Correlated Risk Factors in Currency Markets*

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Abstract

An asset that loads on two risk factors earns benefits of diversification across the factors. A change in the correlation between the factors changes the degree of diversification, which directly affects the volatility of returns and potentially – via volatility timing – future Sharpe ratios. I find strong evidence of these economic links in currency markets. First, I document that the correlation (CORR) between the *dollar* factor and the *carry* factor is highly time-varying, across almost the entire $[-1, 1]$ interval. Second, for high (low) interest rate currency returns, a positive CORR (above 0.25) is associated with low (high) volatility and a high (low) future Sharpe ratio. The reverse holds for negative CORR (below -0.25). These results extend to the standard, high-minus-low carry trade (HML). Comparing negative to positive CORR, the average next-month Sharpe ratio of the HML carry trade is 0.20 and 0.99, respectively. Third, I show that CORR is procyclical, positively related to the US interest rate and global interest rate differentials. CORR is also linked to the time-varying characteristic of the US dollar as a safe haven. Fourth, CORR contains information about the predictability of carry trade crashes.

Keywords: Carry trade; Currency risk factors; FX; Interest rates; Predictability; Time-varying correlation

JEL Classification: E43, F31, G15.

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1 Introduction

In a factor model, consider an asset with positive loadings on two, uncorrelated risk factors. Since the factors are uncorrelated, the asset returns are benefiting from a diversification across the factors. If the two risk factors begin to correlate positively, how do we expect the asset returns to change? Assuming perfect correlation, the asset becomes exposed to only a single factor and, as a result, the benefits of diversification disappear. According to conventional finance theory this should be associated with more volatile returns. Moreover, the literature on volatility timing suggests that a rise in volatility predicts lower Sharpe ratios. For example, Moreira and Muir (2017) show – for a variety of asset classes – that a rise in volatility predicts higher volatility also in the near future but it has no predictability over average returns; hence, the initial rise in volatility predicts a lower Sharpe ratio. Taken together, we may consider the conjecture that an increase in the correlation between the two risk factors is associated with a contemporaneous rise in volatility and a lower predicted Sharpe ratio. Note that if the loadings on the two risk factors were of different signs (one positive and one negative) the implications for the returns would be reversed, i.e. a higher correlation between the risk factors would enhance the diversification benefits and be associated with lower volatility and, therefore, a higher predicted Sharpe ratio.

In this paper, I investigate the empirical support for this conjecture. To obtain a high statistical power it is suitable to study an asset class in which two risk factors can explain a relatively large fraction of the variation in returns. For this purpose, I turn to currency markets. Lustig, Roussanov, and Verdelhan (2011) identify two risk factors that can price baskets of currencies (sorted by their interest rates) against the US dollar. These factors are: (i) the *dollar* factor (DOL), which is the portfolio of holding the US dollar against a basket of other currencies; and (ii) the *carry* factor (HML), which is the dollar-neutral, high-minus-low carry trade portfolio that invests in high interest rate currencies funded by short positions in low interest rate currencies. As shown by Lustig et al. (2011), the two factors can jointly explain roughly 80% of the variation in monthly returns. Lustig et al. (2011), as well as the subsequent related literature, largely treat these factors as orthogonal, which is a desirable feature since it facilitates the interpretation and the relative contribution of the factors.[1] Moreover, the cross-sectional factor loadings are as follows. Since all currency positions are taken against the US dollar they have the same, *negative* loading on the dollar factor (DOL). As for the carry factor, high (low) interest rate currencies have a positive (negative) loading, while currencies with neither high nor low interest rates have a loading close to zero. Hence, an increase in the correlation between the risk factors would enhance (reduce) the benefits of diversification for high (low) interest rate currencies. In other words, according to the conjecture, a higher correlation between the risk factors should, on average, be associated with a lower (higher) volatility of high (low) interest rate currency returns and lead to a higher (lower) future Sharpe ratio.

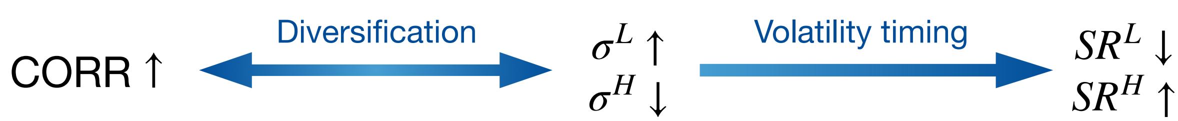

Figure 1: An illustration of the proposed conjecture. Changes in the correlation between the two risk factors (CORR) contemporaneously affect the cross-sectional volatilities of returns because of changes in the diversification benefits. Via volatility timing, changes in the cross-sectional volatilities potentially lead to changes in the Sharpe ratios of future returns.

I find strong empirical support of the conjecture along with several important implications. First, I document that while the unconditional correlation between DOL and HML is indeed – as suggested by Lustig et al. (2011) – close to zero (-0.18 in my sample), their conditional, time-varying, correlation (CORR) is fluctuating significantly across almost the entire $[-1, 1]$ interval. While the baseline case computes CORR as an exponential moving average across a rolling window of 112 daily observations (as found optimal when computing correlations in

[1] Lustig et al. (2011) derive the two factors by essentially mapping them to the first two principal components from the cross-section of returns. By construction, principal components are orthogonal; hence, the implicit assumption that the risk factors are uncorrelated. Moreover, there is an ongoing discussion about the extent to which the dollar can be interpreted as a risk factor. See, for example, Aloosh and Bekaert (2017), Avdjiev et al. (2019), Boudoukh et al. (2018), and Panayotov (2019). However, the empirical results presented in this paper are immune to this discussion, as the dollar risk factor can simply be viewed as a traded portfolio.

currency markets (RiskMetrics™, 1996)), the results are robust also to using a simple equal-weighted moving average, as well as to varying the size of the rolling window.

Second, I find strong and significant correlations between CORR and the volatility of high interest rate currencies (-0.60) and low interest rate currencies (0.44), respectively.[2] Even more pronounced is the correlation between CORR and the difference between the volatilities of low and high interest rate currencies, $\sigma^L - \sigma^H$, (0.87). Thus, in line with the conjecture, a change in the correlation between the risk factors is indeed associated with a change in the volatility of the test asset.

Third, CORR contains predictive information about Sharpe ratios in the cross-section of currency returns. The same predictive information is also contained in $\sigma^L - \sigma^H$, as indicated by the result above, but the main focus in this paper will be on CORR since it lends itself nicely to economic interpretations. Further, to illustrate the predictability it is useful to divide CORR into three segments; negative, low and positive correlation.[3] For high interest rate currencies, the average next-month Sharpe ratio when CORR is negative is 0.32, while it is 1.03 when CORR is positive. For low interest rate currencies the corresponding next-month Sharpe ratios are 0.28 and -0.19, respectively. Thus, predicted Sharpe ratios of high (low) interest rate currencies are positively (negatively) related to CORR. These results extend to the HML carry trade strategy and are, in fact, even stronger. When comparing periods of negative and positive CORR, the average next-month Sharpe ratio of the HML excess returns are 0.20 and 0.99, respectively.

The predictability results are verified also in a regression analysis. In addition to CORR, the interest rate differential of the HML portfolio, $(r^H - r^L)$, is included as a regressor.[4] It

[2] In this exercise CORR is computed as the correlation between daily carry trade returns and dollar excess returns over the past month. Similarly, the currency volatilities are computed using daily currency returns over the past month.

[3] CORR is considered negative, low and positive in the intervals $[-1, -0.25]$, $(-0.25, 0.25)$ and $[0.25, 1]$, respectively. Across the full sample period, CORR is distributed fairly evenly over these intervals; 37%, 35% and 28%, respectively.

[4] The HML interest rate differential, $r^H - r^L$, is the difference between the average high and low interest rate, i.e. r^H and r^L denote the average interest rates among the currencies that the HML portfolio is taking a long and short position in, respectively. $r^H - r^L$ may also be referred to as the *carry* of the HML portfolio.

is reasonable to include $r^H - r^L$ since interest rate differentials in general are known to contain predictive information about future currency returns. When regressing next-month HML returns on CORR, the interest rate differential, and their interaction term, all three regressors come out highly statistically significant and the adjusted R^2 of the regression is 4.9%. These results are robust to controlling for a large number of known predictors of foreign exchange returns.

Fourth, and finally, I find evidence that carry trade crashes are to a certain extent predictable when CORR is negative. From daily data I identify the 100 worst drawdowns of the HML carry trade strategy.[5] I ask the following question: given a positive return today, what is the likelihood that a carry trade crash starts tomorrow? As a simple test, I regress a crash indicator (1 if crash starts tomorrow; 0 otherwise) on a small set of potential predictors.[6] During periods of positive CORR the results are insignificant with an adjusted R^2 of 0.0%. When CORR is negative, most of the estimated coefficients are significantly different from zero and the adjusted R^2 is 5.2%, which is high given that these data are on *daily* frequency. As a result, one potential explanation for the large excess carry trade returns that I find, on average, for months that follow after observing a positive CORR, is that investors are requiring a compensation for the unpredictability of crashes. However, I leave further interpretations of the crash predictability to future research.

Since CORR holds predictive information about returns – potentially capturing a time-varying risk premium – it becomes important to understand the dynamics of CORR. I present two distinct economic channels that build on the definition of CORR. First, I find that large global interest rate differentials, and a high level of the US interest rate relative to the rest of the world, are associated with a high CORR. Intuitively, when US interest rates are high, the US dollar is more likely to be traded as an *investment* currency, i.e. investing in the carry trade

[5] Following, Daniel et al. (2016) and Sokolovski (2017), I define a *drawdown* as the cumulative return during periods of consecutive, negative daily returns. I then consider the 100 worst drawdowns as *crashes*.

[6] The included regressors are: (i) the S&P 500 index; (ii) the VIX index, which is the option-implied volatility index used to gauge for equity and volatility risk (Daniel et al., 2016); (iii) the TED-spread, defined as the difference between the 3-month USD LIBOR rate and the 3-month US T-bill rate, used to gauge for funding liquidity (Brunnermeier et al., 2009); (iv) the HML interest rate differential; and (v) CORR.

involves taking a long position in the dollar. Subsequently, when carry trade positions are unwound, the US dollar is being sold. Thus, high US interest rates imply a positive relationship between carry trade returns and the US dollar, i.e. a positive CORR. The predictive power of CORR is then consistent with the findings of Atkeson and Kehoe (2009), who link interest rates to risks. They find that changes in short-term interest rates signal changes in bond risk premia, more so than changes in expected inflation. In our case, a higher CORR is associated with higher interest rates, which means more aggregate risk, in a broad sense.

Moreover, since interest rates are procyclical there is also a positive relationship between CORR and the US business cycle. As a result, the time-varying risk premium is procyclical, i.e. the HML carry trade is predicted to deliver high returns in good economic times and low returns in bad economic times. Since HML investors are earning low returns in times when their marginal rate of substitution is high, they will – according to conventional finance theory – require a positive average return for holding the carry trade portfolio over long periods of time. This is consistent with most risk-based explanations for the average, excess returns of carry trades.[7] Hence, the procyclical risk premium that CORR captures adds to our understanding of these abnormal returns.

The second economic channel is that CORR may capture the time-varying characteristic of the US dollar as a safe haven. When the conditional correlation between HML and DOL is negative, a sudden unwinding of carry trades is associated with an appreciation of the US dollar. The literature shows mixed evidence as to whether the US dollar can be regarded as a safe haven or not.[8] The mixed evidence itself is consistent with the view that the safe haven characteristic of the US dollar is, indeed, time-varying.

The rest of this paper is organized as follows. The next section provides a brief discussion on the related literature. Section 3 describes the data and how we construct carry trades

[7] For example, Menkhoff et al. (2012) argue similarly as they economically motivate FX volatility as a risk factor that can price carry trade returns. In a related paper, Christiansen, Ranaldo, and Söderlind (2011) find that carry trade strategies become more exposed to stock market risk during times of high FX volatility.

[8] See, for example, Kaul and Sapp (2006), Ranaldo and Söderlind (2010) and Hossfeld and MacDonald (2015).

and the conditional correlation, CORR. Section 4 presents empirical evidence supporting the conjecture, i.e. CORR is associated with the cross-sectional variation in volatilities and it holds predictive information about future currency returns. These results are shown using first a comparative statics approach and then in a regression analysis. In Section 5 we gain some understanding of the drivers of CORR by studying how it relates to other common financial and economic variables. Section 6 discusses the implications of these findings for the extant literature, that relies on the assumption that the carry factor and the dollar factor are orthogonal. In Section 7 I show that CORR contains information about the predictability of carry trade crashes. Finally, Section 8 concludes.

2 Related literature

This is not the first paper to study correlations between returns in international capital markets. Ang and Bekaert (2002) introduce a regime-switching model to capture the empirical finding that correlations between international equity returns tend to increase during periods of high market volatility. Pollet and Wilson (2010) show that higher aggregate risk in equity markets is associated with higher correlation between stocks. Following Pollet and Wilson (2010), Cenedese, Sarno, and Tsiakas (2014) decompose foreign exchange market variance into average variance and average correlation. They find that average variance holds predictive power of the left tail of future carry trade returns, while for the average correlation they find no predictive power. Moreover, Mueller, Stathopoulos, and Vedolin (2017) study correlations between FX pairs and find evidence that correlation risk is priced in FX markets. Aloosh and Bekaert (2017) study the co-movement of the G10 currencies, and use a new clustering technique to construct a novel risk factor. Berg and Mark (2018) find that global macroeconomic uncertainty is priced in currency markets. In contrast to these papers, I study the correlation between risk factors which, among other things, facilitates the economic intuition behind the variation in risk premia.

