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The Crash Risk Premia of Efficient Carry Trades.

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Abstract

Carry trade strategies in which investors sell forward currencies that are at a forward premium and buy forward currencies that are at a forward discount are, on average, profitable. According to the uncovered interest rate parity they should not. A risk premia story might justify the high returns to the carry trades. In this paper we study the relationship between the cross section of excess returns of portfolios invested in carry trade positions and a renewed set of candidate risk factors. Asset pricing theory applies to the currency market: those currencies that have larger loading on risk, especially crash risk, offer a larger mean return in compensation. Also, we show that crash risk as measured by quantile based statistics such as VaR or CVaR prices better the return to the carry trades than moments based factors such as standard deviation or skewness. This result holds at the portfolio level and at the single currency level. As a result, we show that carry trade strategies that take account of the dispersion of interest rates dominate strategies in which bets are normalized.

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1 Introduction

On average, selling forward currencies that are at a forward premium and buying forward currencies that are at a forward discount is profitable. This is the carry trade strategy. In theory this strategy should fail because, according to the uncovered interest rate parity (UIP), arbitrage should eliminate the gain arising from the differential of interest rate. But in reality, the theory fails and the strategy generates large profits for practitioners and a puzzle for academics. The recent crises (2008-2011) that followed another favourable period for the strategy (2003-2007) has renewed attention on the carry trade puzzle (Figure 1). Burnside (2011) re-examines the most prominent works, especially those applying an asset pricing approach with factor mimicking portfolios. The conclusion is twofold: linear stochastic discount factors (SDF) built from traditional models such as the CAPM[1], the Fama-French three factor model and the consumption-CAPM[2] fail to explain the returns to the carry trade. But some non traditional factors, constructed specifically to price currency returns, seem to offer a partial resolution to the puzzle.

In non traditional models, factors are derived directly from currency returns. For instance, following Fama and French (1993), Lustig, Roussanov and Verdelhan (2011) build equally weighted portfolios of currencies sorted according to their forward premium against the US dollar. Then they create two risk factors: RX which is the average excess return of all the portfolios and HML-FX which is the return to an equally weighted portfolio of carry trade positions. Using the traditional Fama-McBeth procedure, they find both candidate factors as being statistically significant in justifying carry trade returns. In the same way, Menkhoff, Sarno, Schmeling and Schrimpf (2011) find that a factor that measures global currency volatility is also an acceptable candidate if combined with RX[3]. Finally Rafferty (2010) following the work of Brunnermeir, Nagel and Pedersen (2009) finds that an indicator of common crash in currency market (i.e. a global currency skewness indicator) might be important in explaining the return to the carry trade. Burnside (2011) challenges some of these results. Especially, re-testing the different factors, he rejects the initial specification of Lustig, Roussanov and Verdelhan (2011) for too large pricing errors, but confirms that systemic indicators of volatility as in Menkhoff and al. (2011) or skewness as in Rafferty (2010) produce acceptable results.

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 problem has also received renewed attention in the literature (see Barro and Ursua (2011) and Gourio (2008)). Jurek (2008), Farhi, Fraiberger, Gabaix, Ranciere, Verdhelan (2009) and Burnside, Eichenbaum, Kleshchelski and Re-

[1]this might hold only for the linear version of the CAPM as Christiansen, Ranaldo and Söderlind (2011) explain carry trade returns using a regime-dependent CAPM.

[2]Lustig and Verdelhan (2007) justify carry trades returns in the Durables Consumption CAPM setting of Yogo (2006). However Burnside (2011) and Burnside, Eichenbaum, Kleshchelski and Rebelo (2010) disputes the significance of their findings.

[3]Clarida, Davis and Pedersen (2009), Brunnermeier, Nagel and Pedersen (2009) and Christiansen, Ranaldo and Söderlind (2011) find carry trade returns as being significantly sensitive to volatility regimes.

belo (2011) use hedged versions of the carry trade to test the possibility that out of sample rare events explain returns. In hedged versions of the strategy, currency options protect the investor from the large negative payoffs associated with peso events. The difference in return between hedged and unhedged strategies is an estimation of the crash risk premium. Jurek (2010) and Farhi, Fraiberger, Gabaix, Ranciere, Verdhelan (2009) find comparable results: the anticipation of rare but large events might justify respectively around 35% and 25% of carry trade returns[4]. These results are challenged by Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) who find a negligible difference in returns between the two portfolios. They conclude that losses associated to rare events are relatively small supporting the alternative view that the salient feature of a peso state is a large value of the SDF[5].

In this paper, we test a new set of candidate risk factors that might justify the risk premium. We find results that are in line with Burnside (2011), Lustig, Roussanov and Verdelhan (2011) and Menkhoff and al. (2011). Asset pricing theory applies to the currency market: those currencies that have larger loading on global risk offer a larger mean return in compensation. This looks particularly true when we consider crash risk factors. Especially those derived from quantile-based statistics such as the Value at Risk (VaR) and the Conditional Value at Risk (CVaR). In our sample, they price better the returns to the carry trade than factors tested earlier in the literature such as volatility or skewness. This finding has two appealing justifications: i) often regulators[6], then investors favor quantile-based statistics rather than volatility or skewness to estimate risk and crash risk. Even, in many investment firms, quantile-based statistics define thresholds constraining funding for investment strategies. When the threshold is exceeded, leveraged traders may face the risk to unwind their positions as described in Brunnermeier, Nagel and Pedersen (2009). Therefore it seems natural to look primarily for a premium compensating for holding this risk rather than the risk of facing volatile or skewed returns ii) the second justification is algebraic: as quantile-based statistics depend, even though in a non-linear fashion, of both skewness <u>and</u> kurtosis (see Cornish-Fisher expansion in annex I), they carry more significant information about the true shape of the distribution, hence crash risk, than the volatility or the skewness alone.

We work on a large sample of 16 currencies covering the period 1999 to 2011. In line with the literature we document the failure of UIP and find that including emerging markets currencies increases significantly the sharpe ratio of the carry trade strategy. Following Burnside, Eichenbaum and Rebello (2007) we confirm that an investor that do not take into account transaction costs might invest in portfolios which are not prof-

[4]However Jurek (2010) notes also that once portfolios are constrained to simultaneously maintain a zero net exposure to the U.S. dollar, excess returns to crash-hedged portfolios become negligible, and statistically indistinguishable from zero.

[5]This might be the case because investors are loss averse as defined by Kahneman and Tversky (1979). Under loss aversion, decision-makers exhibit superior sensitivity to losses or tail risk than to gains which in turns might produce unusually high values of the stochastic discount factor (SDF) in peso states. Utility functions that account of loss aversion are kinked (there is a jump in marginal utility) at the reference point distinguishing gains or acceptable losses from unacceptable losses. See for instance Berkelaar, Kouwenberg and Post (2004)

[6]See standards and guidelines of the Basel Committee on Banking Supervision

itable ex-ante, hence not efficient. Also, we show that the global crash risk premia story applies well both at the portfolio and the currency level. As a consequence, we show that the strategies, that use all the information conveyed by the dispersion of interest rates, are, on average, more profitable, even accounting for risk and tail risk, than strategies with normalized bets. When we run GMM-SDF tests of linear factor models we find that quantile-based crash risk measures do a good job in pricing the return to the carry trade, particularly in samples including emerging markets where interest rate differential are larger. This result is also much more significant when tests are run on ex-ante profitable (efficient) portfolios rather than pre-defined portfolios.

This paper is organised as follow: following this introduction, in section two, we present the data and introduce four ways of specifying carry trade positions. In section three, we provide the return to these portfolios and discuss why these portfolios, all invested in carry trade positions, produce payoff with significant differences. Especially we show why using the popular long short strategy might be inefficient. In section four, we document the SDF-GMM procedure. In section five, we report the GMM estimation of linear factor models with a renewed set of candidate SDF, including quantile-based measures of risk. We conclude in a sixth section.

