Crowds, Crashes, and the Carry Trade*

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Abstract

Currency carry trades exhibit sudden and extreme losses. A popular explanation is that these losses are to some extent driven by leveraged carry trade speculators amplifying negative shocks through forced unwinding of their positions. A testable implication is that the likelihood and intensity of large carry trade losses (crashes) increases with the level of carry trade activity (crowdedness). To test it, I develop a measure of crowdedness based on daily abnormal currency return correlation among the target currencies. This measure is related to other indicators of FX market activity. I show that between 40% and 50% of the largest carry trade losses occur in periods of high crowdedness. I further demonstrate that high levels of crowdedness double the probability of realizing an extreme carry trade loss after controlling for FX volatility, FX liquidity, equity volatility and funding liquidity. The level of crowdedness amplifies negative carry trade returns and has no effect on the positive ones. The results hold at multiple time horizons.

Keywords: Currency carry trade, currency risk factors, FX, hedge funds, liquidity, frictions, limits to arbitrage, predictability, systemic risk.

JEL Classification: C23, C53, F31, G11

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1 Introduction

"We have some very crowded trades in some areas [of currency markets] now . . . and leverage is increasing. Taken together, this leverage and carry trades create the prospect that we could have rapid repricing in financial markets."

Malcolm Knight (Managing Director of the Bank for International Settlements, 2007)[1]

The carry trade is a formulaic trading strategy of borrowing in low interest rate currencies and investing in those with higher interest rates. Historically, the currency carry trade has yielded high Sharpe ratios and its returns have been largely uncorrelated with standard systematic risks, which presents a challenge to traditional asset pricing theories (Eichenbaum, Burnside and Rebelo, 2007). However, the carry trade is also known to experience sudden and extreme losses or crashes. It is well documented that the carry trade returns are significantly negatively skewed (Brunnermeier, Nagel and Pedersen, 2009), and market commentators often characterize the carry trade as "picking up nickels in front of steamrollers" (The Economist, 2007).

Our understanding of the exact drivers of these carry trade (exchange rate) crashes is, however, limited. Carry trade crashes do not seem to be driven primarily by fundamental risks. Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and Jurek (2014) find that hedging the carry trade with options preserves the bulk of the expected returns. Morevover, Chernov, Graveline and Zviadadze (forthcoming) show, many large carry trade losses occur in the apparent absence of any relevant economic, political, or financial news. In contrast, policy makers and practitioners frequently assert that carry trade crowdedness (roughly defined as the size of the carry trade activity) is largely responsible for these crashes. It is also often implied that elevated levels of carry trade activity foreshadow the impending carry trade crash. However, to the best of my knowledge, the link between trade crowdedness and currency carry trade returns has not yet been empirically established. This paper examines this link with a particular focus on whether and how crowdedness increases the likelihood and intensity of a carry trade crash.

A large body of research exists on the currency carry trade, but the literature is yet to reach a consensus on the explanation for the high risk-adjusted returns on these currency

[1]Quoted in "Fears over Leverage and Crowded Carry Trade" by Gillian Tett and Chris Giles, The Financial Times, 26 January 2007.

strategies.[2] One view is that carry trade returns are, at least in part, a consequence of the carry trade activity (see Brunnermeier et al., 2009; Jylhä and Suominen, 2011; Nirei and Sushko, 2011; Plantin and Shin, 2014). In this paradigm, the buildup of carry trade positions may have some positive effect on the returns of the strategy as the demand of the carry traders leads to the strengthening of the investment currencies (associated with high interest rates) and a corresponding weakening of funding currencies (associated with low interest rates). More interesting is the implication that carry trades are prone to crashes because a negative shock could spark off a self-reinforcing loss spiral brought on by the unwinding of the large build-up of carry trade positions.

The mechanism driving carry trade crashes is based loosely on the theories of Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Pedersen (2009), among others, and can be summarized bearing two assumptions in mind. Firstly, we assume carry traders are on average highly leveraged and funding constrained (which is almost universal in currency trading). Secondly, we assume that, after a negative shock, many traders may be forced to rapidly unwind their entire position due to a number of (non-mutually exclusive) reasons such as margin calls and risk management technology constraints (for example stop-losses as in Osler (2005) and value-at-risk as in Brunnermeier and Pedersen (2009)). Given these assumptions, a large negative, but not necessarily extreme, shock to the carry trade portfolio could be amplified by a chain reaction of leveraged and funding-constrained traders forcefully unwinding their positions (particularly during times of low liquidity). This, in turn, puts further pressure on exchange rates and triggers more forced unwinding, thus culminating in a spiral of losses, i.e. a crash.

This mechanism appears both intuitive and economically plausible. However, for at least two reasons, *ex ante*, it is not obvious whether carry trade activity can have a systematic impact on carry trade returns. First, the notion that trading activity and the inner workings and frictions of the foreign exchange (FX) market have a non-trivial effect on exchange rates (beyond the very high frequency) represents a conceptual shift because it is not explicitly considered by traditional macro models of exchange rates. In those models, exchange rate changes, large and small, are driven by fundamental shocks, so that even carry trade crashes are simply the product of the unfavorable changes in fundamentals (see, for example, Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan (2009), and Farhi and Gabaix, 2016). Second,

[2] The currency carry trade is closely related to the literature on the forward premium anomaly that dates back to Hansen and Hodrick (1980), Fama (1984) and Bilson (1981). Engel (1996) provides a comprehensive survey of the forward premium anomaly literature, while Burnside (2012) specifically surveys the research on the currency carry trade.

the colossal size of the FX market presents another challenge. The FX market is unique in that it is characterized by a myriad of heterogeneous participants and is also the world's largest and most liquid market with daily average trading volumes in excess of five trillion U.S. dollars (King, Osler and Rime, 2012; BIS, 2016). Given this fact, it is possible that the trading activity of a single group of participants (i.e., the carry traders) may simply not be significant enough to have a price impact. Therefore, a comprehensive test on a long time series is necessary to establish whether there is persuasive evidence of the carry trade activity's effect on currency returns beyond the few publicized anecdotes.[3]

One implication of the carry trade activity loss amplification mechanism leads naturally to an empirically testable hypothesis. If this mechanism is present, and holding all else constant, elevated carry trade activity (crowdedness) should be associated with a higher likelihood of a carry trade crash (conditional on some exogenous shock process).[4] Moreover, this hypothesized relationship is predictive. The intuition is that the occurrence of a very large loss is more likely in periods of high carry trade activity because, relative to the periods of low carry trade activity, a negative shock of a given magnitude would be amplified to a greater degree in a period of high crowdedness. I test this hypothesis by exploiting the time series variation in carry trade activity.

A key input for the empirical test of this hypothesis is a reliable measure of carry trade crowdedness that is available at a reasonable frequency for analysis. Ideally one would require, at each point in time, the exact composition of the FX market containing the number of carry traders, their invested capital and their proportion relative to the other market participants. Unfortunately, no such information is available.[5] Despite being the world's largest market, the FX market is characterized by limited transparency and market fragmentation (King et al., 2012). With this in mind, I propose an indirect measure of carry trade crowdedness that can be constructed, using easily accessible data, for an extended time period. Lou and Polk (2013) develop a methodology for measuring "arbitrage activity" in the equity momentum strategy (they dub their measure "co-momentum"). I adapt their methodology to the currency carry trade and construct a measure of carry trade

[3] A frequently cited example of a currency crash that has been attributed to carry trade activity is the rapid appreciation of the Yen in October 1998 (see Cai, Cheung, Lee and Melvin, 2001).

[4] Particularly elevated levels of carry trade activity are often termed "crowded" periods. Hence, I use the terms carry trade activity and crowdedness interchangeably.

[5] Heath, Galati and McGuire (2007) review sources of data that could be used to gauge the levels of carry trade activity, only to conclude that measuring the volume of carry trades is "notoriously difficult" primarily due to data incompleteness. Curcuru, Vega and Hoek (2010) mirror the same sentiment and call for more comprehensive regulatory reporting in the FX market.

crowdedness that is based on the rolling correlation of the residual daily spot exchange rate changes of the most likely target currencies. The rolling correlations are calculated after purging the effects of the global FX and U.S. shocks using the dollar factor of Verdelhan (forthcoming). The measure is based on the premise that when traders take currency positions, their trades can have simultaneous price impacts on those currencies and thus cause return comovement. This premise is reasonable in the context of the FX market as Evans and Lyons (2002) demonstrate the existence of a significant positive link between currency order flow and nominal exchange rates. Essentially, the measure is designed to pick up on any footprints of carry trade activity left on the exchange rates.

As a motivating example, consider two currencies that are regarded as prototypical carry trade "funding" currencies: the Swiss franc (CHF) and Japanese yen (JPY). Over the last decade, a typical carry trader would most likely have been short both of these currencies. Figure 1 plots the 30-day rolling partial correlation between the daily changes in the CHF and JPY for the period 2000-2015. The partial correlation between their respective daily exchange rate changes between 1976 and 2006 is around 9% as one would expect for countries that are relatively unconnected; their economies are arguably very different, they are geographically distant and their bilateral trade links are minor (trade with Switzerland (Japan) represents less than 1.5% (9.5%) of Japan's (Switzerland's) total trade). Yet, over the two year period between 2006 and early 2008, the rolling partial correlation between these two exchange rates increased steadily from around zero to almost 85%, before reverting back to its mean. This increase in correlation coincided with one of the calmest periods in global markets, hence it is unlikely to have been driven by any increase in correlation during a crisis episode. Such a significant and steady increase in the correlation of the two currencies would be possible if the bulk of the day-to-day order flow was primarily driven by carry traders and their activity increased steadily over that period. Indeed, the existing literature documents strong growth in carry trade activity during that period (see, for example, Hattori and Shin, 2009). My proposed crowdedness measure is a generalization of this example. It is designed to capture most of such instances, irrespective of what the carry trade target currencies might be. Rather than using a fixed pair of currencies, the measure is comprised of the rolling partial correlations of the most likely funding and investment currencies. Using G10 currencies (the most liquid and most heavily traded currencies) spanning four decades, I construct a daily time series of the spot-FX-correlation-implied crowdedness measure for the full sample period. The measure exhibits meaningful time series variability and captures the trends in carry trade activity reported in the existing literature.

Next, I choose an exact carry trade formulation and define a carry trade crash. I focus on the equal-weighted portfolio of simple G10 currency carry trades that are constructed from daily data on spot and forward exchange rates. Taking the perspective of a U.S. investor, at the end of each month this strategy goes long the currencies that have a corresponding one-month interest rate higher than the U.S. interest rate, and goes short the currencies that have an interest rate that is lower.[6] This particular carry trade formulation is the most common choice in the literature and its returns exhibit the typical carry trade characteristics, namely low unconditional correlation with classical risk factors, a high Sharpe ratio and negative skewness. I define a carry trade crash as a drawdown belonging to the largest (most negative) 100 drawdowns in my sample.[7] A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns (Sornette, 2009).[8] The largest carry trade drawdowns occur, on average, over four days and represent key observations that give the sample distribution of carry trade returns its distinct negative skewness. The losses realized during these episodes are substantial (depending on the severity of the drawdown, losses vary between 50% and 100% of the carry trade's average annual profit). I also take an event time perspective and examine the returns of the U.S. equity market (a fair proxy for fundamental shocks) at the time of the largest carry trade drawdowns. I document that, on average, periods during carry trade crashes are also associated with negative equity returns. However, only 28 of the largest 100 carry trade drawdowns coincide with the similarly defined largest drawdowns in the equity market. This suggests that, although there is a link between fundamentals and carry trade crashes, it cannot be the full story, which is reassuring regarding the hypothesis tested in this paper.

Having established a carry trade crowdedness proxy and defined a crash, I turn to the main question of whether high crowdedness is associated with a higher likelihood of carry trade crashes. My results reveal that the bulk of carry trade crashes occur in periods with highly elevated levels of carry trade crowdedness. Figure 2 presents the summary of the main results. I categorize each day of the sample into carry trade crowdedness quintiles (lowest to highest) based on the level of my crowdedness measure taken on the previous day. I find that 41% of the 100 largest drawdowns begin on the days in the highest

[6] Although portfolio rebalancing is typically done monthly, returns (ignoring transaction costs) can be calculated over any horizon.

[7] All the main results are robust to instead defining a crash as the largest 20 or 120 drawdowns. As long as the measure is capturing most of the "worst-case" scenarios for a carry trade investor, the results hold.

[8] This choice is guided by the recent work of Daniel, Hodrick and Lu (forthcoming) who, utilizing this drawdown measure, document that the largest carry trade losses occur almost exclusively as clusters of negative returns and suggest that the negative carry trade return skewness calculated at the monthly frequency is significantly magnified by these negative daily return clusters.

crowdedness quintile. At this point, it is important to note that the relationship between carry trade activity and carry trade returns appears to be non-linear. This is in line with the theoretical predictions because a necessary condition for the unwinding amplification mechanism is that selling pressure generated by the carry trade unwinding is large relative to the other available capital on the sideline i.e. the forced unwinding is able to have a significant impact on exchange rates (Pedersen, 2009). Given the size of the FX market, this condition is likely to hold only at highly elevated levels of crowdedness.

Additionally, I show, using the full sample in a univariate probability model framework, that the elevated level of crowdedness significantly increases the probability of a crash (conditioning on high crowdedness doubles the unconditional probability). I then proceed to test whether the effect remains in the presence of other predictors. Of particular interest are predictors for which elevated levels may forecast lower (negative) carry trade returns. I consider four alternative predictors that have been documented in the literature as having some predictive power: global FX volatility, aggregate FX illiquidity, the stock market volatility and funding illiquidity (proxied by the TED spread). I find that the elevated level of carry trade crowdedness retains its predictive power even after controlling for the alternative predictors.

I also test for potential interaction effects between crowdedness and each of the other predictors. The results provide support for the presence of the amplification mechanism. The interaction between an elevated level of crowdedness and elevated levels of the other predictors is in all cases positive and significant. The positive marginal effect of FX volatility (illiquidity) on the probability of a carry trade crash increases more than 2.5 times in high-crowdedness periods. In the case of elevated levels of the stock market volatility and funding illiquidity, the results suggest that their predictive power stems primarily from their interaction with carry trade crowdedness. The case of funding illiquidity is particularly illuminating. Correlation with other factors aside, poor funding liquidity would be predictive of extreme carry trade losses only if there were a large number of leveraged speculators who would be affected by these deteriorated funding conditions and thus more likely to rapidly unwind their positions. This pattern is supported by the data. While elevated crowdedness retains its marginal and positive effect irrespective of the level of funding illiquidity, low funding liquidity only increases the probability of crashes during times of high crowdedness.

Next, instead of considering the likelihood of crashes, I examine crash intensities. I ask whether a high level of crowdedness is associated with magnification of the individual daily negative returns. The question posed is as follows: conditional on the carry trade return falling into a certain bottom percentile of its distribution, is the return more negative during crowded periods? The results show that, while the level of crowdedness does not affect median returns, conditional on returns falling into the bottom decile of their distribution, daily returns during periods of elevated crowdedness are significantly more negative than in uncrowded periods. The empirical non-linearity of the effect is in line with the hypothesized loss amplification mechanism, as only sufficiently negative returns are likely to trigger the forced unwinding. Controlling for other predictors and the interaction effects does not change these implications.

I also examine carry trade returns calculated at the monthly frequency in order to facilitate a comparison with the existing literature. I retain the non-linear approach and examine the conditional monthly returns of the carry trade following the months corresponding to each of the crowdedness quintiles. Of particular interest are the negative returns that are realized following crowded periods. I focus on the 25$^{\text{th}}$ percentile of conditional monthly carry trade returns. Following those months that fall into the lowest crowdedness group, the 25$^{\text{th}}$ percentile of carry trade returns is around -0.25% per month (-3% annualized), while the 25$^{\text{th}}$ percentile of returns following the months in either of the two highest crowdedness groups is -0.85% per month (around -10% annualized). In contrast, examining the 75$^{\text{th}}$ percentile of the conditional monthly returns, I find no significant difference between the crowdedness quintiles (the returns following the months that have lowest and highest crowdedness levels are 1.27% and 1.07% respectively). In line with the hypothesized mechanism, crowdedness has no effect, conditional on returns being positive. Meanwhile, if returns are negative elevated crowdedness contributes to the magnification of the losses. I also show that the level of crowdedness displays significant predictive ability in the monthly predictive regression framework. In sum, irrespective of empirical specification or time horizon, I find strong empirical evidence in favor of the hypothesis that elevated levels of carry trade crowdedness increase the probability of carry trade crashes.

Lastly, as robustnes test and to ensure that the spot-FX-correlation-implied crowdedness measure is sensible, I construct an additional measure based on hedge fund style analysis, which could be regarded as more direct, but is only available from 2000 to 2016. The alternative measure is constructed from the rolling regression coefficients of daily hedge fund returns, following the methodology of Pojarliev and Levich (2011). Specifically, the measure of carry trade crowdedness in each period is calculated as a count of hedge funds that positively and significantly load on a carry trade (controlling for other factors) during the previous three months as a proportion of the total number of funds in the sample. I show that the spot-FX-correlation-implied crowdedness measure is correlated with the hedge-fund-loading implied crowdedness measure.[9] Importantly, I find that the alternative crowdedness measure is also able to forecast carry trade crashes and has no significant effect on positive carry trade returns.

Related literature. This paper are complementary to the expansive literature that aims to reconcile carry trade profitability with risk. I build on the aforementioned theoretical and empirical work examining the relationship between carry trade activity and carry trade payoffs (Brunnermeier et al., 2009; Jylhä and Suominen, 2011; Plantin and Shin, 2014). I expand on the existing work primarily by taking advantage of the methodological developments and constructing a proxy for carry trade crowdedness over a long time period. In contrast to the existing studies, this allows me to test the theoretical implications more directly by exploiting the time series variation in my measure of carry trade crowdedness. This paper is closely related to the recent work on the predictability of currency carry trades (Cenedese, Sarno and Tsiakas, 2014; Bakshi and Panayotov, 2013; Egbers and Swinkels, 2015). In particular, Bakshi and Panayotov (2013) document the significant predictability of the dynamically rebalanced carry trade, but find that the predictability appears inconsistent with a theoretical model comprised of the two extant FX risk factors.[10] I find that the power of their proposed predictors is positive related to the level of carry trade crowdedness, which suggests a plausible economic channel through which to interpret their empirical findings. Thus, predictability of the carry trade returns may be linked to the size of carry trade activity. Finally, this paper also fits into the research agenda set forth in Stein's (2009) AFA presidential address, arguing that large volumes of arbitrage activity can become destabilizing.

2 Hypothesis development

In this section, I first introduce the notation and the key definitions. Then I state the main hypothesis of the paper and review the relevant literature in order to motivate the empirical strategy.

[9]For example, the results show that around 10% of the sample of hedge funds had a significant positive loading on a currency carry trade in June 2006, which steadily increased to its local peak of 29% by April 2008 (the difference is statistically significant).

[10]They consider the dollar factor of Lustig, Roussanov and Verdelhan (2011) and the innovations of aggregate FX volatility as in Menkhoff, Sarno, Schmeling and Schrimpf (2012).

