected (HAC) covariance matrix, using four Newey-West lags. As long as the risk variables are all FMP's, the constant α can be interpreted as risk adjusted monthly return. The OLS results will be checked for robustness against a model based on *Generalized Method of Moments* (GMM), which tests for possible errors-in-variables in the FMP's return series.

4 Empirical Results

As outlined in the previous sections, the empirical analysis concentrates on the evaluation of the comprehensive risk profile of the FX carry trade strategy (CT). In order to show that historically high and efficient CT returns are compensation for bearing risk, the analysis in Table 3 uses factor mimicking portfolio returns sorted on a various set of global FX moment risks.

[*Insert Table 3 about here*.]

Panel A of Table 3 starts with time series regression results, using factor risks of realized and implied variance and skewness risk as well as their risk premiums that are defined as *Rvar-Ivar*, for the variance risk premium (VRP), and *Iskew-Rskew*, for the skewness risk premium (SRP), on contemporaneous carry trade returns (rx^{CT}). The first two columns show significantly high results for the realized variance and skewness risk, respectively - both on the 1% significance level and an impressive high R^2 of 35.9% for $Rvar^{FMP}$. The next two regressions compute the impact of the option-implied versions of both return moments. While $Ivar^{FMP}$ has a significantly positive relation to rx^{CT} with T-statistics of 7.2, which is comparable to $Rvar^{FMP}$, the coefficient result of $Iskew^{FMP}$ is much stronger compared to its realized counterpart $Rskew^{FMP}$. $Iskew^{FMP}$ exhibits a negative loading on rx^{CT} with T-statistics of -6.79, which is more than twice as much compared to $Rskew^{FMP}$ and quite high R^2 of 41.7%. These first regressions demonstrate that CT returns are highly dependent on global FX second and third order moment risk. One can state that FX variance and skewness risk are economically relevant risk sources for CT returns. While the positive coefficient on variance risk means that CT returns are exposed to the long side of the FMP, the negative loading on skewness risk means a significant exposition to the short side of the FMP. Hence, as a first result, one can state that rx^{CT} is significantly dependent on high global FX variance risk and on negative global FX skewness or FX crash risk. Turning now to the risk premiums of both moment risks in regression five and six, we see a highly significant coefficient for the global FX VRP (1% level) and a slightly lower impact of the global FX SRP (10% level) on CT returns. The R^2's are much lower with 13.9% and 4.3%, respectively, compared to the factor risks on the implied second- and third-moment. In column seven, a multiple time series regression with all six factor risks shows that $Rvar^{FMP}$ and $Iskew^{FMP}$ seem to be the only significant risk sources when regressed together. But this result is biased towards high multi-collinearity, since the values for the variance inflation factor (VIF) for $Rvar^{FMP}$ and $Ivar^{FMP}$ reach 13.1 and 9.7, respectively. Therefore, in order to minimize multicollinearity effects, $Rvar^{FMP}$ is dropped out in the following regression and it turns out that $Ivar^{FMP}$ and $Iskew^{FMP}$ are now highly significant with T-statistics of 6.67 and -11.14, respectively. But a high correlation of about -70% remains between $Rskew^{FMP}$ and SRP^{FMP} , so that the last regression also drops $Rskew^{FMP}$. As a result, SRP^{FMP} becomes significant at the 5% level, which means that the global FX skewness risk premium seems to capture additional information for describing contemporaneous CT returns, beneath the global FX option-implied variance and skewness risk.

In sum, we have seen that especially high global FX implied variance and negative implied skewness risk are economically important risk sources that impact CT returns. Interestingly, the two risk sources are not significantly correlated (-0.15) to each other. Together with the skewness risk premium, they explain nearly 72% of CT return variation. Nevertheless, the constant factor, which is interpreted as the risk adjusted return, is still highly significant at the 1% level. This indicates that not all relevant risk sources are identified.

The results on $Rskew^{FMP}$ are in line with the global skewness variable proposed by Rafferty (2012). He found that realized skewness is a significantly priced risk source that is able to describe cross-sectional returns of currency portfolios. Jurek (2014) analysed tail risk hedged CT returns and he states that crash risk can account for nearly one third of the total risk, which is comparable to the negative loading of $Iskew^{FMP}$ on rx^{CT} and a R^2 of about 42%. Also, Burnside et al. (2011a) have shown that CT returns continue to be significantly positive—even when hedged by at-the-money FX options, which mirrors the significant risk adjusted return from the third regression with $Ivar^{FMP}$. However, the advantage of using risk-mimicking portfolio returns is that one can put these various pieces of evidence on FX moment risk into perspective with each other, and thus draw a more profound risk profile of the carry trade strategy over all.

While the FMP's in *Panel A* have been sorted on the level of the underlying moment risks, Panel B changes the perspective and quantifies standardized variance and skewness risk changes.[20] Looking at the first four regressions, one can see that changes of realized moments do not exhibit significance; both implied variables are significantly positive in relation to CT returns. Nevertheless, R^2 values appear to be relatively low at around 5%. When regressing all four variables together in a multivariate setting, $dIvar^{FMP}$ and $dIskew^{FMP}$ lose a bit of strength but continue to be significant. The last regression compares both factor risks with Panel A's most significant variables. It turns out that the FMP's on *Ivar*, *Iskew* and the *SRP* matter more in explaining CT returns, since $dIvar^{FMP}$ and $dIskew^{FMP}$ lose their significance.[21]

Impact of Macroeconomic risk on CT returns

We will turn now to macroeconomic factors that are possibly connected to currency risk through changes of foreign real money (dRM^{FMP}), real production (dRP), inflation (dCPI), or equity returns (dEQ). The same procedure applies for these variables as for the FX moment risk premiums, where foreign currencies are sorted on these specific risks forming a FMP.

[*Insert Table 4 about here*.]

Table 4 presents the impact of macroeconomic aggregates and equity risk on carry trade returns. The first four columns show that foreign real money and CPI inflation changes are highly significant (1% level) on a single regression setup. In contrast, the FMP's on foreign real production and equity risk changes do not explain CT returns at all. In a multiple regression setup in the fifth regression, we see that former results are confirmed, where the coefficients on dRM^{FMP} and $dCPI^{FMP}$ becoming even stronger - with high T-statistics of 5.49 and 5.10, respectively, and explaining more than 28.2% of the CT return variation. In order to see whether foreign macro risk can cope with results from the previous Table 3, the last two columns augment the regression with implied moment factor risks. One can observe that even with inclining moment risk into the regression, the coefficients on the money risk aggregates are remarkably stable. The coefficient for dRM^{FMP} loses half of its strength, being only significant at the 5% level, while $dCPI^{FMP}$ are almost identical with slightly lower T-statistics of still high 4.19. Furthermore, the macro aggregates drive out the SRP^{FMP} that are no longer significant. All variable correlations vary between +/-27%, so that multi-collinearity problems can be refused. The result shows that the positive coefficients on dRM^{FMP} and $dCPI^{FMP}$,

[20] The standardization is done using the simple differences of past moment risk changes divided by its sample standard deviation, in order to account for the high variability among FX moment risk. The same regressions were also run without using standardized values, which lead to similar results but somehow lower T-statistics.
[21] All regressions in Table 3 have been repeated with factor mimicking portfolios sorted on the same moment risks with 3m time frames. The results are qualitatively the same and are therefore omitted to save space.

interpreted as high foreign real money and high foreign CPI changes are important drivers for explaining CT return risk, together with global implied variance and skewness risks. This result can be linked to findings of Jylhä and Suominen (2009) and Buraschi and Jiltsov (2005). They have found evidence that inflation risk and money supply are significantly positively related to nominal interest rates levels of a particular currency. Since the carry trade is constructed out of high minus low nominal interest rate currencies, a significant effect on CT returns can therefore be expected. Furthermore, the T-statistic of the risk adjusted return is significantly reduced to only 0.21, indicating, that the majority of the CT risk exposure is sufficiently described by global FX moment and foreign real money and CPI growth risks. The last regression omits insignificant variables, which leads to even higher T-statistics for especially $dCPI^{FMP}$ and $Ivar^{FMP}$ and a remarkably high R^2 of almost 75%.

Impact of Carry Trade Activity on CT returns

The *Carry Trade Activity Index* (CTI) mirrors relative future position changes traded on the CME for currencies that are likely to be part of the investment scope of carry traders. Therefore, changes to this index (dCTI) are supposed to resemble risk exposure changes to the carry trade—and in this respect, influence CT returns.

[*Insert Table 5 about here*.]

The first three regressions of Table 5 report on the contemporaneous effect of $dCTI_a^{k=i}$ on CT returns (rx^{CT}). The superscript k indicates the number of long/short currencies involved in the carry trade. To control for possible new in- or outflows in future contracts, the regressions adds up the respective 1y log change of future's open interest ($dOI^{k=i}$). It becomes visible that with increasing currencies k, the positive significance of *dCTI* on rx^{CT} becomes stronger. The positive coefficient indicates that increasing (decreasing) CT trade coincides with higher (lower) CT returns. The T-statistic reaches 4.28 with R^2 of 13.2% for a CTI, composed of three long and short currencies. The next three columns extend the CTI composition to the group of "Non-Reportable" traders, which is indicated by the subscript *b*. This trader group exhibits similarities to the already known "Non-Commercial" trader group, so that they can be characterized as *retail* or *small speculators*. Here we can observe an even stronger effect on CT returns for $dCTI_b^{k=2}$and $dCTI_b^{k=3}$, reaching T-statistics of 4.53 and 5.34, and an even higher R^2 of 14.6% and 17.3%, respectively. The next regression tests in a multivariate setting for robustness against $Ivar^{FMP}$, $Iskew^{FMP}$, dRM^{FMP}, and $dCPI^{FMP}$. It shows that $CTI_b^{k=3}$

continues to be significant at the 1% level, with remarkably stable results for the other factor risks. While these results seem to be more than plausible, this paper is the first to my knowledge that reports such strong effects of CT activity changes on contemporaneous CT returns. Figure 1 plots a six-month moving average[22] of the $CTI_b^{k=3}$ as well as the cumulative CT returns, in order to visualize the former results.

[*Insert Figure 1 about here*.]

One can see that a long horizon of rising returns coincides with increasing CTI values. Likewise, it's clear that carry trade crashes come with abrupt declines in carry trade positions. This picture has been analysed by Brunnermeier et al. (2009), who concentrated on liquidity spirals that affect CT risk positions. They find evidence that a sudden decline in risk capital leads to unwindings of CT positions and consequently to negative skewness in the CT return distribution. In order to clarify this idea, the next regression uses changes of the TED spread (dTED), where high values indicate states of illiquidity, and changes of the VIX (dVIX) control for the level of investor's risk aversion. The results show that both variables are significant negatively related to $dCTI_b^{k=3}$, which means that rising TED-spreads or higher VIX values lead to significant CT unwindings. This finding supports Brunnermeier and Pedersen's (2009) thesis, which argues that funding liquidity and market liquidity risk variables are mutually reinforcing and can lead to higher trader margins, a decline in a speculator's position, and more negatively skewed returns.[23]

The last two regressions check whether the global FX implied moment risks $Iskew^{FMP}$ and $Ivar^{FMP}$ alter the above results on $dVIX$ and $dTED$. It turns out that $dVIX$ becomes insignificant, whereas $dTED$ and $Iskew^{FMP}$ seem to play a central role in explaining $dCTI_b^{k=3}$. The negative coefficient on $Iskew^{FMP}$ means that negative returns on negatively skewed currencies coincides with contemporaneous carry trade unwindings, and *vice versa*. It is important to note that the correlation between $Ivar^{FMP}$ and $dVIX$ is significant at -0.56. Therefore, the last regression uses the variable $dVIX^{ortho}$ instead of $dVIX$. The new variable explains the risk of investors risk aversion that is orthogonalized to $Ivar^{FMP}$.[24] We can now

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[22] The *CTI* is shifted 2-month backward in order to mitigate the lagging effect of the moving average.

[23] The finding here extends that of Brunnermeier et al. (2009), who did not find a significant relationship between *dTED* on FX future changes. In contrast to this analysis, they used country-fixed effect panel regressions with weekly data observations for the six currencies AUD, CAD, JPY, CHF, GBP, and EUR looking at the pre-crisis period 1992-2006. When the crisis period 07/2008-06/2009 is omitted in the regression here, the results become even stronger for *dTED* reaching a T-statistic of 4.07.

[24] $dVIX^{ortho}$ can still be used as a tradable asset, since it is composed of a weighted portfolio of VIX futures and a factor mimicking portfolio of currencies sorted on implied variance risk.

observe that $Ivar^{FMP}$ becomes also significant at the 5% level, and $Iskew^{FMP}$ and *dTED* are more or less unchanged. The positive coefficient on $Ivar^{FMP}$ certifies that rising global FX variance comes with reductions in CT positions.[25] All in all, one can state that beneath the effect of decreasing risk capital, high levels of implied FX crash risk and FX variance risk contribute to unwindings in CT positions.[26]

Liquidity Risk on Carry Trade Returns

As outlined in the last section, we use two different liquidity risk proxies; the change of spot price bid-ask spreads (dBAS) and variations of the TED spread. Both variables will be used in form of FMP's sorted on two different FX samples, due to the data restrictions regarding TED spread equivalents of emerging countries. Therefore, the FMP on *dBAS* is sorted using all *Sample I* currencies, whereas the FMP on TED equivalents is restricted to the *G10-Sample* ($dTED_{G10}^{FMP}$). Also, encouraged by the existing literature, there has been applied a *TED Index* consisting of single country TED spread equivalents for the G-10 universe, including the US-TED. Two different weighting schemes will be used. The first one is a simple, equally weighted TED Index (TED_{G10}^{EQW}), and the second one is weighted according to a principal component analysis[27] (TED_{G10}^{PCA}).[28] The regression of Table 6 concentrates on monthly changes to these TED indexes.

[*Insert Table 6 about here*.]

The first two columns of Table 6 present univariate regression results of $dBAS^{FMP}$ and $dTED_{G10}^{FMP}$, respectively, but both coefficients lack statistical significance. The following three regressions are much more promising. The changes of the $dTED_{G10}^{EQW}$ as well as the $dTED_{G10}^{PCA}$ are highly significant at the 1% level, with T-statistics of -2.93 and -3.40, respectively. Also, changes to the original *US-TED* spread show a comparably negative impact in terms of T-statistics, all pointing to the fact that CT returns are decreasing with increasing states of illiquidity. The last regression nevertheless reveals that these effects vanish when regressed

[25] The last statement implies that a higher level of FX variance leads to on average declining foreign currency returns, which is usually the case.

[26] The regressions on *dCTI* uses also *dSKEW* as control variable with no significant effects, which has been omitted for convenience. *dSKEW* is the monthly first difference of the SKEW index, which is essentially the option-implied skewness of the S&P 500 equity index that is computed and published by the CBOE.

[27] The weights from the first principal component are taken into account, which explains almost 61% of the TED's variation.

[28] Asness et al. (2013) applied innovations taken from an AR(2)-model from such a TED index. However, this paper also experiments with these innovations, but does not find any notably differences to simple changes of the US-TED or TED index. Therefore, results on TED's innovations are omitted.

jointly with global FX implied moment risks, foreign macro risks and changes to CT activity.[29] The overall results can be compared to findings in Menkhoff et al. (2012a), who showed in an asset pricing test that liquidity risk is priced in the cross-section of FX portfolios, but lack significance when tested jointly with e.g. FX volatility risk.

The Impact of Other Risk Sources on Carry Trade Returns

Other risk sources defined here are those associated with implied variance ($dVIX^{CBOE}$) and implied skewness ($dSKEW^{CBOE}$) changes to the S&P 500 index[30], as well as innovations to the *US Economic Policy Uncertainty* (uPUI) and *US News Uncertainty Index* (uNUI) that are supposed to resemble investor's states of risk aversion. While the implied moments are used as simple differences, the variables of uncertainty are defined as residuals taken from an AR(2)-model. These innovations can be interpreted as *unexpected* changes of the underlying indexes, since they are, by definition, uncorrelated to last two lags of the index. Also, the factor risks of FX momentum and FX value to CT returns will be applied using FMP's that are sorted on 1m-past FX momentum returns ($FX\text{-}Mom^{FMP}$) and the 5y deviation from UIP[31] ($FX\text{-}Value^{FMP}$), respectively.

[*Insert Table 7 about here*.]

Starting with the first regression of Table 7, we see that $dVIX^{CBOE}$ is negatively and significantly related to CT returns, with a remarkable high T-statistic of -7.46 controlling for $dSKEW^{CBOE}$. The later does not exhibit any significance. While the crash risk of the equity index is not priced in CT returns, the negative impact on implied variance has been reported in numerous papers and is often viewed as an indicator for the overall risk aversion of investors. Nevertheless, the risk adjusted return continues to be significant after controlling for equity implied moment risk. This is comparable to findings in Caballero and Doyle

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[29] The other TED spread variables have been also tested jointly, but with even lower impact on CT returns. Furthermore, following Korajczyk and Sadka (2008) who studied alternative measurements for liquidity risk, it's been tested whether shocks to the TED^{US}, TED^{EQW}, and TED^{PCA} have a higher impact on CT returns. These shocks were defined as the residuals taken from autoregressions, using 1,2, and 3 lags, respectively. All of these variables do not contribute significant coefficient results in the multivariate regression.

[30] Also, implied volatility changes to the DAX, FTSE, and Nikkei have been analysed, where the volatility indexes of all three countries are significantly and negatively related to CT returns at the 1% level. This is due to a high correlation among these variables that range between 70% and 90%. Contrary to this, changes to contemporaneous realized volatility changes of the countries equity indexes do not have any significant effect on CT returns. This underlines the importance of option-implied moment variables over their realized counterpart.

[31] This FX-Value definition has been used in Asness et al. (2013), which is equal to the sum of consecutive 1m forward rate returns over the past five years. Since UIP predicts zero forward excess returns, it can be interpreted as the five-year deviation from UIP. In this respect, a positive value factor characterizes an overvalued currency and vice versa.

(2012). They constructed a hedging strategy for CT returns with rolling VIX contracts, but the resulting risk adjusted returns have still been found significant.

The second regression deals with the impact of *FX-Mom*^{FMP} and *FX-Value*^{FMP} factor risks on contemporaneous CT returns. Both coefficients show a negative sign, while momentum risk exhibits strong significance at the 1% level.[32] The *FX-Mom*^{FMP} factor risk is almost identical to the currency strategy that is used in practice to earn a risk premium associated with past short-term momentum. The correlation to this strategy is mildly negative with -0.24, but the effects to CT returns seem to be strong, leaving risk adjusted excess returns still to appear significant. This contrasts the findings of Ang and Chen (2010), who reported a positive but insignificant loading of CT returns on 3m currency momentum, and a negative loading for the FX-value factor risk using a longer sample period from 1985 to 2009. In a comprehensive work on momentum strategies, Menkhoff et al. (2012b) states that both, momentum and CT strategies exhibit similarities in significant excess returns, but the return series are far from identical, with almost no correlation (0.04). Also Burnside et al. (2011b) highlighted differences of both strategies and showed that a combined portfolio strategy would strengthen the efficiency in terms of higher Sharpe ratios.

The following two regressions concentrate on the impact of innovations to PUI and its news subindex NUI, respectively. Both regressions show, as expected, a negative impact on rx^{CT}, although the coefficients of *uPUI* and *uNUI* are far from being significant with T-statistics of about -1.1 and low R^2 around 0.5%. The next regression puts all six variables together with significant factor risks from the previous tables. This leads to some interesting results. While $dVIX^{CBOE}$ stays significant only at the 5% level, with a dramatically reduced T-statistic of -2.14, the coefficient on *FX-Mom*^{FMP} fails to retain a significant impact. At the same time, *uNUI* changes signs and becomes significant at the 10% level. Also, the impact of $Ivar^{HML}$ is reduced to a T-statistic of 7.9, following the 10.16 reported in Table 6.

However, the regression results are biased due to a negative correlation of -0.56 between $Ivar^{HML}$ and *dVIX,* and a close to unity correlation between the two innovation terms *uPUI* and *uNUI* (0.96). Therefore, in the next regression *dVIX* is replaced by the orthogonalized factor risk $dVIX^{ortho}$ used in Table 5, whereas *uPUI* is dropped out. It turns out that $Ivar^{HML}$ becomes even stronger, reaching a T-statistic of 11.79 and a retired, significantly negative loading of $dVIX^{ortho}$ at the 5% level on rx^{CT}. Interestingly, the positive significance of *uNUI* increases to the 5% level. While the negative effects of $dVIX^{ortho}$ are economically

[32] The factor risks on 3m and 6m past momentum returns do not exhibit any significant relation to CT returns and are omitted in the table. This is comparable to results of Menkhoff et al. (2012b), where the strongest FX momentum effects in the currencies cross section have been found for the shortest 1m period.

compelling, the positive effects on *dNUI* are not. Given the fact that *uNUI* showed a negative but insignificant effect on rx^{CT} in an univariate regression, the positive and significant coefficients in a multivariate regression can be regarded as a positive relation to "residual risks" of CT returns. This effect becomes even more pronounced in the next regression, which omits the insignificant variables *dSKEW*, *FX-Mom*^{FMP}, and *FX-Value*^{FMP}, so that both *uNUI* and $dVIX^{ortho}$ become significant at the 1% level. As a result, we can conclude that a significantly high excess return to the FX carry trade is a compensation for bearing risks. These risks have been characterized as (i) high global FX implied variance risk, (ii) negative global FX skewness risk, (iii) high foreign real money growth, (iv) high foreign CPI growth, (v) changes to the *Carry Trade Activity Index,* (vi) changes to the orthogonalized VIX index, and (vii) innovations to the US News Uncertainty Index. The risk adjusted returns to the CT are no longer significant after controlling for these risks and adjusted R^2 reaches a remarkably high value of 77%, which adequately describes the risk anatomy of the CT.

Moreover, the most important risk variables, except for *CTI* and *NUI*, are tradable assets and can therefore be used as hedging instruments. Figure 2 compares monthly return observations of the unhedged (bar-chart) and hedged CT returns with all tradable factor risks (line-chart). The table below presents summary statistics that highlights the reduced return moments with respect to hedge activity. In particular, the annualized mean returns are close to zero and the standard deviation shrinks from 8.86% to only 4.30%. The Skewness and excess kurtosis coefficients are also reduced by 37.7% and 42.6%, respectively. Additionally, the interquartile range, minimum and maximum returns confirm the main picture with reductions of more than 50%.

[*Insert Figure 2 about here*.]

Furthermore, Figure 3 offers an overview of the autocorrelation structure of the residuals from the last OLS regression in Table 7. The autocorrelation function (ACF), together with the partial ACF (PACF), does not show any significant coefficient for the first 12 lags. This fact ultimately means that the residual risk resembles a white noise process, and therefore the underlying risk variables sufficiently describe the risk structure of carry trade excess returns.

[*Insert Figure 3 about here*.]

Errors-in-Variables Problem

It is well-known that most data used in the empirical analysis contain errors of measurement. These errors-in-variables (EIV) lead to inconsistent ordinary least squares

(OLS) estimators, so that some researchers suggest using instrumental variables to circumvent this problem (see Bowden and Turkington, 1990). While it is often the case that suitable instruments are not easy to find, Coën et al. (2009) propose an estimation technique that only requires higher moments of the variable in order to mitigate EIV.[33] With the use of the Generalized Method of Moments (GMM) estimation procedure (see Hansen, 1982), they showed that their iGMMHM (iterated GMM Higher Moments) model performs well at purging EIV and analysing the mimicking portfolios of the Fama and French model. They argue that FMP's, constructed out of high minus low portfolios contain many nonlinearities that cannot be captured by classical CAPM or APT models because they assume a linear relationship between the returns to be explained as well as their risk factors. Their main idea to correct these nonlinearities is to add instrumental variables for all FMP's variables that are expected to contain EIV, using their own lagged values up to the fifth order moment. They outlined that in a classical OLS regression the coefficients $\hat{\beta}$ are underestimated in terms of lower absolute coefficients or less significant results. A complete picture of the properties and functionality of the iGMMHM estimation procedure are outlined in Appendix D.

The last regression of Table 7 presents coefficient results of the iGMMHM model, taken as a robustness test to the previous OLS regression. To be more specific, in the iGMMHM calculation, an additional 25 instrumental variables are used, which are omitted to save space. These instruments are the first lagged higher moment variables for the five FMP risk portfolios $Iskew^{FMP}$, $Ivar^{FMP}$, dRM^{FMP}, $dCPI^{FMP}$ *and* $dVIX^{ortho}$, respectively. We can observe that the coefficient estimates for the *iGMMHM* are almost identical for $Iskew^{FMP}$, $Ivar^{FMP}$, and $dCPI^{FMP}$ meaning that EIV is not present for these FMP's and OLS lead to unbiased results. This is not the case for dRM^{FMP} and $dVIX^{ortho}$. While dRM^{FMP} appears stronger in magnitude relative to the OLS estimation, the impact of $dVIX^{ortho}$ weakens and is only significant at the 10% level. The coefficient for dRM^{FMP} is higher and more significant, which is expected to be the case when EIV contamination is present. Almost all instrumental variables for dRM^{FMP} exhibit significant coefficient results. However, $dVIX^{ortho}$ as a mixed portfolio of $Ivar^{FMP}$ and VIX futures, appears with much lower significance in the iGMMHM. Since the instrumental variables of $dVIX^{ortho}$ do not show high evidence of strong EIV contamination, the impact of VIX changes have been just overestimated by OLS. Furthermore, the innovation term *uNUI* is fortunately not positively significant anymore in the iGMMHM estimation, which can also be regarded as evidence for an overestimation of the OLS procedure.

[33] Their technique builds on the work of Dagenais and Dagenais (1997), which is a variant of using higher moments to remove errors-in-variables.

Additional Robustness Tests

To ensure that the regression results coming from factor mimicking portfolios are independent from the choice of the fraction size, it has been tested whether the coefficients change dramatically when increasing or decreasing fraction sizes by 10%, respectively. It turned out that the main results are unaffected. Furthermore, all regressions are re-examined omitting the financial crisis period from July 2008 to June 2009. This step uncovers the sensitivity of all coefficient results due to this extraordinary event. As a result, the level of significance is fairly untouched, while the strength in terms of T-statistics is only slightly reduced.[34]

5 Conclusion

It has been shown that the excess returns of the carry trade act as compensation for risk bearing; especially the risks from global FX option-implied variance and skewness risks. These are predominantly a source to uncover the risk anatomy of the carry trade. These findings are not only crucial for investors engaged in the carry trade, but also for understanding the risk inherent in any exchange rate market. This conclusion is due to the findings of Lustig et al. (2011), who found that cross-sectional currency portfolios are all, to some degree, exposed to the carry trade measured as a risk factor, and additionally to a constant factor - namely the dollar risk factor.

However, six main drivers have been identified for driving carry trade excess returns, which are (i) high FX implied variance risk, (ii) negative FX implied skewness risk, (iii) high foreign real money growth, (iv) high foreign CPI growth, (v) changes to the *Carry Trade Activity Index*, and (vi) changes to the VIX index. The latter is the option-implied variance of the S&P 500 equity index, which is used here in an orthogonalized form. These variables explain almost 80% of the return variation in carry trade returns, leaving the risk adjusted return indifferent from zero. Moreover, the risk variables are constructed as factor mimicking portfolios, which can be used as hedging instruments for carry trade investments. Also, this paper delivers support for the theoretical model of the occurrence of the crash risk of an asset due to liquidity spirals (see Brunnermeier and Pedersen, 2009). More specifically, it has been shown that a decreased level of funding liquidity, proxied by the US-TED spread, accompanied by increased FX option-implied variance and skewness levels, leads to reductions of carry trade positions and ultimately to carry trade losses.

[34] All robustness tests are available upon request.

Figures and Tables

Table 1. Summary Statistics of Currency Portfolios

This table offers summary statistics about six currency portfolios sorted on their interest rate differentials ($IRD^f = i^f$-i), where P-1 contains currencies with lowest and P-6 with highest IRDs. The carry trade portfolio return (CT) is P-6 minus P-1. Portfolio means, interest rate differentials (IRD^f), spot changes (Δspot) are in terms of annualized log returns. P-values are based on HAC standard errors, with 4 Newey-West lags. Also, portfolio standard deviation (Std.Dev.), skewness and excess kurtosis, as well as the *Sharpe ratio* and *Higher Moment Sharpe ratio* (SR^{HM}) are presented for any portfolio formation. Mean (ba) is the average portfolio return accounting for bid-ask spreads. AC(1) is the first order autocorrelation coefficient of portfolio returns. The sample period uses monthly observations from September 2003 to July 2015.

Portfolio	**P-1**	**P-2**	**P-3**	**P-4**	**P-5**	**P-6**	**CT**
Mean	-0.75	0.18	0.75	1.70	2.55	3.43	**4.18**
p-values	*0.73*	*0.90*	*0.73*	*0.51*	*0.38*	*0.28*	***0.07****
IRD^f	-1.39	-0.22	0.81	2.06	3.77	7.08	**8.47**
Δspot (s_T-s_t)	0.64	0.40	-0.06	-0.36	-1.22	-3.65	**-4.29**
Std. Dev.	7.50	8.13	8.51	8.37	10.34	12.01	**9.05**
Skewness	-0.08	-0.42	-0.32	-0.79	-0.89	-0.56	**-0.34**
Excess kurtosis	0.40	1.51	1.10	2.39	2.12	0.82	**0.68**
Sharpe ratio	-0.27	-0.13	-0.06	0.05	0.12	0.18	**0.32**
SR^{HM}	-0.002	-0.001	-0.001	0.029	0.067	0.122	**0.239**
Mean (ba)	-1.73	-0.61	0.33	0.50	1.33	1.70	**2.82**
AC(1)	0.02	-0.00	0.00	0.09	0.09	0.05	**0.11**
p-value	*0.77*	*0.97*	*0.99*	*0.30*	*0.28*	*0.52*	***0.19***

Table 2. Average Portfolio Moment Risk Pre- and Post-Crisis

This table summarizes average time-series values for realized and implied volatilities (Rvol and Ivol), which is defined as the square root of *Rvar* and *Ivar*, respectively, and for realized and implied skewness (Rskew and Iskew). The averages correspond to the six FX currency baskets, sorted on interest rate differentials, and are additionally splitted into four different time frames. The differences between *Rvol* and *Ivol*, as well as *Rskew* and *Iskew*, are each regressed on a constant. The inference is based on a bootstrap method that uses 10.000 replications and the appropriate t-distribution for building confidence bounds. T_BS presented in brackets mean the respective T-statistic of the regressions. Bold figures indicate significance at least at the 5% significance level and cursive at the 10% level.

Panel A: Pre-crisis (09/2003-06/2008)

	P-1	P-2	P-3	P-4	P-5	P-6
Rvol	7.85	8.26	8.25	7.54	9.93	13.45
Ivol	7.97	8.52	8.27	8.09	9.92	13.47
T_BS	[-1.39]	[-1.54]	[-1.13]	**[-3.54]**	[-0.7]	[-0.76]
Rskew	0.21	-0.26	0.01	-0.41	-0.13	-0.31
Iskew	0.24	0.08	0.03	-0.07	-0.22	-0.31
T_BS	[0.42]	[1.12]	[0.66]	[1.39]	[-1.20]	[-0.64]

Panel B: Crisis (07/2008-06/2009)

	P-1	P-2	P-3	P-4	P-5	P-6
Rvol	18.90	18.32	19.06	21.38	20.96	25.09
Ivol	19.91	17.77	18.33	20.68	20.92	24.16
T_BS	[-0.65]	[0.25]	[0.34]	[0.32]	[-0.22]	[-0.11]
Rskew	-0.05	-0.14	-0.18	-0.23	-0.32	-0.56
Iskew	0.12	0.01	-0.03	-0.20	-0.36	-0.36
T_BS	[1.43]	[1.15]	[0.84]	[0.16]	[-0.23]	[1.18]

Panel C: Post-crisis (07/2009-06/2015)

	P-1	P-2	P-3	P-4	P-5	P-6
Rvol	9.74	8.93	9.75	10.10	11.41	12.91
Ivol	9.81	9.47	10.15	11.18	12.44	13.52
T_BS	[-1.29]	**[-3.32]**	**[-2.33]**	**[-3.96]**	**[-3.82]**	**[-2.52]**
Rskew	-0.36	-0.42	-0.49	-0.52	-0.59	-0.67
Iskew	-0.13	-0.25	-0.29	-0.38	-0.40	-0.38
T_BS	**[5.13]**	**[3.31]**	**[3.32]**	**[3.05]**	**[2.35]**	**[4.97]**

Panel D: Full sample period

	P-1	P-2	P-3	P-4	P-5	P-6
Rvol	10.24	9.80	10.42	10.67	12.10	14.67
Ivol	10.50	10.05	10.52	11.25	12.62	14.86
T_BS	[-1.59]	**[-2.45]**	*[-1.80]*	**[-3.21]**	**[-2.47]**	*[-1.91]*
Rskew	-0.09	-0.30	-0.26	-0.42	-0.37	-0.47
Iskew	0.05	-0.09	-0.13	-0.22	-0.31	-0.34
T_BS	**[4.16]**	**[2.03]**	**[3.15]**	**[2.11]**	[0.81]	**[2.26]**

Table 3. Impact of FX Moment Risk on Carry Trade Returns

This table presents OLS time-series coefficient results in each column of monthly carry trade returns (rx^{CT}) regressed on contemporaneous returns to factor mimicking portfolios (FMP) linked to global FX moment risk. The moment risks in Panel A are the FX realized and implied variance, denoted as $Rvar^{FMP}$ and $Ivar^{FMP}$ respectively, and realized and implied skewness risk, denoted as $Rskew^{FMP}$ and $Iskew^{FMP}$, respectively. Also, FMP returns on the variance risk premium (VRP^{FMP}), and the skewness risk premium (SRP^{FMP}) are analysed. Additionally, Panel B adds FMP results that are sorted on standardized changes ("d") to the variance and skewness risks, presented in Panel A, in realized and implied form. Inference is based on HAC standard errors, using four Newey-West lags. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively, with T-statistics in brackets. The last row presents adjusted R^2 values. The sample period is September 2003-June 2015.

Panel A

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}
constant	0.006***	0.014***	0.003*	0.001	0.008***	0.012***	0.005**	0.005**	0.005***
	[3.16]	[4.19]	[1.96]	[0.46]	[4.19]	[3.31]	[2.52]	[2.60]	[2.62]
$Rvar^{FMP}$	0.576***						0.442***		
	[7.48]						[3.53]		
$Rskew^{FMP}$		-0.669***					-0.002	-0.018	
		[-3.11]					[-0.02]	[-0.123]	
$Ivar^{FMP}$			0.687***				0.128	0.528***	0.528***
			[7.20]				[0.99]	[6.67]	[6.67]
$Iskew^{FMP}$				-1.042***			-0.952***	-0.907***	-0.914***
				[-6.79]			[-11.44]	[-11.14]	[-12.56]
VRP^{FMP}					0.576***		-0.072	0.110	0.109
					[3.81]		[-0.654]	[1.17]	[1.16]
SRP^{FMP}						0.426*	0.185	0.199	0.213**
						[1.91]	[1.23]	[1.35]	[2.15]
adj. R^2	35.9%	16.0%	39.1%	41.7%	13.9%	4.3%	72.8%	71.3%	71.5%

Panel B

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}
constant	0.005**	0.003***	0.008***	0.002	0.004*	0.005**	0.006***
	[2.05]	[4.19]	[1.96]	[0.89]	[1.71]	[2.42]	[2.93]
$dRvar^{FMP}$	-0.237				-0.222		
	[-1.51]				[-1.46]		
$dRskew^{FMP}$		-0.088			-0.085		
		[-0.63]			[-0.64]		
$dIvar^{FMP}$			0.380**		0.278**	0.306**	0.087
			[2.58]		[2.03]	[2.28]	[1.25]
$dIskew^{FMP}$				0.387***	0.280**	0.285**	0.037
				[2.88]	[2.21]	[2.54]	[0.47]
$Ivar^{FMP}$							0.540***
							[7.40]
$Iskew^{FMP}$							-0.913***
							[-12.32]
SRP^{FMP}							0.239**
							[2.18]
adj. R^2	1.6%	0.0%	5.4%	4.2%	7.8%	7.1%	71.3%

Table 4. Impact of Macroeconomic Aggregates and Equity Risk on Carry Trade Returns

This table presents OLS time-series coefficient results in each column of monthly carry trade returns (rx^{CT}) regressed on contemporaneous returns to factor mimicking portfolios (FMP) linked to macroeconomic and global FX moment risk. The macroeconomic risk sorts are done on real production growth (dRP^{FMP}), real money growth (dRM^{FMP}), and inflation growth rates ($dCPI^{FMP}$), and foreign equity index returns (dEQ^{FMP}). The moment risks are the global FX option-implied variance and skewness risk, denoted as $Ivar^{FMP}$ and $Iskew^{FMP}$, respectively, and the skewness risk premium (SRP^{FMP}). Inference is based on HAC standard errors, using four Newey-West lags. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively, with T-statistics in brackets. The last row presents adjusted R^2 values. The sample period is October 2003-June 2015.

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}
constant	0.004*	0.003	0.003*	0.004*	0.002	0.000	0.001
	[1.90]	[1.62]	[1.73]	[1.85]	[1.37]	[0.21]	[0.25]
dRP^{FMP}	-0.239				-0.070	0.038	
	[-1.36]				[-0.48]	[0.48]	
dRM^{FMP}		0.445***			0.590***	0.195**	0.194**
		[3.43]			[5.49]	[2.38]	[2.42]
$dCPI^{FMP}$			0.521***		0.618***	0.279***	0.277***
			[3.47]		[5.10]	[4.19]	[4.76]
dEQ^{FMP}				-0.054	-0.077	0.034	
				[-0.45]	[-0.65]	[0.49]	
$Ivar^{FMP}$						0.550***	0.546***
						[9.82]	[10.78]
$Iskew^{FMP}$						-0.795***	-0.798***
						[-10.82]	[-10.51]
SRP^{FMP}						0.019	
						[0.28]	
adj. R^2	1.5%	7.7%	14.8%	-0.1%	28.2%	74.4%	74.8%

Table 5. Carry Trade Activity Index (CTI)

This table presents OLS time-series coefficient results in each column of monthly carry trade returns (rx^{CT}) regressed on contemporaneous changes to various versions of the *Carry Trade Activity Index* (dCTI). The CTI is superscripted with the number of k currencies used for the high and low portfolio, respectively. The subscript *a* means that future contract data is collected only from the *Non-Commercial* trader group, while *b* also includes futures data from the *Non-Reportable* trader group. The variable *dOI* is the past one-year log change of the *open interest* in future contracts of the respective number of currencies used for the CTI. The FMP returns of FX implied variance and skewness ($Ivar^{FMP}$ and $Iskew^{FMP}$), macroeconomic risk sorts on foreign real money growth (dRM^{FMP}), and foreign inflation growth rates ($dCPI^{FMP}$) will be applied. Also, the first differences to the US-TED and VIX index ($dTED^{US}$ and dVIX) are used, respectively. The variable $dVIX^{ortho}$ is the risk of dVIX that is orthogonal to $Ivar^{FMP}$. The dependent variable changes to $dCTI_b^{k=3}$ for the last three regressions. Inference is based on HAC standard errors, using four Newey-West lags. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively, with T-statistics in brackets. The last row presents adjusted R^2 values. The sample period is September 2003-June 2015.

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	$dCTI_b^{k=3}$	$dCTI_b^{k=3}$	$dCTI_b^{k=3}$
constant	0.003	0.004*	0.003	0.003	0.004*	0.003	0.000	0.005	-0.007	-0.010
	[1.56]	[1.66]	[1.50]	[1.51]	[1.69]	[1.55]	[0.33]	[0.31]	[-0.44]	[-0.73]
$dCTI_a^{k=1}$	0.015**									
	[2.33]									
$dCTI_a^{k=2}$		0.025***								
		[3.79]								
$dCTI_a^{k=3}$			0.037***							
			[4.28]							
$dCTI_b^{k=1}$				0.014*						
				[1.94]						
$dCTI_b^{k=2}$					0.034***					
					[4.53]					
$dCTI_b^{k=3}$						0.051***	0.015***			
						[5.34]	[3.39]			
$dOI^{k's}$	0.001	-0.003	0.000	0.000	-0.002	0.001	-0.016	-0.028	-0.037	-0.048
	[0.10]	[-0.56]	[0.07]	[0.02]	[-0.43]	[0.18]	[-0.46]	[-0.50]	[-0.67]	[-1.03]
$Ivar^{FMP}$							0.517***		-0.335	1.76**
							[10.24]		[-0.26]	[2.27]
$Iskew^{FMP}$							-0.744***		-4.341***	-3.72***
							[-10.92]		[-3.17]	[-3.36]
dRM^{FMP}							0.191**			
							[2.37]			
$dCPI^{FMP}$							0.265***			
							[4.28]			
$dTED^{US}$								-0.231**	-0.197**	-0.141**
								[-2.57]	[-2.29]	[-2.01]
dVIX								-0.009**	-0.009	
								[-2.14]	[-1.59]	
$dVIX^{ortho}$										-0.006
										[-1.52]
adj. R^2	4.6%	11.4%	13.2%	1.8%	14.6%	17.3%	76.0%	7.6%	13.0%	16.3%

Table 6. Impact of Liquidity Risk on Carry Trade Returns

This table presents OLS time-series coefficient results in each column of monthly carry trade returns (rx^{CT}) regressed on contemporaneous changes to different liquidity risk variables. $dBAS^{FMP}$ and $dTED_{G10}^{FMP}$ represent FMP returns that are sorted on relative bid-ask spread changes of *Sample I* currencies and sorts on changes to TED spread equivalent on the *G10 Sample*, respectively. The variable $dTED^{US}$ is the first difference of the US-TED spread, while $dTED_{G10}^{EQW}$ and $dTED_{G10}^{PCA}$ apply to changes of an aggregated TED spread index over the *G10 Sample* countries, including the US-TED. They are constructed as an equal weighted and a first principal component weighted index, respectively. Also, The FMP returns of FX implied variance and skewness ($Ivar^{FMP}$ and $Iskew^{FMP}$), and macroeconomic risk sorts on foreign real money growth (dRM^{FMP}), and foreign inflation growth rates ($dCPI^{FMP}$) will be used together with the change of the *Carry Trade Activity Index* ($dCTI_b^{k=3}$). Inference is based on HAC standard errors, using four Newey-West lags. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively, with T-statistics in brackets. The last row presents adjusted R^2 values. The sample period is November 2003-July 2015.

