Detecting Crowded Trades in Currency Funds

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The financial crisis of 2008 highlights the importance of detecting crowded trades due to the risks they pose to the stability of the financial system and to the global economy. However, there is a perception that crowded trades are difficult to identify. To date, no single measure to capture the crowdedness of a trade or a trading style has developed. We propose a methodology to measure crowded trades and apply it to professional currency managers. Our results suggest that carry became a crowded trading strategy towards the end of Q1 2008, shortly before a massive liquidation of carry trades. The timing suggests a possible adverse relationship between our measure of style crowdedness and the future performance of the trading style. Crowdedness in the trend following and value strategies support this hypothesis.

Our sample period covers 63 months, of which 27 months are effectively an out-of-sample period. The out-of-sample results confirm the usefulness of our measure of crowdedness. After a period when carry returns were very favorable, carry became crowded again in fall 2009, and then experienced a sharp reversal during the European sovereign debt crises and after the "flash crash" in May 2010.

We apply our approach to currencies but the methodology is general and could be used to measure the popularity or crowdedness of any trade with an identifiable time series return. Our methodology may offer useful insights regarding the popularity of certain trades – in currencies, gold, or other assets – among hedge funds. Further research in this area may be relevant for investors, managers and regulators.

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1. Introduction

Over the last twenty years, institutional investors have greatly increased their allocations to alternative investments like hedge funds, and away from traditional assets like equities and bonds. For example, a survey conducted by the National Association of College and University Business Officers (2008) found that US university endowments larger than $1 billion allocated more than 20% of their assets to hedge funds. This strategy was partly the result of a conventional belief that hedge funds could pursue more diverse strategies, that diversification is the key for successful investing and that the returns on alternative assets will have little or no correlation with returns on traditional investments.

However, the transfer of substantial assets under management to hedge funds harbored considerable risks for investors and the broader financial system. Addressing the Economic Club of New York in 2004, Timothy Geithner, then President of the Federal Reserve Bank of New York, put the matter quite bluntly. "While there may well be more diversity in the types of strategies hedge funds follow, there is also considerable clustering, which raises the prospect of larger moves in some markets if conditions lead to a general withdrawal from these 'crowded' trades."[1] In many ways, Geithner's conjecture about returns in crowed trades was realized during the global financial crisis.

[1] Remarks by Timothy F. Geithner before the Economic Club of New York, May 27, 2004.

In turbulent periods, positioning and being aware of crowded trades become crucial as traders may try to exit trades at the same time and in the same direction. The phenomenon of large numbers of traders exiting similar trades at the same time creates liquidity problems as everyone is rushing to exit a "burning house." However, in order to leave a "burning house," it is not enough to reach the exit, but rather to persuade someone from the outside to take your place, i.e. to take the other side of the trade. Therefore, it is hardly a surprise that "positioning" and the concentration, or popularity, or the crowded nature of certain trades and trading styles are highly discussed topics among investment managers.[2]

To illustrate the importance of positioning, as a part of their periodic foreign exchange research commentaries some banks have introduced Commodities Futures Trading Commission data on market positioning in currency futures.[3] These analyses focus on the positioning of the non-commercial or speculative accounts. Custodians also are able to take advantage of their proprietary equity flow data in order to gauge positioning. For example, State Street Bank and Trust (SSBT) is said to make use of their proprietary flow data to gauge positioning across different currencies.[4] To date, however, no single measure to capture the crowdedness of a trade or trading style has developed. Identifying crowded trades is challenging due to the large number of asset classes hedge funds could

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[2] At the Quant Invest 2009 conference in Paris, Robert Litterman of Goldman Sachs is reported to have said that computer-driven hedge funds needed to identify new areas to exploit, as some areas had become so overcrowded that they are no longer profitable. "Quant Hedgies Must Fish In Fresh Waters – Goldman," Reuters, December 1, 2009.

[3] See Deutsche Bank, Global Markets Research, DB FX Positioning Indices," May 18, 2009.

[4] See Froot and Ramadorai (2005, 2008) for analyses that rely on the SSBT equity flow data.

be invested in. Furthermore, given that most databases collect monthly returns, these data would allow gauging crowdedness only over long term periods.

In this paper, we make use of a new data base of daily data on currency funds to develop a new approach to detect positioning and identify crowded trades. Because currency funds have a clearly defined investment universe, they offer a good laboratory for developing an approach for detecting crowded trades. Furthermore, the high-frequency data in our sample allow us to develop measures of crowdedness over economically relevant horizons.[5] We apply our approach to currencies but the methodology is general and could be used to measure the popularity or crowdedness of any trade with an identifiable time series return.

Currencies may become more highly correlated when investors pursue similar trading strategies. For example, there is little fundamental reason to expect high correlation between currency returns on the GBP/CHF cross and the NZD/JPY cross. However, a carry trader, who establishes a long position in high yielding currencies by taking a short position in low yielding currencies, could very likely have been long the two crosses (long GBP vs. CHF and long NZD vs. JPY) over much of the last twenty years, as interest rates in New Zealand and the United Kingdom were generally higher than interest rates in Japan and Switzerland, respectively.[6] Increasing popularity of the carry trade could help account for the greater correlation of these two crosses in recent years

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[5] Gross (2005) suggests that three to four years is the "average life" of investment firms, i.e. the time frame before an average client will leave if performance disappoints.
[6] See Froot and Thaler (1990) for a survey of the carry trade.

(see Exhibit 1). Indeed, the rolling annual correlation of the GBP/CHF and NZD/JPY cross rates rose above 0.50 in the late 1990s, and then fell sharply after the liquidation of the Yen carry trade between June 1998 and December 1999.[7] The correlation again rose above 0.50 in 2007 and peaked in the fourth quarter of 2008, before falling sharply in the first half of 2009, a period which once again experienced massive liquidation of carry trades.[8]

Analyzed in this way, currency traders appear more focused on exposure to a particular risk factor or trading strategy and less so on exposure to particular currencies. A large short JPY exposure might be offset by long CHF exposure as both currencies rallied during the recent carry trade liquidation. And a seemingly small short JPY exposure becomes more risky when combined with exposures to other carry trade proxies. For these reasons, measuring crowdedness by investment style rather than by individual currency pairs seems preferable, which is a property our technique will exploit.

Previous research (see Pojarliev and Levich (PL), 2008a) has shown that four factors (or styles), which represents the return on several well-known currency trading strategies and the foreign exchange volatility explain a significant part of the variability of the returns of professional currency managers. Thus, exposures to these factors might be a

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[7] The USD/JPY spot rate fell from levels above 145 to almost 100 during this time period.

[8] This rolling correlation could be interpreted as a simple measure of carry crowdedness until the end of 2008. Indeed, the correlation between this measure and our measure of crowdedness from September 2005 until the end of 2008 is 49%. However, it drops to -72% from January 2009 until June 2010, a period in which the Swiss National Bank (SNB) intervened massively to stem the appreciation of the Swiss franc. The SNB sold CHF valued at roughly $200bn between 2009 and mid-2010, including $73bn in May 2010 alone. These calculations suggest that the Swiss franc was no longer considered as a funding currency after 2008, as investors sought safety and preferred to own CHF.

useful way to gauge the popularity or crowdedness of a trading strategy.[9] We define style crowdedness as the percentage of the funds with significant positive exposure to a given style less the percentage of the funds with significant negative exposure to the same style (contrarians).[10] To estimate crowdedness, we rely on data for 107 currency managers covering a little over five years between April 2005 and June 2010.[11] We estimate style betas using the four factor model proposed in PL (2008a). We use higher frequency, weekly return data to obtain efficient parameter estimates for rolling 26-week periods.

