Attractive and non-attractive currencies

In the foreign exchange market, time-varying transaction costs and interest rates may define the time-varying set of attractive currencies for investors. Our study shows that when the currencies are attractive, they tend to deviate from the uncovered interest rate parity and to comove with the global stochastic discount factor (SDF). Inversely, when they are non-attractive, currencies tend to conform more closely to uncovered interest parity and do not comove with the global SDF. As a consequence, both investors and policy makers may want to know the status of a currency as it conveys important information about the future return of the currency. We illustrate our point in a sample including 26 currencies over the period 1985-2017.

JEL Classification numbers: F31, G12

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1. Introduction

According to Uncovered Interest rate Parity (UIP), arbitrage should eliminate the gains arising from the differential of interest rates across currencies. Yet, the carry trade which consists in buying high yielding currencies and selling low yielding currencies has been profitable on average (Figure 1) and the failure of the UIP is one of the main puzzle for academics in finance. Recently the profits of the carry trade have been even rationalized in an Asset Pricing setting (APT): investors would demand time varying risk premia associated with a stochastic discount factor (SDF). If investing in currencies that are at a forward discount delivers lower returns during bad times, investors then expect larger average profits in compensation for this risk.

We confirm the failure of the UIP in our data: on average high yielding currencies tend to appreciate while low yielding currencies tend to depreciate. However, our results suggest that only attractive currencies - defined to be those for which the cost of trading (the bid-ask spread) does not outweigh the expected return (the carry) - tend to breach the UIP relationship and to comove with the global SDF. For these currencies, larger returns are associated with larger forward discounts, and vice versa. On the other hand, carry trade type positions in non-attractive currencies tend to exhibit lower Sharpe ratios which are often not significantly different from zero on average. These currencies conform more closely to UIP and they do not covary with the global SDF.

Our definition of attractive and non-attractive currencies is not new. Notably, Liu (2004) proposed a general model in which investors take transaction costs into account to define price levels triggering transactions. There is also a growing literature considering directly transaction costs in the decision rule of the carry trade investor, see for instance Burnside et al. (2007), Baroso, Santa Clara (2015) and Maurer, Pezzo and Taylor (2019). However, while these papers take the point of view of the investor and extensively study strategies investing in attractive currencies, they do not fully explore the related questions of the failure of UIP and its rationalization in an APT framework. This is precisely the aim of this paper and our contribution to the literature.

In our sample, the average cost of trading (bid-ask spread) of the forward instrument is around 0.14% (median 0.07%). This means that, on average, a currency is attractive if the annualized interest rate differential with the US is above 1.7% for a one month investment horizon ($0.14\% * 12 \approx 1.7\%$). In our sample, the mean interest rate differential between the USD and the foreign currencies is 3.62% (median 2.46%) with a standard deviation of 4.12%. On average, currencies are attractive but our sample also contains about 30% of observations that concern non-attractive currencies. In this paper, we show that the behavior of the currencies differ significantly if they belong to one group or the other. As the bid - ask quotes may be only indicative, we are particularly careful when a currency switches from being attractive to non-attractive and vice versa. In particular, we produce robustness tests with simulated bid-ask spreads.

Our paper is primarily related to the extensive literature on UIP. Since the seminal works of Hansen and Hodrick (1980) and Fama (1984), the literature has often concluded that on average currencies breach the UIP. But, recently, Clarida, Davis and Pedersen (2009) report that the coefficient in the Fama regression may be regime dependent: currencies tend to breach UIP mainly in low volatility regimes, much less in high volatility regimes. Our contribution to the literature mirrors this finding: currencies tend to breach UIP mainly when they are attractive and much less when they are not attractive. Our paper is naturally related to the literature on extreme interest rates differentials (IRD) such as Huisman et al. (1998), Lothian and Wu (2011) and Tims and Mulders (2015) among others. However, we clearly differ from these papers by the way we define the set of currencies of interest. While these papers use ad-hoc definitions of extreme IRD (for instance the 10% higher IRD), we propose to rely on the rational investors' rule to characterize IRD (attractive IRD, equivalently attractive currency, versus non-attractive ones).

Finally, our paper is related to the recent rationalization of the failure of the UIP in an Asset Pricing Theory framework as proposed by Lustig, Roussanov and Verdhelan (2011) and Menkhoff et al. (2012). In particular, we show that when the currencies are not attractive to investors in the carry trade, they do not comove significantly with the global SDF.

Our sample contains 26 currencies and covers the period January 1985 to January 2017. The data are extracted from both Bloomberg and Datastream. Our main sample is extracted from Bloomberg and covers the period January 1999 to January 2017. This sample exhibits interesting characteristics for our study, especially when we consider the dynamic of the bid-ask spreads which is central for the definition of the time-varying set of attractive currencies. The same sample extracted from Datastream does not exhibit these characteristics. We relate the differences between the two sets of data to the way providers process information. However, as the coverage is sparse in Bloomberg before 1999, we complement our sample with data for the G10 countries only available in Datastream.

Taken as a whole, our findings might be particularly interesting for policymakers and forecasters as they suggest that the status of the currency being attractive or non-attractive may contain information about its future return. In particular, our result shows that non-attractive currencies may impair returns to the carry trade and simply add noise to the asset pricing relationship. As a consequence, the classical equally weighted portfolio which mixes long positions in all the currencies which pay a discount and short positions in all the currencies which pay a premium does not produce high enough risk-adjusted returns to be appealing to the investors. Rather, investors may want to limit the investment universe to the set of currencies that are attractive.

Our results indicate that central banks should be particularly careful when the interest rate attached to the domestic currency nears the tipping point between the attractive and the non-attractive status. Changing the level of the interest rate further in that region may significantly change the behavior of the currency. Indeed, our results indicate that high yielding currencies would tend to appreciate more when they are attractive while low yielding currencies would depreciate more. Also attractive currencies exhibit greater crash risks both under physical and risk-neutral measures. Finally, using Commodity Futures Trading Commission (CFTC) Commitments of Traders (COT) data, we show that on average, traders tend to increase their speculative long positions in high yielding currencies when they are attractive. Conversely, they tend to increase their short positions in low yielding currencies when they are attractive. This might give an insight about changes in capital flows to the countries as the futures market and the cash market is closely linked through arbitrage (e.g. Lyons, 2001).

The carry trade is central to FX investment but investors also rely on other signals to define currency attractiveness such as momemtum and value (e.g. Kroencke, Schindler and Schrimpf, 2014). Therefore, we complement our analysis by studying currencies for which the attractiveness is defined on the back of momemtum and value signals together with carry. We rely on the Asness, Moskowitz and Pedersen (2013) definition of FX momemtum and FX value factors. For instance, in complementary work, we consider that only high yielding currencies for which the cost of trading does not outweigh the carry and which exhibit a positive momemtum are attractive investment currencies. Low yielding currencies for which the cost of trading does not outweigh the carry and which exhibit a negative momemtum are considered attractive financing currencies. In all other occasions, the currency is considered as being non-attractive (we use the value factor in a comparable fashion). This version of attractiveness is harsher, in that it defines a smaller set of attractive currencies, but the results we obtain in this set confirm the preceding ones. Only attractive currencies breach UIP whether we use momemtum or value as factors defining attractiveness. This failure of the UIP might be rationalised in an APT framework for attractive currencies, especially when we use the momemtum factor, but not when the currencies are non-attractive. This confirms our main finding.

The rest of this paper is organized as follows: in section two we design carry trade portfolios taking transaction costs into consideration. This defines the set of attractive currencies and the set of non-attractive currencies. In section three, we present the data sets and report descriptive statistics for various investments in the carry trade. In section four, we study the relationship between the forward discount and the future return of the currencies in both the subsets of attractive and non-attractive currencies. In section five we study the return of the currency carry trade in an APT framework differentiating again between the subset of attractive and non-attractive currencies. We extend the analysis in a sixth section, by including the momemtum factor and the value factor in the definition of attractiveness. We conclude in the seventh section.

2. Attractive currencies and the carry trade

The no-arbitrage condition states that currencies that pay a discount should depreciate on average. In this case uncovered interest rate parity holds. Instead, the data show that higher yielding currencies tend to appreciate and lower yielding currencies tend to depreciate on average. Investors take profit from the failure of the UIP by building portfolios of carry trades. However not all currencies are attractive to investors: market imperfections (i.e. transaction costs) dynamically define the set of currencies which investors prefer to invest in. In this section, first we quickly recall how investors may profit from the failure of UIP and how they may discriminate between attractive and non-attractive currencies.

2.1. The return to currency speculation

The carry trade consists of buying (selling) forward high (low) yielding foreign currencies at time t and selling (buying) them back at the prevailing spot exchange rate at maturity. It is therefore usual in both the market and the literature to first rank the currencies from low to high interest rates currencies on the basis of their forward discount *(f-s)* observed at the end of each month t. The currency with the lowest forward discount receives rank 1 while the currency with higher forward discount receives rank N. Investors then sell forward the lower ranked curencies and buy the currencies with the higher ranks. The monthly excess return for holding any foreign currency i is then: $r^i_{t+1} = f^i_t - s^i_{t+1}$ with r^i_{t+1} the log monthly excess return of currency i observed in $t+1$, f^i_t the log forward rate of currency i observed at time t and s^i_{t+1}, the log spot exchange rate observed at time t+1.

When agents are risk neutral and think $1/s_{t+1}$ is a martingale[1], the decision rule is the following (e.g. Sokolowski, 2019):

$$\begin{cases} \text{Buy the FCU if} \quad E(f_t/s_{t+1}) = f_t/s_t > 1 \\ \\ \text{Sell the FCU if} \quad E(f_t/s_{t+1}) = f_t/s_t < 1 \end{cases} \tag{1}$$

Accounting for the bid-ask spread (with prices denoted b or a as appropriate), investing in the carry trade is profitable at the currency level (r) if:[2]

$$\begin{cases} r_{t+1}^{long} = f_t^b - s_{t+1}^a > 0 & \text{if the investor buys the FCU} \\ \\ r_{t+1}^{short} = -f_t^a + s_{t+1}^b > 0 & \text{if the investor sells the FCU} \end{cases} \tag{2}$$

It is usual in the literature to package currencies in portfolios of carry trades. For instance, Lustig, Roussanov and Verdelhan (2011) and Menkhoff et al. (2012) build equally weighted portfolios of currencies while Asness et al. (2013), Jurek (2014) and Daniel, Hodrick and Lu (2017) build discount (i.e. $f - s$) weighted portfolios of carry trades.

The returns (R) to the equally weighted portfolio of long positions and the equally weighted portfolio of short positions are:

$$\begin{cases} R_{t+1}^{long} = \frac{1}{(\sum w_i)} \sum_{i=1}^{nl} w_i * r_{t+1}^i \\ \\ R_{t+1}^{short} = \frac{1}{\sum w_j} \sum_{j=1}^{ns} w_j * r_{t+1}^j \end{cases} \tag{3}$$

with nl the number of currencies in which the investor has a long position and ns the number of currencies in which she has a short position. Finally, with $w_i > 0$ and $w_j < 0$, the return of the carry trade strategy is the sum of R_t^{long} *and* R_t^{short}.

2.2. The cost of trading and the subset of attractive currencies

The question of the optimal number of currencies that investors should combine in portfolios remains an open one in the literature. In the absence of transaction costs, Liu (2004) shows that the optimal policy involves investing a constant dollar amount in each currency according to Equation 1. However, researchers tend only to combine currencies with the higher (lower) interest rates, de facto considering that not all currencies are attractive to the investors.

For instance, Lustig, Roussanov and Verdelhan (2011) build portfolios of six currencies each, Menkhoff et al. (2012) work with portfolios of five currencies while Bakshi and Panayotov (2013) test portfolios of three currencies only. Indeed, when transaction costs are non-zero and proportional, they define a transaction region in which investors buy and sell currencies and a no-transaction region in which they do not invest (e.g. Liu, 2004). Recently, Burnside et al. (2007), Barroso and Santa Clara (2015) and Maurer, Pezzo and Taylor (2019) relied on this proposition to precisely define the currencies which are attractive to the investors. In these papers, when investors consider trading costs, the decision rule is the following:

$$\begin{cases} \text{Buy the FCU if} & E(f_t^b/s_{t+1}^a) = f_t^b/s_t^a > 1 \\ \\ \text{Sell the FCU if} & E(f_t^a/s_{t+1}^b) = f_t^a/s_t^b < 1 \\ \\ \text{No Transaction if} & f_t^a/s_t^b > 1 \text{ and } f_t^b/s_t^a < 1 \end{cases} \tag{4}$$

This decision rule defines the time varying set of attractive currencies and therefore the number of currencies that investors should mix in portfolios. From the researcher point of view, this definition of the attractive currencies might offer an interesting opportunity to study exactly when currencies may attract speculative flows and when they may not. This is precisely what we do in this paper.

The maturity of the forward contracts f_t used in Equation (4) is key to determine the set of attractive currencies. Indeed, the time varying size of the bid-ask spread sets the ex-ante breakeven of the speculative position in the currency. In turn, this breakeven enforces the minimum holding period for the investors (to offset the transaction costs). With longer term forward contracts (6-month for instance), most currencies are attractive because even a small differential of interest rate, held over a long period of time may offset the transaction costs. However, they constrain investors to bear currency risk over this exact period of time. Conversely, with shorter term forward contracts (one week for instance), few currencies are attractive, notably only the ones with the largest interest rate differentials.

In this paper, we consider that investors define attractive currencies as the ones that break even in less than one month, i.e. currencies for which Equation (4) holds with one-month or shorter forward contracts. This horizon offers a good balance in terms of observations between longer term contracts which basically define most currencies as attractive and shorter term contracts that define most currencies as non-attractive. Also, as reported by Granger, Harvey, Rattray and Van Hemert (2019), investors usually consider, at least once a month, whether they need to rebalance their portfolio to maintain their strategic asset allocation unchanged. Furthermore, the recent literature on the carry trade uses one-month forward contracts in benchmark tests (see section 3 and 4 for robustness tests on this point). Finally, note that our objective in this paper is not to come up with the best version of the carry trade. We only look at the impact of discriminating between attractive and non-attractive currencies. For recent contributions on the carry trade, see Daniel, Hodrick and Lu (2017) and Bekaert and Panayotov (2018) among others.

3. Data Analysis

We use data collected by Bloomberg and both by Barclays and Reuters and available on Datastream (WM/Reuters). These data sets cover the period from January 1985 to January 2017 for 26 different currencies: Australia, Brazil, Canada, Czech Republic, Denmark, Euro Area, France, Germany, Hong Kong, India, Italy, Japan, Mexico, the Netherland, New Zealand, Norway, Philippines, Poland, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand and the UK[3]. The euro series starts in January 1999 replacing in our dataset the currencies of the countries which joined the Euro (i.e. France, Germany, Italy and the Netherland).