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}
constant	0.004*	0.004*	0.003	0.004	0.003	0.001
	[1.76]	[1.71]	[1.51]	[1.57]	[1.48]	[0.90]
$dBAS^{FMP}$	-0.043					
	[-0.46]					
$dTED_{G10}^{FMP}$		-0.097				
		[-0.59]				
$dTED_{G10}^{EQW}$			-0.055***			
			[-2.93]			
$dTED_{G10}^{PCA}$				-0.020***		
				[-3.40]		
$dTED^{US}$					-0.021***	-0.004
					[-2.89]	[-1.21]
$Ivar^{FMP}$						0.516***
						[10.16]
$Iskew^{HML}$						-0.731***
						[-10.73]
dRM^{FMP}						0.177**
						[2.19]
$dCPI^{FMP}$						0.301***
						[5.42]
$dCTI_b^{k=3}$						0.013***
						[2.98]
adj. R^2	-0.5%	-0.2%	5.4%	7.7%	4.0%	77.2%

Table 7. Impact of Equity Moment, FX Momentum and Value Risk on Carry Trade Returns

This table presents OLS time-series coefficient results in each column of monthly carry trade returns (rx^{CT}) regressed on contemporaneous changes of a variety of risk variables. $dSKEW^{CBOE}$ and $dVIX^{CBOE}$ represent first differences to the option-implied skewness and variance indexes computed at the CBOE on the S&P 500 Index, respectively. $FX\text{-}Mom^{FMP}$ and $FX\text{-}Value^{FMP}$ are FMP returns sorted on past 1m FX momentum returns and the 5y difference to the UIP, respectively. *uPUI* and *uNUI* mean innovations taken from an AR(2)-model from the *US Policy Uncertainty Index* and *US News Uncertainty Index*, respectively. Also, the FMP returns of FX implied variance ($Ivar^{FMP}$) and skewness risk ($Iskew^{FMP}$), macroeconomic risk sorts on foreign real money growth ($dRM_{t:T}^{FMP}$), and inflation growth rates ($dCPI_{t:T}^{FMP}$) will be used together with the change of the *Carry Trade Activity Index* ($dCTI_b^{k=3}$). $dVIX^{ortho}$ means the risk of *dVIX* that is orthogonal to $Ivar^{FMP}$. Inference is based on HAC standard errors, using 4 Newey-West lags. Last column coefficient estimates are taken from an iterated GMM optimization procedure that is specified in Appendix *D*. Here the instrumental variables are omitted, and $dVIX^{CBOE}$, $dVIX^{ortho}$, $dSKEW^{CBOE}$, *uPUI, uNUI* are divided by 1000 for convenience. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively, with T-statistics in brackets. The last row presents adjusted R^2 values. The sample period is November 2003-June 2015.

	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}	rx^{CT}
constant	0.004*	0.004**	0.004*	0.004*	0.001	0.001	0.000	***0.000***
	[1.92]	[2.18]	[1.78]	[1.79]	[0.62]	[0.63]	[0.55]	**[0.01]**
$dSKEW^{CBOE}$	0.103				1.362	1.242		
	[0.03]				[0.74]	[0.67]		
$dVIX^{CBOE}$	-2.536***				-0.566**			
	[-7.52]				[-2.12]			
$FX\text{-}Mom^{FMP}$		-0.277***			-0.043	-0.043		
		[-3.25]			[-0.98]	[-0.98]		
$FX\text{-}Value^{FMP}$		-0.319			-0.003	-0.000		
		[-1.44]			[-0.06]	[-0.01]		
uPUI			-0.136		-0.121			
			[-1.10]		[-0.97]			
uNUI				-0.093	0.146*	0.072**	0.075**	***0.039***
				[-1.11]	[1.86]	[2.44]	[2.60]	**[1.21]**
$Ivar^{FMP}$					0.461***	0.527***	0.531***	***0.529****
					[7.72]	[11.59]	[11.21]	**[10.90]**
$Iskew^{HML}$					-0.757***	-0.755***	-0.766***	***-0.753****
					[-10.68]	[-10.66]	[-11.13]	**[-10.99]**
dRM^{FMP}					0.183**	0.180**	0.178**	***0.197****
					[2.48]	[2.50]	[2.23]	**[2.79]**
$dCPI^{FMP}$					0.259***	0.255***	0.264***	***0.272****
					[4.09]	[3.95]	[4.06]	**[3.94]**
$dCTI_b^{k=3}$					0.015***	0.015***	0.015***	***0.017****
					[3.65]	[3.63]	[3.59]	**[2.60]**
$dVIX^{ortho}$						-0.573**	-0.664***	***-0.582****
						[-2.16]	[-2.64]	**[-1.65]**
adj. R^2	19.5%	15.0%	0.5%	0.6%	76.5%	76.6%	77.0%	76.5%

Figure 1. Carry Trade Activity Index and CT Returns

This figure presents a time-series of the cumulative FX carry trade excess returns as a solid line (left scale) and a six-month moving averages of the *Carry Trade Activity Index* (CTIb(MA-6)) as solid line with crosses (right scale). The composition of the CTI is according to formula (12) with K=3. The future-contract data include the scope of *Non-Commercial* and *Non-Reportable* traders defined by the *US Commodity Futures Trading Commission* (CFTC). The grey background indicates *NBER* recession periods. The sample covers the time period between December 2003 and June 2015.

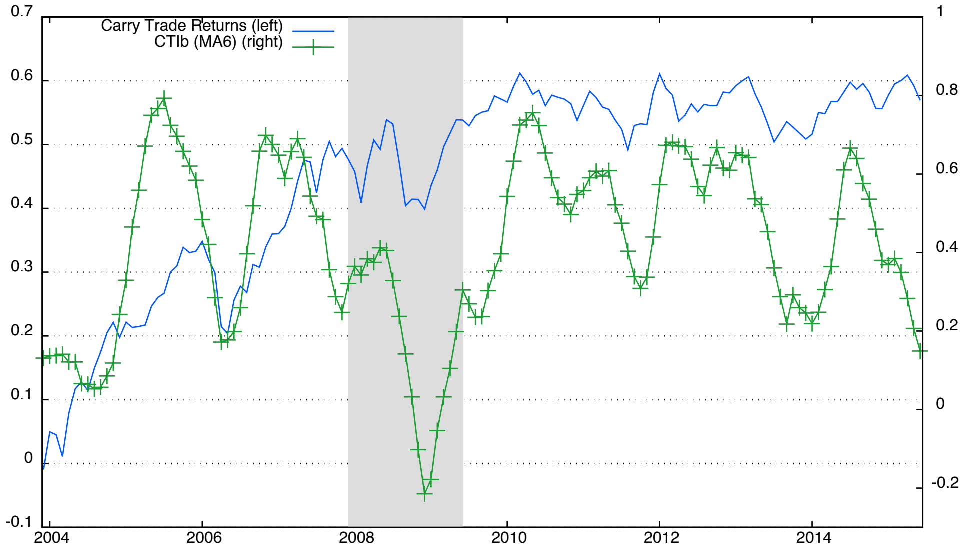
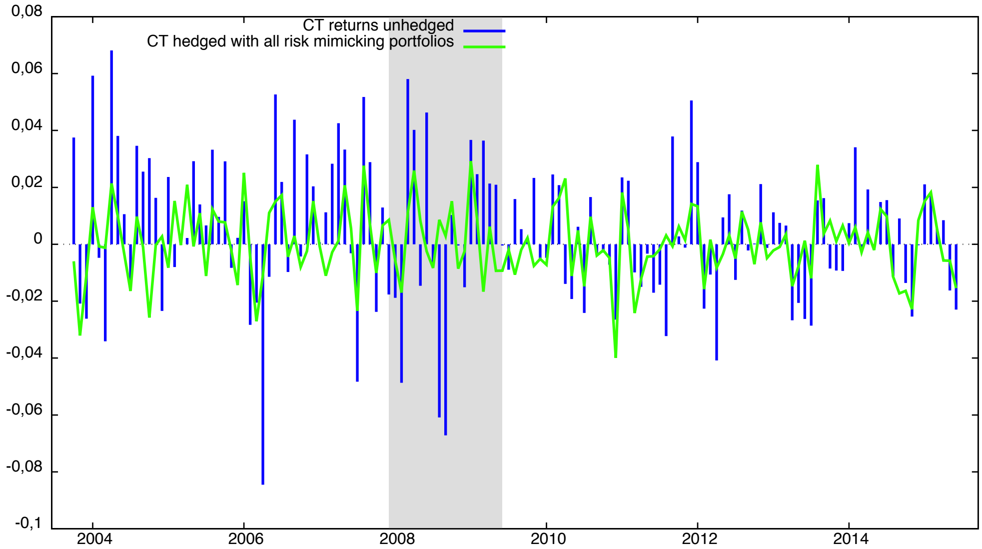


Figure 2. Hedged and Unhedged Carry Trade Return Series

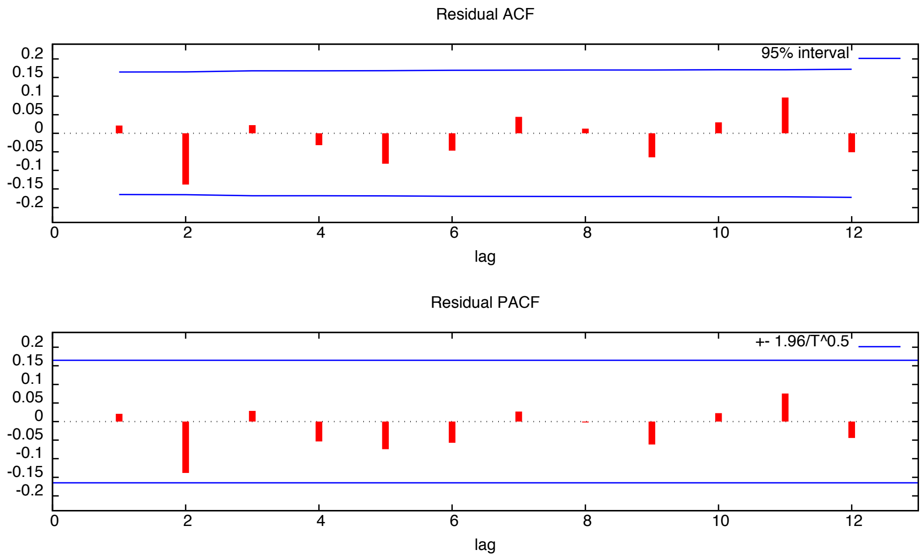
This figure presents monthly unhedged (bar chart) and hedged carry trade returns (line chart). The hedging instruments involved are the factor mimicking portfolios (FMP) of $Ivar^{FMP}$, $Iskew^{FMP}$, dRM^{FMP}, $dCPI^{FMP}$, and $dVIX^{ortho}$, which is a combination of a portfolio of VIX futures and $Ivar^{FMP}$. The grey background indicates *NBER* recession periods. The sample covers the time period between October 2003 and June 2015. The table below offers portfolio summary statistics of the two strategies about annualized mean and standard deviation (Std.Dev.), skewness and excess kurtosis (ex. Kurtosis), the interquartile range (IQR), minimum (Min) and maximum (Max) log return observations. The last row indicates the percentage difference (% Diff.) between unhedged and hedged carry trade returns.



	Mean	Std.Dev.	Skewness	ex. Kurtosis	IQR	Min	Max
CT unhedged	4.85%	8.86%	-0.268	0.620	3.41%	-8.45%	6.82%
CT hedged	0.37%	4.30%	-0.167	0.356	1.61%	-3.99%	2.93%
% Diff.	-92.3%	-51.5%	-37.7%	-42.6%	-52.8%	-52.7%	-57.1%

Figure 3. ACF and PACF Correlogram

This figure presents the time-series autocorrelation function (ACF) in the upper chart, as well as the partial autocorrelation function (PACF) in the lower chart, of the residuals coming from the last OLS regression of Table 7. The ACF and PACF observations are shown as bar charts, respectively, up to the 12th lag. The upper and lower lines indicate the 95% confidence bands.



APPENDIX

Appendix A. The Higher Moment Sharpe Ratio

The *Higher Moment Sharpe ratio (SR^{HM})* was developed by Broll (2016b). It extends the original Sharpe ratio (Sharpe 1964) by incorporating the second- and third-moment risk of the portfolio return. This measure of portfolio efficiency ensures that portfolio return series that are prone to fat tailed and skewed return distributions are adequately compared to more Gaussian distributed portfolios. It is equal to the original Sharpe ratio, when the portfolio return series has 0 skewness (γ_1) and 0 excess kurtosis (γ_2).

$$SR^{HM} = \frac{\mu - r^f}{\left[\left(\sqrt{\sigma^2}\right)\left(\sqrt[3]{(1+a|\gamma_1|)}\right)^{-E}\left(\sqrt[4]{1+b|\gamma_2|}\right)^{B}\right]^{(\mu - r^f/|\mu - r^f|)}} \tag{A.1}$$

$$E = \begin{cases} +1, & if\ \gamma_1 > 0 \\ -1, & if\ \gamma_1 \leq 0 \end{cases} \quad \text{and} \quad B = \begin{cases} +1, & if\ \gamma_2 > 0 \\ -1, & if\ \gamma_2 \leq 0 \end{cases}$$

$$\gamma_1 = \frac{E[(X-\mu)^3]}{\sigma^3} \tag{A.2}$$

$$\gamma_2 = \frac{E[(X-\mu)^4]}{\sigma^4} - 3 \tag{A.3}$$

The numerator describes the portfolios excess return, where μ means the pure portfolio return, and r^f the corresponding risk free rate. The denominator deflates the excess return by multiplication of the standard deviation with factors of skewness and excess kurtosis. The variables *a* and *b* are adjustment factors with values of 1.8 and 1.0. respectively, identifying this metric as a maximizer of investor's exponential utility.

Appendix B. Definition of Implied Variance (*$Ivar^E$*)

This measure of variance has been developed in Neuberger (2012) as an ingredient of his measure of realized skewness. It is called the variance of an *entropy contract*, which has an expected future payoff of $\mathbb{E}_t\ [S_T lnS_T]$. The corresponding implied variance to the entropy contract can then be defined as follows:

$$Ivar_{t,T}^{E} = 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{S_T}{F_{t,T}}\ln\frac{S_T}{F_{t,T}} - \frac{S_T}{F_{t,T}} + 1\right] \tag{B.1}$$

$\mathbb{E}_t^{\mathbb{Q}}$ means the risk-neutral expectation with today's (*t*) information set, with S_T and $F_{t,T}$ as the future spot rate and the today's forward rate maturing in *T*, respectively. Using the spanning approach from Bakshi and Madan (2000), the implied variance at time *t* can be computed as follows:

$$Ivar_{t,T}^{E} = 2\left(\int_0^{F_t}\frac{P_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK + \int_{F_t}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK\right) \tag{B.2}$$

$P_{t,T}(K)$ and $C_{t,T}(K)$ are put and call prices with strike price K, and $B_{t,T}$ is the domestic zero bond price. One can transform (B.2) into its discrete form using the same method applied for $Ivar_{t,T}$ (see (5) and (6)).

Appendix C. Implied Skewness Risk

Considering g^{ThM} of equation (7), under risk-neutral expectations one gets the implied measure for the third-moment risk:

$$Ithm_{t,T} = E_t^{\mathbb{Q}}\left[3\Delta Ivar_{t,T}^{E}\left(\frac{S_T - F_{t,T}}{F_{t,T}}\right) + 6\left(2 - 2\frac{S_T}{F_{t,T}} + ln\frac{S_T}{F_{t,T}} + \frac{S_T}{F_{t,T}}ln\frac{S_T}{F_{t,T}}\right)\right] \tag{C.1}$$

It is assumed that the foreign exchange rate price process is martingale,[35] so that the first term in (C.1) becomes zero in expectation and only the second term is relevant for pricing the implied measure. Neuberger (2012) defines the implied third-moment risk as the difference of the implied variance of the entropy contract and the implied variance defined in equation (5):

$$Ithm_{t,T} = 3\left(Ivar_{t,T}^{E} - Ivar_{t,T}^{L}\right) \tag{C.2}$$

In order to show how the implied third-moment risk is connected to these measures of variance, we now substitute the risk-neutral values of equation (4) and (B.1) into (C.2). This results in the same expected value for the implied third-moment risk as in (C.1):

[35] Be reminded that the future spot price in *T*, can also be expressed in terms of a forward contract, $S_T = F_{T,T}$. It follows from the martingale property of the forward price process that $E_t[F_{T,T} - F_{t,T}] = 0$.

$$Ithm_{t,T} = 3\left\{2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{S_T}{F_{t,T}}\ln\frac{S_T}{F_{t,T}} - \frac{S_T}{F_{t,T}} + 1\right] - 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{S_T}{F_{t,T}} - 1 - \ln\frac{S_T}{F_{t,T}}\right]\right\}$$
$$Ithm_{t,T} = 6\left\{\mathbb{E}_t^{\mathbb{Q}}\left[\frac{S_T}{F_{t,T}}\ln\frac{S_T}{F_{t,T}} - \frac{S_T}{F_{t,T}} + 1 - \frac{S_T}{F_{t,T}} + 1 + \ln\frac{S_T}{F_{t,T}}\right]\right\}$$
$$Ithm_{t,T} = 6\,\mathbb{E}_t^{\mathbb{Q}}\left[2 - 2\frac{S_T}{F_{t,T}} + \ln\frac{S_T}{F_{t,T}} + \frac{S_T}{F_{t,T}}\ln\frac{S_T}{F_{t,T}}\right]$$

The implied third-moment risk can also be expressed as a portfolio of a continuum of options. Using the third-moment risk definition provided by Neuberger (2012) in (C.2), one can just replace Ivar^{E} and Ivar^{L} with their respective contingent claim prices, defined in (B.2) and (5), respectively, to get the result of equation (9):

$$Ithm_{t,T} = 3\left(2\left(\int_0^{F_{t,T}}\frac{P_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK\right) - 2\left(\int_0^{F_{t,T}}\frac{P_{t,T}(K)}{B_{t,T}K^2}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K^2}dK\right)\right)$$
$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_0^{F_{t,T}}\frac{P_{t,T}(K)K}{K^2\,F_{t,T}}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)K}{K^2\,F_{t,T}}dK\right) - \left(\int_0^{F_{t,T}}\frac{P_{t,T}(K)F_{t,T}}{K^2F_{t,T}}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)F_{t,T}}{K^2F_{t,T}}dK\right)$$
$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_{F_{t,T}}^{\infty}\frac{(K - F_{t,T})}{K^2\,F_{t,T}}C_{t,T}(K)dK - \int_0^{F_{t,T}}\frac{(F_{t,T} - K)}{K^2\,F_{t,T}}P_{t,T}(K)dK\right)$$

Appendix D. The *Iterated GMM Higher Moments* Procedure (*iGMMHM*)

The usual estimation problem for the econometrician using factor mimicking portfolios as risk variables (x_i's) to explain, e.g. excess returns, can be formalized as follows:

$$y_t = \alpha + \sum_{i=1}^{N}\beta_i\,x_{i,t} + \varepsilon_t \tag{D.1}$$

In Coën et al. (2009), they introduce a model that corrects for errors-in-variable (EIV) problems by augmenting (D.1) with instrumental variables. These instruments are the first lagged value of each regressor x_i expressed up to the 5^{th} power, so that z_i's are a function of the corresponding underlying risk variable x_i:

$$z_{i,t} = f\left(x_{i,t-1}, x_{i,t-1}^2, \dots, x_{i,t-1}^5\right) \tag{D.2}$$

The augmented model will be estimated using the iterated GMM procedure that is formalized as follows:

$$y_t = \alpha + \sum_{i=1}^{N}\beta_i\,x_{i,t} + \sum_{j=1}^{M}\beta_j\,z_{i,t} + \varepsilon_t \tag{D.3}$$

A moment condition is applied to the matrix Z of instrumental variables z_i, so that each instrumental variable is orthogonal to the innovation term ε, which is:

$$E(Z'\varepsilon) = 0 \tag{D.4}$$

With $\varepsilon = h(Y, X, \theta)$, where θ is the parameter vector to be estimated. These moment conditions are approximated by their sample averages:

$$\frac{1}{N}\sum_{i=1}^{N} Z_i \varepsilon_i = G(Y, X, Z; \theta) \tag{D.5}$$

In order to estimate the vector of parameters $\hat{\theta}$, the minimization problem applies as follows:

$$\underset{\theta}{argmin}\ G'(Y, X, T; \theta)\ W\ G(Y, X, Z; \theta) \tag{D.6}$$

With W representing the inverse of the covariance matrix. One reasonable estimator for the weighting matrix W is the well-known White matrix:

$$\hat{\Phi}_{White} = \hat{\Gamma}_0 = \frac{1}{T-k}\sum_{t=1}^{T} G_t' G_t \tag{D.7}$$

With T as the number of observations and k the number of regressors. Coën et al. (2009) propose for W the HAC covariance estimator ($\hat{\Phi}_{HAC}$) in accordance with the iterated GMM method, which is:

$$\hat{\Phi}_{HAC} = \hat{\Gamma}_0 + \sum_{j=1}^{T-1} \kappa(j, q)(\hat{\Gamma}_j + \hat{\Gamma}_j') \tag{D.8}$$

The algorithm of the iterated GMM procedure computes the optimal covariance matrix using κ in the form of the quadratic spectral, where j is the lag length, and q defines the bandwidth, which is optimally selected following the technique known as *VAR prewhitening* developed by Andrews and Monahan (1992).

Table A. 1. Foreign Currency Exchange Rate Data Coverage

This table gives an overview of the coverage of foreign exchange rates used. It is divided into developed (Panel A) and emerging currencies (Panel B), and distinguishes between Sample I (middle partition) and Sample TFF (right partition). The left partition characterizes the foreign exchange rates by their number (No.), *ISO 4217* currency code, and their country. The middle and right part gives an overview of the various start and end dates of the time-series and the number of monthly observations (Obs.).

No.	*Currency codes*	*Country*	*Sample I* Start date	*Sample I* End date	*Sample I* Obs.	*Sample TFF* Start date	*Sample TFF* End date	*Sample TFF* Obs.
Panel A: Developed Market Currencies (G10)								
1	AUD	Australia	09/2003	06/2015	142	09/2003	06/2015	142
2	CAD	Canada	09/2003	06/2015	142	09/2003	06/2015	142
3	EUR	Europe	09/2003	06/2015	142	09/2003	06/2015	142
4	GBP	Great Britain	09/2003	06/2015	142	09/2003	06/2015	142
5	JPY	Japan	09/2003	06/2015	142	09/2003	06/2015	142
6	NZD	New Zealand	09/2003	06/2015	142	11/2005	06/2015	116
7	DKK	Denmark	02/2005	06/2015	125	./.	./.	./.
8	NOK	Norway	02/2005	06/2015	125	./.	./.	./.
9	SEK	Sweden	02/2005	06/2015	125	./.	./.	./.
10	CHF	Swiss	02/2005	06/2015	125	09/2003	06/2015	142
Panel B: Emerging Market Currencies								
11	PLN	Poland	09/2003	06/2015	142	./.	./.	./.
12	SGD	Singapore	09/2003	06/2015	142	./.	./.	./.
13	ZAR	South Africa	09/2003	06/2015	142	./.	./.	./.
14	KRW	South Korea	09/2003	06/2015	142	./.	./.	./.
15	TWD	Taiwan	09/2003	06/2015	142	./.	./.	./.
16	THB	Thailand	09/2003	06/2015	142	./.	./.	./.
17	ILS	Israel	03/2004	06/2015	136	./.	./.	./.
18	CLP	Chile	02/2005	06/2015	125	./.	./.	./.
19	COP	Colombia	02/2005	06/2015	125	./.	./.	./.
20	CZK	Czech Republic	02/2005	06/2015	125	./.	./.	./.
21	HUF	Hungary	02/2005	06/2015	125	./.	./.	./.
22	INR	India	02/2005	06/2015	125	./.	./.	./.
23	MXN	Mexico	02/2005	06/2015	125	09/2003	06/2015	142
24	BRL	Brazil	11/2005	06/2015	116	./.	./.	./.
25	TRY	Turkey	11/2005	06/2015	116	./.	./.	./.
26	RUB	Russia	04/2006	06/2015	111	02/2009	06/2015	77
27	MYR	Malaysia	09/2006	06/2015	106	./.	./.	./.
28	IDR	Indonesia	06/2007	06/2015	97	./.	./.	./.
29	PHP	Philippines	06/2007	06/2015	97	./.	./.	./.
30	PEN	Peru	06/2008	06/2015	85	./.	./.	./.
31	RON	Romania	06/2008	06/2015	85	./.	./.	./.
32	SKK	Slovakia	06/2008	05/2014	70	./.	./.	./.

Table A. 2. Time Frames Subject to Large CIP Violations

This tables summarizes the time frames that are excluded due to large covered interest rate parity (CIP) violations. CIP violations applies, when the forward rate according to CIP, in the majority of daily observation within a month, differs more than 0.1% of the markets forward bid-ask spread. The first two columns specify the foreign currency code and country, followed by the start and end dates of exclusion, the number of monthly excluded observations in that period (Excl.Obs.), and the total number of monthly excluded observations for any currency (Total Excl.Obs.), respectively. The last row sums up all excluded observations.

Code	Country	Start date	End date	Excl. Obs.	Total Excl. Obs.
BRL	Brazil	11/2005	11/2006	13	
		12/2007	04/2008	5	
		10/2008	11/2008	2	
		09/2010	10/2011	14	
		01/2013	04/2013	4	*38*
CLP	Chile	06/2008	10/2008	5	
		06/2009	12/2009	7	*12*
COP	Colombia	06/2010	07/2011	14	
		10/2011	01/2012	4	
		08/2015	09/2015	2	*20*
HUF	Hungary	12/2011	01/2012	2	*2*
INR	India	02/2008	05/2008	4	
		09/2008	10/2008	2	
		01/2009	02/2009	2	
		06/2011	11/2011	6	*14*
MXN	Mexico	10/2008	12/2008	3	*3*
MYR	Malaysia	11/2008	01/2009	3	
		02/2010	07/2010	6	
		09/2010	12/2010	4	
		02/2011	05/2011	4	
		07/2011	08/2011	2	*19*
PEN	Peru	08/2010	11/2010	4	
		02/2011	03/2011	2	
		02/2012	05/2012	4	
		11/2012	04/2013	6	
		02/2015	06/2015	5	*21*
RUB	Russia	10/2008	02/2009	5	*5*
SKK	Slovakia	11/2010	12/2010	2	
		08/2011	06/2012	11	*13*
THB	Thailand	09/2006	10/2006	2	
		12/2006	01/2007	2	*4*
TWD	Taiwan	04/2007	05/2007	2	
		01/2008	06/2008	6	
		01/2009	06/2010	18	*26*
				Σ	***177***

Chapter 3

Using Option-Implied Information to Improve Currency Carry Trade Profits

USING OPTION-IMPLIED INFORMATION TO IMPROVE CURRENCY CARRY TRADE PROFITS*

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Abstract

This study investigates an efficient parametric portfolio policy model to improve the return distribution of the well-known currency carry trade investment strategy. This carry trade strategy invests into high-yielding currencies that are subsequently funded by low-yielding currencies. Following this investment procedure has led to significantly excess returns for the investors, at least over the past four decades. However, these returns were subject to a high crash risk, which hit its peak during the US subprime crisis in 2008/2009 with portfolio losses of up to one third of the investment value. The constructed model overcomes these bad portfolio properties through computing the optimal carry trade portfolio weight for any monthly revolving investment period. This is done by modeling the optimal weight as a function of the carry trade's risk characteristics. Especially, when using global FX option-implied variance risk, as well as global consumer price inflation and commodity prices as background risk factors, the model delivers extremely-efficient out-of-sample results with annualized mean returns of up to 8.4% over an eight-year period, accompanied with a low standard deviation, positively skewed returns and leading to Sharpe ratios around unity, including transaction costs. These promising statistics are largely maintained when allowing for higher leveraged portfolios.

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1 Introduction

Carry trade is one of the most famous currency investment strategies, where the investor borrows in currencies with low interest rates, also known as funding currencies, and purchases currencies with high interest rates, also called investment currencies. The main idea behind it is to lock-in the resulting interest rate differential using a monthly rebalancing investment procedure. Many studies have shown that the carry trade excess returns appear to be significant over long horizons (Burnside, Eichenbaum, and Rebelo 2011b; Menkhoff et al. 2012a), which is at odds with the *uncovered interest rate parity* (UIP). The UIP theory postulates that future excess returns to any currency pair are supposed to be zero in expectation, so that any advantage of a positive interest rate spread should vanish through a depreciation of the higher-yielding to the lower-yielding currency. Many studies have shown that investment currencies do not depreciate much to mitigate this relationship, which is known in the literature as *forward rate anomaly*. Therefore, the overall profitability of the carry trade comes with a cost of high negative skewed returns and periods of high negative drawdowns.

Lustig et al. (2011) propose a no-arbitrage model for exchange rates that explicitly uncovers the relationship of both country's stochastic discount factor (SDF) dynamics and the resulting risks to exchange rates, which can reproduce the forward rate anomaly in the data. They conclude that the risk premium earned by the carry trade is particularly dependent on the difference of the global risk exposure between funding and investment currencies and the variation of one or more global state variables.[1] As a result, negative shocks to the global risk factor, as well as the heterogeneity of global risk exposures, lead to high negative skewed and fat tailed returns, which characterizes the carry trade return distribution. Hence, identifying state variables that mirror global risk is key for predicting carry trade excess returns.

Therefore, this paper focuses on finding risk factors that can be interpreted as common global risks to develop an efficient portfolio policy in order to increase carry trade returns without having the burden of fat tails and negative skewness. The main idea of the portfolio model has its origin from the pioneering work of Brandt et al. (2009).[2] The authors propose modelling the optimal stock portfolio weights as a function of firm characteristics, e.g. the three factors' defined by Fama and French (1993). Laborda et al. (2014) operationalize this

[1] Proposition 4.1 and 4.2 in Lustig et al. (2011) provide a brief overview of the model dynamics for the carry trade risk premium.

[2] Barroso and Santa-Clara (2015) use the model to enhance currency strategies based on momentum, interest rate differentials, and long-term reversals to optimize any currency position weight and show in out-of-sample tests that relying on these risk variables leads to efficient currency portfolios reaching Sharpe ratios of up to 1.06 compared to 0.57 for the carry trade portfolios in the sample period from March 1996 to December 2011.

idea to optimize single portfolio strategies that follow a specific revolving investment procedure, such as the currency carry trade. This model imposes a strict linear functional form between future carry trade returns and a set of state variables that represent the dynamically-changing macroeconomic environment. It operates within an optimal asset allocation setting, which maximizes the investor's utility function with respect to the individual risk aversion. The main advantage over the baseline carry trade investment scheme is that the model computes an optimal portfolio weight each month, considering the global risk environment. The weights can switch between long and short investments in any desired leverage, leaving the individual composition of each exchange rate of the currency carry trade unchanged.

This study concentrates on three main categories to reliably characterize the global risk environment: (i) option-implied variance risk, (ii) macroeconomic risk, and (iii) speculators trade positions. The set of information presented here differs remarkably from the choice in Laborda et al. (2014). The importance of option-implied risk factors, which mirrors the investor's future perception, has been proven to be a reliable source to describe risk patterns inherent in the currency carry trade (see Broll, 2016a; Farhi et al., 2015; Jurek, 2014). Studies from Aloosh (2014) and Della Corte et al. (2016) report increased currencies' return predictability using the variance risk premium (VRP) as a state variable. While Aloosh (2014) focuses on a global equity-based VRP,[3] Della Corte et al. (2016) find that currency sorting on individual VRP levels leads to significant excess returns, which is primarily driven by spot rate predictability rather than interest rate spreads. The VRP, defined as the difference between realized and option-implied variance, can be regarded as a measure of relative insurance cost against high volatility. Della Corte et al. (2016) pointed out that one source of sufficient predictability of VRPs lies in their ability to capture fluctuations in investor's aversion to volatility risk. The lower the dispersion between realized and implied variance for an exchange rate, the higher the returns in subsequent months and vice versa. The second category of global risk variables are macroeconomic risk aggregates. Following the evidence of Lustig et al. (2011) that the carry trade is a compensation for carrying global risk exposure, we form an aggregated global economic growth factor out of each country's real industrial production growth. Furthermore, Lustig et al. (2014) show that the real countries' pricing kernel are the nominal SDFs minus inflation. Since the carry trade is exposed to short positions in funding currencies, with relatively low interest and inflation rates and, at the same time, long positions of investment currencies with relatively high inflation rates (see Lustig et

[3] Aloosh (2014) shows in a multivariate regression setting that the *global equity VRP* is the only significant variable to predict future carry trade returns when regressed jointly with the FX volatility factor and the commodity risk factor of Bakshi and Panayotov (2013) between January 2000 and December 2011.

al., 2011),[4] we expect that this difference plays a role in predicting excess returns to the carry trade. The last category examines the role of trade flows in carry trade. Broll (2016a) and Brunnermeier et al. (2009) found evidence that lower market liquidity, measured by the US-TED spread, leads to an unwinding in carry trade positions. Tracking these trading flows is supposed to improve carry trade returns' predictability. Broll (2016a) constructed a simple procedure to aggregate these trading flows of a generic carry trade portfolio called the *Carry Trade Activity Index* (CTI), using forward positions from currency speculators provided by the *U.S. Commodity Futures Trading Commission* (CFTC).

Taking these three main categories as the baseline risk environment to predict future carry trade returns through this asset-allocation framework leads to significantly-improved portfolio statistics over the baseline carry trade portfolio and also outperforms the model proposed by Laborda et al. (2014). In fact, the empirical results presented here extend the findings of Laborda et al. (2014) with several aspects: (i) under the G10 carry trade portfolio formation, a more global carry trade portfolio is additionally constructed, containing up to 32 currencies as underlying assets, (ii) a higher leverage for the optimal carry trade weights is considered, (iii) a more parsimonious model significantly increases out-of-sample profitability, and (iv) transaction costs are taken into account.

The main results can be summarized as follows: in-sample as well as out-of-sample tests suggest that the most significant variables to improve the carry trade return distribution are: (i) the implied variance spread between investment and funding currencies, (ii) the global FX-based VRP, (iii) the global CPI differential, and (iv) the CRB commodity price index. While higher values of the *implied variance spread* signal higher carry trade weights, the opposite is true for the other three variables. As a result, the optimized carry trade portfolio takes advantage of financial stress periods through an effective system that variably switches between long and short holdings and, additionally, delivers gradual returns in relatively calm periods. This is reflected in mean annual returns of up to 8.38%, accompanied by a positive skewness of 0.58, low standard deviation, and tremendously-reduced maximum draw downs, leading to Sharpe ratios around unity.

This paper is organized as follows: Section 2 describes the data and the parametric portfolio policy model and outlines the computation of the global risk variables. Section 3 briefly describes the historical properties of the global and G10 carry trade portfolios and

[4] Lustig et al. (2011) report average nominal and real interest rate differentials for a variety of currency baskets sorted on their forward discount levels. Their statistics imply, for their "All Country" sample, a moderate average inflation rate of 1.76% for funding currencies and, on the other hand, a substantially higher average inflation of 8.15% for investment currencies, annually. Their sample period is from November 1983 to December 2009, with on average US annual inflation of 2.92%.

presents empirical evidence of in-sample and out-of-sample return profitability. Section 4 provides conclusions to the information presented.

2 Data and Methodology

This section starts with a characterization of the data basis, which incorporates the data source, restrictions, and foreign exchange (FX) samples used. The study focuses on global state variables that incorporate the use of option-implied information, as has been outlined in the introduction. Specifically, the role of FX's realized and implied variance risk, in particular the variance risk premium (VRP), will be taken into consideration as a primary source of global risk that impacts the currency carry trade risk environment. As a first step, the computational background for the second-moment risk will be introduced, followed by the transformation into a global state variable. After some preliminaries about the recovery of FX option prices and exchange rate return definitions, the parametric portfolio policy developed by Laborda et al. (2014) will be presented.

2.1 Data

The FX data primarily consists of foreign daily bid/ask spot rates, one-month (1m) and three-month (3m) forward rate data from WM/Reuters fixings. There are two currency samples used for computing carry trade returns, which are the *Global-Sample,* containing 32 different exchange rates, and a smaller subsample of only 10 developed currencies, denoted as the *G10-Sample*. All FX rates are quoted against the US-dollar (USD), covering the sample period from September 2003, at the earliest, to June 2015.[5] The G10-Sample consists of the countries/regions: Australia (AUD), Canada (CAD), Denmark (DKK), Europe (EUR), Great Britain (GBP), Japan (JPY) New Zealand (NZD), Norway (NOK), Sweden (SEK), and Switzerland (CHF). The Global-Sample additionally contains FX rates of 22 emerging countries: Brazil (BRL), Chile (CLP), Colombia (COP), Czech Republic (CZK), Hungary (HUF), India (INR), Indonesia (IDR), Israel (ILS), Malaysia (MYR), Mexico (MXN), Peru (PEN), the Philippines (PHP), Poland (PLN), Romania (RON), Russia (RUB), Singapore (SGP), Slovakia (SKK), South Africa (ZAR), South Korea (KRW), Taiwan (TWD), Thailand (THB), and Turkey (TRY).

The study uses two different *Carry Trade Activity Indexes* (CTI's) developed by Broll (2016a), which track the degree of long exposure of the global and G10 carry trade portfolio held by speculators. The underlying dataset is restricted to only nine different FX rates,

[5] Table A. 2 in the appendix provides an overview of the various start and end dates of each currency.

trading at the *Chicago Mercantile Exchange* (CME), which are the AUD, CAD, CHF, EUR, GBP, JPY, MXN, NZD, and RUB. Seven exchange rates are available over the sample period, while the data on the New Zealand Dollar (NZD) and Russian Ruble (RUB) start later, in November 2005 and February 2009, respectively. The CFTC provides information about aggregated FX future long, short, and spread positions for a variety of different trader groups for any single currency. The data is publically available at a weekly frequency on the CFTC's homepage in the *Traders in Financial Futures* (TFF) report. The last month *future-only* report serves as proxy for end-of-month observation. In order to attain relative conformity with regard to the G10-Sample and the Global-Sample coverage, the CTI^{G10} consists of seven G10 currencies, whereas the CTI^{Global} makes use of all nine currencies.

The FX option data contains information about end-of-month 1m and 3m option-implied volatility mid-quotes of the 25 delta butterfly and risk reversal strategy, as well as the at-the-money (ATM) volatility levels. There is also equity-based data derived from the four major indices: the US S&P-500, the British FTSE-100, the German DAX-30, and the Japanese Nikkei-225 Index. The realized data contains daily closing prices, where the option-implied data consist of end-of-month closing prices coming from the volatility indices: VIX, VFTSE, VDAX-NEW, and VSJ. These prices proxy the 1m-implied volatility level of the four country indices, respectively.

The interest rate data is comprised of end-of-month 1m and 3m maturity London interbank offered rates (LIBOR) for all Global-Sample currencies and the USD. In cases where the LIBOR are unavailable, implied rates were computed using the covered interest rate parity (CIP).[6] Furthermore, the time-series on the US-TED spread is used, which essentially mirrors the interest rate difference between 3m LIBOR and 3m T-Bill rates. The risk-free rate for the US-investor is proxied by the four-week (4w) T-Bill rate.

Macroeconomic data comprises monthly information on the money stock (M3),[7] consumer price index (CPI), and industrial production data for all currencies covered. Additionally, the data on key rate changes for all G10 countries was collected. All data was obtained using Datastream, the CFTCs, and the G10 countries' central bank websites.

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[6] The CIP relationship is proxied by $f_{t,T} = s_t + i_{t,T} - i_{t,T}^f$, where $f_{t,T}$ and s_t denote the current log forward and log spot rate at time t, $i_{t,T}^f$ means the foreign interest rate, and $i_{t,T}$ the corresponding US-rate for period [t,T]. CIP-implied foreign rates have been computed for the 1m-KRW interest rate from 2003:09 to 2004:07, the 1m-TRY rate from 2005:11 to 2006:06, the 1m-CLP rate from 2014:01 to 2015:06 and for 1m- and 3m-SKK rates from 2009:01 to 2015:06 and 2013:10 to 2015:06, respectively.

[7] For the following countries, M2 data is used as the biggest available money aggregate. M3 is used for the USA, Indonesia, Russia, and Taiwan.