Our overall results are quite promising and consistent with a view that crowded trades harbour potential risk once a change in fundamentals or sentiment induces liquidation of positions. Our analysis shows that Carry became a crowded strategy in spring 2008, just a few months before the crash in October/November 2008. And Carry grew increasingly crowded through 2009, peaking at the beginning of 2010, several months before the European sovereign debt crises and the "flash crash" in spring 2010 when managers in our sample became neutral on carry. Value trading exhibits a similar pattern. In spring 2008, Value became a popular contrarian strategy (a high proportion of the funds exhibited significant negative value exposure) just a few months before performing

[9] These factors are specific to the currency funds. Clearly, when measuring crowdedness for different types of hedge funds, i.e. global macro, a researcher should make use of different factors, for example those identified in Fung and Hsieh (2002).
[10] Alternatively, each manager could be weighted by their assets under management (AUM). In a related paper, Jylhä and Suominen (2009) find that AUM at hedge funds are significantly related to contemporaneous and expedited future returns from a risk-adjusted carry trade. Unfortunately, we do not have data on AUM for the managers in our sample to experiment with this alternative measure.
[11] An earlier version of the paper was based only on a 3-year sample, from April 6, 2005 until March 26, 2008. We updated the paper when more data became available. The results post March 26, 2008 can be interpreted as out-of-sample and highlight the usefulness of our framework to measure crowded trades.

exceptionally well. Value again became a popular contrarian strategy by the beginning of 2010, to be followed by a surge upward in the performance of Value several months later. Trend trading shows a somewhat different pattern. By the spring of 2008, investors seemingly "gave up" on trend as a relatively highly level of crowdedness disappeared only months before the trend trading style delivered big gains in the crisis period. Our results suggest that style crowdedness varies considerably over time and may impact the future performance of its respective style.

In the next section of the paper, we lay out our methodology for estimating crowdedness. In section 3, we report our estimates of crowdedness and present some empirical evidence on its determinants. Conclusions and implications of our findings are in the final section.

2. Data Description and Definition of Crowdedness

To measure exposure to styles, we follow the approach used in PL (2008a) and use a standard factor model of the form:

$$R_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t \qquad (1)$$

where

> R is the excess return generated by the currency manager, defined as the total return (R_t^*) less the periodic risk-free rate ($R_{F,t}$)
>
> α is a measure of active manager skill,
>
> F is a beta factor, that requires a systematic risk premium in the market,

β is a coefficient or factor loading that measures the sensitivity of the manager's returns to the factor, and

ε is a random error term.

To implement this approach, we require data on currency manager returns and factors that proxy for types of trading strategies and exposures that currency managers would be likely to utilize.

We make use of the same data base as used in Pojarliev and Levich (2008b), i.e. daily return data for currency managers listed on the Deutsche Bank FXSelect trading platform.[12] While FXSelect is a new venture, the platform is designed to offer an attractive means for professional currency managers to enhance their visibility and grow their client base. As such, we believe that the FXSelect data offer a fair means of assessing performance in the currency management industry.[13] Because investors who use FXSelect may buy and sell positions continuously, daily prices of funds are available and allow us to measure crowdedness at shorter intervals. Our sample includes daily data

[12] Launched in March 2005, FXSelect is an open platform, which allows clients of Deutsche Bank to allocate their funds to different currency managers. Any currency manager can apply for registration in the platform and be accepted if he satisfies the following criteria: a) Managers must be able to provide a daily track record for at least the last 18 months verified by a third party, b) They cannot have had more than a 20% performance drawdown over the last 12 months, c) Assets under management must be at least 15 million USD, and d) Satisfactory criminal and regulatory searches on key individuals. We are grateful to Neville Bulgin and Rashid Hoosenally from Deutsche Bank for supplying the data. More information about FXSelect can be find in the brochure "FXSelect: An Asset Allocation Solution," Deutsche Bank, Global Markets Foreign Exchange, 2006.

[13] Many (about 25%) of the managers in the FXSelect database are also included in other well known hedge fund databases (CISDM and TASS). In our initial 3-year sample, the correlation between the monthly returns on a "fund-of-funds" (FoF) portfolio, compromised of equally weighted positions in each of the funds available on the platform and the monthly returns on two other well-known currency hedge fund indices, the Parker FX index and the Barclay Trades Currency Index, is 67% and 65%, respectively. As another example for the visibility of the platform, in February 2007 Deutsche Bank launched the Mercer Currency Manager Index – a multimanager product based on managers from the FXSelect platform chosen by Mercer Investment Consulting. According to information posted on its website,

on returns for 107 funds between April 2005 and June 2010.[14] Only 10 of these funds have a complete 63-month track record. However, there are 18 funds with more than 5 years of data, and 48 funds with 3 years or more data. To correct for accounting errors and eliminate data outliers, we transform the daily returns into 156 weekly returns by using Wednesday observations.[15] The data base is especially useful as it provides us with high frequency returns and allows for the correction of backfill and survivorship bias.[16]

Data for Risk Factors

As risk factors we make use of the same proxies as in PL (2008b).

Carry Factor

We use the Deutsche Bank G10 Harvest Index as the proxy for the returns of a carry strategy. This index reflects the return of being long the 3 high-yielding currencies against being short the 3 low-yielding currencies within the G10 currency universe. The index is rebalanced quarterly. Every quarter the currencies are re-ranked according to their current 3-month Libor rate. The Bloomberg code for this factor is DBHVG10U Index.

FXSelect has attracted $3.5 billion in AUM from pension funds, fund of funds, private banks, insurance companies, and other investors.

[14] We use the terms “fund” and “manager” interchangeably. A currency management firm could have multiple funds or programs on the platform.

[15] We use Wednesday as fewer bank holidays fall on Wednesday. Managers are based in different locations (US, UK, Australia, Switzerland, Monaco, Spain, Sweden, Germany, Ireland and Canada).

[16] For more information see Pojarliev and Levich (2008b).

Trend Factor

As a proxy for the trend-following factor, we use the AFX Currency Management Index.[17] The AFX Index is based on trading in seven currency pairs weighted by their volume of turnover in the spot market, with returns for each pair based on an equally-weighted portfolio of three moving average rules (32, 61 and 117 days).[18]

Value Factor

We use the Deutsche Bank FX PPP Index as the proxy for the returns of a value strategy. To gauge relative value, Deutsche Bank prepares a ranking based on the average daily spot rate over the last three months divided by the PPP exchange rate as published annually by the OECD. The FX PPP index reflects the return of being long the 3 currencies with the highest rank (undervalued currencies) against being short the 3 currencies with the lowest rank (overvalued currencies) within G10 currency universe. The Bloomberg code for this factor is DBPPPUSF Index.

Currency Volatility Factor

We use the Deutsche Bank Currency Volatility Index as the proxy for foreign exchange volatility. This index is calculated as the weighted average of 3-month implied volatility for nine major currency pairs (as provided by the British Bankers Association) with

[17] Monthly data for this index are available at the AFX web site (http://www.ljmu.ac.uk/LBS/95327.htm). We are grateful to Pierre Lequeux from Aviva Investors for providing daily data. We transformed the daily returns into weekly returns by using the Wednesday observations.
[18] The seven currency pairs are EUR-USD, USD-JPY, USD-CHF, GBP-USD, EUR-JPY, EUR-GBP, and EUR-CHF.

weights based on trading volume in the BIS surveys.[19] The Bloomberg code for this factor is CVIX Index. We use the first difference for this factor in equation (1) as it is not a trading strategy. In the case of the previous three factors, we use returns.

Definition of Crowdedness

We define the crowdedness of style F at time t ($C_{F,t}$) as the percentage of the funds with significant positive exposure to style F less the percentage of the funds with significant negative exposure to the same style (contrarians).

$$C_{F,t} = a_{F,t} - b_{F,t} \tag{2}$$

where

$a_{F,t}$ is the percentage of funds with significant positive exposure to risk factor F over the period *t-25* through t, i.e. we use rolling windows of 26 weeks to estimate the exposures to the risk factors with equation (1).

$b_{F,t}$ is the percentage of funds with significant negative exposure to risk factor F over the period *t-25* through *t-25*, i.e. we use rolling windows of 26 weeks to estimate the exposures to the risk factors with equation (1).