While forward rates may be available for a larger basket of currencies, there would have been virtually no liquidity in many of them (2019 *BIS Triennial Survey*). Those illiquid currencies might suffer from measurement error especially concerning the bid-ask spread (e.g. Cochrane, 2005). All currencies are quoted as the number of Foreign Currency Unit (FCU) per dollar. We use only data collected by Bloomberg for our main tests because the bid-ask spreads are much more dynamic than in the dataset available in Datastream (see Appendix A for a comparison).

These data extracted from Bloomberg cover the period January 1999 to January 2017. In a second step and for robustness tests only, we consider data for G10 countries from 1985 to 1998 which are available in Datastream.

We start from daily data including the spot exchange rates and the one-month forward exchange rates with bid and ask rates for each observation (we use NDF quotes for the Brazilian and the Indian currencies). We convert the daily data into monthly data by sampling the daily data on every last available day of each month. As recommended by Darvas (2009), we carefully check for errors in the data. Notably, we replace 4.89% of the total of observations in our main sample extracted from Bloomberg (the replacement process is extensively described in Appendix A). For comparison, we would replace 5.01% of the total of observations in the comparable sample extracted from Datastream. Finally the data are winsorized at the 1% level, mainly to be able to perform the asset pricing tests[4] of section 5.

3.1. The information content of the bid-ask spread

In our sample, the average bid-ask spread of the forward quotes is around 0.14% (median 0.07%). For the G10 currencies, this number falls to 0.09% with a minimum at 0.01% but for certain emerging currencies, it jumps to 0.58% in severe episodes of crises. As already mentioned, this means that, on average, a currency is attractive if the annualized interest rates differential with the US is around 1.7%p.a. for a one month investment horizon (1% for G10 currencies but more than 7% for certain emerging ones). In our sample, the average interest rate differential is 3.62% with a standard deviation of 4.12% when the foreign currencies exhibit a higher interest rate than the USD (investment currencies). These numbers are respectively -1.56% and 4.84% for the financing currencies which exhibit a lower interest rate than the USD (see Table XVII and XVIII in appendix A for descriptive statistics for both the bid ask spreads and the interest rate differentials). As a result, in our sample, around 30% of the observations concern currencies which are not attractive.

We know since Stoll (1989) that bid-ask spreads cover various costs among which processing costs, inventory holding costs and adverse infomation costs. These costs may increase during spikes of volatility which in turn may enlarge the set of non-attractive currencies. For instance, Bollerslev and Melvin (1994) using DEM/USD intraday estimations of volatility and spreads during 3 months in 1989 found a strong and positive relationship between the two. Therefore it seems natural to question the value-added of bid-ask spreads for portfolio construction especially when investors already control for risks using the information content of the variance-covariance matrix.

Dow and Ribeiro da Costa Werlang (1992) relate the marginal information contained in the bid-ask spread to uncertainty (subjective probabilities) as opposed to risk (objective probabilities) and use it for theoretical asset allocation. Recently, in the FX market, Maurer, Pezzo and Taylor (2019) show that taking transaction costs into account in a mean variance portfolio optimization significantly improves the achievable after costs Sharpe ratio out of sample. Their findings confirm the conclusions of Burnside et al. (2007), Barroso and Santa Clara (2015) on the importance of transaction costs for portfolio construction in the FX market. They also confirm the conclusion of Egbers and Swinkels (2015) who do not see implied volatility as a stand alone indicator for currency carry trade in real life decisions.

In our sample, the correlation between the bid-ask spreads and implied volatilities as extracted from the option market remains low at 0.15 (sd-error 0.17) on average in the cross section of the currencies[5]. This correlation falls to 0.09 (sd-error 0.12) in normal times when we exclude observations related to the financial crises (April 2008 to March 2009). This confirms the findings of Galati (2000) who find a correlation of 0.08 for the JPY/USD cross in 1998 but higher numbers for emerging markets currencies affected, at that time, by the Russian crises. Similarly, Menkhoff et al. (2012) report a correlation of 0.2 between innovations of FX volatility and innovations of the bid-ask spread. They qualify it as being "not impressive quantitatively": there is marginal information contained in the bid-ask spread which is not captured in the variance-covariance matrix, especially in normal times. This point is important because we will see later that the carry trade (together with the UIP failure) works much better during low volatility regimes (e.g. Clarida, Davis and Pedersen, 2009)

3.2. The return to attractive currencies and non-attractive currencies

In Table I, we report the summary statistics for the ranked currencies packaged in portfolios as defined in section 2. We report the annualized mean, standard-deviation, skewness and kurtosis of the distribution of returns[6] as well as a series of risk-adjusted returns, as defined in Appendix B. We also report the non annualized version of these ratios and their standard-errors obtained by bootstrapping the statistics[7]. Portfolios are rebalanced at the end of every month. Table I, confirms that considering transaction costs in the decision rule improves the returns to the carry trade, as reported by Burnside et al. (2007), Barroso and Santa Clara (2015) and Maurer, Pezzo and Taylor (2019). Indeed, the equally weighted benchmark carry trade ($Carry$) exhibits a small Sharpe ratio of 0.36 for the period 1999 to 2017. This is equivalent to a non annualized ratio of 0.10 which might not be different from 0 (p-value 0.14) if we consider the value of the standard-errors estimated by bootstraping the statistics (0.07). When we consider only the attractive currencies ($Carry_{ba}$) the Sharpe Ratio increases to almost 0.48 and becomes significantly different from zero (p-value 0.05). Conversely when we consider only the non-attractive currencies, the Sharpe ratio is significantly lower, standing at just 0.11, and a test of the equality of the Sharpe Ratios as proposed by Ledoit and Wolf (2008) rejects this possibility with a p-value of less than 0.01. Similarly, as reported in Table II, in the subset of G10 currencies over the period 1985 to 1998, the carry trade based on attractive currencies offers a significantly higher risk adjusted ratios (0.67) than the carry trade based on non-attractive currencies (Sharpe ratio of 0.00).

Table I and Table II about here

It is important to note that the aim of this paper is not to proposed a new carry trade strategy. Including transaction costs in the decision rule has been already extensively examined by Burnside et al. (2007), Barroso and Santa Clara (2015) and Maurer, Pezzo and Taylor (2019). Therefore, we do not want to focus too much on the difference between the benchmark strategy and the strategy using only the attractive currencies. We report that the difference in Sharpe ratios is marginally significant in the set extracted from Bloomberg including G10 and emerging markets currencies (p-value 0.08). This is not surprising since the strategy based on attractive currencies and the benchmark strategy share about 70% of the observations available in the dataset. When we look at the set of G10 currencies extracted from Datastream, we see that the difference in Sharpe ratio is not significant at all. Again, this is not surprising when we recall that the bid-ask spread is much less dynamic in the set extracted from Datastream (see again Appendix A). However, in both samples, the Sharpe ratio of the strategy based on attractive currencies is significantly higher than the strategy based on non-attractive currencies confirming the importance of discriminating between the two sets.

The results we obtain for our carry trade might be quite conservative as we did not distinguish in the calculations between new and rolled-over positions which can be executed at a much lower cost (e.g. Cenedese, Sarno and Tsiakas, 2014). Also, Karnaukh, Ranaldo and Soderlind (2015) report that the mean bid-ask spreads might be inflated compared to real trades which might further penalize the returns to our carry trades. One might be concerned that these bigger spreads might distort the set of ex-ante profitable currencies and the conclusion of our work by excluding trades that might be marginaly profitable in real data. However, traders, facing volatile signals (Equation 4), may not engage in such trades automatically. This is in line with the assumption of Bacchetta and Van Wincoop (2010) that investors' portfolios of foreign exchange positions are not rebalanced constinuously. We report robustness tests with simulated bid ask spreads later in this section.

3.3. All currencies can be attractive

In Table III, we report the risk-adjusted returns of the ranked currencies when they are attractive SR_{at} and when they are not[8] SR_{no}. We also report the skewness (SK_{at} and SK_{no}) and the 5% left quantile (Q_{at} and Q_{no}) of the distribution of returns. Finally, we use risk reversals (RR_{at} and RR_{no}) to report the skewness of the risk neutral distribution[9]. At each point in time, the currency with the smallest interest rate is located in C1 and the currency with the highest interest rate is in C22. The identity of the ranked currencies is time varying. For instance, in our sample, the funding currency C1 is most of the time alternatively the CHF or the JPY [10].

Looking at columns 2 and 6 of Table III, we see that almost every single high yielding ranked currency exhibits a higher risk-adjusted ratio when it is attractive and a lower one when it is non-attractive. Conversely, lower yielding currencies exhibit a lower risk-adjusted ratio when they are attractive and a higher one when they are non-attractive: the transaction cost based strategy works at the currency level even for middle range currencies. The strategy does not need to rely on diversification to produce appealing returns. This improvement suffers from few exceptions. These exclusively concern currencies which delineate the frontier between funding and investment currencies. These currencies tend to switch regularly from the status of attractive to non-attractive currency which may impair their performance (like C7, C9 and C10). Together, these results indicate that the strategy based on a fixed number of bets, the traditional basket of N currencies, may not be optimal. Indeed, investors using a fixed number of currencies may alternately invest in non-attractive currencies and miss some attractive ones which in turn may lower the return to the carry trade.

In column 3 and 7 of Table III, we report the skewness of the ranked currencies. We see that almost every single high yielding currency exhibits a lower skewness when they are attractive than when they are non-attractive. This skewness is negative when they are attractive, indicating that high yielding currencies are exposed to bigger crash risks (appreciation of the dollar). Conversely, financing currencies tend to exhibit a larger positive skewness when they are attractive than when they are non-attractive, suggesting that financing currencies tend to have lower crash risk when they are attractive. For C1 and C3, skewness is even positive, indicating a risk of sudden depreciation of the dollar. This might happen in bad times when investors near their funding constraints as reported in Brunnermeier, Nagel and Pedersen (2009). We reach similar conclusions by looking at the return associated with the 5% left quantile even though the results are more mixed for the financing currencies (columns 4 and 8).

We reach similar conclusions by looking at risk neutral skewness extracted from option prices (colummns 5 and 9). On average, the implied volatility of the call option (USD/FCU) is bigger than the implied volatility of the put option for the investment currencies (positive risk reversal): traders see more chances for a dollar appreciation (against depreciation) for these currencies. This risk is bigger when the currencies are attractive and lower when they are non-attractive confirming the findings obtained in the distribution of returns (columns 3 and 7). Looking at the financing currencies, we can see that the risk reversal is negative which indicates a bigger risk of depreciation of the dollar and an upside risk for the FCU. Again, this risk is bigger when the currencies are attractive than non-attractive. We again capture the risk of sudden reversal described in Brunnermeier, Nagel and Pedersen (2009)

Table III about here

In Table IV, we look at the robustness of our findings in other samples. We can see that the risk-adjusted return is also higher for the attractive currencies in the subset of G10 currencies[11] in both samples before 1999 and after 1999. Indeed, when we look at the investing currencies, we see that their Sharpe ratios are bigger on average when the currencies are attractive. Similarly, when we look at the attractive financing currencies, we see that, on average, they exhibit smaller Sharpe ratios than the non-attractive ones. This result holds also when, following Bekaert and Panayotov (2016), we remove well known carry trade currencies such as the AUD, JPY and the NOK which indicates that our results are not dependent on a single currency. We reach very similar conclusions to those reported earlier when we look at the skewness of the distribution of returns and the risk reversals (not reported).

Table IV about here

We know that the bid-ask spreads are indicative quotes sometimes recalculated by providers. Therefore, we want to know whether our conclusions are robust to larger and smaller spreads than reported in the data. To answer this question, we simulate bid-ask spreads of varying size. Increasing the bid-ask spread tightens the investment constraint: fewer currencies are attractive because the cost of trading is higher. This is equivalent to running the tests with shorter term forward contracts: investors would only consider currencies with higher interest rates (see Appendix A). Our results indicate that, in the main sample, we have to lower the indicative bid-ask spread by about 50% to obtain Sharpe ratios that would be non significantly different from zero. In other words, this means that the difference from zero of the Sharpe ratio we document is significant as long as bid-ask spreads extracted from Bloomberg are not inflated by more than 100% compared to real trades. Given the way Bloomberg processes information, we think we can reasonably assume this is not the case.

We conclude that considering transaction costs in the decision rule, improves the return to the carry trade whether the currencies are packaged in portfolios or considered in isolation. Notably, when currencies are attractive they tend to exhibit significantly higher risk adjusted returns. In the next two sections, we re-examine the relationship between the return to the currencies and the forward discounts taking into account the existence of attractive and non-attractive currencies.

4. Attractive currencies and the interest rate parities

According to uncovered interest rate parity, arbitrage should eliminate the gains arising from the interest rate differential between currencies, and the return to the strategy should be zero on average. In this case, if the covered interest rate parity (CIP) holds[12] the forward rate is a good predictor of the future exchange rate. However, many papers have rejected UIP since the initial tests of Hansen and Hodrick (1980) and Fama (1984). While the regression of the change of the foreign rate on the forward discount should produce a β of 1, the parameter is often negative and close to -1. Recently, the failure of UIP has been rationalized in a standard Asset Pricing Theory (APT) framework by Lustig, Roussanov and Verdelhan (2011) and Menkhoff et al. (2012) among other.

However, Clarida, Davis and Pedersen (2009) report that the coefficient to the Fama regression might be regime dependent. This is also reported in Bekaert and Hodrick (2013). When FX market volatility is low, the carry trade is profitable and the coefficient to the regression is negative and significant. Conversely, when FX volatility is high, the carry trade is unprofitable and the coefficient in the regression is close to one, in line with UIP. Mulder and Tims (2015) confirm this finding and condition investments in the carry trade to volatility regimes especially for high yielding currencies.

We find a comparable change in the β of the regression of the mean returns of the ranked currencies on their forward discount when the currencies switch from being attractive to being non-attractive. In particular, our results indicate that we reject UIP mainly when currencies are attractive. We reach this conclusion for ranked currencies in section 4.1 and for non-ranked currencies in section 4.2. However, it is important to note, following Hassan and Mano (2019), that the relationship between the failure of UIP and the carry trade might not be straightforward. Indeed, the beta in the regression may not be informative about actual and future returns to the carry trade. Rather, the beta captures only the realized elasticity of the foreign exchange to the forward discount over a long sample (more than 20 years in our case). Only the contemporaneous discount/volatility regime seems to give indications about the future return to the carry trade.

4.1. Portfolio sorts and cross-sectional regressions

in Figure 2a and 2b, we plot the mean returns of the ranked currencies on their forward discount. According to uncovered interest rate parity, the returns of the currencies should be zero on average as the change in the foreign exchange should compensate for the differential of interest rate. Yet, when the currencies are attractive (2a-upper graph), we see that higher mean returns tend to be associated with higher forward discounts and lower mean returns with lower forward discounts. This is in contradiction to UIP. The observation is different in the subset when the currencies are non-attractive currencies (2a-lower graph): there is no association between mean returns and forward discounts. The currencies tend to conform more closely to the theory in this subset. We can find a similar pattern in the subset of G10 currencies, there is an association between mean returns and forward discounts when the currencies are attractive (2b-upper graph) but not when they are non-attractive (2b-lower graph).