When calculating payoffs to currency trading strategies, one has to take a perspective of some kind. I follow the literature and assume the perspective of a US investor. Let the level of the spot exchange rate of currency j at time t, quoted as foreign currency units per one U.S. dollar, be S_t^j. The forward exchange rate is denoted as F_t^j and quoted in the same way as the spot rate. Let the one-period dollar interest rate be $i_t^{\$}$ and let the one-period foreign currency j's interest rate be i_t^j. Ignoring transaction costs, I denote the one-period (usually a month) U.S. dollar excess return of borrowing one dollar in the U.S. money market and investing in the money market of a foreign currency j as:

$$z_{t+1}^j \equiv \left(1 + i_t^j\right) \frac{S_t^j}{S_{t+1}^j} - \left(1 + i_t^{\$}\right). \tag{1}$$

If covered interest rate parity (CIP) holds, then the payoff, z_{t+1}^j can be perfectly replicated in the forward market:

$$z_{t+1}^j = \left[\frac{F_t^j}{S_{t+1}} - 1\right] \left(1 + i_t^{\$}\right), \tag{2}$$

which can be interpreted as an excess return earned at $t+1$ of one dollar invested at t in a long forward foreign currency contract, scaled by one plus the one-period dollar interest rate. Similarly, the return to borrowing the appropriate amount of foreign currency j so as to invest one dollar in the dollar money market (or the scaled return of one dollar invested in a short forward foreign currency contract) is equal to $-z_{t+1}^j$.

The dollar payoff on the simple single foreign currency carry trade is

$$Z_{t+1}^j = w_t^j z_{t+1}^j, \tag{3}$$

where

$$w_t^j = \begin{cases} +1 & \text{if } i_t^j \geq i_t^{\$} \\ -1 & \text{otherwise.} \end{cases}$$

Depending on the interest rate differential, a carry trader either borrows one dollar and invests in the foreign currency money market, or borrows the appropriate amount of foreign currency and invests one dollar in the dollar money market. It is important to note that a carry trader locks in the positive interest rate differential (the "carry"), but remains exposed to exchange rate fluctuations. Hence, all the carry trade losses are driven entirely by unfavorable exchange rate movements.

Given the seminal result of Evans and Lyons (2002), who demonstrate the strong positive link between currency order flow and nominal exchange rates, it is possible that, if carry trade flows are large enough, the process of carry trade activity could affect exchange rates. The carry trade flows are particularly likely to be large and coordinated during carry trade unwinding. In those instances, strong and rapid demand for buying the funding currency and selling the investment currency could drive the price of the former down and the price of the latter up.

I begin with the basic premise that carry traders are, on average, highly leveraged and funding-constrained. The carry trade is a zero-cost strategy. Hence, in theory, leverage could be infinite. In reality, margin requirements may vary, but typically range from 2% to 5% (see Darvas, 2009). Moreover, given that the average carry trade returns are relatively low (around 3.5% per annum), it is likely that many investors would opt for the use of leverage, since to generate substantial profits speculators must wager large sums of money. Carry traders may also be subject to a number of non-mutually exclusive risk management constraints such as (i) margin constraints, (ii) value-at-risk constraints and (iii) automatic stop loss orders.[11] These self-imposed and financial-intermediary-imposed constraints only bind in the event of losses, and most likely only in the event of substantial losses. When any of these constraints binds a carry trader may be forced to immediately unwind his or her entire position. As these constraints stem from the institutional framework, they are also likely to be similar across traders and bind at the same time.

Thus, one large, but not necessarily extreme, unfavourable exchange rate shock could trigger a mass liquidation of carry trade positions as traders are forced to unwind due to the binding of their constraints. This simultaneous unwinding results in a large order flow that further depreciates the investment currency and appreciates the funding currency. This is the quintessential "run for the exit" that Pedersen (2009) describes. Therefore, this hypothesized amplification mechanism leads to the main empirically testable hypothesis.

H1: The likelihood of an extreme negative carry trade return realization (crash) is higher during times of elevated carry trade crowdedness.

Assuming, for a moment, that the exogenous shocks to carry trade returns are identically and independently distributed (i.i.d.) and ignoring other frictions, this hypothesis can be tested in a univariate framework. However, carry trade returns are shown to be time-

[11] For example, using high-frequency data Osler (2005) finds empirical evidence of stop-loss orders leading to downward "price cascades" in the FX market.

varying, hence it is imperative to adequately account for other known factors that may also increase the likelihood of a carry trade crash. It is worth noting that while there is a voluminous literature on both the equity return and exchange rate predictability, the literature on the predictability of dynamically rebalanced currency trading strategies such as the carry trade is still in its infancy. Nonetheless, at least four factors, that have been documented in the literature to have an impact on carry trade returns, need to be considered: global FX volatility, aggregate FX illiquidity, the Chicago Board Options Exchange (CBOE) VIX (options-implied volatility of the S&P 500 index) and funding illiquidity (usually proxied by the TED spread).[12] Elevated levels of each of the four factors could be expected to increase the probability of carry trade crashes. Hence, when testing the main hypothesis it is important to adequately control for the other factors. Moreover, taking into account the other factors stems an additional testable hypothesis.

H2: Elevated carry trade crowdedness amplifies any positive effects of the other factors on the likelihood of a carry trade crash.

If there is reasonable variation in carry trade crowdedness across time, both hypotheses can be tested in a time series framework. I do that in the next part of the paper.

3 Data

3.1 Currency data

For the construction of the carry trade returns, I restrict the sample to the G10 currencies, which historically have been the world's most liquid and most actively traded currencies

[12]The empirical literature finds strong links between FX volatility and currency carry trades. For example, Menkhoff et al. (2012) show that innovations in aggregate currency volatility perform very well in cross-sectional asset pricing tests of interest-rates sorted currency portfolios, whilst Christiansen, Ranaldo and Söderlind (2011) show that, in a factor model framework, the loading of the carry trade returns on the global equity market is dependent on the FX volatility regime. In turn, Bakshi and Panayotov (2013) show change in FX volatility to be important predictor of currency carry trade returns at multiple horizons. Brunnermeier et al. (2009) find that changes in the VIX and TED spread display some limited predictive power for carry trade returns, while Bakshi and Panayotov (2013) show a global equivalent of the TED spread negative forecasts carry trade returns. Additionally, recent work documents a strong commonality in liquidity across currencies and suggests that deterioration in aggregate FX liquidity is related to negative carry trade returns (Mancini, Ranaldo and Wrampelmeyer, 2013; Karnaukh, Ranaldo and Söderlind, 2015).

(BIS, 2016). This is also the most common choice in the literature.[13] Given the focus on the extreme returns, I deliberately exclude all emerging market currencies so as not to contaminate the sample with large idiosyncratic shocks. The sample consists of the Australian dollar (AUD), the British pound (GBP), the Canadian dollar (CAD), the euro (EUR), appended with historical data for the Deutsche mark (DEM), the Japanese yen, (JPY), the New Zealand dollar (NZD), the Norwegian krone (NOK), the Swedish krona (SEK), the Swiss franc (CHF), and the U.S. dollar (USD). I sourced the daily data on spot and one-month forward exchange rates from Datastream. Each exchange rate is quoted as foreign currency units per USD, making nine exchange rate series in total. The exchange rate data are supplemented with eurocurrency interest rates data that are also sourced from Datastream. For most currencies, the sample starts on 2 January 1976, and ends on 1 April 2016, which amounts to a total of 10 501 daily observations.[14]

For the construction of the global FX illiquidity measure I follow the methodology of Karnaukh et al. (2015). To this end, I sourced data on the daily high and low spot exchange rates from Thomson Reuters (via Datastream) and the daily bid and ask spot FX rates from Bloomberg for the nine G10 exchange rates *vis a vis* the USD. Following Karnaukh et al. (2015), I supplement the initial G10 currency sample with data on all the available cross-rates between the G10 currencies.[15] I only deviate from Karnaukh et al. (2015) in that I exclude all non-G10 currencies.[16] Hence, the sample for the calculation of illiquidity is comprised of twenty-three exchange rates in total (nine exchange rates vs. the USD plus fourteen cross-rates). The sample period for the global FX illiquidity measure runs from January 1991 to April 2016.

3.2 Other data

I sourced daily data on the TED spread (the difference between the three-month U.S. LIBOR and U.S. T-Bill interest rates) and the CBOE VIX index (options implied volatility of the S&P 500 index) from the Federal Reserve Economic Data (FRED). The sample periods are January 1986 to April 2016 for the TED spread and January 1991 to April 2016

[13]See for example Christiansen et al. (2011), Daniel et al. (forthcoming) and Jurek (2014).

[14]Data for the JPY start on 8 June 1978. Data for AUD and NZD start on 14 December 1984. The DEM series ends and EUR series begins on 1 January 1999.

[15]The included cross-rates are AUD/EUR, CAD/EUR, JPY/EUR, NZD/EUR, NOK/EUR, CHF/EUR, GBP/EUR, AUD/GBP, CAD/GBP, JPY/GBP, NZD/GBP, NOK/GBP, SEK/GBP and CHF/GBP.

[16]I exclude the Indian Rupee, Mexican Peso, Singaporean Dollar and South African Rand.

for the VIX. Daily data on the three Fama-French factors came from Kenneth French's data library (those data were available for the same period as the main currency data). I sourced the AUD turnover data from the Reserve Bank of Australia. I sourced the quarterly total assets under management (AUM) of currency hedge funds from Barclay Hedge.

4 Definitions

4.1 Currency carry trade

I focus on the equal-weighted simple carry trade portfolio of N_t currencies, which is the version that is most often studied in the literature (see, for example, Eichenbaum et al., 2007). For most of the sample the number of currencies is equal to nine (the G10 currencies against the U.S. dollar). Following previous work, the strategy is rebalanced monthly. Then, if t is the end of a given month, and $t+1$ is the end of the following month, the carry trade portfolio monthly excess return is

$$R_{\text{Carry},t+1} = \frac{1}{N_t} \sum_{j=1}^{N_t} Z_{t+1}^{j}, \tag{4}$$

where Z_{t+1}^{j} is as defined in Equation 3. I divide by N_t to normalize the total size of the portfolio exposure to one USD. For each currency j in the sample, I use the eurocurrency interest rate inferred from the forward exchange rate and USD interest rate under the assumption of covered interest rate parity.

I also calculate the daily returns for a monthly carry trade strategy. Following the approach of Daniel et al. (forthcoming), I assume a trader has one dollar of capital (collateral) deposited in the bank at $t-1$ and earns the one-month dollar interest rate, $i_t^{\$}$, prorated per day. I further assume traders borrow and lend at the prorated one-month euro-currency interest rates. At time $t-1$, the trader enters the carry trade strategy defined above, which is rebalanced at the end of month t. Let $P_{t,\tau}$ denote the cumulative carry trade profit realized on day τ during month t. The accrued interest on the one dollar of committed capital is $\left(1+i_t^{\$}\right)^{\frac{\tau}{D_t}}$ by the τ^{th} trading day of month t with D_t being the number of trading days within the month. The daily excess carry trade return can then be calculated as follows:

$$R_{\text{Carry},t,\tau} = \frac{P_{t,\tau} + \left(1+i_t^{\$}\right)^{\frac{\tau}{D_t}}}{P_{t,\tau-1} + \left(1+i_t^{\$}\right)^{\frac{\tau-1}{D_t}}} - \left(1+i_t^{\$}\right)^{\frac{1}{D_t}}. \tag{5}$$

4.2 Carry trade crashes

In order to relate carry trade crowdedness to carry trade crashes, it is important to establish a well-defined notion of what is classified as a crash. If a crash is brought on by the forced, rapid unwinding of carry trade positions, it is likely to be realized very quickly. Although, the literature predominately examines monthly returns, the theory being tested in this paper calls for a suitable definition at a higher frequency. What is needed is a measure that is able to capture from the data the "worst-case scenarios" for the carry trade investors.

One fitting measure is a drawdown, defined as the cumulative loss from consecutive daily negative returns (Sornette, 2009).[17] Daniel et al. (forthcoming) analyze the largest (most negative) carry trade drawdowns. They document that the largest drawdowns occur, on average, over several days. In contrast to the practitioners' adage, exchange rates seem to go down the escalator rather than the elevator. They further show that the negative skewness of the carry trade returns measured in the data at the monthly or weekly frequency stems primarily from these sequences of persistent negative daily returns that are captured by the drawdown measure. Finally, they show that the drawdowns of the equal-weighted G10 carry trade observed in the data never occur in stationary bootstrap simulations. Hence, there appears to be significant time-varying autocorrelation of the negative daily carry trade returns, but its exact source is not currently clear.[18]

In sum, the extreme drawdowns of the currency carry trade seem to allow us to identify the key episodes in the data that give the monthly carry trade returns their characteristic

[17]Two alternative candidates are extreme negative daily and weekly returns, but both have shortcomings. It is limiting to consider a measure based only on single-day returns because the largest carry trade losses occur, almost exclusively, as a sequence of negative, but not necessarily extreme returns (Daniel et al., forthcoming). The shortcoming of defining a crash in terms of weekly returns, on the other hand, is that the realized dynamics of large carry trade losses may not, in a given sample, abide by calendar time. For example, a large loss may occur from Thursday of one week to Tuesday of the next. A definition involving non-overlapping weekly returns would underestimate the magnitude of such a loss.

[18]For example, the daily autocorrelation is unlikely to be purely an artefact of slow information diffusion because it is well established in the literature that, in the FX market, news are incorporated into prices within minutes (see, for example, Andersen, Bollerslev, Diebold and Vega (2003)).

negative skewness.[19] Therefore, I classify a carry trade crash as a drawdown belonging to the top (most negative) 100 drawdowns in the sample.[20] The following subsections present detailed descriptive statistics of the carry trade crashes and test formally whether carry trade crowdedness increases the likelihood of occurrence of these crashes.

4.3 Factors

4.3.1 Dollar factor

The dollar factor is defined as the average currency excess return of all other currencies against the USD. At time t, the dollar factor, denoted DOL_t, is given by

$$\text{DOL}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} z_{t+1}^j,$$

where N_t denotes the number of available currencies at time t and z_{t+1}^j is the one-period excess return on currency j defined in Equation 1. The dollar factor is essentially the average return of a strategy that borrows money in the U.S. and invests in global money markets outside the U.S. The dollar factor relates to both global and U.S. shocks.

The dollar factor was first introduced by Lustig et al. (2011) in the context of explaining the cross-sectional spread in the average returns of currency portfolios sorted based on interest rates. Lustig et al. (2011) interpret the dollar factor as capturing the level effect, as all the interest-rate-sorted currency portfolios appear to load equally on it. The second proposed factor, HML_{FX} (a return on a high-minus-low strategy that goes long a portfolio of highest-interest-rate currencies and short a portfolio of lowest-interest rate currencies), by construction orthogonal to the dollar factor, is used to capture the slope.

More recently, Verdelhan (forthcoming) has shown that the dollar factor and the carry trade factor, HML_{FX}, account for 18 to 80% of the variation in bilateral exchange rate movements. The results appear to hold at daily, monthly, quarterly and annual frequencies.

[19] To further demonstrate that a drawdown is a good metric in capturing the key features of the carry trade return process, I perform an informal experiment. I ask what is the minimum number of the top 100 drawdowns, that need to be excluded to yield a point estimate of the monthly carry trade returns skewness that is positive. The answer is that only the top 16 drawdowns (around 80 trading days which amounts to 0.78% of the sample) need to be excluded for this to occur.

[20] All the main results are robust to changes in the definition, for example, defining the crash as the top 60, 80 or 120 drawdowns instead.

It is important to note that Verdelhan (forthcoming) also shows that, for all the exchange rates in his sample, the dollar factor captures the lion's share of the explained time-series variation in the bilateral exchange rate changes, at all frequencies.[21]

4.3.2 FX volatility

As the main proxy for global FX volatility, I use the same measure as Bakshi and Panayotov (2013). For each currency in the sample, I construct monthly volatility as the square root of the sum of squares of daily log changes in the spot exchange rate against the USD over a month. The global FX volatility in the month ending at time t is the simple average across the available currencies and is given by

$$\sigma_t^{\mathrm{FX}} = \frac{1}{N_t} \sum_{j=1}^{N_t} \left[\sum_{\tau \in D_t} \left(\ln \frac{S_\tau^j}{S_{\tau-1}^j} \right)^2 \right]^{\frac{1}{2}}, \tag{6}$$

where N_t denotes the number of available currencies on day τ and D_t denotes the total number of trading days in the month ending at time t.[22]

4.3.3 FX illiquidity

To proxy for global FX illiquidity I use the measure proposed by Karnaukh et al. (2015). Until recently an accessible and reliable measure of FX market liquidity was not available. Karnaukh et al. (2015) provide a methodology for calculating a reliable spot FX illiquidity for individual currencies using daily and readily available data.[23] Importantly, Karnaukh

[21] For example Verdelhan (forthcoming) reports that the adjusted R^2 of a regression of daily changes in the JPY/USD spot exchange rate, with both factors and just the dollar factor, are 56.30 and 55.10 respectively.

[22] Menkhoff et al. (2012) use a very similar measure, with the main difference being that they use absolute daily log returns instead of squared returns so as to minimize the impact of outlier returns. However, in my sample of G10 currencies, the two measures are almost identical (correlation of 0.98) and all the results are robust to the use of either of the two measures.

[23] For each spot exchange rate a monthly illiquidity measure is constructed as a simple average between a relative bid-ask spread (calculate each day from Bloomberg's bid and ask quotes snapped at 5 p.m. EST and averaged over the month) and the Corwin and Schultz (2012) bid-ask estimator (implied from the daily high and low values under the assumption that the high price is buyer-initiated and the low price seller-initiated. Karnaukh et al. (2015) show that their proposed illiquidity measure is highly correlated to an FX illiquidity benchmark that is calculated using precise high-frequency (intraday) data. Refer to Karnaukh et al. (2015) and the accompanying internet appendix for full details of the liquidity measure's construction and properties.

et al. (2015) propose a measure of global FX illiquidity that is calculated as a simple average of all the individual spot exchange rate illiquidity measures. The monthly time series of the global FX illiquidity measure is constructed by taking the simple average across the individual monthly illiquidity measures of the twenty three exchange rates in my sample.[24]

4.3.4 Stock market volatility and funding liquidity

The equity market is a good barometer of the economics conditions. Hence, I use the equity market volatility as a proxy for fundamental volatility and uncertainty. I measure stock market volatility using the CBOE VIX, which is the implied volatility of Standard and Poor's 500 index options. Elevated levels of the VIX may not only capture U.S. equity volatility, but also more general financial distress and uncertainty, which is an additional advantage of the measure. The VIX has been shown to have a significant negative contemporaneous relationship with the returns of carry trade strategies (see Clarida, Davis and Pedersen, 2009) as well as some predictive ability (see Brunnermeier et al., 2009; Nirei and Sushko, 2011).

To gauge funding liquidity I use the TED spread (the difference between the London Interbank Offered Rate and T-Bill rate), which is a commonly used proxy for funding liquidity. Similarly, to the VIX the TED spread has been shown to have a negative contemporaneous and predictive relationship with carry trade returns.

4.4 Carry trade crowdedness

One cannot measure carry trade activity directly, due to both data incompleteness and inability to distinguish carry trade positions from other trades (see Heath et al. (2007) for a detailed discussion of these issues). Therefore, I consider indirect measures of carry trade crowdedness.