For both positive and negative exposures, we use a standard 95% confidence level and t-value with absolute value greater than or equal to 1.96 to indentify significant exposure.

By restricting our measure to only those funds with significant style betas, we intend to exclude funds where the point estimate of exposure while non-zero may not be meaningful. As a robustness check, in the empirical section we present several other measures of crowdedness based only on the magnitude of style betas regardless of their significance.

[19] The nine currency pairs are EUR-USD, USD-JPY, USD-CHF, USD-CAD, AUD-USD, GBP-USD, EUR-JPY, EUR-GBP, and EUR-CHF.

3. Empirical Results

a. Time Variation in Crowdedness

To determine which funds have significant exposure to each trading strategy, we estimate equation (1) using a rolling sample of 26 weekly observations over the 63-month (274 weeks) sample period, April 6, 2005 – June 30, 2010. Thus, we are able to estimate crowdedness on 249 dates commencing September 28, 2005 running through June 30, 2010. Funds on the platform for less than 26 weeks are excluded from our analysis.[20]

The number of funds used to estimate crowdedness varies from week to week, as new funds join the platform and some funds exit the platform. Exhibit 2 plots the number of funds used to estimate crowdedness. The number of funds is the lowest (22) at the beginning of the sample. It then rises steadily toward 60 in late 2006 as funds join the platform and then oscillates between 50 and 60 for the remainder of the sample as funds list and delist from the platform. Delisting funds tend to outnumber newly listed funds between January 2007 and spring 2009 when net new listings resume for the remainder of the sample.

To illustrate the methodology, Exhibit 3 plots the estimated t-statistics for alpha and the betas for fund #6 (indicating fund #6 in the data base). This fund has a track record of slightly more than 3 years (170 weeks) from the launch of the trading platform until fund #6 delisted on June 25, 2008. Using this sample, we obtain t-statistics for 144 weeks,

[20] There are seven funds on the platform with a track record of less than 26 weeks.

using a rolling window of 26 weeks. Exhibit 3 shows that over the entire sample period, fund #6 never achieved a significant alpha. Fund #6 generally had positive exposure to carry and trend and negative exposure to value and volatility.[21] However, these exposures were not consistently significant throughout the entire sample period, i.e. the t-statistics of the factor loadings were not constantly above 1.96 (or below -1.96).[22] For example, the exposure to value was most of the time not significant, but there were periods (at the beginning of 2006 and towards the middle of 2007) when this manager exhibited strong contrarian value positioning, i.e. the t-statistics of the value factor were between -2 and -3. Thus, manager #6 appears to have discretionary trading authority, tracking Value at some times and not at others, and taking other positions not significantly related to the Carry and Trend factors.

Crowdedness

Using t-values from equation (1), we estimate crowdedness using equation (2) for three of the four factors, i.e. carry, value and trend. As the fourth risk factor does not represent return on a trading strategy, but simply the first difference of the implied foreign exchange volatility, we do not estimate crowdedness for volatility.

Carry Crowdedness

Exhibit 4 plots our measure for carry crowdedness between September 28, 2005 and June 30, 2010. We also plot $a_{carry,t}$ and $b_{carry,t}$ representing the percentage of the funds

[21] This positive carry exposure might explain his delisting from the platform during the period of massive underperformance of carry trades.

with significant positive exposure to Carry and the percentage of the funds with significant negative exposure to Carry (the contrarians) and include the performance of the carry strategy.

Exhibit 4 suggests an interesting story. At the beginning of our sample, Carry Crowdedness was minimal (around 5%) as only about 10% of the funds in our analysis were significantly exposed to Carry and the "contrarians" were about 5%. As Carry started to exhibit very strong performance between mid-2006 and mid-2007, the number of both carry managers and contrarians increased. The first group appeared to be chasing the good performance of the carry strategy; while the second group was betting that carry was overdone. As the first group was only slightly larger than the second, Carry Crowdedness increased steadily to about 15%. In the summer 2007, the contrarians started to "die-out" as the performance of the carry strategy accelerated.[23] As a result Carry Crowdedness reached a peak at 32% in early April 2008 as the contrarians either gave up or were forced out of the market. Interestingly, the carry strategy exhibits a substantial decline just a few months later. While the popular press attributes the liquidation of the carry trade to the credit crunch and the decline of the equity markets, a possible reason behind the rapid liquidation of carry trades might be that this strategy had become crowded. This result is consistent with the "liquidity spiral" story suggested

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[22] We are referring here to the results of the rolling regressions. PL (2008b) show that manager #6 exhibits significant positive exposure to carry and trend and no significant exposure to value and volatility over a 3 year period, from April 6, 2005 until March 26, 2008.

[23] PL (2008b) show that managers who did not survive had as a group significant negative exposure to Carry between April 2005 and March 2008. Ironically, although the liquidation of the carry trade might have hurt carry managers, the strong performance of the carry strategy until the credit crunch was devastating for managers betting too early on liquidation of carry trades.

by Pedersen (2009) and the shrinking hedge fund asset base discussed in Jylhä and Suominen (2009).

With the Lehman Brothers bankruptcy in September 2008 and the ensuing global financial crisis, managers unwound carry trades and Carry Crowdedness collapsed. A flight to quality led managers into relative safe, low interest rate assets. After a decline of nearly 30%, by spring 2009 the performance of Carry resumed an upward trend and crowdedness in the carry trade advanced again to 32% in late 2009. Crowdedness subsided in early 2010 but dropped precipitously (along with performance) after the "flash crash" in May 2010.

Trend Crowdedness

Exhibit 5 plots our measure for Trend Crowdedness. In contrast to the Carry Crowdedness, Trend was a relative crowded strategy at the beginning of our sample period. The percentage of the funds which had significant positive trend exposure was between 25% and 35%, with only a very small percentage of the funds being "contrarians". As most of the currency research in the 1990s (see for example Levich and Thomas, 1993) advocated trend-following strategies, this is not a surprise. However, as Trend failed to deliver returns, crowdedness declined to near zero or slightly negative (contrarian) by May 2008. This change did not result from a rise in the numbers of contrarians, but rather that trend-followers appeared to be "giving up." Ironically, the trend strategy began to deliver excellent performance a few months later in the fall and winter 2008. Crowdedness in Trend increased in the midst of this favorable performance, before returning to single digit levels by the start of 2009, actually ahead of a 10% correction in Trend through spring 2009.

Crowdedness in Trend returned reaching 21.6% in November 2009 and after following a jagged course, returned to near zero or slightly negative at the end of our sample.

Value Crowdedness

Exhibit 6 plots our measure for Value Crowdedness. The pattern is different, but the main story bears a strong similarity to our interpretation for Carry Crowdedness. The percentage of the funds which exhibited positive significant exposure to Value was relatively small and constant around 10%. On the other hand, the percentage of the contrarians (funds with significant negative value exposure) was rising steadily through the spring 2008, peaking at 32%. Thus the contrarian value trade became progressively more crowded reaching 28.3% in April 2008. A few months later in the summer 2008, the financial crisis intensified and undervalued currencies rose, causing substantial losses to contrarian value traders, who had crowded into this position. The contrarians closed down their positions until Value reached a small positive crowdedness level of 7.8% in May 2009. The performance of Value was stunning with the factor rising from 90 (in the summer 2008) to over 120 (in the summer 2009).

The contrarian Value trade re-emerged in the summer 2009 and into the fall, peaking at -24.5% in January 2010 and into March. Concern over Greek external debt in spring 2010 coincided with a flight toward undervalued currencies. The Value trade earned a quick 8% return, leading Value contrarians to exit their positions. Once again, crowdedness in a trading strategy proved to be unrewarding for those holding the relatively popular trading position. At the end of the sample, pro-Value and contrarian traders were small both a small percentage of managers on the platform, and crowdedness was nearly zero.

b. Determinants of Crowdedness

As we can see from Exhibits 4, 5 and 6, our measure of crowdedness can vary considerably. For example, Carry Crowdedness varied between a low of -10% to a high of 32% reached on two dates separated by nearly two years. Trend Crowdedness ranged between -3% and 34%. And Value Crowdedness varied between about 12% early in the sample to about -28%. Selected extreme values of crowdedness for each of the trading strategies are summarized in the first column of Table 1.