Figure 2a and 2b about here

In Table V, we report the results of the regression of mean returns on forward discounts. Again, to account for the various frequencies at which the currencies are attractive or not (see Table III), we report the summary statistics of weighted OLS, the weights being the number of observations in this case. However, unweighted OLS generate largely similar conclusions which confirm the visual impression of Figure 2. In the subsample of attractive currencies including G10 and Emerging markets currencies, we obtain a significant and positive loading[13] to the regression (0.0060) with an R^2 of 0.46. This indicates that when the currencies are attractive, high yielding currencies exhibit positive returns and low yielding currencies negative returns in contradiction to UIP[14]. Baillie and Chang (2011) reach comparable conclusion but for high yielding currencies only. Together, we confirm the finding of Clarida, Davis and Pedersen (2009): the beta to the regression is positive and significant when the FX market volatility[15] is low (below the 25th percentile) but non significant when the volatility is high (above the 75th percentile).

Conversely, when the currencies are non-attractive, we do not find a significant relationship between mean returns and forward discounts. The R^2 of the regression is 0.06 and neither the constant term nor the beta are significant. On average, the forward discount is compensated by the change in the value of the currency in line with UIP. This result holds whether the FX market volatility is high (above 75th percentile) or low (below 25th percentile).

In the subset of G10 currencies, the results are largely comparable: when the currencies are attractive, there is a significant relationship between mean returns and forward discounts in the cross section. The R^2 of the regression is 0.51 and the loading is positive and significant (0.0244). Conversely, when the G10 currencies are not attractive, there is no relationship between the returns and the forward discounts. The R^2 of the regression is -0.04 and none of the coefficients are significant. We also confirm in this sample the findings of Clarida, Davis and Pedersen (2009) regarding volatility regimes (not reported).

Table V about here

As in section 3, we use simulated bid-ask spreads to challenge our choice to work with one-month contracts. First, we increase the bid-ask spread by either 100% or 200%. In this case, the distribution of the mean returns of the ranked currencies is better explained by the forward discount for the attractive currencies: the R^2 of the regression increases from 0.46 under normal bid-ask spreads to 0.49 and 0.58, respectively. The loading of the regression remains positive and in contradiction with UIP. Under these conditions, the relationship is again non significant and fits better with UIP when the currencies are non-attractive.

Next, we lower the bid-ask spread by 50%. In this case, the fit is poorer, but the loading of the regression is still significant despite more statistical noise. The R^2 decreases to 0.40. When we look in detail at the results, we see that the noise tends to be conveyed by the middle ranging currencies. These currencies become marginally attractive when we lower bid-ask spreads; they switch frequently from the attractive to the non-attractive status.

Together, these observations indicate that it is mostly the currencies at the margin that breach UIP. However, it is important to note that the beta of the regression remains significant and relatively stable around 0.0060 for all values of the spread.

While returns seem to obey UIP when the currencies are non-attractive, they do not compensate for the large positive returns of the carry trade. On average, currencies breach UIP as is usually found by the literature. We now ask what should mean returns be when currencies are non-attractive to compensate for the violation of UIP when they are attractive? To answer this question, we simulate a large number of vectors of returns B that verify the following equation:

$$\frac{cov\left[\left(\overline{r^i_{t+1}} + B_i\right); \overline{f_t/s_t}\right]}{var\left(\overline{f_t/s_t}\right)} + \beta = 0 \tag{5}$$

where $\overline{r^i_{t+1}}$ is the mean return of currency i when it is attractive and $\overline{f_t/s_t}$ its mean forward discount (see 2a upper graph).

We estimate 10.000 vectors B of 22 currency returns that minimize the absolute value of Equation 5. We consider several values for parameter β ranging from -0.2 to 0.2. Initial vectors are generated randomly by drawing in the uniform distribution[16]. Simulated returns data are obtained by adding generated *iid* errors of mean zero and variances matching those of the idiosyncratic errors in the actual data. We consider only economically interesting results[17]. Figure 3 shows that the mean annualized currency returns of the funding currencies should be 0.042 when they are non-attractive against 0.015 in the observed sample. Similarly, the mean annualized currency returns of the investment currencies should be -0.061 when they are non-attractive against 0.0007 in the observed sample. In this case, the non-attractive currencies do not conform to the UIP either but the beta to the regression of their mean returns on their forward discounts is negative against positive for the attractive currencies. Taken as a whole, these results indicate that the downside risk for carry trade investors might turn to be much bigger than that observed so far, especially for the attractive currencies during a crisis that would restore the UIP.

Figure 3 about here

4.2. Non-ranked currencies and panel regressions

So far, our results derive from portfolio sorts and cross-sectional analysis. In this section, we use pooled time-series information for the non-ranked currencies. In particular, we run state dependent regressions of the monthly return of the currency on the forward premium when the currencies are attractive and when they are not. We define the forward premium x for each currency i at time t in the two states as follows:

State attractive (transaction region):

$$x_{it}^{+} \begin{cases} f_{it}/s_{it} & if \quad f_{it}^{b}/s_{it}^{a} > 1 \quad or \quad f_{it}^{a}/s_{it}^{b} < 1 \\ \\ 0 & if \quad f_{it}^{b}/s_{it}^{a} \leq 1 \quad and \quad f_{it}^{a}/s_{it}^{b} \geq 1 \end{cases} \tag{6}$$

State non-attractive (no-transaction region):

$$x_{it}^{-} \begin{cases} f_{it}/s_{it} & if \quad f_{it}^{b}/s_{it}^{a} \leq 1 \quad and \quad f_{it}^{a}/s_{it}^{b} \geq 1 \\ \\ 0 & if \quad f_{it}^{b}/s_{it}^{a} > 1 \quad or \quad f_{it}^{a}/s_{it}^{b} < 1 \end{cases} \tag{7}$$

The variables x_{it}^{+} and x_{it}^{-} separate the forward premium into regimes where the currencies are attractive or non-attractive (transaction/no-transaction regions). Our test consists of a regression of the time-varying return of the currencies on both x_{it}^{+} and x_{it}^{-} and a constant. Table V presents the results from time-series cross sectional regressions. For ease of comparison between G10 countries and emerging market countries we restrict our sample to the one covering the period from January 1999 to January 2017 (we do not consider G10 countries before 1999). All results are presented for panel regressions including time fixed-effect (country fixed-effects are not significant and are excluded).

In the full sample, we obtain a result close to the one obtained in the cross-section of the ranked currencies: when the currencies are attractive, high yielding currencies tend to appreciate while low yielding currencies tend to depreciate. The slope of the relationship $\beta_{at} = 0.0072$ is significant at the 5% level and slightly larger than the one we obtained in the cross-section of the ranked currencies (0.0060 in Table V). When the currencies are non-attractive they tend to exhibit a β_{no} which is not significantly different from zero indicating that they conform closely to UIP. We reach very similar conclusions whether we look at G10 countries or emerging markets countries. In particular, the slope of the regression is 0.0076 for the subset of G10 currencies and 0.0070 for the subset of emerging markets currencies. In both subsets, when currencies are non-attractive they tend to conform to UIP.

As in the preceding section, we consider a low volatility regime (below 25th percentile) and a high volatility regime (above 75th volatility regime). In the low volatility regime, β_{at} is positive and significant whether we look at the full sample, at the subset of G10 countries or at the subset of emerging markets currencies. Conversely, the betas are non significant or negative in the high volatility regime. This confirms again the results of Clarida, Davis and Pedersen (2009) in panel regressions. Interestingly, we can see that the values of β_{at} differ whether we look at the subset of G10 countries or at the subset of emerging markets countries. Notably, in the low volatility regime, while high yielding currencies tend to appreciate for both G10 and emerging countries, the slope-coefficient is significantly different. The beta for the G10 countries is bigger (i.e. the difference between 0.0218 and 0.0043 is significant at the 5% level) indicating that the appreciation of the high yielding currencies is stronger for a given value of the forward premium.

This observation confirms the initial results of Bansal and Dahlquist (2000) who conclude that assuming that the slope-coefficients are the same across all economies may be too strong. In particular, in their sample covering the period 1976 to 1998, they show that the forward premium puzzle is mainly confined to developed economies. Using a more recent sample, we confirm the presence of the forward premium puzzle for G10 countries notably when the currencies are attractive in the low volatility regime. When these currencies are non-attractive and/or in the high volatility regime, there is only weak evidence in favor of the puzzle. Interestingly, in the high volatility regime, G10 high yielding currencies tend to depreciate more than can be expected using the forward premium (the beta is negative) which suggests that the forward puzzle might be only temporary for these currencies.

Finally, we estimate the regression for each individual currency. Of course, for these regressions, the imprecision is larger, notably, the mean R^2 is very small at 0.02. The results (not reported) indicate that some prototypical carry currencies like the JPY, CHF, NOK, ZAR, MXN and HKD exhibit a positive and significant beta to x_{it}^{+} and a non significant beta to x_{it}^{-} in the full sample. However, many currencies do not exhibit a beta significantly different from zero whether they are attractive or not. This would indicate that the forward puzzle is confined to a few currencies when they are attractive in the low volatility regime. However, we do not want to overstate this results given the weakness of the estimation when the currencies are considered in isolation.

Table VI about here

4.3. Traders' positions in attractive currencies

In this section, we study the impact of the status of the currencies on traders' positioning in the foreign exchange market using the Commodity Futures Trading Commission (CFTC) Commitments of Traders (COT) data. In particular, we would like to know whether we can relate not only price but also quantity changes to currencies' attractivness. This might give an insight about changes in capital flows to the countries. Indeed, futures trading may potentially play an important role in the process of price discovery across markets as the futures market and the cash market are closely linked through arbitrage (e.g. Lyons, 2001). The COT data have been studied closely by market practitioners and academia in a variety of context such as predictability of traders, risk premia, hegdging pressure effects among others (e.g. Tornell and Yuan, 2012).

The CFTC issue the number of open future contracts (open interest) held by registered traders each week. We gather data for 10 currencies for the period January 1999 to January 2017: Euro-area, Japan, UK, Australia, Canada, New-Zealand, Switzerland, South-Africa, Brazil and Mexico. These data report long positions and short positions for each foreign currency (FCU). The CFTC also differentiate between positions held for commercial purposes (hedging of an underlying asset) and non-commercial purposes (speculation). Being long a contract in one FCU is equivalent to being long this currency (i.e. short USD/FCU). While the COT data have been used extensively by academics, it is important to note that they are not without limitations. In particular, the data contains about 25% of points for which the information is not available. Also, they aggregate positions for different contract maturities and various type of traders (hedgers/non hedgers) for which the designation might not be accurate (e.g. Tornel and Yuan, 2012).

We define market's net position as the difference between the number of contracts associated to long positions (Positions long all in the COT report) and the number of contracts associated to short positions (Positions short all). To compare positions across time and currencies, we standardized this difference by the total number of positions (Open Interest all). The net position variable (NP) for currency i in month t is defined as:

$$NP_{it} = \frac{LongPositions_{it} - ShortPositions_{it}}{OpenInterestall_{it}} \tag{8}$$

We collect weekly data of futures-only positions and transform them into monthly data by calculating their monthly average. After imposing data availability requirements, the final sample consists of 1442 currency-month observations of the NP variable.

In Table VII we report descriptive statistics for traders' net positions in the foreign exchange future market. We see that, on average, speculators have negative net positions in most currencies, that is, they hold larger short positions than long positions. However, we also can see that speculators are, on average, long NZD and BRL, two prototypical carry trade currencies. When we look at the commercial positions, not surprisingly, we see the opposite: on average hedgers exhibit positive net positions except again in NZD and BRL. However, it is important to note that these mean net positions might not be significantly different from zero when we consider the associated standard-deviations (columns 2 and 6). This indicates that neither speculators nor hedgers are consistently net buyers or net sellers in the currency futures markets (e.g. Tornell and Yuan, 2012).

Table VII about here

As in the preceding section, we run state dependent regressions of traders' monthly average net position on the forward premium when the currencies are attractive (x_i^+) and when they are not (x_i^-). Our test consists of a regression of the time-varing net position NP as measured during month t on the lagged observations of the status indicator (x_{it-1}^+) and (x_{it-1}^-) and a constant. Table VIII presents the results of time-series cross sectional regressions for positions held for commercial and non-commercial purposes. They confirm our main conclusion. The beta of net positions to the forward discount is positive (0.0989): on average, traders tend to increase their speculative long (short) positions in high (low) yielding currencies when the differential of interest rate is widening. This tends to indicate that traders expect high yielding currencies to appreciate while low yielding currencies would tend to depreciate. However, we see again that only when currencies are attractive do the investors tend to significantly increase their positions (only $beta_{at}$ is significantly different from zero). When the currencies are not attractive, we cannot find any significant relationship between net positions and (x_{it-1}^-).

We confirm this result in the set of commercial positions: $beta_{at}$ is significantly different from zero but not $beta_{no}$. Interestingly, in this set the betas exhibit negative signs indicating that hedgers increase their short positions in high yielding currencies when the differential of interest rate is widening. This makes sense since we know that high yielding currencies exhibit bigger crash risk. Finally, we also confirm these conclusions when we limit the sample to G7 countries only by excluding Brazil, South Africa and Mexico from the analysis. Again, we see that $beta_{at}$ is significantly different from zero but not $beta_{no}$ for both commercial and non-commercial positions.

Table VIII about here

In this section, we show that the status of a currency may dictate traders' positioning. Specifically, speculators tend to increase their long positions in attractive high yielding currencies when the differential of interest rate is widening. This observation is in line with the results of the preceding sub-sections: when the currencies are attractive, high yielding currencies exhibit positive returns and low yielding currencies negative returns in contradiction to UIP. Conversely, when the currencies are non-attractive, we do not find a significant relationship between either quantities or returns and the forward discount. Recently, the literature has rationalised the deviation from UIP in an asset pricing setting. We study this in the next section.

5. Risk Factors in the Currency Market

We know from Lustig, Verdelhan and Roussanov (2011) that investors might demand time-varying risk premia associated with a small number of common risk factors. If investing in currencies that are at a forward discount delivers lower returns during bad times, investors then expect larger average returns to compensate for this risk. In this section, we show that only the returns of attractive currencies can be rationalized in an APT framework, not the returns of the non-attractive currencies. This confirms our conclusions from the preceding section about UIP.

5.1. Asset pricing tests

The risk based explanation of the returns to the carry trade implies that the returns to currencies, sorted on their forward discount, covary with some risk factors in the time series and in the cross-section. This is the common two-step procedure inspired by Fama and Mc Beth (1973). Indeed, investors might demand time-varying risk premia associated to a small number of common risk factors. These factors factors are state variables that convey information about market circumstances and the investment opportunity set. Lustig, Roussanov and Verdelhan (2011) test a factor called HML-FX which is the return to a portfolio combining long positions in high yielding currencies and short positions in low yielding ones. Similarly, Menkhoff et al. (2012) and Burnside (2012) test a global volatility factor extracted from the currency market while Della Corte et al. (2016) and Della Corte et al. (2015) find respectively a relationship with global imbalances and sovereign risk. Together, Mancini et al. (2013) explore a link with liquidity and Dobrynskaya (2014) with crash risk[18].