Over the years, the research literature has discovered a large number of risk factors and asset characteristics that contain predictive information about returns, mainly in equity markets. However, there is a growing concern about the actual contribution of these pricing factors. If there are significant correlations between some of the factors then the number of true sources of risk may be much smaller than the number of factors. In recent years, several papers have been applying different statistical techniques in an effort to reduce the number of pricing factors; see, for example, Feng, Giglio, and Xiu (2019) and Freyberger, Neuhierl, and Weber (2018), and a summary of over 300 of these pricing factors by Harvey, Liu, and Zhu (2016). This paper contributes to the literature by studying the cross-sectional effects of correlations between pricing factors and thereby further motivating the need for reducing the number of factors.

This paper is also related to the literature on volatility timing, which has already been applied to momentum strategies in equity markets (Barroso and Santa-Clara, 2015) and currency markets (Dahlquist and Hasseltoft, 2017), as well as to carry trade strategies (Daniel, Hodrick, and Lu, 2016). More generally, Moreira and Muir (2017) construct managed portfolios that are timing the returns in a variety of asset classes by switching away from risky assets when the return volatility is high. Consistent with this literature I find that high volatility is associated with low future Sharpe ratios. However, while Moreira and Muir (2017) attribute the low Sharpe ratios solely to the increase in volatility, I find that higher average returns are contributing just as much. Moreover, this literature struggles with the puzzle of understanding why it is optimal for investors to switch away from risk during times of high volatility (when risk aversion tends to be high), while conventional finance theory suggests that expected returns should be high during those times. This paper contributes by allowing us to study the correlation between two risk factors, rather than changes in volatility as captured by $\sigma^L - \sigma^H$, and thereby provides additional economic intuition and understanding.

Another related strand of the literature links the special properties of the US dollar to risk premia in foreign exchange markets. For example, Rey (2015) studies the global financial cycle and suggests that the United States has a central role in determining the flow of global capital. In addition to the paper by Lustig et al. (2014) mentioned above, Verdelhan (2018) builds on the work by Lustig et al. (2011) and studies the dollar risk factor in a time-series regression of bilateral exchange rates. While these papers treat the dollar factor as being orthogonal to the carry trade factor, I show that the time-varying correlation between the two factors contain predictive information about future carry trade returns. As such, the findings in this paper pose a challenge to the existing models to account for this time-varying risk premia.

3 Empirical setting

In this section, I describe how the carry trade strategy is implemented and present the data. I also construct the correlation measure, CORR, and study some of its fundamental properties.

3.1 The carry trade strategy

Before constructing the carry trade strategy we introduce some notation and describe currency excess returns in general. Let the home currency be the US dollar, and any position (long or short) in a foreign currency is taken against the US dollar. Specifically, let S_t^j denote the exchange rate of currency j, expressed as the amount of US dollars per unit of currency j. Thus, an increase in S_t^j is associated with an appreciation of currency j relative to the US dollar. Similarly, let F_t^j denote the forward exchange rate at time $t+1$. Finally, let r_t denote the interest rate in the United States. Next, consider the trade of taking a long position in the foreign currency, and a corresponding short position in the US dollar. One way of implementing this trade is to use forward contracts. Specifically, the trade translates into buying currency j forward and then selling it in the spot market in the next period. The excess return, measured in US dollar, from doing this trade is

$$rx_{t+1}^j = \frac{1 + r_t}{F_t^j} \left(S_{t+1}^j - F_t^j \right), \tag{1}$$

where the term $\frac{1+r_t}{F_t^j}$ is a scaling factor which ensures that the size of the position, at time t, is normalized to one US dollar.[9] Note that the trade could also be implemented in the spot market, as opposed to using forward contracts. However, these two alternatives are equivalent under the assumption that covered interest parity (CIP) holds.[10]

A carry trade strategy invests in high interest rate currencies, funded by short positions in low interest rate currencies. Correspondingly – since we are using forward contracts – a carry trade takes long (short) forward positions in currencies that are trading at a forward discount (premium); $F_t < S_t$ ($F_t > S_t$). To facilitate the interpretation of the results, throughout the remainder of this paper I will refer to interest rates rather than forward discounts/premiums. Moreover, let K_H and K_L denote sets of high and low interest rate currencies, respectively. Assume also that these sets contain the same number of currencies; K. We then consider an equal-weighted, dollar-neutral, carry trade strategy. Following the notation by Lustig et al. (2011), we refer to this strategy as *HML*, for high-minus-low interest rate currencies. The excess return is then given by

$$rx_{t+1}^{HML} = \frac{1}{2K}\left[\sum_{i\in K_H} rx_{t+1}^{i} - \sum_{j\in K_L} rx_{t+1}^{j}\right]. \tag{2}$$

The total number of positions that the strategy takes is $2K$, which implies that the weight on each position is $1/2K$. Note that equal weights, and the same number of long and short positions, imply that the strategy is dollar-neutral, i.e. the short dollar exposure from positions in high interest rate currencies is exactly offset by the long dollar exposure from positions in low interest rate currencies.

Some papers take into account bid/ask spreads, in order to provide more realistic results.

[9] Normalizing the size of the position to one US dollar will facilitate the building of equal-weighted currency portfolios.

[10] Akram, Rime, and Sarno (2008) shows that prior to the financial crisis in 2008, deviations from CIP were small and insignificant for data on monthly frequency and higher. However, during and after the financial crisis, deviations from CIP have become both sizable and persistent; see, for example, Levich (2017) for a recent survey of the literature that looks at CIP deviations. Importantly however, these deviations have no implications for the monthly carry trade excess returns considered in this paper since we are using actual forward and spot rates, i.e. we do not, for example, rely on CIP to compute foreign interest rates.

However, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) show, using a similar set of currencies and a similar carry trade strategy, that while bid/ask spreads are important in terms of quantities of payoffs, they do not explain the profitability of their carry trade. Hence, I follow them in abstracting from bid/ask spreads, and use mid-quotes for both long and short positions.

3.2 The dollar factor

The dollar factor, DOL, is the average change in exchange rates between the US dollar and a basket of foreign currencies. An increase in DOL will then correspond to an average appreciation of the US dollar. Given a basket of N foreign currencies, DOL is defined as

$$DOL_{t+1} = -\frac{1}{N}\sum_{j=1}^{N}\frac{S_{t+1}^{j}}{S_{t}^{j}}. \tag{3}$$

3.3 Data

Although the general analysis is carried out at the monthly frequency, we need daily data to construct several important quantities along the way; for example, the correlation measure, CORR. Therefore, we start from daily data on spot and 1-month forward prices, denominated in US dollars, for the G10 currencies. In addition to the US dollar (USD), these currencies include the Australian dollar (AUD), the British pound (GBP), the Canadian dollar (CAD), the Euro (EUR)[11] , the Japanese yen (JPY), the New Zealand dollar (NZD), the Norwegian krone (NOK), the Swedish krona (SEK), and the Swiss franc (CHF). The data are obtained from Reuters and Barclays (via Datastream), and the sample period stretches from December 31, 1984 to July 31, 2017. These data are available for all currencies over the entire sample period. The US interest rate is the 1-month USD LIBOR, downloaded from Bloomberg.

[11] For data on the Euro prior to its introduction in 1999, we use the German Mark.

3.4 Excess carry trade returns

The HML carry trade strategy is implemented at the monthly frequency. At the end of each month, the G10 currencies (excluding the US dollar) are sorted by interest rates. The strategy then takes a long forward position in the three currencies with the highest interest rates, and a short forward position in the three currencies with the lowest interest rates. All positions are taken with equal weights, and against the US dollar, which leaves the total carry trade portfolio with no direct exposure to movements in the US dollar. The portfolio is then rebalanced at the end of each month.

In order to compute the correlation measure, CORR, we also need returns at the daily frequency. We obtain these from the monthly returns, in a procedure that partly follows the one by Daniel et al. (2016). The main idea is to mark the portfolio to market each day. More specifically, we define a cumulative value function that starts each month with the value of zero, and ends each month with the corresponding monthly return. On each day within the month, the value function grows by the daily changes in exchange rates as well as a daily, equally weighted, proportion of the interest rate differential earned over the given month. Finally, using the value function, we follow Daniel et al. (2016) to back out the daily returns. The details of this procedure are presented in Appendix A.

The HML strategy is basic, yet sophisticated enough to capture the typical carry trade characteristics.[12] Table 1 presents the summary statistics for the HML returns, on both monthly and daily frequency. Returns are annualized, so monthly (daily) average returns are multiplied by 12 (252), and standard deviations are multiplied by $\sqrt{12}$ ($\sqrt{252}$). The Sharpe ratio is the annualized mean return divided by the annualized standard deviation. As mentioned above, the HML returns exhibit the usual carry trade characteristics. The mean return on the monthly data is 2.28%, which is statistically different from zero. The average profitability of the carry

[12] The strategy is basic in the sense that we are using equal weights, as well as restricting our attention to the ten most liquid currencies. In the industry, examples of two carry trade investment products that focus on the G10 currencies are the iPath Optimized Currency Carry ETN and the Exchange Traded Fund Powershares DB G10 Currency Harvest Fund. There is a large number of papers in the academic literature that consider equal-weighted strategies for the G10 currencies, e.g. Bakshi and Panayotov (2013) and Daniel et al. (2016).

	Monthly	Daily
Mean	2.28	2.18
	[0.81]	[0.82]
Std dev	4.58	4.64
	[0.25]	[0.10]
Skewness	−0.76	−0.71
	[0.22]	[0.23]
Sharpe Ratio	0.50	0.47
	[0.19]	[0.18]
N obs	391	8357

Table 1: Summary statistics of the HML returns, at monthly and daily frequency. Returns and standard deviations are expressed as percentages, in annualized form; monthly (daily) mean returns are multiplied by 12 (252), and standard deviations are multiplied by $\sqrt{12}$ ($\sqrt{252}$). Reported in brackets are standard errors from a stationary bootstrap procedure following Politis and Romano (1994), with the average block size according to Politis and White (2004). The sample period is 12/31/1984 - 7/31/2017.

trade is also depicted in Figure 2, which shows the cumulative HML returns over the sample period. Moreover, the standard deviation of 4.58% implies a Sharpe ratio of 0.50, which is close to what most other papers find. We also see the typical, negative skewness; in our case −0.76 for monthly returns.

Finally, we compare the summary statistics of the monthly and daily returns. We immediately see that these statistics are similar in magnitude. Thus, the method for computing daily returns is preserving the carry trade statistics, which is reassuring and gives credence to the method.

3.5 Constructing CORR

The correlation measure, CORR, is designed to capture the time-varying correlation between the carry trade returns (HML) and the average change in exchange rates between the US dollar and a set of foreign currencies (DOL). To compute the correlation I use a equal-weighted rolling window of 40 daily observations.[13]

[13] In Appendix B I replicate the main findings of the paper using rolling windows of 20 and 60 days, as well as a method that uses exponentially distributed weights. All results are robust to these variations.

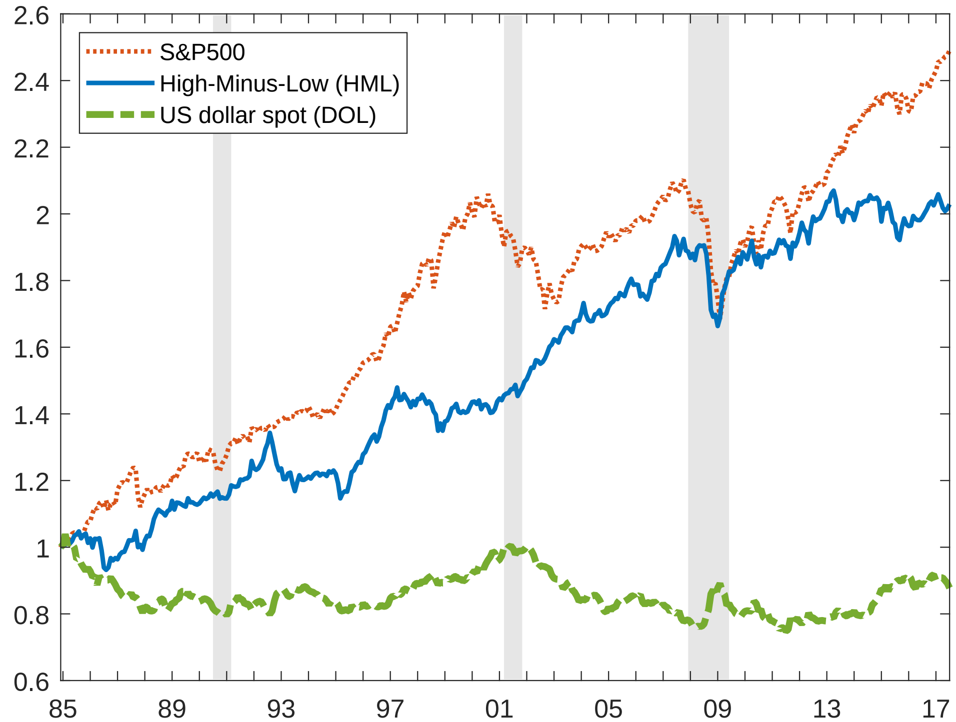

Figure 2: Cumulative excess returns and changes in exchange rate indexes. The figure plots cumulative returns from investing 1 US dollar in January 1985 in the S&P500 equity index, as well as the high-minus-low (HML) carry trade. The HML carry trade strategy takes a long (short) position in the three currencies, among the G10 currencies, with the highest (lowest) interest rates. The figure also shows the average change in the exchanges rates between the US dollar and the other G10 currencies; labelled *DOL*, a high value corresponds to a strong US dollar. Computed from monthly returns. Shaded areas are NBER recessions. All strategies are scaled to have the same volatility as the HML strategy.