In this section we consider the question of what drives crowdedness. There are two channels which impact the crowdedness of a trading strategy: (1) Through existing managers adopting or abandoning a strategy, and (2) by managers entering or exiting the trading platform which determines the number of funds in our data sample. Table 1 summarizes the composition of our universe of managers at the peaks and troughs in crowdedness for each style.

Carry Crowdedness was at a trough on December 28, 2005. At that point, 41 funds were active on the platform (only 16 of these funds (40%) survived until the end of our sample).[24] Of the 41 funds, 2 had significant carry exposure, 5 were betting against carry and 34 had no significant carry exposure. Carry Crowdedness reached an interim peak on April 9, 2008. At that point, 53 funds were active on the platform (with a track record of at least 26 weeks). From these 53 funds, 28 were active as of December 28, 2005 and 25 were new funds.

Of the new funds, 12 (or 48%) had significant carry exposure. Furthermore, a significant proportion from the existing funds with no carry exposure (9 funds or 22%) converted to having positive carry exposure. Thus, only one of the carry managers at the peak of Carry Crowdedness was a carry manager when Carry Crowdedness was at its low. The increase in the Carry Crowdedness seems to have been driven by 1) many new funds with positive carry exposure joining the platform, and 2) a large number of the existing funds with no carry exposure, adopting a carry style.

In the next cycle, Carry Crowdedness drops to -10.5% on November 5, 2008 reflecting that 9 funds (out of 57) hold contrarian styles while only 3 fund have positive carry exposure and fully 45 funds have no exposure. The increase in funds with no exposure, from 26 to 45 over the interval, is largely by 21 funds that switched their style betas, and only 4 new funds whose returns also showed a zero style beta.

In important ways, the subsequent cycles of Carry Crowdedness – peaking at 32.1% on January 13, 2010 and then reaching a trough of 1.6% on June 16, 2010 – mimic the prior

[24] This low survivorship rate highlights the importance of including dead funds in the analysis.

two descriptions. The rise in crowdedness is the result of a few new funds (3) that follow carry joining the platform, and a larger number of existing funds (16) switching to a positive carry strategy. The decline in crowdedness is the result also of a few new funds (7) with no exposure to carry joining the platform, and a larger number of existing funds (18) switching to a neutral carry strategy.

Trend Crowdedness emulates many of the same patterns. Trend Crowdedness was at its peak of 33.9% on December 6, 2006. At that point, 59 funds were active on the platform (only 23 of these funds (39%) did not survive until the end of our time horizon). Of these 59 funds, 21 had significant trend exposure, 1 was positioned against trend and 37 had no significant trend exposure. Trend Crowdedness reached an interim low value (-1.6%) on May 14, 2008. At that point, 56 funds were active on the platform (with a track record of at least 26 weeks). Of these 56 funds, 40 were active as of December 28, 2005 and 16 were new funds. Of the new funds, 13 (or 81%) had no significant trend exposure. Furthermore, of the 21 funds with positive trend exposure, 16 funds (or 76%) exited the trend style, i.e. had no exposure to trend as of the end of the time horizon. From the 21 managers with trend following exposure at the time of the peak in Trend Crowdedness, only 1 manager exhibited trend exposure at the time of the low in the Trend Crowdedness. Thus, the decline in the Trend Crowdedness seems to be driven by 1) new funds joining the platform with no trend exposure, and 2) a large number of the initial trend-followers "giving up" on trend.

In the subsequent cycles of Trend Crowdedness which reaches a peak of 21.6% on November 4, 2009 and then a trough of 3.4% on June 9, 2010 the changes in crowdedness seem driven by a similar pattern. The rise (or fall) in crowdedness is the result of a large number of existing firms switching to follow (or desist following) the trend strategy, and a relatively smaller number of funds.

Further emulating this pattern, Value Crowdedness was at a peak on January 18, 2006. At that point, 41 funds were active on the platform and only 16 of these funds (or 39%) survived until the end of our time horizon. Of these 41 funds, 6 had significant value exposure, 1 was betting against value and 34 had no significant value exposure. From the 6 funds with positive value exposure, 4 funds left the value style and 2 funds exited the platform. None of the value funds as of January 18, 2006 remained positively exposed to value as of April 9, 2008 when Value Crowdedness reached an interim through. At that point, 53 funds were active on the platform (with a track record of at least 26 weeks). From these 53 funds, 28 were active as of December 28, 2005 and 25 were new funds. Of the new funds, eight (32%) had significant negative value exposure (contrarian). The decline in Value Crowdedness seems to be driven by a) new funds joining the platform betting against value, and b) a large number of the existing funds (10 funds) converting to a value contrarian strategy.

In the subsequent cycles of Value Crowdedness which reaches a peak of 7.8.6% on May 20, 2009 and then a trough of -24.5% on January 13, 2010 the changes in crowdedness seem driven by a similar pattern. The rise (or fall) in crowdedness is again largely the result of a large number of existing firms switching to follow (or desist following) the trend strategy, and a relatively smaller number of funds.

A general conclusion we can draw from Table 1 is that the change in crowdedness across the different styles is driven by the change in styles of the existing managers, but also in the different styles characteristics of the new managers on the platform. What may be behind these shifts?

In theory, managers should be attracted by expected returns. As expected returns on a strategy rise, the desired portfolio allocation to that strategy rises also. However, specifying the formation of expected returns is always problematic. We consider two possibilities. First, managers could form expected returns based on the logic of each trading strategy. For carry trades, as the interest rate differential widens, the expected return (conditional on a given exchange rate change) rises. For value trades, as deviations from PPP widen, the expected return rises. We found only weak evidence that crowdedness in Carry and Value responded to expected returns modelled in this way.[25]

A second possibility is to model the expected returns on a strategy directly as a function of past returns on that strategy. If managers form expectations in this way, we would expect to observe herding in the sense that positive returns on a strategy attracts newcomers, and negative returns on a strategy encourage managers to abandon a

[25] For trend, most simple trend following rules provide only an indication of the future trend, and not the magnitude, of future exchange rate developments. With trend, therefore, we cannot readily test whether conditions are more or less favourable for managers to shift in or out of this style.

strategy. As we measure crowdedness over 26 weeks, we cumulate the performance of the different strategies also over 26 weeks. Our methodology (of confirming whether or not a manager is following some strategy) relies on estimating betas, and needs a number of weeks before we can determine whether or not a manager has shifted his allocations in response to higher expected returns in any strategy. So there is a lag of 26 weeks between when returns on a strategy first appear and when we (the researcher) can identify a statistically significant relationship, or style beta. Therefore, we have to lag the cumulative past performance of the strategies by 26 weeks to explore the linkage with our measure of crowdedness.

Table 2 summarizes the correlations between our measure of crowdedness and the lagged performance of the trading strategies. Panel A contains results over the whole sample period. Panels B and C show results for the first and second halves of the sample. Table 2 suggests some herding in the carry strategy: good past performance attracts newcomers. There is weaker support for herding in the value strategy, but no support in our sample for herding in the trend strategy.