Since Liu (2004) and later Burnside et al. (2007) and Maurer et al. (2019), we know that non-attractive currencies may be excluded from the investment opportunity set because they fall in the no-transaction region. As a consequence, according to the APT, their exposure to global risk may be lower. Especially, they might not bear HML-FX risk as defined by Lustig et al. (2011). Conversely, attractive currencies form the investment opportunity set. Therefore, they may offer a premia associated to a small number of state variables. In this section, we test the risk based explanation in both the subset when the currencies are attractive and the subset when they are not attractive. Especially, we expect that the returns of the attractive currencies should exhibit the largest covariances, in absolute terms, with the candidate SDF while the returns of the non-attractive currencies should be orthogonal to the global risk factor.

First we look whether a linear combination of factors can significantly justify the returns to the carry trades, in the time series, for each currency or portfolio of currencies i in both subsets:

$$R_{it+1} = \alpha_i + f'_{t+1}\beta_i + \epsilon_{it+1} \tag{9}$$

Then, we test whether the betas of Equation (6) combined with estimates of risk premia (λ) might justify the returns to the carry trade in the cross section. To do so, in the traditional Fama and McBeth (1973) procedure, one runs a cross-sectional regression of average excess returns on betas. Instead, following Cochrane (2005), Burnside (2012), Lustig, Roussanov and Verdelhan (2011) and Menkhoff et al. (2012) among others, we co-estimate the vector of SDF parameters and their moments using the Generalized Method of Moments of Hansen (1982).

We test four risk factors similar to those proposed in Lustig, Roussanov and Verdelhan (2011) and Menkhoff et al. (2012): RX, a dollar risk factor which is the average excess return of the p portfolios of $Carry_n$, $HML - FX$, the difference between the returns of the two extreme portfolios defined in each strategy, VOL_{EQTY}, a proxy for the volatility of global equity market returns; and VOL_{FX}, a proxy for the volatility of global currency market returns. We report the results for the largest cross section of currencies we have in hand, i.e. 22 currencies observed from 1999 to 2017 and on a smaller cross section of G10 currencies from 1985 to 2017.

5.2. Empirical results

The papers in this literature typically follow the same methodology: to reduce errors in parameter estimation, they form equally weighted portfolios of currencies sorted on their forward discount. Then, they look for a significant spread across these portfolios in the covariance, β, between their return and the SDF. Following Lustig, Roussanov and Verdelhan (2011), we form 6 equally weighted portfolios of ranked currencies in the subset of attractive currencies and 6 equally weighted portfolios of ranked currencies in the subset of non-attractive currencies as defined by Equation 4 (only 5 portfolios in the sample of G10 currencies).

In Table IX, we report the results for the first step of the asset pricing tests, i.e. the time-series regression of the portfolios' excess returns on the four risk factors RX, $HML - FX$, VOL_{FX}, VOL_{EQTY}. We report the results in the three samples: the full sample, the sample of attractive currencies and the sample of non-attractive currencies. As in Lustig, Roussanov and Verdelhan (2011), in the time series, the betas of the RX factor are all close to one in value and statistically significant independent of the sample or of the second factor tested[19].

In the full sample (columns 1, 2 and 3), we see that the betas of $HML - FX$, VOL_{FX}, VOL_{EQTY} are significant with the expected signs. Indeed, the betas of $HML - FX$ exhibit an increasing pattern in return from $P1$ to $P6$ while the betas of VOL_{FX} and VOL_{EQTY} exhibit a decreasing pattern in return from $P1$ to $P6$. Also, for $HML - FX$ the difference between the betas of the extreme portfolios adds up to almost one as expected. The result is largely similar in the subset of attractive currencies (columns 4 to 6).

On the other hand, for the subset of non-attractive currencies (columns 7 to 9), the betas do not exhibit a clear pattern. In particular, the beta of P6 for $HML - FX$ and VOL_{FX} and P1 for VOL_{EQTY} do not exhibit the expected sign. When the currencies are non-attractive they do not covary significantly or in an economically interesting fashion with the global SDF. This would tend to clearly reject the risk premia story for the non-attractive currencies. However, even with betas not significantly different from zero, Lustig and Verdelhan (2007) accept the risk premia story in a consumption-based asset pricing model. Therefore, below, we also present results for the second step of the asset pricing tests.

Table IX about here

In Table X we summarize the results of estimating candidates SDF for currency factor models. In both the full sample and the sample of attractive currencies, the asset pricing tests produce significant parameters for all factors. We find a positive and significant market price of risk attached to $HML - FX$ implying higher risk premia for portfolios whose returns comove positively with $HML - FX$. Similarly, we find a negative and significant market price of risk for VOL_{FX} and VOL_{EQTY}. For all factors, the model is not rejected on the basis of the $J - test$ or the R^2. Interestingly, in the subset of attractive currencies, the point estimates for the parameter λ are larger in absolute terms than the ones obtained in the full sample: in the subset of attractive currencies the market price of risk attached to the global SDF is larger[20].

Results are different for the subset of non-attractive currencies. The tests again produce insignificant parameters or reject the model for over-large pricing errors. This is not surprising since we know that the betas in this subset are not economically meaningful. However, this result confirms that the global SDF does not explain the returns to currencies when they are not attractive.

Table X about here

Figure 4 reveals a key feature of the cross section of currencies which helps to explain some of our previous observations. In this figure, we rank the full set of currencies by their betas to the risk factor HML-FX and VOL-FX. We see that the returns of the currencies when they are attractive (black points) are widely spread around the X-axis and almost perfectly ordered according to the betas. In that case, the market risk premia are precisely estimated and the pricing errors are minimized. Considering the non-attractive currencies (the empty points) makes clear the noise they add to the relationship. Their distribution appears essentially orthogonal to the factor line: they exhibit significant variation in mean returns but have largely similar βs which, in most cases, are not significantly different from zero. This is what we expect since rational carry traders would not invest in these ex-ante non profitable currencies.

Figure 4 about here

In Table XI, we report the results of estimating candidate SDFs for currency factor models for the G10 currencies only over the period 1985 to 2017. First step betas correspond to the ones presented in Table V and are not reported. In the full sample we see that the asset pricing tests produce significant parameters for $HML-FX$ and weakly significant parameters for VOL_{FX}. These parameters are also significant in the subset of attractive currencies confirming the results already obtained. Coversely, in the subset of non-attractive currencies the model is rejected for non significant parameters for both $HML-FX$ and VOL_{FX}. Looking at VOL_{EQTY}, we see that the parameters are not significant in the full sample and that they do not exhibit the expected sign in the sample of non-attractive currencies. Interestingly, in the sub sample of attractive currencies, the parameters are significant, with the expected sign and the model is not rejected by the test of pricing errors. We stress that our intention in this paper is to point out the importance of the differentiation between attractive currencies and non-attractive currencies but not to validate or dismiss the factors proposed earlier in the literature.

Table XI about here

Finally, we use the UIP conforming simulated returns of section 4 to estimate the risk premia of the strategy in case of a downturn in the market that would erase the gains to the carry trade. We find a λ of -0.16% when the risk factor is HML-FX and a λ of 0.25% when the factor is Vol_{FX}. This calculation is based on the assumption that the betas would remain unchanged in all economic states which tends to be rejected by the recent contribution of Byrne, Ibrahim and Sakemoto (2017). This paper suggests that time variation of the betas of the carry trade in varying economic states might justify the return to the strategy.

Taken together, our results indicate that only when the currencies are attractive do they tend to breach UIP, this deviation being explained in an APT framework. When the currencies are not attractive, they conform more closely to UIP and therefore they do not comove significantly with any of the risk factors we have tested. The non-attractive currencies impair the statistics of the carry trade and investors should focus primarily on attractive currencies for their investment.

6. Value, momemtum and currency attractiveness

The carry trade is central to FX investment but investors also rely on other signals to define currency attractiveness. Kroencke, Schindler and Schrimpf (2014) report for instance that style-based management of the foreign exchange component of international investments with carry, FX momemtum and FX value provides economically large and significant diversification benefits. In this section, we complete our analysis of the attractive currencies versus non-attractive ones by including FX momemtum and FX value as factors defining currency attractiveness.

We follow the methodology of Asness, Moskowitz and Pedersen (2013): the momemtum MoM_{it} observed at time t for currency i is defined as the 12-month cumulative raw return on the currency, skipping the most recent month's return to avoid possible 1-month reversal. Investors may want to buy currencies with positive momemtum and may want to sell currencies with negative momemtum. The currency value measure $Value_{it}$ observed at time t for currency i is the 5-year return on real effective exchange rates based on unit labor costs as calculated by the World Bank and available on Datastream. A positive number indicates a real appreciation of the currency over the past 5 years. Investors may want to sell currencies that have appreciated in real terms and may want to buy currencies that have depreciated. Asness, Moskowitz and Pedersen (2013) allocate the currencies exhibiting the lowest momemtum (largest value) in the financing portfolio P1 while the currencies with the largest momemtum (lowest value) fall in the investment portfolio P5.

In this paper, we define an attractive currency using the momemtum factor as follows:

$$\begin{cases} \text{Buy the FCU if} & E(f_t^b/s_{t+1}^a) = f_t^b/s_t^a > 1 \text{ and } MoM_t > 0 \\ \\ \text{Sell the FCU if} & E(f_t^a/s_{t+1}^b) = f_t^a/s_t^b < 1 \text{ and } MoM_t < 0 \\ \\ \text{No transaction in all other cases} \end{cases} \tag{10}$$

Similarly, we define an attractive currency using the value factor as follows:

$$\begin{cases} \text{Buy the FCU if} & E(f_t^b/s_{t+1}^a) = f_t^b/s_t^a > 1 \text{ and } Value_t < 0 \\ \\ \text{Sell the FCU if} & E(f_t^a/s_{t+1}^b) = f_t^a/s_t^b < 1 \text{ and } Value_t > 0 \\ \\ \text{No transaction in all other cases} \end{cases} \tag{11}$$

We could have considered a definition of currency attractiveness based only on the momemtum signal $MoM_t < 0$ and the value signal $Value_t > 0$. However, the signals proposed by Asness, Moskowitz and Pedersen (2013) exhibit much bigger values than the average cost of trading. As a consequence, currencies end up being attractive most of the time for both signals. For instance, the mean annualized positive momemtum is 9.12% (-8.05% for the currencies exhibiting a negative momemtum) while we know that the threshold triggering investment stands at around 1.7% in annualized terms[21]. Therefore, in this section, we mix the carry signal and a factor signal (momemtum or value) to define currency attractiveness. This definition is harsher than the one only based on the carry signal, as a consequence it downsizes the set of attractive currencies significantly. Notably, based on the carry and momemtum factors together, currencies remain attractive in only 36% of the sample against about 70% when we only consider the carry factor.

In Table 1 and 2 of the internet appendix we report the Sharpe ratios of the ranked currencies for the momemtum factor and value factor, respectively. The results show that attractive investment currencies produce larger risk-adjusted returns on average than non-attractive currencies especially when we rely on the momemtum factor. This confirms the results of the preceding sections. Similarly, financing currencies produce lower risk-adjusted returns on average than non-attractive currencies. When we consider the value factor the results are more mixed, especially when it concerns financing currencies. This may be an indication that value strategies are less used by investors than momemtum ones.

In Table XII and XIII, we report the results of the regression of the mean returns of the currency on the forward discounts. This mirrors our work made in section 4.1. Notably, we report the summary statistics of weighted OLS, the weights being the number of observations. In the sub-sample of attractive currencies we obtain again a significant and positive loading whether we look at the momemtum strategy or the value strategy. This indicates that when the currencies are attractive according to both the carry factor and the signal (momemtum or value), high yielding currencies exhibit positive returns and low yielding currencies negative returns still in contradiction to UIP. For the set of non-attractive currencies, we do not find a significant relationship between mean returns and forward discounts, neither when we look at the momemtum strategy nor when we look at the value strategy.

When we follow Clarida, Davis and Pedersen (2009) and discriminate between regimes of volatility, we also obtain similar results notably in the low volatility regime when the attractiveness is defined with the momemtum factor: the beta in the regression is significant for the attractive currencies but not significant for the non-attractive currencies. In this case, on average, the forward discount is compensated by the change in the value of the currency in line with UIP. However, when we look at the high volatility regime, we find that the beta of the attractive currencies is again positive and significant in contradiction with the findings of Clarida, Davis and Pedersen (2009). While we expect high (low) yielding currencies to depreciate (appreciate) in the high volatility regime, they tend to appreciate (depreciate) further. This makes sense, since only currencies maintaining positive (negative) momemtum and carry remain attractive. By construction, these currencies tend to exhibit larger (lower) returns, even in the high volatility regime (autocorrelation).

When attractiveness is defined on the basis of the carry and value factor, the results are different. Currencies conform with UIP in the low volatility regime as the regression beta is not statistically significant whether they are attractive or non-attractive. In the high volatility regime, attractive currencies tend to reject UIP (with a positive and significant beta) while non-attractive currencies bear negative and significant betas. This makes sense again, and we may be capturing the value effect here. During spikes of volatility, attractive high yielding undervalued currencies tend to converge toward their equilibrium value exhibiting a positive return while attractive low yielding overvalued currencies exhibit negative returns, both contradicting UIP. Non-attractive high yielding overvalued currencies would tend to depreciate while non-attractive low yielding undervalued currencies would appreciate. However, it is important to note that the beta of the regression for the non-attractive currencies is small and not economically significant.

Table XII and XIII about here

Finally, in Table XIV we summarize the results of estimating candidate SDFs for currency factor models. First step betas are available in Tables 3 and 4 of the internet appendix. Again, when we use the momemtum factor we obtain very similar results to those reported in preceding sections: the asset pricing tests produce significant parameters for all factors particularly in the set of attractive currencies. The parameter for VOL_{FX} which is not significant in the full sample is significant in the set of attractive currencies. However, the model is still rejected by the J-test. In the set of non-attractive currencies, none of the factors exhibit a significant parameter. Looking at the results for the value factor in Table XV, we see that the model is rejected for all sets except for $HML - FX$ in the full sample. In particular, HML-FX and VOL_{FX} are rejected by the J-test. This indicates that currencies filtered on the basis of the value factor do not convey $HML - FX$ or VOL_{FX} risks, suggesting again that value strategies might not be that fashionable among FX investors.

Table XIV and XV about here

7. Conclusion

In this paper we study the return of currencies when they are defined to be attractive or non-attractive. We follow the literature and define attractive currencies as the ones for which the transaction costs, i.e. the bid-ask spread, do not outweigh the differential of interest rates between the currencies. As both the transaction costs and interest rates are time varying, this dynamically defines the set of attractive currencies and the set of non-attractive currencies. Carry trade positions in attractive currencies exhibit larger Sharpe ratios whether the currencies are packaged in portfolios or considered in isolation. Non-attractive currencies exhibit lower Sharpe ratios often insignificantly different from zero. Simulation-based evidence considering alternative definitions of attractive currencies confirm this observation.