The resulting data series for CORR is at daily frequency, with 8318 observations. Since the main analysis in this paper uses monthly data, we construct the monthly series for CORR by using end-of-month observations. The summary statistics for CORR is presented in Table 2. The mean is −0.06, which is indeed close to zero, and also the *unconditional* correlation between HML and DOL is close to zero; −0.18 in our sample (not reported in the table). Moreover, CORR varies strongly over the sample period. This is clear from the high standard deviation (0.44) as well as from the minimum and maximum values; −0.92 and 0.92, respectively.

Mean	−0.06
	[0.09]
Std dev	0.44
	[0.04]
Min	−0.92
Max	0.92
N obs	390
% of sample above zero	
% of sample indifferent from zero	
% of sample below zero	

Table 2: Summary statistics of CORR. CORR is defined as the conditional correlation between the carry factor, HML, and the dollar factor, DOL. It is computed using daily data and a 40-day rolling window. The data in the table are at monthly frequency, constructed from using end-of-month daily observations. Reported in brackets are standard errors from a stationary bootstrap procedure following Politis and Romano (1994) with the average block size according to Politis and White (2004). The same stationary bootstrap is used to compute the 90% confidence bands that are used to determine whether each observation is above, below or indifferent from zero.

These characteristics of CORR are also visible in Figure 3, which plots CORR over the full sample period. Included in the figure are 90% confidence bands, showing that CORR is indeed statistically different from zero over large parts of the sample. Specifically, CORR is statistically significantly above (below) zero during XX% (YY%) of the sample period. From Figure 3 we also see that CORR is fairly persistent. For example, in an AR(1) regression of CORR on the one-month lagged CORR, the estimated slope coefficient is 0.87. This persistence is of course partly mechanical, from the rolling window used in the construction of CORR. However, as a robustness check I restrict the rolling window to contain only the daily observations within each given month. That way, there is no mechanical correlation between the monthly observations of CORR. The corresponding estimated slope coefficient from the AR(1) regression is still large, at 0.66 and highly statistically significant. Most importantly, the main results of the paper are robust to using CORR constructed this way; with a non-overlapping rolling window.

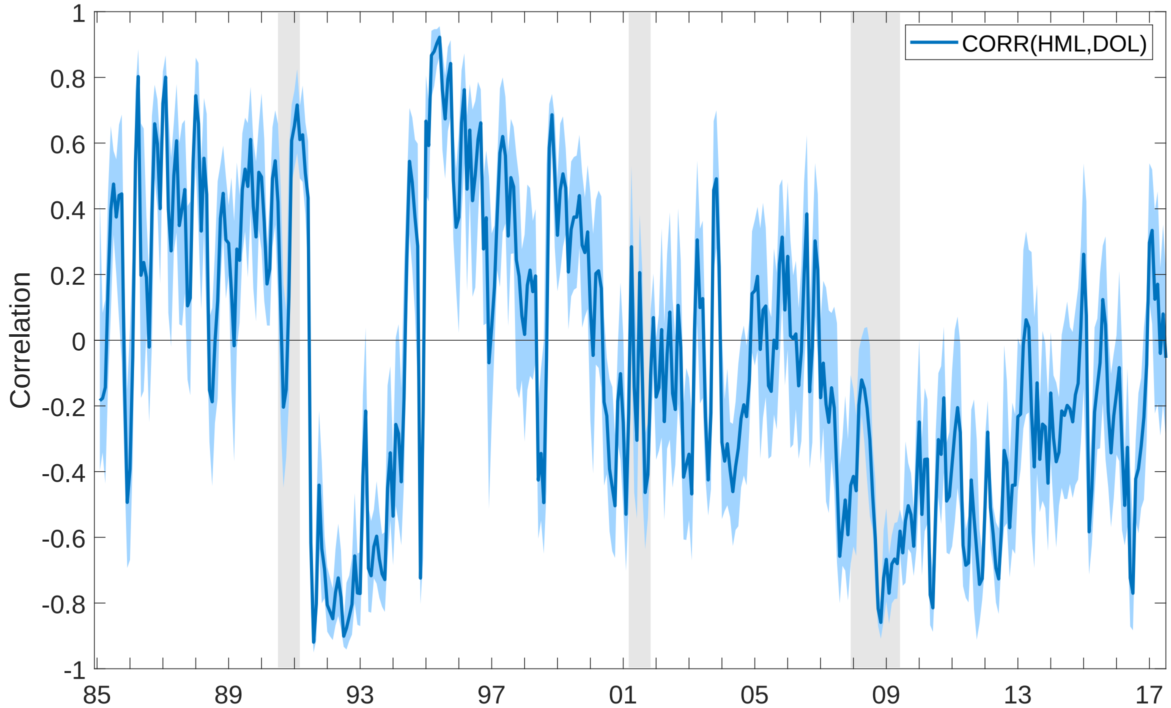

Figure 3: CORR across time. The figure plots CORR, which is the conditional (time-varying) correlation between the excess returns of the high-minus-low (HML) carry trade strategy and the average change in the bilateral exchange rates between the US dollar and the other G10 currencies (DOL). The data are at monthly frequency, constructed from end-of-month daily observations. Each observation is computed using a rolling window of 40 daily observations. The figure shows 90% confidence bands, constructed from a stationary bootstrap procedure following Politis and Romano (1994) with the average block size according to Politis and White (2004). Shaded areas are NBER recessions.

4 Empirical links between CORR and currency returns

In this section I present empirical evidence of the connection between CORR and currency returns. As a first approach, I divide CORR into three different regimes and observe how the characteristics of currency returns differ depending on the current regime. As a second approach I apply a linear regression framework showing how CORR contains predictive information about the HML carry trade returns.

4.1 A comparative statics approach

In order to study the cross-section of currency returns it is useful to consider *portfolios* of currencies, rather than bilateral currency pairs, since it reduces the noise in returns coming from currency-specific factors.[14] At the end of each month, the nine non-USD G10 currencies are sorted by interest rates. The currencies are then placed in three portfolios, denoted P1, P2 and P3, where portfolio P1 contains the currencies with the lowest interest rates, and P3 contains the currencies with the highest interest rates. Note that our HML carry trade portfolio is, by definition, equivalent to taking a long position in P3 funded by a short position in P1.

4.1.1 Portfolios of currencies sorted by interest rates

Table 3 reports, in the third column, the summary statistics of the three portfolios, without conditioning on CORR. As expected, the annualized average returns of the portfolios are increasing with the interest rate; portfolios P1 and P3 have average returns of 0.6% and 5.2% respectively. The Sharpe ratios follow the same pattern, increasing from 0.07 for P1 to 0.49 for P3. Standard deviations, on the other hand, seem to show no clear pattern, which is consistent with the findings of Menkhoff et al. (2012). Hence, while unconditional standard deviations do not vary in the cross-section, standard deviations conditioning on CORR vary significantly, as we will see below.

One might be surprised to see a positive average return for the low-interest rate portfolio, P1. Lustig et al. (2011) report a negative average return on their portfolio containing the lowest interest rates. However, this can be explained by the negative excess return on the US dollar over our sample period. Since all portfolios (P1, P2 and P3) are short the US dollar, a depreciation of the US dollar elevates the returns of all portfolios. Specifically, the cumulative change in exchange rates between the US dollar and the other G10 currencies, over our sample period, is −63%. Most of these negative changes are realized during the first three years of

[14] Here, I follow Lustig and Verdelhan (2007) who were the first to study portfolios of currencies sorted by interest rates.

the sample; see Figure 2.

Following Lustig et al. (2011), we assume a stochastic discount factor which is linear in the two factors; HML and DOL. Based on the implied beta-representation we can estimate the factor loadings from the following regression:

$$rx_t^P = \alpha + \beta_P^{DOL} \cdot DOL_t + \beta_P^{HML} \cdot HML_t + \epsilon_t, \tag{4}$$

where β_P^{DOL} and β_P^{HML} are the factor loadings on DOL_t and HML_t, respectively, and rx_t^P is the excess returns on a portfolio of currencies against the US dollar. For the three portfolios, we estimate the factor loadings and report them in Table 3.

As expected, all portfolios have a similar, negative loading on the dollar factor. The loading on the carry factor is negative for the low interest rate portfolio (P1) and positive for the high interest rate portfolio (P3). Portfolio P2 has no significant exposure to the carry factor. These findings are all consistent with those of Lustig et al. (2011).

At this point we may remind ourselves of the conjecture that motivated this paper, as illustrated in Figure 1. An increase in the correlation between the two risk factors should enhance the benefits of diversification for high interest rate currencies, which follows from the two factor loadings having different signs. This should be reflected in a contemporaneous decrease in the volatility of returns and, potentially – through the effects of volatility-timing – lead to a higher Sharpe ratio in the following periods. The implications for low interest rate currencies are reversed since their factor loadings are of the same sign; both are negative.

4.1.2 CORR and the cross-section of currency returns

We test the conjecture by observing how the returns of the currency portfolios varies for different levels of CORR. It is natural to split the correlation interval into three parts, to capture the characteristics of negative, low, and positive correlation; these intervals are set to $[-1, -0.25]$, $(-0.25, 0.25)$ and $[0.25, 1]$, respectively. That way, CORR is well-represented across the sample period in all three intervals, as 35%, 37% and 28% of the observations are classified as negative, low and positive, respectively. A similar representation is obtained if we use the distribution from the statistically significant deviations from zero presented in Table 2 and illustrated by the confidence bands in Figure 3.

The contemporaneous standard deviations of returns display a pattern consistent with the conjecture. For high interest rate currencies, the standard deviation is, on average, 13.2% when CORR is negative. When CORR is positive the corresponding standard deviation is reduced to only 7.3%. For low interest rate currencies the relationship with CORR is reversed as the average standard deviation of returns are 7.3% and 10.8% during periods of negative and positive CORR, respectively. These results hold also if the correlation interval is split into finer sub-intervals. Figure 4 contains three panels – one for each portfolio – where CORR is split into six sub-intervals and the bars display the standard deviation of returns. In line with the previous results, there is a clear positive (negative) relationship between CORR and the standard deviation of low (high) interest rate currency returns.

In an additional test I compute the contemporaneous correlation between CORR and the time-varying standard deviation of the portfolio returns which I construct in the same way as CORR; using a 40-day rolling window. The estimated correlation for the high (low) interest rate currencies is 0.45 (-0.61) and highly statistically significant (see Table 3). When considering the difference between the standard deviations of low and high interest rate currencies, $\sigma^{P1} - \sigma^{P3}$, the correlation is even more pronounced, at 0.88. In connection to Figure 1 this difference corresponds to $\sigma^{L} - \sigma^{H}$ and captures well the first part of the conjecture. Taken together, there is strong evidence supporting our conjecture that a change in the correlation between the risk factors has effects on the diversification benefits across the factors and thereby direct effects on the volatilities of the cross-sectional returns.

We now turn to the predictive power of CORR, as suggested by the second part of the conjecture. To that end, we consider CORR as being observed at the end of a given month, while the currency returns are observed over the following month. The summary statistics for the next-month currency portfolio returns are presented in the last three columns of Table 3. We first note that the next-month standard deviations are similar to those in the contemporaneous case, as low (high) interest rates currencies display a positive (negative) relationship with CORR.

The pattern for next-month Sharpe ratios are also in line with the conjecture. For high (low) interest rate currencies, the next-month Sharpe ratio is, on average, 0.36 (0.28) when CORR is negative, whereas periods of positive CORR are followed by a significantly larger (smaller) Sharpe ratio of 1.05 (−0.22). Note that the differences in Sharpe ratios are not solely driven by the changes in volatilities, as found in the cross section considered by Moreira and Muir (2017). The average returns tend to change in the direction that further amplifies the change in Sharpe ratios. For example, when comparing negative to positive periods of CORR, the next-month average return for high (low) interest rate currencies is 3.5% (2.8%) and 8.6% (−2.4%), respectively.

The variation in the average returns suggests that "volatility timing" may not be the only plausible explanation for the pattern in Sharpe ratios. Rather, there may be a time-varying risk premium present.

Alternative explanation, the pattern in the average returns across CORR are consistent with a time-varying risk premium. Risk premium when CORR is positive?

As pointed out above, in the unconditional case, high interest rate currencies (P3) earn higher average returns and higher Sharpe ratios than low interest currencies (P1). This is a well-documented empirical fact which underlies the profitability of the carry trade. However, when conditioning on CORR, this cross-sectional pattern is distinct and highly statistically significant when CORR is positive. The pattern is less distinct when CORR is low, and it disappears when CORR is negative.

Naturally, this manifests itself in the HML carry trade strategy as it takes a long position in P3 and short position in P1.

Section 7.2

The skewness in the cross-section exhibit another interesting pattern, with implications for the US dollar. For all three portfolios, the highest skewness is found when CORR is low, i.e. when HML and DOL are roughly uncorrelated. During periods of a more distinct correlation – positive or negative – the skewness is significantly lower. Here are two potential implications. First, to the extent that crash risk is related to the unwinding of carry trade positions (Brunnermeier et al., 2009), one would expect that periods when high interest rate currency returns are negatively skewed coincide with periods when low interest rate currency returns are positively skewed. However, this is not the pattern that emerges in Table 3. Rather, low interest rate currency returns exhibit the highest skewness after CORR is low (uncorrelated risk factors), while high interest rate currency returns (as well as the middle portfolio, P2) are most negatively skewed after CORR is negative. This poses a challange to the view that carry trade crashes are caused by the unwinding of trading positions, suggesting that there are additional explanations for these crashes. Second, the same pattern persists throughout the cross-section, which may suggest that it is capturing a characteristic of the US dollar (recall that all portfolios are short the US dollar) rather than the cross section of foreign currencies. Hence, the lower skewness when CORR is either negative or positive could imply a higher risk of a sharp *appreciation* of the US dollar, potentially connected to a flight-to-safety mechanism.