2.2 Recovering Option Prices

It is a common practice in the FX market that option-implied volatilities are assigned to option deltas rather than fixed option strike prices. The option delta determines the moneyness of an option and, therefore, the sensitivity of the option price due to changes in the price of the underlying asset. In order to translate these option delta volatilities into strike price volatilities, Reiswich and Wystup (2012) developed a procedure to recover FX option prices by modelling market-conform option smiles. The option smile or skirt describes the various implied volatility levels relative to their option strike for the respective exchange rate and option maturity. They call their procedure the *simplified parabolic interpolation* model, using the 25-delta butterfly, 25-delta risk reversal, and ATM volatility quotes as input parameters.[8] Reiswich (2011) has empirically shown that this calibration method delivers robust results that are comparable to other well-known smile procedures used in practice; e.g. the vanna-volga method by Castagna and Mercurio (2007), among others.

2.3 Currency and Carry Trade Return Definition

It is assumed that the FX market is arbitrage-free and without friction. The exchange rate is expressed in USD per one foreign currency unit. Therefore, an appreciation of the exchange rate translates into an appreciation of the foreign currency holding of a US-investor relative to his home currency, the USD. S_t denotes the current spot rate in t and $F_{t,t+1}$ the corresponding forward rate with maturity in $t+1$. Assuming that the covered interest parity (CIP) holds, the forward rate can be priced as follows:

$$F_{t,t+1} = S_t e^{(i_{t,t+1} - i^f_{t,t+1})\tau} \quad (1)$$

Here $i^f_{t,t+1}$ denotes the one-period foreign LIBOR[9] and $i_{t,t+1}$ the corresponding US-LIBOR, where τ means the difference between start and maturity date expressed in years. This study solely expresses FX returns in logarithmic form, where forward and spot FX prices are then denoted as lower case letters. The one period log return $r_{t,t+1}$ for a US-investor holding foreign currency units is then defined as

$$r_{t,t+1} = s_{t+1} - f_{t,t+1} \quad (2)$$

When we plug the forward price definition (1) into (2) and maintain the log return format, we can see that the exchange rate return is composed of two main sources, on the one hand, the spot rate change ($\Delta s_{t,t+1}$) and, on the other hand, the interest rate differential (IRD):

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[8] Table A. 1 in the appendix provides a detailed overview of option delta conventions used to recover option smiles for any exchange rate in the coverage.

[9] The *London Interbank Offered Rate* (LIBOR) is usually used as a benchmark rate to price forward contracts and other financial contracts in the foreign exchange market.

$$r_{t,t+1} \approx \Delta s_{t,t+1} + \left(i_{t,t+1}^{f} - i_{t,t+1}\right) \quad (3)$$

The key objective of the currency carry trade strategy is therefore to *lock-in* the IRD. This is done in a portfolio context to mitigate country-specific risk through diversification effects. There is some evidence that the significance of carry trade returns increases when one increases the number of currencies involved (see e.g. Bakshi and Panayotov, 2013; Brunnermeier et al., 2009). The currency composition for the global carry trade strategy consist of one sixth of all currencies with the highest foreign rates, and one sixth of currencies with the lowest foreign interest rate levels for any monthly revolving investment period. The monthly carry trade return $r_{t,t+1}^{CT}$ is then defined as the difference between the average log returns of M_t individual investment currencies and the average log returns of N_t individual funding currencies:

$$r_{t,t+1}^{CT} = \frac{1}{M_t}\sum_{m=1}^{M_t} r_{t,t+1}^{m} - \frac{1}{N_t}\sum_{n=1}^{N_t} r_{t,t+1}^{n} \quad (4)$$

In the forthcoming analysis, we use two different carry trade portfolio compositions. The first one is composed of the Global-Sample currencies, the global carry trade portfolio, while the second one's composition relies only on the G10-Sample, the G10 carry trade portfolio that primarily serves as control sample. The number of available currencies for the global carry trade varies over time, so that N and M are subscripted by t, whereas the composition for the G10 carry trade portfolio always consist of two investment and two funding currencies.

2.4 Parametric Portfolio Policy Model Description

This section introduces the investment procedure used here to obtain optimal portfolio weights for the currency carry trade strategy. The procedure has its origins in the pioneering work of Brandt et al. (2009) and has been operationalized by Laborda et al. (2014) to fit the optimization process for the currency carry trade. The key objective for this investment procedure is to compute an optimal weight ω_t for the carry trade that can change from long to short positions, depending on the changing nature of the global economic environment. As input variables for the model serves a range of global risk variables that have potential to predict the carry trade return distribution. The output is the time-varying optimal weight ω_t, which simultaneously maximizes the investor's utility. The carry trade positions are executed in the forward market and it is assumed that no collateral is needed to underline the forward market operations. Hence, the entire capital can be invested into the risk-free asset with return $rf_{t,t+1}^{US}$. The resulting optimized portfolio return $r_{t,t+1}^{Opt}$ can be defined as follows:

$$r_{t,t+1}^{Opt}(\omega_t) = rf_{t,t+1}^{US} + \omega_t r_{t,t+1}^{CT} \tag{5}$$

The basic idea of the optimization process is to choose a portfolio weight ω_t in each period that maximizes the conditional expected utility $\mathbb{E}_t[U]$ of the portfolio's return $r_{t,t+1}^{Opt}$, given a set of risk variables X_t:

$$\max_{\theta} \mathbb{E}_t\left[U\left(r_{t,t+1}^{Opt}(\omega_t)\right) \mid X_t\right] \tag{6}$$

It is assumed that the investor's utility function is *CRRA* (Constant Relative Risk Aversion), which is standard in portfolio theory (see Brandt, 1999):

$$U\left(r_{t,t+1}^{Opt}\right) = \begin{cases} \frac{\left(1+r_{t,t+1}^{Opt}\right)^{1-\gamma}}{1-\gamma} & \text{, for } \gamma \neq 1 \\ log\left(1 + r_{t,t+1}^{Opt}\right) & \text{, other.} \end{cases} \tag{7}$$

The risk aversion parameter of the representative US-investor is denoted as γ and takes on a value of 10.[10] The optimal weight ω_t is parameterized as a function of the carry trade's global risk structure, in the following simple linear form:

$$\omega_t = \omega_t\left(X_t; \hat{\theta}\right) = \hat{\theta}^{\intercal} X_t = \hat{\theta}^1 x^1 + \hat{\theta}^2 x_t^2 + \cdots + \hat{\theta}^n x_t^n \tag{8}$$

where $\hat{\theta}$ is a vector of coefficients to be optimized, X_t is a matrix of risk variables and x^1 serves as the intercept value, while all other $x^{\neq 1}$ values represent risk variables that are standardized across time to have zero mean and unit standard deviation. This time-series standardization ensures, on the one hand, stationarity of the variables, and, on the other hand, that any particular risk source is treated balanced to each other, so that risk variables with particularly high volatilities are not over-weighted. After the optimization procedure, the values of ω_t will be restricted to lie between -1 and 1, in the following form:

$$\omega_t^{restr.} = \begin{cases} +1, for\ \omega_t > 1 \\ -1, for\ \omega_t < -1 \\ \omega_t, \quad other. \end{cases} \tag{9}$$

While this step is not obligatory, since the investments are executed in the forward market and can be leveraged to any desirable level, the initial results are primarily addressed to the conservative investor who is not necessarily interested in highly-leveraged investments. On the other hand, the results become ultimately comparable to the original work of Laborda et al. (2014). In the empirical section it will be shown that higher leveraged optimized carry trade portfolios are also reasonable without loss of portfolio efficiency.

[10] The standard level of investor's risk is set to $\gamma = 10$, which leads, on the one hand, to volatility levels comparable to the baseline carry trade portfolio, and, on the other hand, ensures comparability to the results in Laborda et al. (2014).

Given the above-mentioned maximization problem and restrictions for the investor, we can now reformulate equation (6) to have a testable representation, which can be implemented into an optimization process using the iterated generalized method of moments (GMM) (see Hansen, 1982). The GMM method requires as many moment conditions *m* as one is supposed to estimate the number of k parameters $\hat{\theta}$. This is done by using the first derivative of the maximization problem in (6) with respect to $\hat{\theta}$:

$$m(\hat{\theta}) = U'(r_{t,t+1}^{Opt})\, r_{t,t+1}^{CT} \otimes X_t = 0 \tag{10}$$

with U' as the marginal utility of the investor, $m(\hat{\theta})$ as the k x 1 vector of moment conditions, and ⊗ denoting Kronecker's product. In order to make the representation in (10) operational, the corresponding sample analogue of this allocation problem is:

$$M_T = \frac{1}{T}\sum_{t=0}^{T-1} m_t(r_{t,t+1}^{Opt}, X_t; \hat{\theta}) = 0 \tag{11}$$

Optimization is then achieved by minimizing the following scalar:

$$\left[\frac{1}{T}\sum_{t=0}^{T-1} m_t(r_{t,t+1}^{Opt}, X_t; \hat{\theta})\right]^{\top} W_T \left[\frac{1}{T}\sum_{t=0}^{T-1} m_t(r_{t,t+1}^{Opt}, X_t; \hat{\theta})\right] = 0 \tag{12}$$

where W_T is a $k \times k$ spectral density matrix of the population moment functions. Since we have as many moment conditions as parameters by definition, the model is called "just-identified" and the restrictions are perfectly satisfied. The weighting matrix W_T determines the relative importance of all k moment conditions to each other. Hansen (1982) shows that setting W_T equal to the inverse of a covariance matrix of the k moment conditions ($W = S^{-1}$), yields optimal estimates of $\hat{\theta}$ with the smallest variance. A popular choice for the covariance matrix estimator that also corrects for autocorrelation and heteroscedasticity (HAC) is the Newey-West estimator:

$$\hat{S} = \hat{S}_0 + \sum_{j=1}^{J}\left(1 - \frac{j}{J+1}\right)(\hat{S}_j + \hat{S}_j^{\top}) \tag{13}$$

with J indicating the lag length, and:

$$\hat{S}_j = \frac{1}{T}\sum_{t=j+1}^{T} m_t(r_{t,t+1}^{Opt}, X_t; \hat{\theta})\, m_{t-j}(r_{t,t+1}^{Opt}, X_t; \hat{\theta})^{\top} \tag{14}$$

Basically, the optimal spectral density matrix W_T requires an estimate of the parameter vector $\hat{\theta}$. However, it is common practice that in the first estimation step the matrix W_T is set equal to the identity matrix. In subsequent optimization steps, W_T will be replaced by the optimal inverse of the Newey-West HAC covariance estimator outlined in (14) to obtain consistent estimates of the parameter vector $\hat{\theta}$.[11]

As a result, the optimized parameter vector $\hat{\theta}$ will be used to compute the optimal portfolio weight ω_t according to (8), which advises the representative investor with individual risk aversion γ to invest in the baseline carry trade strategy.

Statistical inference is based on the asymptotic covariance matrix Γ_T for the vector $\hat{\theta}$:

$$\Gamma_T = (1/T)[G_T W_T G_T^{\intercal}]^{-1} \tag{15}$$

with

$$\mathrm{G}_T = \frac{1}{T}\sum_{t=1}^{T} \frac{\partial M_T\left(r_{t,t+1}^{Opt}, X_t; \hat{\theta}\right)}{\partial \theta} \tag{16}$$

2.5 Variance Risk Definition

The variance risk definition presented here slightly differs from the definitions in other studies or the variance swap approach used in practice. The conventional view of measuring an asset's variance risk is determined by the aggregation of an asset's squared discrete or log returns over a predetermined period, e.g. $\sum_T r^2$. Jiang and Tian (2005) noted that the usual variance definition leads to imperfect variance swap replication.[12] Neuberger (2012) developed a function g^V that overcomes this merit and leads to a perfect match between the realized and option-implied variance for every price process and partition size (e.g. hourly, daily, monthly, etc.). He describes this perfect match as satisfying the Aggregation Property, which means that the quantity measured using higher frequency - usually the realized variance - is an unbiased estimate of its low frequency counterpart, the option-implied variance risk.[13] Under the proposition that the underlying price process is martingale, he defined the generalized variance of log returns as $g^V(\mathrm{r}) \equiv 2(e^r - 1 - \mathrm{r})$, which has all the properties of variance (see also Bondarenko, 2014). Following the proposition of g^V as a measure of variance, the realized variance ($Rvar_{t,T}^i$) of foreign exchange rate k in the time interval [t,T] is defined as follows:

[11] The GMM estimation process is executed using the publically-available software package from Michael Cliff's homepage (see Cliff, 2003). The search algorithm is based on the Gauss-Newton procedure and the lag length is set to $J = floor(T^{1/3})$.

[12] They noted that the replication is only true in the limiting case where the observed time period is close to zero and the price process is continuous.

[13] See especially Proposition 2 and 3 in Neuberger (2012) and proofs therein.

$$Rvar_{t,T}^{k} = \sum_{t=0}^{T}\left[2\left(\frac{F_{t+1,T}^{k}}{F_{t,T}^{k}} - 1 - ln\frac{F_{t+1,T}^{k}}{F_{t,T}^{k}}\right)\right] \approx \sum_{t=0}^{T}\left[2\left(\frac{S_{t+1}^{k}}{S_{t}^{k}} - 1 - ln\frac{S_{t+1}^{k}}{S_{t}^{k}}\right)\right] \tag{17}$$

Investments in the foreign exchange markets imply a compounding of the interest rate differential of both currencies involved. Therefore, one should make use of forward data when computing realized moment risk. Since there is no such data available on Datastream, the price process is approximated using daily spot rates.

The corresponding option-implied variance ($Ivar_{t,T}^{k}$) uses only the price information at time t from option prices with maturity T. Given the underlying function g^{V} and applying the spanning approach of Bakshi and Madan (2000), $Ivar_{t,T}^{k}$ can be priced using a continuum of options:

$$Ivar_{t,T}^{k} = \frac{2}{B_{t,T}}\left(\int_{0}^{F_{t,T}}\frac{P_{t,T}^{k}(K)}{K^{2}}dK + \int_{F_{t,T}}^{\infty}\frac{C_{t,T}^{k}(K)}{K^{2}}dK\right) \approx \frac{2}{B_{t,T}}\left(\sum_{K_j \le F_{t,T}}\frac{P_{t,T}^{k}(K_j)}{K_j^{2}}\Delta J(K_j) + \sum_{K_j > F_{t,T}}\frac{C_{t,T}^{k}(K_j)}{K_j^{2}}\Delta J(K_j)\right) \tag{18}$$

$B_{t,T}$ is the USD zero-bond price with same maturity. It turns out that $Ivar_{t,T}^{i}$ consist of a long portfolio of out-of-the-money (OTM) call and put options that are weighted by their squared strike prices *K*. However, in real world, there is no such continuum of options and, therefore, $Ivar_{t,T}^{k}$ is approximated using twenty call and put option prices, respectively, which are equally spaced between +/- 0.10 delta options.[14] The infinitely small strike price difference dK is replaced by $\Delta J(K_j)$, which is approximated as:[15]

$$\Delta J(K_j) \equiv \begin{cases} K_{j+1} - K_{j-1}, for\ 0 \le j \le N\ (with\ K_{-1} \equiv 2K_0 - K_1, K_{N+1} \equiv 2K_N - K_{N-1}) \\ 0, \qquad otherwise. \end{cases} \tag{19}$$

As noted above, the variance risk premium is then defined as the simple difference between the realized and implied variance risk for the same time interval [t,T]. Since $Rvar_{t,T}^{k}$ is only observable at the end of the period, whereas $Ivar_{t,T}^{k}$ is computed out of option prices in t, the $VRP_{t,T}^{k}$ is a measure of dispersion between the ex-post observed realized variance to its ex-ante option-implied variance counterpart:

$$VRP_{t,T}^{k} = Rvar_{t,T}^{k} - Ivar_{t,T}^{k} \tag{20}$$

[14] Jiang and Tian (2005) also investigated into the approximation errors in a discrete world setting when computing implied moment risks. They conclude that the approximation errors are supposed to lie around 0.5% away from the true implied volatility level, when OTM options are struck at 1.5 standard deviations away from the forward price. The 0.10 delta strikes are roughly 1.4 standard deviations away from the forward, so that the expected errors are expected to be negligibly-small.

[15] Kozhan et al. (2013) studied the variance and skewness risk premiums for the S&P 500 equity index using the same finite approximation procedure as that presented here.

The VRP is supposed to measure investor's perceptions about aggregate uncertainty in the economy and, therefore, provide a good benchmark to a shock to economic state variables.

In order to translate the single $Rvar_{t,T}^{k}$*'s,* $Ivar_{t,T}^{k}$*'s,* and $VRP_{t,T}^{k}$*'s* interpretation into a global context, this paper aggregates all single exchange rate variances into an equal weighted basket of all *N* currencies of their respective sample. The global state variable is then defined as:

$$Var_{t,T}^{Global/G10} = \frac{1}{N}\sum_{k=1}^{N} Var_{t,T}^{k} \quad (21)$$

2.6 Global Equity Variance Risk Premium

Following Aloosh (2014), we also consider a global variance risk variable based on the equity market. Aloosh (2014) has shown that his *global equity VRP* ($VRP^{Global\text{-}EQ}$) has predictive power for future exchange rates and the carry trade portfolio return. Therefore, we follow his composition of the underlying equity index markets, but stick to the realized variance definitions of Neuberger (2012) defined in (17). The global variance risk contains the four equity market indices: (i) S&P 500, (ii) Nikkei-225, (iii) FTSE-100, and (iv) the DAX-30. While the realized variance is computed from daily spot prices, the implied variance is taken from the end-of-month closing prices of the corresponding 1m-option-implied volatility indices, which are: the VIX, the VXJ, the VFTSE, and the VDAX-NEW. The resulting global $VRP^{Global\text{-}EQ}$ is constructed as the equally-weighted average of any single equity market VRP. While Aloosh (2014) used a market-capital weighting scheme, he noted that, in a robustness check, the results are similar when using an equal weighted VRP.

2.7 Macroeconomic State Variables

As described in the introduction, the following two macroeconomic variables play a central role in predicting carry trade returns. These are (i) the past global 1m real industrial production growth rate[16] (RP) and (ii) the past global 1m inflation differential between the average of all foreign countries CPI's and the US-CPI growth rate (CPI). The *RP* represents an equal weighted aggregate of the respective currency sample's real industrial production growth rate. The transformation from nominal to real terms is done through deflation by its country's CPI index.[17]

[16] The following six countries' currencies do not provide monthly data on industrial production growth: AUD, NZD, CHF, CLP, PEN, and PLN. For these cases, industrial production growth is approximated by quarterly GDP figures transformed into monthly observations by the cubic splines routine.

[17] The aggregation procedure for RP and CPI is equal to the applied methodology for variance risk in equation (21).

Since the data exhibits significant annual seasonality, both macro fundamentals are de-seasonalized using the Box-Jenkins methodology. This adjustment is done for the aggregated data series using the best fit of three different seasonality models: (i) an AR(1) with seasonal moving-average, (ii) a multiplicative autoregressive, or (iii) the multiplicative moving average model.[18]

The use of these fundamentals as global risk variables is encouraged by findings of de Zwart et al. (2009). They found evidence that in a trading application using *real interest rates* and *GDP differentials* are useful, as trading signals on individual exchange rate levels as well as on equal weighted currency portfolio levels. The results presented in the empirical section will prove that the global aggregates on *CPI* and *RP* will exhibit similar efficient effects on the optimization process for the currency carry trade portfolio.

However, one important thing about the data is worth noting here; macroeconomic figures are often revised through time. Some papers robustness check their results with vintage data series, which refers to *not-revised* or *real-time* data. Unfortunately, the robustness check for this study cannot be performed due to a lack of macroeconomic vintage data for all countries being covered.

2.8 Measuring Carry Trade Activity

The definition of the *Carry Trade Activity Index* (CTI) is taken from the definition in Broll (2016a). It provides a useful aggregation procedure to mirror the degree of long investments into a virtual carry trade portfolio. The set of information is primarily driven by the publically-available foreign exchange data supplied by the CFTC in its weekly TFF report. In order to track the positions of speculators in the carry trade, one computes first the investment exposure of any foreign exchange rate and then aggregates it into a portfolio setting. The most common group that has been identified as financial speculators is the group of "Non-Commercial" traders (see Breedon et al., 2015; Brunnermeier et al., 2009), which is extended by the "Non-Reportables" traders group in Broll (2016a) due to a high positive correlation of position changes.

It follows that the degree of a long speculation in currency *k* at time *t* is defined as follows:

$$SCF_t^k = \frac{long\ futures_t^k - short\ futures_t^k}{long\ futures_t^k + short\ futures_t^k} \tag{22}$$

[18] A detailed discussion about time-series' seasonality effects can be found in Enders (2014: 97-103).

The *SCF* (speculator's capital in futures) captures the relative future market exposure to the long or short side of a single foreign exchange rate. The *SCF* always lies between -1 and 1, where a positive (negative) realization translates into a net long (short) investment in the foreign currency funded by the USD. In order to capture the future market exposure to the carry trade portfolio, these single *SCF* values are aggregated with the following procedure: the average *SCF* of the three FX rates with the highest interest rate differentials (IRD) are deducted by the average *SCF* of the three FX rates with the lowest IRD levels:

$$CTI_t = \frac{1}{3}\sum_{k=1}^{3} \max_{IRD} SCF_t^k - \frac{1}{3}\sum_{k=1}^{3} \min_{IRD} SCF_t^k \tag{23}$$

Hence, the resulting *Carry Trade Activity Index* (CTI) is now supposed to mirror the degree of speculation in the carry trade portfolio. The empirical section will make use of two different *CTI*'s to differentiate between the global and G10 sample, as has been outlined in the data section. Furthermore, the empirical analysis concentrates on a simple moving average of the *CTI* over the past six month due to the high variability of the monthly data series.

2.9 Benchmark Model

In order to take the results into perspective, Laborda et al.'s (2014) model is used as the benchmark model. Under the same parametric portfolio policy procedure introduced above, it reported quite well the improvements over the baseline carry trade investment, with 50% increased average returns, positively skewed return distributions, and Sharpe ratios around unity in out-of-sample tests. While they used an almost-doubled sample size from January 1990 to July 2012, they exclusively investigated the G10 carry trade portfolio as an underlying asset without incorporating transaction costs. In particular, they rely on six major state variables as key drivers for predicting carry trade returns: (i) the 1m-lagged carry trade return, (ii) the average G10 forward discount, (iii) the VIX-index, (iv) the US-TED spread, (v) the CRB commodity index return, and (vi) a global monetary policy indicator (GMPI).[19] The *GMPI* is related to negative key rate changes of the G10 countries' central banks. This one-sided binary index sums all reduced key rate changes in the respective month and then standardized this time-series to have zero mean and unit standard deviation.

[19] The data on the *GMPI* used in the original work of Laborda et al. (2014) was fortunately provided by the author and adapted to match the sample size in this study.

3 Empirical Results

This section starts with a brief introduction of the time-series properties of the global and G10 carry trade portfolios. It then follows in-sample tests using the parametric portfolio policy with (i) the effects of FX and equity based variance risk, (ii) macroeconomic effects and influence of the CTI, and (iii) a round-up covering the most promising risk factors and the benchmark model. The last part of the section deals with the out-of-sample performance of a relatively parsimonious fitted parametric portfolio policy relying especially on option-implied information. This model is taken into perspective with the benchmark and carry trade portfolios and is extended to higher leveraged investments.

3.1 Historical Returns to the Carry Trade Strategy

The success of the carry trade as a popular currency strategy has been reported in many studies in terms of significant excess returns and high portfolio efficiency (e.g. Burnside et al., 2011b). These excess returns have lost their glamour in the recent subprime crisis, starting in 2008, where financial institutions engaged in the carry trade suffered from losses of up to one third of their value within a six-month period (G10 carry trade). Table 1 reports a brief summary of statistics about the carry trade return distribution, contrasting the carry trade returns build up by the G10-Sample ($\mathrm{CT}^{\mathrm{G10}}$) and Global-Sample ($\mathrm{CT}^{\mathrm{Global}}$) currencies.[20] The analysis covers the investment period from September 2003 to June 2015 and is divided into Panel A and B, where the latter incorporates transaction costs. Starting with Panel A, we see that despite the occurrence of the financial crisis, the average mean return for the CT^{Global} stays significant at the 10% level, reaching a mean return of 4.93%. The corresponding CT^{G10} return is slightly smaller and has a much lower T-statistic of 1.28. Another interesting aspect is that the forward discount levels between the global and G10 carry trade, which mirrors the average interest rate differential between investment and funding currencies[21] is twice as big as for the global carry trade with an average of 8.76%.

[*Insert Table 1 about here.*]

[20] It should be noted that the reported average mean carry trade return defined in 4 is increased by the average 4w T-Bill rate, with regard to the assumption that the entire cash exposure is invested in the US risk-free asset.

[21] The forward discount value is the difference between the forward and spot price of the respective exchange rate. Given that the covered interest rate parity holds (see equation (1)), the forward discount equals the exponent of the interest rate differential times the forward duration in years (τ).

While this is not surprising, since we know from the data that emerging market countries are paying a much higher interest on average compared to those with developed markets, the CT^{G10} collects almost all the interest rate differential, on average (FD=4.56%). This is not the case for the CT^{Global}, where almost half of the interest rate spread is lost due to currency depreciation. While UIP suggests that currencies' interest rate advantage should vanish completely through spot rate depreciations, on average, the same picture has been observed in Broll (2016a) and Lustig et al. (2011). Another interesting aspect is that both return series are exposed to negative skewness, which has led some authors to suggest that the significant excess returns are compensation for bearing crash risk (see Brunnermeier et al., 2009; Farhi et al., 2015; Jurek, 2014). This is especially true for the CT^{G10}, reaching a negative skewness of -0.44 with a tremendously-high maximum drawdown (MDD) of -28.48%. The much higher sample size of the CT^{Global} seems to balance the returns more properly with half of the MDD (-13.27%) and higher portfolio efficiency in terms of the *Higher Moment Sharpe ratio* (SR^{HM}),[22] reaching 0.42, compared to just 0.29 for the CT^{G10}. Figure 1 plots both carry trade time series, illustrating the sharpe slowdown during the subprime crisis of 2008-2009 and its ultimate reversal period.

[*Insert Figure 1 about here.*]

Another interesting portfolio metric in this context is the certain equivalent return (CER).[23] This indicates the level of guaranteed return, which makes the representative investor indifferent between the risky and the riskless strategy paying off CER in expectation. Using a risk aversion level of $\gamma = 10$, we see that the investor would only demand a minimum of 0.74% to step away from the risky CT^{Global} strategy. The CER figure for the CT^{G10} is even worse, here the investor would accept an annual loss of 2.44% to avoid the carry trade investment. The last two columns indicate that both return series are not significantly auto-correlated to first lagged returns. The *Jarque-Bera* test statistic (JB) in the last column cannot reject the normal distribution of the CT^{Global} return series, but for the CT^{G10}, which is not surprising due to lower skewness, higher excess kurtosis, and a much lower maximum drawdown. Panel B reports the same return statistics considering transaction costs. These costs are approximated by bid-ask spreads in the forward market, where it is assumed that, at

[22] The SR^{HM} has been developed by Broll (2016b), as a higher moment extension of the classical Sharpe ratio. It extends the Sharpe ratio by the third and fourth moment risks, including the original Sharpe ratio as a special case (see Appendix B).
[23] The certain equivalent return is defined in Appendix B.

initiation, investment (funding) currencies trade at ask (bid) prices, and the trade is settled at the end of each one-month period on spot mid-prices.[24] It results that the average annual cost of 79bps for CT^{Global} is more than twice as high as for the CT^{G10}, with only 35bps, where CT^{Global} mean returns are not statistically significant any more.

3.2.1 Parametric Portfolio Policy: In-Sample Tests

This section starts by investigating the parametric portfolio policy's ability to find a risk-adjusted carry trade weight that optimizes the return process in-sample. Therefore, we will focus on two main risk sources, which are the impact of global variance risk variables and the impact of global macro risk. The forthcoming tables are divided into two parts, where Panel A always uses the CT^{Global} as the underlying portfolio, and Panel B the CT^{G10} presented in the top row. All return statistics are in log format and incorporate transaction costs. All optimized portfolios include a constant value in its parameter set, which is not presented here due to space limitations.

The first two columns of Table 2 characterize carry trade returns and the global variance risk variables used as input parameters for the GMM optimization procedure, followed by statistical inference of the various parameter values and portfolio return statistics.

The first four global state variables focus on the impact of FX-based variance risk, which are: (1) the current global 3m option-implied variance risk ($Ivar_{t,t+3}^{Gl./G10-FX}$), (2) the past global 3m realized variance risk ($Rvar_{t-3,t}^{Gl./G10-FX}$), (3) the past global 3m variance risk premium ($VRP_{t-3,t}^{Gl./G10-FX}$), and (4) the current difference of 3m option-implied variance between investment and funding currencies ($Ivar_{t,t+3}^{CT(-G10)}$).

[*Insert Table 2 about here.*]

With respect to the portfolio statistics of the CT^{Global}, the average mean returns for strategy (1) and (2), are somehow lower, with only 2.32% and 2.15%, respectively, but with sharply-reduced standard deviations and maximum drawdowns (MDD). The dCER value in the last column refers to the *marginal* CER, which is the difference of the respective CER of the optimized portfolio relative to the carry trade portfolio. A positive level indicates that the representative investor would prefer the optimized carry portfolio over the baseline carry

[24] Mancini et al. (2013) point out that the effective transaction costs are much lower than those imposed by official WM/Reuters bid-ask spreads. Taking half of the bid-ask spread leads to better approximated transaction costs. This procedure has also been used in Barroso and Santa-Clara (2015).

trade. However, the results on the next two variables look much more promising. Continuing with $VRP^{Global\text{-}FX}$, we see that the mean return of 3.87% stays at a similar level to the CT^{Global} return, but with much lower standard deviation, leading to an almost doubled SR^{HM} value of 0.6. The $VRP^{Global\text{-}FX}$ parameter is statistically significant at the 5% level, where higher VRP levels lead to lower optimal carry trade weights. Using $Ivar^{CT}$ as the only state variable leads to even slightly improved results. While there is a lack of statistical significance, the portfolio efficiency is well improved to 0.73 SR^{HM}, which comes especially from the positive skewness of 1.12 compared to -0.13 for the $VRP^{Global\text{-}FX}$ parametrization. Also, the MDD value is sharply reduced to only -5.66%. The overall results of Panel A look very similar to those of Panel B, except for $Ivar^{CT\text{-}G10}$. Here, the portfolio statistic is the weakest among the four variables and the T-statistic is close to zero.

The next three variables under investigation are the complementary risk variables on the equity side. These are: (5) the past global equity 1m realized variance risk ($Rvar_{t-1,t}^{Global-EQ}$), (6) the current global equity 1m option-implied variance risk ($Ivar_{t,t+1}^{Global-EQ}$), and (7) the past global equity 1m VRP ($VRP_{t-1,t}^{Global-EQ}$). The variables (5) and (6) show similar results compared to their FX-based counterparts, variable (1) and (2). Both lack statistical significance and do not contribute to great portfolio results. The results on the equity-based VRP look much more promising. The $VRP^{Global\text{-}EQ}$ is significantly negatively related to future carry trade returns at the 5% significance level. Opposed to $VRP^{Global\text{-}FX}$, the optimized mean returns, skewness, and SR^{HM} are higher, with an extraordinarily low MDD level of only -6.69%. Looking at Panel B, one can state that the results are similar to the Global-Sample with the exception that $Rvar^{Global\text{-}EQ}$ exhibits statistical significance at the 10% level. However, the significance of the $VRP^{Global\text{-}EQ}$ is even stronger at the 1% level compared to a slightly higher dCER level of 5.62% (compared to 5.35% for $Rvar^{Global\text{-}EQ}$). On the other hand, although the portfolio skewness reaches a very high level of 1.67, the excess kurtosis of 11.38 leads to a lower SR^{HM} level of 0.60, compared to 0.66 for $Rvar^{Global\text{-}EQ}$.

The next two optimizations concentrate on results using multiple state variables as risk sources. Beginning in Panel A with a combination of the most promising FX-based variables, $VRP^{Global\text{-}FX}$, and $Ivar^{CT}$ shows interesting results. While $Ivar^{CT}$ did not exhibit any statistical significance in the univariate case, it exhibits strong positive significance at the 5% level in this multivariate setting, while $VRP^{Global\text{-}FX}$ keeps on being significant at the 1% level. The portfolio results are even stronger with a mean return and standard deviation of about 7% and the SR^{HM} nearly reaches unity. Moreover, the higher moment risks are more than amazing, with positive skewness of 0.45, along with a very low excess kurtosis near zero. This is confirmed by the results in Panel B. Adding the equity-based VRP it can be seen, in the last row, that the results in both panels slightly improve, while the significance of $VRP^{Global\text{-}EQ}$ becomes insignificant in Panel A, and the MDD level in Panel B worsens to -15.2%.

All in all, it can be stated that the contribution of option-implied variance risk, coming from the FX or equity market, significantly improves the portfolio results of the baseline carry trade investment scheme, which results in higher mean returns, higher skewness, lower standard deviation, and, therefore, more efficient portfolios.

3.2.2 Macro-Fundamentals and Carry Trade Activity

The second part of the analysis concentrates on the parametric portfolio policy using global macro variables, along with information on carry trade activity as a source of global risk. The macro risk variables are: (8) the past global 1m real industrial production growth rate ($RP_{t-1,t)}^{Gl./G10}$), and (9) the past global 1m inflation differential ($CPI_{t-1,t)}^{Gl./G10}$). The market microstructure-based *Carry Trade Activity Index* ($CTI_{avg(t-6,t)}^{Gl./G10}$) is constructed as a 6m moving average from end-of-month observations.

[*Insert Table 3 about here.*]

Table 3 summarizes the results on the portfolio policy, starting with the individual effects of *RP, CPI*, and *CTI* on the optimal portfolio formation. Starting with Panel A, we see that RP^{Global} and CPI^{Global} exhibit significant impacts on future carry trade returns but with different signs. While an increase on global inflation leads to a reduced optimal portfolio weight, increased global real production has the opposite effect. The portfolio return statistics are similar to each other and as strong as the VRP results from Table 2, leading to mean returns of about 4.5% and low 6% standard deviation. The skewness is positive for both strategies with mild excess kurtosis. Compared to the G10-Sample, CPI^{G10} appears to be the only parameter with significant impact*,* leading to an extremely efficient portfolio with a SR^{HM} of 0.94. This is due to an extraordinarily high mean return of 6.84%, accompanied with positive skewness and a dCER level of 7.13%.

Also, these effects on inflation and production growth are economically-meaningful. With regard to RP^{Global}, a higher value corresponds with a growing global economy and implicitly lowers the probability of economic distortions, which stimulates the carry trade return distribution. On the other hand, a higher global inflation relative to the US is a sign of reduced foreign purchase power and lead to future currency depreciations relative to the USD, in particular for emerging countries. Therefore, $CPI^{Gl./G10}$ is significantly negatively-related to carry trade returns at the 1% level, leading to decreased or negative optimal carry trade weights.

In the univariate parametrization with CTI^{Global}, we see a somehow weaker result as opposed to the macro fundamentals. The coefficient appears to be insignificantly negative (except for Panel B), which means that the higher the observed long exposure in the carry trade, the lower the proposed optimal carry trade weight. This countercyclical result is probably due to a lag-effect of the 6m average. In unpublished optimizations with past 1m *CTI*s, the effect was statistically-weaker but positively-related to future carry trade returns.

However, looking at the multivariate parametrization using the two fundamentals, both panel portfolio results look similar and very promising. In Panel A, the $Macro^{Global}$ reaches a higher mean return than the baseline carry trade, along with a positive skewness of 0.30 and lower standard deviation. The MDD is even lower at -7.73% and the portfolio efficiency with regard to the SR^{HM} achieves a fantastic value of 0.93. This result is confirmed by the G10-Sample, but the major effect has to be assigned to the CPI^{G10} value. Adding the *CTI* into the $Macro^{Gl./G10}$ parametrization also improves the portfolio statistics for Panel A, leading to even higher mean returns of 6.89% and a tremendous portfolio efficiency of 1.03 SR^{HM}. With regard to Panel B, the marginal effect of adding CTI^{G10} is negligible.

To summarize, the effect of past *CPI* realizations on future carry trade returns are significantly negative in both samples. Using this variable in the GMM optimization leads to quite-efficient portfolio returns in univariate and multivariate parametrizations. The real production growth risk and the *CTI* moving average are pro- and counter-cyclical risk measures, respectively, which only play a minor role for the carry trade return distributions.

3.2.3 Comparison with the Benchmark Model

We will now turn to the question of how well the model created by Laborda et al. (2014) performs in an extended global currency sample. This benchmark model has been developed with a greater sample period, ranging between January 1990 and July 2012, using only the G10 carry trade portfolio as the underlying asset. The baseline parametrization relied on six different variables plus a constant, all of which have been introduced at the end of the last section. In order to improve clarity, the portfolio statistics of the various strategies and the corresponding parameter values and their inference in Table 4 are arranged in an upper and lower table within each panel.

[*Insert Table 4 about here.*]

The first two rows of Panel A start with the comparison of the benchmark model to the CT^{Global}. The benchmark mean returns are almost identical but the standard deviation is about 30% lower. As a result, the SR^{HM} is slightly higher, with 0.57 compared to 0.35, but the MDD value is even worse with 15.76% and accompanied with a relatively low dCER of 2.18%. In contrast to this, the Panel B results for the benchmark model look much better. The returns are positively skewed with a mean return of 6.10%. The SR^{HM} is slightly higher compared to Panel A, resulting with 0.68 and a half reduced MDD of -14.53% relative to CT^{G10}.

However, when optimizing, the carry trade portfolio returns with the most promising option-implied risk variables, which are (i) the current 3m implied variance differential between investment and funding currencies ($Ivar_{t,t+3}^{CT/(G10)}$), (ii) the past global 3m FX-VRP ($VRP_{t-3,t}^{Gl./G10-FX}$), and (iii) the past global 1m equity-VRP ($VRP_{t-1,t}^{Gl.-EQ}$), along with global macro fundamentals and the market microstructure variable, which are: (iv) the past global 1m real production growth ($RP_{t-1,t}^{Gl./G10}$), (v) the past global 1m CPI differential ($CPI_{t-1,t}^{Gl./G10}$), and (vi) the 6m moving average of the *Carry Trade Activity Index* ($CTI_{avg(t-6,t)}^{Gl./G10}$), the portfolio return statistics significantly improve from the baseline carry trade portfolio. This parametrization is denoted as the *All-in* model in the third row in both panels. Looking at Panel A, the *All-in* model delivers an impressive mean return of 10.36%, positive skewness of 0.50 and an explosively high SR^{HM} of 1.36. The MDD is even more reduced to only -6.33% and the dCER more than triples to 7.71% as compared to the benchmark. With regard to Panel B, the results are better than the benchmark model but not to the same degree. The mean returns are quite high, with 10.88%, a positive skewness of 0.81, and a high SR^{HM} of 1.18, while the MDD cannot be reduced to the same extent as in Panel A.

Looking at the statistical inference of the benchmark model's state variables, it becomes apparent that the overall level of significance is quite weak and mixed for both panels. While in Panel A the constant and the 1m lagged carry trade return (CT_{t-1}) appears significant, in Panel B only the CRB returns (dCRB) have a significantly positive effect on future carry trade returns. Additionally, in Panel B there is information about the parameter values taken from the original work of Laborda et al. (2014), found in parenthesis for comparison. It becomes visible that especially the *TED* and the *GMPI,* exhibit much lower impact here, or put differently, the funding liquidity risk and central bank's tapering effects do not significantly impact carry trade returns in the sample period.[25]

An interesting question is: "Do any risk parameters of the benchmark model help to improve the *All-in* model's results?" The only parameter that contributed to better portfolio statistics and significant parameter results was the CRB index (CRB), used instead of the CRB returns (dCRB). While in Panel A the SR^{HM} value increases to 1.57 compared to 1.38 with a slightly improved dCER of 8.5% for the new *All-in+CRB* model, the marginal portfolio effects in Panel B are more articulated. The mean return increases to 13.08% (from 10,88%) with unchanged standard deviation, leading to only a marginal rise in the SR^{HM} by 15bps to 1.33, due to lower skewness of 0.55 (from 0.81). The commodity index parameter *CRB* is also significant at the 10% (5%) level for the Global (G10) Sample. Taking the level parameter instead of the return of the *CRB index* does not have the same but, instead, similar economic relevance. The *dCRB* value in the benchmark model has a positive sign, which implies a pro-cyclical investment scheme for the investor. Compared to the level parameter *CRB,* which has a negative impact, it shows that the investor follows a more forward-looking investment behavior, where he is especially long-invested in the carry trade at depressed commodity prices and increasingly shorter at relative high levels, leading to much more appealing portfolio results.

Furthermore, there is some interesting evidence of commodity price risk on currency returns that supports the above-seen results. Roussanov et al. (2016) find that the carry trade risk premium can be largely explained by a portfolio that consists of long currencies of commodity export countries and short currencies that are largely commodity importers and producers of complex goods. They state that the aggregate consumption of commodity countries is less risky compared to producers and such heterogeneity in countries' risk exposure can be explained by trade costs, a friction that potentially leads to segmented markets. Under these regularities, carry trade returns co-move with commodity price changes, as "commodity export currencies" mostly represented by investment currencies, react sensitively to commodity price shocks. The increased level of the heterogeneity of countries' risk exposures in crisis periods additionally reinforces the crash risk for commodity currencies, which is manifested in highly-negative skewed returns for the currency carry trade (see also Powers, 2015).

[25] It should be noted that in the original work of Laborda et al. (2014) the benchmark model outperformed the baseline carry trade even after the subprime crisis of 2008/2009. This is not the case here, which is maybe due to a much smaller sample period. This probably means that the benchmark model is more data-consuming than the model based on option-implied risk parameters presented here, or that the major effects take place in the first half of their data sample.