The main measure of crowdedness I use is constructed from the abnormal daily return pairwise correlation among the currencies that a typical carry trade speculator would use to execute her carry trade strategy. The methodology is inspired by the Lou and Polk (2013)

[24] My monthly global illiquidity measure based only on G10 currencies has a correlation of 0.97 with the the original Karnaukh et al. (2015) measure that is available for download via their web-page with data up to May 2012.

who propose a measure that they dub "co-momentum" that aims to gauge crowdedness in the equity momentum strategy. The measure is based on the premise that when traders take positions, their trades can have simultaneous price impacts on those assets and thus cause return comovement. This is related to the phenomenon known as "price-pressure" that is discussed in the microstructure literature. In the presence of price pressure the price at which investors can buy or sell an asset depends on the quantity they wish to transact. Importantly, the decentralized structure of the foreign exchange market and the bilateral nature of its trade (customers trade with dealers and brokers) make the presence of price pressure particularly likely due to both asymmetric information and inventory motives (see for example Easley and O'Hara (1987)). This appears to be the case empirically. In their seminal paper, Evans and Lyons (2002) show that order flow and nominal exchange rates are strongly positively correlated, indicating that price increases with buying pressure. Thus, it is reasonable to look at price (exchange rates) directly for traces of significant carry trade activity. That is the goal of the spot FX rate correlation-implied crowdedness measure.

The measure is constructed daily using a rolling window. Each day, I sort the set of available currencies based on their average interest rate $\bar{i_t}$ over the previous 30 days. I identify the two currencies with the highest interest rates (investment currencies) and two with the lowest (funding currencies) during the 30 days window. The carry trader is assumed to short the funding currencies and go long the investment currencies. Those four currencies are assumed to be the most likely carry trade targets that would receive the bulk of carry trade order flow during a given time period.

Focusing on the top and bottom two currencies is motivated by two considerations. First, in practice, carry traders almost always construct carry trade strategies out of portfolios of currencies because this dramatically improves the Sharpe ratio.[25] Second, carry traders, most likely, tilt their allocation towards the currencies with the highest and lowest interest rates by either only trading currencies with the highest (lowest) interest rates or spread weighting their portfolios (for example Jurek (2014) considers interest rate spread weighted carry trade portfolios).[26] Thus, from an empirical perspective, focusing on the

[25] All all investable carry trade indices are portfolios of currencies. For example, the widely tracked Deutsche Bank G10 FX Carry Basket Index is constructed by going long the three currencies with the highest three-month Libor rates and going short the three currencies with the lowest three-month Libor rates.

[26] See Bekaert and Panayotov (2016) for a comprehensive list of different carry trade portfolio specifications that are considered in the literature and in practice.

subset of the most likely carry trade target currencies is reasonable as that ought to increase the power of the measure in picking up evidence of carry trade order flow.

For each of the identified target currencies and on each trading day, τ, I estimate the following regression using ordinary least squares on daily data over the previous 30 days:

$$\left(\frac{S^j_{\tau+1} - S^j_{\tau}}{S^j_{\tau}} \right) = \alpha + \beta_{\mathrm{DOL}}\, \mathrm{DOL}_{\tau+1} + e^{\mathrm{j}}_{\tau+1} \tag{7}$$

where all the variables are defined as before. The motivation for the regression specification is that it is an attempt to purge from daily spot exchange rate changes the U.S. and global effects, thus leaving only the country specific effects.[27]

Next, I use the regression residuals to calculate six correlations coefficients:

$$\begin{aligned} \mathrm{corr}_t^{I_1 I_2} &= \mathrm{Corr}\left(e^{I_1}, e^{I_2}\right) & \qquad \mathrm{corr}_t^{F_1 F_2} &= \mathrm{Corr}\left(e^{F_1}, e^{F_2}\right) \\ \mathrm{corr}_t^{I_1 F_1} &= \mathrm{Corr}\left(e^{I_1}, e^{F_1}\right) & \qquad \mathrm{corr}_t^{F_2 I_1} &= \mathrm{Corr}\left(e^{F_2}, e^{I_1}\right) \\ \mathrm{corr}_t^{I_2 F_1} &= \mathrm{Corr}\left(e^{I_2}, e^{F_1}\right) & \qquad \mathrm{corr}_t^{F_2 I_2} &= \mathrm{Corr}\left(e^{F_2}, e^{I_2}\right) \end{aligned}$$

where, I_1, I_2 and F_1, F_2 refer to the two investment and funding currencies respectively. For example, $\mathrm{corr}_t^{I_1 I_2}$ is the estimate of the correlation coefficient between the two investment currencies over the period $t - 30$. Similarly, the $\mathrm{corr}_t^{F_1 I_1}$ the estimate of the correlation coefficient between the currency with the lowest interest rate (the first funding currency) and the currency with the highest with highest interest rates (the first investment currency).

Each of these six correlation coefficients could be considered a proxy of carry trade crowdedness.[28] During periods in which the carry traders are responsible for the bulk of the FX order flow, we would expect to see higher levels of correlations between the two investment currencies and also higher levels of correlation between the two funding currencies. The correlation between an investment and a funding currency is expected to be relatively more negative during periods of high carry trade activity.[29] However, due

[27] The dollar factor in each regression does not include the bilateral exchange rate j that is the dependent variable.

[28] In a similar vein, Lou and Polk (2013) consider the average correlations among the winner stocks, the loser stocks and the correlations between the winner and loser stocks as separate measures.

[29] As a carry trade short sells the funding currency and goes long the investment currency, the observed price patterns should correspond do increased negative correlation between the funding and investment currency.

to the limited cross-section of currencies I, instead, consider the signed average of all the correlation in order to reduce the noise.

My spot exchange rate correlation implied crowdedness is denoted $\text{Crowd}_t^{\text{FX}}$ and defined as follows.

$$\text{Crowd}_t^{\text{FX}} = \frac{\text{corr}_t^{I_1 I_2} + \text{corr}_t^{F_1 F_2} - \text{corr}_t^{I_1 F_1} - \text{corr}_t^{F_2 I_1} - \text{corr}_t^{I_2 F_1} - \text{corr}_t^{F_2 I_2}}{6} \tag{8}$$

where the correlations between investment and funding currencies enter with a negative sign because in those cases larger negative correlation would correspond to larger carry trade flows.

It is worth mentioning that it should not be a concern that many carry trade transactions are executed in the forward market, while my measure is based on correlation of spot exchange rate changes. First, the spot market is significantly larger than the forward market.[30] Second, any excess demand from the forward transactions, which is most informative, would be directed to the cash market by the financial intermediaries.

5 Descriptive statistics

5.1 Carry trade returns

Table 1 reports the descriptive statistics for the monthly and daily returns of the equal-weighted carry trade portfolio of G10 currencies. For the full sample, the carry trade portfolio has a statistically significant annual return of around 3.5% (t-statistic based on Newey-West standard errors is 3.95). More impressive is the annualized Sharpe ratio of 0.7, which is due primarily to the large gains to diversifying the carry trade across different currencies (Burnside, Eichenbaum and Rebelo (2008) come to a similar conclusion).[31]

As Brunnermeier et al. (2009) note, diversification has little effect on the pronounced negative skewness of the carry trade strategies. I find that the equal-weighted carry trade portfolio has monthly skewness equal to – 0.55. I also find that the daily carry returns are

[30] As of April 2016 the spot daily trading volume was 1.7 trillion USD and the trading volume of outright forwards was 700 billion USD.

[31] The Sharpe ratio for the U.S. stock market was around 0.5 for the same sample period.

negatively skewed, but less so than the monthly returns (the point estimate of the skewness of daily returns is equal to – 0.38). Daniel et al. (forthcoming) note that the difference between skewness measured at the monthly and daily frequencies is significant and stems from the fact that large negative daily returns tend to occur in clusters. I explore this issue in more detail when I examine carry trade crashes. There is no evidence of significant autocorrelation in either the monthly or daily carry trade returns.

Finally, for illustrative purposes, Figure 3 displays the plots for cumulative and monthly carry trade returns respectively. The cumulative returns are calculated assuming that in February 1976 an investor deposits 1 USD collateral into an interest bearing bank account (earning USD Libor) and commits to the carry trade strategy. The investor reinvests the proceeds monthly. Over the last four decades the currency carry trade was very profitable (the 1 USD in 1976 grew to 37 USD by 2016), however carry trade investors have also endured a few extreme negative monthly returns throughout the period.

5.2 Carry trade crowdedness

Table 2 presents the basic descriptive statistics of the end-of-month crowdedness measure. The mean level is 0.2 and the measure varies substantially from the minimum of -0.37 to the maximum of 0.86. The crowdedness measure exhibits significant autocorrelation, but the autocorrelation is not perfect (the autocorrelation coefficient is 0.67). Given that the crowdedness measure is constructed from correlations of the daily changes in exchange rates, it is imperative to ascertain that it is not just picking up patterns in the average FX correlation. Table 2 also presents descriptive statistics for the end-of-month average pairwise correlation among my sample of currencies. First, we see that the mean, minimum and maximum of the average pairwise correlation of currencies is very different from those of the crowdedness measure. The average aggregate FX correlation is slightly negative (-0.1) and aggregate FX correlation varies relatively little during the sample period. Second, and most importantly, the correlation between my crowdedness measure and the average pairwise currency correlation is only 0.1 (tabulated in Panel B of Table 2). Hence, my crowdedness measure is not simply capturing the average currency correlation.

Similarly, it is important to ascertain that the crowdedness measure is not capturing trends in aggregate FX volatility. Panel A of Table 2 also presents the summary statistics of aggregate FX volatility and Panel B shows its correlation with my measure of carry trade crowdedness. The crowdedness measure is slightly correlated with aggregate FX volatility (the correlation coefficient is 0.22), however the main patterns of the carry trade crowdedness measure do not seem at all related to FX volatility. The top panel of Figure 4 displays the three-months moving average of the monthly time series of the crowdedness measure. The bottom panel of Figure 4 shows the three-months moving average of the monthly time series of the crowdedness measure that has been orthogonalized with respect to FX volatility (i.e. the residuals from the regression of carry trade crowdedness on FX volatility). Visually, the two figures appear almost identical, hence my crowdedness measure is unlikely to be driven by aggregate FX volatility.

The absolute levels of the measure, however, are not very meaningful because the measure is a proxy and is best suited for identifying trends in carry trade activity and for ordinal characterization of different time periods. In the empirical tests that follow, I use predominately the ordinal measure of crowdedness. Hence, in the section, I concentrate on examining the general patterns in the FX correlation-implied carry trade crowdedness measure and relating it to other available indicators of carry trade activity.

Figure 4 demonstrates that there is substantial temporal variation in the crowdedness measure over the four decades. The first prominent peak is in the mid-eighties and the measure reaches its local maximum in February 1987. This is in line with the rapid growth of the Eurocurrency market over that period.[32] Levich, Corrigan, Sanford and Votja (1988) documents that between 1980 and 1986 the size of the Eurocurrency deposit market increased from 730 billion USD to 1.584 trillion USD on a net basis. Then, the crowdedness measure appears to increase moderately in the few years prior to the onset of the Asian financial crisis, reaching two local maxima in October 1996 and April 1997 respectively. That period is known to be associated with increased international capital flows from the lower interest rate countries to those with relatively higher interest rates and the bulk of this international capital was going to the emerging Asian economies (see for example Radelet and Sachs (1998)). It is noteworthy that the measure registers an increase despite it being comprised solely of the G10 currencies.

Fortunately, additional data is available to check the soundness of the crowdedness measure during the later periods. Panel (a) of Figure 5 displays the total global FX turnover taken from the BIS triennial surveys. This is not an ideal proxy for carry trade crowdedness because total FX turnover is directionless and it could be driven by variety

[32] The Eurocurrency market is a market for deposits denominated in a currency different from the indigenous currency of the financial center.

of different strategies, however it still offers certain insights. For example, in 2001 there was a decrease in FX turnover relative to the previous survey year of 1998. Similarly, my crowdedness measure is at its lowest during the two years before the start of the 2001 U.S. recession. The timing of this carry trade activity trough makes sense because during that time the U.S. interest rates were relatively high (around 5% per annum on average) making the carry trade relatively less attractive. Additionally, that period followed the well-publicized collapse of Long Term Capital Management, which could have lowered the popularity of quantitative investment strategies. In contrast, between 2001 and 2007 we observe an exponential growth in FX turnover. According to my measure, the period from around 2002 to the onset of the 2008 financial crisis is also associated with a very strong increase in carry trade crowdedness. The growth of the carry trade activity during that period is well supported by a myriad of circumstantial evidence.[33] After the 2008 crisis, the crowdedness measure decreased from its peak, but remained elevated relative to its full-sample mean.

I am able to check further the soundness of the crowdedness measure during the period between the years 2000 and 2016. Panels (b) and (c) of Figure 5 present the time series of my measure of carry trade crowdedness alongside the time series of the quarterly total AUM of currency hedge funds and quarterly total turnover in Australian dollars (in AUD billion). Currency hedge funds can be assumed to invest, at least partially, in the carry trade strategy. Hence, the growth of their AUM should be naturally related to carry trade crowdedness. The AUD is known as the proverbial carry trade investment currency, hence it is reasonable that AUD turnover should be related to carry trade activity as well. It is worth noting that the AUD has become a prime carry trade target only in the new millennium as before that it seldom had either the highest or the second-highest interest rate among the G10 currencies. Indeed, my measure of crowdedness appears highly correlated to both the currency hedge fund AUM and the turnover in AUD. The correlation between my

[33] For example, in discussing the results of the 2004 BIS FX turnover survey, Galati and Melvin (2004) argue that the surge in FX turnover was driven primarily by increased carry trade activity. Hattori and Shin (2009) document a large increase in the Japanese Yen denominated liabilities (with a smaller increase in assets) of the foreign banks in Japan particularly between the years 2005 and 2008. They also find a corresponding increase in net inter-office accounts of foreign banks in Japan, which is suggestive of carry trade flows. Terada, Higashio and Iwasaki (2008) presents evidence of the dramatic increase in FX margin trading by individual investors in Japan between the years 2006 and 2008, a phenomenon that was also widely covered in the financial press at the time (see for example "Yen absorbs 'Japanese housewife effect" by Peter Garnham, The Financial Times, 3 July 2007.) Finally, it may be worth noting that the first carry trade exchange traded fund (ETF), the PowerShares DB G10 Currency Harvest (DBV) was launched in September 2006, which further suggests that the period was associated with a carry trade activity surge because the carry trade strategy was beginning to be marketed to retail investors.

crowdedness measure and the series is around 0.7 (tabulated in Panel B of Table 2). Both the currency hedge fund AUM and AUD turnover increase aggressively from 2000 to 2008 similar to my crowdedness measure. Moreover, similar to my measure, both the currency hedge fund AUM and AUD turnover appear to plateau at the elevated levels after the 2008 financial crisis and neither of the series reverts to their levels of the early 2000s.

In sum, the evidence presented in this section is highly suggestive of my measure being related to carry trade activity. Thus, I will interpret my measure as carry trade crowdedness in the analysis that follows.

5.3 Anatomy of a carry trade crash

This section describes the average dynamics of a carry trade crash. In total there are 416 daily returns (around 4% of the sample) that form part of the 100 worst carry trade crashes (100 largest drawdowns). Panel A of Table 3 presents the average magnitude, the average duration (the number of days over which the drawdown occurred), and the average first-day return for the top (most negative) 20, 40, 60, 80 and 100 carry trade drawdowns.[34]

The average magnitude of the top 100 drawdowns is – 2.32% and both the mean and median duration of these carry trade drawdowns is four days.[35] The fact that the largest drawdowns occur over a number of days makes it more appropriate to think of the extreme carry trade losses as cascades rather than jumps. In absolute terms, this loss is roughly equal to two thirds of the average annual return of the carry trade, while the average magnitude of the top 20 drawdowns is – 3.35% (a little under the mean annual carry trade return in absolute terms) and their average duration is five days. Thus, on average, in just four days, during these drawdown episodes, the equal-weighted carry trade lost between 50 and 100% of its average annual profit. If one considers that the carry traders are almost always leveraged, the economic significance of these episodes is even clearer. For example with a 10% margin requirement, a leveraged carry trader would have lost around 25.52% of their capital during an average top-100 drawdown.[36]

[34]Due to the non-parametric nature of the analysis, I report the interquartile range for each of the drawdown statistics as that is more informative regarding the cross-sectional properties within each of the top N drawdown groups than the standard deviation.

[35]The minimum and maximum duration are one and ten days respectively.

[36]Margin requirements may vary, but for the one-month-maturity forwards of major currencies, they typically range from 2% to 5% (see Darvas, 2009).

Daniel et al. (forthcoming) stress that the largest carry trade losses are realized in clusters of daily negative returns. I confirm this. In my full sample, negative single-day returns rarely qualify as the largest carry trade drawdowns (losses). Of the top 100 drawdowns, 60 occur over either three, four or five days (with equal frequencies). Moreover, of the top 100 drawdowns only 6 occur over one day, while only a single drawdown out of the top 50 drawdowns does so.[37]

Additional insight emerges when examining these carry trade crashes in "pseudo event time".[38] To better illustrate the dynamics of a typical, large drawdown, Figure 6 plots, in event time, the average cumulative and average daily carry trade returns twenty trading days around the four-day and five-day drawdowns that are in the top 100.[39] The daily mean of the carry trade returns is also shown on the plot, along with a band delimiting plus and minus one standard deviation. Visual inspection of the average daily returns in event time, plotted in Figure 6, reveals the sharpness of the losses accrued during these episodes, especially in contrast to the returns before and after the start of a drawdown. More importantly, the plot shows that each of the negative daily returns realized during the top 100 drawdowns is substantial (all, on average, appear more than one standard deviation below the daily mean). Moreover, as reported in Panel B of Table 3, the average daily return realized on the first day of the top 100 drawdowns is large. It is equal to – 0.6%, which is roughly two standard deviations away from the mean daily carry trade return.[40] It is clear that the potency of the largest carry trade losses is indeed magnified by the clustering of the negative daily returns. However, it also appears that the absolute magnitudes of the individual, negative daily returns that make up these greatest negative-return clusters are, on average, although not extreme, still relatively large.

In sum, the carry trade crashes identified in the data are four-day negative return clusters of economically significant magnitudes that usually begin with a substantial one-day loss and represent key observations that give the sample distribution of carry returns

[37]The large single-day drawdown corresponds to the minimum recorded daily equal-weighted G10 carry trade return of – 2.74% that occurred on 19 December 1980. This was arguably an outlier as it occurred on the day of an interest rate shock during the time when the U.S. had the highest interest rate in the sample of available currencies (i.e. the constructed carry trade strategy was short all currencies vs. the U.S. dollar), and only seven currencies are available in my sample for that time period.

[38]The practice of plotting returns around the event is standard in event studies. However, in this case, the "event" is not exogenous, but is identified in sample. Nevertheless, the event-time approach is useful for learning about the dynamics of carry trade drawdowns.

[39]Given that drawdowns vary in duration, the average dynamics for drawdowns of different durations are plotted separately.

[40]The median return on the first day, across the top 100 drawdowns, is equal to – 0.4% (approximately 1.25 times the daily standard deviation).

its distinct negative skewness. An obvious question is whether these carry trade crashes coincide with large unfavorable shocks to the fundamentals, i.e. very bad states of the world. To see if that is the case, I make a simplifying assumption that significant fundamental shocks are reflected in the daily U.S. stock market premium (Mkt−RF).[41] Then, I examine, in event time, the excess returns of the stock market during the carry trade crashes. This approach is also motivated by the recent literature that argues that currency carry trades are exposed to similar risk as the global equity markets (see for example Christiansen et al. (2011); Dobrynskaya (2014); Lettau, Maggiori and Weber (2014)).