4.1.3 CORR and carry trade returns

Finally, we turn to the HML carry trade strategy, which takes a long position in P3 and a short position in P1. The next-month summary statistics for the HML strategy are displayed in the last three columns at the bottom of Table 3. We first note that the next-month standard deviations show no clear relationship with CORR. The reason is that the positive relationship between the standard devations for portfolio P1 is offset by the corresponding negative relationship for portfolio P3. However, the cross-sectional patterns in the average returns imply a strong positive relationship between CORR and the average carry trade returns. When CORR is negative the next-month average return is only 0.4% and statistically insignificant from zero, while it increases to 5.5% and highly statistically significant when CORR is positive. As a result, the next-month Sharpe ratios for the carry trade returns display a distinct positive relationship with CORR. When CORR is negative the next-month Sharpe ratio is on average 0.08, while it increases significantly to 1.19 when CORR is positive.

The skewness of the carry trade returns is most negative when CORR is low, while it is slightly higher when CORR is either negative or postive. Hence, this pattern is the reverse of the pattern observed in the cross section. The skewness and crash risk of the carry trade returns are discussed in more detail in Section 7 as we connect CORR to the predictability of carry trade crashes.

4.2 Regression analysis

While the results presented in Table 3 show that a higher CORR is associated with a higher next-month Sharpe ratio of the HML portfolio, the relationship is not a simple linear one. However, once we include the interest rate differential of the HML portfolio and its interaction term with CORR (referred to as "conditional CORR")[15] , in a regression framework, the results become highly statistically significant. Thus, the main regression of next-month carry trade returns takes the following form:

$$rx_{t+1}^{HML} = \beta_0 + \beta_1 \left(r_t^H - r_t^L\right) + \beta_2 CORR_t + \beta_3 \left(r_t^H - r_t^L\right) CORR_t + \epsilon_{t+1}, \quad (5)$$

where $r_t^H - r_t^L$ is the interest rate differential of the HML portfolio, i.e. the difference between the average interest rate of the three high-interest-rate currencies and the average interest rate of the three low-interest-rate currencies.

[15] A similar notation is used by Verdelhan (2018) who refers to the interaction term between the carry factor and the interest rate differential as the "conditional carry".

4.2.1 A simple look at the data

Together, CORR and the interest rate differential span a two-dimensional plane which contains information about future excess returns of the carry trade strategy. In order to visualize this in a graph, we discretize the two variables in the following way. CORR is grouped into six bins across the $[-1, 1]$ interval. The interest rate differential is grouped into either 'high' or 'low' relative to the median interest rate differential over the sample period. Figure 6 shows two panels, with bars that measure the average next-month carry trade return. The top (bottom) panel contains observations with high (low) interest rate differentials, at time t. Note that Figure 6 simply plots the data, without imposing any model or other types of restrictions.[16]

Both panels in Figure 6 display distinct patterns. In the top panel – when the interest rate differential is high – there is a *positive* relationship between CORR and next-month carry trade returns. Whereas in the bottom panel – when the interest rate differential is low – the relationship between CORR and next-month carry trade returns is *negative*. Moreover, months with large, positive carry trade returns are, on average, preceded by months of either high interest rate differentials and strongly positive CORR (above 0.3), or low interest rate differentials and strongly negative CORR (below -0.6). On average, large losses of the carry trade strategy are preceded by months of high interest rate differentials and low CORR (below -0.3). This pattern can, at least partially, be explained by crashes in the carry trade connected to the US business cycle, which will be discussed more in Section 5.

In Figure 6, there are 12 bins in total. Over the sample period, we do not spend the same amount of time in each bin. Therefore, one concern may be that the bars in the figure are misleading in terms of displaying when the excess returns (gains and losses) are actually taking place. For example, the large average excess return when the interest rate differential is high and CORR is greater than 0.6 might be driven by only a few extreme observations. However, in a similar figure not included in the paper, I show that even after controlling for

[16] If we only had one independent variable, the straight-forward way of visualizing the data would be to use a scatter plot. With two independent variables, however, it is useful to discretize the variables somehow, in order to produce an intuitive picture of the data.

the time spent in each bin, the patterns that we see in Figure 6 remain just as clear.

4.2.2 Regression results

The general patterns in the data – as observed in Figure 6 – are captured also in the estimation of equation (5). The results are presented in Table 4, where the baseline case is presented in regression specification (iii). The estimated coefficients for the interest rate differential, CORR, as well as their interaction term come out highly statistically significant. The adjusted R^2 is 4.9%, which is high given the relatively short forecast horizon of one month. Note that by themselves, neither the interest rate differential nor CORR is significant; see specification (i) and (ii). However, once we include the interaction term, all coefficient estimates become highly significant.

How do we interpret the signs of the estimated coefficients in the main regression specification (iii), and can we connect them to the observed patterns in Figure 6? The estimated coefficients for both the interest rate differential and CORR are negative, while the interaction term has a positive estimate. When conditioning on a low interest rate differential, only the estimate on CORR matters for the next-month returns. Then, the negative sign on the estimate for CORR is capturing the downward slope in the lower panel in Figure 6. Next, when conditioning on a high interest rate differential, the estimate on the interaction term will dominate. That estimate has a positive sign, implying the upward slope in the upper panel in Figure 6.

These results are also economically significant. Let us see how the predicted next-month carry trade return changes as CORR changes from 0 to 0.5. The corresponding change in the interest rate differential is obtained from the fitted regression of the interest rate differential on CORR.[17] Expressed as effective annual rates, the interest rate differentials are 5.55% and 7.10% when CORR is 0 and 0.5, respectively.[18] Then, the predicted next-month carry trade return changes from 0.63% to 4.34% as CORR changes from 0 to 0.5. That is, the predicted re-

[17] The results from regressing the interest rate differential on CORR are as follows. The estimates for the intercept and the slope coefficient are 0.005 and 0.002, respectively, and both estimates are highly statistically significant. The adjusted R^2 is 18%.

[18] Note that the average interest rate differential over the sample period is 5.54%.

turn changes by 3.71 percentage points, which almost corresponds to a one-standard-deviation change; recall from Table 1 that the standard deviation of HML returns is 4.58%.

One concern might be that these results are driven by a particular event in history, such as the financial crisis, or another extreme period such as the late 1980s and early 1990s when interest rates were high relative to the rest of the sample period. To address this I perform an out-of-sample test by first splitting the sample period in the middle and then estimating the main regression on each subsample. As reported in Appendix B.3, the results remain robust, with statistically significant coefficient estimates and large adjusted R^2s.

Another potential concern is that CORR may be picking up the effect of some other variable(s). To address this I control for a large set of other variables that could be linked to carry trade returns. Some of the results from those regressions are included in Table 4, in specifications (iv) - (ix). For each variable I also include its interaction term with the interest rate differential. The results show that the predictive power of CORR and its interaction term with the interest rate differential remain highly statistically significant even after controlling for all other potential predictors. Nevertheless, from these regressions we make some useful observations about the other variables.

The proxy for FX volatility (Menkhoff et al., 2012) comes out significant when interacted with the interest rate differential. As expected, it carries a negative sign implying that higher FX volatility (coupled with large interest rate differentials) predicts lower excess carry trade returns. This is consistent with the previous literature; see, for example, Menkhoff et al. (2012) and Bakshi and Panayotov (2013).

Moreover, I also control for US payrolls, which is a common US macroeconomic indicator, available at monthly frequency. In regression specification (viii) its estimated coefficient is negative, which is counter-intuitive since we would expect good macroeconomic conditions to predict higher excess returns. However, if we exclude the interaction term between Payrolls and the interest rate differential (not reported in the table), the estimated coefficient on Payrolls itself becomes insignificant. On the other hand, in the final regression specification (ix), all control are included, and both variables with Payrolls come out significant. As with the case of CORR, the interaction term is positive, indicating that good economic conditions imply higher excess carry trade returns. Finally, we also note that when including all control variables, the coefficient for the TED-spread interacted with the interest rate differential becomes significant, with a negative sign. This is intuitive, since a higher TED-spread is often interpreted as increased funding illiquidity, which should be associated with lower future excess returns.[19]

Not reported in the table are some other variables that I have controlled for, which also came out insignificant. For example, the foreign exchange volatility proxy introduced by Bakshi and Panayotov (2013), and the measure for global market illiquidity by Karnaukh, Ranaldo, and Söderlind (2015). Finally, the results are essentially unchanged if I substitute $\sigma^L - \sigma^H$ for CORR, i.e. the predictive information contained in CORR is reflected also in $\sigma^L - \sigma^H$, and the latter does not contain any new predictive information. In a horse race between the two (regressing next-month carry trade returns on the CORR, $\sigma^L - \sigma^H$, as well as their interaction terms with the interest rate differential and the interest rate differential itself), all variables come out insignificant, except for the interest rate differential, indicating that the regression model is unable to determine which variable is more significant.

[19] For a longer discussion on the connection between carry trades and the TED-spread see Brunnermeier, Nagel, and Pedersen (2009).

			CORR$_{t-1}$		
		Unconditional	Negative $[-1,-0.25]$	Low $(-0.25,0.25)$	Positive $[0.25,1]$
P1 (low interest rates)	Contemp. Std. Dev.		7.3	9.0	10.8
	$Corr(\text{CORR}_t,\sigma_t)$	0.45			
	β^{DOL}	-1.04^{***}			
	β^{HML}	-1.04^{***}			
	Mean	0.6	2.8	1.3	−2.4
	Std Dev	9.0	7.6	8.2	11.1
	Skewness	0.21	0.23	0.48	0.18
	Sharpe Ratio	0.07	0.36	0.15	−0.22
P2	Contemp. Std. Dev.		9.7	7.7	6.7
	$Corr(\text{CORR}_t,\sigma_t)$	−0.39			
	β^{DOL}	-0.93^{***}			
	β^{HML}	0.01			
	Mean	2.4	1.3	3.1	3.5
	Std Dev	8.2	9.6	7.5	6.9
	Skewness	−0.37	−0.51	0.04	−0.15
	Sharpe Ratio	0.29	0.14	0.41	0.51
P3 (high interest rates)	Contemp. Std. Dev.		13.2	9.1	7.3
	$Corr(\text{CORR}_t,\sigma_t)$	−0.61			
	β^{DOL}	-1.04^{***}			
	β^{HML}	0.96^{***}			
	Mean	5.2	3.5	4.4	8.6
	Std. Dev.	10.4	12.7	9.5	8.2
	Skewness	−0.32	−0.52	0.15	0.11
	Sharpe Ratio	0.49	0.28	0.47	1.05
HML (P3-P1)	$Corr(\text{CORR}_t,\sigma_t^{P3}-\sigma_t^{P1})$	−0.88			
	Mean	2.3	0.4	1.6	5.5
	Std Dev	4.6	4.9	4.1	4.6
	Skewness	−0.76	−0.43	−1.23	−0.84
	Sharpe Ratio	0.49	0.08	0.38	1.19
	Nr. of observations (% of full sample)	390 (100%)	138 (35%)	143 (37%)	109 (28%)

Table 3: Summary statistics of excess returns. Portfolio P3 (P1) consists of the three currencies with the highest (lowest) interest rates among the non-USD G10 currencies. CORR is the 40-day rolling window correlation between the carry factor and the dollar factor. In the last three columns, the reported statistics for the mean, standard deviation, skewness and Sharpe ratio are computed for month t, conditioning on CORR as observed at the end of month $t-1$. *Contemp. Std. Dev.* is the standard deviation observed during the same month as CORR is observed, $t-1$. The reported values for β^{DOL} and β^{HML} come from estimating the regression: $rx_t^P = \alpha + \beta^{DOL} \cdot DOL_t + \beta^{HML} \cdot HML_t + \epsilon_t$, where rx_t^P corresponds to the excess returns of portfolio $P1$, $P2$ and $P3$. The frequency of the data is monthly, and the sample period is December 1984 to July 2017. Returns and standard deviations are expressed as percentages, and in annualized form; mean returns are multiplied by 12 and standard deviations are multiplied by $\sqrt{12}$. Sharpe ratios are computed by dividing the annualized mean return by the annualized standard deviation. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