2 Data and carry trade portfolios

Our data are from the Bloomberg database. They cover the period from January 1999 to April 2011 for 16 countries[7]. All countries are included through-out the sample covering January 1999 to April 2011. Data represent quotes taken daily from the Bloomberg system at London closing time. They are average rates quoted by leading market participants. All currencies are quoted as foreign currency units per one US dollar, that is the direct quotation of the USD. We convert the daily data into weekly and monthly data by sampling the daily data respectively on every Friday and every last open day of each month[8]. Our data include the spot exchange rates and the forward exchange rates with bid and ask rates for each observation.
In the literature, one can find several ways to build a carry trade position. In this paper we consider four of them:

1. Equally weighted portfolios of carry trade (EQW)
2. Efficient carry trade (ECT)
3. Efficient carry trade enhanced (ECTh)
4. Naive carry trade (NCT)

Equally weighted portfolios of carry trade (EQW)

The strategy based on equally weighted portfolios (EQW) is the most popular in the literature. It consists in ranking the currencies according to their forward premium and to form, often 5, equally weighted portfolios. The first portfolio contains those currencies with the smallest discounts, then the second portfolio contains the currencies with the second smallest discounts and so on to the fifth portfolio which contains those currencies with the largest discount. We call these portfolios P1, P2...P5. Then the carry trade strategy consists in investing one dollar in P5 and -1 dollar in P1. The return to the carry trade strategy is the sum of the returns of the two, equally weighted, portfolios. There is no rule to define the number of currencies in each portfolio. It seems rather empirical. For instance, Lustig, Roussanov and Verdelhan (2011) build portfolios of five currencies each while Menkhoff, Sarno, Schmeling and Schrimpf (2011) build portfolios of eight currencies each. This number falls to three in Christiansen, Ranaldo and Söderlind (2011) while Brunnermeier, Nagel and Pedersen (2009) test portfolios with 1 to 3 currencies in each. Let n be the number of currencies in each equally weighted portfolio and S_t and F_t denote spot and forward mid quotes, that is the average of the bid quote and the ask quote for respectively spot and forward exchange rates. Building

[7]The 16 currencies are as follows: Australia, Brazil, Canada, Euro, Japan, Mexico, New-Zealand, Norway, Russia, South Africa, South-Korea, Sweden, Switzerland, Thailand, Turkey and UK.

[8]Data for 1-week maturity contracts were not available on a daily basis for certain currencies in the early 2000. As a consequence, the sample of weekly data covers only the period from October 2002 to May 2011

the portfolios consists in allocating all the N currencies in the sample in p portfolios, usually five, of n currencies each on the basis of their forward discount, F_t/S_t. The rank of the currency with the smallest discount is 1. At time t, the position x_t for each currency in the two extreme portfolios P_1 and P_p are:

$$x_t = \begin{cases} Buy & +1/n \quad \text{if} \quad 1 < Rank_{F_t/S_t} < n, \\ Sell & -1/n \quad \text{if} \quad N-n+1 < Rank_{F_t/S_t} < N, \end{cases} \tag{1}$$

Then the returns to the extreme portfolios are:

$$\begin{cases} R_t^1 = \frac{1}{n}\sum_{i=1}^{n} r_t^i \\ R_t^p = \frac{1}{n}\sum_{i=N-n+1}^{N} r_t^i \end{cases} \tag{2}$$

and finally the return of the carry trade strategy is the sum of the return of $P1$ and Pp that is $R_t^1 + R_t^p$.

Efficient carry trade (ECT)

Burnside, Eichenbaum and Rebelo (2007) and Burnside (2011) define carry trade differently. We call their way to invest in currencies, the efficient carry trade (ECT). They build portfolios on the basis of the trade rationale for currency speculation. The number of currencies in these portfolios might not be equal. Let S_t^b and S_t^a be respectively the bid and ask spot exchange rate observed at time t and F_t^b and F_t^a standing for the bid and ask forward exchange rate observed at time t for deals maturing in t+1. Currency speculation or hedging is profitable if at maturity, in t+1, for one dollar sold or bought forward:

$$\begin{cases} F_t^b > S_{t+1}^a & \text{if sold} \\ F_t^a < S_{t+1}^b & \text{if bought} \end{cases} \tag{3}$$

Transposing this result to time t sets the usual rationale for currency trading if agents think S_t^b and S_t^a are martingales[9]:

$$x_t = \begin{cases} Buy & +1 \quad \text{if} \quad F_t^b/S_t^a > 1, \\ Sell & -1 \quad \text{if} \quad F_t^a/S_t^b < 1, \end{cases} \tag{4}$$

[9]Martingale: $S_t^b = E_t(S_{t+1}^b)$ and $S_t^a = E_t(S_{t+1}^a)$

Here, the size of the bets is normalized to one USD but the number of long positions and short positions are not equal. For instance, x_t can be equal to zero which means there is no position on that particular currency at time t. Currencies for which x_t is non zero are given equal weights which means that at any time t the number of long positions or short positions is only limited by the number of currencies in the sample. There are 3 portfolios: P1 which is the portfolio of currencies with the smallest discount, P3 which is the portfolio containing those currencies with the largest discount and P2 which contains currencies that do not verify the trade rationale for currency speculation. The return of this strategy is the sum of the returns in each ex-ante profitable portfolio namely, P1 and P3.

Efficient carry trade enhanced (ECTh)

In this paper, we consider an alternative way to build portfolios: we use all the information conveyed by the signals. We call this strategy the enhanced efficient carry trade (ECTh). We build portfolios on the basis of the trade rationale for currency speculation but we do not normalize the bets to one. Instead, we weight the bets according to the size of the discount of each currency. We do this because normalizing may destroy information by shrinking the dispersion of signals. We sell x_t forward according to the rule:

$$x_t = \begin{cases} F_t^b/S_t^a - 1 & \text{if} \quad F_t^b/S_t^a > 1, \\ \\ F_t^a/S_t^b - 1 & \text{if} \quad F_t^a/S_t^b < 1, \end{cases} \tag{5}$$

For this strategy x_t can be equal to zero and currencies for which x_t is non zero are given weights adjusted to the signal. Again, the return of this strategy is the sum of the returns in each position.

Naive carry trade (NCT)

Finally, for aim of comparison, we also test a 'naive carry trade', or NCT, as in Burnside, Eichenbaum and Rebelo (2007) in which we sell x_t dollars forward according to the rule:

$$x_t = \begin{cases} +1 & \text{if} \quad F_t/S_t > 1, \\ \\ -1 & \text{if} \quad F_t/S_t < 1, \end{cases} \tag{6}$$

This strategy is realistic only in the case where agents can trade at the mid market quote. As in Burnside, Eichenbaum and Rebelo (2007), the size of the bet is normalized to one USD. In the naive strategy, x_t is always different from zero. As above, the return of this strategy is the sum of the returns in each position.

3 Empirical Results

In this section, we provide the return to currency speculation on a large sample including G10 and emerging markets currencies. As mean of robustness test, we also provide results on a smaller sample that includes only G10 currencies. Table 1 reports the descriptive statistics for the payoffs to the four different specification of the carry trade strategy. All returns calculations, even for the naive carry trade, take account of the bid - ask spread. Especially, the return to long positions is $F_t^b/S_{t+1}^a - 1$ and the return to short position is $F_t^a/S_{t+1}^b - 1$. As the four alternative specifications involve bets for which the size differs, mean, median and standard deviation of the returns are informative but not comparable. Especially, EQW is leveraged twice compared to ECT while ECTh involves smaller bets which have the size of the value of the discounts. Following Burnside, Eichenbaum and Rebello (2007), we confirm that including emerging markets currencies substantially increases the sharpe ratio associated with the carry trade. This result is robust to the recent crises. Using weekly data, we find the annualized Sharpe ratio of an efficient carry trade strategy (ECT) in the large sample to be 0.71. Limiting the sample to G10 currencies erases all the return to carry trade producing a Sharpe ratio close to zero (0.09). We also confirm that carry trades that ignore the bid-ask spreads (NCT) yield lower Sharpe ratios that turn to be negative at the weekly horizon. Instead of 0.71 for the ECT strategy, the Sharpe ratio to the naive strategy on the large sample falls to -0.26. The popular equally weighted strategy (EQW) produces lower returns than the efficient strategy. EQW produces a Sharpe ratio of -0.69 in the large sample which turns to be -0.71 in the small sample. Finally the enhanced strategy, ECTh, offers the best trade-off between risk and return. The Sharpe ratio of the efficient carry trade strategy for which the size of the signal is used to calibrate the bets jumps from 0.71 to 0.88 in the large sample. If the sample is limited to G10 currencies, the effect is still visible: the Sharpe ratio jumps from 0.09 to 0.28. At the one-month horizon, results are largely similar albeit Sharpe ratios do not turn negative: the Sharpe ratio of the ECT strategy is 0.82 in the large sample but 0.66 in the small sample; The Sharpe ratios of NCT, ECTh and EQW are respectively 0.66, 0.84 and 0.67 in the large sample and 0.66, 0.75 and 0.44 in the small sample.