Together, our results show that attractive currencies tend to breach uncovered interest rate parity while non-attractive currencies conform more closely to UIP. We observe this result in both a sample including only G10 currencies and a larger sample including G10 currencies and emerging markets ones. As a confirmation of this result, we find that the deviation from UIP can be rationalised in an Asset Pricing setting as proposed by Lustig, Roussanov and Verdelhan

(2011) and Menkhoff et al. (2012) among others, but only for attractive currencies. These currencies tend to comove significantly with the global stochastic discount factor. Non-attractive currencies do not seem to comove with the global SDF and one cannot rationalise their behaviour in an APT framework.

Our results complement Clarida, Davis and Pedersen (2009) who show that currencies mainly breach UIP in high volatility regimes. They also confirm the results of Bansal and Dahlquist (2000) who conclude that assuming that the slope-coefficients are the same across all economies may be too strong an assumption. Our findings complement Byrne, Ibrahim and Sakemoto (2017) who show that the relationship between currencies and the global stochastic discount factor may be regime dependent. Finally, we contribute to the literature on extreme interest rates differentials (IRDs) by using a new definition of the attractive and non-attractive currencies (i.e. IRDs) based on trasaction costs. We also extend this definition of attractiveness by including factors such as FX momemtum and FX value.

Taken as a whole, our findings indicate that non-attractive currencies tend to impair the return to the carry trade. Investors should stay away from these currencies. Our results indicate that policy makers should be particularly careful when their domestic currencies near the limit of being attractive and non-attractive. Pushing the currency through this limit by revising the reference interest rate may change the future return of the domestic currency significantly. In particular, we show that when the currencies become attractive they tend to exhibit greater crash risk both under physical or risk-neutral measures. Finally, the fact that only when currencies are attractive to investors do they breach UIP suggests that the failure of this theory is possibly due to the activity of carry traders in the foreign exchange market. Our analysis of CFTC-COT data would tend to support this conclusion.

Appendix A: descriptive statistics.

How different are bid-ask spreads in Bloomberg and Datastream? We gathered data covering the period January 1999 to January 2017 from both Bloomberg and Datastream for the following countries: Australia, Brazil, Canada, Czech Republic, Denmark, Euro Area, Hong Kong, India, Japan, Mexico, New Zealand, Norway, Philippines, Poland, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand and the UK. Table XVI reports the summary statictics of the carry trade in this sample: the improvement observed when investors bet on attractive currencies is visible in the dataset extracted from Bloomberg but not in the sample extracted from Datastream. Indeed, the Sharpe ratio of the strategy is 0.48 in the dataset extracted from Bloomberg but only 0.41 in the dataset extracted from Datastream. We justify these findings by the way Bloomberg and Datastream process bid-ask spreads.

Table XVI about here

In table XVII, we report the summary statistics of the bid-ask spreads in both data sets. The mean bid-ask spread is similar in both samples for the spot exchange rates (0.10%) and equal for the forward exchange rates (0.14%). But the picture is different for the volatility of these spreads: the spread is much more dynamic in the data set extracted from Bloomberg. Indeed, the standard-deviation of the forward prices is 0.32% in this data set against 0.16% in the data available in Datastream. This difference comes from the way both providers process the information they gather from the dealers during trading hours[22]. Reuters uses pre-defined standard spreads[23] for each currency (e.g. Thomson Reuters, 2018) while Bloomberg provides observed spreads (e.g. Bloomberg, 2018) which would only be recalculated if the market is not active. As a consequence, for as much as 23% of the observations coming from Reuters the bid-ask spread remains unchanged from one point in time to the other. This concerns less than 9% of the data extracted from Bloomberg.

Table XVII about here

Of course different bid-ask spread dynamics define different sets of attractive currencies. Especially, during episodes of crises when spreads may widen suddenly, they may be capped by the process applied by Datastream. As a consequence, while some currencies may be defined as non-attractive in the data collected by Bloomberg they may remain attractive in the data available in Datastream. These currencies may impair the returns to the carry trade and our analysis based on the discrimination between attractive and non-attractive currencies. Therefore, in this research, the main sample uses data collected by Bloomberg for the period 1999 to 2017. As the coverage is sparse in Bloomberg before 1999, we complement our sample with data for the G10 countries available for this period in Datastream.

As we know that the bid-ask spreads are only indicative quotes sometimes recalculated by providers, we would like to know whether our conclusions remain acceptable with lower/bigger spreads. To answer this question, we simulate bid-ask spreads of varying size. Increasing the bid-ask spread tightens the investment constraint: fewer currencies are attractive because the cost of trading is bigger. Inversely, lowering the spread makes more currencies attractive.

Interestingly, we can also use the simulated spreads to challenge our choice of working with one-month forward contracts. Indeed, we know that the status of a currency - attractive or not - hinges on the term of the forward contract f_t used in Equation 4. With shorter-term contracts, fewer currencies would be attractive every month (see section 2.2). This is similar to the effect of an increase of the bid-ask spread. Together, the number of attractive currencies would rise with longer-term contracts or lower bid-ask spreads. This similarity enables us to bypass the limit posed by the small availability of alternative liquid tenors (basically 1-week, 3-month and 6-month contracts). Also, using longer-term contracts lowers the number of observations on which we can run the tests. For instance, with 6-month contracts, we would work with only two observations per year.

We have simulated data for which the bid-ask spread increases from the benchmark value up to 300% the benchmark value by steps of 10%. When we increase the bid-ask spread by 50%, the number of attractive currencies is reduced to 7 on average (against 8 for the benchmark spread). The currencies which are marginally attractive are excluded. In this case, for instance, we obtain a larger Sharpe ratio of 0.54 for the carry trade strategy based on Equation 4. This Sharpe ratio ends up at 0.62 (5 attractive currencies on average) when the spreads are increased by 300%. This makes sense, facing larger bid-ask spreads, investors consider fewer currencies as attractive, especially the higher yielding ones and the risk-adjusted return to the portfolio of carry trade positions increases.

On the other hand, when we lower the bid-ask spread we include more marginally attractive currencies. This dilutes the impact of the higher yielding currencies and the Sharpe Ratio decreases. This confirms the result of Daniel, Hodrick and Lu (2017) who show that portfolios of discount weighted carry trade positions tend to overperform their equally weighted counterpart. However, we have to lower the indicative bid-ask spread by about 50% to obtain Sharpe ratios that would be non significantly different from zero.

Interest rates differential. Table XVIII reports the summary statistics of the interest rate differential between the USD and the foreign currencies. The numbers may be compared with the bottom line of table XVII. In panel A, a currency is attractive on average when the interest rate differential is about 1.7% (the bid ask spread of the forward quote is 0.14% in table XVII). The currencies exhibiting a positive differential with the USD (High-Y CCY) are attractive on average: the mean interest rate differential is 3.62%. This is not the case of the currencies exhibiting a negative differential with the USD (Low-Y CCY). Their mean interest rate differential is -1.56% below, in absolute terms, the threshold defining attractive currencies (i.e. 1.7%). For the G10 currencies, the threshold stands at 1.0% (not reported). Finally, we report that the interest rate differential calculated in the dataset extracted from Datastream produces very similar figures.

Table XVIII about here

Cleaning process: we follow Darvas (2009), every time the bid and ask prices are equal for the spot exchange rate and/or for the forward exchange rate we recalculate both spot and forward ask prices by adding the previous day's bid-ask spread, respectively of the spot and forward rate, to their respective current bid price. Similarly we can recalculate both bid prices by substracting the previous day's bid-ask spreads to the current ask prices. Both methodologies yield very similar results. This is slightly different from Darvas (2009) who, in this case, would replace the present day's observation with the previous day's observation. With our methodology, we better keep the structure of the data in the time series as we do not erase the information we have about the direction of the change in prices. Together, we do the same when the spread of the spot exchange rate is higher than the spread of the forward exchange rate. Finally, when only the spot moves but the forward stays constant and/or the forward moves but the spot stays constant, we replace the present day's observation with the previous day's price. It is important to note that the cleaning process might not be key for this study. For instance, we report that the Sharpe ratio of the carry trade strategy is 0.3632 when we apply the process described above (see Table I) but 0.3775 when we do not. When we apply Darvas' exact cleaning process, we obtain a Sharpe ratio of 0.3650.

Appendix B: Risk statistics.

As with most financial returns, carry trades returns are not normally distributed. They exhibit large negative skewness and substantial kurtosis (see Table I in Appendix D). Therefore, the two first moments of the distributions are not sufficient to describe them. In this Appendix, we introduce several popular risk ratios that have been developed by academics and the financial industry to account for non-normal distributions and complement the traditional Sharpe ratio. These ratios relate the mean return of the distribution to different risk statistics: the standard-deviation for the Sharpe ratio, a quantile-based statistics such as VaR for the modified Sharpe ratios and some measures of drawdown for several ratios which are alternative definitions of the Sterling ratio.

We study the generic risk ratio (RR):

$$RR = \frac{mean(x_t)}{risk(x_t)} \tag{.1}$$

with $risk(x_t) \in \{sd(x); VaR(x); \mathcal{D}_{mean}; \mathcal{D}_{Max}\}$

The standard-deviation, sd(x), is a sufficient measure of risk only if the distribution is symmetrical. But since most distributions are not, one needs to focus more precisely on negative outcomes to estimate the risk. Especially, agents might fear infrequent but profound outcomes that might cause their ruin. In this case, the risk is measured by estimating the extreme quantiles of the distribution of returns. The likely loss associated to these quantiles is then called the Value at Risk in practitioners' words. A quantile is defined as a number μ that set

$$Prob\,(x \leq \mu) = p \tag{.2}$$

As it is traditional, in this paper, we estimate the quantile for $\mu = 95\%$ such as: $Prob\,(x \leq \mu) = 95\%$. Now, the question is: how to estimate the quantile? Arguably, the simplest way is to use the sample quantile extracted from the historical data. When these estimations are conditional, they might be very sensitive, especially in short samples, to the inclusion or not of some extreme values. One way to mitigate this bias is to extrapolate the VaR with a parametric method. For instance, initially, RiskMetrics (1996) estimated the VaR from the variance of the distribution of the returns. But this estimation is valid only if returns are normally distributed otherwise the statistic might be only a rough approximation of the true one. Hence we follow Longerstaey and Zangari (1996) correct for the non-normality of the distributions, especially for excess skewness and kurtosis using another parametric method based on the Cornish-Fisher expansion. These estimations will give a larger loss estimate than traditional quantile calculations when outcomes are negatively skewed or highly kurtotic. Conversely it will give smaller loss magnitude when historical outcomes are positively skewed or leptokurtic. This approximation is based on a Taylor series expansion using higher moments of the distribution. The approximation of the Q_α quantile to the fourth moment can be written as[24]:

$$Q_\alpha \cong \mu - \left(Z_\alpha + \frac{1}{6}\left(Z_\alpha^2 - 1\right) SK + \frac{1}{24}\left(Z_\alpha^3 - 3Z_\alpha\right) K \right) \sigma \tag{.3}$$

with Z_α the critical value associated to the standard normal distribution q_{th} quantile, μ, σ, SK and K the in-sample mean, standard-deviation, skewness and excess kurtosis of the returns. To take account of tail risk, Favre and Galeano (2002) propose modifying the traditional Sharpe ratio by substituting the VaR to the standard-deviation. In this paper the modified Sharpe ratios is reported under the name M_{VaR}.

Beside this measure of tail risk, we look at the risk of severe outcomes. According to Thaler and Johnson (1990) economic agents might also exhibit preferences in term of the distributions of cumulative returns especially negative ones, i.e. drawdowns. Long lasting episodes of negative outcomes might be particularly painful. We measure this risk by the maximum drawdown and the average drawdown observed in the series of returns. A drawdown is defined as the difference in value of the series of cumulated returns between any local maximum and the next local minimum. Obviously, less pronounced drawdowns are preferred. With X a vector of time series observations of length T, we define any drawdown $\mathcal{D}_t$ in X as:

$$\mathcal{D}_t = x_t^{max} - x_t \tag{.4}$$

with

$$x_t^{max} = max\{x_i \,| i\, [0, t]\} \, (.5)$$

then

$$\forall x_t \quad x_t = x_t^{max} \Leftrightarrow \mathcal{D}_t = 0$$

otherwise

$$\mathcal{D}_t \geq 0$$

The mean drawdown in X is then defined as:

$$\mathcal{D}_{mean} = \frac{1}{n} \sum_{i=1}^{n} \mathcal{D}_t \tag{.6}$$

n being the number of drawdowns in X.

and the maximum drawdown is defined as:

$$\mathcal{D}_{Max} = max\,(\mathcal{D}_t) \tag{.7}$$

In this paper the ratio of the mean return to the mean drawdown is called M_{DD} while the ratio of the mean return to the maximum drawdown is called M_{MaxDD}.

Appendix C: Asset Pricing.

The carry trade is a zero-cost investment (see section 2), hence its excess returns in level, R_{t+1}, satisfy the basic Euler equation:

$$\mathbb{E}_t(M_{t+1}.R_{t+1}) = 0 \tag{.1}$$

with M_{t+1} a linear SDF of the form:

$$M_{t+1} = \xi\,[1 - (f_{t+1} - \mu)'b)] \tag{.2}$$

b being the vector of SDF parameters, f the vector of risk factors and μ the vector of the sample mean of the risk factors. ξ is a scalar we set at one (see Cochrane, 2005).

Equation (2) implies a beta representation of the model in which expected excess returns depend on factor risk premia λ and risk loadings β:

$$\mathbb{E}(R_{t+1}) = cov(R_{t+1}, f_{t+1})b \tag{.3}$$

or

$$\mathbb{E}(R_{t+1}) = \beta\lambda_{t+1} \tag{.4}$$

β is the vector of coefficients of the regression of R_{t+1} on f_{t+1}, in the sample, while λ is a vector of risk premia.

To estimate this relationship, the literature follows the common two-step procedure inspired by Fama and Mc Beth (1973). First we look whether a linear combination of factors can significantly justify the returns to the carry trades, in the time series, for each currency or portfolio of currencies i:

$$R_{it+1} = \alpha_i + {f_{t+1}}'\beta_i + \epsilon_{it+1} \tag{.5}$$

Then, following Cochrane (2005) among others, we estimate the parameters of Equation (2) using the Generalized Method of Moments of Hansen (1982). To remove estimation uncertainty, as recommended by Burnside (2010), factor means, μ and the variance covariance matrix of factors Σf are co-estimated. The vector of moment conditions is:

$$g(R_{t+1}, f_{t+1}, \theta) = \begin{bmatrix} [1 - (f_{t+1} - \mu)' b)]\, R_{t+1} \\ f_{t+1} - \mu \\ \Sigma((f_{t+1} - \mu)(f_{t+1} - \mu)') - \Sigma f_{t+1} \end{bmatrix} \tag{.6}$$

where θ contains the parameters (b, μ, Σf_{t+1}).