Panel B of Table 3 presents, for each top N drawdowns group, (i) the average U.S. stock market one day excess return on the first day of the carry trade drawdown, (ii) the average cumulative return on the stock market during the time of the carry trade drawdowns and (iii) the conditional correlation between daily carry trade returns and daily excess stock market returns. For the top 100 drawdowns, the equity market excess return is on average – 0.6% on the first day of the drawdown (which is statistically significant) and the average cumulative equity excess return during the carry trade drawdown is – 2.3%. The pattern is the same for the top 20, 40, 60 and 80 drawdowns. Interestingly, on average, the magnitudes of the negative carry trade and stock market returns on the first day of the carry trade drawdown are almost identical.[42] Carry trade crashes are, on average, also accompanied by unfavourable stock market moves. This is further supported by the correlation between the carry trade returns and stock market returns during carry trade drawdowns, which is higher than the unconditional correlation between the two series. For the top 100 drawdowns the correlation coefficient is 0.38, while the unconditional correlation is 0.25 (in an untabulated test the difference is found to be statistically significant). It is worth stressing that the correlation is far from perfect (for example the interquartile range for the cumulative equity excess return during the carry trade top 100 drawdowns is between – 4.7% and 0.5%). Nevertheless, on average, carry trade crashes coincide with negative fundamental shocks as proxied by the stock market excess return.

However, the majority of the worst carry trade drawdowns in the sample do not coincide with the worst equity drawdowns. To demonstrate this, I calculate the worst U.S. stock market drawdowns (not tabulated) and evaluate how frequently the time periods of the Top N equity drawdowns match those of the the top N carry trade drawdowns. The last

[41] The correlation coefficient between the U.S. stock market and global market indices (for example the MSCI All Country World Index) is over 0.8, hence the excess return on U.S. market should be a fair proxy.

[42] The unconditional sample daily mean and standard deviation of the stock market excess return are 0.03% (7.4% annualized) and 1.05% (17% annualized) respectively.

column of Panel B in Table 3 (Match) presents the fraction of top N carry trade drawdowns that coincide with the top N equity market drawdowns. For example, only 28 out of the top 100 carry trade drawdowns coincide with stock market drawdowns that fall into the corresponding stock market's top 100 drawdowns.[43] More starkly, only 3 out of the top 20 carry trade drawdowns (arguably the worst in-sample realizations of carry trade payoff) coincide with the 20 largest stock market drawdowns. Although the analysis is informal, it clearly illustrates that many carry trade crashes do not coincide with extreme, negative fundamental shocks.[44] Hence, there is space for alternative channels.

The observed pattern is in line with what one would intuitively expect from a forced unwinding of the carry trade. A negative fundamental shock (or even two consecutive shocks) leads to losses on the carry trade portfolio and triggers rapid, possibly forced, unwinding of positions of some of the carry traders (mostly likely the most levered ones). In turn, this leads to further price decreases and additional losses realized on the day after the initial shock. This sets off further unwinding which continues until the arrival of either a positive shock or additional liquidity (or both) that terminates the loss sequence. Holding all else equal, if that were indeed the underlying mechanism, one would expect more of these extreme loss episodes to occur during the times of elevated carry trade activity i.e. when the carry trade is crowded. The intuition is that, *ceteris paribus*, given any negative shock of a fixed magnitude on a given day, the fewer carry traders there are, the lower is the amplifying effect on that day's return as well as the subsequent returns. The less crowded the carry trade, the less likely is the loss sequence to last more than a day, the less likely is each negative return in a loss sequence to be large, and hence the less likely is the drawdown to qualify as one of the top 100. I investigate this mechanism formally in the sections that follow.

[43] When matching the carry trade and equity drawdowns, I do not consider the exact rank, but only whether the carry trade and equity drawdowns fall into their respective top N drawdowns.

[44] This evidence challenges the strict interpretation of the view that the carry trade loading on the equity market is simply a function of the market return being sufficiently negative as for example in Dobrynskaya (2014).

6 Results

6.1 Carry trade crashes and crowdedness

I now turn to the main empirical question of the paper – the link between carry trade crowdedness and crashes. As a first pass at evaluating the relationship between crowdedness and crashes, I ask whether a greater proportion of carry trade crashes occur during highly crowded periods. I begin by sorting each day of the sample into crowdedness quintiles based on the rolling crowdedness measure that is calculated using the information up to, but not including, that day.[45] Quintile 5 refers to the highest levels of carry trade crowdedness in the sample, and quintile 1 to the lowest. Next, I calculate the fraction of carry trade crashes that occur in each crowdedness quintile.

Table 4 tabulates the fraction of the top 20, 40, 60, 80 and 100 drawdowns and that of all the drawdowns (2554 in total), in each of the crowdedness quintiles. To highlight the results, Figure 4 displays the same information in a panel of six histograms. A clear pattern emerges. Irrespective of whether one looks at the top 20, 40, 60, 80 or 100 drawdowns, the bulk of carry trade crashes occur during the most crowded periods (the fifth quintile of crowdedness). Forty percent of the top 100 carry trade drawdowns and fifty-five percent of the top 20 carry trade drawdowns occurred in periods identified as having the highest crowdedness. Interestingly, this pattern disappears when one considers all the drawdowns (all the negative returns). This is in line with what one would expect from the amplification mechanism: elevated crowdedness is not associated with a greater number of negative returns, only with a greater number of extreme negative returns.

In order to test the significance of this pattern, I instead reformulate the question to ask whether a greater proportion of crowded periods are found among the sample of days corresponding to carry trade crashes. By construction, the crowdedness quintiles are uniformly distributed among the full sample of days. They would therefore also be uniformly distributed in any randomly drawn sub-sample. If crowdedness has no relationship with carry trade returns (for example if crowdedness quintiles were randomly assigned), drawing a sub-sample of days based on the carry trade returns should also produce a sub-sample in

[45] Given the strong persistence in carry trade crowdedness, sorting the days based on crowdedness calculated one, two or three weeks prior to that day produces the same results.

which the crowdedness quintiles are uniformly distributed. This formulation leads to the following null hypothesis that can be tested using a goodness-of-fit test:

$$H_0 : \mathcal{F}(c) = \mathcal{U}(c) \text{ for all } c, \tag{9}$$

where c denotes the crowdedness quintiles (i.e. it can take on values 1,2, 3, 4 and 5), $F(c)$ is the sample cumulative distribution of crowdedness quintiles, and $\mathcal{U}(c)$ is the discrete uniform distribution. The alternative hypothesis is that the distributions are not equal.

I test this null hypothesis separately for the sub-samples of the top 20, 40, 60, 80 and 100 drawdowns as well as the sample of all the drawdowns using the Kolmogorov-Smirnov test. The test is based on the maximum difference between an empirical and a hypothetical cumulative distribution. The test remains valid for discrete distributions because the proof of the consistency of the Kolmogorov-Smirnov test does not assume continuity of the distribution functions. However, in discrete distributions, the standard Kolmogorov-Smirnov p-value is shown to be a conservative upper bound for the actual p-value, especially in small samples (Conover, 1972). Hence, I also compute the bootstrapped p-value.

The last two columns of Table 4, KS [p] and KS [p boot], display the standard and bootstrapped (based on 10 000 draws) two-sided p-values respectively for the test. The null hypothesis that crowdedness quintiles are uniformly distributed is rejected at the 5% significance level for all the top-drawdown sub-samples, except for the top 20 drawdowns where the null is rejected at the 10% significance level. In line with the visual intuition and theoretical prediction, the null cannot be rejected in a sub-sample that includes all the drawdowns. In sum, there appears to be evidence of a positive relationship between elevated levels of my measure of carry trade crowdedness and the occurrence of carry trade crashes. Of course, there may be confounding factors. Thus, in the next sub-section, I utilize regression analysis to address these concerns.

6.2 Carry trade crashes, crowdedness and alternative factors

In this section, I investigate whether elevated crowdedness significantly increases the probability of a carry trade crash, while controlling for alternative channels.

I consider four alternative factors: (1) FX volatility, (2) FX illiquidity, (3) equity market volatility and (4) funding illiquidity. Highly elevated levels of either one or several of the four factors could increase the probability of a carry trade crash. However, there are subtle differences in the implicit mechanism through which an elevated level of each of the factors could lead to a carry trade crash. Also, the factors are highly correlated (especially at the peaks) and the sample periods vary due to data availability. Therefore, first, I consider each factor separately. For each of the four factors, denoted $\mathrm{X^k}$, I estimate, using ordinary least squares (OLS), the following predictive linear probability model on the full sample of daily data:

$$\mathbb{P}\left(\mathrm{Crash_t}=1\right)=b_0+b_1\,\mathrm{I_{t-1,Crowd,Q(5)}}+b_2\,\mathrm{I_{t-1,X^k,Q(5)}}\ , \tag{10}$$

where $\mathrm{Crash_t}$ is a binary variable that takes the value one on the day of the start of the carry trade crash and zero otherwise. $\mathrm{I_{t,Crowd,Q(5)}}$ is an indicator variable that takes the value one on the days when the carry trade crowdedness is above the 80th percentile (fifth quintile) of its sample distribution. Similarly, $\mathrm{I_{t,X^k,Q(5)}}$ equals one on the days when the factor variable, $\mathrm{X^k_t}$, is in the fifth quintile of its distribution, and zero on all the other days. The time subscript, $\mathrm{t}-1$ on the indicator variables implies that crowdedness and the factor $\mathrm{X^k}$ are measured on the day prior to the crash.[46]

The specification in Equation 10 is the benchmark specification that attempts to answer the question of whether the high level of crowdedness has a significant marginal effect on the crash probability in the presence of other predictors. The linear probability model has a convenient feature that, assuming the explanatory variables are not functionally related to each other, the coefficients b_i ($\mathrm{i}=1$ or $\mathrm{i}=2$) can be interpreted as the difference in the crash probability between the cases when $\mathrm{I}_{\mathrm{t}-1,i}=1$ and $\mathrm{I}_{\mathrm{t}-1,i}=0$, holding the other variables fixed.

In order to better understand the mechanism through which carry trade crowdedness may increase the probability of a carry trade crash, I also estimate using OLS the following extended specification:

$$\mathbb{P}\left(\mathrm{Crash_t}=1\right)=b_0+b_1\,\mathrm{I_{t-1,Crowd,Q(5)}}+b_2\,\mathrm{I_{t-1,X^k,Q(5)}}+b_3\,\mathrm{I_{t-1,Crowd,Q(5)}}\cdot\mathrm{I_{t-1,X^k,Q(5)}}\ , \tag{11}$$

where all the variables are defined as in Equation 10 and $\mathrm{I_{t,Crowd,Q(5)}}\cdot\mathrm{I_{t,X^k,Q(5)}}$ is an interaction between the two indicator variables.

[46] More generally, the predictors can be lagged by k periods. The results are very similar for all k between 1 and 30.

6.2.1 FX volatility and FX illiquidity

Panels A and B of Table 5 present the results of the regression specifications shown in Equations 10 and 11 for FX volatility and FX illiquidity respectively.

I begin the analysis with Panel A. The unconditional sample probability is displayed in the first column and is around 1% (100 crash days out of 40 years). Column 2 demonstrates that conditioning on the information that crowdedness is in the highest quintile increases the probability of the crash by 1.25%, which is statistically significant at the 1% level. This is in line with the results from the previous section. It is worth noting that, although the absolute magnitudes appear small, conditioning on elevated crowdedness essentially doubles the probability of observing a crash.

Column 3 of Panel A displays the specification that only contains the indicator for high FX volatility and a constant as regressors. The variable $\mathrm{I}_{\text{FX-Vol},Q(5)}$ can be viewed as a non-parametric, in-sample, identification of high-volatility regimes. Consistent with the results in the literature, an elevated level of FX volatility is a significant predictor of carry trade crashes, which is reasonable because extreme outcomes are more likely when volatility is elevated. Columns 4 and 5 present the results of the full benchmark and extended regression specifications. Column 4 shows that the estimated coefficients for both the high-crowdedness and high-volatility indicators remain positive and strongly significant when both are included in the regression. The point estimate of the coefficient on the high-crowdedness indicator is smaller relative to the specification without the FX volatility, but the Z-test for the difference in magnitudes of the coefficients suggests that the decrease is not significant.

The results of the specification that includes the interaction term are presented in Column 5. The estimated coefficient of the interaction term is equal to 2.25% and is strongly significant, but the coefficient on the high crowdedness indicator loses its significance. This suggests that the predictive power of crowdedness is driven by periods with both elevated levels of FX volatility and crowdedness. This is in line with both the theoretical predictions and the patterns observed in the data. Carry trade crashes need to be triggered by a substantial negative shock for any effect of elevated crowdedness to be activated. An additional result is that the coefficient of the elevated FX volatility indicator retains its sign and significance, but registers a significant decrease in magnitude. This points to an amplification channel. While the elevated level of FX volatility increases the probability of a carry trade crash, its predictive effect is significantly higher in periods that also happen to be crowded.[47]

The inference drawn from the analysis that considers FX illiquidity is similar. Panel B of Table 5 presents the corresponding regression results. Each column is laid out identically to that in Panel A, the sole difference being that the sample period is shorter due to data availability. Column 3 of Panel B displays the regression specification that contains only the indicator for high FX illiquidity and a constant as regressors. The coefficient is positive and significant, implying that an elevated level of FX illiquidity is predictive of carry trade crashes.[48] The results from the main specification with both the high-crowdedness and high-illiquidity indicators show that the coefficients on both the indicators are positive and significant. Thus, an elevated level of crowdedness retains its predictive ability even when controlling for elevated illiquidity. Additional insight emerges from analysis of the results of the specification that includes the interaction term between the two indicators (presented in Column 5). The addition of the interaction term leads to the coefficient on the high crowdedness indicator losing its significance and the marginal effect of high illiquidity decreasing from 2% to 1% (it remains weakly significant). The estimated coefficient of the interaction term is equal to 2.6% and is strongly significant. The evidence again points to the amplification channel. There is a small, positive marginal effect of high FX illiquidity on the probability of a carry trade crash (conditional on crowdedness not being in the top quintile). However, the effect is significantly magnified when high FX illiquidity is combined with high crowdedness.

6.2.2 Equity volatility and funding illiquidity

I now turn to the VIX and the TED spread, which are the two factors examined by Brunnermeier et al. (2009). Panels A and B of Table 6 present the regression results. The results suggest that their predictive power stems primarily from their interaction with carry trade crowdedness.

[47]In unreported results I confirm that neither the significance nor the magnitude of the coefficient of the interaction term changes when controlling for extreme levels of FX volatility. To proxy for extreme FX volatility I use an indicator that takes on a value of one when FX volatility is above the 95th percentile. Given these results the interaction effect is unlikely to be driven purely by the periods of extreme volatility.

[48]It is important to bear in mind that FX illiquidity is correlated with FX volatility. Hence, in the univariate, specification the coefficient could be capturing some of the FX volatility effect.

Column 3 of Panel A displays the regression specification that contains only the indicator for the high VIX level and a constant as regressors. The coefficient is positive and significant, which is in line with earlier work. Notwithstanding that the VIX proxies for more than just U.S. equity market volatility, all else being equal, elevated levels of the VIX imply a higher probability of realizing a large negative equity market shock. Given that equity and carry trade returns are correlated, it is reasonable that elevated levels of the VIX also forecast carry trade crashes. However, the regression results from the extended specification, presented in Column 5 of Panel A, suggest that the predictive power of the VIX is driven mainly by the states when carry trade crowdedness is also elevated. This is consistent with the results in Table 3, which show that U.S equity market crashes often do not coincide with carry trade crashes. This suggests that elevated carry trade crowdedness may be a key component for the propagation of negative shocks from the equity market to the FX market.

Finally, I examine the effect of tight funding liquidity and elevated crowdedness on the probability of carry trade crashes. By doing so, I attempt to look deeper at the hypothesized crash mechanism. The carry traders are assumed to be highly leveraged. While I am unable to reliably observe variation in the stock of leverage in the FX market, the TED spread proxies for the market price of leverage. I reason that high levels of the TED spread represent periods when funding constraints are binding and margin calls to carry traders are expected to be strict. In these periods, forced unwinding of carry trade positions is more likely, hence carry trade crashes could be more likely too. Panels B of Table 6 presents the regression results. Univariate regressions specification results in Column 3 confirms that elevated level of the TED spread predicts carry trade crashes, although the marginal effect is not very large (0.73%) and significant at the 5% level. Column 4 adds an additional indicator for high carry trade crowdedness, the magnitude and the significance of the elevated TED spread decreases, but remains borderline significant. In contrast, the marginal effect of elevated crowdedness is similar to the univariate specification in Column 2. Importantly, Column 5 shows the interaction effect between high levels of crowdedness and TED spread. Low funding liquidity only increases the probability of crashes during times of high crowdedness, while elevated crowdedness retains its marginal and positive effect irrespective of the level of funding illiquidity. In other words, poor funding liquidity is predictive of extreme carry trade losses only if there are a large number of leveraged speculators who would be affected by these deteriorated funding conditions and thus more likely to rapidly unwind their positions and affect exchange rates.

6.3 Daily carry trade returns and crowdedness

The analysis thus far has centered on the likelihood of crashes. I now turn to the individual daily carry trade returns in order to examine crash intensity. I ask whether higher crowdedness is, on average, associated with negative daily returns of a larger absolute magnitude.

The theory implies both an asymmetric and a non-linear effect. The asymmetry is implicit because, as I discussed earlier, losses are amplified due to the combination of leverage and binding constraints (such as margin calls) generating the hypothesized loss amplification mechanism. Additionally, most likely it is only negative returns of a substantial magnitude that trigger the carry-trade-unwinding amplification channel since, holding all else equal, to trigger a forced unwinding, the loss to the carry traders' portfolios would need to be large enough to be of concern to either the traders' financial intermediaries or internal risk management or both.

What is required is a methodology for describing the relationship between crowdedness and carry trade returns at different points in the conditional distribution of returns. Quantile regression achieves just that as it models conditional quantiles as functions of predictors (Koenker, 2005). Hence, I estimate the following predictive quantile regression:

$$Q_{R_{\text{Carry},t}}(q) = \alpha_q + \beta_q \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} \,, \tag{12}$$

where $Q_{R_{\text{Carry},t}}(q)$ is the q-th quantile function of one-day ahead carry trade returns conditional on the information available on day $t-1$. As before, $\mathrm{I}_{\mathrm{Crowd,Q(5)}}$ in an indicator variable that takes the value one on the days when carry trade crowdedness is above the 80th percentile (fifth quintile) of its sample distribution.

Similarly to the previous section, I also estimate a regression that attempts to control (separately) for the effect of elevated levels of FX volatility, FX illiquidity, the VIX and the TED spread as well as the respective interaction between those variables and carry trade crowdedness. The extended specification is as follows:

$$Q_{R_{\text{Carry},t}}(q) = \alpha_q + \beta_q \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} + b_2 \, \mathrm{I}_{\mathrm{t-1,X^k,Q(5)}} + b_3 \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} \cdot \mathrm{I}_{\mathrm{t-1,X^k,Q(5)}} \,, \tag{13}$$

where $\mathrm{I}_{\mathrm{t,X^k,Q(5)}}$ and $\mathrm{I}_{\mathrm{t\,Crowd,Q(5)}} \cdot \mathrm{I}_{\mathrm{t,X^k,Q(5)}}$ are the same as in Equation 11.

Panel A of Table 7 present the results of the regression specifications shown in Equations 12 and 13 for FX volatility anc crowdedness. Due to space considerations, I report only the regression results of the full specification for FX liquidity in Panel B of Table 7. Table 8 presents the regressions results of both specification for the TED spread. Estimated coefficients for q equal to 0.05, 0.1, 0.2, 0.3, 0.4 and 0.5 are shown. For comparative purposes, I also report the OLS coefficient estimates in the last column.