3.3 Parametric Portfolio Policy: Out-of-Sample Tests

As the previous results should be not overstated because they rely on in-sample estimations only used for estimating the strength of the individual parameters on carry trade returns, we will now turn to out-of-sample (OOS) tests to evaluate their forecasting performance. The OOS predictions start with an initial period length of 48 months. The monthly re-estimation is done with an expanding window procedure, starting in September 2007. The representative investor, with a risk aversion level of $\gamma = 10$, chooses the optimal carry trade weight in his information set.[26]

[*Insert Table 5 about here.*]

Table 5 presents the OOS results for various global risk parametrizations, including the benchmark portfolio of Laborda et al. (2014). The first row of Panel A starts with a very weak CT^{Global} performance in the OOS estimation period. The carry trade mean return and skewness is negative with a relatively high standard deviation of 8.22%. The benchmark portfolio performs slightly better with a mean return of 1.79% and positive skewness of 0.14. However, the most promising *All-in+CRB* parametrization of Table 4 delivers a mean return of about 3.47% with positive skewness of 0.27 and relative low volatility (6.57%). This ultimately leads to an efficient portfolio with a doubled SR^{HM} of 0.47 compared to the benchmark and a dCER of 5.39%. As it is well known in the literature that too many parameters tend to be harmful for OOS forecast performances, the analysis considers a more parsimonious parameter set. After a few tests it becomes clear that the most important sources that jointly forecast carry trade returns for both samples are represented by four major risk variables: (i) the carry trade's implied variance differential ($Ivar^{CT}_{t,t+3}$), (ii) the global FX based VRP ($VRP^{Gl./G10-FX}_{t-3,t}$), (iii) the global CPI differential ($CPI^{Gl./G10}_{t-1,t}$), and (iv) the CRB commodity price index (CRB_t). This model will be denoted as *TOP-4*$^{Gl./G10}$ parametrization in Table 5.

Figure 2 plots the time-series of three risk variables in terms of their global or G10 currency composition and the CRB commodity index. The variables are not standardized in the charts and cover the period between September 2003 and July 2015.

[*Insert Figure 2 about here.*]

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[26] The use of a rolling window estimation has been abandoned due to the overall short sample size of about twelve years. The same OOS tests have been robustly checked with γ-values of 1, 5, 20, and 50, which has led to comparable results. The statistics can be provided upon request.

The most pronounced movements become visible when observing the two charts above. Both variables contain information from option-implied variance risks, $Ivar^{CT}$ (Chart a), and VRP^{FX} (Chart b). Beneath the most pronounced hike, stemming from the *subprime crisis* in 2008, we can also observe two other major events: the *European Sovereign Crisis* at the end of 2011 and the *Ruble Crash* in 2015. All these events lead to significant portfolio shifts due to the GMM optimization procedure, which reliably avoids crash risk in carry trade due to accurately timed short positionings and, additionally, the ability to identify turning points in which long investments are advantageous.

Considering these three events, one can derive similar interdependencies with regard to optimally-computed carry trade weights: a crisis leads to time-delayed inflation increases (Chart c) and to a slowdown in commodity prices (Chart d). While inflation development can be attributed to second-round effects due to global central banks' tapering policy, the second effect indicates a slowdown in global economic activity due to the decreased demand of baseline commodities. Both variables are negatively-related to future carry trade returns (see Table 4) and therefore lead to proposed short positions. The interdependencies between both option-implied variables are far more complex. While the variables are positively correlated to each other (≈55%), $Ivar^{CT}$ has a positive and VRP^{FX} a negative relation to future carry trade returns. The general picture in crisis periods is as follows: both variables increase to similar magnitudes while the GMM procedure mostly overweighs the effect of the VRP^{FX} variable, leading - in sum - to negative proposed weightings. After the peak of the crisis, the VRP^{FX} reverses its sign, as investors quickly adapt their expectations of the high volatility stage, while $Ivar^{CT}$ is slower to adjust to normal levels. This leads to an effective reversal pattern within a turmoil period.[27]

These effective portfolio shifts are also mirrored in higher efficient out-of-sample results for the *TOP-4* parametrization model in Table 5. The results of Panel A are remarkably strong: the mean return reaches 5.58% combined with an almost identical volatility level of 5.92% and positive skewness of 0.13. This is reflected in a tremendously-high 1.05 SR^{HM} value and a dCER of 7.89%. The maximum drawdown (MDD) is also reduced to one third compared to the benchmark of only -8.55%. These overall optimistic results are confirmed for the G10-Sample in Panel B. While the mean return is fairly identical to the *Allin+CRB* model with 8.38%, the portfolio efficiency almost doubles in terms of a SR^{HM} reaching an impressive 0.93, which is especially due to an improved positive skewness of 0.58 from -0.32 and a relatively low excess kurtosis of 1.

[27] For a closer inspection, Figure A. 1 plots a time-series of the monthly computed optimal carry trade weights coming from the $TOP\text{-}4^{Global}$ restricted and unrestricted model of Table 5.

The right part of each panel additionally provides information about bootstrapped 95% confidence intervals[28] for the mean return, skewness, and the SR^{HM} value. To assess the performance of the *TOP-4* parametrization in Panel A, we see that the lower bound of the mean return (1.5%)*,* the skewness (-0.28), and SR^{HM} (0.26) are always higher compared to the portfolio statistics of the CT^{Global}*,* which indicates statistical significance at the 5% level with regard to these measures. Additionally, the portfolio efficiency (SR^{HM}) is also significantly-higher compared to the benchmark model. Panel B confirms the results.

The next estimation step involves the analysis of more leveraged optimized carry trade portfolios. All the above results were constructed under the premise that the optimal portfolio weight is restricted to lie between -1 and +1, which is equal to a leverage of 1. The portfolio results for leverage values 2 and 3, as well as a completely unrestricted leverage for the *TOP-4* parametrization, can be found below the dotted lines in each panel. For example, under the *TOP-4 Lev2* model, the optimal portfolio weight can lie between -2 and +2, while under *TOP-4 Unr.* the portfolio weighting is not restricted at all. With regard to Panel A, a leverage of 2 improves the mean return to 8.51% from 5.58% and to even higher levels at 10.19% and 10.95% for the $TOP\text{-}4^{Gl.}$*-Lev3* and *-Unr.* models, respectively. These return improvements are accompanied with higher positive skewness and with stable portfolio efficiency. This is only partially true for the *G10-Sample*. While the mean returns are also rocketing to levels between 14.43% and 16.35% from 8.38%, the portfolio efficiency tends to decline with higher leverage.

[*Insert Figure 3 about here.*]

The charts in Figure 3 on the left-hand side (A1 and B1) visualize the time-series evolution of 1 USD invested in the OOS period, using the carry trade (red line), the benchmark model (blue line – circles), the *TOP-4* model (light green line – stars), and the *TOP-4 Unrestricted* model (dark green line). Chart A1 and B1 show a clear outperformance of both *TOP-4* models, respectively, relative to the carry and benchmark portfolio. The dollar value for the *TOP-4* model reaches 1.56 (1.94) in Panel A (Panel B), and even higher levels for the unrestricted model with 2.38 (3.64), compared to only 1.15 (1.18) for the benchmark model. Also, the average trend is positive, with some strong corrections, especially for the unrestricted model, while the trend for the benchmark model is downward-sloping after 2010.

Another perspective of the strong results based on the *TOP-4* model is characterized in bar charts A2 and B2. Each bar chart characterizes the excess return of the *TOP-4's* performance

[28] The bootstrap method uses 10'000 replications of the empirical return distribution. The confidence intervals are constructed using the bootstrapped variance estimation with the appropriate student's-t quantiles.

over the carry trade (blue bar) and benchmark return (green shaded bar) for any single 12-month period,[29] respectively. While in chart A2 the quantity of outperformance periods over the benchmark is balanced (4:4), the respective magnitude is not. Despite the largest negative difference in 2008 (-9.1%), the other values are relatively small (-3.6%, -1.3%, and -1.0%). Even when we consider 2012-2015, with three outperformance periods for the benchmark model, the *TOP-4* model outperforms by an annualized return of 2.7% on average. The outperformance relative to the baseline carry trade appears even stronger. The negative excess returns only appeared twice around 2012 and 2014 with underperformances of -8.3% and -4.3%, in contrast to six outperformance periods with an average of 10.2% return advantage annually, ranging between 4.2% and 15.9%. With regard to Panel B, the results are even stronger. Chart B2 highlights that the *TOP-4* model underperformed only once (-11.3%) relative to the baseline carry trade and always outperformed the benchmark model, which demonstrates the strength and return consistency of the proposed model.

[*Insert Figure 4 about here.*]

Figure 4 provides a time-series plot about the parameter values of the $TOP\text{-}4^{Global}$ model during the out-of-sample estimation period. We can see that nearly all parameter estimates changed quite erratically during the subprime crisis in 2008-2009. While this is not surprising due to the relatively short pre-estimation period of only 48 months, followed by the world economic crisis, which definitely had significant impact on any quantitatively-based model fed with financial data. After this crisis period, all parameter estimates are less volatile and look pretty stable, suggesting the absence of structural breaks.[30]

4 Conclusion

This study investigates a portfolio policy procedure for currency carry trade investments that models directly the optimal portfolio weight as a function of its underlying risk characteristics. As the underlying asset, a global carry trade portfolio has been constructed consisting of 32 different currencies, whereas a smaller carry trade portfolio consisting of a developed countries' sample served as the control strategy. While the in-sample results look

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[29] The first 12-month bar chart covers the period between 2007:09 to 2008:08 denoted as 2008, the second one covers the period between 2008:09 to 2009:08 denoted as 2009, and so forth. Hence, the last bar chart means the outperformance over the last 10-month of the OOS period, denoted as 2015.

[30] Again, the volatility of the parameter estimates for the G10-Sample are only slightly higher, but mirror image the results presented for the Global-Sample. The figure can be provided upon request.

very promising, out-of-sample tests confirmed the overall strong performance. Especially four aggregated risk variables provided significant information to improve portfolio efficiency of currency carry trade returns: (i) the current global 3m option-implied variance differential between investment and funding currencies ($Ivar_{t,t+3}^{CT}$), (ii) the past global 3m FX variance risk premium ($VRP_{t-3,t}^{Gl./G10-FX}$), (iii) the past global 1m CPI differential relative to US-CPI ($CPI_{t-1,t}^{Gl./G10}$), and (iv) the CRB commodity price index (CRB_t). As a result, the optimized global (G10) carry trade portfolio in out-of-sample tests reaches an averaged mean return of 5.6% (8.4%), accompanied with low volatility of 5.9% (9.6%), positive skewness of 0.13 (0.58), and *Higher Moment Sharpe ratios* of 1.05 (0.93), including transaction costs. These statistics are not only significantly higher compared to the baseline carry trade portfolio, but clearly outperforms the proposed model by Laborda et al. (2014) presented in the literature.

This outperformance is especially due to the use of option-implied variance risk information, which warns the investor precociously about crash risk inherent in currency carry trades. Furthermore, while former results assumed that the optimized portfolio weights for the global (G10) carry trade have to lie between -1 and 1, a relaxation of the leverage restriction produces even higher annualized returns for the out-of-sample period of up to 10.95% (16.35%) with Sharpe ratios around unity, while higher leveraged G10 carry trade portfolios tend to lose efficiency. Nevertheless, the overall strong portfolio results should encourage investors to rely on option-implied information to improve currency portfolio investments.

Figures and Tables

Table 1. Summary Statistics of Carry Trade Strategies

The table offers summary statistics of two carry trade (CT) strategies, where CT^{Global} is computed from Global-Sample currencies, while CT^{G10} consists of only G10-Sample currencies. Portfolio average mean returns (Mean), forward discount (FD), and standard deviation (SD) are all annualized and expressed in %. The T-statistics (T-Stat.) measures the significance of the carry trade mean returns to be different from zero, which are based on HAC standard errors with 4 Newey-West lags. Furthermore, portfolio skewness (Skew) and excess kurtosis (Kurt), as well as the Sharpe ratio (SR), Higher Moment Sharpe ratio (SR^{HM}), and the respective maximum drawdown in % (MDD) are presented for all portfolio formations. Additionally, there is information about the certainty equivalent return in % (CER), the first lag autocorrelation coefficient ACF(1), and the Jarque-Bera statistic (JB). The sample covers the period from 2003:09 to 2015:06 using 143 end-of-month observations.

Panel (A): Carry trade portfolio statistics

Strategy	Mean	T-Stat.	FD	SD	Skew	Kurt	SR^{HM}	SR	MDD	CER	ACF(1)	JB
CT^{Global}	4.93*	1.73	8.76	9.03	-0.33	0.43	0.42	0.53	-13.27	0.74	0.13	3.62
CT^{G10}	4.85	1.28	4.56	11.71	-0.44	0.68	0.29	0.40	-28.48	-2.44	0.09	7.43**

Panel (B): Carry trade portfolio statistics with transaction costs

Strategy	Mean	T-Stat.	FD	SD	Skew	Kurt	SR^{HM}	SR	MDD	CER	ACF(1)	JB
CT^{Global}	4.14	1.46	8.76	9.02	-0.33	0.43	0.35	0.45	-14.01	-0.05	0.13	3.73
CT^{G10}	4.50	1.18	4.56	11.71	-0.44	0.69	0.27	0.38	-28.75	-2.79	0.09	7.50**

Table 2. Parametric Portfolio Policy with Variance Risk Variables

This table presents currency portfolio statistics from the baseline carry trade strategies ($CT^{Gl./G10}$) and the optimized portfolio policy strategy in-sample estimation results based on variance risk parameters. Panel A uses the Global-Sample currencies, while Panel B is based on the G10-Sample. The left part of the table characterizes the variable numbers (VNs) used in the optimization model and the strategy's name. The middle and right parts of the table provide information about statistical inference of the parameters and portfolio return statistics, respectively. Inference is based on a HAC matrix using 5 Newey-West lags, where $\hat{\theta}$ means the parameter estimate and the corresponding P-value (Pval) under H_0=0 against $H_1 \neq 0$. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively. Portfolio return statistics are the average annualized mean return in % (Mean), standard deviation in % (STD), skewness (Skew), excess kurtosis (Kurt), the Higher Moment Sharpe ratio (SR^{HM}), Sharpe ratio (SR), maximum drawdown in % (MDD), and the marginal CER in % (dCER). The sample covers the period from 2003:09 to 2015:06 using 143 end-of-month observations.

(Panel A: Global-Sample)

		Statistical Inference			*In-Sample Portfolio Return Statistics*							
VN	**Strategy**	**VN**	$\hat{\theta}$	**Pval**	**Mean**	**STD**	**Skew**	**Kurt**	SR^{HM}	**SR**	**MDD**	**dCER**
./.	CT^{Global}	./.	./.	./.	4.14	9.02	-0.33	0.43	0.35	0.45	-14.01	0.00
(1)	$Ivar^{Global\text{-}FX}$		0.15	0.67	2.32	4.21	-0.27	0.82	0.40	0.53	-9.35	1.48
(2)	$Rvar^{Global\text{-}FX}$		0.07	0.84	2.15	4.12	-0.32	0.40	0.39	0.50	-8.57	1.35
(3)	$VRP^{Global\text{-}FX}$		-1.12**	0.05	3.87	5.45	-0.13	0.36	0.60	0.69	-9.37	2.43
(4)	$Ivar^{CT}$		0.42	0.16	4.13	5.26	1.12	4.26	0.73	0.77	-5.66	2.88
(5)	$Rvar^{Global\text{-}EQ}$		-0.30	0.38	2.83	4.75	-0.27	1.72	0.39	0.57	-7.45	1.74
(6)	$Ivar^{Global\text{-}EQ}$		-0.05	0.89	2.13	4.08	-0.30	0.62	0.38	0.50	-7.87	1.34
(7)	$VRP^{Global\text{-}EQ}$		-0.86**	0.03	4.66	5.93	0.22	1.57	0.68	0.77	-6.69	2.98
(3)(4)	$Implied^{Global\text{-}FX}$		./.	./.	6.93	7.08	0.45	0.98	0.99	0.96	-7.84	4.57
		(3)	-1.92***	0.00								
		(4)	1.28**	0.01								
(3)(4)(7)	$Implied^{Global}$		./.	./.	7.89	7.06	0.18	0.97	1.02	1.10	-7.52	5.49
		(3)	-1.62**	0.01								
		(4)	1.21**	0.02								
		(7)	-0.59	0.21								

(Panel B: G10-Sample)

		Statistical Inference			*In-Sample Portfolio Return Statistics*							
VN	**Strategy**	**VN**	$\hat{\theta}$	**Pval**	**Mean**	**STD**	**Skew**	**Kurt**	SR^{HM}	**SR**	**MDD**	**dCER**
(0a)	CT^{G10}	./.	./.	./.	4.50	11.71	-0.44	0.69	0.27	0.38	-28.75	0.00
(1a)	$Ivar^{G10\text{-}FX}$		-0.09	0.65	2.03	3.36	-0.41	0.17	0.46	0.57	-5.76	4.25
(2a)	$Rvar^{G10\text{-}FX}$		-0.10	0.49	2.17	3.56	-0.47	0.28	0.45	0.58	-5.97	4.33
(3a)	$VRP^{G10\text{-}FX}$		-0.60***	0.01	4.54	6.07	0.19	2.44	0.59	0.73	-8.95	5.51
(4a)	$Ivar^{CT\text{-}G10}$		0.01	0.94	1.85	3.10	-0.39	0.85	0.40	0.56	-9.28	4.16
(5a)	$Rvar^{Global\text{-}EQ}$		-0.46*	0.09	4.47	6.27	0.39	1.49	0.66	0.70	-8.55	5.35
(6a)	$Ivar^{Global\text{-}EQ}$		-0.19	0.36	2.68	4.25	-0.23	-0.21	0.57	0.61	-8.48	4.57
(7a)	$VRP^{Global\text{-}EQ}$		-0.50***	0.01	4.97	6.85	1.67	11.38	0.60	0.71	-10.28	5.62
(3a)(4a)	$Implied^{G10\text{-}FX}$		./.	./.	6.58	7.29	0.85	4.51	0.79	0.89	-11.11	6.85
		(3a)	-1.45***	0.01								
		(4a)	0.94**	0.02								
(3a)(4a)(7a)	$Implied^{G10}$		./.	./.	7.66	8.44	1.05	3.98	0.85	0.90	-15.20	7.17
		(3a)	-1.21***	0.00								
		(4a)	0.96**	0.04								
		(7a)	-0.69**	0.01								

Table 3. Parametric Portfolio Policy with Other State Variables

This table presents currency portfolio statistics from the baseline carry trade strategies ($CT^{Gl./G10}$) and the optimized portfolio policy strategy in-sample estimation results based on macroeconomic and carry trade activity parameters. Panel A uses the Global-Sample currencies, while Panel B is based on the G10-Sample. The left part of the table characterizes the variable numbers (VNs) used in the optimization model and the strategy's name. The middle and right parts of the table provide information about the statistical inference of the parameters and portfolio return statistics, respectively. Inference is based on a HAC matrix using 5 Newey-West lags, where $\hat{\theta}$ means the parameter estimate and the corresponding P-value (Pval) under H_0=0 against $H_1 \neq 0$. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively. Portfolio return statistics are the average annualized mean return in % (Mean), standard deviation in % (STD), skewness (Skew), excess kurtosis (Kurt), the Higher Moment Sharpe ratio (SR^{HM}), Sharpe ratio (SR), maximum drawdown in % (MDD), and the marginal CER in % (dCER). The sample covers the period from 2003:09 to 2015:06 using 143 end-of-month observations.

(Panel A: Global-Sample)

		Statistical Inference			***In-Sample Portfolio Return Statistics***							
VN	**Strategy**	**VN**	$\hat{\theta}$	**Pval**	**Mean**	**STD**	**Skew**	**Kurt**	**SR^{HM}**	**SR**	**MDD**	**dCER**
	CT^{Global}		./.	./.	4.14	9.02	-0.33	0.43	0.35	0.45	-14.01	0.00
(8)	RP^{Global}		0.48*	0.07	4.15	5.81	0.25	1.28	0.64	0.70	-8.62	2.54
(9)	CPI^{Global}		-1.00**	0.01	4.56	6.02	0.25	1.45	0.67	0.74	-6.89	2.83
(10)	CTI^{Global}		-0.53	0.20	3.43	5.55	0.69	3.62	0.53	0.60	-8.49	1.99
(8)(9)	$Macro^{Global}$		./.	./.	5.75	6.41	0.30	0.41	0.93	0.88	-7.73	3.80
		(8)	0.56*	0.07								
		(9)	-1.18***	0.00								
(8)(9)(10)	$Macro^{Gl.}+CTI^{Gl.}$		./.	./.	6.89	7.00	0.27	0.33	1.03	0.97	-8.76	4.56
		(8)	0.63**	0.04								
		(9)	-1.24***	0.00								
		(10)	-0.65	0.14								

(Panel B: G10-Sample)

		Statistical Inference			***In-Sample Portfolio Return Statistics***							
VN	**Strategy**	**VN**	$\hat{\theta}$	**Pval**	**Mean**	**STD**	**Skew**	**Kurt**	**SR^{HM}**	**SR**	**MDD**	**dCER**
	CT^{G10}		./.	./.	4.50	11.71	-0.44	0.69	0.27	0.38	-28.75	0.00
(8a)	RP^{G10}		0.18	0.42	2.37	3.83	-0.33	0.66	0.45	0.59	-7.02	4.42
(9a)	CPI^{G10}		-0.95***	0.00	6.84	7.28	0.76	1.91	0.94	0.92	-11.89	7.13
(10a)	CTI^{G10}		0.10	0.66	2.02	3.37	-0.20	0.78	0.44	0.57	-5.90	4.24
(8a)(9a)	$Macro^{G10}$				6.79	7.10	0.49	1.40	0.93	0.94	-11.16	7.16
		(8a)	0.15	0.58								
		(9a)	-0.97***	0.00								
(8a)(9a)(10a)	$Macro^{G10}+CTI^{G10}$				6.85	7.13	0.51	1.36	0.95	0.95	-11.15	7.20
		(8a)	0.17	0.58								
		(9a)	-0.97***	0.00								
		(10a)	-0.03	0.92								

Table 4. In-Sample Return Results

This table presents currency portfolio statistics from the baseline carry trade strategies ($CT^{Gl./G10}$) and the optimized portfolio policy strategy in-sample estimation results based on different parameter strategies. Panel A uses the Global-Sample currencies, while Panel B is based on the G10-Sample. The upper part of each panel provides information about portfolio return statistics, while the lower part is dedicated to statistical inference of the parameter estimates. Inference is based on a HAC matrix using 5 Newey-West lags, where $\hat{\theta}$ means the parameter estimate and the corresponding P-value (Pval) under H_0=0 against $H_1 \neq 0$. The asterisk values (***), (**), and (*) indicate statistical significance at the 99%, 95%, and 90% confidence level, respectively. Portfolio return statistics are the average annualized mean return in % (Mean), standard deviation in % (STD), skewness (Skew), excess kurtosis (Kurt), the Higher Moment Sharpe ratio (SR^{HM}), Sharpe ratio (SR), maximum drawdown in % (MDD), and the marginal CER in % (dCER). The sample covers the period from 2003:09 to 2015:06 using 143 end-of-month observations.

(Panel A: Global-Sample)

In-Sample Portfolio Return Statistics

Strategy	Mean	STD	Skew	Kurt	SR^{HM}	SR	MDD	dCER
CT^{Global}	4.14	9.02	-0.33	0.43	0.35	0.45	-14.01	0.00
Benchmark	4.16	6.36	-0.19	0.07	0.57	0.64	-15.76	2.18
All-in	10.36	7.52	0.50	1.22	1.38	1.36	-6.33	7.71
All-in+CRB	10.87	7.15	0.59	1.22	1.57	1.51	-6.37	8.50

Statistical Inference of Predictable Regressors

Benchmark Strategy								
Variables	***Const.***	***$r^{CT}lag$***	***FD^{Avg}***	***VIX***	***TED***	***dCRB***	***GMPI***	
$\hat{\theta}$	0.84**	0.65*	-0.25	0.47	-0.30	0.23	0.05	
Pval	0.03	0.07	0.52	0.36	0.46	0.55	0.90	
All-In Strategy								
Variables	***Const.***	***$Ivar3^{CT}$***	***$VRP3^{Global-FX}$***	***$VRP^{Global-EQ}$***	***RP^{Global}***	***CPI^{Global}***	***$CTI^{Avg(6m)}$***	***CRB***
$\hat{\theta}$	0.53	1.54**	-1.08	-0.76	0.51	-1.22***	0.36	./.
Pval	0.22	0.01	0.18	0.16	0.21	0.01	0.49	./.
All-In+CRB Strategy								
$\hat{\theta}$	0.56	1.72***	-1.30	-0.91	0.52	-1.20***	0.99	-1.04*
Pval	0.17	0.01	0.11	0.14	0.20	0.01	0.15	0.07

(Panel B: G10-Sample)

In-Sample Portfolio Return Statistics

Strategy	Mean	STD	Skew	Kurt	SR^{HM}	SR	MDD	dCER
CT^{G10}	4.50	11.71	-0.44	0.69	0.27	0.38	-28.75	0.00
Benchmark	6.10	7.50	0.86	5.43	0.68	0.80	-14.53	6.22
All-in	10.88	9.05	0.81	2.45	1.18	1.19	-15.76	9.86
All-in+CRB	13.08	9.16	0.55	2.20	1.33	1.42	-14.79	11.88

Statistical Inference of Predictable Regressors

Benchmark Strategy								
Variables	***Const.***	***$r^{CT}lag$***	***FD^{Avg}***	***VIX***	***TED***	***dCRB***	***GMPI***	
$\hat{\theta}$	0.39	-0.06 (0.01)	-0.29 (-0.42)	0.22 (0.05)	-0.39 (-2.84)	0.50* (0.25)	0.06 (1.16)	
Pval	0.17	0.79	0.29	0.48	0.15	0.07	0.81	
All-In Strategy								
Variables	***Const.***	***$Ivar3^{CT}$***	***$VRP3^{G10-FX}$***	***VRP^{G10-EQ}***	***RP^{G10}***	***CPI^{G10}***	***$CTI^{Avg(6m)}$***	***CRB***
$\hat{\theta}$	0.54*	1.16**	-0.98*	-0.84**	0.19	-0.78**	0.40	./.
Pval	0.06	0.03	0.08	0.02	0.64	0.05	0.26	./.
All-In+CRB Strategy								
$\hat{\theta}$	0.56*	1.32**	-1.31**	-0.60*	0.02	-0.62	0.52	-0.76**
Pval	0.05	0.02	0.04	0.09	0.97	0.14	0.14	0.05

Table 5. Out-of-Sample Return Results

This table presents currency portfolio statistics from the baseline carry trade strategies ($CT^{Gl./G10}$) and the optimized portfolio policy strategy out-of-sample estimation results based on different parameter strategies. Panel A uses the Global-Sample currencies, while Panel B is based on the G10-Sample. The left part of each panel provides information about portfolio return statistics, while the right part reports the lower and upper bound of a 95% confidence interval for the Mean, Skew, and SR^{HM} using a bootstrap method. Portfolio return statistics are the average annualized mean return in % (Mean), standard deviation in % (STD), skewness (Skew), excess kurtosis (Kurt), the Higher Moment Sharpe ratio (SR^{HM}), Sharpe ratio (SR), maximum drawdown in % (MDD), and the marginal CER in % (dCER). The sample covers the period from 2007:09 to 2015:06 using 95 end-of-month observations.

(Panel A: Global-Sample)

Out-of-Sample Portfolio Return Statistics									**Bootstrapped 95% CI for**		
Strategy	**Mean**	**STD**	**Skew**	**Kurt**	**SR^{HM}**	**SR**	**MDD**	**dCER**	**Mean**	**Skew**	**SR^{HM}**
CT^{Global}	-0.55	8.22	-0.38	0.34	0.00	-0.07	-14.01	0.00	{-6.2 5.2}	{-0.82 0.16}	{-0.0 0.58}
Benchmark	1.79	7.14	0.14	0.79	0.23	0.25	-13.23	3.30	{-3.1 6.7}	{-0.54 0.77}	{-0.0 1.11}
All-in+CRB	3.47	6.57	0.27	1.6	0.47	0.52	-9.54	5.39	{-1.1 8.0}	{-0.55 1.01}	{-0.0 1.11}
$TOP\text{-}4^{Gl.}$	5.58	5.92	0.13	-0.17	1.05	0.94	-8.55	7.89	{1.5 9.7}	{-0.28 0.53}	{0.26 1.87}
$TOP\text{-}4^{Gl.}$ Lev2	8.51	8.55	0.39	0.36	1.10	0.99	-11.73	9.05	{2.5 14.5}	{-0.09 0.82}	{0.35 1.96}
$TOP\text{-}4^{Gl.}$ Lev3	10.19	10.3	0.81	1.98	1.01	0.99	-13.47	9.35	{3.3 17.4}	{-0.06 1.40}	{0.31 1.81}
$TOP\text{-}4^{Gl.}$ Unr.	10.95	10.82	0.88	2.03	1.05	1.01	-13.87	9.66	{3.7 18.7}	{0.05 1.49}	{0.34 1.87}

(Panel B: G10-Sample)

Out-of-Sample Portfolio Return Statistics									**Bootstrapped 95% CI for**		
Strategy	**Mean**	**STD**	**Skew**	**Kurt**	**SR^{HM}**	**SR**	**MDD**	**dCER**	**Mean**	**Skew**	**SR^{HM}**
CT^{G10}	-0.67	12.41	-0.22	0.52	0.00	-0.06	-28.75	0.00	{-9.2 7.6}	{-0.80 0.39}	{-0.02 0.62}
Benchmark	2.13	10.61	0.15	2.53	0.16	0.2	-16.26	5.14	{-5.2 9.5}	{-0.93 1.16}	{-0.01 0.88}
All-in+CRB	8.30	10.42	-0.32	2.46	0.50	0.79	-15.1	11.24	{1.0 15.3}	{-1.20 0.79}	{0.05 1.79}
$TOP\text{-}4^{G10}$	8.38	9.55	0.58	1.00	0.93	0.87	-8.9	12.76	{1.8 15.2}	{-0.05 1.15}	{0.20 1.78}
$TOP\text{-}4^{G10}$ Lev2	14.43	14.93	0.71	1.30	1.03	0.96	-11.37	12.99	{4.3 25.0}	{0.09 1.26}	{0.29 1.89}
$TOP\text{-}4^{G10}$ Lev3	16.23	18.49	0.74	3.14	0.81	0.88	-14.84	8.84	{3.9 29.1}	{-0.37 1.71}	{0.15 1.65}
$TOP\text{-}4^{G10}$ Unr.	16.35	20.86	0.48	5.24	0.61	0.78	-19.66	0.99	{2.2 31.0}	{-1.18 2.05}	{0.05 1.52}

Figure 1. Cumulative Carry Trade Returns

This figure presents the time-series charts of the cumulative log-returns coming from a global carry trade (green thick line) and a G10 carry trade portfolio (blue thin line). Both return statistics incorporate transaction costs. The sample covers the period between 2003:09 to 2015:06, with the grey background indicating an NBER recession period.

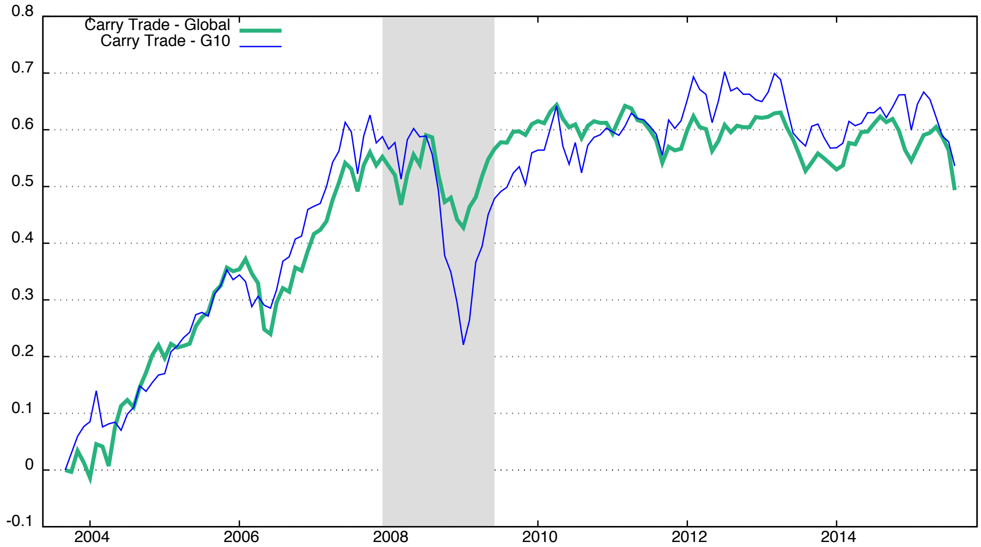
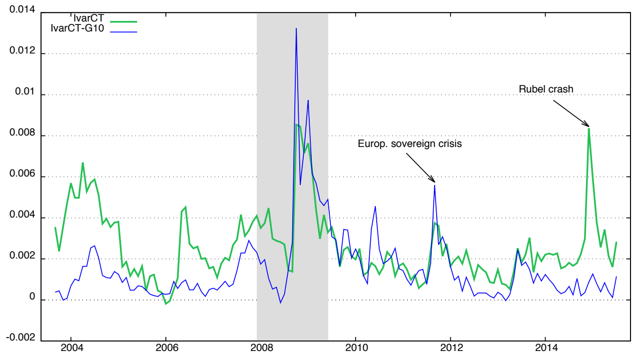


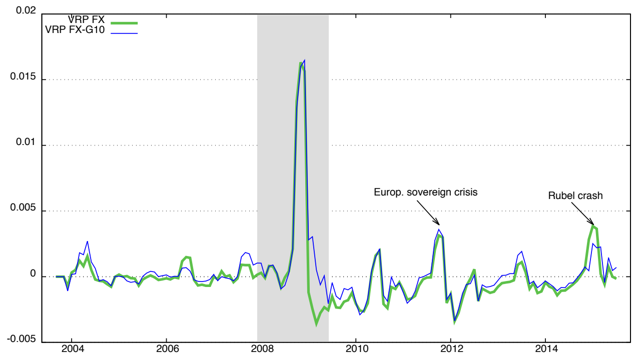
Figure 2. Global Risk Variables Predicting Carry Trade Returns

This figure presents four charts characterizing the time-series properties of: (Chart a) the carry trade's implied variance differential, (Chart b) the global FX variance risk premium, (Chart c) the global inflation differential, and (Chart d) the CRB commodity price index. The two lines within each chart (except in Chart d) distinguish between the aggregation level using the Global-Sample (green thick line) and the G10-Sample (blue thin line). The sample covers the period between 2003:09 to 2015:06, with the grey background indicating an NBER recession period.

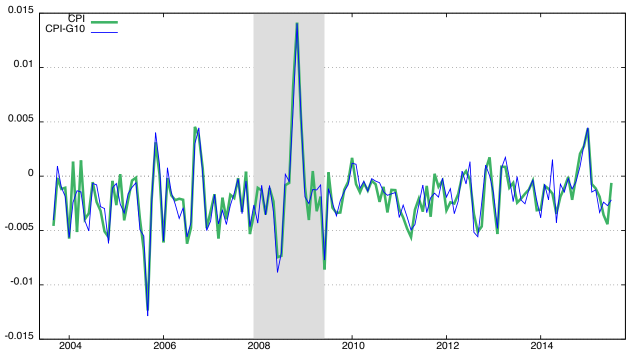
(a: Implied variance^{CT})



(b: FX variance risk premium)



(c: Inflation differential)



(d: Commodity price index)

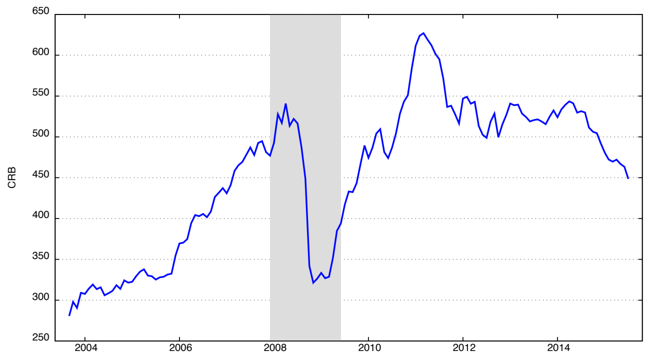
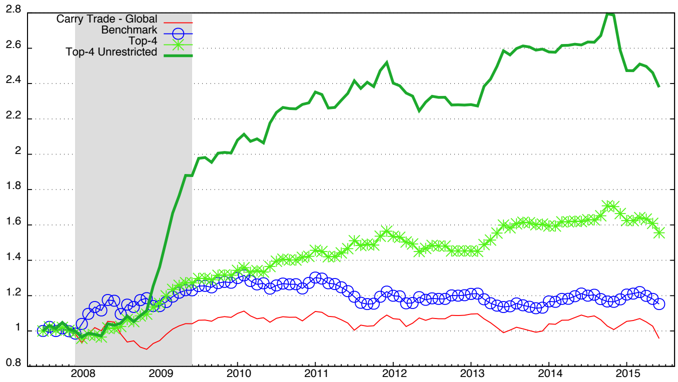


Figure 3. Performance of OOS Cumulative Returns

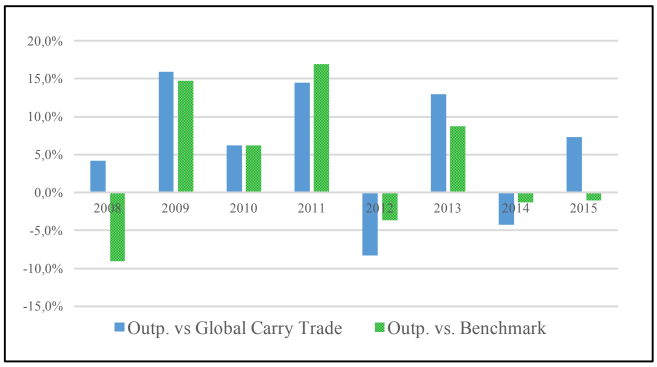
The figure consists of four charts. On the left-hand side (LHS) the cumulative returns on four different currency investments are presented, while the right-hand side (RHS) bar charts present 12-month periods return figures. All results are based on the out-of-sample tests of Table 5 and the figure distinguishes between Global-Sample (Panel A) and G10-Sample (Panel B) calculations. The LHS charts carry investment performance on an initially-invested 1 USD in: (i) the carry trade, (ii) the benchmark model, (iii) the TOP-4 model, and (iv) the TOP-4 unrestricted model. The RHS bar charts present the 12-month log-return outperformances of the TOP-4 model with the carry trade returns (blue bars) and the benchmark model returns (green shaded bars), respectively. The sample covers the period between 2007:09 to 2015:06, with the grey background indicating an NBER recession period.

(Panel A: Global-Sample)

(A1)

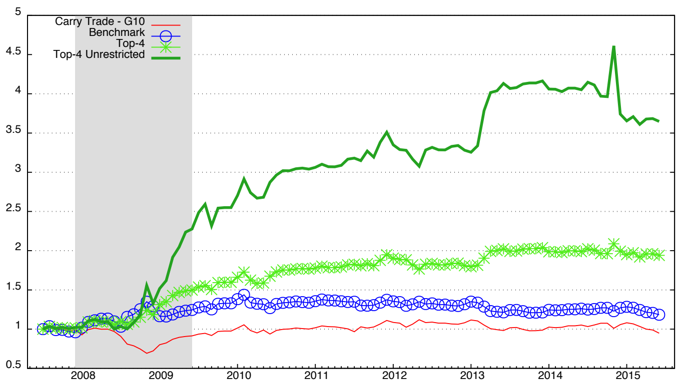


(A2)



(Panel B: G10-Sample)

(B1)



(B2)

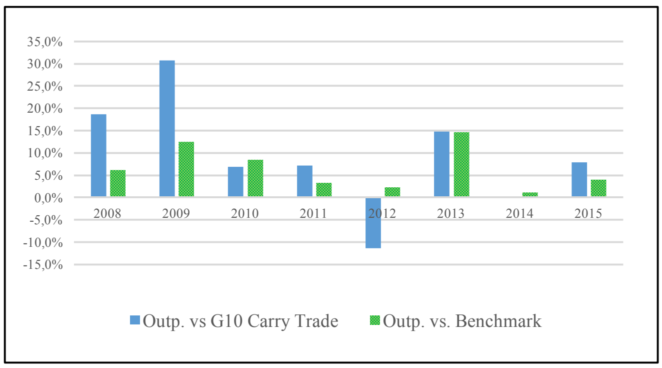
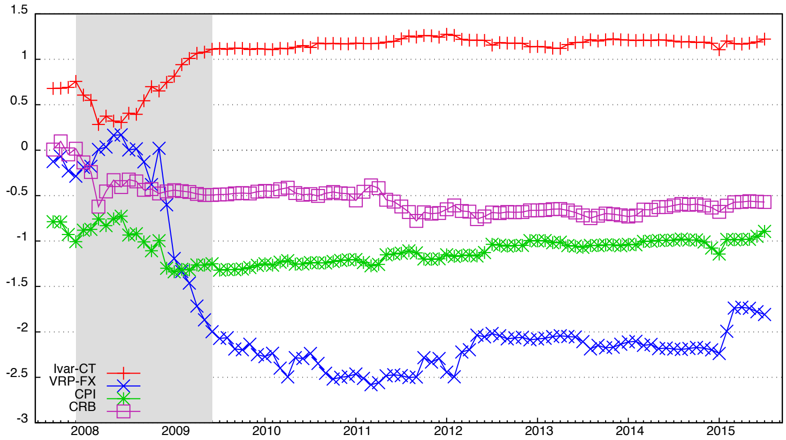


Figure 4. Parameter Stability of Top-4 Risk Variables

The figure presents monthly parameter estimates of the TOP-4 model during the out-of-sample optimization period outlined in Table 5. The respective lines belong to: (i) the carry trade's implied variance differential (Ivar-CT, red line), (ii) the global FX variance risk premium (VRP-FX, blue line), (iii) the global CPI differential (CPI, green line), and (iv) the CRB commodity price index (CRB, purple line). The sample covers the period between 2003:09 to 2015:06, with the grey background indicating an NBER recession period.