Then, estimates of λ are obtained from $\hat{b}$ and $\hat{\Sigma f}$ as $\hat{\lambda} = \hat{b}\hat{\Sigma f}$. Standard errors of λ come from the estimation of the variance of the function $\hat{b}\hat{\Sigma f}$.

We use the iterated GMM estimator starting from the identity matrix as weighting matrix $W_T = I$. The iterated GMM estimator has much greater power to reject mispecified models than the two-step version (e.g. Burnside, 2010). In this case, GMM treats all assets symmetrically. However, when we package them, we impose a structure on the primitive assets which forces the GMM to pay less attention to some of them. We could deemphasized further the assets with the largest variance by starting, for instance, from the optimal matrix of Hansen (1982) instead of the identity matrix. However, as mentioned by cochrane (2005), with the iterated version of the GMM, the estimates should not much depend on the initial weighting matrix[25].

Reported standard errors are estimated by the Newey-West procedure, with the number of lags determined according to Andrews (1991). Predicted mean returns are $cov(R, f)\hat{b}$ and pricing errors are $\hat{\alpha} = \mu_R - cov(R, f)\hat{b}$. As a mean to test the validity of the model, we run a test of the pricing errors $J = T\hat{\alpha}' V_T^{-1}\hat{\alpha}$ where V_T is a consistent estimate of the asymptotic covariance matrix of $\sqrt{T}\hat{\alpha}$. The test statistic is asymptotically distributed as a χ^2 with $n - k$ degrees of freedom, n being the number of test assets and k the number of risk factors f. Also we estimate the cross-sectional fit of the model as $R^2 = \Sigma\bar{\alpha}^2 / \Sigma(\bar{R_i}t - \bar{R_t})^2$.

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Notes

[1]Martingale: $E_t(1/s_{t+1}) = 1/s_t$

[2]We study the payoff for the strategy of buying the currencies with a forward discount and selling the currencies with a forward premium. The payoff for this strategy differs by a factor $(1 + r^{US})$ from the strategy that borrows funds in a low-interest-rate currency and lends them in a high-interest-rate currency.

[3] We share 16 currencies with DB GCH which does not include Thailand and the European countries which have adopted the EUR.

[4]In our main sample containing 217 observations, this is equivalent to replacing the two higher (lower) observations by the third higher (lower) one. Winsorizing or not the data produce similar conclusions to this paper. However, for the asset pricing tests, the optimizer produces near singular matrices when the data are not winsorized. See Menkhoff et al. (2012) for the estimation process of the risk premia in the currency markets.

[5]The data we use are extracted from Bloomberg. They consist in 10-delta one month from expiry options. They cover the period from October 2003 to January 2017. We reached similar conclusions using 25-delta options one month and six months from expiry date. Time-series correlations per currency between bid-ask spreads and implied volatilities are as follows: EUR 0.05 ; JPY 0.28 ; GBP 0.16 ; AUD 0.17 ; CAD 0.16 ; NZD 0.07 ; CHF 0.17 ; NOK 0.09 ; SEK 0.13 ; DKK 0.00 ;ZAR 0.16 ; BRL 0.12 : MXN 0.09 ; KRW 0.60 ; THB -0.05 ; SGD 0.26 ; HKD 0.18 ; HUF 0.35 ; INR -0.13 ; PHP -0.12 ; PLN 0.48 ; TWD 0.10.

[6]The results are presented for a total position standardized to 1 dollar for each period (sum of the long and the absolute of the short positions). The fact that the number of currencies and/or the sum of the weights might differ between the two portfolios is not a problem *per se* since each position is already a fully financed long-short position. Alternatively, we could have presented the results for a strategy investing one dollar in the portfolio of long positions and minus one dollar in the portfolio of short positions.

[7]We estimate the distribution of the statistics by generating 10000 block bootstrap samples of the carry trade returns. We presents the results with non-annualized figures so as to follow Lo (2002) who shows that annualization is correct only under very special circumstances.

[8]Some ranked currencies, like C1 and C2 for the funding currencies and C19 to C22 for the investment currencies are never non-attractive therefore we cannot produce a Sharpe ratios for them in this subset.

[9]In a risk reversal strategy, traders simultaneously buy an out-of-the-money call and sell an out-of-the-money put. The risk reversal measures the difference between the implied volatilities of these two options. A positive (negative) risk reversal implies that the risk-neutral exchange rate distribution is positively (negatively) skewed. The data we use are extracted from Bloomberg. They consist in 10-delta one month from expiry options. They cover the period from October 2003 to January 2017 as available in Bloomberg. We reached similar conclusions using 25-delta options one month and six months from expiry date.

[10]In our sample, many currencies are alternatively funding or investment currencies but the CHF, the JPY and the SGD are never investment currencies while the AUD, the BRL, the MXN, the NZD and the ZAR are never funding currencies.

[11]The data set includes 10 different currencies: Australia, Canada, Denmark, Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, and the UK. Before 1999, the Euro is replaced by the German Mark, the French Franc, the Italian Lira and the Netherland Gilt. Therefore there are 13 countries included in the sample from 1985 to 1999 but only 10 from 1999 to 2017.

[12]We consider that the covered interest rate parity holds which has been validated empirically by Juhl et al. (2006) and Akram et al. (2008). Large deviations from CIP occurred at the onset of the global financial crises of 2008 as reported by Baba et al. (2009). But Rime, Schrimpf and Syrstad (2019) confirm the validity of CIP in post-crisis financial markets especially when they consider money market rates that reflect banks' true marginal funding costs. Only Du et al. (2018) report persistent deviations from CIP. But they concern long term cross-currency swap contracts, a segment of the market which is irrelevant for our research.

[13]Of course, the way we build the test produces a loading with the opposite sign to the one of the traditional Fama regression. But the conclusion is similar.

[14]Our conclusions do not dependent on a single currency, even though they are more significant when we exclude the KRW or the SEK from the sample. We obtain similar results whether we run the regressions on the mean returns, the cumulated returns or the Sharpe ratios of the ranked currencies. Also results are similar when we winsorize both the returns and the bid-ask spreads.

[15]We capture the aggregate variance in FX by estimating the volatility of the excess return to the FX market portfolio defined as the equally weighted average of the excess returns of all the currencies of the universe of

investment. This can be thought of as the excess return to a naive $1/N$ currency trading strategy. A simple and popular way of estimating a realized measure of monthly market variance (MV) is to use daily excess returns as follows:

$$MV_t = \sum_{d=1}^{D_t} r^2_{M,t+d}/D_t + 2\sum_{d=2}^{D_t} r_{M,t+d}/D_t * r_{M,t+d-1}/D_t \tag{.7}$$

where D_t is the number of trading days in month t (typically $D_t = 21$). This measure of market variance accounts for the auto-correlation in daily returns (e.g., Bali, Cakici, Yan and Zhang, 2005).

[16]We did not consider cross-sectional correlations among the returns when calibrating the simulated data.

[17]Both initial and final vectors of currency returns are constrained within bounds. Notably we constrain the sum of the returns $(r^i_{t+1} + B_i)$ to be zero with all elements being non-zero.

[18]An alternative solution to the puzzle is the peso story: risk averse agents assign small but non-zero probabilities to rare events with larger negative payoff than can be observed in sample. This rare event solution has also received renewed attention in the literature. For instance, Jurek (2014), Farhi et al. (2009) and Burnside et al. (2010) use hedged versions of the carry trade to test the possibility that rare events outside the sample may explain returns. The results seem to indicate that losses associated with rare events are relatively small supporting the alternative view that the salient feature of a peso state is a large value of the SDF.

[19]To save space, we do not report the betas of the RX factor but they are available upon request.

[20]We reach very similar conclusions using factor mimicking portfolios. See Lustig et al. (2011).

[21]We could rely on a simple forecasting model relating MoM_t or $Value_t$ to the future one-month return of the currencies. However this may introduce estimation errors in the analysis.

[22]Reuters captures data at 4pm UK time while Bloomberg captures them at 5pm UK time. See Thomson Reuters (2018) and Bloomberg (2018)

[23]Reuters' spreads may widen in case of spike of volatility but only up to a pre-fixed maximum.

[24]Higher moments expansion can be found in Stuart and al. (1999).

[25]This point can be extended to the second-moment matrix of Hansen and Jagannathan (1997). However, as reported by Cochrane (2005), the second-moment matrix is often nearly singular providing an unreliable weighting matrix when inverted. This is precisely what we find in our sample and probably the reason why none of the papers studying the carry trade in an APT framework use it, with the noticeable exception of Menkhoff et al. (2012).

Appendix D: the return to the carry trade

Table I: Portfolios' descriptive statistics

Panel A: All countries 99-17									
		mean	sd	SK	KT	SR	M_{VaR}	M_{DD}	M_{MaxDD}
$Carry$	*annualized*	0.0166	0.0456	-0.6088	5.3943	0.3632	0.2632	0.0750	0.0135
	monthly					0.1049	0.0759	0.0750	0.0135
	sd-dev					*(0.0721)*	*(0.0537)*	*(0.0530)*	*(0.0128)*
$Carry_{ba}$	*annualized*	0.0260	0.0546	-0.6260	4.9523	0.4758	0.3342	0.0911	0.0191
	monthly					0.1373	0.0964	0.0911	0.0191
	sd-dev					*(0.0718)*	*(0.0546)*	*(0.0528)*	*(0.0129)*
$Carry_{no}$	*annualized*	0.0064	0.0547	-0.3412	4.9298	0.1181	0.0749	0.0219	0.0047
	monthly					0.0341	0.0216	0.0219	0.0047
	sd-dev					*(0.0685)*	*(0.0451)*	*(0.0926)*	*(0.0421)*

The table reports the mean returns, standard deviation, skewness and kurtosis of currency portfolios invested in the carry trade. $Carry$ is an equally weighted strategy in which investors buy all the currencies with higher interest rate than the USD and sell the currencies with lower interest rate than the USD. $Carry_{ba}$ is an equally weighted strategy in which the set of investable currencies is determined dynamically by time varying transaction costs as in Equation (4). $Carry_{no}$ is a strategy based on the time-varying set of currencies for which $F/S > 1$ but $Fb/Sa < 1$ or $F/S < 1$ but $Fa/Sb > 1$. The statistics are reported for annualized log excess returns accounting for transaction costs (bid-ask spreads). The data are monthly. We also report the annualized Sharpe Ratios (SR), modified Sharpe Ratio M_{VaR}, and the ratios of the mean return to the mean drawdown M_{DD} and to the maximum drawdown M_{MaxDD} as defined in Appendix B. Monthly ratios and their standard-errors are also reported (e.g. Lo, 2002). They are obtained by bootstrapping the sample 10000 times. The figures are in basis points not percentages. The panel uses all countries with data from January 1999 to January 2017.

Table II: Portfolios' descriptive statistics

Panel B: G10 countries 85-98		mean	sd	SK	KT	SR	M_{VaR}	M_{DD}	M_{MaxDD}
$Carry$	*annualized*	0.0303	0.0504	-0.6559	4.7861	0.6008	0.4085	0.1090	0.0200
	monthly					0.1734	0.0340	0.1090	0.0200
	sd-dev					*(0.0821)*	*(0.0694)*	*(0.0630)*	*(0.0172)*
$Carry_{ba}$	*annualized*	0.0398	0.0590	-0.4914	3.6478	0.6744	0.4496	0.1287	0.0238
	monthly					0.1947	0.0374	0.1287	0.0238
	sd-dev					*(0.0835)*	*(0.0654)*	*(0.0671)*	*(0.0192)*
$Carry_{no}$	*annualized*	0.0001	0.0470	-0.3278	3.8060	0.0024	0.0013	0.0004	0.0001
	monthly					0.0007	0.0003	0.0004	0.0001
	sd-dev					*(0.0775)*	*(0.0440)*	*(0.0664)*	*(0.0315)*

The table reports the mean returns, standard deviation, skewness and kurtosis of currency portfolios invested in the carry trade. $Carry$ is an equally weighted strategy in which investors buy all the currencies with higher interest rate than the USD and sell the currencies with lower interest rate than the USD. $Carry_{ba}$ is an equally weighted strategy in which the set of investable currencies is determined dynamically by time varying transaction costs. $Carry_{no}$ is a strategy based on the time-varying set of currencies for which $F/S > 1$ but $Fb/Sa < 1$ or $F/S < 1$ but $Fa/Sb > 1$. The statistics are reported for annualized log excess returns accounting for transaction costs (bid-ask spreads). The data are monthly. We also report the annualized Sharpe Ratios (SR), modified Sharpe Ratio M_{VaR}, and the ratios of the mean return to the mean drawdown M_{DD} and to the maximum drawdown M_{MaxDD} as defined in Appendix B. Monthly ratios and their standard-errors are also reported (e.g. Lo, 2002). They are obtained by bootstrapping the sample 10000 times. The figures are in basis points not percentages. Panel B uses G10 countries with data from January 1985 to December 1998.