Table 1 about here

In table 2, we study the crash risk of these strategies. As in table one, we report the Sharpe ratio, then four alternative ratios which are the ratio of mean return to semi volatility, or Sortino ratio, to maximum drawdown or Sterling ratio, to VaR and to CVaR which are two versions of the modified sharpe ratio (see appendix I for definitions). In the large sample, the efficient carry trade strategy (ECT) produces returns

with a modified Sharpe ratio of 5.53% on the basis of the VaR and 2.49% on the basis of the CVaR. These numbers are 0.71% and 0.36% in the smaller sample which means that including emerging markets improve the return to currency speculation even controlling for crash risk. Of course not accounting for the bid and ask spread as in the naive strategy (NCT) deteriorates the payoff producing lower ratios. Finally, the ECTh strategy, based on the size of the signal, produces better ratios in both sample, albeit crash risk as measure by the CVaR deteriorates in the large sample. At the monthly horizon, and considering other risk ratios give similar results: i) including emerging markets in the sample improve the return to currency speculation even accounting for tail risk ii) building the portfolios on the basis of the rationale to currency speculation produces payoffs with better risk and tail risk characteristics, especially when compared to the naive (NCT) or equally weighted strategy (EQW) iii) using all the information conveyed by the signal further improves the payoff to the carry trade by increasing the mean return with a limited cost in term of risk and tail risk. All in all it seems appropriate from the investor point of view to rank the four strategies as follow: 1) ECTh 2) ECT 3) EQW 4) NCT with ECTh exhibiting the best set of risk return ratios and NCT the worst.

Table 2 about here

Discussion

Shall we be surprised by these results? Burnside and all (2007) show that carry trade ignoring transaction costs (NCT) leads to grossly misleading inference about the profitability of currency speculation strategies. This is because in the NCT type strategy, naive traders do not take into account transaction costs in their calculations. In this case, they might invest in bets which are ex-ante non profitable, that is bets in currencies for which $\mathbb{E}_t(R_{t+1}) < 0$.
The equally weighted strategy carries the same bias. However, as this strategy is based on a pre-fixed number of bets, chances to invest in ex-ante non profitable currencies are lower. But the inverse is also true, chances to miss ex-ante performing currencies for which $\mathbb{E}_t(R_{t+1}) > 0$ is also larger. By construction these two strategies might include ex-ante non profitable trades or forget ex-ante profitable trades. Then, by definition, these positions cannot be considered as *efficient* carry trade positions. So why considering non-efficient positions? The equally weighted strategy seems inherited from the literature on stock markets in which there is a long tradition of factor based stock selection. Especially, following Fama and French (1993), researchers rank stock according to factors such as size or value and then study the relative performance of the n stocks with the largest capitalization (or value) and the n stocks with the smallest capitalization

(or value). Studying the relative performance of equally weighted portfolios of ranked currencies seems to be the direct transposition of this methodology. However, the story is somewhat different for currencies: i) carry trade returns measure the relative performance of one currency against another one. It is already a zero-cost or balanced position combining a long in one currency and a short in another one. Therefore building equally weighted portfolios seems unnecessary. ii) in the stock market, there is a continuum of stock that can be ranked according to factors. In the currency market this continuum does not exist, simply because the rationale to currency speculation set the precise number of efficient currency positions. Then pre-defining the number of currency in each portfolio, might create a bias by breaching the rationale to currency speculation[10].
Contrary to the EQW strategy, the efficient carry trade (ECT) is a combination of ex-ante performing trades as defined in equation (4). This equation says that if the discount is larger enough to cover the bid-ask spread then the position is ex-ante profitable. It also sets the binding minimal horizon of investment in one currency which helps understanding why certain strategies exhibit positive sharpe ratios at the monthly horizon but negative sharpe ratios at the weekly horizon. Using the definition of a forward rate we can rewrite the necessary but not sufficient condition for currency speculation to be profitable as follow:

$$\begin{cases} \frac{(r_t^{a^f} - r_t^{b^{US}})n/b}{(1+r_t^{b^{US}} n/b)} > \frac{S_t^a}{S_t^b} - 1 & \text{if sold} \\ \\ \frac{(r_t^{b^f} - r_t^{a^{US}})n/b}{(1+r_t^{a^{US}} n/b)} < \frac{S_t^b}{S_t^a} - 1 & \text{if bought} \end{cases} \tag{7}$$

$r_t^{a^f}$ is the foreign short term interest rate at time t, $r_t^{b^{US}}$ is the US short term interest rate at time t, n is the maturity of the forward and b is the number of reference period in one year. For instance, for a 3-month forward contract, $n = 3$ and $b = 12$.

rearranging these two inequalities we find:

$$\begin{cases} \text{if sell} \quad \frac{n}{b} > \frac{\frac{S_t^a}{S_t^b} - 1}{(r_t^{a^f} - r_t^{b^{US}}) - (\frac{S_t^a}{S_t^b} - 1) r_t^{b^{US}}} \\ \\ \text{if buy} \quad \frac{n}{b} < \frac{\frac{S_t^b}{S_t^a} - 1}{(r_t^{b^f} - r_t^{a^{US}}) - (\frac{S_t^b}{S_t^a} - 1) r_t^{a^{US}}} \end{cases} \tag{8}$$

These two equations set the binding horizon for investment in one currency to be ex-ante profitable. They show that any rise in transaction costs commands a revision of

[10]However, diversification might increase the Sharpe ratio of the portfolio even including ex-ante non profitable positions. But, this is not the case in our sample in which diversification reduces more the mean return than risk, hence downsizing the Sharpe ratio.

the investment horizon all else being equals. The non revision of the investment horizon turns some bets into ex-ante non profitable ones. The same is true for a decrease of the interest rate differential. As a consequence, over the same period, the same portfolio of currency can generate positive sharpe ratio at the monthly horizon but negative one at the weekly horizon.
Finally, weighting the bets according to the differential of interest rate (ECTh), boosts further the ratios of the carry trade strategy. This is because large interest rate differentials are associated with larger ratio of mean return to risk and crash risk measures. This is particularly true for ex-ante performing carry trade positions. Figure 2 plots the vector of mean returns to crash risk, as measured by the VaR of the positions, sorted on the differential of interest rates. Average returns increase monotonically from the funding currencies to the investment currencies, even when the return is corrected for crash risk: there seems to exist a premium for holding positions in large interest rate crash risky currencies. Using all the information conveyed by the signal enables one to better capture this premium. The case is particularly significant in the larger sample where the inclusion of emerging markets currencies adds return at a limited cost in term of risk. Of course the existence of this premium might be simply due to a peso problem: there is a premium because investors anticipate, with a low probability, larger negative returns than can be seen in sample. In this case, weighting the bets according to the dispersion of the signals may expose investors to future dramatic losses. Then the natural question arising is: do crash risk measures help to price carry trades? a positive answer would minimize the potential role of the peso story, comforting investors engaged in ECTh type strategies.

4 Risk factors in currency speculation

In this section, we follow Cochrane (2005) and explore if there exists a Stochastic Discount Factor (SDF) that prices the returns to the carry trade. As mentioned in section II, the carry trade is a zero-cost investment, hence its excess returns in level, R_{t+1}, satisfy the basic Euler equation:

$$\mathbb{E}_t(M_{t+1}.R_{t+1}) = 0 \tag{9}$$

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

$$M_t = \xi \left[1 - (f_t - \mu)'b)\right] \tag{10}$$

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

$$\mathbb{E}(R) = cov(M, f)b \tag{11}$$

or

$$\mathbb{E}(R) = \beta\lambda \tag{12}$$

β is the vector of coefficients of the regression of R_t on f_t, in sample, while λ is a vector of risk premia.
To estimate this relationship, we follow 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 carry trades, in the time series, for each currency or portfolio of currencies i:

$$R_{it} = \alpha_i + f_t'\beta_i + \epsilon_{it} \tag{13}$$

Then, we test whether the betas of equation 3 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 run a cross-sectional regression of average excess returns on betas. Instead, following Cochrane (2005), Burnside (2011), Lustig, Roussanov and Verdelhan (2011) and Menkhoff and al. (2011) we estimate the parameters of equation (9) using the Generalized Method of Moments of Hansen (1982). To remove estimation uncertainty, as recommended by Burnside (2011), factor means, μ and the variance covariance matrix of factors Σf are co-estimated. The vector of moment conditions is:

$$g(R_t, f_t, \theta) = \begin{bmatrix} [1 - (f_t - \mu)'b)]\, R_t \\ f_t - \mu \\ \Sigma((f_t - \mu)(f_t - \mu)') - \Sigma f \end{bmatrix} \tag{14}$$

where θ contains the parameters (b, μ, Σf).