APPENDIX

Appendix A. Delta Conventions

The term *delta* (Δ) in the financial option market literature means the first partial derivative of the option value with respect to the underlying price. The FX market uses various sets of option-delta conventions for any respective exchange rate market. This becomes a crucial fact when dealing with option-implied volatilities that are assigned to a certain option-delta level. The questions are: (i) what kind of option-delta stays behind a specific market quote? And (ii) what at-the-money (ATM) strike conventions are used? Before recovering a market-conform option volatility smile based on option-implied volatility quotes, it is advisable to follow these restrictions. Before answering these questions, it is useful to first define the value of a FX option $v_{t,T}$, which goes back to the definition in Garman and Kohlhagen (1983):

$$v_{t,T} = \phi\left[e^{-i^f\tau}S_tN(\phi d_+) - e^{-i\tau}KN(\phi d_-)\right] \tag{A.1}$$

where

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

$\sigma_{t,T}$: the option-implied volatility level,

$\phi = +1$ for a call, $\phi = -1$ for a put,

$N(x)$: the cumulative normal distribution.

The option price $v_{t,T}$ is expressed in terms of USD per one unit of foreign currency. There are four different option-delta types used to quote implied volatilities, which are: (i) the spot delta (Ds), (ii) the forward delta (Fs), (iii) the premium adjusted spot delta (paDs), and (iv) the premium adjusted forward delta (paDf). These are defined as follows:

$$Ds = \phi e^{-i^f\tau}N(\phi d_+) \tag{A.2}$$

$$Df = \phi N(\phi d_+) \tag{A.3}$$

$$paDs = \phi e^{-i^f\tau}\frac{K}{F_{t,T}}N(\phi d_-) \tag{A.4}$$

$$paDf = \phi\frac{K}{F_{t,T}}N(\phi d_-) \tag{A.5}$$

In addition to the definition of the delta type that underlines the volatility quote, using the right ATM convention is the next issue one might think about. The most obvious is to choose the current FX spot level as the middle of the spot rate distribution. According to the conventions used in practice, this study follows two different definitions: the ATM-forward strike (Fs) and the ATM-Δ-neutral strike (Dn):

$$Fs = F_{t,T} \tag{A.6}$$

$$Dn = \begin{cases} \frac{1}{2}\phi e^{-i^f\tau} & , for\ Ds \\ \frac{1}{2}\phi & , for\ Df \\ \frac{1}{2}\phi e^{-i^f\tau}e^{-\frac{1}{2}\sigma^2\tau} & , for\ paDs \\ \frac{1}{2}\phi e^{-\frac{1}{2}\sigma^2\tau} & , for\ paDf \end{cases} \tag{A.7}$$

While the current forward level simultaneously defines the ATM forward strike, regardless of the option delta definition, this is obviously not true when determining the ATM-Δ-neutral strike. Here, the knowledge of the underlying delta convention is obligatory in order to define a delta neutral strike basis.

Table A. 1 gives a brief overview of the delta conventions used in this study. It is hard to find a systemic pattern as a basis for these conventions, so the applied calculations are primarily based on suggestions in Clark (2011) and Reiswich and Wystup (2012).

Appendix B. Measures of Portfolio Efficiency

Sharpe Ratio

The well-known Sharpe ratio is a measure of an investment performance relative to its volatility or risk (see Sharpe 1964). The performance, as such, is the excess return (μ) of the asset over a risk-free return (r^f), divided by the standard deviation (σ):

$$SR = \frac{\mu - r^f}{\sigma} \tag{B.1}$$

While the proposed ratio (SR) originally uses expected risk and return figures, this study uses ex-post annualized returns and standard deviations to properly evaluate the relative investment performance of the underlying asset. The risk-free rate for the representative US investor is the 4w T-Bill rate.

Higher Moment Sharpe Ratio

The *Higher Moment Sharpe ratio* (SR^{HM}) was developed by Broll (2016b). It extends the original Sharpe ratio by incorporating the second- and third-moment risks of the portfolio return. This measure of portfolio efficiency ensures that portfolio return series that are prone to fat tailed and skewed return distributions are adequately compared to more Gaussian distributed portfolios. It is equal to the original Sharpe ratio when the portfolio return series has zero skewness (γ_1) and zero excess kurtosis (γ_2). The SR^{HM} is defined as follows:

$$SR^{HM} = \frac{\mu - r^f}{\left[\left(\sqrt{\sigma^2}\right)\left(\sqrt[3]{(1 + a|\gamma_1|)}\right)^{-E}\left(\sqrt[4]{1 + b|\gamma_2|}\right)^{B}\right]^{(\mu - r^f/|\mu - r^f|)}} \tag{B.2}$$

$$E = \begin{cases} +1, & if\ \gamma_1 > 0 \\ -1, & if\ \gamma_1 \leq 0 \end{cases} \quad \text{and} \quad B = \begin{cases} +1, & if\ \gamma_2 > 0 \\ -1, & if\ \gamma_2 \leq 0 \end{cases}$$

$$\gamma_1 = \frac{E[(X - \mu)^3]}{\sigma^3} \tag{B.3}$$

$$\gamma_2 = \frac{E[(X - \mu)^4]}{\sigma^4} - 3 \tag{B.4}$$

While the numerator is equal to the original Sharpe ratio, the denominator deflates the excess return by the standard deviation accompanied with factors of skewness and excess kurtosis in a multiplicative fashion. The exponent of the denominator takes on the level of 1 or -1, conditional on positive and negative excess return, respectively. It ensures a proper way of sorting relative investment performances when the excess return is negative. Thus, it gives the SR^{HM} an identification with regard to an investor's exponential utility function, as has been used in Pézier and White (2008) defining their *Adjusted Sharpe ratio* (ASR). The variables *a* and *b* are adjustment factors with values of 1.8 and 1.0, respectively.

Certainty Equivalent Return

Another portfolio metric is the *certain equivalent return* (CER). It indicates the level of a guaranteed return for an investor to be indifferent between the risky investment and the riskless strategy paying off CER in expectation. One has to define the form of the investor's utility function (U) and the individual level of risk aversion (γ). CER is then defined as:

$$CER = \left[(1 - \gamma)T^{-1} \sum_{t=1}^{T} U(1 + \mu_{t+1})\right]^{1/(1-\gamma)} - 1 \tag{B.5}$$

Maximum Drawdown

While the maximum drawdown is not directly a measure of portfolio efficiency, it provides information about the maximum shortfall during a defined period of time. This period contains the last peak price (P) of an underlying asset and the lowest price value (L) after the peak event. Both prices can be measured in any desired frequency, which is restricted here to end-of-month observations. The MDD return is then defined as:

$$MDD = log\left(\frac{L}{P}\right) x\ 100 \tag{B.6}$$

Table A. 1. Option Delta Conventions

This table reports option delta conventions used in practice. The left section of the table introduces the various FX rates in the coverage with the corresponding country, while the right section informs about the underlying conventions. The abbreviations of the *Delta* and *ATM type,* introduced in Appendix A, are found in the third and fourth column, respectively.

Exchange Rate	***Country***	***Delta Conventions***	
		Delta Type	*ATM Type*
Developed Market Currencies (G10)			
AUDUSD	Australia	Ds	Dn
USDCAD	Canada	paDs	Dn
EURUSD	*Europe*	Ds	Dn
GBPUSD	Great Britain	Ds	Dn
USDJPY	Japan	paDs	Dn
NZDUSD	New Zealand	Ds	Dn
USDDKK	Denmark	paDs	Dn
USDNOK	Norway	psDs	Dn
USDSEK	Sweden	paDs	Dn
USDCHF	Switzerland	paDs	Dn
Emerging Market Currencies			
USDPLN	Poland	paDf	Dn
USDSGD	Singapore	paDf	Dn
USDZAR	South Africa	paDf	Dn
USDKRW	South Korea	paDf	Dn
USDTWD	Taiwan	paDf	Dn
USDTHB	Thailand	paDf	Dn
USDILS	Israel	paDf	Dn
USDCLP	Chile	paDf	Fs
USDCOP	Colombia	paDf	Fs
USDCZK	Czech Republic	paDf	Dn
USDHUF	Hungary	paDf	Dn
USDINR	India	paDf	Dn
USDMXN	Mexico	paDf	Fs
USDTRY	Turkey	paDf	Dn
USDRUB	Russia	paDf	Dn
USDMYR	Malaysia	paDf	Dn
USDIDR	Indonesia	paDf	Dn
USDPHP	The Philippines	paDf	Dn
USDBRL	Brazil	paDf	Fs
USDPEN	Peru	paDf	Fs
USDRON	Romania	paDf	Dn
USDSKK	Slovakia	paDf	Dn

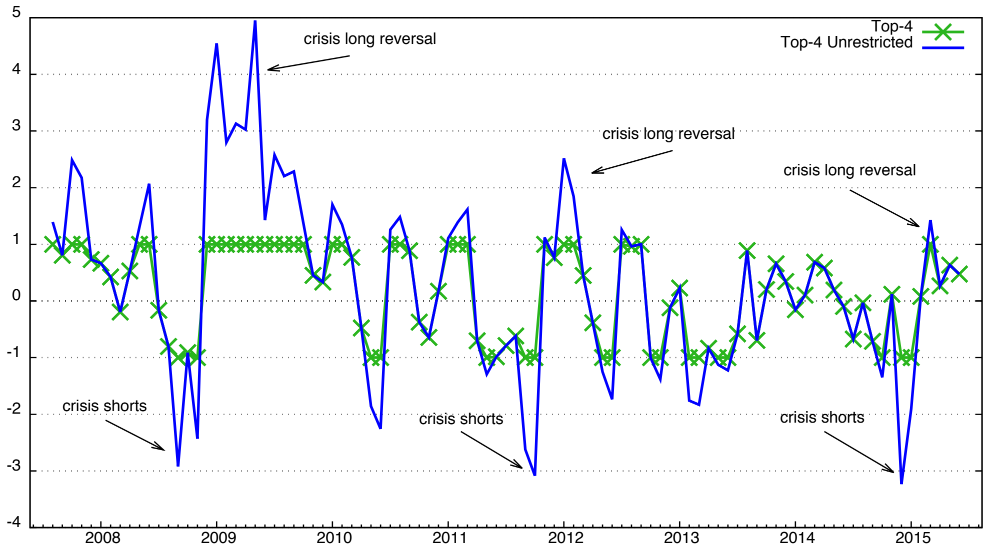
Table A. 2. Foreign Currency Exchange Rate Data Coverage

This table provides an overview of the foreign exchange rates coverage. The left section characterizes the foreign exchange rates by their number (No.), *ISO 4217* currency code, and their country. The middle and right sections give an overview of the various start and end dates of the risk variables used in the optimization process and the number of monthly observations (Obs.). Furthermore, the rates are divided into developed (Panel A) and emerging currencies (Panel B).

No.	***Currency codes***	***Country***	-	***Global- and G10-Sample***			-	***CFTC Sample***		
				Start date	*End date*	*Obs.*		*Start date*	*End date*	*Obs.*
Panel A: Developed Market Currencies (G10)										
1	AUD	Australia		09/2003	06/2015	142		09/2003	06/2015	142
2	CAD	Canada		09/2003	06/2015	142		09/2003	06/2015	142
3	EUR	*Europe*		09/2003	06/2015	142		09/2003	06/2015	142
4	GBP	Great Britain		09/2003	06/2015	142		09/2003	06/2015	142
5	JPY	Japan		09/2003	06/2015	142		09/2003	06/2015	142
6	NZD	New Zealand		09/2003	06/2015	142		11/2005	06/2015	116
7	DKK	Denmark		02/2005	06/2015	125		./.	./.	./.
8	NOK	Norway		02/2005	06/2015	125		./.	./.	./.
9	SEK	Sweden		02/2005	06/2015	125		./.	./.	./.
10	CHF	Switzerland		02/2005	06/2015	125		09/2003	06/2015	142
Panel B: Emerging Market Currencies										
11	PLN	Poland		09/2003	06/2015	142		./.	./.	./.
12	SGD	Singapore		09/2003	06/2015	142		./.	./.	./.
13	ZAR	South Africa		09/2003	06/2015	142		./.	./.	./.
14	KRW	South Korea		09/2003	06/2015	142		./.	./.	./.
15	TWD	Taiwan		09/2003	06/2015	142		./.	./.	./.
16	THB	Thailand		09/2003	06/2015	142		./.	./.	./.
17	ILS	Israel		03/2004	06/2015	136		./.	./.	./.
18	CLP	Chile		02/2005	06/2015	125		./.	./.	./.
19	COP	Colombia		02/2005	06/2015	125		./.	./.	./.
20	CZK	Czech Republic		02/2005	06/2015	125		./.	./.	./.
21	HUF	Hungary		02/2005	06/2015	125		./.	./.	./.
22	INR	India		02/2005	06/2015	125		./.	./.	./.
23	MXN	Mexico		02/2005	06/2015	125		09/2003	06/2015	142
24	TRY	Turkey		11/2005	06/2015	116		./.	./.	./.
25	RUB	Russia		04/2006	06/2015	111		02/2009	06/2015	77
26	MYR	Malaysia		09/2006	06/2015	106		./.	./.	./.
27	IDR	Indonesia		06/2007	06/2015	97		./.	./.	./.
28	PHP	The Philippines		06/2007	06/2015	97		./.	./.	./.
29	BRL	Brazil		02/2008	06/2015	89		./.	./.	./.
30	PEN	Peru		06/2008	06/2015	85		./.	./.	./.
31	RON	Romania		06/2008	06/2015	85		./.	./.	./.
32	SKK	Slovakia		06/2008	02/2014	67		./.	./.	./.

Figure A. 1. Out-of-Sample Optimal Carry Trade Weights

This figure presents the time-series charts of the optimized weightings for the global carry trade portfolio, using the *TOP-4* (green solid line with crosses) and the *TOP-4 Unr.* model (blue solid line) discussed in Panel A of Table 5. The former model weights are restricted to lie between -1 and +1, whereas the latter are completely unrestricted. The sample covers the out-of-sample period between 2007:09 and 2015:06.



Chapter 4

The Skewness Risk Premium in Currency Markets

THE SKEWNESS RISK PREMIUM IN CURRENCY MARKETS

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Abstract

This paper examines the relationship between currency option's implied skewness and its future realized skewness, where the difference is known as the skewness risk premium (SRP). The SRP indicates whether investors pay a premium to be insured against future crash risk. Past investigations about implied and realized skewness within currency markets showed that both measures are loosely connected or even exhibit a negative relationship that cannot be rationalized by no-arbitrage arguments. Therefore, this paper studies time-series of *future* and *option contract positions* data in order to explain the disconnection in terms of investor's position-induced demand pressure. While demand pressures on options do not sufficiently contribute to the disconnection, there is evidence that, surprisingly, demand pressure in currency future markets have the power to explain this market anomaly. Furthermore, currency momentum also plays an important role, which leads to a strong cyclical demand for OTM calls in rising or OTM puts in declining markets. In order to exploit the disconnection of skewness, a simple skew swap trading strategy proposed by Schneider and Trojani (2015) have been set up. The resulting skew swap returns are relatively high, but the return distribution is extremely fat-tailed. To appropriately compare different skew swap strategy returns, this paper proposes a *Higher Moment Sharpe Ratio* that also takes higher moments into account.

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1 Introduction

While it is quite common to use the second moment or variance as a measurement of risk, the focus of this paper lies on the third moment risk or skewness of a return distribution in the currency market. Strictly speaking, the investigation here concentrates on the relationship between future realized skewness ($Rskew_{t:t+1}$) and its ex ante known risk-neutral counterpart, the implied skewness ($Iskew_t$). The difference between the two variables is known as the skewness risk premium ($SRP_{t:t+1}$). While *Rskew* measures the physical asymmetry of a return distribution, *Iskew* is supposed to measure investors' future perception of an asymmetrical return distribution under the risk-neutral measure. Literature has used skewness to predict large and rare disasters and estimate crash risks in any desired setting. Hence, one can state that *Rskew* measures the future realized crash intensity and *Iskew* measures the option-implied crash risk and can be characterized as the current price for ensuring against future crashes. Taking these definitions as a basis, one can imagine that both variables are closely related to each other. It is also well-known that realized and implied moment risks are also used to design swap contracts to make the difference tradable. While the design of second-moment swap contracts or variance swaps are frequently used in practice, third-moment swaps or skew swaps have only been considered in academic literature.

However, empirical evidence for the currency market provided by Jurek (2014) and Brunnermeier et al. (2009) suggests that *Rskew* and *Iskew* are, on average, negatively related to each other. This is quite puzzling, since it means that, especially in times of fragile markets, the insurance price against crashes gets cheaper. In a study of skewness in the commodity market, Ruf (2012) found similar results that realized and implied skewness are somehow disconnected from each other. He found mounting evidence to suggest that this disconnectedness of skewness (DS) is primarily driven by option demand-based market pressures. Ruf (2012) showed that, especially in times where "arbitrageurs" faced large net long option positions[1], they became restricted to offer more option contracts. Subsequently, the option prices started to rise, and, as a consequence, the implied skew degenerated from its realized counterpart. In a different study that focused on *Iskew* for the equity market, Gârleanu et al. (2009) analysed the disconnection between the heavily negative *Iskew* of the S&P 500 Index compared to the much flatter *Iskew's* of its single stock constituents. They rationalized their findings by comparing with different net

[1] "Net option positions" refer to the aggregate option positioning of an arbitrary number of market participants belonging to a special group of traders, e.g. end-users. If a trader group is exposed to a net long put position it means that the group of traders, as a whole, has a greater number of long put positions in contrast to short put positions.

option positions of "end-users"[2] in their respective index or single stock markets. End-users are, on average, net long puts on the index side, which has led to a more negative *Iskew*. On the other hand, end-users have been, on average, more exposed to net short puts in the various single stock option markets, leaving the volatility smile more positively-skewed. Again, different positioning of market participants seems to play a big role in explaining some unusual market anomalies and, therefore, encourages an investigation of the DS in currency markets.

Therefore, the aim of this paper is (1) to study the existence of a skewness risk premium in currency markets and (2) to identify the source of the disconnectedness of realized and implied skewness (DS) in the time-series. While the first part gives an overview of the historical situation of about 30 different currency pairs against the US-dollar (USD), with investors paying an extra premium to be insured against crash risk, the second part more thoroughly investigates the dependency of skewness to market pressures. Here, using a subsample of up to 8 currencies, the study concentrates on future and option contract data provided by the *U.S. Commodity Futures and Trading Commission (CFTC)* in order to find a demand-based explanation of the DS in the currency market.

Why is the DS relevant for an economic investigation? And, how can skew risk be defined? The DS is not consistent with no-arbitrage arguments of financial markets and can therefore be characterized as a kind of market anomaly. This becomes clear when one starts to exploit the DS through the use of a skew swap. This paper will use the methodology of a synthetic skew swap, recently developed by Kozhan et al. (2013) (KNS) to describe the skewness risk premium. The advantage of KNS is that realized and implied skew perfectly aggregate to each other. This has been achieved by Neuberger' pioneering work (2012), which accurately derived a measure of realized skew that perfectly aggregates to its implied skew counterpart. KNS used this evidence to investigate the relationship between second and third-moment risk for the S&P 500 Index market.

This paper's empirical framework is broadly identical to Ruf's work (2012). In a panel regression framework, it will be shown that the DS in currency markets are primarily driven by market pressures from the future market. Beside market pressures, the role of past currency momentum also exhibits a strong relation to the DS. Market concentration patterns, market illiquidity, macroeconomic risk, equity risk, and market volatility risk factors are also taken into account in the forthcoming analysis. At the end of this paper a more practical version of a skew

[2] "End-Users" are a group of traders who do not offer option contracts to the public and, therefore, only trade long positions in call or put contracts.

swap (see Schneider and Trojani, 2015) will be briefly introduced and a trading strategy will be implemented using the evidence of panel regressions results to exploit the DS.

All implied variance or skewness measures are primarily based on the existence of a volatility smile of the respective currency pair and option maturity. Therefore, the option-implied volatility smile will be rebuilt, using 25-delta out-of-the-money (OTM) butterfly, 25-delta OTM risk reversal, and at-the-money (ATM) volatility quotes provided by Bloomberg. In order to calibrate such a volatility smile and translate it into option prices, the simplified parabolic interpolation model developed by Reiswich and Wystup (2012) has been chosen. This model has proven to be robust against other well-known smile procedure approaches (see Reiswich, 2011) that are used in practice, e.g. the vanna-volga method by (Castagna and Mercurio, 2007).

The remainder of this paper is organized as follows: section 2 gives an introduction to how second- and, especially, third-moment swaps are designed; section 3 describes the variables used in the empirical analysis; section 4 presents empirical evidence for why realized and implied skewness are disconnected in currency markets, a fact exploited in section 5. Finally, section 6 concludes the paper and sums up the argument.

2 Moment Swaps

Neuberger (2012) developed a trading strategy that is completely attributed to the third-moment risk. While his approach is a trading strategy, the returns from it can be viewed as a pure bet on the third-moment risk and can be interpreted as a moment risk premium. The functionality of the strategy is similar to a swap contract. The buyer of a contract pays the option-implied level at inception time t of the corresponding moment risk, also known as the fixed leg or swap strike price. Then, she will subsequently receive the realized moment risk, known as the floating leg, until expiration date T. The fixed leg is usually characterized as a contingent claim and therefore priced with using the spanning approach from Bakshi and Madan (2000).

An integrated part of Neuberger's (2012) derivations of second or third moment swaps is that they conform to the Aggregation Property (AP). To get a first impression of the meaning of the AP and how one can link it to the fixed and floating leg of a swap contract, take a look at the following equation:

$$\mathbb{E}_0[g(X_T - X_0)] = \mathbb{E}_0\left[\sum_{t=1}^{T} g(X_t - X_{t-1})\right] \quad (1)$$

On the left-hand side (LHS), one can see the expected value of a function g that is dependent on a price change of a variable X over the period [0,T]. On the right-hand side (RHS), there is the expected value of g-function's sum of price changes over more frequent observations of X. Suppose that the function g is composed of a moment risk and X is a stochastic price process that follows a martingale. Then, the LHS describes the expected value of that moment risk using the price change over the entire period, for example - a month. This should be equal to the expected value of the summation term of this moment risk, subsequently computed on a daily frequency over the same period. Interpreting this result in terms of a swap contract, one can state that the RHS summation term, priced under a physical measure $\mathbb{P}$, represents the fair price of that moment risk and is equal in expectation to the contingent claim price $E_0[g(X_T\text{-}X_0)]$ evaluated under the implied (or risk-neutral) measure $\mathbb{Q}$ [3]. A frequently used approach for the second, third and fourth implied-moment risk has been established by Bakshi et al. (2003), also known as the BKM approach. The challenging question was to define a g-function that perfectly aggregates to the contingent claim price or implied measure of the third-moment risk. Neuberger (2012) introduced a g-function that perfectly matches the third-moment risk of log returns that has the AP and therefore can be priced at any desired frequency and is also robust to jump processes.

Under the following circumstances, it is assumed that the market is arbitrage-free and without frictions, and that calls and puts are available for any strike price K.[4] All prices are in USD terms, with i and i^f denoting the USD and foreign short term interest rates, respectively. There are also forwards and bonds available, where the prices are denoted as $F_{t,T}$, and $B_{t,T}$ respectively, subscripted with its initiation date t and maturity date T. The forward price is defined as $F_{t,T} = S_t\, e^{(i-i^f)(T-t)}$ and the USD zero coupon bond $B_{t,T}$ equals $e^{-i(T-t)}$. The forward log return is defined as $r_{t,T} = ln(F_{T,T} / F_{t,T})$.[5] [6] Call and put options will be priced according to Garman and Kohlhagen (1983) proposed option price formula, denoted as $C_{t,T}(K)$ and $P_{t,T}(K)$ respectively, with strike price K in parentheses and the same time subscripts.

[3] The theory of pricing contingent claims with static option positions was primarily developed by Breeden and Litzenberger (1978).
[4] It is assumed that the stochastic spot price process S_t follows a standard Wiener process and therefore has the martingale property.
[5] Please be reminded that the term $F_{T,T}$ is equal to the spot exchange rate at time T, S_T.
[6] For notational convenience, the time subscript of the log return r is dropped out.

In the following sections, two newly developed variance definitions will be briefly introduced that also play a role in deriving the third-moment risk. All measures of moment risk are based on log returns of the underlying asset and have the desired AP. A thorough derivation of the proposed g-functions is well beyond of the scope of this paper, so these functions are taken as given and well-defined.[7]

Generalized Variance Measures

Besides the widely used variance definitions of squared returns or log returns, Neuberger (2012) proposes a function g^V that resembles the variance of an asset and has the AP. It is defined as $g^V(r) \equiv 2(e^r - 1 - r)$. Under the implied probability measure Q, the implied variance can be expressed as follows:

$$Ivar_{t,T}^{L} = 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}} - 1 - \ln\frac{F_{T,T}}{F_{t,T}}\right] \tag{2}$$

Neuberger (2012) uses a superscript L for the implied variance, indicating that this variance measure is the variance of a *log contract* that has a future payoff of $\mathbb{E}_t\left[lnF_{T,T}\right]$. Using the spanning approach from Bakshi and Madan (2000), the payoff from the *log contract* can be priced with a continuum of options of the underlying asset at inception time *t*. The resulting implied variance for this *log contract*, can be regarded as the fixed leg of a variance swap and is defined as follows:

$$Ivar_{t,T}^{L} = \frac{2}{B_{t,T}}\left(\int_{0}^{F_{t,T}} \frac{P_{t,T}(K)}{K^2}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{K^2}dK\right) \tag{3}$$

This is the same model-free implied variance that has been used from Britten-Jones and Neuberger (2000). The measure of implied variance is priced with an option portfolio consisting of positive put and call-weights that subsequently decreases with higher strike prices. Its corresponding realized or floating leg also follows from g^V and since it has the AP, it can be computed on arbitrary frequency:

$$Rvar_{t,T}^{L} = \sum_{i=t}^{T}\left[2\left(\frac{F_{i+1,T}}{F_{i,T}} - 1 - ln\frac{F_{i+1,T}}{F_{i,T}}\right)\right] \tag{4}$$

[7] Especially Proposition 2 in Neuberger (2012) is recommended for a more thorough derivation of g-functions that approximate the second or third moment risk of log returns and their corresponding proofs in Appendix.

Besides the variance of this *log contract*, another variance measure is important with regard to the construction of a third-moment swap. This variance measure is called the variance of an *entropy contract*. This contract has a future payoff of $\mathbb{E}_t\left[F_{T,T} ln F_{T,T}\right]$ and its corresponding implied variance is defined as follows:

$$Ivar_{t,T}^{E} = 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}} - \frac{F_{T,T}}{F_{t,T}} + 1\right] \tag{5}$$

Using again the spanning approach from Bakshi and Madan (2000), the fair price at time t can be computed as follows:

$$Ivar_{t,T}^{E} = 2\left(\int_0^{F_t}\frac{P_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK + \int_{F_t}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK\right) \tag{6}$$

In the following paragraphs, one can see how the variance of the *entropy contract* will emerge into the third-moment of risk.[8]

Third-Moment Swap Definition

Neuberger (2012) shows how a third-moment swap or skew swap can be designed so that the implied and realized parts perfectly aggregate to each other. He considered a twice-differentiable function g^{ThM} that has the AP and approximates the third-moment of log returns.[9]

$$g^{ThM}(\delta Ivar^{E}, r) \equiv 3\,\delta Ivar^{E}(e^{r} - 1) + M(r) \tag{7}$$

$$with \quad M(r) = 6(2 - 2e^{r} + r + re^{r})$$

Considering g^{ThM} under risk neutral expectations, one will get the implied measure for the third moment risk:

$$Ithm_{t,T} = E_t^{\mathbb{Q}}\left[3\delta Ivar_{t,T}^{E}\left(\frac{F_{T,T}}{F_{t,T}} - 1\right) + 6\left(2 - 2\frac{F_{T,T}}{F_{t,T}} + ln\frac{F_{T,T}}{F_{t,T}} + \frac{F_{T,T}}{F_{t,T}}ln\frac{F_{T,T}}{F_{t,T}}\right)\right] \tag{8}$$

Since the underlying process is martingale, the first term in (8) is zero in expectation and only the second term *M(r)* becomes relevant for pricing the implied measure. Recalling the

[8] Appendix A. 1 provides a more complete derivation of how the implied variance measures of the *log* and *entropy contract* can be transformed to the resulting option price strips.
[9] $\delta Ivar^{E}$ means the simple first difference of the implied variance of the entropy contract and can therefore be written as $Ivar_{T,T}^{E} - Ivar_{t,T}^{E}$.

generalized variance definitions of the *log* and *entropy contract* (see (2) and (5)) the implied third moment of log returns can also be expressed as follows: [10]

$$Ithm_{t,T} = 3\left(Ivar_{t,T}^{E} - Ivar_{t,T}^{L}\right) \tag{9}$$

If we now substitute equations (3) and (6) into (9),[11] one can see how the implied third moment can be priced with a continuum of options of the underlying asset at inception time t:

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_{F_{t,T}}^{\infty} \frac{(K - F_{t,T})}{K^2\, F_{t,T}} C_{t,T}(K)dK - \int_{0}^{F_{t,T}} \frac{(F_{t,T} - K)}{K^2\, F_{t,T}} P_{t,T}(K)dK\right) \tag{10}$$

We see that the fixed leg *Ithm* is comprised of a portfolio of options that are long OTM calls and short OTM puts using the appropriate scaling factors. When the implied distribution function resembles a Gaussian distribution, the value of the fixed leg will be zero (as in the Black-Scholes world).[12]

The corresponding floating leg or the realized third moment is indeed also derived from the g^{ThM}–function and is derived, given a partition length *j,* as follows:

$$Rthm_{t,T} = \sum_{j=t}^{T}\left[3\delta Ivar_{j,T}^{E}\left(\frac{F_{j+1,T}}{F_{j,T}} - 1\right) + 6(2 - 2\frac{F_{j+1,T}}{F_{j,T}} + ln\frac{F_{j+1,T}}{F_{j,T}} + \frac{F_{j+1,T}}{F_{j,T}}ln\frac{F_{j+1,T}}{F_{j,T}})\right] \tag{11}$$

The first term contains the covariation between the change of the implied variance of the *entropy contract* and the simple return, also known as the leverage effect[13]. The second term (or *M(r)*-term) is an unconventional expression of cubed returns.[14] If we now reconsider the AP in equation (1) and replace g with g^{ThM}, and likewise label its left hand side term as the true third-moment risk, obtained from the price change over the entire period (or low frequency), then *Rthm* can be seen as an unbiased estimate of this true third-moment risk, given the price and variance process is martingale. Some further conclusions can be made as well. First, the skew in high-frequency returns (*M(r)* in (11)) can only partly explain the true third-moment risk. Second, if the mesh of the partition *j* converges to zero, the leverage effect becomes the

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[10] Please check Appendix A. 3 a) for closer inspection.
[11] This will be shown in Appendix A. 3 b) in more detail.
[12] In practice it is not possible to trade a continuum of options, therefore it is shown in Appendix A. 2 how to construct a finite set of options to approximate the second or third implied moment risk.
[13] The leverage effect was first documented by Black (1976) and is described as the inverse relation of volatility and financial leverage. If firm value plunges in times of turmoil, the stock price volatility rises due to increased leverage of the firm, assuming no change in firm's debt. This leverage is accounted for in practical option pricing applications like the stochastic volatility model proposed from Heston (1993).
[14] In Appendix A. 4 a Taylor series expansion for M(r) is considered to show that it is equal to cubed log returns up to the third order term.

only part that explains the true third-moment. Third, if the true third-moment is priced under the implied measure $\mathbb{Q}$, as it is done in (10), one can use *Ithm* and *Rthm* to perfectly replicate a skew-swap portfolio, or use the difference of both to detect risk premium associated with third moment risk. Formerly, proposed skew-swap contracts that pay the sum of cubed daily returns, e.g. Schoutens (2005), indeed were able to capture the third moment by pricing cubed returns, but failing to capture the leverage effect.

When the above fixed leg *Ithm* is scaled by the implied variance $Ivar^L$ to the power of 3/2, one can get an implied skew coefficient (or implied skewness), which is comparable to the conventional measure of skewness and therefore can be easily interpreted.[15]

$$Iskew_{t,T} = \frac{Ithm_{t,T}}{{Ivar_{t,T}^{L}}^{3/2}} \tag{12}$$

For the realized part, *Rthm* is scaled with the corresponding measure of variance $Rvar^L$ to the power of 3/2, which represents the realized skewness of the return distribution.

$$Rskew_{t,T} = \frac{Rthm_{t,T}}{{Rvar_{t,T}^{L}}^{3/2}}. \tag{13}$$

Why not use the more obvious third-moment definition with the g-function $g(r) = r^3$? Kozhan et al. (2013) point out that it is indeed possible to create a feasible skew-swap using this g-function. While they did not find significant differences of a *cubic swap,* when analyzing the moments of the S&P equity index, the corresponding definitions lack some appealing properties. The replicating options portfolio of a cubic swap $Ithm^{cubic}$ for instance, is short OTM puts and long OTM calls and again short OTM calls for high strikes. Also, the realized leg $Rthm^{cubic}$ captures only the leverage effect and does not contain cubed returns.[16]

3 Data and Variables

All my exchange rate data consists of spot and 1-month forward bid-ask prices taken from WM/Reuters (WMR) fixings, are quoted against USD, and cover 30 different exchange rates. The spot and forward exchange rates are defined as USD per foreign currency unit, where an appreciation of the rate translates into a USD depreciation. Also, 1-month interest rates are

[15] The terms third moment and skew are used interchangeably throughout this paper. Also skew coefficient and skewness have got the same meaning.

[16] To conserve space, Appendix A.5 gives a brief overview of the definition of the implied and realized leg of a cubic swap contract. Additionally, all upcoming panel regressions including *Iskew* and *Rskew* values have been robustness checked with $Iskew^{cubic}$ and $Rskew^{cubic}$. All regression results are qualitatively the same.

needed in order to compute the volatility smile function. Therefore, 1-month interbank offered rates (LIBOR) are primarily used, or if not available in Datastream, the database of the particular central bank's homepage has been accessed. In cases of absolute non-availability of interbank rates, the foreign currency interest rate is approximated with a forward implied rate. This can be computed using the covered interest rate parity (CIP) $f_{t,T} = s_t + i^f - i$, where f and s apply to the log price of spot and forward rates respectively, while i^f and i refer to the foreign and domestic interest rates.[17]

Two different samples are used in this paper. *Sample I* covers all 30 exchange rates with varying inception dates, starting from September 2003 until October 2013. *Sample II* is a subsample and it is restricted to the availability of futures and option data provided by the *U.S. Commodity Futures Trading Commission (CFTC),* which will be introduced in the following section. It covers the period from June 2006 to February 2014. Both samples are calculated on a monthly frequency with end-of-month data points. Since the relevant data in the *Traders in Financial Futures (*TFF) report is available at a weekly frequency, the last week report will be interpreted as end-of-month observation for *Sample II*. Table 1 presents the various foreign exchange rates and their respective data coverage.

[*Insert Table 1 about here.*]

In order to rebuild volatility smiles and recover call and put market prices with the proposed simplified parabolic interpolation model developed from Reiswich and Wystup (2012), three volatility input parameters are needed. That is the 25-delta butterfly, the 25-delta risk reversal and at-the-money (ATM) volatility mid quote. Furthermore, the use of bid-ask quotes makes it possible to incorporate transaction costs for the last section's trading strategy. All European style option quotes for 30 foreign currencies against the USD are obtained from Bloomberg in daily frequency.

Traders in Financial Futures (TFF) Report Data

The CFTC offers weekly data in a futures-only or futures-and-options TFF report to the public. In the futures-only report, they separately aggregate the amount of all future long, short, or spread positions for five different trader categories. Additionally, the futures-and-options

[17] This procedure has been used for the Slovakian koruna (SKK) from January 2009 to October 2013, the Turkish lira (TRY) from December 2005 until June 2006 and the South Korean won (KRW) from September 2003 to June 2004.

report takes the options market risk (or delta risk) into account by simply computing future equivalents for each option positions. This means that a long ATM put option with a delta of around -0.50 is viewed as half a future short position.

The TFF report distinguishes between the following five trader categories: *Dealer intermediary, Asset Manager/Institutional*, *Leveraged Funds*, *Other Reportables* and *Non-Reportables*. To adopt the traditional view of a market microstructure within financial marketplaces, the groups can be further divided into the *sell-side* and *buy-side*. This does not mean that one of them only buys or sells futures. However, sell-side participants, in this case the dealer intermediary group, are typically traders that sell financial products to their clients and simultaneously hedge the position in the market. Their primary interest is not building huge risky positions, but earning a commission fee from customers. Therefore, the dealer intermediary group will be denominated as *hedgers* in the following sections. The other four trader categories are assumed to belong to the buying side of the marketplace. They are deemed to be clients of the sell side and should provide risk capital, or in this particular case, futures and option positions. They will be denoted as arbitrageurs in the following sections, since their primarily intent to trade is to invest, speculate or just to manage risk of their primary holdings.

Market Pressure Variables

One main purpose of this paper is to find evidence that options or future-implied demands lead to the obscure disconnection of the realized and implied skew within currency markets. Ruf (2012) has shown that for the commodity market, using option demand pressure multiples, which imitates the current net positioning of hedgers or arbitrageurs, has power to influence the shape of the volatility smile. Therefore, this paper adopts his definitions of market pressure variables to show whether his findings are also applicable to the currency market.

The theory of hedging pressure in future markets is not new and dates back to at least Keynes (1930). He examined the futures commodity market, where a typical producer of a commodity is a natural seller of futures. The futures market for producers serves as an instrument for hedging future price risks posed by the underlying commodity. For instance, Bessembinder (1992) analysed determinants for future premiums in the commodity and financial futures market that consists of five different currency futures,[18] using net holdings of hedgers as a demonstrative variable. These net holdings simply represent the difference of all net short positions to net long positions published from the CFTC. He detected significant predictive

[18] He considered CFTC future data of the Canadian dollar, British pound, Japanese yen, German mark and Swiss franc all quoted against the US dollar with a sample period from 06/1972 to 12/1989.

power for currency future returns after controlling for systematic risk. More recently, De Roon et al. (2000) also used net future holdings of hedgers, but scaled by the total number of futures at risk and confirmed the results for the same currency future markets.

Futures and Options Demand Pressure

For the empirical investigation, the paper will make use of the definitions assigned by Ruf (2012), who defined pressure variables for the buy and sell-side traders respectively and also distinguished between futures and options-only variables within each group. While TFF reports do not provide information of pure option-only positions, this information has been extracted out of both available reports to construct an option-demand variable. The two pressure variables for the hedgers group are defined as follows:

$$HPF_{i,t} = \frac{short\ futures^{Hedgers} - long\ futures^{Hedgers}}{short\ futures^{Hedgers} + long\ futures^{Hedgers}} \tag{14}$$

$$HPO_{i,t} = \frac{short\ option\ \Delta^{Hedgers} - long\ option\ \Delta^{Hedgers}}{short\ option\ \Delta^{Hedgers} + long\ option\ \Delta^{Hedgers}} \tag{15}$$

The pressure variable HPF (HPO) gives an indication to what extent hedgers, as a group, are exposed (at time *t* of currency *i*) to net short or long future (option delta) holdings, relative to the sum of all their positions at risk. A more pronounced, positive multiple would indicate that hedgers are less exposed to currency risk, since short future positions would cover their losses from foreign currency holdings.

In the same manner, the ratios for the group of arbitrageurs are designed. Again, the positions of arbitrageurs are comprised of the four remaining trader groups denoted as *n*. Please note that now a positive value refers to *net* long future/option Δ positions of arbitrageurs, compared to hedger pressure variables.

$$ACF_{i,t} = \frac{\sum_n long\ futures - \sum_n short\ futures}{\sum_n long\ futures + \sum_n short\ futures} \tag{16}$$

$$ACO_{i,t} = \frac{\sum_n long\ option\ \Delta - \sum_n short\ option\ \Delta}{\sum_n long\ option\ \Delta + \sum_n short\ option\ \Delta} \tag{17}$$

An extreme positive or even negative value would indicate that arbitrageurs are highly exposed to one side of the market and their ability for bearing risk is probably restricted.[19] As a consequence, arbitrageurs are likely to provide more risk capital, claiming higher risk provisions.[20]

Long and Short Trader Concentration

The TFF report also publishes concentration ratios, which is defined as the overall long or short futures position in currency *i* among the eight largest traders *j*, independent of their traders group category. The concentration ratio at time *t* is simply the percentage of long (or short) future positions at risk of the top eight traders, relative to the whole futures open interest (OI_{fut}). The long (short) concentration ratio will be denoted as CR8LF (CR8SF) and is defined as follows:

$$CR8L(S)F_{i,t} = \frac{\sum_{j=1}^{j \in Top\ 8} long(short)\ futures_j}{OI_{fut,i,t}} \tag{18}$$

These concentration ratios can be interpreted as another proxy for nearing capital constraints, as long as the traders belong to the arbitrageurs group. On the other hand, if high concentration comes due to highly exposed individual hedgers, an unexpected economic shock could lead to extraordinary demand for insurance and therefore, may increase risk in the form of more negative *Iskew*.