Several factors may influence this weak evidence. First, not all managers have discretionary authority to allocate toward a given currency strategy, even when it appears to be profitable. For example, a fund that specializes in trend following, and has stated so in an investment mandate, cannot shift and take positions in carry trades even when they appear likely to generate profits. Only discretionary managers can shift their trading style in response to a new market environment. So only a small number of managers in the sample have the ability to shift. We should not expect that 100% of all the managers in any sample will follow carry (for example) when carry is profitable, because some of those managers are trend followers or value managers, by design or choice. Second, managers might be constrained in joining the platform; a fund needs 18 months of track record to list on DB FX Select. Therefore, even if a new carry manager might be keen to join the platform (as he expects future carry returns to be high), he would have to wait for the appropriate track record before to join. Finally, the past return of a strategy might not be the best proxy of what managers think regarding the future expected return of a strategy.

c. Robustness Checks

As a robustness check, we calculate several alternative crowdedness measures that are based on the difference in the percentages of those funds with betas above a certain positive cut-off minus those with betas below a certain negative cut-off, regardless of whether the t-statistics are significant or not. Thus, we define an alternative measure of crowdedness of style F at time t ($C^*_{F,t}$) as the percentage of the funds with F-beta greater than X minus the percentage of the funds with F-beta less than -X.

$$C^*_{F,t} = a^*_{F,t} - b^*_{F,t} \tag{3}$$

where

> $a^*_{F,t}$ is the percentage of funds with beta to risk factor F greater than X over the period $t\text{-}25$ through t, i.e. we use rolling windows of 26 weeks to estimate the exposures to the risk factors with equation (1).
>
> $b^*_{F,t}$ is the percentage of funds with beta to risk factor F less than – X over the period $t\text{-}25$ through $t\text{-}25$, i.e. we use rolling windows of 26 weeks to estimate the exposures to the risk factors with equation (1).

Exhibit 7 plots our original measure of crowdedness for Carry, Trend and Value along with the alternative measure of crowdedness for a 0.50 cut-off (X=0.50). There is a high correlation between the two measures for Carry and Value, i.e. 78% and 81%, respectively. For Trend the correlation is smaller at 68%, but still positive and significant.[26] We calculate the alternative measure of crowdedness for different cut-off values X=0.25, 0.50, 0.75 and 1.0. Table 3 summarizes the correlations between our original and alternative measures of crowdedness.

The graphs in Exhibit 7 show that both the original and alternative measures of crowdedness behave quite similarly over our sample. The relationship is very strong for Carry and Value while there is an apparent break for Trend during parts of 2007. During January –May 2007, Trend Crowdedness declined from 17% to 9%, while the alternative measure increased from 19% to 36%. However, for most of the remainder of the sample, the generally close association between C and C* for Trend reasserts itself.

Overall, the alternative measures (C*) show similar patterns as our original measure (C) over much of the sample, with only a small number of instances where the measures move in opposite directions for an extended period.

[26] Testing the significance of the correlation coefficient between C and C* shows that all correlations are highly significant with p-values < 0.00001.

4. Policy and Investment Implications

The financial crisis of 2008 highlights the importance of detecting crowded trades due to the risks they pose to the stability of the financial system and to the global economy. However, there is a perception that crowded trades are difficult to identify.[27] To date, no single measure to capture the crowdedness of a trade or a trading style has developed.

Using a unique data base of professional foreign exchange manager returns, we propose and estimate a new measure for style crowdedness. Our measures of crowdedness offer more perspective on events in currency markets over the financial crisis period. In the first quarter of 2008, the data show that a higher than usual percentage of the funds were significantly exposed to Carry, and these funds suffered during the market turbulence in the last quarter of 2008 when Carry collapsed. Similarly, in the first quarter of 2008 a high percentage of the funds were significantly betting against Value. However, later in 2008 Value delivered strong performance, resulting in substantial losses for the contrarians who were caught wrong-footed. The story for Trend is different: Trend was a crowded strategy at the beginning of our sample period, but this crowdedness led simply to flat performance for the trend strategy during this period. After managers gave up on the trend strategy, Trend delivered strong performance, leading to opportunity costs, but no actual losses.

[27] For example, in attempting to measure the extent of carry trade activity, Galati, Heath and McGuire (2007) analyze various banking and capital flow data. The authors do not offer numerical estimates. They conclude that "growth in carry trades funded in yen and Swiss francs has probably contributed to increased activity in these currencies" but that "the available data do not allow for a more refined measurement of the size of carry trade positions." And on the same theme, in their analysis of carry trading and currency movements in 2008, McCauley and McGuire (2009) conclude that "Carry trades always defy measurement." It is worth stressing that our approach does not provide a quantitative estimate of the volume of carry trades outstanding.

Updating the sample from March 2008 until June 2010 when data became available, confirmed our hypotheses. Following a strong performance of carry in 2009, carry became a crowded strategy once again, only to experience a strong reversal during the European sovereign debt crises in the spring of 2010. The patterns for Trend and Value also reinforced the earlier findings.

Our results suggest that our measure of crowdedness deserves closer monitoring. In our short sample period, the anecdotal evidence shows that crowdedness may provide useful signals regarding the future performance of a given strategy. While our sample period is too short for more formal statistical tests, our analysis suggests that there may be an adverse relationship between crowdedness and style performance, in particular in the carry and value styles. This will hopefully stimulate some future research on this subject.

As more and more funds attempt to exploit market timing strategies by switching among trading styles in order to deliver alpha and not simply beta, crowdedness may again become a significant element of market dynamics. Indeed as US dollar interest rates remained close to zero during 2009, commentators alleged that a surging US dollar based carry trade had developed that will have dire consequences once it begins to unwind.[28] This was realized during the European sovereign debt crises in spring 2010 with the US dollar index surging 15% between January and June 2010. Additional data

[28] Nouriel Roubini, "Mother of all carry trades faces an inevitable bust," *Financial Times*, November 1 2009.

will allow researchers to track when our measure of crowdedness reveals any unwinding and whether changes in crowdedness correlate with exchange rate movements.[29]

Hearings held by the U.S. House Financial Services Committee in 2009 considered proposals for a "systematic risk regulator" who could take into account, among other things, that crowded trades elevate the risk to the financial system because crowding is itself a source of instability. But as some observers have noted, "the sad truth [is] that crowded trades are difficult for the government to identify."[30] Our methodology may offer useful insights regarding the popularity of certain trades – in currencies, gold, or other assets – among hedge funds and provide regulators with another tool for monitoring markets. Although, we apply our approach to currencies, it could be easily extended to other asset classes. Further research in this area could be relevant for investors, managers, and regulators.

[29] Currency managers' returns are usually available on a daily basis to plan sponsors. Thus, some institutional investors could update and follow our measure of crowdedness on a daily basis.
[30] Sebastian Mallaby, "A Risky 'Systemic' Watchdog," *Washington Post*, March 2, 2009.

References

Deutsche Bank. "DB FX Positioning Indices," May 18, 2009.

Brunnermeier, Markus K., Stefan Nagel and Lasse H. Pedersen. (2008) "Carry Trades and Currency Crashes," NBER Working Paper No. 14473, November.

Evans, Martin D. D. and Richard K. Lyons. (2002) "Order Flow and Exchange Rate Dynamics," *Journal of Political Economy*, Vol. 110, no. 1 (Feb): 170-80.

Froot, K. A., and T. Ramadorai. "Currency Returns, Intrinsic Value, and Institutional Investor Flows." *Journal of Finance* 60, no. 3 (June 2005): 1535-1566.

Froot, K. A., and T. Ramadorai. "Institutional Portfolio Flows and International Investments." *Review of Financial Studies* 21, no. 2 (April 2008): 937-971.

Froot, K. and R. Thaler. 1990. "Anomalies: Foreign Exchange," *Journal of Economic Perspectives*, vol. 4, no. 3 (Summer): 179-92.

Fung, W. and D. Hsieh. 2002. "Asset-Based Style Factors for Hedge Funds," *Financial Analysts Journal*, vol. 58, no. 5 (Sept-Oct): 16-27.

Galati, Gabriele, Alexandra Heath and Patrick McGuire. 2007. "Evidence of Carry Trade Activity," *BIS Quarterly Review*, (September): 27-41.

Gross, W. 2005. "Consistent Alpha Generation through Structure," *Financial Analysts Journal*, vol. 61, no. 5 (Sept-Oct): 40-43.

Jylhä, Petri and M. Suominen. (2009) "Speculative Capital and Currency Carry Trade Returns," working paper, Helsinki School of Economics.

National Association of College and University Business Officers (2008), 2007 NACUBO Endowment Study, Washington, D.C.