The quantile regression results are in line with the results of the probability model. The main point to glean is that on the days that the currency carry trade experiences severe daily losses, those losses are, on average, more severe if those days fall into high crowdedness periods. In particular, the results show that, regardless of the controls, high crowdedness level only has a significant negative effect on daily carry trade returns conditional on those returns being in the bottom decile of its distribution. In contrast, OLS estimates suggest that elevated level of carry trade crowdedness has no significant average effect on daily carry trade returns. The level of crowdedness does not significantly affect the median daily carry trade return either. This is in line with the theory because the average and median daily carry trade returns are positive, hence, *a priori*, one would not expect the level of crowdedness to affect either positive returns or small negative returns.

Moreover, the estimated interaction effects between high crowdedness and other predictors are similar to the probability model and suggestive of the amplification channel. For example, the results displayed in the first column in Panel A of Table 7 show that, conditional on the daily carry trade returns falling in the bottom 5 percent of its sample distribution, the interaction effect between elevated crowdedness and high FX volatility is negative and significant. In economic terms, this effect is substantial. The average of this sub-sample of negative daily carry trade returns (the returns that are in the bottom 5 percentile of its distribution) is around -0.42% per day. If a day on which a return is realized is associated with high FX volatility level, but not high crowdedness, it is significantly more negative (around -0.65% per day). Finally, if a day on which a return is realized is associated with both high FX volatility and high carry trade crowdedness, then, on average, it is even more negative (around -1% per day, which is 3 times the daily standard deviation). In sum, among the sub-sample of extreme negative daily returns (i.e. daily crashes), the returns are more extreme on days that are classified as having high levels of FX volatility and crowdedness. To sum up, there is evidence to suggest that carry trade crowdedness increases crash intensity.

6.4 Monthly carry trade returns and crowdedness

In order to facilitate a comparison with the existing literature, I also examine monthly carry trade returns. Focusing on monthly returns offers an additional advantage of increasing the temporal distance between the measurement of crowdedness levels and returns, which should alleviate the concerns of reverse causality.

6.4.1 Non-parametric predictability analysis

I first consider a non-linear approach. Table 9 reports the results of this analysis. In particular, I classify each month of the sample into five groups corresponding to the crowdedness level quintiles. I then examine the conditional monthly returns of the carry trade following the months corresponding to each of the crowdedness quintiles. Importantly, I analyse the whole distribution of conditional returns, rather than focusing solely on average returns. Table 9 displays the average, the first quartile (25^{th} percentile), the median (50^{th} percentile) and the third quartile (75^{th} percentile) of the monthly returns on the carry trade following periods of low to high carry trade crowdedness. It is vital to stress that crowdedness is measured one month before the return realization. The table also reports the coefficients obtained by regressing the monthly series of carry trade returns on the monthly series of one-month-lagged crowdedness ranks.

Clearly perceptible patterns emerge from this analysis. Following those months that fall into the lowest crowdedness group, the 25^{th} percentile of carry trade returns is around -0.25% per month (-3% annualized), while the 25^{th} percentile of returns following the months in either of the two highest crowdedness groups is -0.85% per month (around -10% annualized). The difference is statistically significant. In contrast, examining the 75^{th} percentile of the conditional monthly returns, I find no significant difference between the crowdedness quintiles (the returns following the months that have lowest and highest crowdedness levels are 1.27% and 1.07% respectively). Figure 8 illustrates these results. In line with the hypothesized mechanism, crowdedness appears to amplify the negative returns and has no effect on positive returns. The results also show that the level of carry trade crowdedness has limited effect on the average and median returns, which is congruent with the quantile regression results in the previous section.

The difference in returns following periods of different crowdedness is driven primarily by the difference in the left tails of the conditional return distributions. This pattern is evident even from visual inspection. Figure 9 shows the kernel density estimates of the distribution of carry trade returns conditional on the previous month's level of carry trade crowdedness. While the conditional density functions of carry trade returns appear to align among the positive values of the distribution, the densities diverge among the negative values. The distribution function of carry trade returns conditional on high crowdedness levels seems to have more density in its left tail relative to the distribution of returns conditional on low crowdedness (an unreported Kolmogorov-Smirnov goodness-of-fit test rejects the null that the distribution functions are the same).

Lastly, I perform a simple placebo test to rule out the notion that crowdedness quintiles may be inadvertently capturing some obvious time variation in global risk premium. Specifically, I examine the conditional monthly aggregate U.S. equity market returns following the months corresponding to each of the carry trade crowdedness quintiles. The last column of Table 9 displays the monthly average excess return on the U.S. stock market following periods of low to high carry trade crowdedness. There are no discernible patterns. Carry trade crowdedness is not predictive of U.S. equity returns, hence it is unlikely to be capturing information about shifts in global risk premium.

6.4.2 Predictability regressions

In this subsection, I evaluate the in-sample power of the level of the carry trade measure for predicting future carry trade returns. I examine univariate and multivariate linear predictive regressions at the one-month horizon because that is an established methodology in the literature, which makes it easier to relate the results to previous work. Denote the annualized continuously compounded currency carry trade return by $\tilde{r}_{Carry,t+1} = \ln\left(1 + R_{Carry,t+1}\right) \times 12$. I estimate the OLS predictive regression of the type

$$\tilde{r}_{Carry,t+1} = a_k + \gamma_{\text{Crowd}}\,\text{Crowd}_t + \sum_{x^i \in \mathbf{X}} \gamma_{x^i} x_t^i + \epsilon_{t+1}, \tag{14}$$

where Crowd_t the level of the carry trade crowdedness measure at time t and x_t^i denotes other predictors.

I focus on the changes in global FX volatility as the potential alternative predictor because,firstly, the literature finds robust empirical relationship between carry trade excess returns and exchange rate volatility, and secondly because changes in FX volatility are shown to be predictive of monthly carry trade returns in at least two separate studies (Bakshi and Panayotov, 2013; Cenedese et al., 2014).[49]

To facilitate comparability with existing research, I define the change in volatility exactly as in Bakshi and Panayotov (2013):

$$\Delta\sigma_t^{\mathrm{FX}} = \frac{1}{3}\log\left(\frac{\sigma_t^{\mathrm{FX}}}{\sigma_{t-3}^{\mathrm{FX}}}\right),$$

where σ_t^{FX} is the global FX volatility as defined in Equation 6.[50]

Tables 10 presents the predictive regression results. When evaluating predictive power, especially of persistent predictors, one has to be mindful of computing the appropriate standard errors. Hence, I report the t-statistics computed using both the Newey-West (1987) standard errors and the Hodrick (1992) 1B standard errors that are derived under the null of no predictability and I base my inference on whichever are the most conservative.[51]

Column 1 of Tables 10 presents the results of the univariate regression specification of the one-month ahead carry trade return on the level of carry trade crowdedness. The relationship between the level of crowdedness and future carry trade returns is negative and statistically significant at the 5% significance level. The effect is also meaningful economically. A one standard deviation increase in the crowdedness level corresponds to a 1.9% decrease in annualized expected carry trade returns, all else being equal. Column 2 presents the results of a univariate specification with just the lagged changes in FX volatility. Confirming the results of Bakshi and Panayotov (2013), I find that the relationship is negative, strongly statistically significant and economically meaningful (a one standard deviation increase corresponds to around a 2.3% decrease in annualized carry trade return).

Next, I estimate the bivariate regression. The results, reported in Column 3, show that both predictors remain individually significant and the magnitude of each of the coefficients

[49]In unreported results I also consider the level of FX volatility, however I find that in the monthly return predictability setting the level of FX volatility is not a significant predictor of returns. Moreover, it has no impact on the predictive ability of carry trade crowdedness.

[50]Bakshi and Panayotov (2013) do not explain why they choose to calculate changes over two periods rather than just taking first differences. However, the first differences of the volatility series are strongly negatively autocorrelated. Hence, this specification may be a way to better account for this issue.

[51]Ang and Bekaert (2007) show evidence simulation that suggests that Hodrick (1992)'s 1B standard errors are conservative and display superior small-sample properties to the Newey-West (1987) standard errors.

remains nearly unchanged relative to their respective univariate cases.[52] The adjusted R-squared increases, relative to the univariate cases, to 2.2% (its magnitude is in the region of what is commonly observed in monthly predictive regressions). These results are in line with the results in the previous sections of the paper: the predictive ability of carry trade crowdedness is preserved even after controlling for aggregate FX volatility.

Finally, I consider whether the interaction between the lagged change in FX volatility and lagged crowdedness, $\text{Crowd}_t \cdot \Delta\sigma_t^{\text{FX}}$, has a differential effect. The last column of Tables 10 presents the results for the specification that includes the interaction term. Similar to what we saw in the results of the linear probability model and the daily return quantile regressions discussed earlier in the paper, the interaction term is negative and statistically significant, while the coefficient on the lagged level of crowdedness loses significance. Interestingly, all of the predictive effect of the changes in FX volatility appears to stem from the interaction term. This alters the interpretation of the marginal effect of the FX volatility changes on the one-month-ahead carry trade returns. When the crowdedness level is around its sample mean, a positive change in FX volatility of one standard deviation forecasts a 1.7% decrease in annualized carry trade returns in the next month, which is similar to the forecast of a univariate model. In contrast, when the crowdedness level is elevated and around its 80th percentile, the same change in FX volatility forecasts 3.2% decrease in annualized carry trade returns in the next month. This has important implications because Bakshi and Panayotov (2013) note that the predictive power of changes in FX volatility is puzzling since a pricing model with average currency returns and currency volatility innovations as risk factors encounters great difficulty in replicating the pattern of predictability manifested in the data. The empirical results in this paper suggest a plausible economic channel through which changes in FX volatility could affect future carry trade returns.

7 Robustness

In the previous sections I show that my measure of carry trade crowdedness is able to predict carry trade crashes. The interpretation, however, depends heavily on whether my measure truly captures carry trade activity. In this section, I propose an alternative measure of carry trade crowdedness which is calculated from historic hedge fund exposure

[52]There is, however, a slight decrease in significance of the coefficient on the level of crowdedness (t-statistic drops from – 2 to – 1.82).

to the currency carry trade. I then show that the main results are robust to a different measure of carry trade crowdedness.

7.1 Hedge fund data

The hedge fund data was sourced from Bloomberg.[53] I downloaded the time series of daily hedge fund returns and assets under management, together with static information on fund characteristics. I filtered the data, to ensure that, for each hedge fund in the sample, the daily returns would be reported with minimum gaps. The final sample of hedge funds is an unbalanced panel of 823 unique hedge funds that report their returns on a regular, daily basis. The sample contains both "dead" and "live" individual hedge funds and no funds of funds. The sample of hedge funds that report returns daily has been shown to be representative of the hedge fund universe (see Kolokolova and Mattes, 2014).[54] The sample period for which daily hedge fund return data are available is January 2001 to April 2016.

7.2 Hedge fund "style analysis" implied crowdedness measure

The auxiliary measure of carry trade crowdedness that I consider is based on the hedge fund "style analysis" methodology of Pojarliev and Levich (2011). This crowdedness measure is defined as the percentage of funds with significant positive exposure to the carry trade. This approach is motivated by the fact that hedge funds are often regarded as the quintessential leveraged speculators that, at least in the last decade, have been prominent carry traders. Therefore, it is sensible to try to gauge carry trade activity by examining the proportion of hedge funds that are engaged in currency carry trades.

However for such a measure to be useful, it needs to be timely. Most hedge funds have flexible mandates and can get in and out of positions very quickly. Indeed, Patton and Ramadorai (2013) show that hedge funds reporting on a monthly basis to commercial databases vary their factor exposures even during the month. I am able to overcome this

[53]Bloomberg makes hedge fund data available through their standard Bloomberg Professional subscription for users who qualify as "accredited investors". Academic institutions with existing subscriptions usually qualify as "accredited investors".

[54]Kolokolova and Mattes (2014) show that the characteristics of the sample of hedge funds that report daily to Bloomberg are similar to those of the sample of hedge funds that report on a monthly basis to the commercial databases commonly used in the hedge fund literature (namely BarclayHedge, Eurekahedge, Morningstar, HFR, and TASS).

limitation by utilizing a database of hedge funds that report returns daily. The measure is constructed as follows.

I estimate a standard factor model on 120-day rolling samples of individual daily hedge fund returns, of the form:

$$R_{i,\tau} = \alpha_i + \beta_i^{\text{Carry}} R_{\text{Carry},\tau} + \sum_{\text{k}} \beta_i^{f^k} \, \text{f}_\tau^k + \epsilon_{i,\tau} \ ,$$

where $R_{i,\tau}$ is a daily excess return for hedge fund i, $R_{\text{Carry},\tau}$ is a daily return to the equally weighted carry trade portfolio, as defined in Equation 5 and f_τ^k refers to the three daily Fama-French benchmark factors (Market, Size and HML).

The hedge fund loading implied carry trade crowdedness, $\text{Crowd}_t^{\text{HF}}$, is defined as

$$\text{Crowd}_t^{\text{HF}} = \frac{\text{HF(Carry)}}{N_t^{\text{HF}}} \tag{15}$$

where HF(Carry) is the number of funds with significant (t-statistic greater than 1.96) positive exposure to the carry trade factor over the period $t - r$. $N_{t,\text{HF}}$ is the total number of hedge funds in the database over the same period. I take r to be 120 trading days, in order to have sufficient observations to reliably estimate five parameters.[55]

The measure has the advantage of being relatively intuitive, but it has some limitations. First, I am unable to use the seven Fung and Hsieh (2001, 2004) hedge fund factors in the regression because these factors are only available at a monthly frequency.[56] Second, the measure is constructed from only a sample of hedge funds rather than the market as a whole. There are counterarguments for both of these concerns. Given that carry trade returns have very low correlations with most standard risk factors and that I adequately control for equity factors, the bias from not using the full specification should not be very

[55] Pojarliev and Levich (2011) use a similar rolling window. They use weekly returns and take rolling samples of 26 weeks. Nevertheless, all the results remain qualitatively similar when changing the rolling period.

[56] The original seven factors are comprised of two equity factors (the equity market factor and the size spread factor), two bond factors (the bond market factor and the credit spread factor) and three trend-following factors (bond, commodity and currency).

large.[57] Additionally, it is not clear whether controlling for the Fung and Hsieh (2004) "currency trend factor" is appropriate when measuring a hedge fund's exposure to the carry trade as the trend factor could inadvertently capture carry trade exposure. As for the concern of examining only a sample of hedge funds, as long as my sample of funds is representative of the broader institutional fund management universe (and, as I discussed earlier, there is reason to believe that it is), it may still give an accurate reflection of aggregate carry trade crowdedness.

7.3 Hedge fund implied crowdedness and carry trade returns

The top panel of Figure 10 displays the monthly time series of the hedge fund based carry trade crowdedness measure together with the FX correlation based crowdedness measure. Surprisingly, the two measures are not very highly correlated (the correlation coefficient is equal to 0.32), however, visually it seems that both measures display similar trends and appear to match better at their peaks. For example, the pronounced growth in carry trade activity during the few years leading up to the 2008 financial crisis is well captured by both measures.

The bottom panel of Figure 10 displays the number of hedge funds available in the sample each month. The number of available hedge funds varies from the minimum of 17 to the maximum of 230, with 150 hedge funds available in the sample on average. Hence, on average, I have a sample of a reasonable size to compute the crowdedness measure. As an informal test (not tabulated), I look at the distribution of hedge fund styles among the funds with significant loading on the carry trade. I find that 61% of the funds identify themselves as following styles that could be reasonably expected to engage in carry trade strategies: namely Multi Strategy, Managed Futures or Global Marco (also including the Fixed Income style raises the share to 73%).[58] Thus, it appears this methodology is able to identify the carry traders in the sample of hedge funds.

Next, I examine whether this alternative measure of carry trade crowdedness is related to carry trade crashes. I focus on monthly carry trade returns and follow the approach described in the previous section. In particular, I classify each month of the sample into five

[57] For example, in a regression of monthly returns of an equal-weighted G10 carry trade on the bond factors, Daniel et al. (forthcoming) find that the point estimate of the coefficient on the bond market factor is equal to zero.

[58] 20% of the funds that load significantly on the carry trade are identified as following equity strategies. However, it is unclear which proportion of that represents genuine style drift and which the bias.

groups corresponding to the crowdedness level quintiles. I then examine the conditional monthly returns of the carry trade following the months corresponding to each of the crowdedness quintiles. Crowdedness is measured based on the hedge fund loading derived measure. I examine the 25^{th} and 75^{th} percentiles of carry trade returns following different crowdedness periods. Figure 11 presents the bar chart of returns associated with each crowdedness period. Similar, to the results displayed in Figure 8, higher levels of carry trade crowdedness are associated with significantly larger negative returns, and do not appear to influence positive returns.

In sum, utilizing an alternative measure of carry trade crowdedness, I still find that periods that are classified as having elevated levels of carry trade activity are associated with the realizations of extreme negative carry trade returns.

8 Conclusion

Historically, the currency carry trade has been surprisingly and consistently profitable. However, the carry trade is not a free lunch. Despite the relatively low unconditional volatility of around 5% per annum, currency carry trades are known to experience sharp and large losses. As I demonstrate in this paper, a four-day sequence of negative carry trade returns is often sufficient to wipe out an entire year's worth of profits. One explanation for these crashes, proposed in the literature and favored by practitioners, is that these crashes are endogenously generated as the by-product of highly leveraged and funding constrained carry trade speculators forcefully unwinding their positions in the face of negative shocks, thus amplifying them. This view implies that, if there is variability over time in the relative size of the carry trade activity (carry trade crowdedness), then crowdedness acts as a state variable that affects the dynamics of the carry trade return process.

The hypothesized dynamics are such, that during times of elevated crowdedness, large negative shocks to the carry trade are significantly amplified due to the presence of binding, mechanical constraints such as margin calls, stop-loss orders and value-at-risk metrics that force traders to rapidly unwind their positions. Hence, even in a world with only i.i.d. shocks, crowded periods would be associated with a greater number of extreme negative return realizations relative to non-crowded periods. An empirically testable implication is that the likelihood of large carry trade losses (crashes) increases with the level of crowdedness. To test this mechanism, I construct a measure of currency carry trade crowdedness based on the signed correlations of abnormal daily returns among the target carry trade currencies. Using alternative proxies for carry trade crowdedness, including a measure derived from hedge fund returns, I show that the interpretation of this measure as carry trade crowdedness is sensible. I exploit the time series variation in this crowdedness measure and present a preponderance of evidence linking my measure of crowdedness to the extreme negative return realizations of the currency carry trade.

I find that between 40% to 50% of the most extreme carry trade drawdowns occur following periods that are identified (in-sample) as having the highest levels of carry trade crowdedness. Irrespective of the exact empirical specification or the time horizon, and controlling for a battery of other potential predictors established in the literature, the carry trade crowdedness measure retains its significant predictive ability. Additionally, in line with the hypothesized mechanism, I find pronounced non-linearities in the empirical relationship between crowdedness and carry trade returns (crowdedness has the strongest correlation with the most negative carry trade returns). Moreover, the estimates of the interaction-effect of crowdedness with other factors are in line with the unwinding loss amplification channel (for example, an elevated level of funding illiquidity is only predictive of carry trade crashes when combined with elevated crowdedness). Despite accounting for all the obvious predictors of carry trade crashes established in the literature it is impossible to completely rule out that my measure of crowdedness is a proxy for an alternative, as yet unidentified, factor that is predictive of carry trade returns. However, this is unlikely because not only would such a factor need to specifically predict the extreme negative carry trade returns, but it would also needs to match the empirically observed interaction with the other factors. Hence, there does not seem to appear to be any obvious issues with this alternative measure.