Liquidity and Volatility Risk Factors

In this subsection, the influence of liquidity risk variables on skewness will be investigated in more detail, based on the theoretical framework from Brunnermeier and Pedersen (2009). They showed that funding liquidity and market liquidity variables are mutually reinforcing and can lead to "liquidity spirals". In an empirical investigation, Brunnermeier et al. (2009) found evidence that the TED spread, as an indicator of illiquidity, is indeed positively related to currency crashes (negative skewness), which supported their precedent suggestions.

In the light of these findings, this paper follows the definitions in Asness et al. (2013) who considered shocks to the following three US funding liquidity variables: (i) the Treasury-

[19] A quite similar ratio has been used in the study from Brunnermeier et al. (2009). They analysed crash risk inherent in the carry trade strategy and considered the same group as representative agents for speculative capital in FX markets. In contrast, their denominator consisted of the total open interest of all future positions from the sell-side trader groups.

[20] As a robustness check, the variables ACF^{Lev} and ACO^{Lev} have been considered, which take only the *leveraged trader* group as arbitrageurs into account. The resulting regression results are qualitatively the same.

Eurodollar (*TED*) spread that is the 3-month (3m) T-Bill rate minus 3m LIBOR, (ii) the spread between the 10y-Constant-Maturity Swap rate and the 3m T-Bill rate (*SwTB*), and (iii) the 3m LIBOR minus 3m Repo spread (*LiRe*). Additionally, shocks to the average bid-ask spread, aggregated over 30 different exchange rates (*BAS30*) have been considered as a market liquidity risk measure.[21] Higher bid-ask spreads are an indication of less market activity and therefore should reflect the state of market illiquidity. Asness et al. (2013) defined liquidity shocks as residuals taken from an AR(2)-model. [22] [23] All variables are end-of-month observations and signed that higher values reflect illiquidity.

Furthermore, a reasonable source for crash risk is the overall state of investor's risk aversion. While it is quite hard to find appropriate measures, a frequently used proxy is the S&P 500 option implied VIX index. In the study of Brunnermeier et al. (2009), they found that increasing VIX levels coincided with reduced speculative capital in investment currencies, which in turn resulted in increased crash risk. In order to consider a more currency-related measure of risk aversion, the innovations in global FX volatility (u_Vola^{MSSS}) developed from Menkhoff et al. (2012a) are rebuilt using all *Sample II* currencies. Menkhoff et al. (2012a) found that these innovations capture more than 90% of the cross-sectional excess returns from five different carry-trade portfolios.

In addition to these two risk aversion variables, an aggregated FX implied variance measure (*Ivar30*) that represents the simple average of all 30 *Sample I* currencies is used. The *Ivar30* aggregates the implied variance of the log contracts for each exchange rate as has been defined in (3). Because it was intended to measure the effects of changing risk aversion rather than its level, first differences of the VIX index (*dVIX*) and innovations taken from an AR(2)-model for the *Ivar30* are considered (*u_Ivar30*).

Value and Momentum Factors

Several recent studies have emphasized the effects of momentum and value effects on cross-sectional asset returns. For instance, Asness et al. (2013) studied the momentum and value effect across different asset classes including exchange rates. Their key results suggest that value and momentum portfolio returns across a variety of assets can explain returns to a single class of momentum and value returns. This points to the possibility that value and momentum

[21] The definition follows from Menkhoff et al. (2012a), who aggregated daily relative bid-ask spreads over 48 different currency pairs against the USD.
[22] The methodology is broadly taken from Korajczyk and Sadka (2008) who studied alternative liquidity risk measures.
[23] As a robustness check, residuals taken from AR(1) and AR(3) have been used as liquidity shock variables but the regression results were qualitatively the same.

factors across assets share a common global risk. Moreover, Menkhoff et al. (2012b) have examined cross-sectional currency momentum portfolios that carry surprisingly high excess returns that cannot be explained by traditional risk factors.

In order to review how these factors could potentially affect the measures of skewness, two different momentum horizons for each currency are considered. Both are the past 3- and 6-month cumulative forward returns on each currency. By defining a value factor for each currency, the negative sum of 5-year past forward returns are used, following the approach of Asness et al. (2013). Hence, without being inclined to prefer any specific exchange rate model, the resulting value factor can be interpreted as the five-year deviation from uncovered interest rate parity (UIP)[24] - a positive (negative) value factor translates into an undervaluation (overvaluation) of the respective foreign currency.

Control Variables

Nine different control variables will be used in each panel regression in order to make the results more reliable. Macroeconomic fundamentals have a long tradition in exchange rate determination, dating back to Frenkel (1976) and the monetary model. In a recently published study, Menkhoff et al. (2013) have shown, through a cross-sectional portfolio approach, that macro fundamentals are indeed informative about future excess returns. Four different US macroeconomic variables that are reasonable candidates for potential sources of currency risk to the representative US investor are taken into account: (i) real industrial production growth, (ii) real money (M1) growth (iii) CPI inflation and (iv) log changes of the ISM Manufacturing Index, which is the most important leading indicator of the US economy. The first two variables are deflated using the corresponding CPI index.[25]

Additionally, adjustments for the possibility that equity-related shocks carry over to currency markets are made. From the perspective of a representative US investor these sources of risk could potentially cause portfolio reallocations that are not only restricted to equity risk itself, but are likely to include implicit or explicit foreign exchange risk exposure. While the overall results of close connections between currency and equity markets are relatively thin, Christiansen et al. (2011) found that currency portfolio returns are indeed closely connected to

[24] In the equity literature it is common to use the traditional book-to-market ratio as an indication of how firms equity is priced in relation to its stock market price. Since there is no such objective balance sheet item for currencies that could be used as an indication for its real intrinsic value, Asness et al. (2013) referred to the findings of Fama and French (1996) who showed that equity portfolios sorted on 5 year lagged returns are very similar to those sorting by book-to-market values.

[25] There are macroeconomic variables that are only available in quarterly frequency. These values have been transformed to monthly observations using the cubic spline approach. This was true for AUD, HKD, NZD, and CHF for real production; AUD and NZD for CPI inflation rates and finally for AUD real money growth.

the S&P 500 Index and bond market returns - particularly within high volatility regimes, or to put it differently, the states of investors' high risk aversion. In order to account for a possible relationship from equity driven effects to currency return skewness, three systematic risk factors from Fama and French (1992), augmented by the US stock momentum factor (UMD) were used.

Last but not least, the six-month log change of open interest (*dOI*) taken from the futures-and-options report will be taken into consideration in order to adjust for possible price effects resulting from new capital flows from hedgers or arbitrageurs.[26]

4 Empirical Results

As outlined in the introduction, the aim of this paper is to find an answer to the obscure finding that *Iskew* and future *Rskew* are not positively related to each other. While this constellation is not plausible within a no-arbitrage framework, one should ask how and why this relationship arises in practice. Ruf (2012) answered this question with an option demand based explanation, where he found in the commodity market that option prices, and in this respect the whole option volatility smile, was influenced by net option positions of arbitrageurs who claimed a risk premium whenever they were confronted with extreme net short or long option exposure. This has led to option risk premiums, and therefore to shifts of the implied volatility skew which results in the observed disconnection of *Iskew* and future *Rskew*. If this is also true for the *Sample I* currencies, one should find out whether a statistical significant *SRP* exists. As noted at the beginning, *SRP* is defined as the difference between *Rskew* and *Iskew* and should be positive in markets where investors are willing to pay significant premiums to be insured against foreign currency crashes. The reason for analysing skewness coefficients instead of the third-moment measures *Rthm* and *Ithm,* lies in their very different distributional properties. While *Rskew* and *Iskew* closely resemble a Gaussian distribution respectively, there third-moment counterparts R*thm* and *Ithm* are heavily skewed and have got extreme fat-tailed distributions. Therefore, to prevent all regression results for being dictated by outliers, the skew coefficients instead of the third-moment variables are preferred.[27]

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[26] To clearly present results, any coefficient of control variables will be omitted, but the most important effects will be briefly discussed at the end of the empirical section.

[27] Be reminded, that the skew swap definitions in section 2 purely rely on the relationship between *Rthm* and *Ithm*. Also, the Aggregation Property according to Neuberger (2012) is only strictly true for the measures of realized and implied third moment, and is not directly applicable to the skewness coefficients. However, the skewness coefficients as a standardized third moment measure are supposed to exhibit comparable relations.

Table 2 gives an overview of the cross-sectional evidence on the *SRP* observed for *Sample I* currencies that are additionally divided into 10 developed and 20 emerging market currencies.

[*Insert Table 2 about here*.]

The results suggest that crash risk in foreign currencies, relative to the USD, is significantly priced for the majority of currencies. There are 20 significantly positive values at least at the 10% level and only 3 negative exceptions.[28] The 2 significantly negative currencies are the Japanese yen and the Hong Kong dollar (HKD). Both significant negative *SRP* values suggest that these currencies are seen as so-called safe havens, relative to the USD in times of market turmoil. Ranaldo and Söderlind (2010) find empirical support for the traditional idea that some currencies consist of *safe haven* attributes, e.g. appreciation in high volatility or market illiquidity states. While the HKD was not considered in their study, maybe because of the currency peg to the USD, the yen appeared to have the strongest safe haven currency attributes, a fact that can once more be confirmed in terms of the negative *SRP* value. The HKD has higher positive *Rskew* values on average than the USD, followed by an even higher *Iskew* value. It is the same picture with the yen and therefore, understandably results in a negative *SRP*. Ranaldo and Söderlind (2010) also state that the mirror image to safe haven currencies are the so-called investment currencies that are characterized as high-interest rate currencies. This conclusion can also be confirmed with results in Table 2, where 14 currencies out of 20 significantly positive *SRP*'s have higher than average forward discount values.

The next question is whether *Iskew* can forecast future *Rskew,* or how the two are connected to each other in the time-series. This question is closely connected to the question of whether or not the skewness of the option-implied distribution is positively related to the skewness of the future realized distribution. One would assume that this is true in any financial marketplace – otherwise, arbitrage opportunities would arise. To answer this question for *Sample I* currencies, the following simple regression will be conducted:

$$Rskew_{t:t+1} = \alpha + \beta \; Iskew_t + \varepsilon_t \qquad (19)$$

The regression results are summarized in Table 3 below. While the joint hypothesis test confirms the occurrence of a significant *SRP*, which in turn agrees with the results from Table

[28] The same regressions were run excluding the turmoil period between 31/07/2008-30/06/2009 in order to test whether the *SRP* is a result of periods with high market volatility. This assumption can be rejected since the test regressions are very similar to those of Table 2.

2, the results for the ß coefficient appear to be important. One can observe that in the majority of cases, *Iskew* is not able to forecast future *Rskew.* To put it differently, the variations in the time-series of *Iskew* do not sufficiently resemble the variation in *Rskew*. This is not surprising, since one can show that *Rskew* standard deviations are on average five times higher. Moreover, it is visible that nearly half of all *ß*'s are on average negative (in 13 out of 30 cases). This confirms the findings of Jurek (2014) and Brunnermeier et al. (2009) that both measures on average exhibit an even negative relation (only statistically significant for the Thai baht). Furthermore, one can only observe that *Iskew* accurately forecasts future *Rskew* for the two foreign currencies Russian rubel (RUB) and Malaysian ringgit (MYR). The inference on the intercept α is for the most part, insignificantly different from zero, with only seven exceptions. The overall results confirm the notion that *Iskew* and *Rskew* are loosely connected to each other in the time-series and sometimes exhibit a negative relation.[29]

[*Insert* Table 3 *about here.*]

In the light of findings from Ruf (2012) for the commodity market, this paper raises the hypothesis that the DS arises especially due to market positionings of hedgers and/or arbitrageurs that especially influence the shape of the implied volatility curve. From the perspective of hedgers, the option market can be seen as a market instrument to buy insurance against possible market crashes. On the other hand, arbitrageurs are considered to be providers of insurance or risk capital, since they are supposed to be the natural counterpart of the demand from hedgers needs.

In order to examine whether option price changes are due to changing beliefs or risk premium, remarks from Bates (2003) about the price of earthquake insurance are useful. He states that there are three main reasons why the prices of insurance may change. Either, (i) the expectation about future appearance of earthquakes has changed, (ii) the customers have become more risk-averse about earthquake risk and therefore demand more insurance, or (iii) the risk capacity of insurers is constrained taking additional risk exposure. Translating it into the context of the option market and its implied volatility curve, one can state that the option skew is expected to change, if (i) the physical distribution of future returns is going to change,

[29] As a robustness check, the same regressions have also been run with the third-moment measures, *Rthm* and *Ithm*. In order to dampen the fat-tailed distribution, the extreme data points at the 2.5%, 5% and 10% levels were winsorized respectively. Furthermore, residuals were bootstrapped with 10'000 replications to get more reliable and conservative estimations of standard errors. The used inference is based on the students-t distribution with the appropriate degree of freedoms. The overall results are comparable to Table 3.

(ii) hedgers may become more risk-averse about their current risk positions, or (iii) the risk capacity of arbitrageurs is nearing constraints. In the forthcoming analysis, these three possibilities will be referred to as scenarios 1-3.

The econometric analysis will make use of the multivariate fixed-effects (within) panel regression model, with up to eight currency units from *Sample II*. In order to properly handle unbalanced panels, autocorrelation and the heteroskedasticity structures of the financial market variables, the use of the econometric panel regression tool **xtscc** is required. The econometric tool was developed by Hoechle (2007) and is implemented in STATA. It uses a nonparametric covariance matrix estimator, proposed by Driscoll and Kraay (1998), that produces heteroskedastic- and autocorrelation-consistent (HAC) standard errors that are additionally robust to general forms of spatial (cross-sectional) and temporal dependence. In order to identify cross-sectional dependence among the error terms in the panel regressions, the test proposed by Pesaran (2004) has been used. It turns out that all of the regressions exhibit a statistically significant spatial dependence, mostly at the 1% significance level.

In order to distinguish between scenarios 1, 2 and 3, the presentation format is identical to Ruf (2012) who presented regression results on the dependent variable *Iskew* and *SRP* respectively - one upon the other. This approach has several advantageous that can be characterized as follows: The first panel represents the results from chosen regressors on *Iskew* and the second will be regressed on the *SRP*. Since the premium is the difference between realized and implied skewness, the effect of both terms will be analysed simultaneously. For instance, if *Iskew* is significantly affected by regressor X and the *SRP* is unaffected, it means that both the realized and implied variables are significantly affected at comparable magnitude by regressor X. In this case, scenario 1 applies, and one may conclude that market participants can correctly anticipate a changing future risk environment. This paper is more interested in identifying time-series patterns that can be related to scenario 2 or 3, where *Iskew* and *SRP* are contemporaneously and significantly affected by variable X. This would mean that variable X impacts *Iskew* at a much higher magnitude in contrast to *Rskew*. For example, if regressor X contains information about demand pressure from the hedgers group, the effect on the shape of the implied volatility curve could be rationalized by changing risk aversions of that group (scenario 2 applies), or on the other hand, if variable X is dedicated to the arbitrageurs group, the capacity for bearing additional risk exposure possibly nears its constraint and scenario 3 applies.

The Effects of Market Pressure

The overwhelming results from Table 3 confirm the puzzling fact that realized and implied skewness variables are not significantly and positively related, and they sometimes even exhibit negative relations. In order to shed some light into these obscure findings, this paper will try to rationalize the divergence of the measures of skewness with option and future induced demand pressure.

[*Insert Table 4 about here*.]

The first two panel regressions of Table 4 indicate that both hedging pressure on options (*HPO*) and arbitrageurs' capacity on options (*ACO*) are significantly and positively related to *Iskew*. However, the insignificant values on the premium suggest that both variables separately have a similar effect on *Rskew*, and this result will be assigned to scenario 1, where the physical and implied distribution of future returns is not significantly different. Now, conducting the equivalent market pressure variables on futures (*HPF* and *ACF*) in regressions three and four will reveal a surprising result. Both variables are significantly and positively related to *Iskew* at a comparable magnitude, and even more significantly negatively related to the premium. This result suggests that scenarios 2 and 3 can be respectively applied to the regression results. Moreover, the absolute coefficient values on *SRP* are much higher, compared to the coefficients in panel A. This implies that the impact of net future exposure of hedgers and arbitrageurs is positive for *Iskew*, whereas the impact on *Rskew* is contemporaneously negative. To shed some more light into this finding, regressions five and six divide *ACF* and *HPF* into their positive and negative values, respectively. In regression five, one can observe that the coefficient on *ACF(+)* is significantly and positively related to *Iskew*, whereas it is not different from zero for the premium. This again means that in states of future net long holdings of arbitrageurs, options are accurately priced with regard to future *Rskew*. For the case of *ACF(-),* the coefficient is not different from zero for *Iskew*, but significantly negative on the premium. This means that in states of future net short holdings of arbitrageurs, option prices do not accurately forecast positive future *Rskew*. One would expect a coefficient of about -0.4 on *ACF(-)* in panel A in order to correctly account for positive future *Rskew*. Therefore, the findings in regression three are mostly driven by incorrect option pricings in states of net future short holdings of arbitrageurs. This leads to relatively cheap call and expensive put prices at time t, with a conversely positive future *Rskew*. It seems like arbitrageurs on average incorrectly adjust option prices whenever they are exposed to net future short holdings. This result is quite puzzling and an explanation in terms of scenario 3 is difficult to justify.

Now turning to regression six, one can see that in panel A the coefficient on *HPF(+)* is not different from zero, whereas it is significantly negative for the premium in panel B. A similar conclusion is applicable in the case of *ACF(-).* Whenever hedgers are exposed to net future short holdings, they may profit from relatively cheap put prices for hedging purposes. The more negative coefficient of -0.187 in panel B compared to panel A, implicitly assumes that future *Rskew* is on average negative. This result is applicable to Jurek's (2014)finding that hedging is especially cheap when the probability of a crash is highest. One reasonable explanation for this fact with regard to *HPF(+)* could be that hedgers primarily reduce their risk with currency futures. This could result in a low overall demand for put options as hedging instruments and it may therefore cause an option volatility curve that is too positively skewed. The regressions with *HPF(-)* can be attributed to scenario 1, where a significantly positive relation to *Iskew* is approximately similar in magnitude of future *Rskew*, which leads to a *SRP* value insignificant from zero.

Finally, the last two regressions use a squared term on *ACF* and *HPF*, compared to regressions three and four to check for nonlinear effects. Regarding the results from the linear terms in panel A, one can observe that positive significance is similar in magnitude to the regression without squared terms. Looking at the squared terms in panel A, only HPF^2 exhibits a significantly negative relationship to *Iskew*. In panel B, both regressions show insignificant values on the premium, which suggests that squared terms similarly affect *Iskew* and future *Rskew* values. Taking the results of the last two regressions together, one can conclude that the DS is overall linear in *ACF* and *HPF*.

One big difference to the Ruf (2012) results for the commodity market is that the impact of *ACO* and *HPO* on the *SRP* leads to the DS, whereas *ACF* and *HPF* values in the currency market seem to have more power to explain the market anomaly. The reason for the low impact of *ACO* and *HPO* on *SRP* in the currency market could be the low trading volume. Since there is no daily trading volume available, the open interest on options relative to futures should be a good proxy. The upper chart of Figure 1 presents a time series of futures and options open interest (OI) aggregated over the 8 *Panel II* currencies. It reveals that the overall options OI is relatively small and seemingly unrelated to futures OI over the timespan. This fact is confirmed by the lower chart of Figure 1, which presents time-series averages of futures and options OI respectively for each of the 8 currencies in billion USD. While the average share of options OI compared to futures OI over all currencies reaches only 15%, it also substantially varies in the cross-section, with 24% as the highest share for the EUR/USD option market until 8% for the CHF/USD. Meanwhile, the markets for the Mexican peso and New Zealand dollar are almost non-existent. Low trading activity applies pressure to the variables *ACO* and *HPO*, which are more prone to noisy effects. This is likely to be the reason why one cannot find any direct significant relation of option demand pressure variables to *Iskew* or *SRP*.

[*Insert Figure 1 about here.*]

Effects of Liquidity and Volatility Risk Factors on Skewness

Given the strong results that *HCF* and *ACF* have on skewness, this subsection will now examine whether "liquidity spirals", as outlined in Brunnermeier and Pedersen (2009), or volatility innovations can contribute to the DS. Additionally, in order to account for "flight-to-quality effects" or "safe-haven" properties that have been explicitly investigated by Ranaldo and Söderlind (2010)[30], every liquidity or volatility innovation have been signed by their forward discount value of each of the 8 *Sample II* currencies, respectively. Also, an interaction term between *HPF* and the innovation under consideration is included, in order to find out whether innovations amplify the already strong effect of *HPF* on skewness.

[*Insert Table 5 about here.*]

The first four regressions in Table 5 present the results of the impact of *HPF,* together with various liquidity variables on the measures of skewness. One can only observe significantly negative effects for the *Libor-Repo* and the well-known *TED* spread on *Iskew*. These effects however, do not translate into the premium, so *Rskew* is similarly affected as *Iskew*. In the case of the *Swap-TBill* spread, the pattern is different. While it has no effect on *Iskew*, it significantly affects the *SRP* at the 10% level. Since the coefficient of the *Swap-TBill* spread on the premium is higher in absolute terms, it means that future *Rskew* is negatively affected while *Iskew* exhibits an insignificantly positive relation. Therefore, one can conclude that liquidity variables in terms of the *Swap-TBill* spread possibly contribute to the DS. Also, the interaction terms do not exhibit a significant relationship to *Iskew* or the *SRP*. Therefore, one cannot confirm a clearly amplified picture of liquidity risk based on the imbalance of implied and realized skewness.

The next three regressions examine the effects of volatility on the measures of skewness. It starts with considering (i) first differences of the VIX index (*dVIX*), (ii) innovations in global

[30] They found that especially in turbulent market states, low yielding currencies like the Japanese yen on average appreciated, while the opposite is true for high yielding currencies.

FX volatility (*u_Vola*^{MSSS}), and (iii) innovations of the aggregated implied volatility index (*u_Ivar30)*. All three variables exhibit strong negative effects on *Iskew*, at least at the 5% significance level. The most significant effect on *Iskew* comes from *u_Ivar30*, showing a remarkably high T-statistic of *-6.67*. Nevertheless, all volatility variables are not significantly related to the *SRP* value, so *Rskew* and *Iskew* are similarly affected on volatility changes. Also, the interaction terms are all insignificant for both variables, so no amplifying effect of volatility and *HPF* is observable.[31] One can conclude that when adding volatility and liquidity innovations to the regressions, the significance of *HPF* is in all cases remarkably stable. Furthermore, the added variables do indeed have a significant impact on *Iskew* but not on *SRP,* a fact that then can be attributed to scenario 1. By this logic, *Iskew* correctly anticipate changes in future *Rskew*, leaving the *SRP* unaffected. Only in the case of the *Swap-TBill* spread we observe a significant relationship to the *SRP* while it is insignificant on *Iskew*. This means that the implied volatility curve does not correctly price OTM option prices with regard to future *Rskew*. In states of high (low) *Swap-TBill* spread values or illiquidity (liquidity), OTM put prices are too low (high) relative to call prices, which makes insurance costs against future crashes relatively cheap (expensive).

Effects of Traders Concentration on Skewness

Market concentration ratios offer additional information about the microstructure of the marketplace. This paper will use the share from the eight biggest trader positions expressed as percentage of total open interest (see (18)). Since market concentration is independent of trader groupings, the consequence it has on *Rskew* or *Iskew* cannot be completely attributed to one of these groups. However, several conclusions can be made on whether arbitrageurs or hedgers dominate market share. On one hand, if arbitrageurs dominate market share, (i) individually high future exposure could limit their ability to take on additional positions (scenario 3), or (ii) they might exploit their market strength and be forced to offer less favorable prices. On the other hand, if only a few hedgers dominate the market, they are more exposed to cluster risk, which leads to very tight markets with escalating insurance prices - especially in times of market turmoil. However, all these possibilities would lead to the same effect.

[*Insert Table 6 about here.*]

[31] For brevity, regressions of skewness on *ACF*, liquidity and volatility variables are not reported, since the results are almost equivalent.

Table 6 starts by regressing *Iskew* and *SRP* on long and short concentration ratios (*CR8LF* and *CR8SF*) respectively. While both variables impact *Iskew* significantly in different directions, negatively for long concentration and positively for short future concentration, only *CR8LF* exhibits a strongly significant effect on *SRP*. Hence, unconditional high long future market concentration leads to a negative effect on *Iskew*. Likewise, the higher positive coefficient in absolute terms on *SRP* points to the fact that *Rskew* is controversially and positively related to high-market concentration. A similar picture can be seen in Table 4 for *ACF* and *HPF* values effecting *Iskew* and *Rskew* in positive and negative magnitude, respectively. However, in order to reveal a possible relation to market concentration and net future exposures of arbitrageurs and hedgers, *CR8LF* will be conditioned on extremely high or low values of *ACF* and *HPF* respectively. High (low) values are defined as being above (below) the 75% percentile (25% percentile) of each currency's *ACF* and *HPF* distribution. The percentage in between is defined as the mid values.[32] Therefore, regression three explores the effect of *CR8LF* when arbitrageurs are exposed to net future long ($ACF^{>Q3}$), net future short ($ACF^{<Q1}$) exposures, or values between these extremes (ACF^{mid}). It turns out that especially low or mid values exhibit a significantly negative effect on *Iskew*, while market concentration, conditional on $ACF^{<Q1}$, or net future short positions exhibit a significantly positive relation on *SRP*. A similar picture arises in regression four for the hedgers group. While all three variables have significantly negative impacts on *Iskew*, only market concentration, conditional on $HPF^{<Q1}$, or net long future exposures exhibit a significant relationship on *SRP*. Since *HPF* and *ACF* values are highly and positively correlated, it is difficult to distinguish whether the DS can be attributed to one party or the other. But the fact that long future concentrations together with net long future positions of hedgers have a significant effect on *Iskew* and *SRP*, it is likely that market concentration is due to large positions in the hands of a few positions from hedgers. A higher than normal risk exposure is then the explanation for higher risk aversion for hedgers, which appears most commonly when a market shock takes place. This is when only a few big traders simultaneously demand insurance for their positions, a situation that ultimately results in a tight option market and a high premium for OTM put options. Therefore, scenario 2 is a possible candidate for causing the DS with regard to future market concentration.

[32] Dividing the market pressure variables into equal parts, where high (low) values are defined as being the highest (lowest) 33% values of all data points and the remainder belonging to the middle part, lead to the same regression results.

Effects of Momentum and Value Factors

Now, the forthcoming analysis will try to draw conclusions for how short-term momentum or long-lasting over- or undervaluation affects skewness. As outlined in the data section, 3- and 6-month[33] currency-forward returns from each currency will be considered as momentum factors, in addition to the negative five-year deviation from UIP, where a positive (negative) value factor points to an undervalued (overvalued) foreign currency.

[*Insert* Table 7 *about here.*]

And indeed, the first two regressions of Table 7 present strong, significantly positive effects of momentum on *Iskew,* which are also very strong in magnitude on the *SRP*. The higher absolute coefficient on *SRP* points to the fact that future *Rskew* is on average negative. Regarding the higher absolute coefficient on *SRP,* data shows that momentum conversely exhibits on average a negative relation to *Rskew* and therefore even strengthens the DS. These results lead to the following conclusion: In a case where past currency momentum is unconditionally regressed on *Iskew* and *SRP* in rising (falling) markets, OTM calls (puts) are significantly more expensive as future *Rskew* would suggest on average. The most controversial point on one hand is that past momentum returns exhibit a positive relationship to *Iskew*, while on the other hand, past momentum returns implicitly exhibit a negative relationship to future *Rskew*. This pattern is absolutely not consistent with regard to the expectation hypothesis of implied and realized moment risk (see equation (1)). Therefore, past momentum returns seem to cyclically form the option implied volatility curve instead of future expectations of market participants.

The value factor in the third regression is not significantly related to *Iskew,* but it exhibits a clearly positive effect on *SRP*. As a result, undervalued (overvalued) currencies have, on average, positively (negatively) skewed future realized distributions which are not correctly priced in *Iskew,* preliminarily. In other words, the OTM call (put) prices from undervalued (overvalued) currencies are too cheap, which also lead to the DS.

Turning now to regressions four and five where squared terms are added for 3- and 6-month momentum factors respectively, in order to examine possible non-linear effects. For both momentum factors, the impact of the squared and linear term is significant for *Iskew* (only borderline significant for $RX(6m)^2$, with a p-value of 0.107). However, in panel B, only in cases of the 3-month momentum factor do both coefficients exhibit a significant relationship on *SRP*.

[33] The results on 1-month momentum returns are almost identical to 3-month forward returns, so these results were skipped for brevity.

Hence, especially strong past short-term momentum returns strengthen the abovementioned imbalance even more that exist between *Iskew* and future *Rskew*.

But what is the rationale behind this crucial disconnect between the measures of skewness in states of currency trends, in terms of scenario 2 or 3? To shed some light on this question, one can regress momentum conditional on extreme net short or long positions of arbitrageurs and hedgers respectively. Extreme *ACF* or *HPF* values are similarly defined, as in the case of the market concentration analysis in the previous table, so that they will be denoted as net short or long positions of both trader groups respectively.[34] Regression six reveals that only in times when arbitrageurs are exposed to net long future positions ($ACF^{>Q3}$), they do have a significantly positive impact on *Iskew* and *SRP*. A reasonable explanation for this pattern that is in line with scenario 3, is that the already high future long exposition of arbitrageurs in trending currency markets reduces their ability or willingness to provide additional option risk exposure. While additional short calls for arbitrageurs would mitigate their current delta long exposure, it would raise their short vega exposure (and short gamma exposure[35]). This positioning is especially unfavourable in declining market environments, where on average implied volatility rises and ultimately leads to portfolio losses. Since the first two regression results point to the fact that future *Rskew* is indeed negative in rising markets, the claim for an extra risk premium on OTM call prices seems to be plausible. In the case of negative trends and net long future positions of arbitrageurs, higher than expected OTM put prices are maybe due to past portfolio losses, which leads to tighter risk limits for arbitrageurs and higher option prices. The last regression results seem to be a mirror image of the regressions shown in column six. Here, the returns from the past three months are positively related to *Iskew*, together with extremely low or high *HPF* values. But when regressed on *SRP*, it turns out that past returns and net future short positions of hedgers lead to the DS. An explanation in terms of higher risk aversion of hedgers (scenario 2) seems to be implausible. Moreover, it is hard to distinguish between both groups of trader's positions, since the effects on *Iskew* and *SRP* are at a comparable magnitude. But summarizing the last two regressions, one can observe that the DS takes place in states of net future long positions of arbitrageurs or net future short positions of

[34] Since this analysis concentrated on extreme high or low values of *ACF* and *HPF* market pressure ratios, the coefficients of mid-term values were skipped. Nevertheless, it is important to note that all of them are also highly significant in all cases. Also regressions that are conditional on positive and negative values of *ACF* and *HPF* on market momentum have been tested, and the regression results did not change. Furthermore, *ACF* and *HPF* values change sign at the same time, so a distinction of arbitrageurs or hedgers net positions was not possible. Also market momentum conditional on *ACF* or *HPF* values were divided into equal parts, as in the last subsection, but the results did not change.

[35] Gamma is the second order derivative of the option price function with respect to underlying price changes. It measures the change in delta when the underlying moves one price unit. Short gamma positions lead to increasing long (short) delta positions when the underlying declines (rises).

hedgers together with past 3-month returns. While a higher state of risk aversion of hedgers together with net future short positions seems to be implausible, one can conclude that the arbitrageur's capacity of providing risk capital is likely to be responsible for the DS - as explained above.

To summarize the overall picture, currency momentum seems to play an important role in explaining the DS. *Iskew* is positively dependent on currency momentum, leading to higher than expected OTM call (put) option prices within rising (declining) markets. Furthermore, future *Rskew* is affected in a direction opposite to *Iskew* which strengthens the DS. The effect is even stronger the shorter the past momentum horizon is, especially because the 3-month momentum exhibits a convex dependence on *Iskew* and the *SRP*.

Impact of Control Variables on Measures of Skewness

The overall result of the impact from US macro risk, the three Fama and French factors extended by the momentum risk factor UMD (FF4) can be characterized as follows: While the FF4 factors do not impact currency crash risk significantly, there is a strong and significantly negative coefficient (T-statistics always between -6 and -5) for real production growth on *Iskew* and to somehow lower but still significant magnitude on *Rskew*. This finding can be related to results of Lustig and Verdelhan (2007) who found that the risk of US consumption growth[36] is significantly priced in the cross-section of currency portfolio sorts based on their interest rate differential. Also, Menkhoff et al. (2013) broadly confirmed that production growth is priced in the cross-section of currency portfolio sorts based on interest rate differentials and also macro based sorts. Therefore, based on above regressions it can be concluded that positive currency returns in line with higher US production growth also increase future crash risk and the price for insurance through a more negatively sloped implied volatility curve.

5 Skew Trading Strategy

The empirical section provides evidence about the disconnection of realized and implied skewness in currency markets. Panel regressions using market pressure variables on at least six currencies and other market features such as momentum and value have helped to explain this market anomaly. Since predictive regressions have been used, one can now try to exploit this market feature by simply trading a skew swap, where the price of the option implied skew is swapped against its corresponding realized skew. In section 3, we have learned how a skew

[36] It is well known that consumption growth rates are highly correlated to production growth rates, and therefore the results of one or the other can be regarded as the same source.

swap can be synthesized by constructing a portfolio of options at inception and subsequently hedging futures and options on arbitrary frequency. While future/forward trading is relatively easy to manage in terms of costs and product homogeneity, subsequent trading in various option strikes simultaneously is rather difficult to put into practice. To avoid unnecessary hedging costs, Schneider and Trojani (2015) proposed a *simple skew contract* (SSC) that is of a similar build at inception, and needs only to be subsequently hedged in the futures market and therefore makes a skew swap more tractable and less costly. It also has the desired "Aggregation Property" (AP) so that hedging can be done on arbitrary frequency.

The theoretical construction procedure and the practical application will be briefly described, followed by empirical results.

Theoretical Background

The SSC proposed by Schneider and Trojani (2015) derives the implied skew term as the difference of two measures of implied variance. The first implied variance measure is the already derived implied variance measure defined in equation (3), denoted as $Ivar^L$. It follows from the variance function: $g^V(r) \equiv 2(e^r - 1 - r)$.[37] On the other hand, the second implied variance measure, denoted as $Ivar^S$, follows from the simple squared return function: $g^S(r) = (e^r-1)^2$. Schneider and Trojani (2015) show that going long the underlying option portfolio according to $Ivar^L$ and contemporaneously selling the replication portfolio due to $Ivar^S$, will result in a portfolio that is short OTM puts and long OTM calls comparable to *Ithm* (see equation (10)) and has the desired AP according to Neuberger (2012). When looking at the differences between the associated measures of realized variance, one will see that roughly only third order effects survive. In the following paragraphs, the results from Schneider and Trojani (2015) will be presented and for a more thorough analysis the Appendix A. 6 and Appendix A. 7 are recommended.

Simple Variance Contract

As noted above, the SSC is defined as the difference of two measures of variance. Therefore, one can start by defining the contingent claim price of the simple squared return function g^S. Using the spanning approach from Bakshi and Madan (2000), the contingent claim price or the options replication portfolio can be characterized as follows (see Appendix A. 6):

[37] Recall that r is defined as the log forward return and therefore $R \equiv e^r-1$ is an expression for the simple forward return.

$$Ivar_{t,T}^{S} = \frac{2}{{F_{t,T}}^{2} B_{t,T}} \left\{ \int_{0}^{F_{t,T}} P_{t,T}(K) dK + \int_{F_{t,T}}^{\infty} C_{t,T}(K) dK \right\} \tag{20}$$

Obviously, its realized variance counterpart (or floating leg) is simply defined as

$$Rvar_{t,T}^{S} = \sum_{i=1}^{T} \left(\frac{F_{i+1,T}}{F_{i,T}} - 1 \right)^{2} = \sum_{i=1}^{T} (R_{t+i})^{2} \tag{21}$$

Simple Skew Contract (SSC) Definition

The fixed leg of the *SSC* is defined as the difference between the fixed leg of the variance swap contract $Ivar^{L}$ and the fixed leg of the simple variance contract $Ivar^{S}$.

$$Ithm_{t,T}^{S} = Ivar_{t,T}^{L} - Ivar_{t,T}^{S} \tag{22}$$

While this construction might give the impression of being rather artificial or even implausible in terms of representing a third moment, it is instructive to consider the realized leg of the SSC. Carr and Lee (2009) showed that the realized variance of squared log returns can be defined as follows (see Appendix A.7):

$$Rvar_{t,T}^{logR} = Rvar_{t,T}^{L} - \frac{1}{3} \sum_{i=0}^{N-1} (R_{t+i})^{3} + \mathrm{O}(R_{t}^{4}) \tag{23}$$

Schneider and Trojani (2015) used the results of (23) to refer to the close connection of $Rvar^{logR}$ to the variance measure $Rvar^{L}$, as defined in (4). Furthermore, one can observe that the second term is devoted to cubed simple returns. Schneider and Trojani (2015) also noted that such a relationship between $Rvar^{S}$ and $Rvar^{L}$ does not exist, but when assuming that $Rvar^{logR} \approx Rvar^{S}$, and keeping in mind that the floating leg of the SSC is the difference of $Rvar^{L}$ and $Rvar^{S}$, one can derive following relationship:

$$Rthm_{t,T}^{S} \equiv Rvar_{t,T}^{L} - Rvar_{t,T}^{S} \approx Rvar_{t,T}^{L} - \left(Rvar_{t,T}^{L} - \frac{1}{3} \sum_{i=0}^{N-1} (R_{t+i})^{3} + \mathrm{O}(R_{t}^{4}) \right)$$

$$Rthm_{t,T}^{S} = \frac{1}{3} \sum_{i=0}^{N-1} (R_{t+i})^{3} - \mathrm{O}(R_{t}^{4}) \tag{24}$$

With regard to (24), one can see that the SSC is primarily connected to third order effects, with disappearing higher order effects in the limiting case.

Practical Implications

With regard to the practical implementation of the SSC, one has to deal with several issues. One important thing is the amount of margin one has to allocate to a bank account, in order to be allowed to trade in the futures and options market. While the overall margin rules for futures and options combined can be rather complicated, a rather easy margin requirement scheme will be applied that is taken from the margin calculator of the *Chicago Board of Trade* (CBOE). In the case of entering into a short put and short future contract simultaneously, you have to provide 150% of the margin amount of the corresponding future contract. Translated to the SSC investment, where one goes long calls and short puts or vice versa, hedging the options delta position with futures, one could characterize an aggregated position as, e.g. being long 1 call option (0.25 delta) and short 1 put option (0.25 delta) position and hedging with 0.5 short future contracts. Since margins for long option positions are usually not required, it will be assumed, for our combination, that the overall margin requirement is 125% of one future contract. The easy margin assumption has been compared to the margin requirements of the *Chicago Mercantile Exchange* (CME), and without considering any opportunity for reducing margins, this rule of thumb can be regarded as a conservative margin measurement. Fortunately, the CME provides historical margin costs for their currency future contracts on their website.[38] These historical margins have been implemented into the daily return calculation process, in order to establish a realistic picture of margin increases and reductions.

The dataset of forward and options is comprised of 1-month maturity prices on a daily frequency. In order to exploit the above findings, a 1-month constant-maturity SSC will be constructed, where profit and losses can be computed on a daily frequency. It starts with building an options and forward portfolio at the beginning of each month, followed by future hedges on a daily frequency, until the end-of-month when all positions will be closed out. The option portfolio consists of 3 OTM call and 3 OTM put options that are stripped between the (+/-) 0.175 delta (call/put) option strike and the forward ATM strike, respectively.[39] The strikes

[38] Unfortunately, there is no historical margin information available for the *MXNUSD* exchange rate. Therefore, the historical margin information from seven currency futures have been used to get reasonable estimates for MXNUSD margins. It turns out that the required margin amounts expressed as percentage of future margin regressed on the current and first lag of the implied volatility level have got the most robust estimation results with R^2*'s* of around 60% on average. For the estimation of MXNUSD margins, higher than average coefficient values were used, in order to achieve a conservative margin measure.

[39] In order to establish a consistent forward hedge, the option delta is computed in forward delta terms.

of the OTM option strips are equally spaced. In the daily profit and loss calculations, the end-of-day option prices are computed with the next day's implied volatility smile, where the maturity date will be deducted by 1 day (or 3 days in the case of weekends). The same procedure is done for forward prices, where 1/30 of the forward premium to the next day's forward price will be deducted.[40] In the next subsection, the returns of the SSC will be presented, both with and without transaction costs. As for transaction costs, only the costs induced by trading at bid-ask prices are considered, whereas SSC returns without transaction costs take mid-quotes of futures and options as trading prices.

Simple Skew Contract Returns

Before building a reasonable investment scheme for the skew swap to incorporate the effects of market pressure, the time series behaviour of swap returns for each of the *Sample II* currencies was analysed. It will be referred to short skew investments as the strategy for selling puts and buying calls, with subsequent delta hedging with futures. Comparing returns that show unconditionally long or short skews throughout the sample period for each currency reveals that skew swap returns rely heavily on the steepness of the implied volatility curve. Since most of the currencies have on average a negative *Iskew* (see Table 2), a short skew strategy is superior to being exposed to long skew (the opposite is true for the Japanese yen). This can be rationalized by a positive return drift, created from positive option theta that is due to higher put prices sold and lower call prices purchased.