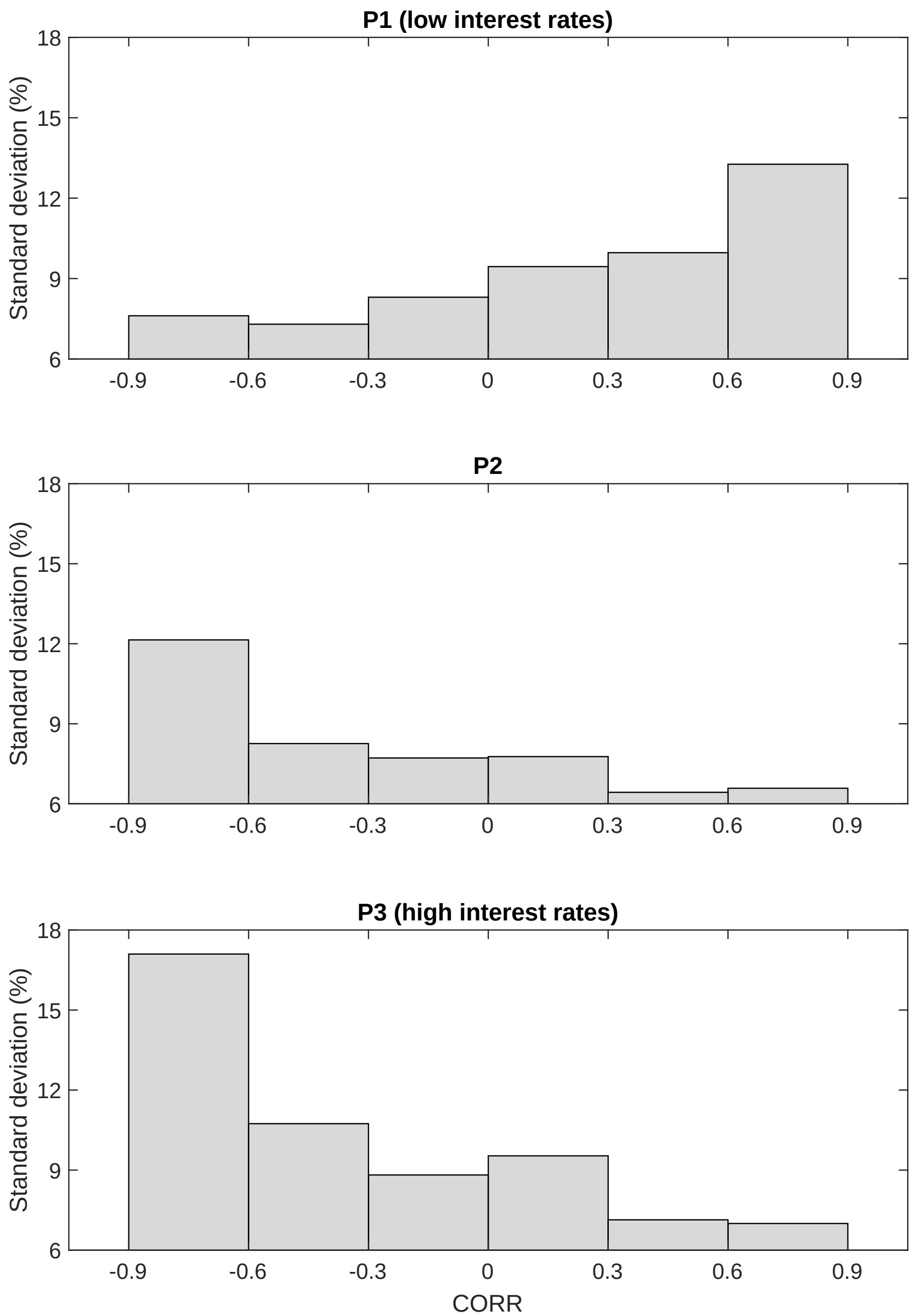

Figure 4: Contemporaneous standard devations of returns. Portfolio P3 (P1) consists of the three currencies with the highest (lowest) interest rates among the non-USD G10 currencies. CORR is the 40-day rolling window correlation between the carry factor and the dollar factor. The bars measure the average next-month standard deviation of portfolio returns after having observed CORR at the end of the current month. Standard deviations are expressed as percentages, and in annualized form; multiplied by $\sqrt{12}$. The data frequency is monthly and the sample period is December 1984 to July 2017.

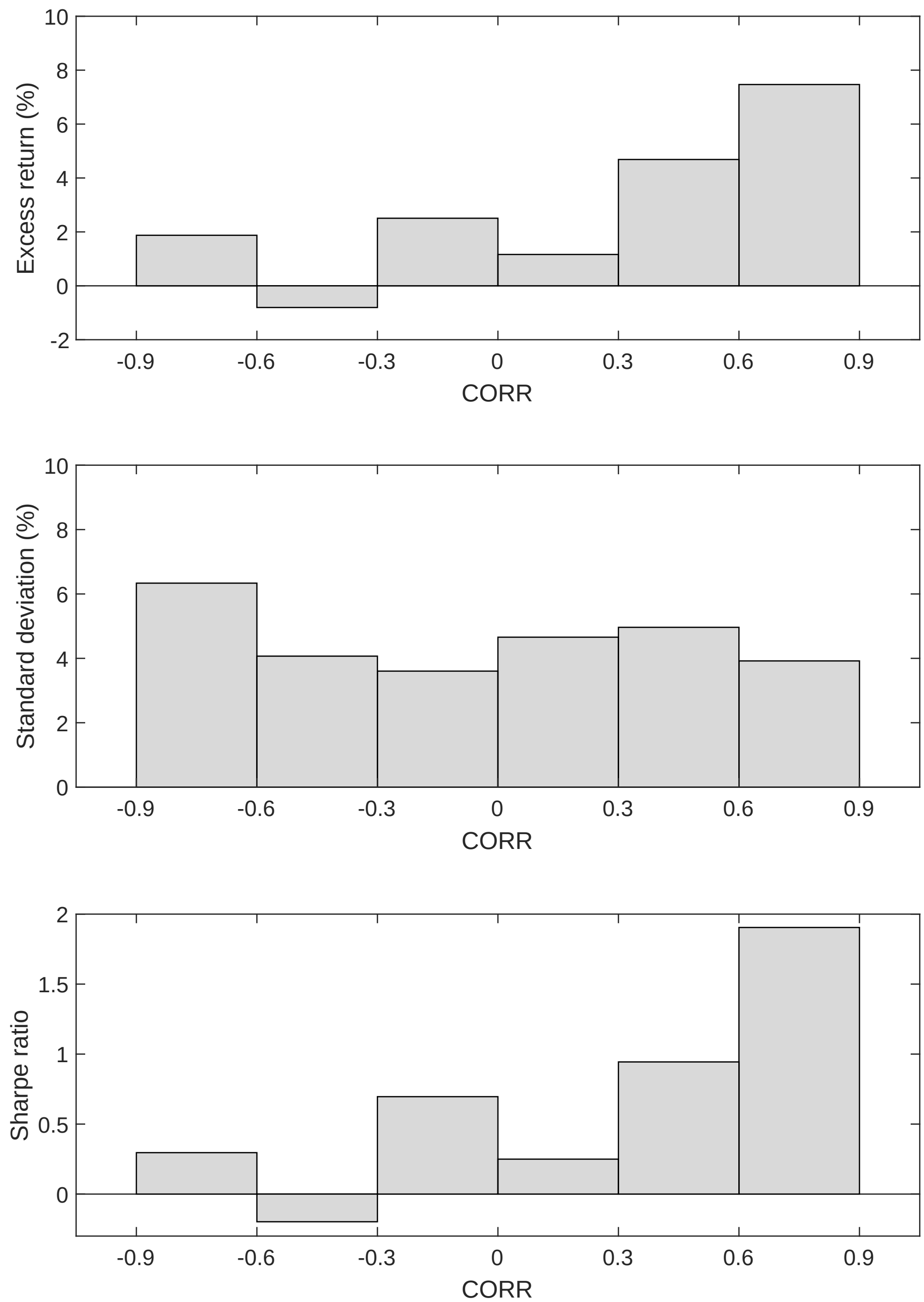

Figure 5: Next-month average returns, standard deviations and Sharpe ratios of the HML carry trade strategy. The HML strategy takes a long (short) position in the three currencies among the G10 currencies with the highest (lowest) interest rates. CORR is the 40-day rolling window correlation between the carry factor and the dollar factor. The bars in the panels from top to bottom display the average next-month return, standard deviation and Sharpe ratio, respectively, for the HML carry trade strategy, after having observed CORR at the end of the current month. Returns and standard deviations are expressed as percentages, and in annualized form; mean returns are multiplied by 12 and standard deviations are multiplied by $\sqrt{12}$. Sharpe ratios are computed by dividing the annualized mean return by the annualized standard deviation. The data frequency is monthly and the sample period is December 1984 to July 2017.

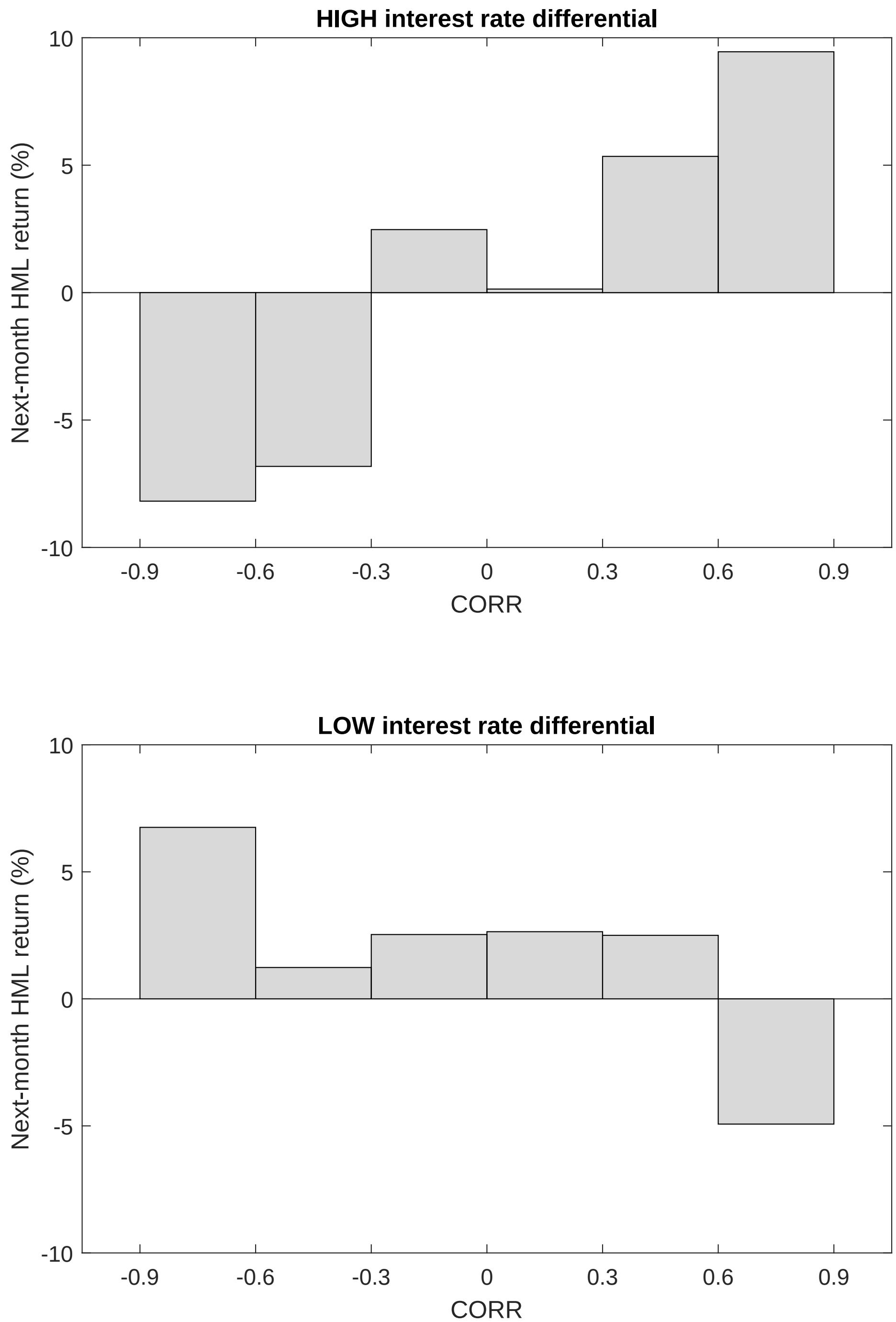

Figure 6: The distribution of next-month HML returns, across CORR and high/low HML interest rate differential. The 392 months in our sample are each placed into one of the 12 bins above. At the end of each month (at time t), we observe CORR (the conditional correlation between HML and DOL) and the interest rate differential (observed at time t, and applicable between t to $t + 1$). The interest rate differential for a given month is then considered high (low) if it is higher (lower) than the median interest rate differential over the sample period. Each month is also placed in one of nine bins across the correlation interval $[-1, 1]$. The bars measure the average next-month excess return (annualized and measured in per cent) on the HML carry trade, earned between time t and $t + 1$. The sample period is December 1984 to July 2017.

Dependent variable: rx_{t+1}^{HML}	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
$r^H - r^L$	0.01		−0.95***	−1.21	1.43	0.05	−1.00***	−1.85**	−0.63
	(0.04)		(−2.67)	(−0.95)	(1.08)	(0.07)	(−2.81)	(−2.13)	(−0.30)
$CORR$		0.003	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01*	−0.01*
		(1.47)	(−2.84)	(−2.80)	(−3.22)	(−2.65)	(−2.77)	(−1.78)	(−1.73)
$\left(r^H - r^L\right) CORR$			3.07***	3.24***	2.95***	3.47***	3.05***	2.33***	2.36***
			(4.15)	(4.27)	(4.57)	(3.77)	(4.19)	(3.31)	(2.64)
$T - bill$				0.00					−0.00
				(0.47)					(−0.60)
$\left(r^H - r^L\right) T - bill$				0.01					0.21
				(0.05)					(1.11)
$FXvol$					1.23				0.06
					(1.21)				(0.05)
$\left(r^H - r^L\right) FXvol$					−473*				−240
					(−1.74)				(−0.77)
TED						−0.00			0.00
						(−0.08)			(0.43)
$\left(r^H - r^L\right) TED$						−0.66			−1.34*
						(−1.14)			(−1.83)
$S\&P500$							−0.04		−0.04
							(−1.38)		(−1.20)
$\left(r^H - r^L\right) S\&P500$							4.87		2.79
							(1.11)		(0.44)
$Payrolls$								−0.03**	−0.04***
								(−2.12)	(−2.62)
$\left(r^H - r^L\right) Payrolls$								5.90	7.49**
								(1.58)	(2.09)
Intercept	0.002	0.002***	0.005***	0.005	−0.002	0.003	0.005***	0.008***	0.009
	(1.55)	(2.86)	(3.41)	(1.26)	(−0.33)	(0.98)	(3.66)	(2.97)	(1.16)
N obs	391	385	385	385	385	378	385	385	378
$Adj R^2 (\%)$	−0.3	0.6	4.9	4.6	6.1	6.1	4.8	6.4	9.5

Table 4: Regressions of next-month carry trade returns on a set of independent variables. $r^H - r^L$ is the interest rate differential in the HML portfolio. CORR is the conditional correlation between HML and the US dollar. $T - bill$ is the yield of the 1-year US Treasury bill. $FXvol$ is the foreign exchange volatility proxy from Menkhoff et al. (2012). TED is the TED-spread; the difference between the 3-month USD LIBOR rate and the 3-month US T-bill rate. $Payrolls$ is Total Non-farm Payrolls of US employees, obtained from the FRED, S:t Louis Fed database. Parentheses are t-stats, computed from Newey and West (1987) standard errors, with optimal lags according to Andrews and Monahan (1992). ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The sample period is December 1984 to July 2017.