McCauley, Robert and Patrick McGuire. 2009. "Dollar Appreciation in 2008: Safe Haven, Carry Trades, Dollar Shortage and Overhedging," *BIS Quarterly Review*, (December): 85-93.

Meese, Richard A., and Kenneth Rogoff, 1983, "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics*, vol. 14, February, pp. 3–24.

Levich, R.M., and L.R. Thomas, III. 1993. "The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach." *Journal of International Money and Finance*, vol. 12, no. 5 (October):451–474.

Pedersen, Lasse Heje. (2009) "When Everyone Runs for the Exit," NBER working paper, No. 15297, August 2009.

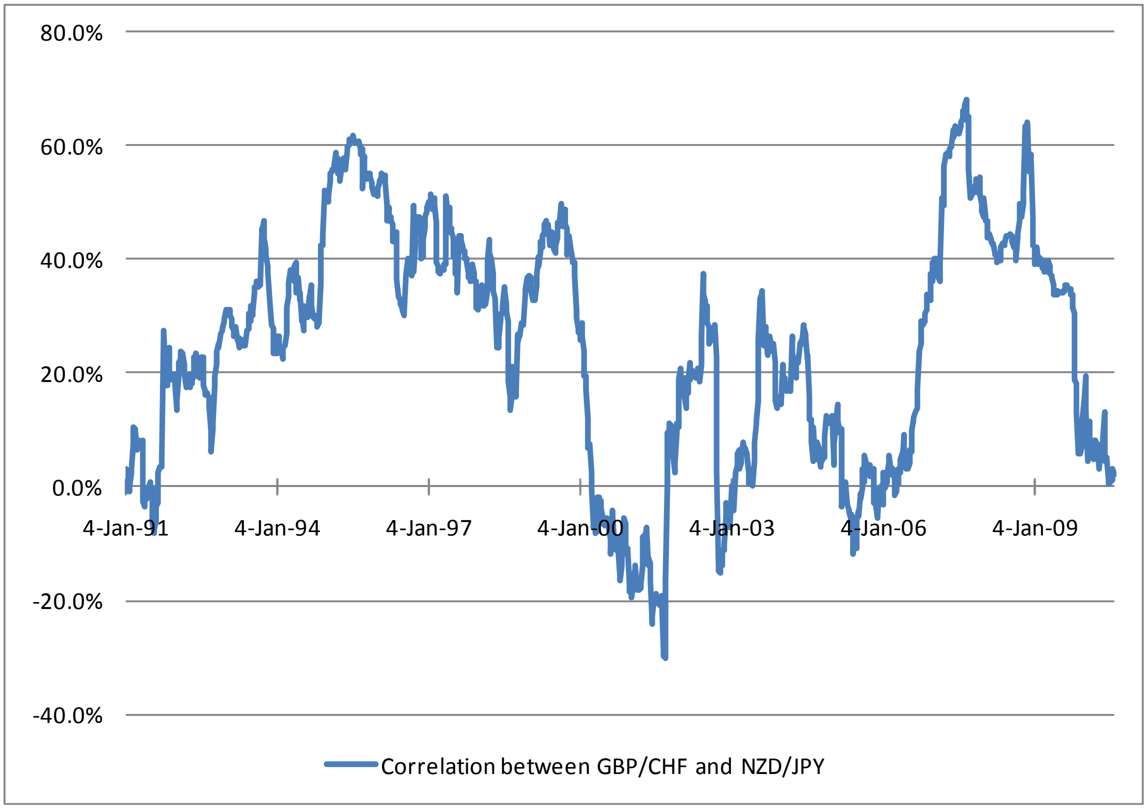
Pojarliev, M. and R.M. Levich. 2008a. "Do Professional Currency Managers Beat the Benchmark?" *Financial Analysts Journal,* (Sep/Oct): vol. 64, no. 5.

Pojarliev, M. and R.M. Levich. 2008b. "Trades of the Living Dead: Style Differences, Style Persistence and Performance of Currency Fund Managers?" NBER working paper 14355, September 2008. (*Journal of International Money and Finance*, forthcoming)

Rogoff, K. and V. Stavrakeva (2008), "The Continuing Puzzle of Short Horizon Exchange Rate Forecasting", NBER Working paper 14071.

Exhibit 1: Rolling Yearly Correlation of Returns on Two Cross Rates

Weekly Data, 01/04/1991 – 07/30/2010

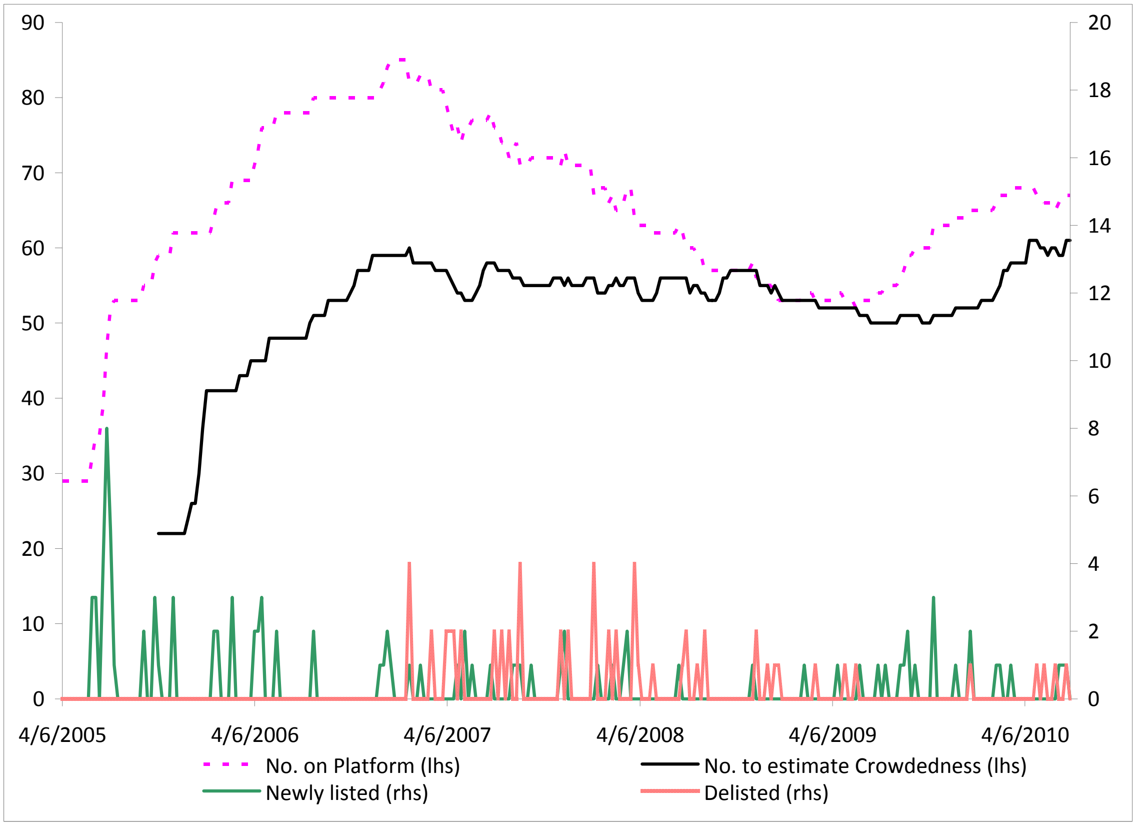


Data source: Bloomberg and authors' calculations.

Note: Correlation is computed by using a rolling sample of 52 weekly observations. The first correlation measure is for January 4, 1991. Currency returns are computed from January 12, 1990 until July 30, 2010.

Exhibit 2: Number of Funds on DB FX Select Platform, Number Used to Estimate Crowdedness, Number Newly Listed and Delisted.

Weekly data: 4/06/2005 - 6/30/2010



Source: Deutsche Bank and authors' calculations

Number of active funds on the platform between week *t* and *t*-25 that are used to estimate Crowdedness on week *t*. For example, 22 funds were active between 4/6/2005 and 09/28/2005. These 22 were used to estimate Crowdedness on 09/28/2005. Funds with a track record of less than 26 weeks (1/2 year) are not used for estimating of Crowdedness.