In sum, my results suggest that carry trade crowdedness varies substantially over time and its level affects carry trade return dynamics. In future research, it would be interesting to investigate what fundamental factors drive this temporal variation in carry trade crowdedness. These empirical patterns are unlikely to be well captured by FX market models that rely solely on homogeneous global investors, which is in line with the poor empirical performance of unconditional models with classic risk factors. Hence, it may be worth considering a "marginal" investor who evolves over time in future theoretical research on the carry trade.

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Table 1: Summary Statistics of Carry Trade Returns

This table presents summary statistics (mean, standard deviation, skewness, kurtosis and autocorrelation coefficient) for the monthly and daily returns of the equal-weighted G10 carry trade returns. The average return and the standard deviation are annualized. The Sharpe ratio is the ratio of the annualized mean and standard deviation. Newey-West standard errors with 3 lags are given in parentheses. The data are daily from 1976:2-2016:04.

	Monthly Ret	Daily Ret
Mean Ret (% p.a.)	3.59	3.52
	(0.91)	(0.79)
Std Dev	5.12	5.1
Sharpe Ratio	0.70	0.69
Skewness	– 0.55	– 0.38
Kurtosis	5.01	9.59
AC(1)	0.1	0.01
Max (%)	4.78	2.52
Min (%)	– 6.02	– 2.74

Table 2: Descriptive Statistics of Carry Trade Crowdedness Measure

Panel A of this table presents the key characteristics of the end-of-month currency carry trade crowdedness measures. Crowd^{FX} measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. Panel B reports the time-series correlations between end-of-quarter Crowd^{FX}, quarterly total AUM of currency hedge funds (Currency Funds AUM) and quarterly total turnover in Australian dollars (AUD Turnover). The sample periods are from 1976:2 to 2016:04 for Crowd^{FX}, and 2000Q1 to 2016:Q1 for Currency Funds AUM and AUD Turnover.

Panel A: Summary statistics

	N	Mean	Std Dev	Min	Max	AC(1)
Crowd^{FX}	482	0.20	0.26	− 0.37	0.86	0.67
$\text{Ave-Corr}^{\text{FX}}$	482	− 0.10	0.03	− 0.17	0.18	0.46
σ_t^{FX}	482	0.03	0.01	0.01	0.10	0.66

Panel B: Correlation

	Crowd^{FX}	$\text{Ave-Corr}^{\text{FX}}$	σ_t^{FX}
Crowd^{FX}	1		
$\text{Ave-Corr}^{\text{FX}}$	0.10	1	
σ_t^{FX}	0.22	0.24	1

Panel C: Correlation with other crowdedness proxies

	Crowd^{FX}	Currency Funds AUM	AUD Turnover
Crowd^{FX}	1		
Currency Funds AUM	0.73	1	
AUD Turnover	0.72	0.88	1

Table 3: Descriptive Statistics of Carry Trade Drawdowns

Panel A presents summary statistics of the top (most negative) N carry trade drawdowns. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. The reported statistics are as follows: the average magnitude of the drawdown (Drawdown), the average number of days over which the drawdown occurred (days) and the average return on the first day of the carry trade drawdown ($R_{\text{Carry}}|_{\text{Draw}}$). Panel B reports, for each top N drawdown group, the average equity market one day excess return corresponding to the first day of the carry trade drawdown ($R_{\text{Mkt-Rf}}|\text{Draw}$), the average cumulative return on the U.S. equity market during the time of the carry trade drawdowns ($\sum(R_{\text{Mkt-Rf}}|\text{Draw})$) and the conditional correlation between daily carry trade returns and daily excess stock market returns, $\rho_{\text{D}}\,(R_{\text{Cary}}, R_{\text{Mkt}})$. The column labelled Match shows the fraction of the top N carry trade drawdowns that coincide with the top N U.S. equity market drawdowns (not tabulated). The interquartile range is reported in square brackets. Heteroskedasticity-robust standard errors are presented in parentheses. For comparative purposes, Panel C presents summary statistics (mean, standard deviation, skewness, and autocorrelation coefficient) of the daily returns of the equal-weighted carry trade portfolio of G10 currencies, R_{Carry}. The mean, standard deviation, minimum and maximum are given as percentages per day. The last column of Panel C, $\rho\,(R_{\text{Cary}}, R_{\text{Mkt-Rf}})$, reports the unconditional sample correlation coefficient between daily carry trade returns and daily excess stock market returns. The data have a daily frequency, covering 1976:2 to 2016:04.

Drawdowns

	Panel A: Carry Trade			**Panel B: U.S. Equity Market**			
	Drawdown	days	$R_{\text{Carry}}\|\text{Draw}$	$R_{\text{Mkt-Rf}}\|\text{Draw}$	$\sum R_{\text{Mkt-Rf}}\|\text{Draw}$	$\rho_{\text{D}}\,(R_{\text{Mkt}}, R_{\text{Carry}})$	Match
Top 20	– 3.35%	5	– 0.74%	– 0.77%	– 3.16%	0.27	3/20
	[– 3.7% – 2.9%]	[3 6]	[– 1.2% – 0.2%]	(0.5)	[– 6.9% 1.0%]		
Top 40	– 2.94%	5	– 0.66%	– 0.51%	– 2.86%	0.42	8/40
	[– 3.2% – 2.5%]	[3 6]	[– 1.2% – 0.2%]	(0.31)	[– 6.2% 1.1%]		
Top 60	– 2.7%	4	– 0.6%	– 0.7%	– 2.87%	0.38	17/60
	[– 2.9% – 2.3%]	[3 6]	[– 0.9% – 0.2%]	(0.23)	[– 5.9% 0.5%]		
Top 80	– 2.49%	4	– 0.61%	– 0.62%	– 2.58%	0.36	23/80
	[– 2.7% – 2.0%]	[3 5]	[– 0.9% – 0.2%]	(0.19)	[– 5.4% 0.2%]		
Top 100	– 2.32%	4	– 0.6%	– 0.6%	– 2.3%	0.38	28/100
	[– 2.6% – 1.8%]	[3 5]	[– 0.9% – 0.2%]	(0.17)	[– 4.7% 0.5%]		

Panel C: Daily Carry Trade Returns

	Mean (% p.d.)	Std. Dev (% p.d.)	Skew	Min (% p.d.)	Max (% p.d.)	AC(1)	$\rho(R_{\text{Mkt}}, R_{\text{Carry}})$
R_{Carry}	0.01	0.32	– 0.38	– 2.74	2.52	0.01	0.25
	(0.003)						
% p.a.	3.52	5.10					
	(0.789)						

Table 4: Carry Trade Crashes and Crowdedness Quintiles

This table presents the fractions of the top (most negative) 20, 40, 60, 80 and 100 equal-weighted G10 currency carry trade drawdowns that occur during periods corresponding to different carry trade crowdedness quintiles $Q(q)_{\text{Crowd}}$. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. Quintile 5 refers to the highest levels of carry trade crowdedness and quintile 1 to the lowest. The columns KS[p] and KS[p boot] display the classic and bootstrapped two-sided p-values, respectively for the Kolmogorov-Smirnov goodness-of-fit test, under the null hypothesis that the carry trade drawdowns are uniformly distributed across crowdedness quintiles. The sample period runs from 1976:2 to 2016:04.

	$Q(1)_{\text{Crowd}}$	$Q(2)_{\text{Crowd}}$	$Q(3)_{\text{Crowd}}$	$Q(4)_{\text{Crowd}}$	$Q(5)_{\text{Crowd}}$	KS[p]	KS[p boot]
Top 20	0.15	0.15	0.10	0.05	0.55	0.135	0.093
Top 40	0.15	0.08	0.10	0.18	0.50	0.043	0.015
Top 60	0.17	0.10	0.12	0.17	0.45	0.039	0.012
Top 80	0.16	0.14	0.11	0.19	0.40	0.071	0.027
Top 100	0.17	0.15	0.11	0.17	0.41	0.031	0.013
All Drawdowns	0.20	0.20	0.19	0.20	0.21	0.998	0.848

Table 5: Crash Probability: Crowdedness, FX Volatility, and FX Illiquidity

This table presents ordinary least squares regression coefficients of the following linear probability model: $\mathbb{P}(\mathrm{Crash_t}=1) = b_0 + b_1\,\mathrm{I_{t-1,Crowd,Q(5)}} + b_2\,\mathrm{I_{t-1,X^k,Q(5)}} + b_3\,\mathrm{I_{t-1,Crowd,Q(5)}} \cdot \mathrm{I_{t-1,X^k,Q(5)}}$. $\mathrm{Crash_t}$ is a binary variable that takes the value of one on the day of the start of the 100 worst (most negative) equal-weighted G10 carry trade drawdowns in the sample and zero otherwise. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. $\mathrm{I_{Crowd,Q(5)}}$ is an indicator that equals one on the days when the carry trade crowdedness is in the fifth quintile ($\geq$ 80th percentile) of its sample distribution. $\mathrm{I_{X^k,Q(5)}}$ equals one on the days that the variable, $\mathrm{X^k}$, is in the 5th quantile of its distribution. $\mathrm{X^k}$ denotes either global FX volatility (Panel A) or global FX illiquidity (Panel B). Heteroskedasticity-robust standard errors are shown in parentheses. All coefficients and their respective standard errors are multiplied by 100 so as to convert them into percentages. The sample periods are from 1976:2 to 2016:04 for FX volatility, and 1991:2 to 2016:04 for FX illiquidity.

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{P}$(Crash=1)	$\mathbb{P}$(Crash=1)	$\mathbb{P}$(Crash=1)	$\mathbb{P}$(Crash=1)	$\mathbb{P}$(Crash=1)
Panel A: FX Volatility					
Constant	0.95***	0.70***	0.58***	0.44***	0.57***
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$		1.26***		0.90***	0.12
		(0.32)		(0.29)	(0.25)
$\mathbf{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$			1.85***	1.66***	0.88***
			(0.35)	(0.33)	(0.34)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$					2.52***
					(0.82)
Observations	10,479	10,479	10,479	10,479	10,479
R-squared	0.000	0.002	0.007	0.008	0.010
Panel B: FX Illiquidity					
Constant	1.22***	0.83***	0.74***	0.56***	0.70***
	(0.14)	(0.13)	(0.12)	(0.13)	(0.13)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$		1.57***		1.00***	0.23
		(0.40)		(0.37)	(0.33)
$\mathbf{I}_{\mathrm{FX\text{-}Illiq,Q(5)}}$			2.38***	2.06***	0.99*
			(0.49)	(0.47)	(0.52)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{FX\text{-}Illiq,Q(5)}}$					2.62***
					(1.01)
Observations	6,568	6,568	6,568	6,568	6,568
R-squared	0.000	0.003	0.008	0.009	0.011

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Crash Probability: Crowdedness, VIX, and TED Spread

This table presents ordinary least squares regression coefficients of the following linear probability model: $\mathbb{P}\left(\mathrm{Crash_t}=1\right) = b_0 + b_1\, \mathrm{I_{t-1,Crowd,Q(5)}} + b_2\, \mathrm{I_{t-1,X^k,Q(5)}} + b_3\, \mathrm{I_{t-1,Crowd,Q(5)}} \cdot \mathrm{I_{t-1,X^k,Q(5)}}$. $\mathrm{Crash_t}$ is a binary variable that takes the value one on the day of the start of the 100 worst (most negative) equal-weighted G10 carry trade drawdowns in the sample and zero otherwise. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. $\mathrm{I_{Crowd,Q(5)}}$ is an indicator that equals one on the days when the carry trade crowdedness is in the fifth quintile ($\geq$ 80th percentile) of its sample distribution. $\mathrm{I_{X^k,Q(5)}}$ equals one on the days that the variable, $\mathrm{X^k}$, is in the 5th quantile of its distribution. $\mathrm{X^k}$ denotes either the CBOE VIX index (Panel A) or the TED spread (Panel B). Heteroskedasticity-robust standard errors are given in parentheses. All coefficients and their respective standard errors are multiplied by 100 so as to convert them into percentages. The sample periods are from 1991:1 to 2016:04 for the VIX, and 1986:1 to 2016:04 for the TED spread.

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{P}$ (Crash=1)	$\mathbb{P}$ (Crash=1)	$\mathbb{P}$ (Crash=1)	$\mathbb{P}$ (Crash=1)	$\mathbb{P}$ (Crash=1)
Panel A: VIX					
Constant	1.21***	0.85***	0.91***	0.62***	0.81***
	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$		1.50***		1.37***	0.47
		(0.40)		(0.39)	(0.37)
$\mathbf{I}_{\mathrm{VIX,Q(5)}}$			1.59***	1.37***	0.26
			(0.45)	(0.43)	(0.38)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{VIX,Q(5)}}$					3.46***
					(1.12)
Observations	6,612	6,612	6,612	6,612	6,612
R-squared	0.000	0.002	0.003	0.005	0.009
Panel B: TED spread					
Constant	1.09***	0.78***	0.91***	0.62***	0.73***
	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$		1.31***		1.30***	0.81**
		(0.36)		(0.35)	(0.36)
$\mathbf{I}_{\mathrm{TED,Q(5)}}$			0.73**	0.59*	– 0.03
			(0.35)	(0.34)	(0.29)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{TED,Q(5)}}$					2.06**
					(0.96)
Observations	7,427	7,427	7,427	7,427	7,427
R-squared	0.000	0.002	0.000	0.003	0.004

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Daily Carry Trade Returns Quantile Regression: FX Volatility and FX Illiquidity

This table presents regression coefficients from the following predictive quantile regression: $Q_{R_{\text{Carry},t}}(q) = \alpha_q + \beta_q \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} + b_2 \, \mathrm{I}_{\mathrm{t-1,FX\text{-}Vol,Q(5)}} + b_3 \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} \cdot \mathrm{I}_{\mathrm{t-1,FX\text{-}Vol,Q(5)}}$, where $Q_{R_{\text{Carry},t}}(q)$ is the q-th quantile function of one-day ahead carry trade returns conditional on the information available on day $t-1$. $\mathrm{I}_{\mathrm{Crowd,Q(5)}}$ is an indicator that equals one on the days when the carry trade crowdedness is in the fifth quintile ($\geq$ 80th percentile) of its sample distribution, and $\mathrm{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$ equals one on the days when global FX volatility is in the fifth quintile of its distribution. Standard errors are shown in parentheses. All coefficients and their respective standard errors are multiplied by 100 so as to convert them into percentages. The sample periods are from 1976:2 to 2016:04 for FX volatility, and 1991:2 to 2016:04 for FX illiquidity.

	Q(0.05)	Q(0.10)	Q(0.2)	Q(0.3)	Q(0.4)	Q(0.5)	OLS
Panel A: FX Volatility							
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$	– 0.069***	– 0.036**	– 0.012	– 0.007	– 0.005	– 0.004	– 0.001
	(0.024)	(0.015)	(0.010)	(0.007)	(0.007)	(0.005)	(0.009)
$\mathbf{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$	– 0.366***	– 0.267***	– 0.111***	– 0.057***	– 0.022***	0.003	– 0.016
	(0.024)	(0.015)	(0.010)	(0.007)	(0.007)	(0.005)	(0.010)
Constant	– 0.408***	– 0.275***	– 0.153***	– 0.077***	– 0.022***	0.021***	0.017***
	(0.012)	(0.007)	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$	0.021	– 0.007	– 0.008	– 0.007	– 0.008	– 0.009	– 0.006
	(0.032)	(0.019)	(0.012)	(0.009)	(0.008)	(0.006)	(0.008)
$\mathbf{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$	– 0.234***	– 0.209***	– 0.099***	– 0.057***	– 0.026***	– 0.003	– 0.021*
	(0.031)	(0.019)	(0.012)	(0.009)	(0.008)	(0.006)	(0.011)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{FX\text{-}Vol,Q(5)}}$	– 0.335***	– 0.214***	– 0.024	– 0.000	0.011	0.015	0.016
	(0.057)	(0.035)	(0.021)	(0.016)	(0.015)	(0.011)	(0.024)
Constant	– 0.423***	– 0.280***	– 0.154***	– 0.077***	– 0.021***	0.022***	0.018***
	(0.012)	(0.008)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Panel B: FX Illiquidity							
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$	0.006	0.013	0.016	0.003	– 0.005	– 0.010	0.002
	(0.038)	(0.028)	(0.015)	(0.012)	(0.012)	(0.011)	(0.012)
$\mathbf{I}_{\mathrm{FX\text{-}Illiq,Q(5)}}$	– 0.091**	– 0.083**	– 0.059***	– 0.043***	– 0.024*	0.002	– 0.020
	(0.045)	(0.033)	(0.018)	(0.014)	(0.014)	(0.013)	(0.015)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{FX\text{-}Illiq,Q(5)}}$	– 0.447***	– 0.330***	– 0.083***	– 0.032	– 0.007	0.002	– 0.000
	(0.071)	(0.052)	(0.028)	(0.022)	(0.021)	(0.020)	(0.029)
Constant	– 0.507***	– 0.345***	– 0.195***	– 0.102***	– 0.036***	0.022***	0.014***
	(0.017)	(0.012)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Daily Carry Trade Returns Quantile Regression: TED Spread

This table presents regression coefficients from the following predictive quantile regression: $Q_{R_{\text{Carry},t}}(q) = \alpha_q + \beta_q \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} + b_2 \, \mathrm{I}_{\mathrm{t-1,TED,Q(5)}} + b_3 \, \mathrm{I}_{\mathrm{t-1,Crowd,Q(5)}} \cdot \mathrm{I}_{\mathrm{t-1,TED,Q(5)}}$, where $Q_{R_{\text{Carry},t}}(q)$ is the q-th quantile function of one-day-ahead carry trade returns conditional on the information available on day $t-1$, $\mathrm{I}_{\mathrm{Crowd,Q(5)}}$ is an indicator that equals one on days when the carry trade crowdedness is in the fifth quintile ($\geq$ 80th percentile) of its sample distribution, and $\mathrm{I}_{\mathrm{TED,Q(5)}}$ equals one on days when TED spread is in the 5th quantile of its distribution. Standard errors are shown in parentheses. All coefficients and their respective standard errors are multiplied by 100 so as to convert them into percentages. The sample period is from 1986:1 to 2016:04.