5 Understanding the dynamics of CORR

Since CORR contains predictive information about currency returns it is important to understand the drivers behind CORR itself. From the previous section we know that it is highly correlated (87%) with the cross-sectional difference in volatilities, $\sigma^L - \sigma^H$, which is a correlation that can be understood through changes in diversification benefits across the risk factors. However, apart from that, it is less clear what characterizes periods of positive CORR compared to periods of negative CORR. While it is difficult to build intuition behind changes in $\sigma^L - \sigma^H$, CORR – being the correlation between a risky asset (carry) and an asset with safe-haven properties (dollar) – lends itself quite nicely. Thus, we proceed by studying how CORR is related to a set of common financial and macroeconomic variables, which then provides us with an economic intuition behind the dynamics of CORR.

Table 5 shows regression results and estimated correlations using seven different variables. Far more variables have been tested, but these seven will suffice in broadly describing the dynamics of CORR. To explain the table, the column labeled $Corr(CORR, \cdot)$ shows the unconditional correlation between CORR and the variable in the first column. Column three and four – labeled β and R^2 – show the results from regressing CORR on the variable in the first column. Reported in the two columns are the estimated slope coefficients, β, and the adjusted R^2. The final column shows the results from regressing CORR on all variables in the first column, in a single regression. Moreover, the following analysis is divided into three parts: interest rates; volatility; and a broad look at equity risk, illiquidity and macroeconomic indicators. Finally, I provide some economic intuition for how CORR is related to the US business cycle.

5.1 Interest rates

CORR is positively related to short term interest rates. The correlation between CORR and the 1-year US T-bill rate is 0.56, and in a regression of CORR on the 1-year T-bill rate, the

	$Corr(CORR,\cdot)$	β	R^2	Regression of CORR
T-bill 1-year	0.56	0.09^{***}	31.2	0.07^{***}
	[0.08]	(8.95)		(2.95)
$r^H - r^L$	0.43	74^{***}	18.0	31
	[0.10]	(6.66)		(0.79)
AFD	0.14	42	1.9	93^{***}
	[0.21]	(1.19)		(2.67)
$FXvol$	−0.33	-92^{***}	9.8	−39
	[0.11]	(−5.39)		(−1.65)
TED	0.23	0.24^{*}	5.4	−0.10
	[0.16]	(1.93)		(−1.07)
$S\&P500$	0.20	1.94^{***}	3.4	1.56^{***}
	[0.04]	(3.45)		(2.63)
VIX	−0.17	-0.01^{*}	2.7	0.001
	[0.17]	(−1.76)		(0.24)
IP	0.14	0.10^{**}	1.5	0.002
	[0.08]	(2.12)		(0.08)
Intercept	-	-	-	-93^{***}
	-	-	-	(−2.67)
N obs	-	-	-	331
$AdjR^2(\%)$	-	-	-	39.3

Table 5: Statistical relationship between CORR and other variables. The column labeled $Corr(CORR,\cdot)$ shows the unconditional correlation between CORR and the variable in the first column. Column 3 and 4, labeled β and R^2, show the results from regressing CORR on the variable in the first column. Reported in the columns are the estimated slope coefficients, β, and the adjusted R^2. The final column shows the results from regressing CORR on *all* variables in the first column, in a single regression. Brackets report standard errors from a stationary bootstrap procedure following Politis and Romano (1994) with the average block size according to Politis and White (2004). Parentheses are t-stats, computed from Newey and West (1987) standard errors, with optimal lags according to Andrews and Monahan (1992). All regressions and correlations are computed on contemporaneous variables, hence the time subscripts are left out to simplify notation. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The sample period is December 1984 to July 2017.

estimated slope coefficient is highly significant and the resulting adjusted R^2 is 31.2%. Also the average interest rate differential of the HML portfolio, $r^H - r^L$, is positively related to CORR, with a correlation of 0.43. Another relevant variable is the average forward discount (AFD), which is essentially the difference between the US interest rate and the average foreign interest rate. Lustig et al. (2014) show that the AFD contains predictive information about the US dollar. Although not statistically significant, the AFD has a positive correlation with CORR of 0.14, suggesting that when the US interest rate is high relative to the average foreign interest rate, CORR tends to be high.

Taken together, a high US interest rate and large differences in global interest rates are associated with a high correlation between carry trade returns and the US dollar. One possible explanation is that when US interest rates are high, the US dollar is more likely to be traded as an investment currency in carry trade strategies. That is, when investors are taking long positions in the carry trade they tend to be buying the US dollar. When carry trade positions are unwound, the US dollar is being sold. That way, a high US interest rate will imply a positive relationship between carry trade returns and the US dollar, i.e. a high CORR.

Importantly, even though the HML strategy is dollar-neutral by construction, actual trading patterns might involve taking the same (or opposite) position in the HML strategy as in the US dollar. Hence, it is reasonable that positive or negative correlations can arise between HML and the US dollar. The findings in this section suggest that the US interest rate and global interest rate differentials might be good indicators of such periods.

5.2 Volatility

To proxy for the volatility in foreign exchange markets, I use the measure introduced by Menkhoff et al. (2012).[20] As reported in Table 5, its unconditional correlation with CORR is -0.32. However, this negative relationship is not equally pronounced across the $[-1, 1]$ correlation interval. Figure 7 shows a scatter plot of FX volatility against CORR. Clearly, much of the negative relationship comes from the 12 monthly observations with the highest FX volatility, which all coincided with severe negative CORR. Thus, spikes in FX volatility are associated with extreme negative correlation between carry trade returns and the US dollar. Note also that the 11 months with the highest FX volatility occurred between September 2008 and October 2011; 8 of those 11 months were in 2008-2009.

These results suggest that there is a flight-to-safety mechanism present. In times of high

[20] Another FX volatility proxy that I have tried is the one used to predict carry trade returns by Bakshi and Panayotov (2013). I have also used equity-based volatility proxies, such as the VIX; the option-implied volatility of the S&P500. However, none of those proxies carries significant information in explaining CORR beyond the information already captured in the Menkhoff et al. (2012) proxy.

uncertainty, investors tend to unwind their risky positions and invest in safer assets (or, so-called, "safe havens"). If the US dollar is considered a safe haven, then higher-than-usual FX volatility may cause investors to unwind their carry trade positions and invest in, for example, US Treasury bills and bonds. That behavior would impose a negative correlation between HML and DOL, which is what we see during extreme levels of high volatility as depicted in Figure 7.

The research literature is providing mixed evidence regarding the safe haven status of the US dollar. Ranaldo and Söderlind (2010) study several currencies over the period 1993-2008 to see if they qualify as safe havens. They find that only the Swiss Franc and the Japanese Yen qualify, while the US dollar does not. However, others have found that the US dollar indeed may serve as a safe haven. For example, Kaul and Sapp (2006) shows that the US dollar was used as a safe haven during the uncertainty surrounding the millennium shift. Moreover, Hossfeld and MacDonald (2015) find that after controlling for the flow of funds attributable to the unwinding of carry trades, the Swiss Franc and the US dollar qualify as safe havens; not the Japanese Yen.[21] Jiang, Krishnamurthy, and Lustig (2019) build a model to study how US monetary policy – and thereby the US dollar – has a specific role in the global economy, in line with the "global financial cycle" described by Rey (2015).

This mixed evidence is consistent with the view that the safe haven characteristic of the US dollar is time-varying. The conditional correlation between carry trade returns and the US dollar may well capture this behavior, i.e. a negative CORR may indicate that the US dollar is currently regarded as a safe haven. CORR was, for example, negative during the financial crisis of 2008–2009; see Figure 3.

[21] Hossfeld and MacDonald (2015) find that the appreciation of the Japanese Yen, in times of financial stress, can solely be attributable to the unwinding of carry trades, which typically involves purchasing the Yen.

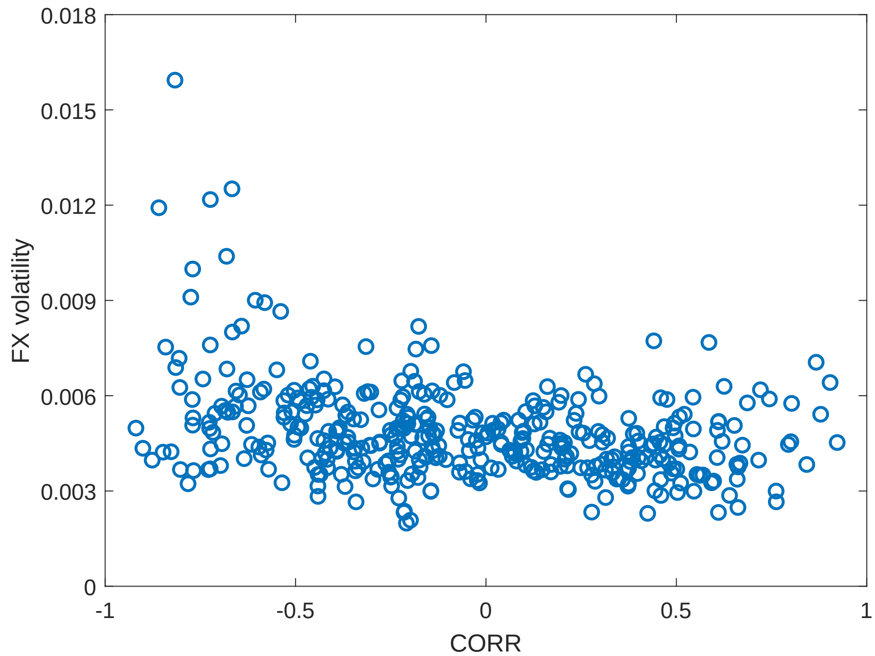

Figure 7: Scatter plot of FX volatility against CORR. The proxy for FX volatility is the one introduced by Menkhoff et al. (2012). CORR is the correlation between the high-minus-low carry trade strategy (HML) and the average change in exchange rates between the US dollar and the other G10 currencies (DOL). The sample period is December 1984 to July 2017.

5.3 Equity risk, illiquidity and macroeconomic indicators

CORR is also weakly related to other types of risks. The correlation between CORR and equity returns (S&P500) is 0.20, and even the coefficient estimate for the S&P500 in the regression using all test variables is positive and statistically significanty. The same relationship holds when considering *global* stock market returns; using the MSCI global stock market index. VIX is negatively related to CORR, with a -0.17 correlation estimate; although not statistically significant. Hence, high volatility in stock markets and low equity returns are associated with a low or negative CORR. To the extent that equity returns can serve as a proxy for risk appetite, these results are consistent with the flight-to-safety mechanism presented in the previous section.

The TED-spread is a common proxy for funding illiquidity and is defined as the difference between the 3-month USD LIBOR rate and the 3-month US Treasury bill rate.[22] A higher value of the TED-spread suggests a higher degree of funding illiquidity. The correlation between TED and CORR is positive and fairly large, at 0.23. While the positive correlation is inconsistent with the flight-to-safety mechanism, the estimated coefficient for the TED-spread in the regression using all test variables is slightly negative and not statistically different from zero. Hence, the importance of the TED-spread in explaining the variation in CORR is subsumed by the other variables in the regression. Most likely, the TED-spread is dominated by the 1-year T-bill rate, since the correlation between those two variables is 0.54 and highly statistically significant. Similar results are obtained when using the measure of global market liquidity presented by Karnaukh et al. (2015).

Finally, as a macroeconomic indicator we use US industrial production (IP), since Ludvigson and Ng (2009), Duffee (2011) and Joslin et al. (2014) have shown that it contains information about bond risk premia which is not captured by interest rates. Given the strong connection that we have already found between interest rates and CORR, IP may hold additional information. Also, Lustig et al. (2014) document that US industrial production can be used to predict returns on baskets of currencies against the US dollar, which makes it a potential candidate for explaining CORR. However, the connection with CORR is only weakly positive, and its estimated slope coefficient in the simultaneous regression on all variables comes out insignificant. The same result is obtained when using data on US payrolls, which is another commonly used macroeconomic indicator.

5.4 Connections to the US business cycle

As we have seen in the previous section, CORR is only weakly related to macroeconomic indicators. However, there is an intuitive connection between CORR and the US business cycle once we take into account the global interest rate differential. In this section I provide some economic reasoning for how the patterns in Figure 6 can be understood across the US

[22] For a more detailed discussion see Brunnermeier et al. (2009).

business cycle.