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 $\hat{b}\hat{\Sigma f}$. This can be done using the Delta Method which is grounded on *Taylor series expansions.*
We use the iterated GMM estimator starting from the identity matrix as weighting matrix $W_T = I$. 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 $R^2 = \Sigma\bar{\alpha}^2/\Sigma(\bar{R_i}t - \bar{R}_t)^2$.

In this paper, the n test assets are alternatively the 5 portfolios of EQW and the 3 portfolios of ECT defined in section II. The k risk factors f are also created from sorted portfolios. As in Burnside (2011), Lustig, Roussanov and Verdelhan (2011) and

Menkhoff and al. (2011) we consider a dollar risk factor which is the average excess return of the five portfolio of EQW. We call this dollar risk factor DOL. The second risk factor, HML, is the return to the carry trade strategy. In this paper, we consider two alternative measures of the return to the carry trade which are: i) the return to the strategy EQW, that is the sum of the returns of P1 and P5 as defined in equation (1) and ii) the return to the strategy ECT, that is the sum of the returns of P1 and P3 of ECT as defined in equation (3)[11]. We also construct four crash risk factors which are indicators of the global volatility of the currency market as in Menkhoff and al. (2011), global skewness as in Burnside (2011) and global tail risk. The volatility factor, VOL, is measured as the average sample standard deviation of the daily changes of the value of the currencies in the large sample. The skewness factor, SKW, is the monthly average realised skewness of the daily changes of the value of the currencies in P5[12]. The quantile based factor VaR is the monthly average realised worst 10% quantile of the daily changes of the value of the currencies in P5. Finally, the quantile based factor CVaR is the monthly average realised mean return within the worst 10% quantile of the daily changes of the value of the currencies in P5[13](see appendix I for further details on crash risk measures).

5 Empirical results

Table 3 summarizes the results of running time series regressions of the monthly excess returns to the five portfolios on the large sample on the five pairs of risk factors DOL and HML, DOL and VOL, DOL and SKW, DOL and VaR and DOL and CVar. Following Lustig, Roussanov and Verdelhan (2011), the risk factors enter in pairs in the time series regressions. The betas of the DOL factor are all close to one in value and statistically significant. The betas of the HML factor go from -0.16 to 0.29. The betas of the extreme portfolios are significant but central ones are all close to zero and non significant. As one standard deviation for HML in sample is 4.02%, if HML increases by one standard deviation then the annualized return of portfolio P1 would be -7.72% lower than normal and the annualized return of P5 would be 13.99% higher than normal. This compares with an annualized mean return of 7.44% for this strategy. Using VOL and the succeeding factors, rather than HML, has a limited impact on the betas of DOL which remain all close to one and significant. The betas with respect to VOL decrease monotonically from 0.01 for P1 to -0.03 for P5 being all statistically significant except P4: when global currency volatility rises, low interest rate currencies offer a hedge against it. Using SKW as a crash risk measure does not produce significant betas except in the central portfolio P3. On the contrary, the betas for VaR increase monotically from P1 to P5 with the

[11]returns are corrected to take account of the difference in leverage of the two strategies as to produce comparable estimates

[12]We have tested several ways of building SKW: including the negative skewness of those currencies in P1 or restricting the sample to G10 currencies only. The results we found were not significantly different.

[13]For VaR and CVaR, the best empirical results are found when the sample is restricted to G10 currencies only.

betas of extreme portfolios being all significant. Using CVaR as a crash risk measure produces largely similar results. Investors demand a high return for high yielding currencies since they record bad performances in period of unexpected common crash risk. Inversely, investors accept lower returns on funding currencies since they offer a hedge for systemic crash episodes.

In table 4, we report the results of running the same regressions using only portfolios that are ex-ante profitable as definied in equation 3. Especially, in table 4, HMLe is the return to the efficient carry trade strategy (ECT). Results for DOL and HMLe in table 4 are largely similar to results in table 3 using HML: the betas of the DOL factor are close to one and significant, the betas of HMLe are significant for the extreme portfolios and monotonically increasing but now economically less meaningful. The conclusion is different for the risk measures. The betas of VOL are not significant, especially for the portfolio of investment currencies P3 and the betas of SKW are not significant and/or wrongly signed: these results suggest that rational carry traders, investing according to the trade rationale to currency speculation, do not demand a significant premia to compensate for volatility or skewness. On the contrary, they demand a significant premia against crash risk: the betas of VaR and CVaR remain statistically significant and economically meaningful. Also these betas are still monotonically increasing from P1 to P3. For instance, the, in sample, standard deviation of VaR is 7.3% which means that if VaR increases by one standard deviation (i.e. indicating a lower crash risk), the return of P1 would be 3.26% lower than normal while the return to P5 would be 8.6% higher than normal (see table 7). This compares with an annualized mean return of 8.53% for this strategy.

If we restrict the sample to G10 currencies as in table 5, we find results largely similar concerning factors DOL, HMLe, VOL and SKW: while DOL and HMLe are significant VOL and SKW are not. The story is different concerning crash risk factors: when estimated in the sample with G10 currencies, the betas of VaR and CVaR turn to be unsignificant or not economically meaningful. Especially, the betas of VaR and CVaR are unsignificant for the portfolio of investment currencies (P3) justifying for it a mere higher than normal annualized return of only 0.89%. This result suggests that rational carry traders do not demand a significant premia to compensate for risk as measured by volatility, skewness nor as measured by VaR or CVaR for G10 currencies as opposed to what we observe for emerging markets ones. Also, this result justifies why trying to capture the premia, ECTh, produces better results in samples including emerging markets currencies.

Table 3, 4 and 5 about here

Table 6 summarizes the results of running time series regressions of the monthly excess returns of single currencies instead of portfolios of currencies as earlier. Of course only

the currencies which are ex-ante profitable according to the rationale for currency speculation are of interest. Results are reported for both the large sample and the small sample. Only betas for factors VOL, VaR and CVaR are reported. Results in table 6 confirm the preceding conclusions at the currency level: betas for DOL are all close to one and significant while betas for SKW are not significant. Also, the betas of crash risk measures such as VaR or CVaR are significant, economically meaningful and monotonically increasing in the large sample but not in the smaller one. It is worth mentioning that, as low discount funding currencies are the same in both sample (C1 and C2 in table 6 and namely the JPY and the CHF), their betas in both sample are very similar. This is not the case for the investment currencies (C12 to C16 in the large sample or C6 to C9 in the small sample) which differ in the two samples. Especially, the betas for VaR and CVaR are large and significant in the sample including emerging markets but non significant in the smaller sample. This would tend to confirm that there is no premium for risk or crash risk in G10 investment currencies but in emerging ones. Also it confirms that carry trading is mainly about investing in emerging currencies what one borrows in G10, low discount, currencies. Asset pricing theory applies to the currency market even at the currency level once emerging markets currencies are included: those currencies that have larger loading on risk, especially global crash risk as measured by quantile based statistics such as VaR or CVar offer a larger mean return in compensation. Moreover, this relationship is monotonous even at the currency level. As a result, carry trade strategies based on the dispersion of interest rates (ETCh) dominate strategies with normalized bets such as ECT. This is particularly true in the sample including emerging markets currencies which command a high and significant crash risk premia (table 1 and 2).

Table 6 about here

The second step of this work is to check whether the betas combined with estimates of λ justify the return to the carry trade strategies. Table 8 summarizes the results of estimating candidate SDF for currency factor models using the iterated version of the GMM estimator on the large sample including emerging market currencies. The b and λ of the DOL factor are not significant. This is because the betas of the DOL factor act as a constant in the cross-sectional regression while the estimation involves only series centered near zero (see Burnside 2011). The parameter b and the risk premia λ associated with HML are significant at the 5% level with the correct sign. Also, the model is not rejected on the basis of the R^2 and the test on the pricing errors. The parameter b associated with VOL is significant at the 10% level with the correct sign but the model is rejected on the basis of the test on the pricing errors. Both models combining DOL with quantile-based statistics produce larger errors than the sample average, hence negative

R^2. Finally, the model combining DOL and SKW produces loading with wrong signs and is rejected by the J-test. These results are largely in line with the recent literature: as in Lustig, Roussanov and Verdhelan (2011) the HML based model has the best fit but risk factors like volatility as tested in Menkhoff et. al. (2011) and Burnside (2011) might also be interesting candidates for pricing carry trades. However, as in Menkhoff et. al. (2011) we cannot validate SKW as a factor pricing the returns to the carry trade.