Table III: Risk measures for attractive and non-attractive currencies

Low yielding currencies										
	$f-s$	SR$_{at}$	SK$_{at}$	Q$_{at}$	RR$_{at}$	SR$_{no}$	SK$_{no}$	Q$_{no}$	RR$_{no}$	Freq
C1	-0.0039	-0.0172	0.36	-0.13	-0.0111	-	-	-	-	1.00
C2	-0.0016	-0.4535	-0.21	-0.15	-0.0036	-	-	-	-	1.00
C3	-0.0013	0.1501	0.44	-0.12	-0.1255	1.1987	-0.58	-0.10	-0.0463	0.92
C4	-0.0013	-0.3315	-0.13	-0.16	-0.0379	0.4605	-0.54	-0.13	-0.0264	0.81
C5	-0.0012	-0.3987	-0.22	-0.14	-0.0088	-0.2402	-1.12	-0.14	0.0273	0.65
C6	-0.0011	-0.4038	-0.19	-0.17	-0.0194	0.0533	-0.15	-0.16	0.0132	0.47
C7	-0.0009	0.3129	0.20	-0.09	-0.0165	0.2162	0.18	-0.12	0.0302	0.35
C8	-0.0008	-0.1011	-0.92	-0.13	-0.0182	-0.0163	-0.32	-0.13	0.0449	0.30
C9	-0.0007	-0.1683	0.29	-0.12	-0.0505	-0.4228	0.18	-0.15	0.0187	0.25
High yielding currencies										
	$f-s$	SR$_{at}$	SK$_{at}$	Q$_{at}$	RR$_{at}$	SR$_{no}$	SK$_{no}$	Q$_{no}$	RR$_{no}$	Freq
C10	0.0010	0.2752	-0.53	-0.14	0.0754	0.3436	0.31	-0.15	0.0944	0.35
C11	0.0012	-0.1242	-1.14	-0.17	0.0746	-0.4393	-0.14	-0.19	0.1312	0.40
C12	0.0013	0.3018	-0.06	-0.15	0.1023	-0.2199	-0.59	-0.16	0.0961	0.44
C13	0.0015	0.2139	-0.07	-0.16	0.0960	0.1929	-0.50	-0.14	0.1134	0.54
C14	0.0018	0.3268	-0.73	-0.18	0.1078	-0.2926	-0.72	-0.12	0.0947	0.62
C15	0.0020	0.1294	-0.52	-0.23	0.1030	0.0249	0.41	-0.12	0.0866	0.73
C16	0.0023	0.3527	-0.31	-0.13	0.1181	0.2808	0.58	-0.10	0.0857	0.87
C17	0.0028	-0.3652	-0.51	-0.26	0.1109	-1.2484	-0.57	-0.10	0.0921	0.93
C18	0.0033	0.0674	-0.66	-0.17	0.1196	-0.3601	0.27	-0.14	0.0359	0.96
C19	0.0041	0.0032	-0.68	-0.20	0.1371	-	-	-	-	1.00
C20	0.0052	0.2802	-0.60	-0.18	0.1618	-	-	-	-	1.00
C21	0.0066	0.2355	-0.80	-0.22	0.1811	-	-	-	-	1.00
C22	0.0106	0.6680	-0.45	-0.22	0.1950	-	-	-	-	1.00

The table reports the annualized Sharpe ratio, skewness, the return associated to the 5% left quantile and risk reversal for currencies sorted on their forward discount $f-s$. For every month, C1 is the lowest yielding currency while C22 is the highest yielding currency. SR_{at} is the annualized Sharpe ratio of the returns when the currencies are attractive. SR_{no} is the annualized Sharpe ratio of the returns when the currencies are non-attractive. SK_{at} and SK_{no} are respectively the skewness of the returns when the currencies are attractive and non-attractive. Q_{at} and Q_{no} are respectively the returns associated to the 5% left quantile when the currencies are attractive and non-attractive. RR_{at} and RR_{no} are respectively the mean standardized risk reversal extracted from prices of 1-month to expiry options (10 delta) when the currencies are attractive and non-attractive. For almost all high yielding currencies $SR_{at} > SR_{no}$ while $SR_{at} < SR_{no}$ for the low yielding currencies. Also, the crash risk tends to be bigger for attractive currencies both under physical and risk-neutral measures. The currencies which have been always attractive in our sample are reported with a $-$ in the column SR_{no}. We also report the mean forward discount for each ranked currency ($f-s$) and the frequency at which the ranked currency was attractive (Freq). The statistics are reported for annualized log excess returns accounting for transaction costs (bid-ask spreads). The data are monthly. The figures are in basis points not percentages. The return associated to the 5% left quantile is annualised. The panel uses all countries with data from January 1999 to January 2017.

Table IV: Sharpe Ratios for attractive and non-attractive currencies

Low yielding currencies								
	G10 countries: 99-17			G10 countries: 85-99			ex AUD, JPY, NOK: 85-99	
	SR_{at}	SR_{no}		SR_{at}	SR_{no}		SR_{at}	SR_{no}
C1	0.0078	-	C1	-0.5439	-	C1	-0.4694	-
C2	-0.0079	0.5109	C2	0.3475	1.3276	C2	0.2185	0.7986
C3	-0.0501	0.5187	C3	0.1176	0.5336	C3	0.2366	1.7458
C4	-0.8101	-0.1205	C4	0.2245	1.3202	C4	0.3980	1.5071
C5	-0.4299	-0.1582	C5	0.6389	1.4567	C5	-0.3259	1.0961
			C6	-0.3080	0.9367			
High yielding currencies								
	G10 countries: 99-17			G10 countries: 85-99			ex AUD, JPY, NOK: 85-99	
	SR_{at}	SR_{no}		SR_{at}	SR_{no}		SR_{at}	SR_{no}
C6	0.3745	0.6007				C6	0.7485	0.3854
C7	0.3187	0.0652	C7	0.8332	-0.3199	C7	0.6341	0.2991
C8	0.1517	0.0824	C8	0.8154	0.3025	C8	0.3912	0.8023
C9	0.1127	0.7881	C9	0.6924	0.7193	C9	0.6772	-0.7450
C10	0.1306	-0.4869	C10	0.5138	0.5279	C10	0.3905	-
			C11	0.4785	-0.6073			
			C12	0.4077	-0.6585			
			C13	0.3841	-			

The table reports the annualized Sharpe ratios for currencies sorted on their forward discount $f - s$. For every month, C1 is the lowest yielding currency while C10 (or C13 when appropriate) is the highest yielding currency. SR_{at} is the annualized Sharpe ratio of the returns when the currencies are ex-ante profitable. SR_{no} is the annualized Sharpe ratio of the returns when the currencies are not ex-ante profitable. As expected, for almost all high yielding currencies $SR_{at} > SR_{no}$ while $SR_{at} < SR_{no}$ for the low yielding currencies. The ranked currencies which have been always attractive are reported with a $-$ in the column SR_{no}. We also report the mean forward discount for each currency $(f - s)$. The statistics are reported for annualized log excess returns accounting for transaction costs (bid-ask spreads). The data are monthly. The last column reports the frequency at which each ranked currency was ex-ante profitable. The figures are in basis points not percentages. The panels use all G10 countries with data from January 1985 to January 2017.

Table V: Regressions of mean returns on forward discounts (weighted OLS estimates).

	attractive ccy			non-attractive ccy		
	α	β	R^2	α	β	R^2
All countries	-0.0055	0.0060**	0.46	0.0087	-0.0207	0.06
Full sample	(0.0066)	(0.0013)		(0.0098)	(0.0145)	
All countries	0.0151	0.0082**	0.39	0.0041	-0.0209	0.01
Low volatility	(0.0113)	(0.0021)		(0.0149)	(0.0230)	
All countries	-0.0134	-0.0040	0.02	0.0065	0.0072	-0.06
High volatility	(0.0150)	(0.0033)		(0.0191)	(0.0248)	
G10 countries	0.0244**	0.0046**	0.51	0.0144	-0.0437	-0.06
	(0.0047)	(0.0014)		(0.0303)	(0.0631)	

Monthly returns from January 1999 to January 2017 for all countries and January 1985 to January 2017 for G10 countries. Test assets are currencies sorted on their forward discount. Excess returns take into account bid-ask spreads. Attractive and non-attractive currencies are defined according to equation (4). Volatility regimes are below 25th percentile (low) and above 75th percentile (high). The table reports frequency weighted OLS estimates of the β of the cross sectional regressions of the mean returns on the forward discount as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table VI: Regressions of mean returns on forward discounts (Panel estimates).

	α	β_{at}	β_{no}	R^2
Panel A: All countries: 99-17				
All countries	0.0113**	0.0072**	-0.0030	0.46
Full sample	(0.0050)	(0.0008)	(0.0046)	
Low volatility 99-17				
	α	β_{at}	β_{no}	R^2
All countries	0.0161**	0.0068**	-0.0061	0.21
	(0.0004)	(0.0014)	(0.0080)	
G10 countries	0.0026	0.0218**	0.0241	0.44
	(0.0049)	(0.0040)	(0.0210)	
EM Countries	0.0220**	0.0043**	-0.0159	0.38
	(0.0072)	(0.0017)	(0.0098)	
High volatility 99-17				
	α	β_{at}	β_{no}	R^2
All countries	0.0073	-0.0004	-0.0013	0.56
	(0.0059)	(0.0027)	(0.0095)	
G10 countries	0.0025	-0.0216**	0.0470	0.66
	(0.0084)	(0.0079)	(0.0441)	
EM Countries	0.0130	0.0015	-0.0024	0.53
	(0.0083)	(0.0031)	(0.0102)	

Monthly returns from January 1999 to January 2017 for all countries. Test assets are currencies sorted on their forward discount. Excess returns take into account bid-ask spreads. Attractive and non-attractive currencies are defined according to equation (4). Volatility regimes are below 25th percentile (low) and above 75th percentile (high). The table reports the results to state dependent regressions of the returns on the forward discount when the currencies are attractive β_{at} and non-attractive β_{no}. We include time fixed-effect and we report heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table VII: Traders' Positions descriptive statistics

	Non-commercial positions				Commercial positions			
	mean	sd	SK	KT	mean	sd	SK	KT
EUR	-0.2491	0.1463	0.9295	3.4156	0.3078	0.1447	-0.9309	3.0934
JPY	-0.1573	0.2755	0.8416	2.3939	0.2661	0.3342	-0.8009	2.2048
GBP	-0.0945	0.1753	-0.1329	2.5767	0.1262	0.2333	-0.1294	2.4637
AUD	-0.0018	0.2626	0.1001	1.5435	0.0409	0.3787	-0.2405	1.6362
CAD	-0.1058	0.2385	0.6797	2.1443	0.1299	0.3501	-0.8541	2.5299
NZD	0.0933	0.3054	0.2806	2.3394	-0.0746	0.3638	-0.1657	2.0529
CHF	-0.0355	0.2515	-0.8718	3.2825	0.2240	0.3158	-0.2250	2.3389
ZAR	-0.2460	0.1649	1.1300	3.5925	0.3018	0.2742	-1.5466	4.5804
BRL	0.0973	0.2142	-0.0719	2.0834	-0.1056	0.2342	0.1850	2.1187
MXN	-0.1150	0.3445	0.6933	1.9016	0.1238	0.3672	-0.7556	2.0181

The table reports the mean returns, standard deviation, skewness and kurtosis of traders' open interest for futures in the foreign exchange market. The data are extracted from the Commodity Futures Trading Commission's website. The variables measure the time-varying difference between the number of contracts for long positions (Positions long all) and short positions (Positions short all). This difference is standardized by the total number of positions (Open Interest All). A positive figure indicates that traders are net buyers of futures. A negative figure indicates that traders are net sellers of futures. We report statistics for Non-commercial positions (speculative positions) and Commercial positions (hedging positions). The data are monthly averages. We report the data for the following countries as available in the CFTC's website: Euro area, Japan, UK, Autralia, Canada, New-Zeland, Switzerland, South-Africa, Brazil and Mexico. The sample covers the period January 1999 to January 2017. The sample is cleaned for missing information. The figures are in basis points not percentages.

Table VIII: Regressions of traders' positions on forward discounts (Panel estimates).

Non-commercial positions				
	α	β_{at}	β_{no}	R^2
All countries	-0.0602	0.0989**	0.1531	0.21
	(0.0901)	(0.0132)	(0.1381)	
G10 countries	-0.1494	0.5431**	0.0952	0.42
	(0.0848)	(0.0813)	(0.2303)	
Commercial positions				
	α	β_{at}	β_{no}	R^2
All countries	0.0529	-0.1104**	-0.2931	0.26
	(0.1138)	(0.0166)	(0.1743)	
G10 countries	0.1270	-0.6302**	-0.3340	0.47
	(0.1111)	(0.1065)	(0.3016)	

Monthly observations from January 1999 to January 2017 for all countries. The table reports the results of state dependent regressions of traders' net standardized positions on the forward discount when the currencies are attractive β_{at} and non-attractive β_{no}. Attractive and non-attractive currencies are defined according to equation (4). The data are extracted from the Commodity Futures Trading Commission's website. We report the data for the following countries as available in the CFTC's website: Euro area, Japan, UK, Autralia, Canada, New-Zeland, Switzerland, South-Africa, Brazil and Mexico. The sample is cleaned for missing information. The dependent variable measures the time-varying difference between the number of contracts for long positions (Positions long all) and short positions (Positions short all). This difference is standardized by the total number of positions (Open Interest All). We report statistics for Non-commercial positions (speculative positions) and Commercial positions (hedging positions). The results indicate that traders tend to increase their speculative positions when the currencies are attractive, the relationship between positions and the forward discount being insignificant when the currencies are non-attractive. Inversely, traders tend to decrease their hedging positions when the currencies are attractive, the relationship between positions and the forward discount being insignificant when the currencies are non-attractive. We include time fixed-effect and we report heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table IX: Statistics of the time series regression of portfolios' excess returns on risk factors.

Panel: All countries 99-17									
	full sample			attractive ccy			non-attractive ccy		
Ptf	HML-FX	δVOL_{FX}	δVOL_{EQTY}	HML-FX	δVOL_{FX}	δVOL_{EQTY}	HML-FX	δVOL_{FX}	δVOL_{EQTY}
P1	-0.39**	0.0042**	0.001**	-0.38**	0.0029**	0.0008**	-0.05**	0.0003	-0.055**
	(0.01)	(0.001)	(0.0005)	(0.02)	(0.001)	(0.0005)	(0.02)	(0.0007)	(0.02)
P2	-0.14**	0.0013**	0.0012**	-0.13**	0.0011	0.0001	0.05	-0.0002	0.057
	(0.02)	(0.001)	(0.0003)	(0.02)	(0.001)	(0.0004)	(0.03)	(0.0014)	(0.04)
P3	-0.04*	-0.00	0.000	-0.047**	0.0011	0.0003	-0.02	-0.0005	-0.022**
	(0.02)	(0.001)	(0.0002)	(0.02)	(0.001)	(0.0002)	(0.03)	(0.0015)	(0.00)
P4	-0.07**	-0.0015	-0.0003	-0.04**	-0.0004	0.0004	-0.03	-0.0017	-0.034**
	(0.02)	(0.001)	(0.0003)	(0.02)	(0.001)	(0.0005)	(0.04)	(0.0016)	(0.004)
P5	0.05**	0.0021**	-0.0003	-0.004	-0.0006	-0.0003	-0.06**	0.0018	-0.065**
	(0.02)	(0.001)	(0.0003)	(0.02)	(0.001)	(0.0004)	(0.02)	(0.0010)	(0.003)
P6	0.60**	-0.0042**	-0.0016**	0.61**	-0.0041**	-0.0014**	-0.07**	0.0002	-0.0073
	(0.02)	(0.002)	(0.0006)	(0.02)	(0.002)	(0.0006)	(0.01)	(0.0002)	(0.005)

Monthly returns from January 1999 to January 2017. Test assets are currency portfolios sorted on their forward discount. Excess returns used as tests assets and risk factors take into account bid-ask spreads. The HML-FX portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. δVOL_{FX} and δVOL_{EQTY} are measures of realized innovations to respectively the global foreign exchange volatility and the stock market volatility. Attractive and non-attractive currencies are defined according to equation (4). The table reports frequency weighted OLS estimates of the β of equation (9) as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table X: Iterated GMM estimates of linear factor models for sorted currency portfolios.

	full sample				attractive ccy				non-attractive ccy			
	b	λ	R^2	J	b	λ	R^2	J	b	λ	R^2	J
HML-FX	12.01**	0.70**	0.98	0.57	8.51**	1.02**	0.91	8.51	3.52	0.12	-0.16	9.31
	(3.40)	(0.19)		(0.96)	(2.29)	(0.29)		(0.07)	(14.4)	(0.50)		(0.06)
δVOL_{FX}	-2.68**	-0.51**	0.54	3.51	-4.25**	-0.83**	0.68	2.78	-2.19	-0.42	0.07	4.70
	(1.28)	(0.26)		(0.47)	(2.12)	(0.43)		(0.59)	(1.81)	(0.39)		(0.31)
δVOL_{EQTY}	-0.49**	-1.12**	0.75	4.30	-0.72*	-1.38*	0.50	8.18	0.039	0.10	-0.20	5.55
	(0.23)	(0.53)		(0.36)	(0.37)	(0.73)		(0.08)	(0.17)	(0.55)		(0.23)

Monthly returns from January 1999 to January 2017. Test assets are currency portfolios sorted on their forward discount. Excess returns used as test assets and risk factors take into account bid-ask spreads. The HML-FX portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. δVOL_{FX} and δVOL_{EQTY} are measures of realized innovations to respectively the global foreign exchange volatility and the stock market volatility. Attractive and non-attractive currencies are defined according to equation (4). The table reports iterated GMM estimates of the SDF parameter, b, and the factor risk premia λ reported in monthly percentages. Cross sectional R^2 as well as test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are in brackets. The p-value of the J test is also in brackets.