When the US business cycle is in an expansionary phase we typically see rising interest rates, as the Federal Reserve is hiking its policy rate to make financial conditions tighter. When interest rate levels are rising we also tend to see rising interest rate differentials.[23] CORR is positively related to the US interest rate, suggesting that it tends to increase during economic expansions. Good economic times are typically also associated with credit growth and high risk appetite, and investors are attracted by risky investments such as the carry trade.[24] Thus, during economic expansions and towards the peak of the business cycle, we see high interest rate differentials and high CORR, as well as good carry trade returns. This is exactly what we see in the data, as depicted in the top panel of Figure 6.

A recession is typically triggered by a shock of some kind; macroeconomic or financial. The immediate reaction in financial markets is a flight to safer assets, which involves sudden drops in the prices of risky assets, such as the carry trade. To the extent that the US dollar is regarded a safe haven, the dollar appreciates, implying a negative CORR. This happens quickly and before the central bank is able to lower their policy rates to provide stimulus. Thus, in the early phase of a recession we tend to see poor carry trade returns, negative CORR, and still large interest rate levels and differentials. This is consistent with the pattern in the top panel of Figure 6.

After the initial market correction, the central bank lowers the policy rate and eventually the investors' risk appetite is restored. This usually results in significant positive excess returns of risky assets, such as the carry trade.[25] Hence, this part of the business cycle is reflected

[23] For example, during the period 1985-2017 the unconditional correlation between the 1-year US T-bill rate and the HML interest rate differential is 0.68. Since the financial crisis of 2008 we have seen extremely low levels of interest rates globally, which may suggest that the high correlation is driven by the post-crisis part of our sample. However, even if we restrict our sample to 1985-2007, the unconditional correlation is 0.56.

[24] Collin-Dufresn, Goldstein, and Martin (2001) have shown that VIX serves as a good proxy for risk appetite, which is a link also made by Brunnermeier et al. (2009). In our data, the macroeconomic indicators (US payrolls and US industrial production) are negatively correlated with both VIX and the FX volatility proxy, suggesting that risk appetite is, in general, high during economic expansions and low during recessions.

[25] For example, in connection to the great financial crisis the HML carry trade suffered large losses between August 2008 and January 2009, with a cumulative return of -13%. Over the five months that followed, the carry trade recovered and delivered a cumulative return of 10%; see Figure 2.

in Figure 6, as the positive carry trade returns when CORR is negative and the interest rate differential is low.

6 Implications for the extant literature

There are several papers that, explicitely or implicitely, rely on the assumption that the carry factor and the dollar factor are orthogonal. For example, Lustig et al. (2011) find that the first and second principal component of excess returns in the cross-section of interest-rate sorted currencies vis-à-vis the US dollar are highly correlated with the dollar factor and carry factor, respectively. Since principal components are, by construction, orthogonal Lustig et al. (2011) are lead to the conclusion that also the factors are orthogonal. While that conclusion is justified in the unconditional case, the findings in this paper suggest that it does not hold when the correlation between the factors is allowed to vary over time.

Another example of a paper that relies on the assumption of orthogonal risk factors is the one by Verdelhan (2018), who builds a reduced-form model of exchange rates based partly on the previous work by Lustig et al. (2011, 2014), among others. In the general version of the model, the dollar and carry factors are not orthogonal, as they depend on the same types of shocks. However, after introducing a set of simplifying assumptions the factors become orthogonal. The original shocks are still accounted for in the model, but the assumptions imply that the factors are not exposed to the same types of shocks. This serves as motivation for Verdelhan (2018) to use the carry factor and the dollar factor to empirically summarize the systematic variation in bilateral exchange rates.

Without specifying the full set of details of the model, I will now discuss the assumptions that are most controversial given the findings presented in this paper. In the model, the stochastic discount factors of all countries are subject to a country-specific shock, as well as two types of global shocks. Let us denote the global shocks as $u_{w,t+1}$ and $u_{g,t+1}$, as they are denoted in the paper by Verdelhan (2018). The former shock can be referred to a as a "world" shock, and examples of such a shock could be a global financial crisis or increased global uncertainty (Lustig et al., 2014). Countries have different exposures to the shock, and the exposure is governed by the parameter δ_i. One of the assumptions by Verdelhan (2018) is that the loading of the US stochastic discount factor on the world shock, δ, is equal to the average loading that the foreign countries' stochastic discount factors have on the world shock, $\bar{\delta}_i$. As a result, the dollar factor becomes independent of the world shock. However, the findings in this paper suggests that both factors are indeed exposed to these types of shocks. Recall from Section 5.2 that CORR is significantly negative during times when FX volatility is high (see Figure 7). Specifically, the 11 months with the highest levels of FX volatility coincided with the global financial crisis. Hence, in response to a world shock, $u_{w,t+1}$, the US dollar tends to appreciate and the carry trade is performing poorly, i.e. there is significant negative correlation between the risk factors.

It is reasonable to believe that the United States has a special role in the global economy when there are large adverse shocks of the types that triggered the global financial crisis. However, this special role is inconsistent with the assumption of $\delta = \bar{\delta}_i$ in the model by Verdelhan (2018).

7 Skewness and crash risk

In this section I begin by exploring how CORR is related to the skewness of currency returns. I then show that CORR contains predictive information about carry trade crashes.

7.1 Skewness of returns across CORR

It has been well documented that standard carry trade strategies are subject to crash risk.[26] A common measure of crash risk is the skewness of returns; the more negatively skewed

[26] See, for example, Brunnermeier, Nagel, and Pedersen (2009), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015), Farhi and Gabaix (2016), Sokolovski (2017) and Chernov, Graveline, and Zviadadze (2018).

the higher the crash risk.[27] As we have seen in Table 3 the returns of the HML carry trade considered in this paper are indeed significantly negatively skewed, with an estimate of −0.76. In Section 4.1.3 we also noted the negative relationship with CORR – recall that when CORR is negative the average skewness in the following month is −0.47, compared to the more substantial −1.15 when CORR is positive (see Table 3). Is it then fair to conclude that the crash risk is higher during months following a positive CORR?

To address this, I explore the properties of carry trade crashes, using daily frequency of carry trade returns and CORR. I define *drawdowns* as the cumulative return during days of consecutive negative returns.[28] I then consider the 100 worst drawdowns as *crashes*. The top panel of Figure 8 shows a bar plot of the distribution of crashes (starting on day $t + 1$) across CORR (observed on day t), where CORR is split into 10 bins of equal size across the $[-1, 1]$ interval. In contrast to the presumption, more crashes occur after having observed a negative, rather than positive, value of CORR.

One concern may be that there are disproportionately many daily observations in the negative part of the CORR interval. To better capture the *likelihood* of observing a crash, the bars in the lower panel of Figure 8 represent the number of crashes scaled by the number of daily observations in each bin. We see that crashes are more likely to occur when the correlation is either strongly negative or strongly positive. Importantly, there is no evidence suggesting that crash risk is increasing with CORR.

Next, what if the average *size* of the crash is different across negative and positive CORR? If so, that could potentially explain the more negative skewness. However, the average cumulative returns of a crash during periods of negative and positive CORR are −2.1% and −1.9%, respectively. The difference between these averages is statistically insignificant (p-value of 37%), suggesting that the size of the crash is unrelated to CORR.

[27] Some papers (e.g. Brunnermeier et al. (2009)) suggest that the excess carry trade returns may be earned as a compensation for negative skewness; interpreted as crash risk. However, Bekaert and Panayotov (2017) are able to create carry trade returns with abnormal excess returns without a significant, negative skewness. The same holds for the dollar carry trade – introduced by Lustig et al. (2014) – which has little skewness.

[28] Drawdowns defined this way have also been studied by, for example, Daniel, Hodrick, and Lu (2016) and Sokolovski (2017).

Further, the negative skewness may be a product of the higher average carry trade returns. We have seen in Table 3 that the average Sharpe ratio of the carry trade, in months that follow a positive (negative) CORR, is 0.99 (0.20), while the skewness is -1.15 (-0.47). One might be tempted to conclude that the higher excess returns are earned as a compensation for the more negative skewness. However, the causality could also be reversed. Suppose that the higher excess returns are earned as a compensation for some other risk, such as the change in diversification benefits across the risk factors, as argued in this paper. Comparing periods of negative to positive CORR, the crashes are of the same size, as well as the standard deviations of returns (4.8% compared to 5.0%), only the average returns differ (1.0% compared to 5.0%). Thus, a crash observed during periods of positive CORR will be further to the left in the distribution of returns, than in the case of negative CORR. Hence, the more negative skewness of returns could be a result of the higher average returns.

7.2 Predicting carry trade crashes

Finally, we investigate the predictability of crashes. Specifically, we ask the following question: given that we observe a positive carry trade return today, what is the likelihood that a crash will start tomorrow? The dependent variable in the following regression analysis will be an indicator variable, that takes the value 1 if there is a crash starting tomorrow, and 0 otherwise. As regressors, we consider some of the common financial variables that we have used earlier in this paper: the interest rate differential; CORR; returns on the S&P 500 equity index; the TED-spread; and the VIX.[29] I apply a standard OLS regression, which may be unsuitable when considering a probability as a dependent variable, since the fitted regression might predict a crash probability that is outside the $[0, 1]$ interval. However, in our case, we are simply looking for statistical significance between the regressors and the depedent variable, to provide us with a general sense of the predictive power. For a more economically robust

[29] I intentionally keep the list of variables short in this test, mainly to save space and facilitate the interpretation of the results. Importantly, the main results are not changed even if I include all of the variables discussed earlier in the paper.

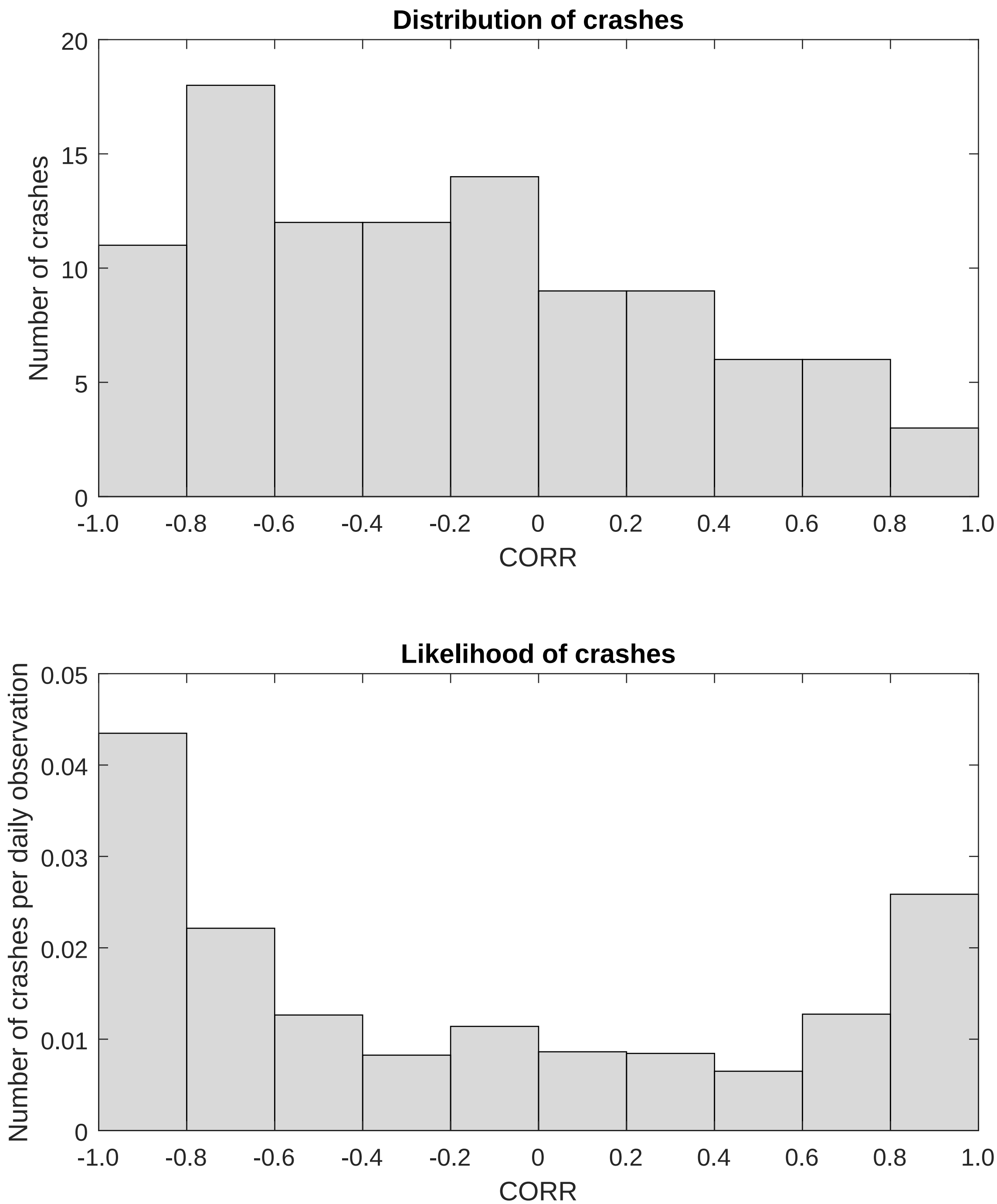

Figure 8: The distribution and likelihoods of carry trade crashes across CORR. CORR is divided in 10 bins of equal size across the $[-1,1]$ interval. The top panel shows the number of carry trade crashes in each bin. The bottom panel shows the number of carry trade crashes scaled by the number of daily observations in each bin, to reflect the likelihood of crashes.

model, one might consider, for example, a probit model, but I leave that to future research.