Table 8 about here

We find these candidates as being particularly important when the empirical work focuses on efficient carry trade positions only. Table 9 presents the results of estimating candidate SDF on three test assets only: P1 and P3 which are respectively the portfolio of short and long positions in carry trade as defined in equation (3), and P2 which contains the ex-ante non profitable currency positions. HMLe stands for the returns of the portfolio of long and short positions strictly limited to ex-ante profitable crosses. The estimation of the models produces results that are largely similar for the pair DOL-HMLe which is still accepted on the basis of the R^2 and the test on the pricing errors. Focusing on ex-ante profitable positions improves the results for the pair DOL-VOL with VOL now being significant at the 5% level and both tests on errors validating the model. More importantly, both models, using VaR and CVaR are, now, accepted on the basis of the R^2 and the test on the pricing errors. Also, parameters b and risk premia (λ) for both VaR and CVaR are significant and with the correct sign. None of the errors produced by these models are significant. On the contrary, the model with risk factor SKW is still rejected on the basis of the test on the pricing errors. These results sugest again that markets operators demand a risk premia to cover the risks as they measure it: volatility, VaR and CVaR not skewness.

Table 9 about here

As a robustness test, we reduce the sample to G10 countries only. In table 10 we report the estimation of candidate SDF on three test assets on 9 currencies. The model using DOL and HMLe produces significant parameters b and risk premia (λ). It is also accepted on the basis of the pricing error tests and R^2. Still the model using SKW is

rejected for non significant parameters. The models using DOL and either VOL, VaR or CVaR do not produce significant errors and are accepted on the basis of J-test and the R^2. However, the significance of the parameters is weaker albeit acceptable at the 10% threshold. These results confirm our findings: the crash risk story applies better in samples which include crash riskier currencies such as emerging markets ones. All in all, they also confirm that the crash risk premia is more visible when only efficient positions are under scrutiny (results of table 8 and 9). Finally, they confirm that markets operators demand a premia to cover for their perception of risk based on VaR and CVaR, rather than skewness.

Table 10 about here

Finally, we test the robustness our findings in shorter sub samples. We split our full sample into 3 shorter sub samples from which we have removed 25% of the observations (or 37). First, we re-estimate the model on the first 111 observations (75% of the sample) then on the 111 last observations and finally on the mid 111 observations. The results we find are largely similar in the three sub samples. First, quantile based risk factors are significant in all sub samples when the estimation is run on ex-ante profitable positions. As expected results are weaker in G10 sub samples albeit often marginally significant. Second, HMLe is significant in all sub samples while SKW is still rejected for wrongly signed coefficients in most sub samples.

6 Conclusion

The aim of this paper is to study the returns to the carry trade by testing a new set of risk factors. Especially, we conjecture that rational carry traders demand primarily a premium against the risk to reach VaR-based funding constraints. To the best of our knowledge, yet the literature has looked only for premia covering the risk to face volatile or negatively skewed returns. In this paper, we show that asset pricing theory applies especially well to the currency market when tail risk factors are considered: those currencies that have larger loading on risk, especially crash risk, offer a larger mean return in compensation. Indeed, we show that global measures of crash risk (i.e. global measures of VaR or CVaR) price better the returns to the carry trade than moments based factors such as volatility or skewness. Moreover we show that results are particularly significant when only, efficient or ex-ante profitable positions, as defined by the rationale to currency speculation, are under scrutiny. Finally we show that strategies using all the information carried by the signal (i.e. the discount rate) capture better the premium for crash risk. As a consequence, these strategies dominate the ones in which the size of the bets is normalized.

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Annex I: risk measures

As most financial returns, carry trades returns are not distributed symmetrically around their means (see table 1 in appendix II). There exits a risk of crash. 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. These ratios are namely the Sortino ratio (Fishburn (1977) and Sortino and Price (1994)), the Sterling ratio and two versions of the Modified Sharpe ratio (Favre and Galeano (2002)). We define the generic risk ratio (RR) we study as:

$$RR = \frac{mean(x_t)}{risk(x_t)} \tag{15}$$

with $risk(x_t) \in \{V(x); SV(x); \mathcal{D}_{mean}; QL(x); ES(x)\}$

V(x) is the variance, the average distance of the different outcomes to the mean. V(x) takes into account both positive and negative deviations. It is a valuable measure of risk if the distribution is normal because of its symmetry. However since most distributions are not symmetrical, one need to focus more precisely on negative outcomes to estimate the risk. This is what semi-variance does. It enables one to estimate the average distance of the negative outcomes to zero, that is to measure the average deepness of any negative outcome.
The semi-variance, SV is defined as follow:

$$SV(x_t) = \sum_{i=1}^{n} p_i \left[(x_i - E(\tilde{x}))^2 \times I_{[x \leq \tilde{x}]}(x) \right] \tag{16}$$

Agents might also be particularly averse to the occurrence of extreme events. Frequent but small negative outcomes even cumulated might be easier to bear than infrequent but deep outcomes that might force agents to unwind their positions. Deep outcomes are all located in the left tail of the distribution. Then, the risk is defined as the likely loss at the quantile confidence level. This is the Value at Risk or VaR in practitioners' words.

We define the quantile as a number μ that set

$$Prob(x \leq \mu) \leq p \tag{17}$$

in this paper we are interested by the value of μ such as: $Prob(x \leq \mu) \leq 5\%$

Also, we study the mean outcome within the worst quantile. This is the Conditional Value at Risk (CVaR) or Expected shortfall (ES) in market's words. It represents the more accurately the risk for investors as it measures the average outcome among the worst case scenarios. Then using the preceding definition of a quantile, expected shortfall is defined as:

$$ES_q = E(x \,|x \leq \mu) \tag{18}$$

When the distribution is not normal which is often the case in short samples, the in sample quantile might be a rough approximation of the true quantile. As reckoned by Campbell and al.(2001) and Favre and Galeano (2002) we use Cornish-Fisher (1937) expansion to get a better approximation of the quantiles of the distribution. It is a parametric method that attempts to mathematically predict the shape of the tail, even when such extreme events have not been previously observed. 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[14]:

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

equation) with Z_α the corresponding quantile for a $N(0,1)$ and SK and K the in sample skewness and excess kurtosis.

Finally, we measure the risk of negative outcomes accumulation. According to Thaler and Johnson (1990) for instance, 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 average drawdown as defined by the average 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:

$$\mathcal{D}_t = x_t^{max} - x_t \tag{20}$$

with

$$x_t^{max} = max\{x_i \,|i\,[0,t]\} \tag{21}$$

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 defined as:

$$\mathcal{D}_{mean} = \frac{1}{n}\sum_{i=1}^{n} \mathcal{D}_t \tag{22}$$

n being the number of drawdowns in X.

[14]higher moments expansion can be found in Stuart and al. (1999).

Annex II: the return to carry trade

Table 1: Carry trade returns: Descriptive Statistics

	mean	median	sd	SR	KT	SK	AtS	AtPV
Weekly - G10								
EQW	-0.21	-0.10	0.29	-0.71	11.58	-1.12	-6.58	0.00
ECT	0.01	0.00	0.18	0.09	8.29	-1.04	-6.04	0.00
ECTh	0.16	0.00	0.57	0.28	12.38	-1.55	-7.98	0.00
NCT	-0.08	0.27	0.52	-0.16	9.67	-1.15	-6.52	0.00
Weekly - G10+EM								
EQW	-0.29	-0.21	0.43	-0.69	11.58	-1.17	-5.35	0.00
ECT	0.27	0.47	0.38	0.71	10.37	-1.51	-6.58	0.00
ECTh	0.08	0.04	0.09	0.88	40.82	-2.12	12.78	0.00
NCT	-0.25	0.57	0.96	-0.26	14.07	-1.61	-6.85	0.00
Monthly - G10								
EQW	0.10	0.09	0.23	0.44	3.94	-0.16	-0.57	56.72
ECT	0.26	0.30	0.39	0.66	4.31	-0.45	-1.48	13.88
ECTh	0.04	0.04	0.06	0.75	6.53	-0.71	-2.23	2.59
NCT	0.30	0.50	0.46	0.65	3.63	-0.15	-0.49	62.13
Monthly - G10+EM								
EQW	0.28	0.33	0.41	0.67	3.59	-0.19	-0.65	51.28
ECT	0.57	0.59	0.69	0.82	5.30	-0.68	-2.13	3.32
ECTh	0.44	0.36	0.52	0.84	11.79	0.00	0.00	99.91
NCT	0.56	0.74	0.85	0.66	4.91	-0.34	-1.14	25.47

January 1999 to May 2011 for monthly data and October 2002 to May 2011 for weekly data. Statistics are reported for annualized excess returns. The EQW is an equally weighted portfolio of 4 long and 4 short positions, the Efficient Carry Trade (ECT) is an unbalanced portfolio of normalized long and short positions which are ex-ante profitable, ECTh is equivalent to ECT but bets are not normalized, NCT is a portfolio of naive positions including ex-ante non profitable ones. SR is the Sharpe ratio of the strategy, KT the kurtosis, SK the skewness. We also report the statistic AtS and p-value AtPV of the D'Agostino normality test. This test is particularly interesting for detecting departure from normality in the extreme quantile of the distribution.