	Q(0.05)	Q(0.10)	Q(0.2)	Q(0.3)	Q(0.4)	Q(0.5)	OLS
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$	– 0.191***	– 0.080***	– 0.037***	– 0.018*	– 0.011	– 0.005	– 0.002
	(0.030)	(0.021)	(0.011)	(0.009)	(0.007)	(0.007)	(0.011)
$\mathbf{I}_{\mathrm{TED,Q(5)}}$	– 0.028	– 0.009	0.019	0.024**	0.020**	0.005	– 0.005
	(0.032)	(0.022)	(0.012)	(0.010)	(0.008)	(0.008)	(0.011)
Constant	– 0.489***	– 0.324***	– 0.183***	– 0.096***	– 0.035***	0.022***	0.015***
	(0.017)	(0.011)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}}$	– 0.054	– 0.007	– 0.007	– 0.006	– 0.008	– 0.010	– 0.005
	(0.035)	(0.023)	(0.014)	(0.010)	(0.009)	(0.008)	(0.011)
$\mathbf{I}_{\mathrm{TED,Q(5)}}$	0.096**	0.071***	0.049***	0.035***	0.022**	– 0.000	– 0.008
	(0.039)	(0.026)	(0.016)	(0.012)	(0.010)	(0.009)	(0.009)
$\mathbf{I}_{\mathrm{Crowd,Q(5)}} \cdot \mathbf{I}_{\mathrm{TED,Q(5)}}$	– 0.487***	– 0.364***	– 0.125***	– 0.078***	– 0.013	0.016	0.012
	(0.070)	(0.047)	(0.029)	(0.021)	(0.018)	(0.016)	(0.030)
Constant	– 0.504***	– 0.340***	– 0.188***	– 0.098***	– 0.036***	0.023***	0.015***
	(0.016)	(0.011)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)
Observations	7426	7426	7426	7426	7426	7426	7426

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Monthly Carry Trade Returns Conditional on Lagged Crowdedness

This table reports monthly excess returns on the the equal-weighted carry trade portfolio of G10 currencies as a function of lagged crowdedness. All months in the sample are classified into five groups based on the level of carry trade crowdedness during the previous month. The carry trade crowdedness measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. Reported below are the average, the first quartile, the median and the third quartile of the monthly returns on the carry trade following low to high carry trade crowdedness. For comparative purposes, the last column reports the average excess return on the U.S. stock market following low to high carry trade crowdedness. Standard errors are given in parentheses. All estimates and their respective standard errors are multiplied by 100 so as to convert them into percentages. "5 – 1" is the difference between the monthly returns following high and respectively low crowdedness. "Slope" is the slope coefficient obtained from the regression of monthly returns on the ranks of the lagged carry trade crowdedness. Quantile regressions are used to estimate the slope coefficients corresponding to Q(0.25), Q(0.5) and Q(0.75) and OLS is used in all other cases. T-statistics are reported in square brackets. The sample period is from 1976:2 to 2016:04.

Crowdedness	Obs.	Ave R_{Carry}	$Q_{R_{\text{Carry}}}(0.25)$	$Q_{R_{\text{Carry}}}(0.5)$	$Q_{R_{\text{Carry}}}(0.75)$	Ave $R_{\text{Mkt-Rf}}$
1 (Low)	97	0.42***	– 0.27	0.48***	1.27***	0.76
		(0.16)	(0.17)	(0.17)	(0.2)	(0.47)
2	96	0.58***	– 0.16	0.59***	1.25***	0.28
		(0.13)	(0.18)	(0.15)	(0.17)	(0.48)
3	96	0.33***	– 0.28	0.49***	1.08***	0.30
		(0.12)	(0.16)	(0.11)	(0.16)	(0.46)
4	96	0.07	– 0.85***	0.30*	1.01***	0.93***
		(0.15)	(0.23)	(0.16)	(0.21)	(0.34)
5 (High)	96	0.09	– 0.86***	0.17	1.07***	0.73
		(0.17)	(0.2)	(0.17)	(0.18)	(0.5)
5-1		– 0.33	– 0.59**	– 0.31	– 0.2	– 0.03
		[– 1.42]	[– 2.2]	[– 1.33]	[– 0.75]	[– 0.05]
Slope		– 0.117**	– 0.185***	– 0.098*	– 0.061	0.059
		[– 2.27]	[– 3.18]	[– 1.79]	[– 1.25]	[0.39]

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Monthly Predictive Regression

This table presents ordinary least squares regression coefficients from the following monthly predictive regression: $r_{\text{Carry},t+1} = a_k + \gamma_1 \,\text{Crowd}_t + \gamma_2 \Delta\sigma_t^{\text{FX}} + \gamma_3 \,\text{Crowd}_t \cdot \Delta\sigma_t^{\text{FX}} + \epsilon_{t+1}$. $r_{\text{Carry},t+1}$ is the (annualized) continuously compounded return on the equal-weighted carry trade portfolio of G10 currencies. Crowd_t is the level of the proxy for the currency carry trade crowdedness calculated from the signed 30-day rolling correlations of abnormal, daily returns among the target carry trade currencies. $\Delta\sigma_t^{\text{FX}}$ is the normalized log change in the global FX volatility. Two t-statistics are reported in square brackets, corresponding to (i) the Newey and West (1987) standard errors with five lags (t-stat[NW]), and (ii) the Hodrick (1992) 1B standard errors estimated under the null of no predictability (t-stat[H]). Stars indicate significance based on the most conservative t-statistic. The sample period is from 1976:2 to 2016:04.

	(1) r_{t+1}	(2) r_{t+1}	(3) r_{t+1}	(4) r_{t+1}
Crowd_t	– 0.077**		– 0.067*	– 0.058
t-stat[NW]	[– 2.00]		[– 1.82]	[– 1.55]
t-stat[H]	[– 2.08]		[– 1.82]	[– 1.54]
$\Delta\sigma_t^{\text{FX}}$		– 0.208***	– 0.194***	– 0.026
t-stat[NW]		[– 2.86]	[– 2.68]	[– 0.31]
t-stat[H]		[– 2.74]	[– 2.55]	[– 0.26]
$\text{Crowd}_t \cdot \Delta\sigma_t^{\text{FX}}$				– 0.626**
t-stat[NW]				[– 2.61]
t-stat[H]				[– 1.90]
Constant	0.053***	0.036***	0.051***	0.051***
t-stat[NW]	[4.42]	[4.41]	[4.29]	[4.20]
R-squared	0.009	0.016	0.022	0.031
Observations	481	479	479	479

*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Rolling Correlation between the Japanese Yen and the Swiss Franc

This figure presents the plot of the monthly time series of the 30-day rolling partial correlation between the spot exchange rate changes in the Japanese Yen (JPY) vs. U.S. Dollar USD) and the Swiss Franc (CHF) vs. USD. The correlations are calculated between the ordinary least squares residuals of the two exchange rate changes after purging the effect of the Verdelhan (forthcoming) dollar factor (the average change in the exchange rate between the U.S. dollar and all other currencies). The data used for the calculation are daily (end of month values are plotted). The shaded areas represent U.S. recessions as defined by the NBER.

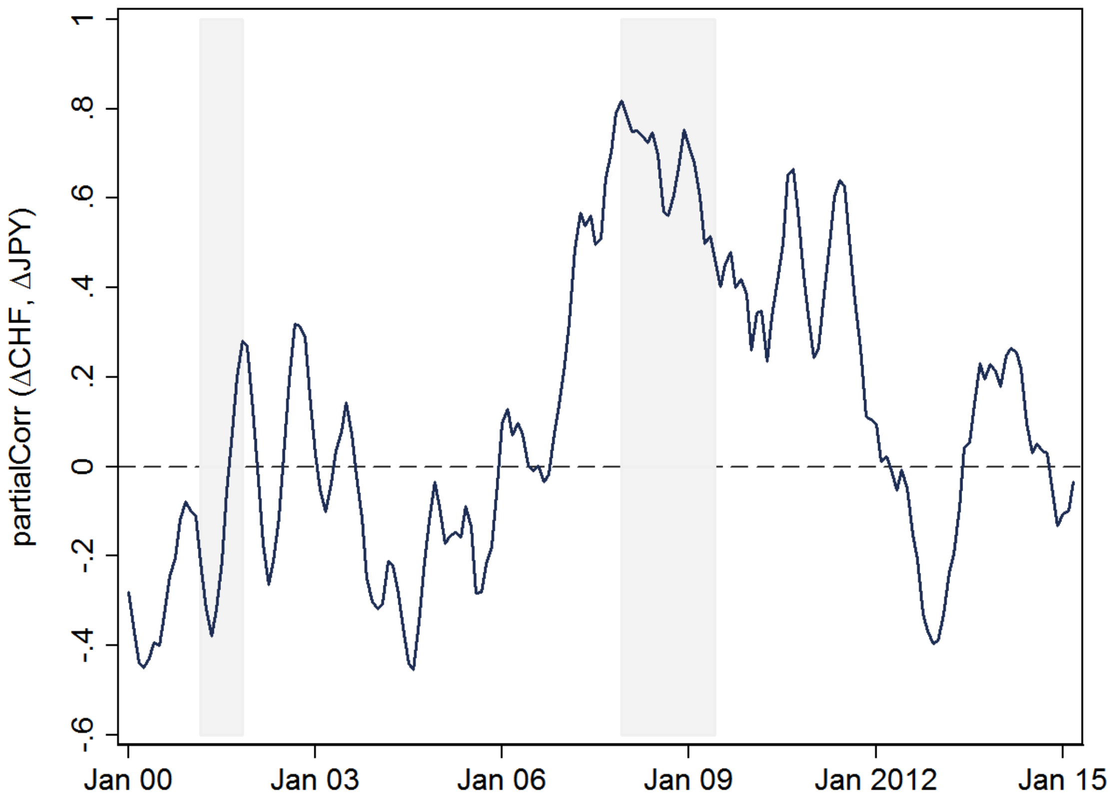


Figure 2: Carry Trade Crashes and Crowdedness

This figure presents a histogram of carry trade crowdedness (size of the currency carry trade activity) quintiles among the sample of the top 100 (most negative) drawdowns of the equal-weighted G10 carry trade portfolio. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. The carry trade crowdedness measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. For each drawdown the measure of crowdedness is calculated only using the data up to and not including the day of the start of the drawdown. Quintile 5 refers to the highest levels of carry trade crowdedness and quintile 1 to the lowest. The sample period is from 1976:2 to 2016:04.

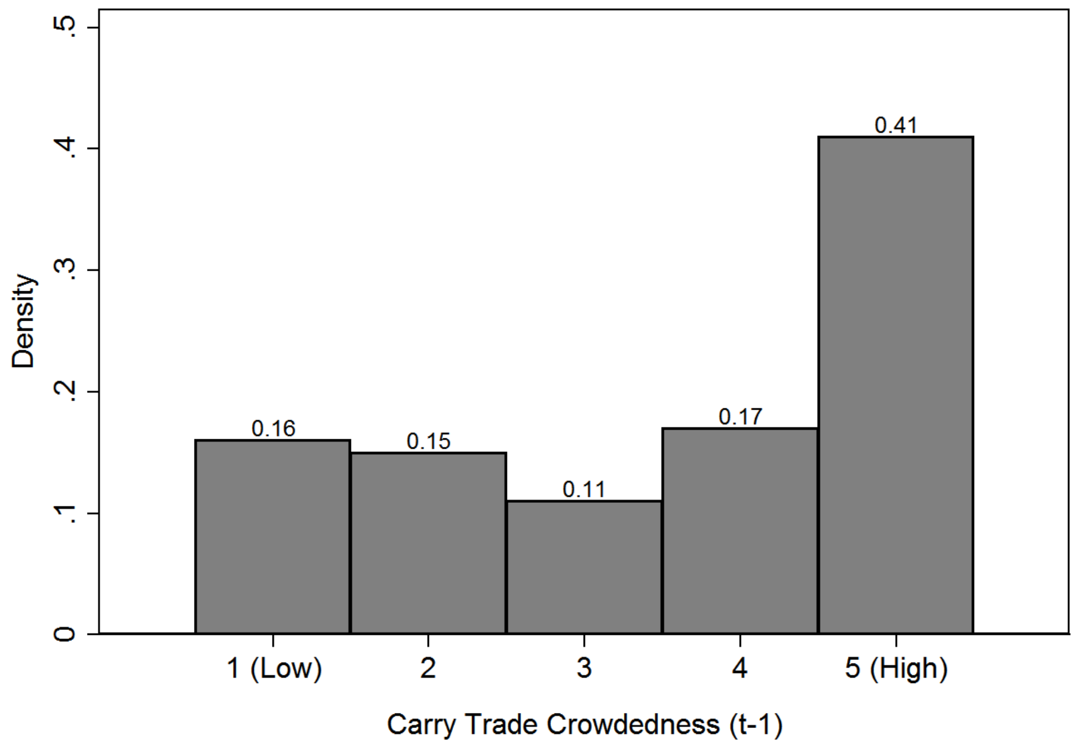


Figure 3: Carry Trade Performance

The top panel of this figure plots the monthly time series of the cumulative returns on $1 invested in a fully collateralized equal-weighted carry trade portfolio of G10 currencies at the beginning of the sample period. The carry trade strategy is rebalanced monthly and the profits or losses are realized at a monthly frequency. The cumulative return of a $1 invested in U.S. dollar LIBOR is also plotted, for comparison. The bottom panel displays the monthly returns of the equal-weighted carry trade portfolio of G10 currencies. The shaded areas represent U.S. recessions as defined by the NBER. The sample period is from 1976:2 to 2016:04.

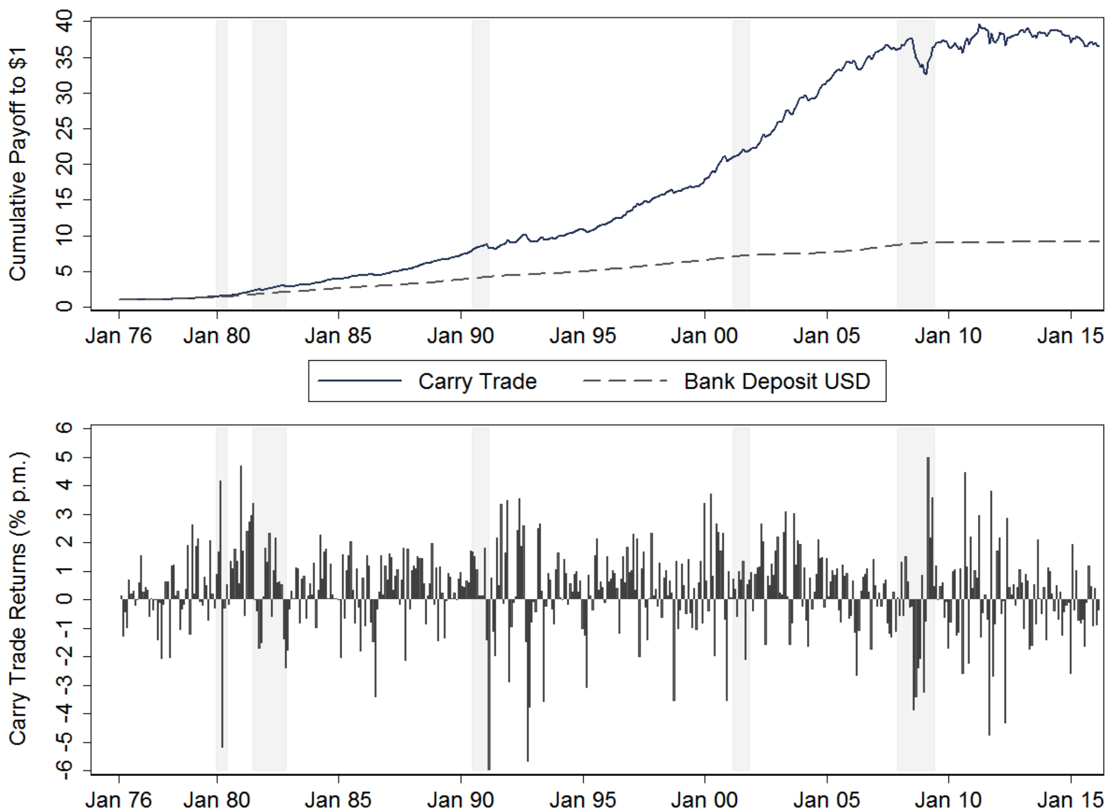
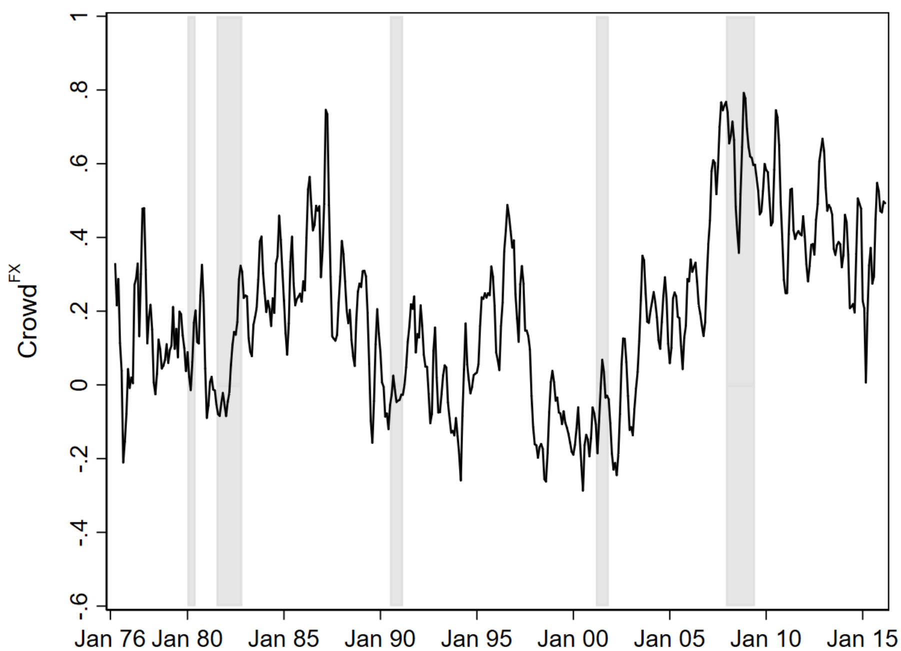


Figure 4: Carry Trade Crowdedness

This top figure displays the three-month moving average of the spot FX rate correlation implied carry trade crowdedness measure, $\text{Crowd}_t^{\text{FX}}$, at the end of each month. The bottom figure presents the three-month moving average of the spot FX rate correlation implied carry trade crowdedness measure that is orthogonalized with respect to FX volatility, $\text{Carry}^{\text{FX}\perp\text{Vol}}$. The shaded areas represent U.S. recessions as defined by the NBER. The sample period is from 1976:2 to 2016:04.