Table XI: Iterated GMM estimates of linear factor models for sorted currency portfolios.

	full sample				attractive ccy				non-attractive ccy			
	b	λ	R^2	J	b	λ	R^2	J	b	λ	R^2	J
HML-FX	0.55**	0.42**	0.61	5.88	0.58**	0.46**	0.74	7.63	-1.01	-0.76	0.18	2.88
	(0.24)	(0.17)		(0.11)	(0.25)	(0.19)		(0.06)	(0.90)	(0.70)		(0.40)
δVOL_{FX}	-0.22*	-0.57*	0.77	3.42	-0.22*	-0.58*	0.59	4.88	-0.29	-0.74	0.44	7.18
	(0.12)	(0.31)		(0.33)	(0.11)	(0.30)		(0.18)	(0.28)	(0.74)		(0.06)
δVOL_{EQTY}	-0.20	-0.68	0.41	6.20	-0.51**	-1.24**	0.62	3.19	0.63	1.54	0.87	0.78
	(0.14)	(0.44)		(0.10)	(0.26)	(0.60)		(0.36)	(0.28)	(0.76)		(0.85)

Monthly returns from January 1985 to January 2017 for G10 currencies only. Test assets are currency portfolios sorted on their forward discount. Excess returns used as test assets and risk factors take into account bid-ask spreads. The HML-FX portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. δVOL_{FX} and δVOL_{EQTY} are measures of realized innovations to respectively the global foreign exchange volatility and the stock market volatility. Attractive and non-attractive currencies are defined according to equation (4). The table reports iterated GMM estimates of the SDF parameter, b, and the factor risk premia λ reported in monthly percentages. Cross sectional R^2 as well as test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are in brackets. The p-value of the J test is also in brackets.

Table XII: Regressions of mean returns on forward discounts (weighted OLS estimates).

Momemtum	attractive ccy			non-attractive ccy		
	α	β	R^2	α	β	R^2
All countries	0.0005	0.0086**	0.53	-0.0004	-0.0019	0.06
Full sample	(0.0006)	(0.0017)		(0.0012)	(0.0013)	
All countries	0.0029	0.0168**	0.37	-0.0012	0.0024	-0.05
Low volatility	(0.0014)	(0.0046)		(0.0024)	(0.0046)	
All countries	0.001	-0.0104*	0.22	0.0018	-0.0014	-0.07
High volatility	(0.001)	(0.0038)		(0.0028)	(0.0041)	

Monthly returns from January 1999 to January 2017 for all countries. Test assets are currencies sorted on their forward discount and momemtum. Excess returns take into account bid-ask spreads. Attractive and non-attractive currencies are defined according to equation (4) and their momemtum as defined in equation (10). Volatility regimes are below 25th percentile (low) and above 75th percentile (high). The table reports frequency weighted OLS estimates of the β of the cross sectional regressions of the mean returns on the forward discount as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table XIII: Regressions of mean returns on forward discounts (weighted OLS estimates).

Value	attractive ccy			non-attractive ccy		
	α	β	R^2	α	β	R^2
All countries	0.0004	0.0056**	0.18	-0.0005	-0.0010	0.01
Full sample	(0.0010)	(0.0023)		(0.0011)	(0.0012)	
All countries	0.0037	-0.0005	0.04	-0.0001	0.0006	0.11
Low volatility	(0.0021)	(0.0047)		(0.0015)	(0.0004)	
All countries	-0.0014	0.022**	0.28	0.002	-0.0012**	0.22
High volatility	(0.0024)	(0.0071)		(0.0015)	(0.0004)	

Monthly returns from January 1999 to January 2017 for all countries. Test assets are currencies sorted on their forward discount and value. Excess returns take into account bid-ask spreads. Attractive and non-attractive currencies are defined according to equation (4) and the value signal as defined by equation (11). Volatility regimes are below 25th percentile (low) and above 75th percentile (high). The table reports frequency weighted OLS estimates of the β of the cross sectional regressions of the mean returns on the forward discount as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table XIV: Iterated GMM estimates of linear factor models for sorted currency portfolios (carry and momemtum).

Momemtum	full sample				attractive ccy				non-attractive ccy			
	b	λ	R^2	J	b	λ	R^2	J	b	λ	R^2	J
HML-FX	12.47	0.52**	0.95	0.90	12.02**	0.50**	0.89	4.91	-8.19	-0.32	0.21	1.33
	(8.91)	(0.17)		(0.92)	(5.66)	(0.15)		(0.29)	(11.63)	(0.48)		(0.85)
δVOL_{FX}	12.83	-0.36	0.88	2.87	13.08	-0.44*	0.62	12.92	-8.73	2.63	0.54	1.00
	(25.49)	(0.46)		(0.57)	(7.91)	(0.23)		(0.02)	(50.26)	(9.10)		(0.90)
δVOL_{EQTY}	8.40	-1.08**	0.50	2.24	10.99	-1.40*	0.74	6.35	-3.30	1.79	-0.25	1.73
	(23.21)	(0.55)		(0.69)	(8.16)	(0.72)		(0.17)	(33.58)	(20.31)		(0.78)

Monthly returns from January 1999 to January 2017. Test assets are currency portfolios sorted on their forward discount and momemtum. Excess returns used as test assets and risk factors take into account bid-ask spreads. The HML-FX portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. δVOL_{FX} and δVOL_{EQTY} are measures of realized innovations to respectively the global foreign exchange volatility and the stock market volatility. Attractive and non-attractive currencies are defined according to equation (10). The table reports iterated GMM estimates of the SDF parameter, b, and the factor risk premia λ reported in monthly percentages. Cross sectional R^2 as well as test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are in brackets. The p-value of the J test is also in brackets.

Table XV: Iterated GMM estimates of linear factor models for sorted currency portfolios (carry and value).

Value	full sample				attractive ccy				non-attractive ccy			
	b	λ	R^2	J	b	λ	R^2	J	b	λ	R^2	J
HML-FX	10.35	0.29**	0.91	1.11	30.84**	0.40**	0.40	7.79	-11.62	-1.51	-0.96	2.61
	(7.86)	(0.13)		(0.89)	(22.15)	(0.31)		(0.09)	(50.51)	(1.69)		(0.62)
δVOL_{FX}	8.89	-1.57	0.14	5.05	31.98	-4.17*	0.40	7.71	-11.62	-1.51	-0.26	4.85
	(30.93)	(5.68)		(0.28)	(79.19)	(8.40)		(0.10)	(50.51)	(1.69)		(0.30)
δVOL_{EQTY}	8.95	-5.52	0.23	4.81	34.63	-14.94	0.53	8.41	4.69	13.28	-0.22	4.59
	(26.31)	(15.36)		(0.30)	(48.73)	(16.67)		(0.07)	(27.04)	(37.22)		(0.33)

Monthly returns from January 1999 to January 2017. Test assets are currency portfolios sorted on their forward discount and value. Excess returns used as test assets and risk factors take into account bid-ask spreads. The HML-FX portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. δVOL_{FX} and δVOL_{EQTY} are measures of realized innovations to respectively the global foreign exchange volatility and the stock market volatility. Attractive and non-attractive currencies are defined according to equation (11). The table reports iterated GMM estimates of the SDF parameter, b, and the factor risk premia λ reported in monthly percentages. Cross sectional R^2 as well as test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are in brackets. The p-value of the J test is also in brackets.

Table XVI: Portfolios' descriptive statistics

		mean	sd	SK	KT	SR	M_{VaR}	M_{DD}	M_{MaxDD}
Bloomberg Dataset									
Carry	*annualized*	0.0166	0.0456	-0.6088	5.3943	0.3632	0.2632	0.0750	0.0135
	monthly					0.1049	0.0759	0.0750	0.0135
	sd-dev					*(0.0721)*	*(0.0537)*	*(0.0530)*	*(0.0128)*
$Carry_{ba}$	*annualized*	0.0260	0.0546	-0.6260	4.9523	0.4758	0.3342	0.0911	0.0191
	monthly					0.1373	0.0964	0.0911	0.0191
	sd-dev					*(0.0718)*	*(0.0546)*	*(0.0528)*	*(0.0129)*
Thomson/Reuters Dataset									
Carry	*annualized*	0.0190	0.0431	-0.6508	5.5226	0.4402	0.3002	0.1000	0.0189
	monthly					0.1270	0.0866	0.1000	0.0189
	sd-dev					*(0.0731)*	*(0.0579)*	*(0.0626)*	*(0.0144)*
$Carry_{ba}$	*annualized*	0.0257	0.0622	-0.6621	6.3256	0.4132	0.3121	0.0933	0.0186
	monthly					0.1192	0.0900	0.0933	0.0186
	sd-dev					*(0.0728)*	*(0.0616)*	*(0.0634)*	*(0.0124)*

The table reports the mean returns, standard deviation, skewness and kurtosis of currency portfolios invested in the carry trade. *Carry* is an equally weighted strategy in which investors buy all the currencies with higher interest rate than the USD and sell the currencies with lower interest rate than the USD. $Carry_{ba}$ is an equally weighted strategy in which the set of investable currencies is determined dynamically by time varying transaction costs as in Equation (4). The statistics are reported for annualized log excess returns accounting for transaction costs (bid-ask spreads). The data are monthly. We also report the annualized Sharpe Ratios (SR), modified Sharpe Ratio M_{VaR}, and the ratios of the mean return to the mean drawdown M_{DD} and to the maximum drawdown M_{MaxDD} as defined in Appendix B. Monthly ratios and their standard-errors are also reported (e.g. Lo, 2002). They are obtained by bootstrapping the sample 10000 times. The figures are in basis points not percentages. The panel uses all countries with data from January 1999 to January 2017.

Table XVII: Bid and Ask spreads statistics.

Spot exchange rates: 99-17				
	mean	sd	min	max
T-Reuters	0.10%	0.14%	0.002%	1.02%
Bloomberg	0.10%	0.17%	0.001%	5.62%
Forward exchange rates: 99-17				
	mean	sd	min	max
T-Reuters	0.14%	0.16%	0.009%	2.57%
Bloomberg	0.14%	0.32%	0.001%	6.76%

The table reports the mean bid and ask spread, standard deviation, minimum and maximum for the sample of G10 and emerging markets currencies over the period January 1999 to January 2017. The data have been winsorized at the 1% level and cleaned for anomalies as described in this appendix.

Table XVIII: Interest rates differential statistics.

Panel A: all countries 99-17					
	mean	median	sd	min	max
High-Y CCY	3.62%	2.46%	4.12%	0.01%	33.3%
Low-Y CCY	-1.56%	-0.94%	4.84%	-0.01%	-7.34%
Panel B: G10 countries 99-17					
	mean	median	sd	min	max
High-Y CCY	1.80%	1.52%	1.37%	0.01%	6.56%
Low-Y CCY	-1.41%	-0.95%	1.40%	-0.01%	-7.34%

The table reports the mean, median, standard deviation, minimum and maximum interest rates differential for the sample of G10 and emerging markets currencies over the period January 1999 to January 2017 (Panel A) and G10 countries only over the same period of time (Panel B). The statistics are reported for currencies exhibiting a positive differential (High-Y CCY) and currencies exhibiting a negative differential (Low-Y CCY). The data have been winsorized at the 1% level and cleaned for anomalies as described in this appendix.

Figure 1: The return to the carry trade

Sample January 1985 to January 2017. Monthly observations. The figure plots the cumulated return of investing one dollar in a portfolio of long positions in high interest rate currencies and in a portfolio of short positions in currencies with low interest rates. The strategy is rebalanced every month and the proceeds are not reinvested. The portfolio is equally weighted and contains 3 currencies of each types. The strategy has offered a large positive mean return over the sample period with few episodes of crises.

Figure 2a: Mean returns for currencies sorted on their forward discount $f - s$. Panel A: All countries 99-17. Attractive (upper graph) and non-attractive (lower graph) currencies.

Sample January 1999 to January 2017 for all countries. Monthly observations. The graphs show the monthly mean returns for currencies sorted on their forward discount for attractive currencies (upper graph) and non-attractive currencies (lower graph). The forward discounts are in annualised basis points in X-axis while the monthly mean returns are reported along the Y-axis. The graphs show that the relationship between the forward discounts and the mean returns is strong for attractive currencies but weak for non-attractive currencies.

Figure 2b: Mean returns for currencies sorted on their forward discount $f - s$. Panel B: G10 countries 85-17. Attractive (upper graph) and non-attractive (lower graph) currencies.

Sample January 1985 to January 2017 for G10 countries. Monthly observations. The graphs show the monthly mean returns for currencies sorted on their forward discount for attractive currencies (upper graph) and non-attractive currencies (lower graph). The forward discounts are in annualised basis points in X-axis while the monthly mean returns are reported along the Y-axis. The graphs show that the relationship between the forward discounts and the mean returns is strong for attractive currencies but weak for non-attractive currencies.

Figure 3: UIP conforming simulated returns sorted on their forward discount. Panel A: All countries 99-17.

Sample January 1999 to January 2017 for all countries. Monthly observations. The graph shows the monthly mean simulated returns for currencies sorted on their forward discount. Initial vectors are generated randomly by drawing in the uniform distribution. Simulated returns data are obtained by adding generated *iid* errors of mean zero and variances matching those of the idiosyncratic errors in the actual data. The forward discounts are in annualised basis points in X-axis while the monthly mean simulated returns are reported along the Y-axis.

Figure 4: Mean returns for currencies sorted on their β to HML-FX and Vol_{FX}

Sample January 1999 to January 2017 for all countries. Monthly observations. The graphs show the monthly mean returns for portfolios of currencies sorted on their beta to the risk factor HML-FX (upper graph) and VOL_{FX} (lower graph). The betas are on the X-axis while the monthly mean returns are reported along the Y-axis. Black points are the mean returns when the currencies are attractive in the sample according to Equation (4). Empty points are the mean returns when the currencies are non-attractive. The graphs show that the returns are orthogonal to the risk factor when the currencies are non-attractive but somewhat monotonic for attractive currencies.