Table 2: Carry trade returns: Risk statistics.

	SR	Sortino	SterR	MS-VaR	MS-CVaR
Weekly - G10					
EQW	-71.5	-86.9	-1.98	-5.2	-2.3
ECT	9.2	10.1	1.5	0.71	0.36
ECTh	28.2	27.5	1.6	2.16	0.86
NCT	-16.5	-19.6	-2.8	-1.25	-0.59
Weekly - G10+EM					
EQW	-69.0	-86.4	-7.9	-5.11	-2.29
ECT	71.1	76.4	58.9	5.53	2.49
ECTh	87.8	106.1	22.9	23.1	0.36
NCT	-26.4	-28.7	-13.1	-1.9	-0.76
Monthly - G10					
EQW	44.1	65.9	18.8	8.2	5.8
ECT	65.8	89.0	28.6	12.2	8.1
ECTh	74.7	92.0	7.5	13.9	7.5
NCT	64.5	100.5	24.4	12.6	9.1
Monthly - G10+EM					
EQW	67.1	103.9	25.4	13.0	9.3
ECT	82.2	98.0	67.6	15.4	9.2
ECTh	84.4	93.3	56.1	20.0	13.5
NCT	65.8	84.4	50.6	12.6	8.0

January 1999 to May 2011 for monthly data and October 2002 to May 2011 for weekly data. Statistics are reported in percentages for annualized excess returns. The EQW is an equally weighted portfolio of 4 long and 4 short positions, the Efficient Carry Trade (ECT) is an unbalanced portfolio of normalized long and short positions which are ex-ante profitable, ECTh is equivalent to ECT but bets are not normalized, NCT is a portfolio of naive positions including ex-ante non profitable ones. SR is the Sharpe ratio of the strategy, the Sortino ratio is the ratio of mean return to semi standard deviation, SterR is the sterling ratio or the ratio of mean return to maximum drawdown as defined is annex 1, MS-VaR is the modified Sharpe ratio based on extreme quantile estimation (here 5% VaR) and MS-CVaR is the modified Sharpe ratio based on the mean of the returns within this 5% extreme quantile (CVaR).

Annex III: Risk factors in currency speculation

Table 3: Statistics of the time series regression of portfolios excess returns on risk factors, sample G10+EM

Portfolio	DOL	HML	R^2	DOL	VOL	R^2	DOL	SKW	R^2	DOL	VaR	R^2	DOL	CVaR	R^2
P1	1.03**	-0.16**	0.72	1.03**	0.01**	0.68	0.98**	0.00	0.66	0.97**	-0.05**	0.67	0.98**	-0.03**	0.67
	(0.05)	(0.03)		(0.06)	(0.003)		(0.05)	(0.002)		(0.05)	(0.02)		(0.05)	(0.01)	
P2	0.79**	-0.06**	0.73	0.81**	0.007**	0.72	0.77**	-0.000	0.71	0.76**	-0.05**	0.73	0.77**	-0.03**	0.73
	(0.04)	(0.02)		(0.04)	(0.002)		(0.04)	(0.001)		(0.03)	(0.01)		(0.03)	(0.01)	
P3	1.02**	-0.02	0.83	1.05**	0.007**	0.83	1.01**	0.003**	0.83	1.01**	-0.02	0.83	1.01**	-0.01	0.83
	(0.03)	(0.02)		(0.03)	(0.002)		(0.03)	(0.001)		(0.03)	(0.01)		(0.03)	(0.011)	
P4	1.14**	-0.03	0.79	1.14**	0.001	0.79	1.13**	0.000	0.79	1.13**	0.01	0.79	1.13**	0.006	0.79
	(0.04)	(0.02)		(0.05)	(0.003)		(0.04)	(0.002)		(0.04)	(0.01)		(0.04)	(0.014)	
P5	0.97**	0.29**	0.60	0.90**	-0.031**	0.57	1.07**	-0.006	0.49	1.09**	0.13**	0.53	1.06**	0.091**	0.52
	(0.08)	(0.04)		(0.088)	(0.005)		(0.09)	(0.004)		(0.08)	(0.03)		(0.08)	(0.02)	

Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount. The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. The table reports OLS estimates of the β of equation (13) as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table 4: Statistics of the time series regression of ex-ante profitable portfolios excess returns on risk factors, sample G10+EM

Portfolio	DOL	HMLe	R^2	DOL	VOL	R^2	DOL	SKW	R^2	DOL	VaR	R^2	DOL	CVaR	R^2
P1	0.99**	-0.057**	0.82	0.93**	0.007**	0.81	0.92**	-0.000	0.80	0.91**	-0.048**	0.81	0.92**	-0.035**	0.81
	(0.04)	(0.014)		(0.03)	(0.002)		(0.03)	(0.001)		(0.036)	(0.014)		(0.03)	(0.011)	
P2	1.00**	0.019	0.72	1.01**	-0.005*	0.73	1.02**	0.002	0.72	1.02**	0.020	0.72	1.02**	0.015	0.72
	(0.05)	(0.020)		(0.05)	(0.003)		(0.05)	(0.002)		(0.052)	(0.021)		(0.05)	(0.015)	
P3	0.96**	0.12**	0.43	1.10**	-0.006	0.40	1.12**	-0.012**	0.42	1.14**	0.129**	0.43	1.11**	0.086**	0.43
	(0.12)	(0.043)		(0.11)	(0.007)		(0.11)	(0.005)		(0.109)	(0.044)		(0.10)	(0.033)	

Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount. The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. The table reports OLS estimates of the β of equation (13) as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table 5: Statistics of the time series regression of ex-ante profitable portfolios excess returns on risk factors, sample G10

Portfolio	DOL	HMLe	R^2	DOL	VOL	R^2	DOL	SKW	R^2	DOL	VaR	R^2	DOL	CVaR	R^2
P1	1.10**	-0.26**	0.87	1.00**	0.007**	0.84	0.99**	-0.0008	0.84	0.98**	-0.03**	0.84	0.99**	-0.02**	0.84
	(0.03)	(0.04)		(0.03)	(0.002)		(0.03)	(0.0019)		(0.03)	(0.01)		(0.03)	(0.01)	
P2	1.02**	0.07*	0.84	1.05**	-0.003*	0.84	1.05**	-0.0015	0.83	1.06**	0.03**	0.84	1.06**	0.02**	0.84
	(0.04)	(0.05)		(0.03)	(0.002)		(0.03)	(0.0020)		(0.03)	(0.01)		(0.03)	(0.01)	
P3	0.98**	0.40**	0.89	1.14**	-0.004*	0.84	1.14**	0.0002	0.84	1.15**	0.01	0.84	1.14**	0.01	0.84
	(0.03)	(0.04)		(0.04)	(0.003)		(0.04)	(0.002)		(0.04)	(0.01)		(0.04)	(0.01)	

Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount. The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. The table reports OLS estimates of the β of equation (13) as well as heteroskedasticity consistent standard errors and R^2. Significant loadings at the 5% level are indicated with two*.