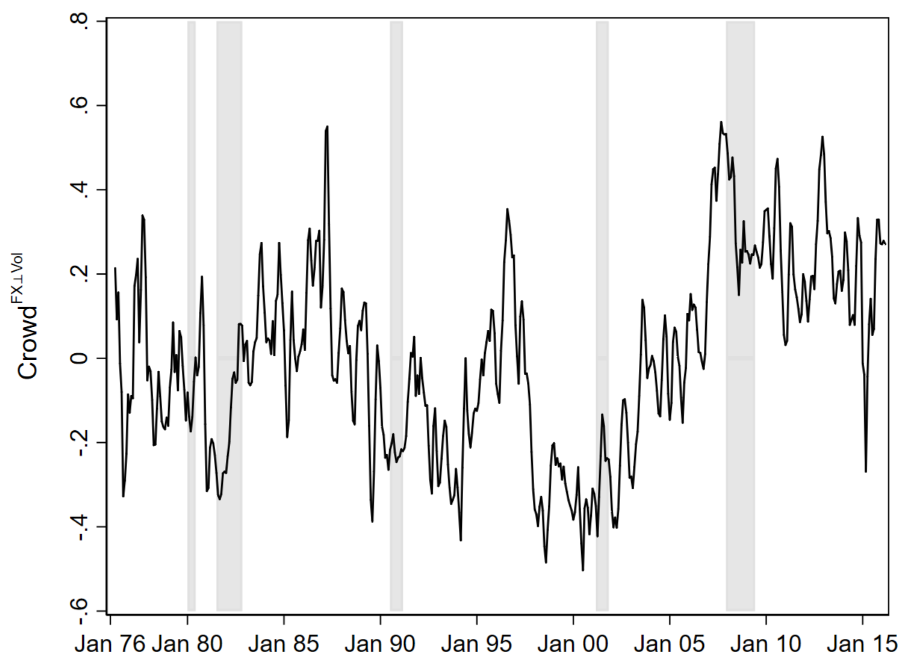
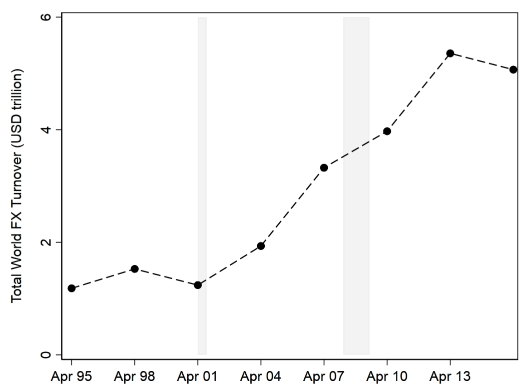
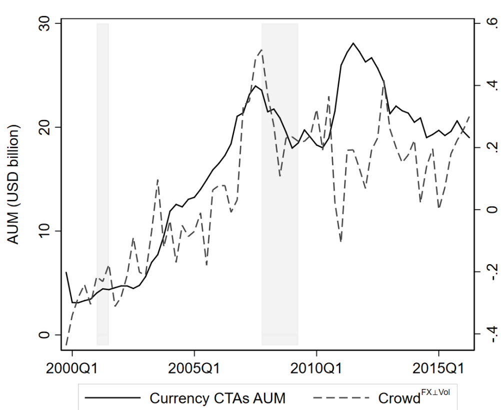


Figure 5: Carry Trade Crowdedness v.s. FX Turnover, FX Funds AUM and AUD Turnover

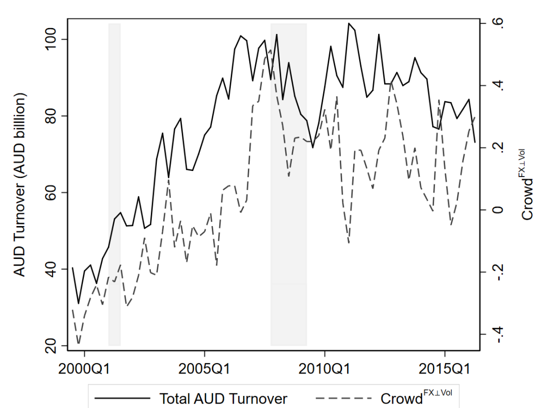
Panel (a) displays the daily average turnover (in USD trillion) of all the foreign exchange instruments globally. These data are from the Bank of International Settlements (BIS) triennial FX survey which is conducted in April of each survey year. The survey data are available from 1995 to 2016. The two figures in panels (b) and (c) plot the time series of the quarterly average spot FX correlation implied carry trade crowdedness measure, $\text{Carry}^{\text{FX}\perp\text{Vol}}$, together with the quarterly total AUM of currency hedge funds (in USD billion) and quarterly total turnover in Australian dollars (in AUD billion). The crowdedness measure is orthogonalized with respect to FX volatility. The shaded areas represent U.S. recessions as defined by the NBER. The sample period is from 2000Q1 to 2016Q1.



(a) Total Global FX Turnover



(b) Total Currency Funds AUM



(c) AUD Turnover

Figure 6: Carry Trade Crashes

The top and bottom panels present the plots of the average cumulative and average daily returns on the equal-weighted carry trade portfolio of G10 currencies around the 100 largest (most negative) four-day and five-day carry trade drawdowns in the sample. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. Drawdowns vary in the number of days over which they occur, and the average among the 100 most negative drawdowns is four days. Both return series are in percentages. In the bottom figures, the thin dotted line plots the unconditional sample mean of the daily carry trade return and the two dashed lines delimit the ±1 standard deviations band. The data are daily and the sample period is from 1976:2 to 2016:04.

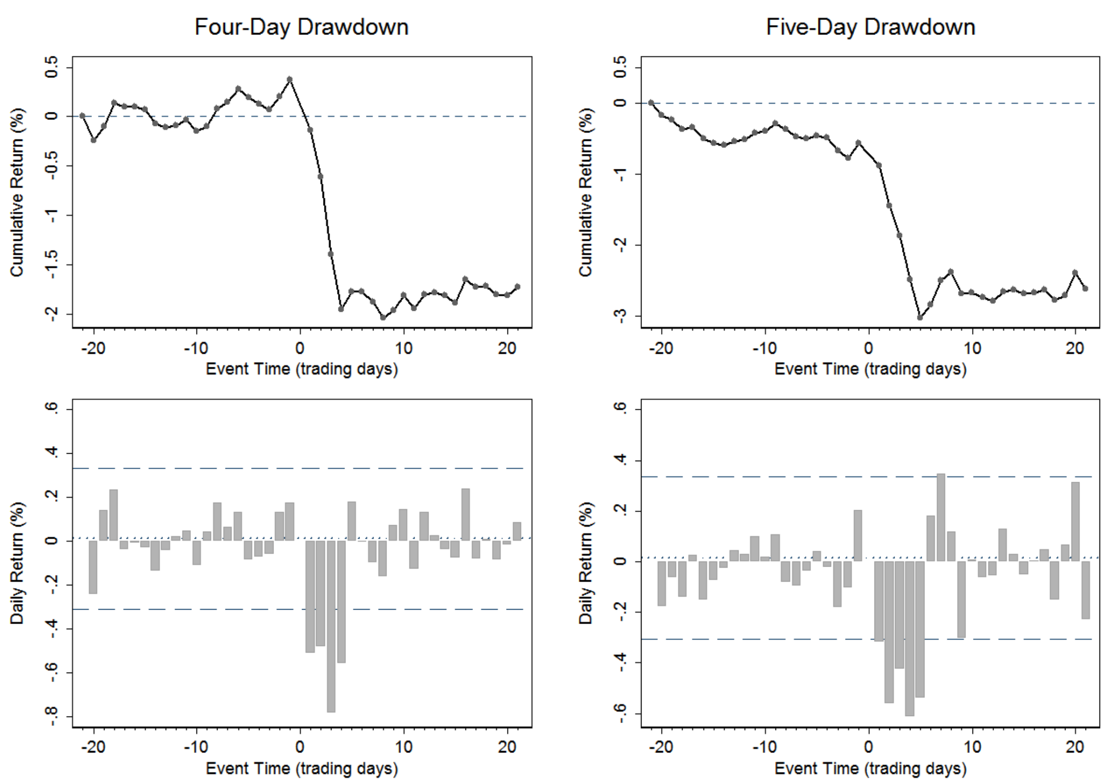


Figure 7: Carry Trade Crashes and Crowdedness

This figure presents histograms of carry trade crowdedness (size of currency carry trade activity) quintiles among the samples of the top 20, 40, 60, 80, and 100 (most negative) drawdowns and all the drawdowns of the equal-weighted G10 carry trade portfolio. A drawdown is defined as the cumulative percentage loss from consecutive daily negative returns. The carry trade crowdedness measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. Quintile 5 refers to the highest levels of carry trade crowdedness and quintile 1 to the lowest. The sample period is from 1976:2 to 2016:04.

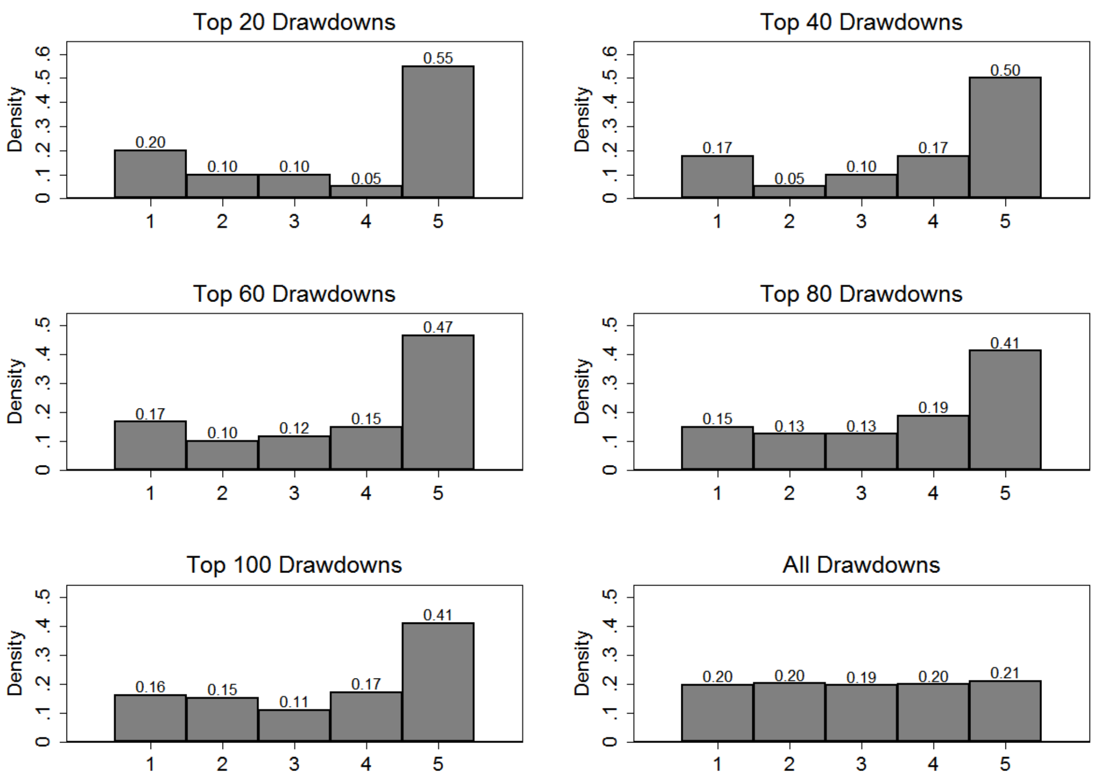
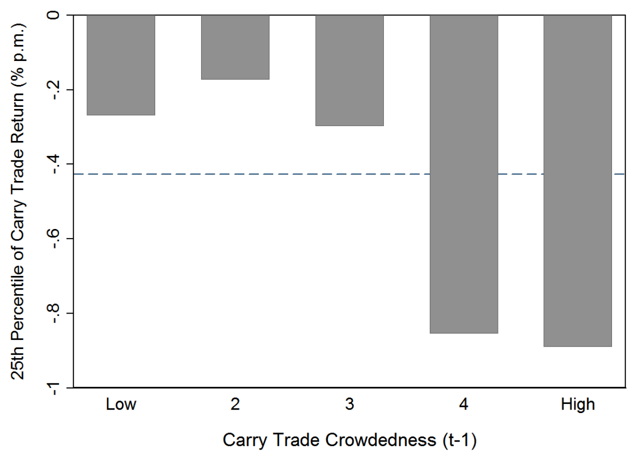


Figure 8: Monthly Carry Trade Returns and Crowdedness

These figures show the 25th and 75th percentiles of the monthly excess return for the equal-weighted carry trade portfolio of G10 currencies, conditional on the carry trade crowdedness in the previous month being within each of the five quintiles of its sample distribution respectively. Carry trade crowdedness measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. Quantile 5 refers to the highest levels of carry trade crowdedness and quantile 1 to the lowest. The thin dashed line indicated the unconditional sample 25th and 75th percentiles respectively in the top and bottom figures. The returns are in percent per month. The sample period is from 1976:2-2016:04.



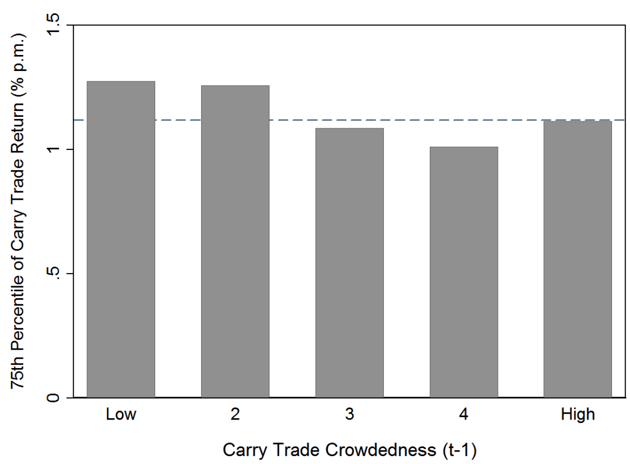


Figure 9: Monthly Carry Trade Returns and Crowdedness Empirical Distribution

This figure shows the kernel density estimates of the distribution of carry trade returns conditional on the previous month's level of carry trade crowdedness. The carry trade is an equal-weighted carry trade portfolio of G10 currencies. The carry trade crowdedness measure is calculated from the signed rolling correlations of abnormal, daily returns among the target carry trade currencies. Quintile 5 refers to the highest levels of carry trade crowdedness and quintile 1 to the lowest. The returns are in percent per month. The sample period is from 1976:2-2016:04.

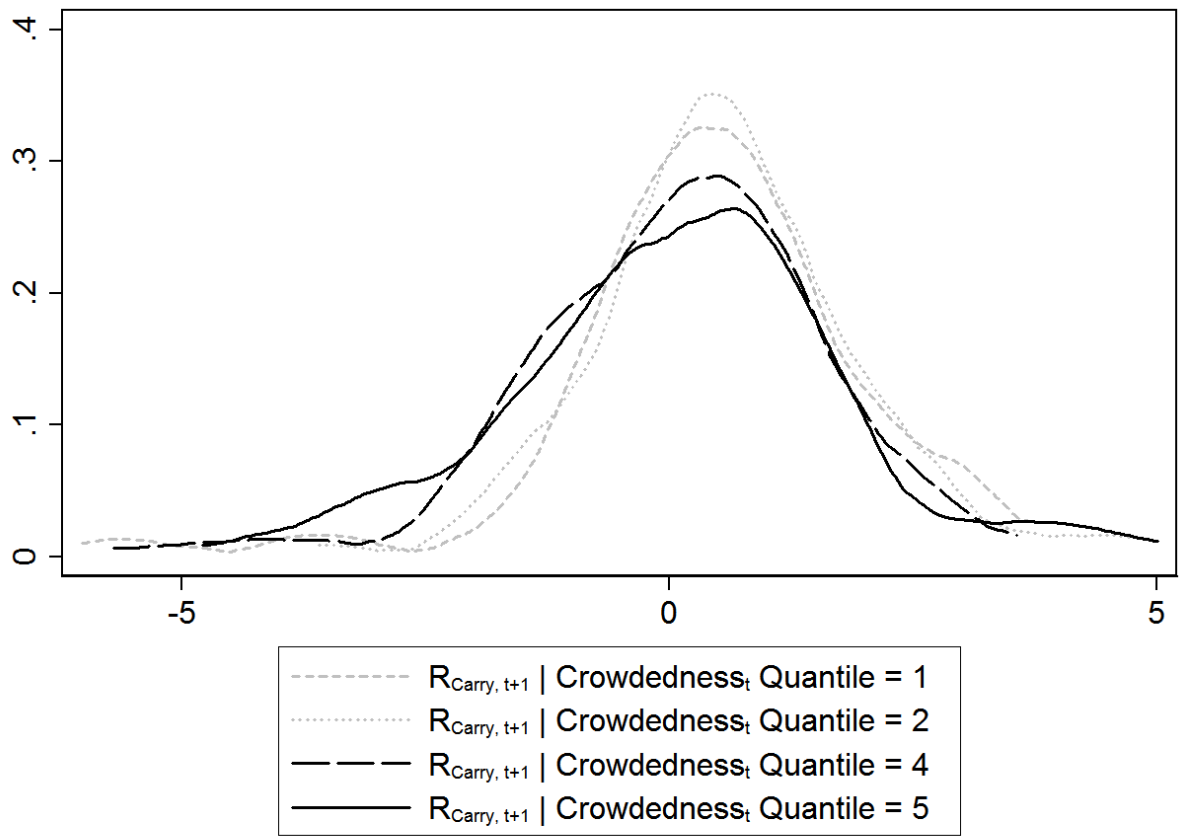
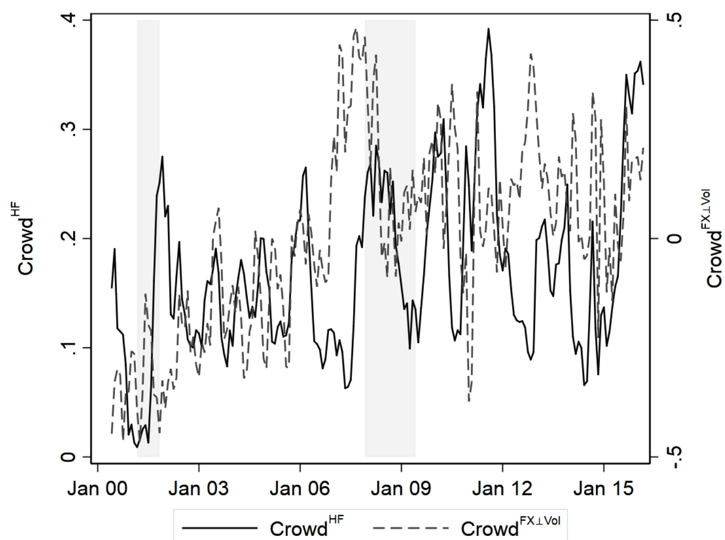


Figure 10: Hedge Fund Loading Implied Carry Trade Crowdedness

The top figures displays the time series of the monthly hedge fund loadings implied carry trade crowdedness measure, Crowd^{HF}, with the monthly average spot FX correlation implied carry trade crowdedness measure, $\text{Carry}^{\text{FX}\perp\text{Vol}}$. Crowd^{HF} measure is calculated as a count of hedge funds that positively and significantly load on the carry trade (controlling for other factors) during the previous three months (scaled by the total number of hedge funds available in the sample in each period). The FX correlation based crowdedness measure is orthogonalized with respect to aggregate FX volatility. The bottom figure presents the total number of hedge funds in the sample each month. The shaded areas represent U.S. recessions as defined by the NBER. The sample period is from 2000:7 to 2016:04.



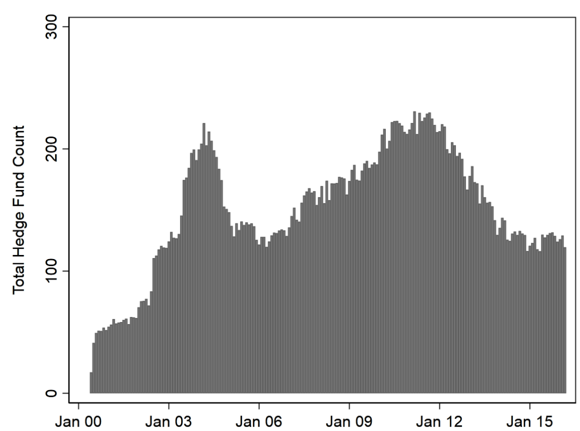


Figure 11: Monthly Carry Trade Returns and Hedge Fund Based Crowdedness

These figures show the 25th and 75th percentiles of the monthly excess return for the equal-weighted carry trade portfolio of G10 currencies, conditional on the hedge-fund-based carry trade crowdedness in the previous month being within each of the five quintiles of its sample distribution respectively. Carry trade crowdedness measure is calculated as a count of hedge funds that positively and significantly load on the carry trade (controlling for other factors) during the previous three months (scaled by the total number of hedge funds available in the sample in each period). Quantile 5 refers to the highest levels of carry trade crowdedness and quantile 1 to the lowest. The thin dashed line indicated the unconditional sample 25th and 75th percentiles respectively in the top and bottom figures. The returns are in percent per month. The sample period is from 2000:7 to 2016:04.