The regression results are presented in Table 6. The sample is split into negative and positive values of CORR, as observed on day t, while the potential crash starts on day $t + 1$. Note that to achieve a relatively high power of the test, I here define negative and positive CORR to be greater than or less than zero, respectively.[30] The top (bottom) panel shows the regression results for the observations given a positive (negative) CORR. Without discussing the significance of each regressor, we clearly see from the table that crashes are quite predictable when CORR is negative, while they are unpredictable when CORR is positive. In specification (vii), which includes all regressors, the adjusted R^2 when CORR is negative is 5.2%, while it is 0.0% when CORR is positive. Thus, we have uncovered yet another potential, non-competing, explanation for the high excess carry trade returns when CORR is positive. That is, during periods of positive CORR, investors may be compensated for the unpredictability of crashes.

To sum up, the evidence for a higher crash risk during periods of positive CORR is mixed. We observe a more negative skewness, but we also note that the causality between skewness and higher excess returns could be reversed. When comparing crashes during periods of negative and positive CORR, we find the average size of the crashes are statistically not different. However, crashes during negative CORR are to a certain extent predictable, which might indicate that the higher excess returns during periods of positive CORR are earned as a compensation for the unpredictability of crashes.

8 Conclusions

This paper presents a conjecture suggesting that there is a link from the correlation between risk factors to future excess returns. Hence, the correlation supposedly contains pre-

[30] One concern might be that the power of these tests is low since the number of crashes (100) is small, compared to the sample size (4514). The number of crashes during positive (negative) CORR is 39 (61). However, the results are robust to vastly increasing the number of crashes. For example, in Appendix B.4 I consider the 1000 worst drawdowns as crashes.

POSITIVE CORR

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$r^H - r^L$	2.62*		4.30				3.07
	(1.71)		(1.60)				(0.39)
$CORR$		−0.01	0.00				−0.05
		(−0.67)	(0.01)				(−0.70)
$\left(r^H - r^L\right) CORR$			−3.46				4.77
			(−0.74)				(0.26)
$S\&P500$				−0.46			−0.39
				(−1.20)			(−0.86)
TED					0.02		0.02
					(1.48)		(1.27)
VIX						0.00	−0.00
						(−0.14)	(−0.55)
Intercept	0.005	0.023**	0.003	0.482	−0.010	0.017	0.390
	(0.74)	(2.06)	(0.35)	(1.24)	(−0.55)	(1.05)	(0.83)
N obs	1982	1982	1982	1942	1847	1392	1358
N crashes	39	39	39	39	37	21	21
$Adj R^2 (\%)$	0.3	−0.0	0.3	0.0	0.2	−0.0	0.0

NEGATIVE CORR

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$r^H - r^L$	2.19		2.36				−18.09**
	(1.14)		(0.58)				(−2.01)
$CORR$		−0.07**	−0.04				0.08
		(−2.39)	(−1.09)				(1.31)
$\left(r^H - r^L\right) CORR$			−6.24				−34.24*
			(−0.60)				(−1.91)
$S\&P500$				−0.77			−1.00*
				(−1.34)			(−1.85)
TED					0.06**		0.06*
					(2.12)		(1.96)
VIX						0.003**	0.002*
						(2.15)	(1.70)
Intercept	0.016*	−0.000	−0.007	0.792	−0.066*	−0.033	0.961*
	(1.90)	(−0.06)	(−0.47)	(1.37)	(−1.83)	(−1.63)	(1.83)
N obs	2532	2470	2470	2467	2337	2337	2279
N crashes	61	61	61	58	54	56	53
$Adj R^2 (\%)$	0.0	0.9	1.2	0.3	2.9	2.1	5.2

Table 6: The predictability of carry trade crashes. The dependent variable is $\mathbb{1}^{HML}_{\{crash,t+1\}}$, which is 1 if there is a crash starting the next day, and 0 otherwise. The top (bottom) panel includes only observations when CORR is positive (negative). $r^H - r^L$ is the interest rate differential in the HML portfolio. CORR is the conditional correlation between HML and DOL. TED is the spread between the 3-month USD LIBOR rate and the 3-month US T-bill rate. VIX is the option-implied volatility of the S&P500 index. Parentheses are t-stats, computed from Newey and West (1987) standard errors, with optimal lags according to Andrews and Monahan (1992). ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

dictive information about excess returns. More specifically, the conjecture states that when the correlation between two risk factors increases, the benefits of diversification for an asset having positive (or negative) loadings on *both* risk factors is reduced. This is a result of the two risk factors essentially merging into a single risk factor as they begin to correlate. The reduced benefits of diversification is directly associated with more volatile returns. Through the effects of volatility timing, the higher volatility should predict lower Sharpe ratios in the near future.

Resorting to currency markets, I find strong evidence in support of the conjecture. Lustig et al. (2011) have shown that two factors can price a large fraction of the returns in the cross-section of currencies (taken against the US dollar) sorted by interest rates. The two factors are the *dollar* factor and the *carry* factor. According to the conjecture, a higher correlation between the risk factors should, on average, be associated with a lower (higher) volatility of high-interest-rate (low-interest-rate) currency returns and lead to a higher (lower) future Sharpe ratio.

First, I document that the correlation (CORR) between the two risk factors is highly time-varying; across almost the entire $[-1, 1]$ interval. Second, I find strong and significant correlations between CORR and the volatility of high interest rate currencies (-0.60) and low interest rate currencies (0.44), respectively. Even more pronounced is the correlation between CORR and the difference between the volatilities of low and high interest rate currencies, $\sigma^L - \sigma^H$, (0.87).

Moreover, I compare periods of negative CORR (below -0.25, which corresponds to 37% of the sample period) to periods of positive CORR (above 0.25, which corresponds to 28% of the sample period). For high interest rate currencies, the average next-month Sharpe ratio when CORR is negative is 0.32, while it is 1.03 when CORR is positive. For low interest rate currencies, the corresponding Sharpe ratios are 0.28 and -0.19, respectively. This predictability extends to the standard, high-minus-low carry trade strategy (HML). Comparing periods of negative and positive CORR, the average next-month Sharpe ratio of the HML strategy is 0.20 and 0.99, respectively. These results are also found in a regression analysis, while being robust to controlling for a large set of known predictors of currency returns.

Finally, I find evidence that CORR contains information about the predictability of carry trade crashes. Specifically, these crashes are predictable – using a small set of common financial variables such as the VIX index and the TED-spread – during periods of negative CORR. When CORR is positive, however, there is no evidence of crash predictability.

To the best of my knowledge, this is the first paper to study the time-varying correlation between risk factors. The findings presented here calls for additional work in this area. In particular, I leave it to future research to investigate if the conjecture presented in this paper extends to other asset classes as well.

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A Constructing daily HML returns

From monthly returns on the HML portfolio we compute *daily* returns. The idea is to mark the carry trade portfolio to market each day within the month. The forward contract is signed on day 0 (the last trading day of the previous month), with maturity on day T (the last day of the current month), and we are marking the portfolio to market on day $j \in (1, T-1)$. The cumulative market value of the portfolio is

$$V_j = \text{sign}(i^*_{0,T} - i_{0,T}) \frac{1 + i_{0,T}}{F_{0,T}} (S_j - F_{0,T}) - \left[i^*_{0,T} - i_{0,T} - \left((1 + \Delta_i)^j - 1 \right) \right], \tag{6}$$

where the daily interest rate differential, Δ_i, solves

$$(1 + \Delta_i)^T - 1 = i^*_{0,T} - i_{0,T}.$$

Note that for $j = 0$, equation (6) boils down to $V_0 = 0$. For $j = T$, we get the end-of-month value,

$$V_T = \text{sign}(i^*_{0,T} - i_{0,T}) \frac{1 + i_{0,T}}{F_{0,T}} (S_T - F_{0,T}). \tag{7}$$

The first term of equation (6) is the value of the contract as if it was the last day of the month, as in equation (7). On days in between, $j \in (1, T-1)$, the second term in equation (6) removes the interest rate differential earned between day j and T.

Finally, following Daniel et al. (2016), the excess daily return becomes

$$rx_j = \frac{V_j + (1 + i^*_{0,T})^{\frac{j}{T}}}{V_{j-1} + (1 + i^*_{0,T})^{\frac{j-1}{T}}} - (1 + i^*_{0,T})^{\frac{1}{T}}. \tag{8}$$

B Robustness checks

In this section I conduct a series of robustness checks.

B.1 Changing the size of the rolling window

Here is how the main results in Table 3 look like if we use an exponentially weighted moving average.

B.2 Computing CORR using an exponential moving average

In the baseline case, CORR is computing using an equal-weighted moving average. The main advantage of using this method is its simplicity, which makes the analysis transparent and easy to grasp. However, there are other, more sophisticated, methods for computing time-varying correlations that might better capture the true correlation. In this section we apply one such method, that uses a rolling window with *exponentially* distributed weights – giving higher weights to the more recent observations. This method requires the user to specify two parameters: the decay parameter, λ, which determines the relative weights; and the number of daily observations to include, T.

The same method for computing conditional correlations has been examined in detail by RiskMetrics™ (1996),[31] and they argue that this method more accurately captures the true time-varying correlation than a simple equal-weighted average. In a study on foreign exchange spot data, RiskMetrics™ (1996) find that at the conservative 0.1% tolerance level, the optimal parameters are 0.94 for the decay parameter, and 112 historical daily observations. I follow RiskMetrics™ (1996) and set $\lambda = 0.94$, and $T = 112$ in my equations below.

Let CORR^e denote this new correlation measure, and it is computed as

$$CORR_t^e = \frac{\sigma_t^{HML,DOL}}{\sigma_t^{HML}\sigma_t^{DOL}},$$

[31] RiskMetrics™ is a joint project between J.P. Morgan and Reuters. Their goal is to enhance the transparency on market risk, and make publicly available a set of techniques and data used to measure market risks. In 2010, RiskMetrics™ was acquired by MSCI. For more details, visit their website at https://www.msci.com/risk-performance.

where

$$\sigma_t^{HML,DOL} = (1-\lambda)\sum_{j=0}^{T-1}\lambda^j\left(rx_{t-j}^{HML} - \overline{rx}_t^{HML}\right)\left(DOL_{t-j} - \overline{DOL_t}\right),$$

$$\sigma_t^{HML} = \sqrt{(1-\lambda)\sum_{j=0}^{T-1}\lambda^j\left(rx_{t-j}^{HML} - \overline{rx}_t^{HML}\right)},$$

$$\sigma_t^{DOL} = \sqrt{(1-\lambda)\sum_{j=0}^{T-1}\lambda^j\left(DOL_{t-j} - \overline{DOL_t}\right)},$$

and where the averages are given by

$$\overline{DOL_t} = \frac{1}{T}\sum_{j=0}^{T-1} DOL_{t-j} \quad \text{and}$$

$$\overline{rx}_t^{HML} = \frac{1}{T}\sum_{j=0}^{T-1} rx_{t-j}^{HML}.$$

The resulting data series for CORR^e is at daily frequency, with 8246 observations. Monthly observations are constructed from end-of-month values, as in the baseline case. Table 7 presents the summary statistics for CORR^e and comparing these statistics to the baseline CORR in Table 2 we see that they are very similar.

		Full sample	CORR from previous month: Negative $[-1,-0.25]$	Low $(-0.25,0.25)$	Positive $[0.25,1]$
P1 (low interest rates)	Mean	0.6	2.1	1.1	−2.1
	Std Dev	9.0	7.3	8.9	10.9
	Skewness	0.21	0.14	0.51	0.14
	Sharpe Ratio	0.06	0.28	0.12	−0.19
	β^{DOL}	-1.04^{***}			
	β^{HML}	-1.02^{***}			
P2	Mean	2.3	1.9	2.4	3.0
	Std Dev	8.2	9.5	7.8	6.6
	Skewness	−0.36	−0.47	−0.08	−0.23
	Sharpe Ratio	0.28	0.20	0.30	0.45
	β^{DOL}	-0.93^{***}			
	β^{HML}	0.04			
P3 (high interest rates)	Mean	5.1	4.0	3.8	7.8
	Std Dev	10.4	12.6	9.6	7.6
	Skewness	−0.32	−0.50	0.15	−0.17
	Sharpe Ratio	0.49	0.32	0.39	1.03
	β^{DOL}	-1.04^{***}			
	β^{HML}	0.98^{***}			
HML (P3-P1)	Mean	2.3	1.0	1.3	5.0
	Std Dev	4.6	4.8	3.9	5.0
	Skewness	−0.76	−0.47	−0.84	−1.15
	Sharpe Ratio	0.50	0.20	0.34	0.99
Nr. of observations (% of full sample)		386 (100%)	143 (37%)	136 (35%)	107 (28%)

Table 7: Summary statistics of next-month excess returns (after observing CORR). From the nine non-USD G10 currencies, the three high (low) interest rate currencies are placed in portfolio P3 (P1). The reported values for β^{DOL} and β^{HML} come from estimating the regression: $rx_t^P = \alpha + \beta^{DOL} \cdot rx_t^{DOL} + \beta^{HML} \cdot rx_t^{HML} + \epsilon_t$, where rx_t^P corresponds to the excess returns of portfolio $P1$, $P2$ and $P3$. The frequency of the data is monthly, and the sample period is December 1984 to July 2017. Returns and standard deviations are expressed as percentages, and in annualized form; mean returns are multiplied by 12 and standard deviations are multiplied by $\sqrt{12}$. Sharpe ratios are computed by dividing the annualized mean return by the annualized standard deviation. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

B.3 Out-of-sample test

[TO BE INSERTED]

B.4 Increasing the number of crashes

TO BE INSERTED: a table when considering the 1000 worst drawdowns as crashes.