With this relationship in mind, only strategies that are exposed to short skew strategies will be considered.[41] In order to exploit the skewness premium, these eight currencies will be sorted by their *ACF, HPF, CR8LF* values respectively, and choose the two highest or two lowest values, whatever would best rationalize a short skew position, to invest in equal weights. This is true for positive *HPF(+)* or *ACF(+)* values and the lowest concentration ratios, *CR8LF(low)*. In the case of only negative values for *ACF* and *HPF*, one will choose to invest in the risk-free 4-week T-Bill rate. If there is only one positive value, all proceeds will be invested into this single currency. The same sorting scheme applies for positive values of 1-month, 3-month, and 6-month-momentum RX(*X*m) and negative FX-value factors, respectively. Additionally, several sub-strategies to sort currencies by some multiples will be tested. For example,

[40] As a robustness check, the option portfolio strips were enlarged to 10 OTM call and 10 OTM put options with the result that the efficiency according to the SR^{HM} has increased. This comes especially due to significant reduced variance, skewness and kurtosis figures at times of market stress.
[41] Any combined strategy that consists of short skew and long skew investments, e.g. selling skew on the two highest ACF values and buying skew on the currencies with lowest ACF values, ends up with overall negative portfolio returns.

ACF(+)/CR8LF, positive *ACF* values divided by *CR8LF*, will allow to filter high positive *ACF* values associated with low overall future market concentration, or *ACF(+)*RX(1m)* will allow to choose high 1-month momentum returns with contemporaneous high positive *ACF* values.

The results of 20 different strategies will be compared to each other, including a naïve investment strategy denoted as the benchmark strategy, which always invests in those two currencies with the most negatively implied skew values (*Iskew(-)*). To appropriately compare these skew swap portfolio returns, a *Higher Moment Sharpe Ratio* (SR^{HM}) will be used in order to accomplish an efficient portfolio ranking according to higher return moments. [42] In addition to the original *Sharpe Ratio* (*SR*), it accounts for the return skewness and excess kurtosis of the return distribution and in the case of negative excess returns, the denominator will be raised to the power of -1, according to suggestions of Israelsen (2005). Also the original *SR* values will be reported for comparison. The average rate of the 4-week T-Bill will be used as the risk-free rate over the *Sample II* period.

[*Insert Table 8 about here.*]

Table 8 summarizes return results sorted on SR^{HM}, in ascending order, without including transaction costs. In Panel A, one can see that the most efficient results according to SR^{HM}, are from sorts on positive 1-month momentum returns, *RX(1m)+,* low future market concentration, *CR8LF(low*), and net future short holdings from hedgers, *HPF(+).* The first three results are as expected to be strong, because of the outcomes in above regressions (see Table 4, Table 6 and Table 7). While the return results from *HPF(+)* compared to *ACF(+)* is nearly identical, the benchmark strategy *Iskew(-),* has the highest monthly return result of impressing 2.1% p.m. . On the other hand, the return distribution is very negatively skewed and fat tailed, which leads to a worse overall rating due to SR^{HM}. The worst strategy result is on sorting on FX-value, which supports the above notion that skew swap results primarily rely on strong shifts in *Iskew* rather than *Rskew*. In Panel B, the turmoil period from the end of July 2008 until the end of June 2009 has been removed, in order to study the influence of extreme events on skew swap investments. During this relatively “normal” period, the benchmark strategy is the most efficient with on average returns of about 38.1% p.a. and almost half the standard deviation, positive skewness, and a much lower excess kurtosis compared to Panel A. The volatility over all strategies is one-third lower and the returns are almost doubled. This impressively highlights the strong negative effects of such a state of market stress on skew swap investments. Especially clear is the strong

[42] A detailed description of the *Higher Moment Sharpe Ratio* will be found in Appendix A. 8.

advancement of the naïve strategy, (*Iskew(-)*) because excluding the turmoil period reveals that investments in currencies are specifically sensitive to turmoil periods. This is also true for investment schemes sorted on positive *ACF* or *HPF* values, multiplied by currency momentum, e.g. *RX(1m)*. On the other hand, sorting low market concentration ratios *CR8LF(low)* is a strategy that is almost immune to crash scenarios. The return and standard deviations are somehow lower, with almost identical negative skewness and excess kurtosis, compared to other strategies.

Figure 2 now presents the cumulative returns of the three most efficient sorting schemes, according to SR^{HM} together with the benchmark strategy. It becomes visible that sorting on negative *Iskew's* results in a highly fat-tailed and negatively skewed return distribution, compared to the others. The success of the *CR8LF(low)* strategy becomes progressive beginning in 2011, while the return paths of *RX(1m)* and *HPF(+)* strategies seem to accumulate smoothly over the entire period.

[*Insert Figure 2 about here.*]

Table 9 now incorporates transaction costs and one can see that all sorting schemes result in negative excess returns. The average costs of all strategies are 230 basis points p.m. - which sounds very high. Future inclined costs represent on average 2/3 of all transaction costs. However, evidence from Lyons (2002) suggests that Reuters future bid-ask spreads are twice as large as the relevant inter-dealer spreads. If a similar picture arises for the option bid-ask spreads taken from Bloomberg, and the futures hedging frequency is reduced, one could easily reduce half of the transaction costs. Therefore, a skew swap strategy for currencies sorted by market pressure variables or currency momentum ratios is likely to exhibit profitable investments in practice.

[*Insert Table 9 about here.*]

6 Conclusion

We have seen that in the majority of 30 different foreign currency markets, there exists a statistically significant skewness risk premium (*SRP*). This ultimately means that foreign currency crash risk against the USD is priced. We have also seen that in the great majority of cases the implied skewness (*Iskew*) does not forecast future realized skewness (*Rskew*), which would be expected in a no-arbitrage environment of financial markets. Moreover, even 13 out of 30 currency markets exhibit on average a negative relationship between *Iskew* and future *Rskew* (only significant for the Thailand baht). These facts not only support the occurrence of a significant *SRP* but also raise the question of whether these imbalances can be attributed to a demand based explanation.

In conjunction with publically available future and option data provided by the *CFTC*, there is evidence that the disconnection of *Iskew* and *Rskew* (DS) is partly due to special constellations in the future market microstructure. Therefore, this paper makes use of market pressure variables, like net future and net option positions of hedgers and arbitrageurs that are supposed to capture the overall positioning in the market. It was surprising that evidence is found that especially market pressures from the FX *futures* market has led to the DS. This contrasts the findings from Ruf (2012) in the commodity market, where *option* market variables primarily have been responsible for the DS. However, four main sources of the observed market anomaly have been identified: (i) past short term currency momentum, (ii) high concentration in the future market, (iii) unconditional net future *short* positions of arbitrageur or hedger groups, and (iv) states of market illiquidity in terms of innovations from the *Swap-TBill* spread.

Past currency returns have the most significant impact on *Iskew* and the *SRP,* which leads to a cyclical demand for OTM calls in rising markets and likewise a demand for OTM puts in declining markets. There is evidence that this is due to a reduced ability for bearing risk of arbitrageurs when they are exposed to long future holdings (scenario 3). In the case of rising markets, arbitrageurs seem to demand an extra risk premium for OTM calls in order to be compensated for short vega positions. This is plausible since future *Rskew* is implicitly negative on average. In the case of declining markets, arbitrageurs demand for an extra premium for OTM puts only makes sense when it is viewed as a compensation for past future losses. Additionally, in the last section one can see that especially a swap strategy using the past 1-month returns has afforded the most efficient portfolio results by exploiting the DS.

High future long concentration has been identified as the second source leading to the imbalance of skewness. The rational behind this pattern is that possibly a high future concentration in the hands of only a few traders from the hedging group seem to trigger a high demand for OTM put options in a state of increased risk aversion or a suddenly negative market event. This could lead to tight option markets as well as especially unfavourable prices for insurance - this therefore can be assigned to scenario 2 for causing the DS. Also, using low states of market concentration with short skew swap investments belongs to the three most successful strategies in terms of the *Higher Moment Sharp Ratio*.

There is also evidence that unconditional net future *short* holdings from arbitrageurs or the hedgers group contribute to the DS. S*hort* holdings from arbitrageurs lead to relatively high costs for OTM puts, which is opposite to the average observed positive *Rskew*. Therefore, an explanation in terms of scenario 3 seems to be implausible. On the other hand, *short* holdings from the hedgers group leads to relatively low OTM put prices. This means that *Iskew* is positively skewed, although future *Rskew* is on average, negative. While this situation is quite favorable for allowing the hedgers group to buy cheap insurance for future crash risk, this pattern also contributes to the existence of the DS. This result is comparable to findings in Jurek (2014) or Brunnermeier et al. (2009) that can be summarized by the following phrase: “hedging is especially cheap when the probability of a crash is highest”. One reasonable explanation for the incorrectly adjusted *Iskew* is that hedging is primarily done in the future market and does not lead to an option demand which would be then consistent with future *Rskew*.

The last observed effect in conjunction with the DS is the sensitivity to innovations of the *Swap-TBill* spread. The innovations are used as a proxy for market illiquidity and there is evidence that the option market does not correctly adjust for future *Rskew* values. This ultimately leads to relatively cheap OTM put prices, or cheap prices for insurance when the state of illiquidity is high. Nevertheless, this result should be viewed with caution since other illiquidity innovations that are taken from the well-known *TED* spread or *Libor-Repo* spread do not confirm this result.

Section 5 has shown that exploiting the DS by replicating a *constant maturity simple skew swap* using the information of net future positions, market concentration and currency momentum leads to high returns of up to 20% p.a. without transaction costs. But when bid-ask spreads on futures and options as transaction costs are taken into account, the high returns almost vanish.

Figures and Tables

Table 1. Sample Overview

This table gives an overview of the used exchange rates against the USD for *Sample I* and *Sample II* currencies within their respective sample periods. It starts on the left with currency numbers, followed by the official *ISO 4217* currency codes and country names. The fourth column indicates whether the country is grouped to the developed (DM) or emerging market (EM). It then follows the inception and end dates of *Sample I* and *Sample II* currencies, with the number of monthly observations used.

No.	*Currency Codes*	*Country*	*DM/EM*	*Sample I Coverage*			*Sample II Coverage*		
				Inception	*End*	*Obs.*	*Inception*	*End*	*Obs.*
1	AUD	Australia	DM	09/2003	10/2013	121	06/2006	02/2014	93
2	CAD	Canada	DM	09/2003	10/2013	121	06/2006	02/2014	93
3	CHF	Switzerland	DM	02/2005	10/2013	104	06/2006	02/2014	93
4	DKK	Denmark	DM	02/2005	10/2013	104	./.	./.	./.
5	EUR	Europe	DM	09/2003	10/2013	121	06/2006	02/2014	93
6	GBP	Great Britain	DM	09/2003	10/2013	121	06/2006	02/2014	93
7	JPY	Japan	DM	09/2003	10/2013	121	06/2006	02/2014	93
8	NOK	Norwegia	DM	02/2005	10/2013	104	./.	./.	./.
9	NZD	New Zealand	DM	09/2003	10/2013	121	06/2006	02/2014	93
10	SEK	Sweden	DM	02/2005	10/2013	104	./.	./.	./.
11	CLP	Chile	EM	03/2005	10/2013	103	./.	./.	./.
12	COP	Colombia	EM	03/2005	10/2013	103	./.	./.	./.
13	CZK	Czech Republic	EM	03/2005	10/2013	103	./.	./.	./.
14	HKD	Hong Kong	EM	09/2003	10/2013	121	./.	./.	./.
15	HUF	Hungary	EM	03/2005	10/2013	103	./.	./.	./.
16	IDR	Indonesia	EM	06/2007	10/2013	76	./.	./.	./.
17	ILS	Israel	EM	09/2003	10/2013	121	./.	./.	./.
18	INR	India	EM	02/2005	10/2013	104	./.	./.	./.
19	KRW	South Korea	EM	09/2003	10/2013	121	./.	./.	./.
20	MXN	Mexico	EM	09/2003	10/2013	121	06/2006	02/2014	93
21	MYR	Malaysia	EM	09/2006	10/2013	85	./.	./.	./.
22	PHP	Philippines	EM	06/2007	10/2013	76	./.	./.	./.
23	PLN	Poland	EM	09/2003	10/2013	121	./.	./.	./.
24	RUB	Russia	EM	10/2005	10/2013	96	./.	./.	./.
25	SGD	Singapore	EM	09/2003	10/2013	121	./.	./.	./.
26	SKK	Slovakia	EM	03/2005	10/2013	103	./.	./.	./.
27	THB	Thailand	EM	09/2003	10/2013	121	./.	./.	./.
28	TRY	Turkey	EM	11/2005	10/2013	95	./.	./.	./.
29	TWD	Taiwan	EM	09/2003	10/2013	121	./.	./.	./.
30	ZAR	South Africa	EM	09/2003	10/2013	121	./.	./.	./.

Table 2. The Skewness Risk Premium in Foreign Exchange Markets

This table presents time-series averages of implied (*Iskew*) and realized skewness (*Rskew*), the conventional unit-free measure of skewness (*Skewness*), as well as the skewness risk premium denoted as *SRP*. Additionally, *Corr(I/Rskew)* means the correlation of *Iskew* and *Rskew*, where bold figures indicate significant correlation at least at the 10% level. *Sample II* currencies are superscripted with *TFF*. *Obs.* stands for the number of monthly observations used in the calculation. Forward discount values (*FD*) are annualized and proxies the interest rate differentials assuming CIP holds. *SRP* values are regressed on a constant using OLS, with HAC standard errors and 3 Newey-West (NW) lags. Asterisk values (***), (**) and (*) represent statistical significance at the 99%, 95% and 90% confidence levels, respectively.

Currency	*Obs.*	*FD_t*	*$Iskew_t$*	*$Rskew_{t:t+1}$*	*$Skewness_{t:t+1}$*	*Corr(RSCs)*	*$SRP_{t:t+1}$*	*t-stat.*	*p-value*
Developed Market Currencies (DM)									
JPY^{TFF}	121	-0.16%	0.29	0.07	0.05	0.81	-0.22***	-3.67	0.000
NOK	104	0.06%	-0.01	-0.08	-0.09	0.79	-0.07	-1.10	0.275
CHF^{TFF}	104	-0.12%	0.08	0.13	0.12	0.82	0.05	0.66	0.512
NZD^{TFF}	121	0.27%	-0.18	-0.11	-0.22	0.79	0.07	1.11	0.269
DKK	104	-0.03%	-0.02	0.07	0.04	0.81	0.09	1.33	0.188
SEK	104	-0.01%	-0.02	0.08	0.07	0.72	0.10*	1.72	0.089
AUD^{TFF}	121	0.26%	-0.19	-0.07	-0.15	0.81	0.12*	1.85	0.066
CAD^{TFF}	121	0.00%	-0.02	0.08	0.07	0.74	0.10*	1.88	0.062
GBP^{TFF}	121	0.07%	-0.11	0.00	-0.05	0.66	0.11**	2.02	0.046
EUR^{TFF}	121	-0.02%	-0.07	0.08	0.02	0.79	0.15**	2.47	0.015
Emerging Market Currencies (EM)									
HKD	121	-0.05%	0.88	0.24	0.24	0.87	-0.64***	-4.98	0.000
KRW	121	0.06%	-0.16	-0.13	-0.17	0.82	0.03	0.44	0.659
INR	104	0.38%	-0.18	-0.14	-0.15	0.81	0.04	0.58	0.560
TWD	121	-0.19%	0.08	0.18	0.21	0.86	0.10	1.15	0.253
ILS	121	0.08%	-0.08	0.02	-0.01	0.79	0.10	1.44	0.153
ZAR	121	0.49%	-0.21	-0.11	-0.09	0.73	0.11**	2.02	0.045
THB	121	0.11%	-0.09	0.13	0.11	0.89	0.22**	2.19	0.031
PLN	121	0.20%	-0.14	-0.01	-0.09	0.70	0.13**	2.23	0.028
SGD	121	-0.06%	-0.05	0.10	-0.02	0.79	0.15**	2.38	0.019
MXN^{TFF}	121	0.36%	-0.27	-0.12	-0.16	0.78	0.14**	2.43	0.017
CZK	103	-0.05%	-0.07	0.10	0.06	0.74	0.17**	2.60	0.011
COP	103	0.25%	-0.30	-0.12	-0.17	0.80	0.18***	2.71	0.008
SKK	103	-0.02%	-0.06	0.15	0.09	0.80	0.21***	3.03	0.003
PHP	76	0.19%	-0.30	-0.09	-0.11	0.68	0.21***	3.09	0.003
HUF	103	0.36%	-0.23	-0.02	0.01	0.73	0.21***	3.48	0.001
TRY	95	0.76%	-0.38	-0.12	-0.11	0.77	0.26***	3.54	0.001
IDR	76	0.48%	-0.53	-0.07	0.03	0.91	0.45***	3.81	0.000
RUB	96	0.47%	-0.27	0.04	-0.04	0.82	0.30***	3.83	0.000
CLP	103	0.18%	-0.31	0.02	-0.01	0.74	0.33***	4.87	0.000
MYR	85	0.02%	-0.17	0.17	0.15	0.86	0.34***	5.77	0.000

Table 3. Implied and Realized Skewness in the Time-Series

This table presents OLS regression results and inference gathered from the regression: $Rskew_{t:t+1} = \alpha + \beta\, Iskew_t + \varepsilon_t$ on each currency. Inference is based on Newey and West (1987) corrected standard errors, using three lags and the asterisk values (***), (**), and (*), represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The first three columns show *ISO 4217* currency codes while *TFF* superscripts indicate *Sample II* currencies, followed by the number of monthly observations used and the adjusted R^2 value of each regression. The next six columns present coefficient estimates and inference of *α* and/or *ß*. Columns 4-6 test the hypothesis H_0: α=0 against H_1:α≠0 and columns 7-9 test the hypothesis H_0: ß=0 against H_1:ß≠0. The inference is based on a two-tailed t-test and HAC standard errors using three Newey-West lags. The last two columns then present the F-statistics and p-values of the joint hypothesis *H_0:* α=0 *and ß=1* against *H_1:* α≠0 *and ß≠1.* The *Sample I* currencies are divided into developed and emerging market currencies and each part is sorted on *ß* t-statistics in ascending order. The sample periods vary over currencies according to Table 1, but always lie between 09/2003 – 10/2013.

Currency	Obs.	adj.R^2	α	t-stat.	p-value	ß	t-stat.	p-value	F-stat.	p-value
			H_0: α=0 *H_1:* α≠0			*H_0: ß=0 H_1: ß≠0*			*H_0:* α=0 *and ß=1*	
Developed Market Currencies (DM)										
CHF[TFF]	104	-0.2%	-0.17**	-2.28	0.02	-0.45	-0.81	0.42	4.29**	0.016
AUD[TFF]	121	-0.3%	0.14	0.94	0.35	-0.40	-0.69	0.49	8.27***	0.000
NZD[TFF]	121	-0.5%	0.17	1.19	0.23	-0.33	-0.56	0.58	4.76***	0.010
CAD[TFF]	121	-0.7%	-0.08	-1.60	0.11	0.14	0.43	0.67	5.90***	0.003
DKK	104	-0.7%	-0.07	-1.12	0.27	0.22	0.53	0.60	3.09**	0.050
EUR[TFF]	121	-0.6%	-0.09	-1.40	0.16	0.24	0.59	0.55	5.18***	0.007
NOK	104	-0.6%	0.08	1.14	0.26	0.34	0.70	0.49	1.38	0.257
GBP[TFF]	121	-0.2%	-0.04	-0.58	0.57	0.38	0.90	0.37	3.09**	0.049
JPY[TFF]	121	-0.3%	0.01	0.10	0.92	0.27	0.91	0.36	9.61***	0.000
SEK	104	1.0%	-0.09	-1.58	0.12	0.68	1.58	0.12	1.79	0.173
Emerging Market Currencies (EM)										
THB	121	2.6%	-0.04	-0.40	0.69	-1.06**	-2.14	0.03	11.94***	0.000
MXN[TFF]	121	0.2%	0.25**	2.55	0.01	-0.49	-1.46	0.15	12.43***	0.000
IDR	76	0.1%	0.38	1.61	0.11	-0.58	-1.36	0.18	13.18***	0.000
HUF	103	0.0%	0.16	0.98	0.33	-0.65	-1.06	0.29	15.44***	0.000
KRW	121	0.0%	0.17**	2.08	0.04	-0.27	-1.02	0.31	11.83***	0.000
PHP	76	-0.8%	0.19	1.62	0.11	-0.35	-0.89	0.38	8.30***	0.001
ILS	121	-0.6%	-0.01	-0.17	0.87	-0.16	-0.58	0.56	10.08***	0.000
TRY	95	-0.7%	0.23	1.24	0.22	-0.28	-0.58	0.56	10.00***	0.000
ZAR	121	-0.6%	0.17	1.13	0.26	-0.30	-0.47	0.64	4.71**	0.011
CLP	103	-0.9%	0.04	0.21	0.84	-0.19	-0.37	0.71	17.81***	0.000
PLN	121	-0.8%	0.00	0.02	0.98	0.05	0.09	0.93	3.23**	0.043
CZK	103	-1.0%	-0.11	-1.58	0.12	0.07	0.17	0.86	7.20***	0.001
HKD	121	-0.8%	-0.21	-1.62	0.11	0.04	0.29	0.77	47.62***	0.000
TWD	121	-0.6%	-0.16	-1.61	0.11	0.17	0.47	0.64	2.82*	0.064
SKK	103	-0.5%	-0.17*	-1.85	0.07	0.38	0.56	0.58	6.50***	0.002
INR	104	-0.5%	0.09	0.90	0.37	0.31	0.82	0.42	1.70	0.187
COP	103	-0.3%	0.00	0.02	0.99	0.39	0.97	0.33	6.09***	0.003
SGD	121	0.5%	-0.12*	-1.87	0.06	0.39	1.56	0.12	6.03***	0.003
RUB	96	4.8%	-0.31*	-1.92	0.06	1.04*	1.74	0.09	7.72***	0.001
MYR	85	2.6%	-0.29***	-3.73	0.00	0.73**	2.51	0.01	17.29***	0.000

Table 4. Effects of Market Pressure on Skewness

This table presents results from a fixed-effects (fe) panel regression of *Iskew* (Panel A) and the *SRP* (Panel B) on a number of variables related to market pressure. The regression framework produces HAC standard errors (5 NW lags). Asterisk values (***), (**) and (*) represent statistical significance at the 99%, 95% and 90% confidence levels, respectively, with t-stats in brackets. HPF_{t-1} (ACF_{t-1}) is the scaled net future short (long) exposure of hedgers (arbitrageurs). HPO_{t-1} (ACO_{t-1}) is the same multiple for the option market. (+) and (-) means only positive or negative outcomes of the variable. ACF^2_{t-1} and HPF^2_{t-1} means the square of the exposure variable. At the end of each panel, simple within R^2 results are reported and additionally, currency units and the total number of observations. Coefficients from control variables and their constants are omitted.

Market Pressure and Skewness								
Panel A: Implied Skewness ($Iskew_t$)								
ACO_{t-1}	0.273***							
	[3.76]							
HPO_{t-1}		0.147**						
		[2.60]						
ACF_{t-1}			0.069**				0.064**	
			[2.76]				[2.54]	
HPF_{t-1}				0.036**				0.041**
				[2.59]				[3.10]
$ACF(+)_{t-1}$					0.083*			
					[1.99]			
$ACF(-)_{t-1}$					0.047			
					[0.80]			
$HPF(+)_{t-1}$						-0.021		
						[-0.79]		
$HPF(-)_{t-1}$						0.103**		
						[3.27]		
ACF^2_{t-1}							0.028	
							[0.56]	
HPF^2_{t-1}								-0.056**
								[-2.55]
R^2	22.27%	21.17%	17.03%	16.72%	17.07%	17.88%	17.08%	17.72%
Panel B: Skewness Risk Premium ($Rskew_{t:t+1}$ - $Iskew_t$)								
ACO_{t-1}	0.089							
	[0.54]							
HPO_{t-1}		0.116						
		[1.00]						
ACF_{t-1}			-0.274***				-0.316***	
			[-4.00]				[-5.27]	
HPF_{t-1}				-0.157***				-0.154***
				[-4.00]				[-3.88]
$ACF(+)_{t-1}$					-0.167			
					[-1.18]			
$ACF(-)_{t-1}$					-0.445**			
					[-2.88]			
$HPF(+)_{t-1}$						-0.187*		
						[-2.07]		
$HPF(-)_{t-1}$						-0.121		
						[-1.12]		
ACF^2_{t-1}							0.222	
							[1.18]	
HPF^2_{t-1}								-0.027
								[-0.32]
R^2	3.50%	4.10%	4.27%	4.31%	4.36%	4.33%	4.39%	4.32%
Currency units	8	7	8	8	8	8	8	8
Observations	553	520	688	688	688	688	688	688

Table 5. Effects of Liquidity Risk and Volatility Risk on Skewness

This table presents results from a *fe* panel regression of *Iskew* (Panel A) and the *SRP* (Panel B) on a number of variables related to market pressure, volatility, and liquidity risk. The regression framework produces HAC standard errors (5 NW lags). Asterisk values (***), (**) and (*) represent statistical significance at the 99%, 95% and 90% confidence levels, respectively, with t-stats in brackets. HPF_{t-1} is the scaled net future short exposure of hedgers. The innovations from the TED-spread (u_TED_{t-1}), the LIBOR-Repo spread (u_LiRe_{t-1}), the Swap-T-Bill spread (u_SwTB_{t-1}), and the average bid-ask spread (u_BAS30_{t-1}) are used as liquidity risk. Furthermore, the changes of the VIX ($dVIX_{t-1:t}$), innovations in global FX volatility ($u\_Vola^{MSSS}_{t-1}$), and innovations of the aggregated FX implied variance (u_Ivar30_{t-1}) are used as volatility risk measures. Additionally, all liquidity or volatility variables are signed (SN) by the FD value in each currency unit, respectively. The variable *X* means the currently used liquidity or volatility risk variable that is multiplied by the *HPF* value. The variable *SN*dVIX* is multiplied by 100 for convenience.

Liquidity, Volatility Risk and Skewness

Panel A: Implied Skewness ($Iskew_t$)							
HPF_{t-1}	0.035**	0.034**	0.037**	0.039**	0.037**	0.041**	0.038**
	[2.51]	[2.48]	[2.63]	[2.66]	[2.74]	[2.99]	[2.73]
$SN*u\_TED_{t-1}$	-0.047*						
	[-2.33]						
$SN*u\_LiRe_{t-1}$		-0.086**					
		[-2.53]					
$SN*u\_SwTB_{t-1}$			0.031				
			[1.25]				
$SN*u\_BAS30_{t-1}$				-172.9			
				[-1.08]			
$SN*dVIX\ (x100)_{t-1}$					-0.486**		
					[-3.20]		
$SN*u\_Vola^{MSSS}_{t-1}$						-17.59**	
						[-3.12]	
$SN*u\_Ivar30_{t-1}$							-42.16***
							[-6.67]
$HPF_{t-1}*X$	-0.048	-0.083	-0.016	185.7	-0.352	-0.193	-35.97
	[-1.20]	[-1.32]	[-0.66]	[1.37]	[-1.87]	[-0.02]	[-1.55]
R^2	17.92%	18.65%	17.09%	17.38%	20.41%	19.66%	20.44%
Panel B: Skewness Risk Premium ($Rskew_{t:t+1}$ - $Iskew_t$)							
HPF_{t-1}	-0.157***	-0.156***	-0.156***	-0.145***	-0.156***	-0.155***	-0.170***
	[-3.98]	[-3.96]	[-4.08]	[-3.70]	[-4.01]	[-3.74]	[-4.18]
$SN*u\_TED_{t-1}$	-0.031						
	[-0.79]						
$SN*u\_LiRe_{t-1}$		0.036					
		[0.53]					
$SN*u\_SwTB_{t-1}$			-0.165*				
			[-1.90]				
$SN*u\_BAS30_{t-1}$				-455.5			
				[-1.52]			
$SN*dVIX\ (x100)_{t-1}$					-0.039		
					[-0.09]		
$SN*u\_Vola^{MSSS}_{t-1}$						-17.62	
						[-0.77]	
$SN*u\_Ivar30_{t-1}$							-6.74
							[-0.23]
$HPF_{t-1}*X$	-0.029	0.127	-0.192	877.7	0.160	9.28	34.31
	[-0.34]	[0.68]	[-0.84]	[1.73]	[0.17]	[0.21]	[0.25]
R^2	4.33%	4.36%	5.15%	4.60%	4.32%	4.61%	4.82%
Currency units	8	8	8	8	8	8	8
Observations	688	688	688	688	688	664	656

Table 6. Effects of Market Concentration on Skewness

This table presents results from a panel regression of implied skewness ($Iskew_t$) and the skewness risk premium ($SRP_{t:t+1}$) on a number of variables related to market pressure and market concentration risk. The fixed-effects panel regression framework produces HAC standard errors and is robust to general forms of spatial and temporal dependence (5 NW lags). Asterisk values (***), (**) and (*) represent statistical significance at the 99%, 95% and 90% confidence levels, respectively. The dependent variable in Panel A is $Iskew_t$ and in Panel B the *SRP*. *CR8LF* (*CR8SF*) is the market share of the largest 8 trader positions being long (short) in the futures market. $CR8LF|ACF^{>Q3}$ ($CR8LF|ACF^{<Q1}$) is *CR8LF* conditional on *ACF* value being above (below) the 75% percentile (25% percentile), and $CR8LF|ACF^{mid}$ represents the remainder. Hence, $CR8LF|HPF^{>Q3}$ ($CR8LF|HPF^{<Q1}$) is *CR8LF* conditional on *HPF* being above (below) the 75% percentile (25% percentile), and $CR8LF|HPF^{mid}$ represents the remainder. At the end of each panel, simple within R^2 results are reported and additionally, the last two rows characterize the number of currency units and the total number of observations used in the regression. Coefficients from control variables and their constants are omitted.

Market Concentration and Skewness				
Panel A: Implied Skewness ($Iskew_t$)				
CR8LF	-0.256**			
	[-3.07]			
CR8SF		0.292***		
		[4.07]		
CR8LF $\|ACF^{>Q3}$			-0.198	
			[-1.74]	
CR8LF $\|ACF^{mid}$			-0.252*	
			[-2.25]	
CR8LF $\|ACF^{<Q1}$			-0.236**	
			[-2.65]	
CR8LF $\|HPF^{>Q3}$				-0.256*
				[-2.08]
CR8LF $\|HPF^{mid}$				-0.223*
				[-1.98]
CR8LF $\|HPF^{<Q1}$				-0.258**
				[-2.82]
R^2	18.34%	18.45%	18.84%	18.73%
Panel B: Skewness Premium ($Rskew_{t:t+1}$ - $Iskew_t$)				
CR8LF	0.731**			
	[2.74]			
CR8SF		-0.397		
		[-1.67]		
CR8LF $\|ACF^{>Q3}$			0.278	
			[0.78]	
CR8LF $\|ACF^{mid}$			0.332	
			[0.98]	
CR8LF $\|ACF^{<Q1}$			0.564*	
			[1.96]	
CR8LF $\|HPF^{>Q3}$				0.251
				[0.75]
CR8LF $\|HPF^{mid}$				0.333
				[1.04]
CR8LF $\|HPF^{<Q1}$				0.573*
				[2.06]
R^2	4.11%	3.24%	4.72%	5.77%
Currency units	8	8	8	8
Observations	688	688	688	688

Table 7. Effects of Momentum and Value on Skewness

This table presents results from a *fe* panel regression of *Iskew* (Panel A) and the *SRP* (Panel B) on a number of variables related to market pressure, momentum, and FX-value risk. The regression framework produces HAC standard errors (5 NW lags). Asterisk values (***), (**) and (*) represent statistical significance at the 99%, 95% and 90% confidence levels, respectively, with t-stats in brackets. *RX(Xm)* means the past X-month forward log return, and *Value* is the negative sum of the past 5 year forward log returns. $RX(Xm)^2$ means the square of past X-month forward returns and $RX(Xm)|ACF_t^{>Q3(<Q1)}$ is the past X-month return conditional on *ACF* belongs to the upper (lower) third of the data. The same is true for conditional HPF variables.

Momentum, Value and Skewness							
Panel A: Implied Skewness ($Iskew_t$)							
$RX(3m)_{t-3:t}$	1.085***			1.140***			
	[7.49]			[5.96]			
$RX\ (6m)_{t-6:t}$		0.611***			0.652***		
		[7.05]			[6.61]		
Value			-0.067				
			[-0.88]				
$RX\ (3m)^2_{t-3:t}$				1.927*			
				[1.93]			
$RX\ (6m)^2_{t-6:t}$					0.815		
					[1.85]		
$RX\ (3m)_{t-3:t}\|ACF_t^{>Q3}$						1.510***	
						[6.50]	
$RX\ (3m)_{t-3:t}\|ACF_t^{<Q1}$						0.741***	
						[4.19]	
$RX\ (3m)_{t-3:t}\|HPF_t^{>Q3}$							1.273***
							[6.05]
$RX\ (3m)_{t-3:t}\|HPF_t^{<Q1}$							0.867***
							[4.63]
R^2	30.3%	26.0%	15.6%	31.3%	26.8%	31.4%	30.7%
Panel B: Skewness Risk Premium ($Rskew_{t:t+1}$ - $Iskew_t$)							
$RX(3m)_{t-3:t}$	-2.271***			-2.433***			
	[-4.33]			[-5.24]			
$RX\ (6m)_{t-6:t}$		-1.763***			-1.838***		
		[-5.04]			[-4.56]		
Value			0.914***				
			[3.87]				
$RX\ (3m)^2_{t-3:t}$				-5.720**			
				[-2.57]			
$RX\ (6m)^2_{t-6:t}$					-1.514		
					[-0.71]		
$RX\ (3m)_{t-3:t}\|ACF_t^{>Q3}$						-5.133***	
						[-3.65]	
$RX\ (3m)_{t-3:t}\|ACF_t^{<Q1}$						-0.706	
						[-0.84]	
$RX\ (3m)_{t-3:t}\|HPF_t^{>Q3}$							-5.046**
							[-3.28]
$RX\ (3m)_{t-3:t}\|HPF_t^{<Q1}$							-0.683
							[-0.80]
R^2	5.8%	6.9%	6.5%	6.2%	7.0%	7.3%	6.9%
Currency units	8	8	8	8	8	8	8
Observations	688	688	688	688	688	688	688

Table 8. Skew Swap Trading Strategies Depending on Signals (no transaction costs)

This table presents portfolio return and risk figures from investments in a *1-month constant maturity simple skew contract* (SSC) without transaction costs. The SSC consists of a maximum of two exchange rate option portfolios that are equally weighted, rebalanced every month and future hedged at a daily frequency. The option portfolio consists of three OTM call and three OTM put options, respectively. The two currencies are chosen out of the *Panel II* universe and are sorted on different multiples (investment criteria). The investment criteria are as follows: *ACF(+)* (*HPF(+)*) means SSC investments in currencies with most positive coefficients of net long (short) future positions of arbitrageurs (hedgers). The symbol (+) (or (-)) means that a coefficient must be strictly positive (negative) to be chosen. Also, the past forward returns *RX*, the FX-value factor (*Value*), or a multiple of two different variables are used as a sorting scheme. Sorting currencies simply on *Iskew* refers to the benchmark investment rule. Panel A shows return figures for the investment period 30/06/2006-31/01/2014 without transaction costs and Panel B incorporates bid-ask spreads. The return and risk figures are the average monthly (*RX p.m.*) and annual returns (*RX p.a.*), standard deviations (*Std.Dev.*), skewness (*Skew*) and excess kurtosis (*Kurtosis*) of the log returns at monthly frequency. The table results are sorted according to the *Higher Moment Sharpe Ratio* (SR^{HM}); *SR* means the original Sharpe ratio.

Panel A

Investment criteria	RX p.m.	RX p.a.	Std.Dev.	Skew	Kurtosis	SR^{HM}	SR
RX(1m)(+)	1.4%	17.0%	25.8%	1.7	11.9	0.52	0.62
CR8LF (low)	1.6%	19.2%	25.2%	-0.8	5.6	0.33	0.72
HPF(+)	1.4%	16.8%	19.8%	-1.7	4.9	0.32	0.80
RX(1m)(+)/ CR8LF	0.8%	10.1%	26.4%	1.4	11.9	0.28	0.35
HPF(+)*Value	1.5%	18.5%	27.1%	-1.3	5.6	0.27	0.65
ACF(+)	1.2%	14.0%	22.5%	-1.6	4.1	0.24	0.57
HPF(+)/CR8LF	1.0%	11.4%	20.0%	-1.4	5.9	0.21	0.52
ACF(+)*Value	1.5%	17.5%	29.4%	-1.9	8.6	0.20	0.56
RX(3m)(+)	1.0%	12.1%	24.1%	-1.5	4.4	0.20	0.46
Iskew(-)	2.1%	24.7%	37.7%	-3.8	23.8	0.14	0.63
RX(3m)(+)/ CR8LF	0.8%	9.9%	25.4%	-2.0	5.8	0.13	0.35
ACF(+)/CR8LF	0.7%	8.6%	23.7%	-2.1	6.2	0.12	0.32
HPF(+)*RX(6m)	1.5%	17.7%	37.2%	-3.4	22.7	0.11	0.45
ACF(+)*RX(6m)	1.3%	15.8%	34.5%	-4.6	32.4	0.08	0.43
RX(6m)(+)/ CR8LF	0.3%	3.0%	28.3%	-1.5	3.7	0.03	0.07
ACF(+)*RX(3m)	0.8%	9.6%	52.2%	-6.8	55.3	0.03	0.16
RX(6m)(+)	0.2%	3.0%	29.5%	-2.1	7.2	0.02	0.07
ACF(+)*RX(1m)	0.7%	8.3%	52.0%	-6.8	56.1	0.02	0.14
HPF(+)*RX(3m)	0.5%	5.7%	55.4%	-6.0	43.5	0.01	0.08
HPF(+)*RX(1m)	0.4%	4.4%	55.4%	-5.9	43.8	0.01	0.06
Value(-)	-0.3%	-3.6%	57.8%	-5.4	35.9	-0.14	-0.08

Panel B: without Turmoil Period

Investment criteria	RX p.m.	RX p.a.	Std.Dev.	Skew	Kurtosis	SR^{HM}	SR
Iskew(-)	3.18%	38.12%	20.37%	0.6	8.9	1.31	1.82
ACF(+)*RX(6m)	2.39%	28.64%	17.71%	-0.2	1.1	1.14	1.56
ACF(+)*RX(1m)	2.17%	26.09%	20.10%	-0.5	2.4	0.74	1.25
ACF(+)*RX(3m)	2.37%	28.47%	20.46%	-0.8	2.4	0.73	1.34
RX(3m)(+)	2.03%	24.31%	19.11%	-0.7	2.5	0.67	1.22
HPF(+)*RX(1m)	2.03%	24.31%	19.86%	-0.6	2.6	0.67	1.17
HPF(+)	1.86%	22.34%	16.20%	-1.3	4.3	0.58	1.31
RX(1m)(+)	1.44%	17.31%	18.99%	-0.6	2.4	0.50	0.86
HPF(+)*RX(6m)	2.39%	28.65%	21.83%	-1.4	7.2	0.49	1.27
HPF(+)/CR8LF	1.52%	18.28%	17.06%	-0.9	7.0	0.44	1.01
HPF(+)*RX(3m)	2.37%	28.41%	21.99%	-1.9	8.1	0.44	1.25
CR8LF (low)	2.16%	25.88%	23.92%	-1.0	8.6	0.42	1.04
ACF(+)	1.82%	21.83%	20.25%	-1.7	5.2	0.41	1.03
RX(6m)(+)/ CR8LF	1.67%	20.01%	21.26%	-1.6	7.8	0.33	0.89
RX(3m)(+)/ CR8LF	1.79%	21.44%	21.26%	-2.2	9.1	0.31	0.96
HPF(+)*Value	1.57%	18.87%	23.72%	-2.4	8.0	0.25	0.75
ACF(+)/CR8LF	1.31%	15.72%	21.99%	-2.5	9.2	0.21	0.67
Value(-)	1.66%	19.87%	27.58%	-2.8	11.7	0.20	0.68
RX(6m)(+)	1.56%	18.67%	24.09%	-3.1	18.1	0.19	0.73
RX(1m)(+)/ CR8LF	0.75%	8.97%	19.90%	-1.3	3.5	0.18	0.40
ACF(+)*Value	1.46%	17.56%	26.81%	-2.9	12.8	0.17	0.62

Table 9. Skew Swap Trading Strategies Depending on Signals (transaction costs)

This table presents portfolio return and risk figures from investments in a *1-month constant maturity simple skew contract* (SSC) with transaction costs. The SSC consists of a maximum of two exchange rate option portfolios that are equally weighted, rebalanced every month and future hedged at a daily frequency. The option portfolio consists of three OTM call and three OTM put options, respectively. The two currencies are chosen out of the *Panel II* universe and are sorted on different multiples (investment criteria). The investment criteria are as follows: *ACF(+)* (*HPF(+)*) means SSC investments in currencies with most positive coefficients of net long (short) future positions of arbitrageurs (hedgers). The symbol (+) (or (-)) means that a coefficient must be strictly positive (negative) to be chosen. Also, the past forward returns *RX*, the FX-value factor (*Value*), or a multiple of two different variables are used as a sorting scheme. Sorting currencies simply on *Iskew* refers to the benchmark investment rule. Panel A shows return figures for the investment period 30/06/2006-31/01/2014 without transaction costs and Panel B incorporates bid-ask spreads. The return and risk figures are the average monthly (*RX p.m.*) and annual returns (*RX p.a.*), standard deviations (*Std.Dev.*), skewness (*Skew*) and excess kurtosis (*Kurtosis*) of the log returns at monthly frequency. The table results are sorted according to the *Higher Moment Sharpe Ratio* (SR^{HM}); *SR* means the original Sharpe ratio.