Table 6: Statistics of the time series regression of currencies excess returns on risk factors, samples G10+EM and G10

	Currencies G10+EM				Currencies G10		
	β_{VOL}	β_{VaR}	β_{CVaR}		β_{VOL}	β_{VaR}	β_{CVaR}
C1	0.014**	-0.17**	-0.12**	C1	0.014**	-0.13**	-0.10**
	(1.97)	(-4.07)	(-4.05)		(2.44)	(-4.01)	(-4.13)
C2	0.009*	-0.06**	-0.04**	C2	0.010**	-0.07**	-0.05**
	(1.57)	(-1.98)	(-1.90)		(1.85)	(-2.24)	(-2.14)
C12	-0.002	-0.007	-0.12	C6	0.013**	-0.13**	-0.10**
	(-0.30)	(-0.18)	(-0.37)		(1.97)	(-3.49)	(-3.64)
C13	-0.004	0.05	0.03	C7	-0.005	-0.02	-0.009
	(-0.64)	(1.23)	(1.34)		(-1.24)	(-0.83)	(-0.46)
C14	-0.02**	0.06	0.04	C8	-0.003	-0.003	-0.0008
	(-2.57)	(1.29)	(1.37)		(-0.68)	(-0.11)	(-0.034)
C15	-0.0013	0.14**	0.09 **	C9	0.003	-0.012	-0.010
	(-0.4)	(2.17)	(1.88)		(0.71)	(-0.43)	(-0.50)
C16	-0.012*	0.20**	0.14**				
	(-1.28)	(3.72)	(3.38)				

Monthly returns from January 1999 to April 2011. Assets are currencies sorted on their forward discount. Only ex-ante profitable positions are considered. C1 is the currency with the smallest discount while C16 for the large sample and C9 far the small sample are the currencies with the largest discount. The VOL factor is a measure of global currency volatility. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. The table reports OLS estimates of the β of equation (13) as well as heteroskedasticity consistent t-values. Significant loadings at the 5% level are indicated with two*.

Table 7: Marginal impact of factors to the return to the carry trade (ECT)

	VOL	VaR	CVaR	SKW
$\overline{\sigma}$	1.53	0.055	0.073	0.46
$\beta P1$	0.007**	-0.048**	-0.035**	-0.000
$\beta P3$	-0.006	0.129**	0.086**	-0.012**
ΔR_{P1t}	12.9%	-3.28%	-3.1%	-0.5%
ΔR_{P3t}	-11.0%	8.6%	7.68%	-6.78%
$\overline{R}_{ECT}$	8.53%	8.53%	8.53%	8.53%

Monthly returns from January 1999 to April 2011. Marginal impact of an increase by one standard deviation of the factors to the returns to the carry trade. $\overline{\sigma}$ is the in sample value of one standard deviation for each factor. $\beta P1$ and $\beta P3$ are respectively the betas of portfolio P1 and P3 on the factors (see table 4). Significant β at the 5% level are indicated with two*. ΔR_{P1t} and ΔR_{P1t} are implied annualized expected changes on the return to portfolio P1 and P3 for a shock of one standard deviation on factors. $\overline{R}_{ECT}$ is the annualized mean return of strategy ECT. For instance, if VaR increases by one standard deviation, the annualized return to portfolio P3 would be 8.6% higher than normal while the return to portfolio P1 would be 3.28% lower than normal. As VaR, CVaR and SKW sample mean are negative, an increase of one standard deviation implies a reduction of risk. The inverse is true for factor VOL.

Table 8: Iterated GMM estimates of linear factor models for sorted currency portfolios, all positions in sample G10+EM

	b	λ (%)	R^2	J	Pricing Errors (α) S1	S2	S3	S4	S5
Lustig, Roussanov and Verdelhan (2011) factors									
DOL	3.31	0.53	0.95	2.65	-0.0135	0.0171**	-0.0114	-0.0047	-0.0193
	(5.58)	(0.30)		(0.44)	(0.0123)	(0.0088)	(0.0096)	(0.0113)	(0.0212)
HML	23.16**	3.86**							
	(8.15)	(1.45)							
Menkhoff et. al. (2011) factors									
DOL	2.08	0.52	0.51	7.89	-0.0782**	-0.0107	-0.0287	-0.0516**	-0.0255
	(7.70)	(0.57)		(0.04)	(0.0155)	(0.0099)	(0.0164)	(0.0184)	(0.0277)
VOL	-2.64*	-27.18							
	(1.48)	(24.80)							
Burnside (2011) and tail risk factors									
DOL	8.15	0.44	0.44	14.33	-0.0601	-0.0047	0.0193**	0.0015	0.0884**
	(5.16)	(0.34)		(0.00)	(0.0104)	(0.0079)	(0.0096)	(0.0105)	(0.0142)
SKW	-2.40	-46.30							
	(1.19)	(23.39)							
DOL	35.16	0.60	-3.17	2.29	-0.1315**	-0.0325	-0.1051**	-0.1650**	-0.1798**
	(20.44)	(1.19)		(0.51)	(0.0315)	(0.0230)	(0.0339)	(0.0384)	(0.0435)
VaR	34.71**	6.20**							
	(15.26)	(3.42)							
DOL	27.91	0.60	-3.34	1.74	-0.1251**	-0.0269	-0.1093**	-0.1657**	-0.1920**
	(19.87)	(1.23)		(0.62)	(0.0358)	(0.0279)	(0.0394)	(0.0439)	(0.0497)
	29.95**	10.26**							
CVaR	(13.42)	(5.09)							

Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount.The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. 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 test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are into brackets. The p-value of the J test is also into brackets.

Table 9: Iterated GMM estimates of linear factor models for sorted currency portfolios, efficient positions only, sample G10+EM

	b	λ	R^2	J	Pricing Errors (α)				
		(%)			S1	S2	S3	S4	S5
Lustig, Roussanov and Verdelhan (2011) factors									
DOL	-18.75	0.48	0.92	0.52	0.01	-0.0011	0.0297		
	(12.23)	(0.92)		(0.46)	(0.0123)	(0.0119)	(0.0218)		
HMLe	21.19**	7.47**							
	(9.06)	(4.15)							
Menkhoff et al. (2011) factors									
DOL	-5.30	0.44	0.81	1.94	0.0007	-0.0195	0.0498**		
	(7.82)	(0.52)		(0.16)	(0.0115)	(0.0173)	(0.0241)		
VOL	-2.64**	-33.91**							
	(1.33)	(17.87)							
Burnside(2011) factors									
DOL	6.94	0.34	0.53	6.25	-0.0283	0.0339	0.0722		
	(5.01)	(0.31)		(0.01)	(0.0084)	(0.0095)	(0.0144)		
SKW	-2.01**	-42.18**							
	(0.85)	(18.29)							
DOL	16.75	0.49	0.86	0.21	-0.0104	-0.0344	-0.0279		
	(16.30)	(0.94)		(0.64)	(0.0199)	(0.0289)	(0.0356)		
VaR	26.72**	8.33**							
	(10.03)	(3.79)							
DOL	13.08	0.52	0.70	0.36	-0.0165	-0.0495	-0.0418		
	(15.95)	(0.96)		(0.54)	(0.0225)	(0.0330)	(0.0390)		
CVaR	22.36**	12.55**							
	(9.03)	(6.13)							

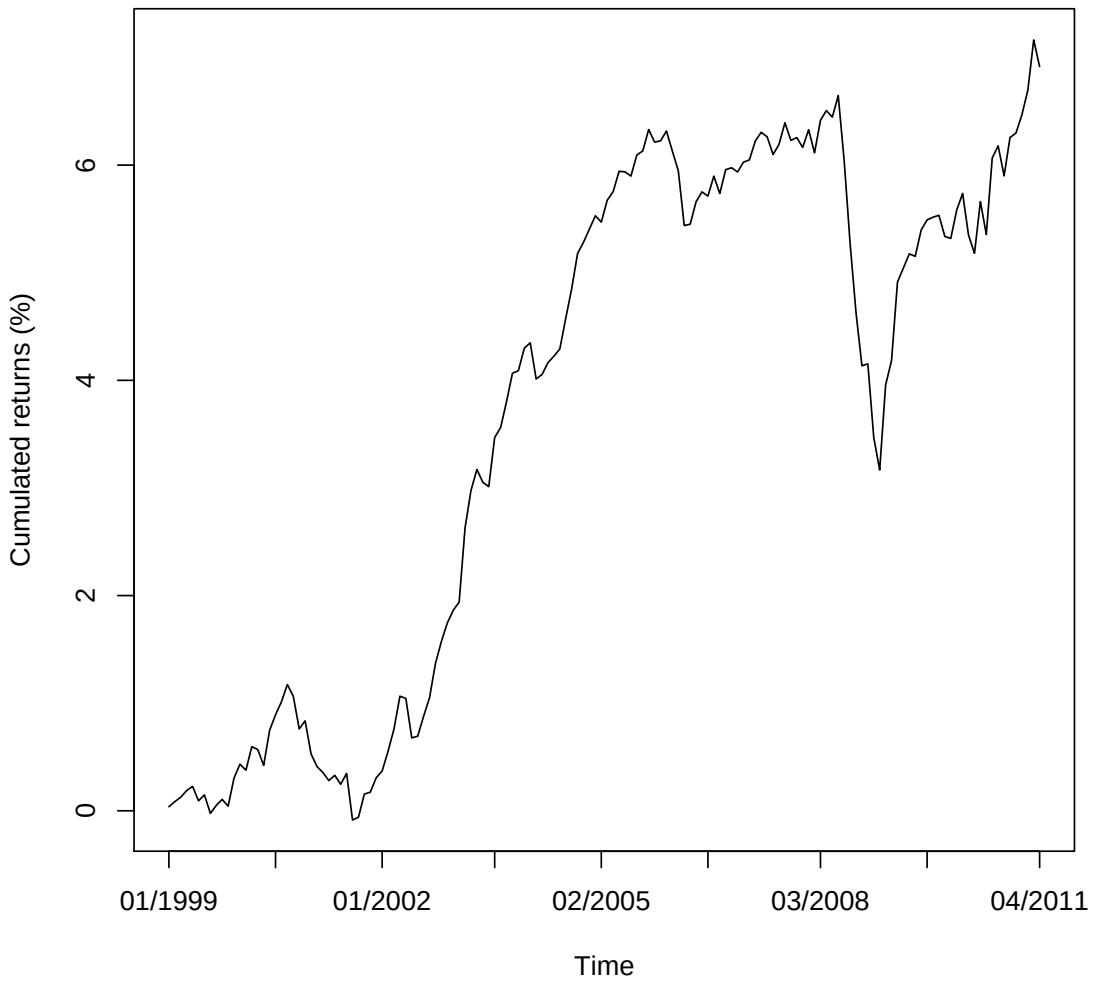
Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount.The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. 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 test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are into brackets. The p-value of the J test is also into brackets.