Exhibit 3: Estimated t-values for alpha and beta coefficients for manager #6

Rolling regression results for $R_t = \alpha + \sum_i \beta_{i,} F_{i,t} + \varepsilon_t$ where R are the returns of manager #6; i = Carry, Trend, Value and Volatility; t = 1, …26 weekly observations.

The first regression is estimated with 26 weekly observations from 4/06/2005 until 6/25/2008 (when manager #6 left the platform). The last regression is estimated with 26 weekly observations from 1/02/2008 until 6/25/2008. The sample contains 144 rolling windows.

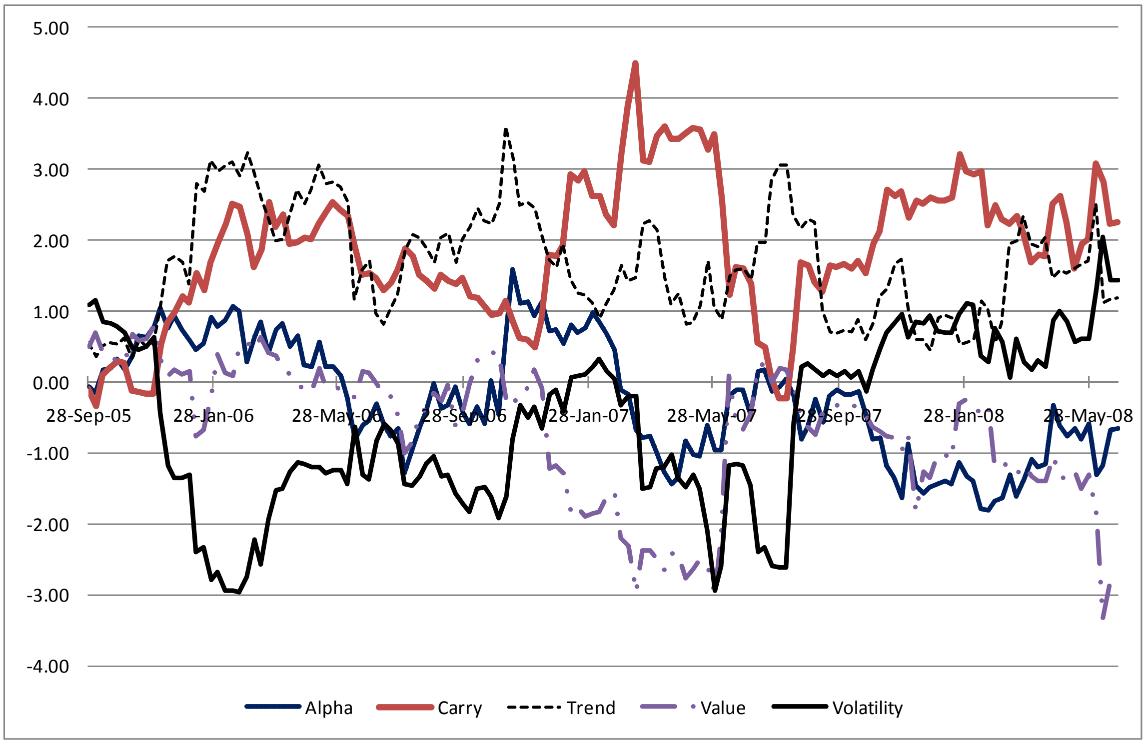
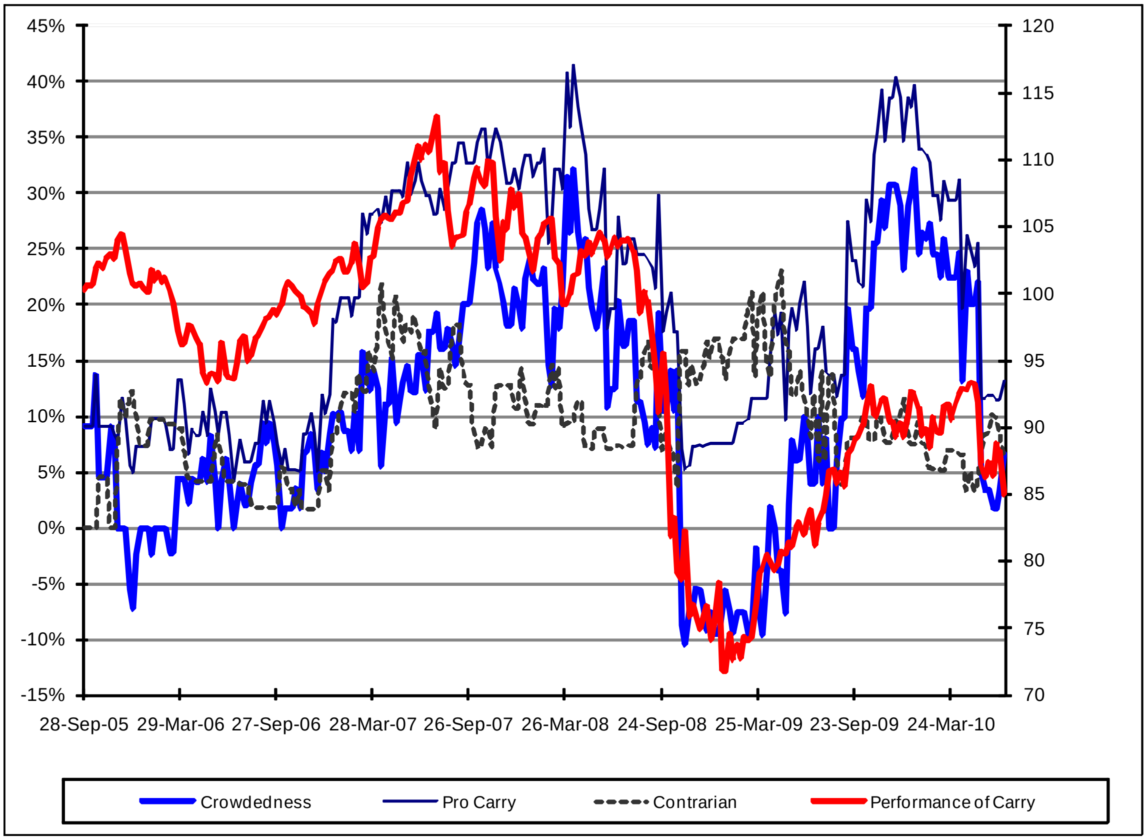


Exhibit 4: Carry Crowdedness

Rolling regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \varepsilon_{j,t}$ for manager j active on the platform at least from week *t-25* onwards. The number of managers varies according to Exhibit 2.

Carry crowdedness is defined as in Equation #2. The first measure for crowdedness is estimated as of 9/28/2005 with 26 weekly observations from 4/06/2005 until 9/28/2005. The last measure of crowdedness is estimated as of 6/30/2010 with 26 weekly observations from 1/06/2010 until 6/30/2010. The sample contains 249 rolling windows.