Panel A

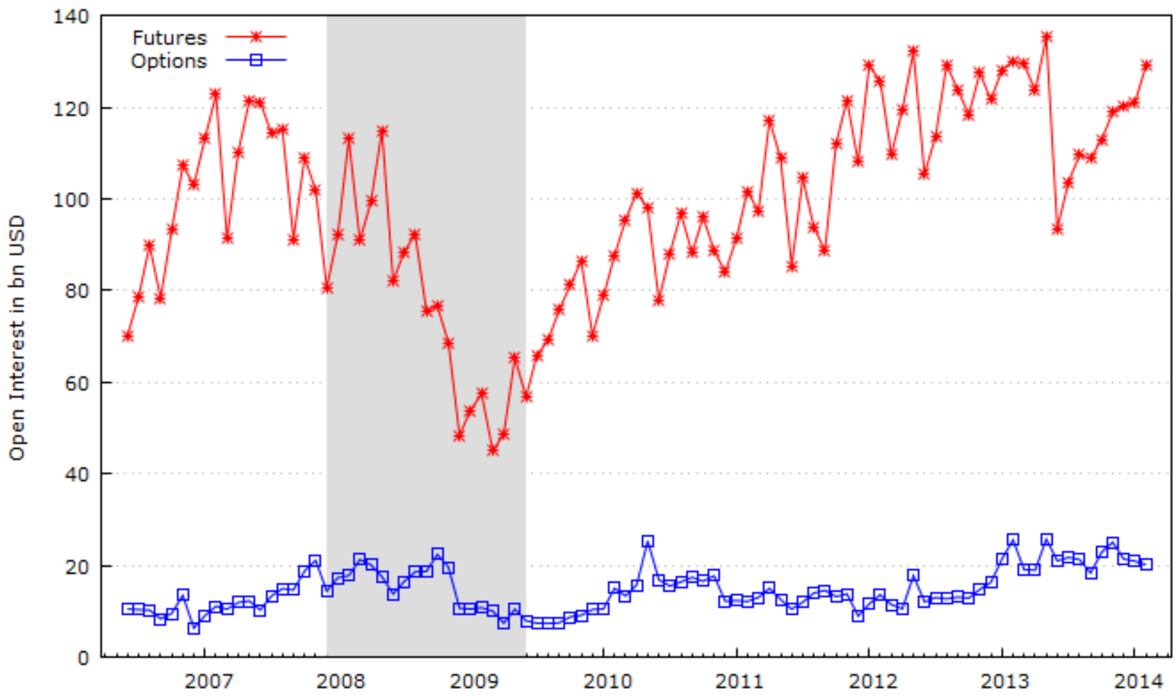
Investment criteria	RX p.m.	RX p.a.	Std.Dev.	Skew	Kurtosis	SR^{HM}	SR
RX(1m)(+)	-0.9%	-10.8%	24.8%	0.8	8.7	-0.04	-0.48
HPF(+)	-0.7%	-8.6%	19.5%	-1.7	5.1	-0.05	-0.49
CR8LF(low)	-0.6%	-7.7%	25.7%	-0.8	4.6	-0.05	-0.34
Iskew(-)	-0.2%	-2.1%	38.9%	-4.0	25.4	-0.06	-0.08
RX(1m)(+)/CR8LF	-1.4%	-16.3%	25.6%	0.5	8.4	-0.06	-0.68
ACF(+)	-1.1%	-12.7%	21.9%	-1.4	3.6	-0.07	-0.62
HPF(+)/CR8LF	-1.2%	-14.5%	19.6%	-1.5	5.9	-0.08	-0.79
HPF(+)*Value	-1.0%	-12.0%	26.2%	-1.4	6.0	-0.08	-0.50
ACF(+)*Value	-1.1%	-13.1%	27.9%	-1.6	7.5	-0.11	-0.51
ACF(+)/CR8LF	-1.4%	-16.2%	23.6%	-2.0	6.2	-0.11	-0.73
RX(3m)(+)	-1.3%	-15.6%	25.2%	-2.1	8.1	-0.12	-0.66
RX(3m)(+)/ CR8LF	-1.4%	-16.4%	27.2%	-2.3	7.6	-0.14	-0.64
HPF(+)*RX(6m)	-0.8%	-9.8%	37.0%	-3.8	25.5	-0.18	-0.29
RX(6m)(+)/ CR8LF	-2.1%	-24.8%	29.6%	-1.7	4.9	-0.19	-0.87
ACF(+)*RX(6m)	-1.0%	-11.5%	34.8%	-4.9	35.8	-0.23	-0.36
RX(6m)(+)	-2.2%	-26.6%	30.1%	-2.1	6.8	-0.24	-0.92
ACF(+)*RX(1m)	-1.5%	-18.2%	53.2%	-7.1	58.8	-0.68	-0.36
ACF(+)*RX(3m)	-1.6%	-19.3%	53.3%	-7.0	58.2	-0.72	-0.38
HPF(+)*RX(1m)	-1.9%	-23.1%	56.8%	-6.1	45.4	-0.82	-0.42
HPF(+)*RX(3m)	-1.9%	-23.1%	56.9%	-6.1	44.8	-0.82	-0.42
Value(-)	-2.9%	-35.2%	59.0%	-5.5	37.8	-1.19	-0.61

Panel B: without Turmoil Period

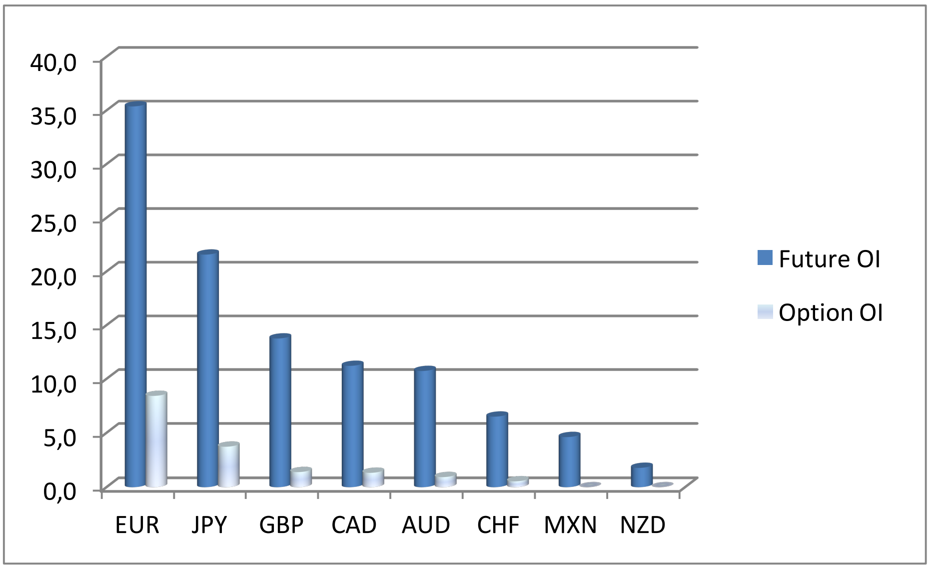
Investment criteria	RX p.m.	RX p.a.	Std.Dev.	Skew	Kurtosis	SR^{HM}	SR
Iskew(-)	1.1%	12.7%	20.1%	0.9	8.5	0.45	0.58
ACF(+)*RX(6m)	0.2%	2.5%	16.8%	-0.2	1.0	0.06	0.09
HPF(+)*RX(6m)	0.2%	2.2%	20.9%	-1.7	8.6	0.02	0.06
HPF(+)*RX(3m)	0.1%	1.2%	21.3%	-2.0	8.6	0.00	0.01
ACF(+)*RX(1m)	0.1%	1.0%	18.9%	-0.6	2.0	0.00	0.00
ACF(+)*RX(3m)	0.1%	0.8%	19.2%	-0.6	1.9	-0.01	-0.01
CR8LF (low)	0.0%	-0.1%	23.9%	-1.0	7.7	-0.01	-0.05
HPF(+)*RX(1m)	-0.1%	-1.5%	18.7%	-0.6	2.0	-0.01	-0.14
RX(3m)(+)	-0.2%	-2.6%	18.0%	-0.9	1.9	-0.01	-0.20
HPF(+)	-0.3%	-4.1%	15.9%	-1.2	3.3	-0.02	-0.32
ACF(+)	-0.4%	-5.2%	19.3%	-1.3	3.6	-0.03	-0.32
RX(1m)(+)	-0.7%	-8.9%	17.8%	-0.8	1.6	-0.03	-0.56
RX(3m)(+)/ CR8LF	-0.3%	-4.1%	21.3%	-2.2	8.7	-0.03	-0.24
HPF(+)/CR8LF	-0.7%	-8.8%	16.7%	-1.0	6.1	-0.04	-0.59
RX(6m)(+)/ CR8LF	-0.6%	-7.3%	21.4%	-1.7	7.8	-0.05	-0.39
ACF(+)/CR8LF	-0.8%	-9.7%	21.8%	-2.4	8.9	-0.07	-0.49
RX(1m)(+)/ CR8LF	-1.3%	-15.9%	19.3%	-1.5	3.6	-0.07	-0.88
HPF(+)*Value	-1.0%	-11.8%	22.9%	-2.4	8.4	-0.09	-0.56
RX(6m)(+)	-0.9%	-10.5%	23.0%	-2.9	15.4	-0.10	-0.50
Value(-)	-0.9%	-10.9%	26.0%	-2.5	10.1	-0.10	-0.46
ACF(+)*Value	-1.1%	-13.0%	25.3%	-2.6	11.0	-0.12	-0.55

Figure 1. Time Series of Aggregated Futures and Options OI in bn USD

The upper figure presents a time-series of aggregated futures and options open interest (OI) in billion USD. The aggregation consists of *Sample II* currencies provided by the CFTC. The grey background indicates NBER (National Bureau of Economic Research) recession periods. The lower figure shows time-series averages of the notional OI in billion USD for each *Sample II* currencies, respectively. The lower table summarizes the respective OI figures for each currency in futures and options, respectively. The last row shows the options OI market share in comparison to the futures market. The last column presents the cross-sectional sum of futures and options OI.



Currencies Futures and Options Open Interest in bn USD



	EUR	JPY	GBP	CAD	AUD	CHF	MXN	NZD	Σ
Future OI	35.4	21.6	13.8	11.2	10.7	6.5	4.6	1.8	**105.6**
Option OI	8.4	3.7	1.4	1.3	0.9	0.5	0.0	0.0	**16.3**
Opt/Fut OI	23.8%	17.3%	10.1%	11.8%	8.6%	8.4%	0.0%	0.0%	**15.4%**

Figure 2. Cumulative Log Returns of the Simple Skew Contract

This table presents cumulative log-returns of a short skew investment using a one-month constant maturity *SSC*. The skew swap returns are taken from the results of Table 8 and do not include transaction costs. The eight *Panel II* currencies are sorted according to four different investment criteria, respectively, isolating the two most favourable currencies with the highest previous 1-month forward returns (RX_1m), highest net future short exposure of hedgers (HPF), or lowest future market concentration among the 8 biggest traders (CR8LF), and lowest implied skewness (Iskew) representing the benchmark investment scheme. The sample period goes from 30/06/2006-31/01/2014 and grey background indicates NBER recession periods.

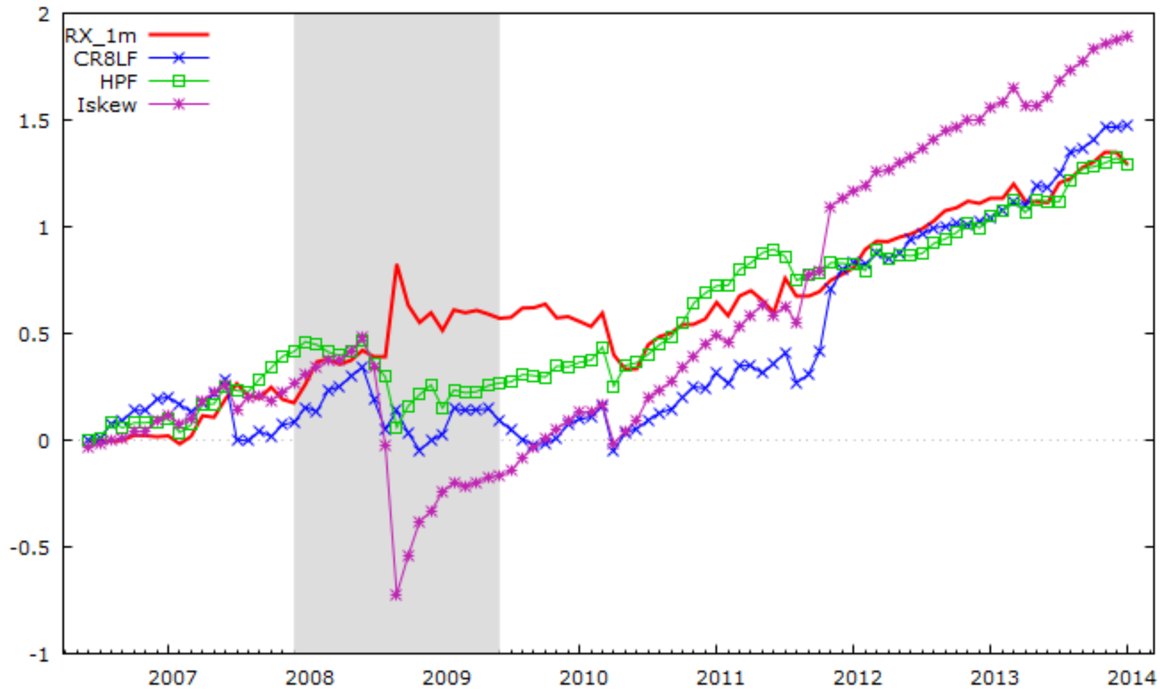
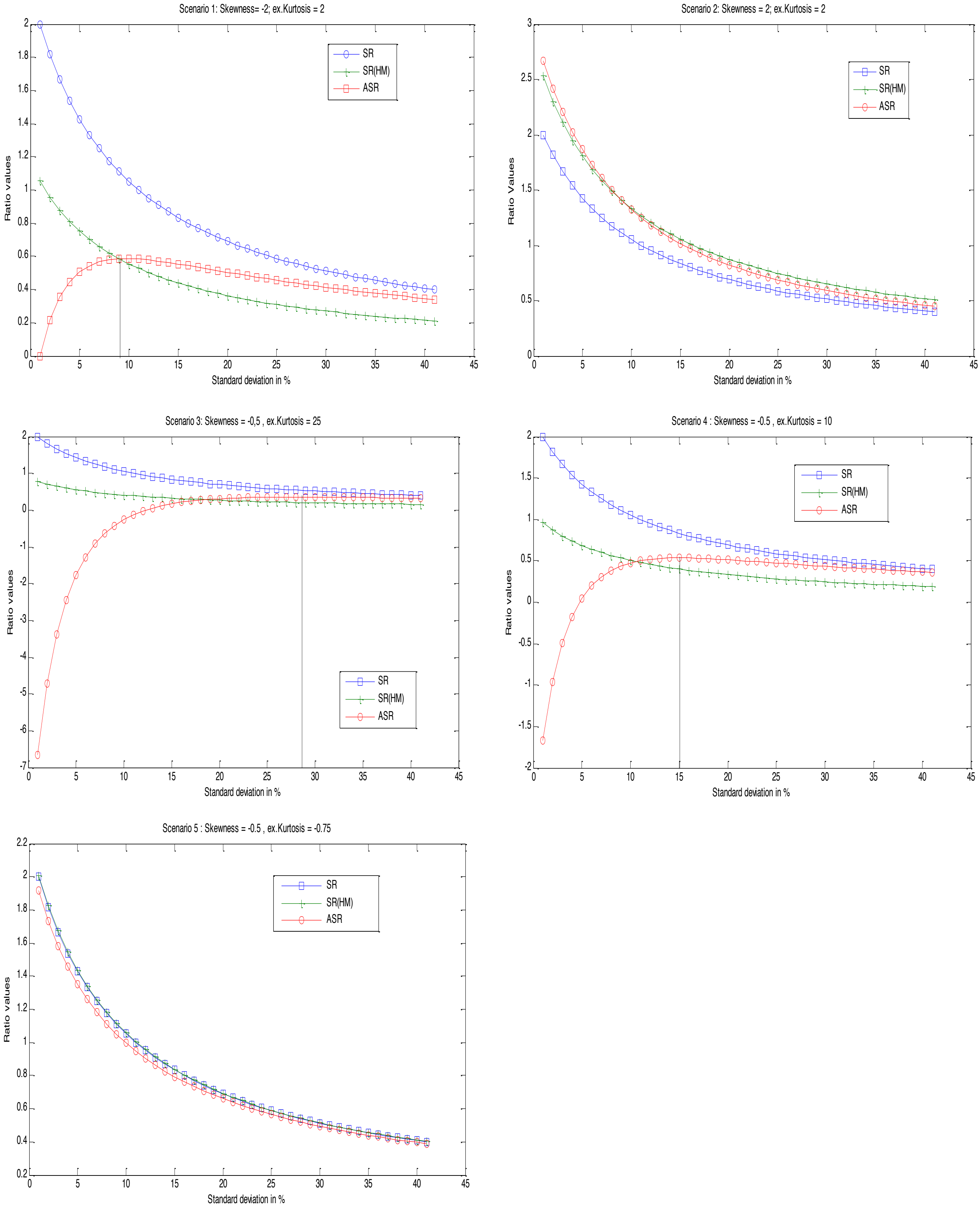


Figure 3. Comparing Five Different Skewness/Kurtosis Scenarios

The various figures present results of function values of the *Sharpe ratio* (SR), the *Higher Moment Sharpe ratio* (SR(HM)) and the *Adjusted Sharpe ratio* (ASR) for different standard deviation values holding skewness and excess kurtosis constant. Therefore, the figures are different in their constant third and fourth moment values. The x-axis describes the level of standard deviation used and the y-axis the level of the three ratios. A black vertical line indicates the inflexion point, where the ASR function starts to decline with increasing standard deviation.



APPENDIX

Appendix A. 1

Generalized Variance Measures

Besides the widely used variance definitions of squared simple or log returns, Neuberger (2012) proposed two other variance measures:

$$Ivar_{t,T}^{L} = 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}} - 1 - \ln\frac{F_{T,T}}{F_{t,T}}\right] \tag{25}$$

$$Ivar_{t,T}^{E} = 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}} - \frac{F_{T,T}}{F_{t,T}} + 1\right] \tag{26}$$

The first equation defines the variance of a *log contract* $L_{t,T}$ that pays off the futures log price of the underlying S_T (or here $F_{T,T}$). The second equation defines the variance of the *entropy contract* that pays off $E_{t,T} = [F_{T,T}\, lnF_{T,T}]$. Rearranging equations (25) and (26) to the respective future payoffs of $L_{t,T}$ and $E_{t,T}$ leads to:

$$L_{t,T} = \mathbb{E}_t\left[\ln F_{T,T}\right] = \ln F_{t,T} - \frac{Ivar_{t,T}^{L}}{2} \tag{27}$$

$$E_{t,T} = \mathbb{E}_t\left[F_{T,T}\ln F_{T,T}\right] = F_{t,T}\ln F_{t,T} + F_{t,T}\frac{Ivar_{t,T}^{E}}{2} \tag{28}$$

Using the illustrative approach from Carr and Madan (2002), the log return of a currency forward $F_{t,T}$ starting in t and maturing in T, can be priced using a continuum of options at inception time t under risk-neutral expectation as follows:

$$\mathbb{E}_t^{\mathbb{Q}}\left[ln\left(\frac{F_{T,T}}{F_{t,T}}\right)\right] = -\int_0^{F_{t,T}}\frac{P_{t,T}(K)}{B_{t,T}K^2}dK - \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K^2}dK. \tag{29}$$

Using the result of (29) for the payoff function of $L_{t,T}$ and $E_{t,T}$ respectively leads to the current price of the *log* and *entropy contracts*:

$$L_{t,T} = \mathbb{E}_t\left[\ln F_{T,T}\right] = \ln F_{t,T} - \int_0^{F_{t,T}}\frac{P_{t,T}(K)}{B_{t,T}K^2}dK - \int_{F_{t,T}}^{\infty}\frac{C_{t,T}(K)}{B_{t,T}K^2}dK \tag{30}$$

$$E_{t,T} = \mathbb{E}_t\left[F_{T,T}\ln F_{T,T}\right] = F_{t,T}\ \ln F_{t,T}\ + \int_0^{F_{t,T}} \frac{P_{t,T}(K)}{B_{t,T}K} dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{B_{t,T}K} dK \tag{31}$$

Furthermore, in order to get the current implied variance level of the *log* and *entropy contract* respectively, we simply need to plug equation (29) into (27) and (28). After some rearrangements, one can get the following results:

$$Ivar_{t,T}^{L} = 2\left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)}{B_{t,T}K^2} dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{B_{t,T}K^2} dK\right) \tag{32}$$

$$Ivar_{t,T}^{E} = 2\left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)}{B_{t,T}K\ F_{t,T}} dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{B_{t,T}K\ F_{t,T}} dK\right) \tag{33}$$

Appendix A. 2

Computing Implied Moments Using a Finite Set of Options

As noted in the introduction, the first step of computing implied moments is to recover market conform call and put prices. This will be done by using the parabolic interpolation model developed from Reiswich and Wystup (2012), which rebuilds the implied volatility curvature. It offers the information of the implied volatility level for any given strike and maturity of an option. Together with the US and foreign interbank offer rates and the spot exchange rate, one can recalculate any FX-option value with Garman and Kohlhagen (1983) proposed option price formula.

With regard to the implied second and third moment formulas (3), (6), and (10), the continuum of options will be replaced by the sum of 20 OTM call and 20 OTM put option strikes K_j. The call and put options will be stripped between the (+/-) 0.175 delta (call/put) option strike and the forward ATM strike, respectively. The strikes of the OTM option strips are equally spaced. The implied variance of the log and entropy contract and the implied third moment risk can be then formulated as follows:

$$Ivar_{t,T}^{L} = \frac{2}{B_{t,T}}\left(\sum_{K_j \le F_{t,T}} \frac{P_{t,T}(K_j)}{K_j^2} \Delta J(K_j) + \sum_{K_j > F_{t,T}} \frac{C_{t,T}(K_j)}{K_j^2} \Delta J(K_j)\right) \tag{34}$$

$$Ivar_{t,T}^{E} = \frac{2}{B_{t,T}}\left(\sum_{K_j \le F_{t,T}} \frac{P_{t,T}(K_j)}{K_j F_{t,T}} \Delta J(K_j) + \sum_{K_j > F_{t,T}} \frac{C_{t,T}(K_j)}{K_j F_{t,T}} \Delta J(K_j)\right) \tag{35}$$

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\sum_{K_j > F_{t,T}} \frac{C_{t,T}(K_j)(K_j - F_{t,T})}{K_j^2 F_{t,T}} \Delta J(K_j) - \sum_{K_j \leq F_{t,T}} \frac{P_{t,T}(K_j)(F_{t,T} - K_j)}{K_j^2 F_{t,T}} \Delta J(K_j)\right) \quad (36)$$

with

$$\Delta J(K_j) \equiv \begin{cases} K_{j+1} - K_{j-1}, for\ 0 \leq j \leq N\ (with\ K_{-1} \equiv 2K_0 - K_1, K_{N+1} \equiv 2K_N - K_{N-1}) \\ 0, \qquad otherwise. \end{cases} \quad (37)$$

Appendix A. 3

Implied Third Moment Risk

a) In order to show how the implied third-moment risk is connected to the generalized variance measures, it is necessary to start from equation (9). Then, simply by plugging in the risk-neutral expected values from $Ivar^E$ and $Ivar^L$ in terms of forward prices, we get the same expected value for the implied third-moment risk as in (8). Note that the first term in (8) is zero, according to the martingale property for forward prices.

$$Ithm_{t,T} = 3\left(Ivar_{t,T}^E - Ivar_{t,T}^L\right)$$

$$Ithm_{t,T} = 3\left\{2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}} - \frac{F_{T,T}}{F_{t,T}} + 1\right] - 2\,\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}} - 1 - \ln\frac{F_{T,T}}{F_{t,T}}\right]\right\}$$

$$Ithm_{t,T} = 6\left\{\mathbb{E}_t^{\mathbb{Q}}\left[\frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}} - \frac{F_{T,T}}{F_{t,T}} + 1 - \frac{F_{T,T}}{F_{t,T}} + 1 + \ln\frac{F_{T,T}}{F_{t,T}}\right]\right\}$$

$$Ithm_{t,T} = 6\mathbb{E}_t^{\mathbb{Q}}\left[2 - 2\frac{F_{T,T}}{F_{t,T}} + \ln\frac{F_{T,T}}{F_{t,T}} + \frac{F_{T,T}}{F_{t,T}}\ln\frac{F_{T,T}}{F_{t,T}}\right]$$

b) The implied third-moment risk can also be expressed as a portfolio of a continuum of options. Again using the result from equation (9), one can just replace $Ivar^E$ and $Ivar^L$ with their respective contingent claim prices defined in (32) and (33), respectively, to get the result from equation (10).

$$Ithm_{t,T} = 3\left(Ivar_{t,T}^E - Ivar_{t,T}^L\right)$$

$$Ithm_{t,T} = 3\left(2\left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{B_{t,T}K\,F_{t,T}}dK\right) - 2\left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)}{B_{t,T}K^2}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)}{B_{t,T}K^2}dK\right)\right)$$

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)K}{K^2\,F_{t,T}}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)K}{K^2\,F_{t,T}}dK\right) - \left(\int_0^{F_{t,T}} \frac{P_{t,T}(K)F_{t,T}}{K^2F_{t,T}}dK + \int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)F_{t,T}}{K^2F_{t,T}}dK\right)$$

$$Ithm_{t,T} = \frac{6}{B_{t,T}}\left(\int_{F_{t,T}}^{\infty} \frac{C_{t,T}(K)(K - F_{t,T})}{K^2\,F_{t,T}}dK - \int_0^{F_{t,T}} \frac{P_{t,T}(K)(F_{t,T} - K)}{K^2\,F_{t,T}}dK\right)$$

Appendix A. 4

Taylor Series Expansion

Given the log return *r* and the function *M(r)*

$$with \quad r = ln\frac{F_{T,T}}{F_{t,T}} \quad and \quad M(r) = 6(2 - 2e^r + r + re^r)$$

The n derivatives of *M(r)* are as follows:

$$M'(r) = 6(-e^r + 1 + re^r)$$

$$M''(r) = 6(re^r)$$

$$M'''(r) = 6(e^r + re^r)$$

$$M^{(n)}(r) = 6((n-2)e^r + re^r)$$

Using the Taylor approximation for *M(r)* results in:

$$T_n(r=0) = x^3 + \frac{12}{4!}x^4 + \frac{18}{5!}x^5 + \cdots$$

$$T_n(r=0) = x^3 + O(x^4)$$

For small x, one can see that the polynomials in $O(x^4)$ converges quickly to zero:

$$O(x^4) = \frac{12}{4!}x^4 + \frac{18}{5!}x^5 + \cdots$$

Hence, the implied third moment of Neuberger (2012) is closely connected to cubed log-returns of the underlying asset:

$$Ithm_{t,T} = \mathbb{E}_t^Q[r^3 + O(r^4)] \tag{38}$$

Appendix A. 5

Fixed and Floating Legs of a Cubic Swap

According to the definitions in Kozhan et al. (2013), the fixed leg of a cubic swap using the g-function $g(r) = r^3$ is defined as:

$$Ithm_{t,T}^{cubic} \equiv \mathbb{E}_t^Q\left[\left(ln\frac{F_{T,T}}{F_{t,T}}\right)^3\right]$$

$$= \frac{3}{B_{t,T}}\left(\int_{F_t}^{\infty}\frac{ln\frac{K}{F_{t,T}}(2-ln\frac{K}{F_{t,T}})}{K^2}C_{t,T}(K)dK - \int_0^{F_t}\frac{ln\frac{F_{t,T}}{K}(2+ln\frac{F_{t,T}}{K})}{K^2}P_{t,T}(K)dK\right) \quad (39)$$

The corresponding realized leg of the cubic swap is defined as:

$$Rthm_{t,T}^{cubic} = \sum_{i=t}^{T}\left[3\,\delta Ivar_{i,T}^Q\,ln\frac{F_{i+1,T}}{F_{i,T}} - \frac{3}{2}(Ivar_{i,T}^Q + Ivar_{i,T}^L)\left(ln\frac{F_{i+1,T}}{F_{i,T}}\right)^2\right] \quad (40)$$

The realized leg of the cubic swap ($Rthm^{cubic}$) also contains an implied variance term that refers to the definition of a quadratic swap according to Kozhan et al. (2013). The definition of $Ivar_{i,T}^Q$ is summarized in (41) for convenience. Note that the term $\delta Ivar_{i,T}^Q$ in (40) is equal to $Ivar_{i+1,T}^Q - Ivar_{i,T}^Q$.

$$Ivar_{t,T}^Q \equiv \mathbb{E}_t^Q\left[\left(ln\frac{F_{T,T}}{F_{t,T}}\right)^2\right]$$

$$= \frac{2}{B_{t,T}}\left(\int_{F_{t,T}}^{\infty}\frac{(1-ln\frac{K}{F_{t,T}})}{K^2}C_{t,T}(K)dK + \int_0^{F_{t,T}}\frac{(1+ln\frac{F_{t,T}}{K})}{K^2}P_{t,T}(K)dK\right) \quad (41)$$

In order to construct implied and realized skew coefficients comparable to the *Iskew* and *Rskew* variables, $Ithm^{cubic}$ and $Rthm^{cubic}$ will be scaled by $Ivar^Q$ to the power of 3/2.

$$Iskew_{t,T}^{cubic} = \frac{Ithm_{t,T}^{cubic}}{{Ivar_{t,T}^Q}^{3/2}} \quad (42)$$

$$Rskew_{t,T}^{cubic} = \frac{Rthm_{t,T}^{cubic}}{{Ivar_{t,T}^Q}^{3/2}} \quad (43)$$

Appendix A. 6

According to Schneider and Trojani (2015), the variance function of the simple return g^S can be characterized as follows:

$$g^S = (e^r - 1)^2 = \left(\frac{F_{T,T} - F_{t,T}}{F_{t,T}}\right)^2 \tag{44}$$

Under iterated expectations and if the martingale property for the forward price process applies, the simple variance function has an interpretation in accordance with the Aggregation Property shown in equation (1). The expected value of the implied variance in g^S under the $\mathbb{Q}$-measure is equal to the expected realized variance under the physical measure $\mathbb{P}$, independent of the measurement frequency.

$$\mathbb{E}_t^{\mathbb{Q}}\left[\left(\frac{F_{T,T} - F_{t,T}}{F_{t,T}}\right)^2\right] = \mathbb{E}_t^{\mathbb{P}}\left[\sum_{t=1}^{T}\left(\frac{F_{t,T} - F_{t-1,T}}{F_{t-1,T}}\right)^2\right] \tag{45}$$

Schneider and Trojani (2015) show how the implied measure can be characterized as contingent claim price using a continuum of option prices:

$$\begin{aligned}
\frac{\left(F_{T,T} - F_{t,T}\right)^2}{{F_{t,T}}^2} &= \frac{2}{{F_{t,T}}^2}\int_0^{\infty}\left(F_{T,T} - K\right)^+ dK - \frac{2F_{T,T}F_{t,T}}{{F_{t,T}}^2} + 1 \\
&= \frac{2}{{F_{t,T}}^2}\left(\int_0^{F_{t,T}}\left(K - F_{T,T}\right)^+ + F_{T,T} - K dK + \int_{F_{t,T}}^{\infty}\left(F_{T,T} - K\right)^+ dK\right) - \frac{2F_{T,T}F_{t,T}}{{F_{t,T}}^2} + 1 \\
&= \frac{2}{{F_{t,T}}^2}\left(\int_0^{F_{t,T}}\left(K - F_{T,T}\right)^+ dK + F_{T,T}F_{t,T} - \frac{{F_{t,T}}^2}{2} + \int_{F_{t,T}}^{\infty}\left(F_{T,T} - K\right)^+ dK\right) - \frac{2F_{T,T}F_{t,T}}{{F_{t,T}}^2} + 1 \\
&= \frac{2}{{F_{t,T}}^2}\left(\int_0^{F_{t,T}}\left(K - F_{T,T}\right)^+ dK + \int_{F_{t,T}}^{\infty}\left(F_{T,T} - K\right)^+ dK\right)
\end{aligned} \tag{46}$$

Hence, by taking risk neutral expectations, the fixed leg of a simple variance swap is defined as follows:

$$Ivar_{t,T}^{s} = \mathbb{E}_t^{\mathbb{Q}}\left[\frac{\left(F_{T,T} - F_{t,T}\right)^2}{{F_{t,T}}^2}\right] = \frac{2}{{F_{t,T}}^2 B_{t,T}}\left\{\int_0^{F_{t,T}} P_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} C_{t,T}(K)dK\right\} \tag{47}$$

Appendix A. 7

Relationship Between Realized Variance of the Log Contract and Realized Variance of Log Returns

Using the definitions in Carr and Lee (2009), the simple and log return of forwards are denoted as follows:

$$R_{t,T} = \frac{F_{t,T} - F_{t-1,T}}{F_{t-1,T}} \quad and \quad r_{t,T} = \ln\frac{F_{t,T}}{F_{t-1,T}}$$

A Taylor series expansion for f(x) = 2 ln(1+x) leads to:

$$2\, lnF_{t,T} = 2\ln\mathrm{F}_{t-1,T} + \frac{2}{\mathrm{F}_{t-1,T}}\left(F_{t,T} - F_{t-1,T}\right) - \frac{2}{\mathrm{F}_{t-1,T}{}^{2}}\left(F_{t,T} - F_{t-1,T}\right)^{2} + \frac{2}{3\mathrm{F}_{t-1,T}{}^{3}}\left(F_{t,T} - F_{t-1,T}\right)^{3} + \mathrm{O}(R_{t,T}^{4}) \tag{48}$$

By using above return definition, one can write:

$$r_{t,T} = \mathrm{R}_{t,T} - \frac{1}{2}R_{t,T}^{2} + \frac{1}{3}R_{t,T}^{3} + \mathrm{O}(R_{t,T}^{4}) \tag{49}$$

Now, squaring both sides and solving for R^2 leads to:

$$R_{t,T}^{2} = \mathrm{r}_{t,T}^{2} - R_{t,T}^{3} + \mathrm{O}(R_{t,T}^{4}) \tag{50}$$

Now, (50) is substituted into (49), and solving for r^2 leads to:

$$r_{t,T}^{2} = 2\mathrm{R}_{t,T} - 2r_{t,T} - \frac{1}{3}R_{t,T}^{3} + \mathrm{O}(R_{t,T}^{4}) \tag{51}$$

Using these results, one can now develop a measure of realized variance of squared log returns with N observations and frequency length Δ:

$$\sum_{i=1}^{N} \ln\left(\frac{F_{t+i\Delta,T}}{F_{t-1+i\Delta,T}}\right)^{2} = 2\sum_{i=1}^{N}\left(\frac{F_{t+i\Delta,T}}{F_{t-1+i\Delta,T}} - 1\right) - 2\sum_{i=1}^{N} ln\left(\frac{F_{t+i\Delta,T}}{F_{t-1+i\Delta t,T}}\right) - \frac{1}{3}\sum_{i=1}^{N} R_{t+i\Delta}^{3} + \mathrm{O}(R_{t+i\Delta}^{4}) \tag{52}$$

Denoting this realized variance measure with $Rvar^{logR}$ and recalling the definition in (4) for the realized variance of the *log contract* leads to following relationship :

$$Rvar_{t,T}^{logR} = Rvar_{t,T}^{L} - \frac{1}{3}\sum_{i=1}^{N} R_{t+i\Delta}^{3} + O(R_{t+i\Delta}^{4}) \tag{53}$$

Appendix A. 8

Higher Moment Sharpe Ratio

This paper briefly introduces an extension of the well-known Sharpe ratio (Sharpe, 1975). It is frequently used as a measure of efficiency for an investment, by simply dividing the excess return of a portfolio with its standard deviation (σ). The excess return is defined as the difference between the portfolio return (μ_1) and a risk free rate (r^f). One of its shortcomings is that it does not account for return distributions apart from normality. Therefore, the *Higher Moment Sharpe Ratio* (SR^{HM}) is supposed to appropriately account for skewness (γ_1) and excess kurtosis (γ_2) of a return distribution and contains the original *SR* as a special case. It is defined as follows:

$$SR^{HM} = \frac{\mu_1 - r^f}{\left[\left(\sqrt{\sigma^2}\right)\left(\sqrt[3]{(1 + a|\gamma_1|)}\right)^{-E}\left(\sqrt[4]{1 + b|\gamma_2|}\right)^{B}\right]^{(\mu_1 - r^f/|\mu_1 - r^f|)}} \tag{54}$$

$$E = \begin{cases} +1, & if\ \gamma_1 > 0 \\ -1, & if\ \gamma_1 \leq 0 \end{cases} \quad \text{and} \quad B = \begin{cases} +1, & if\ \gamma_2 > 0 \\ -1, & if\ \gamma_2 \leq 0 \end{cases}$$

$$\gamma_1 = \frac{E[(X - \mu_1)^3]}{\sigma^3} \tag{55}$$

$$\gamma_2 = \frac{E[(X - \mu_1)^4]}{\sigma^4} \tag{56}$$

The numerator is equivalent to the original *SR,* while the denominator is extended by two additional factors. The first accounts for the skewness of a portfolio return distribution γ_1 and the second for its excess kurtosis γ_2. Both are multiplied by factors *a* and *b*, which are assumed to be 1 for simplicity. If both γ_1 and γ_2 are 0, as in the case for normal distributed returns, *SR* and SR^{HM} are equal. *E* and *B* represent indicator variables that are 1 or -1 depending on the respective γ_i values. In order to account for negative (positive) skewness and excess kurtosis above (below) 0, one would plausibly expect a reduced (increased) *SR*. This is effectively achieved for SR^{HM}, since the terms inside the last two root terms are both higher (lower) than 1, which leads to a reduced (increased) SR^{HM} compared to the original SR.

In order to identify SR^{HM} as a measure of investor utility, the *Adjusted Sharpe Ratio* (*ASR*) proposed by Pézier and White (2008) is considered for calibration purposes. The *ASR* is derived from a Taylor series expansion of expected utility with an exponential utility function of the form

$$ASR = SR + \frac{\gamma_1}{3!}SR^2 - \frac{\gamma_2}{4!}SR^3 \qquad (57)$$

This variable also has its merits, especially for SR values above one and/or high excess kurtosis. In these cases, ASR is an increasing function of the standard deviation, all other input values equal. The calibration process for the SR^{HM} uses five different arbitrarily chosen skewness/kurtosis scenarios for a return portfolio. For each scenario, the values for the standard deviation will be subsequently increased holding the skewness/kurtosis scenario values constant. How the 3 different Sharpe ratios evaluate in these 5 scenarios with regard to increased standard deviation can be seen in the following figure:

[*Insert Figure 3 about here.*]

Then the values a and b for SR^{HM} are optimized simultaneously, by minimizing the sum of squared differences between ASR and SR^{HM} over all five scenarios. Please note that only reasonable ASR values are considered. This means that only ASR values are taken into account which decline when standard deviation increases. The *Generalized Reduced Gradient* (GRG) algorithm proposed by Abadie (1978) is used to find a feasible solution for coefficients a and b respectively. The optimization process finds a solution with a=1.8 and b=1.0. These values are taken to represent the default approach of the SR^{HM}. Additionally, the denominator will be raised to the power of the excess return, divided by its absolute value of the excess return following the idea of Israelsen (2005). While this correction has no effect on positive excess returns, the value becomes -1 in cases of negative returns. Israelsen (2005) points out that the original SR yields only plausible rankings, as long excess returns are positive. This adjustment corrects for negative excess returns, resulting in a more tractable, efficient ranking.

Chapter 5

General Conclusion

General Conclusion

This study analysed, on the one hand, the exchange rate return characteristics of the currency carry trade strategy and, on the other hand, the crash risk premium for a wide range of currencies in the sample. The first part comprehensively showed that the excess return premium of the carry trade is a compensation for risk bearing. The key differences to other studies are: (i) a high variety of risk variables analysed together and (ii) the use of forward-looking option-implied moment risk instead of the realized data. These two ingredients made it possible to uncover 80% of the systematic risk of the carry trade and simultaneously offer investors the possibility of using these risks as hedging instruments. Moreover, it has been documented that constructing a parametric portfolio policy model fed up with option-implied moment risk can dramatically improve the risk-return profile of the carry trade portfolio.

The second part of the analysis found evidence that the observed skewness risk anomaly, which is manifested by the disconnection of the realized and option-implied skewness risk, can be primarily explained by FX short term return momentum effects as well as special constellations in the FX market microstructure. With regard to other studies in the currency and equity or commodity literature, this skewness risk anomaly is unique in terms of its occurrence in other financial markets and also the explanatory evidence. Therefore, this study can be regarded as a starting point for future investigations. After describing the source of disconnection, a novel investment strategy was set up to exploit this anomaly using a skew swap strategy in the FX option and forward market. While the results look very promising in terms of excess returns, after controlling for transaction costs these profits almost completely vanish.

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