Table 10: Iterated GMM estimates of linear factor models for sorted currency portfolios, efficient positions only, sample G10

	b	λ (%)	R^2	J	Pricing Errors (α) S1	S2	S3	S4	S5
Lustig, Roussanov and Verdelhan (2011) factors									
DOL	-8.63	0.26	0.91	0.75	0.0008	0.0140	0.0031		
	(6.63)	(0.58)		(0.38)	(0.0101)	(0.0108)	(0.0116)		
HMLe	31.18**	1.07**							
	(11.25)	(0.52)							
Menkhoff et. al. (2011) factors									
DOL	2.76	0.39	0.82	0.09	-0.0066	-0.0191	-0.0092		
	(10.59)	(0.85)		(0.75)	(0.0213)	(0.0256)	(0.0249)		
VOL	-5.27*	-57.91*							
	(3.30)	(35.98)							
Burnside(2011) factors									
DOL	5.09	0.42	0.06	0.56	-0.0201	0.0389	0.0240		
	(15.11)	(1.30)		(0.45)	(0.0342)	(0.0377)	(0.0372)		
SKW	8.84	192.33							
	(13.07)	(283.6)							
DOL	11.43	0.23	0.43	0.85	0.0074	0.0067	0.0379		
	(16.01)	(1.12)		(0.35)	(0.0190)	(0.0253)	(0.0274)		
VaR	24.16*	5.73*							
	(16.72)	(4.30)							
DOL	7.87	0.25	0.68	1.05	0.0008	-0.0022	0.0295		
	(13.37)	(0.92)		(0.30)	(0.0194)	(0.0261)	(0.0267)		
CVaR	17.42*	7.10*							
	(12.22)	(5.39)							

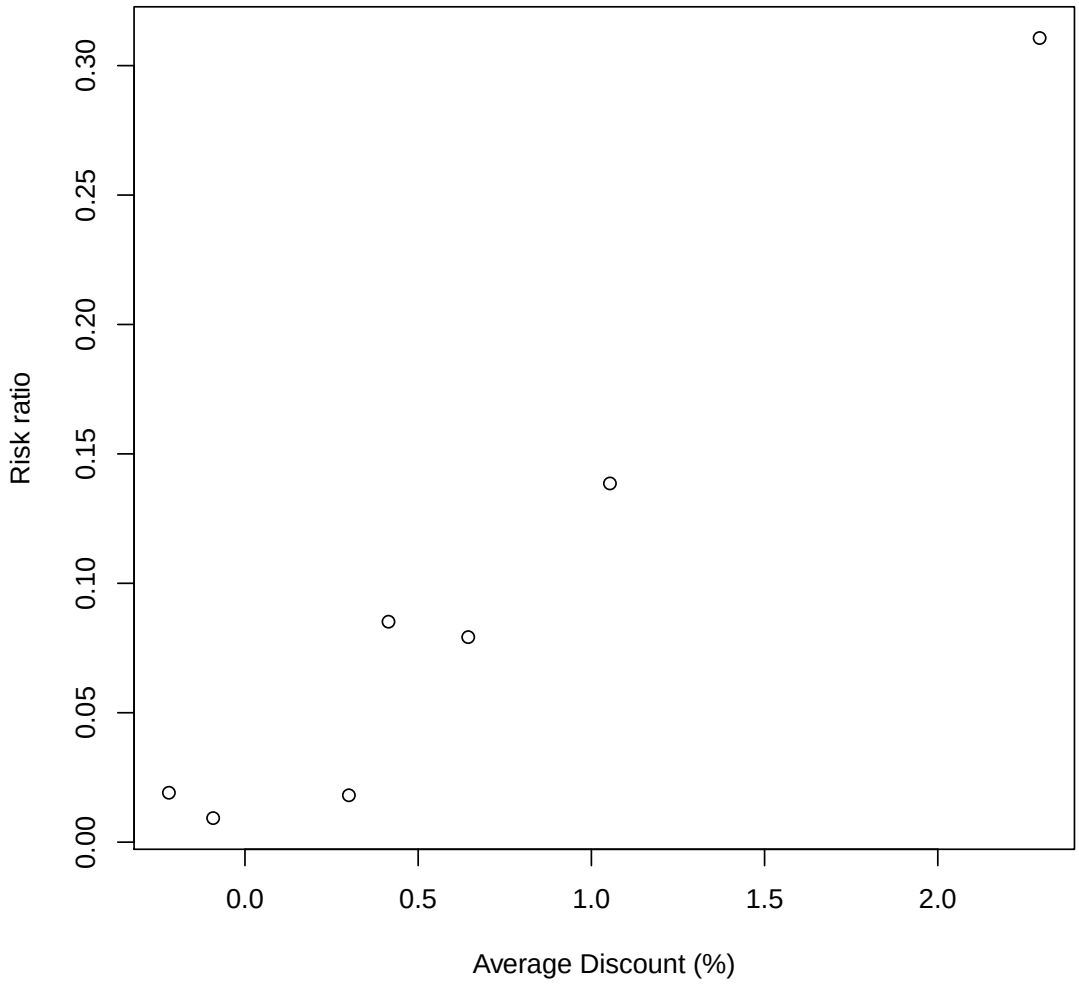
Monthly returns from January 1999 to April 2011. Assets are currency portfolios sorted on their forward discount.The DOL factor is the average excess return to all the currencies included in the strategy. The HML portfolio is the excess return of a strategy buying the currencies with the largest forward discount and selling those with the smallest discount. HMLe is similar to HML except that only currencies with a forward discount larger than the bid-ask spread are included. The VOL factor is a measure of global currency volatility. The SKW factor is a measure of realised global skewness. The VaR and CVaR factors are quantile based statistics measuring realised global tail risk. 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 test statistics J for the overidentifying restrictions are reported. Standard errors for statistics are into brackets. The p-value of the J test is also into brackets.

Figure 1: The return to currency speculation.



Sample January 1999 to April 2011 for emerging markets and G10 currencies. Monthly observations. Cumulated returns in percentage. ECT stands for efficient carry trade strategy which is an unbalanced portfolio of normalized long and short positions which satisfies the rationale for currency speculation defined by equation (4). The strategy has offered a large positive mean return over the sample period with limited risk except two episodes of market crash in 2002 and 2008.

Figure 2: Ratio of mean returns to VaR for ex-ante profitable currencies.



Sample January 1999 to April 2011 for emerging markets and G10 currencies. Monthly observations. Discount in monthly percentage in X-axis and mean to 95% VaR ratio in Y-axis. The ratio is plotted only for ex-ante profitable positions as defined by equation (4). The graph shows a linear relationship between discount and mean return to VaR ratio. This observation suggests that high yielding currencies carry a premium for crash risk as measure by VaR. As a consequence, carry trade strategies that use all the information conveyed by the dispersion of discounts dominate strategies in which bets are normalized even accounting for crash risk.