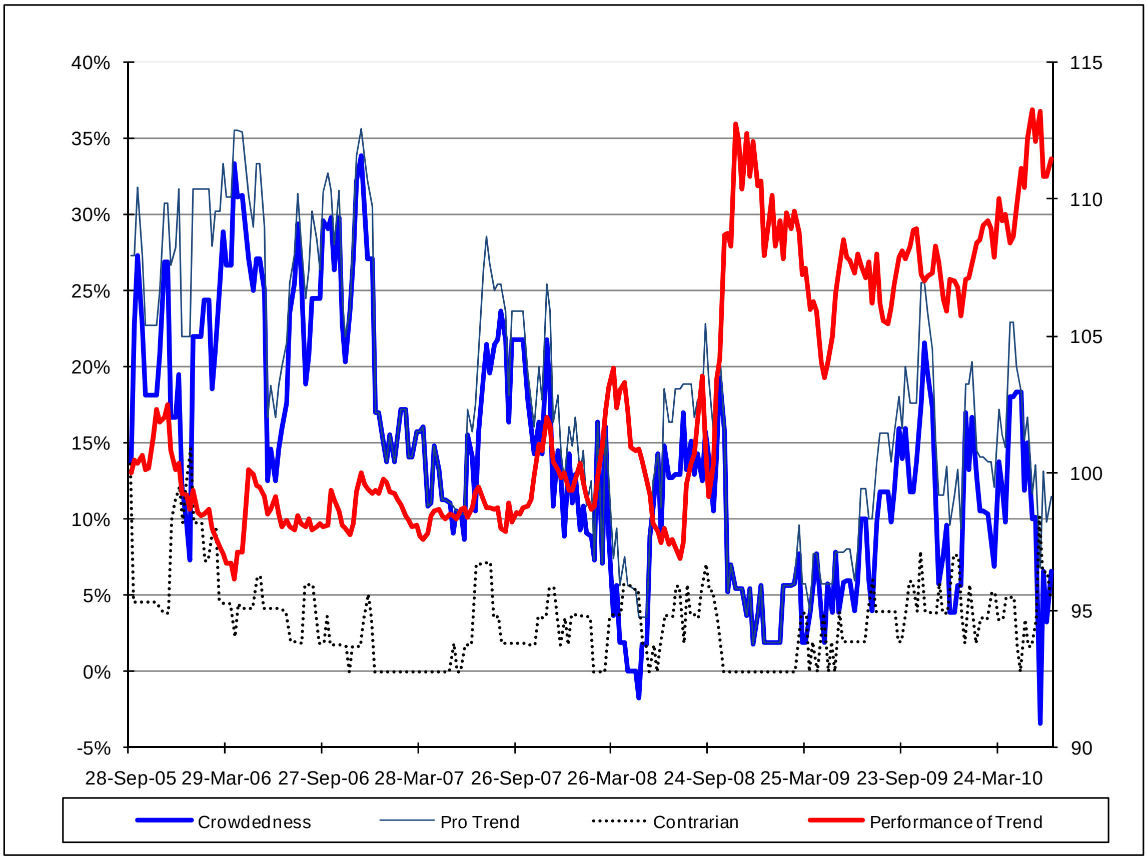


Crowdedness measures are on left-hand scale and Performance measure is on the right-hand scale.

Exhibit 5: Trend Crowdedness

Rolling regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \varepsilon_{j,t}$ for manager j active on the platform at least from week *t-25* onwards. The number of managers varies according to Exhibit 2.

Trend crowdedness is defined as in Equation #2. The first measure for crowdedness is estimated as of 9/28/2005 with 26 weekly observations from 4/06/2005 until 9/28/2005. The last measure of crowdedness is estimated as of 6/30/2010 with 26 weekly observations from 1/06/2010 until 6/30/2010. The sample contains 249 rolling windows.

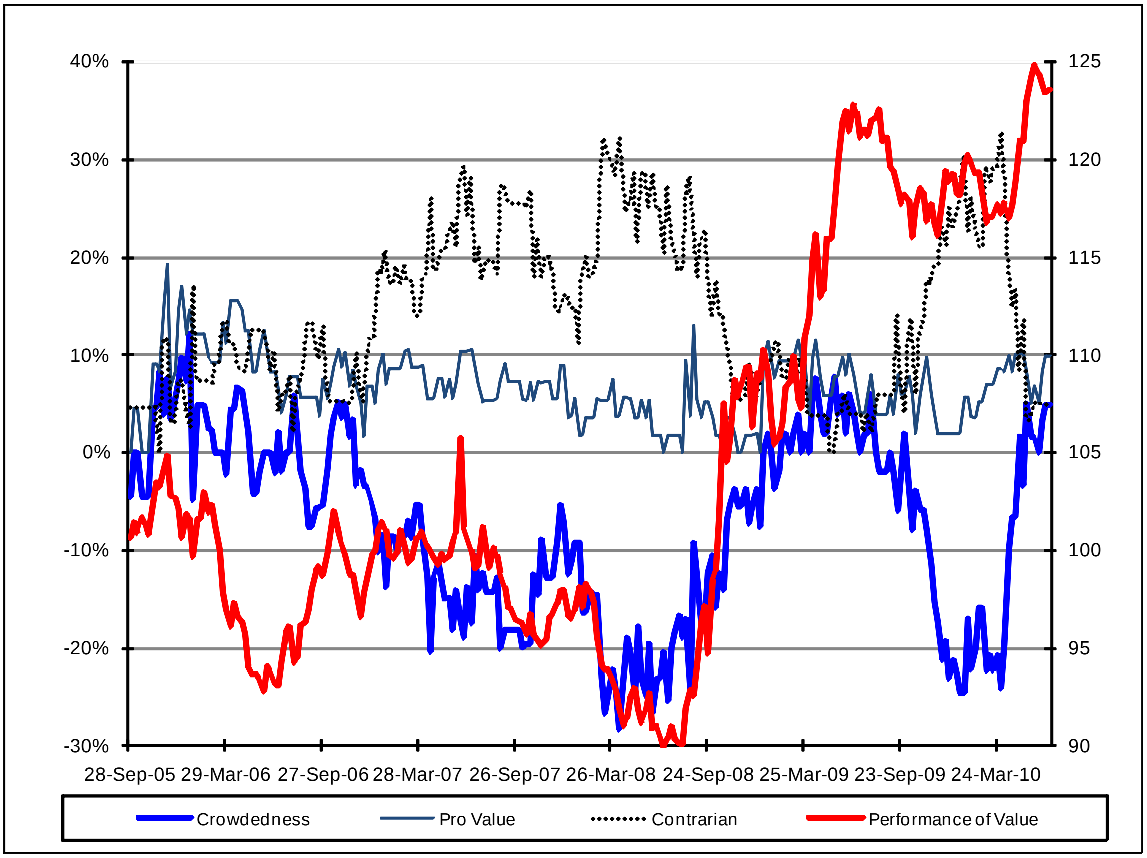


Crowdedness measures are on left-hand scale and Performance measure is on the right-hand scale.

Exhibit 6: Value Crowdedness

Rolling regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \varepsilon_{j,t}$ for manager j active on the platform at least from week *t-25* onwards. The number of managers varies according to Exhibit 2.

Value crowdedness is defined as in Equation #2. The first measure for crowdedness is estimated as of 9/28/2005 with 26 weekly observations from 4/06/2005 until 9/28/2005. The last measure of crowdedness is estimated as of 6/30/2010 with 26 weekly observations from 1/26/2010 until 6/30/2010. The sample contains 249 rolling windows.

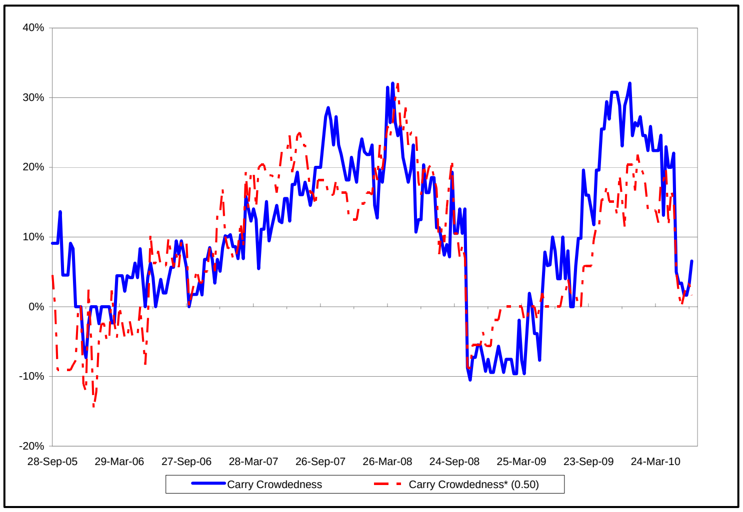


Crowdedness measures are on left-hand scale and Performance measure is on the right-hand scale.

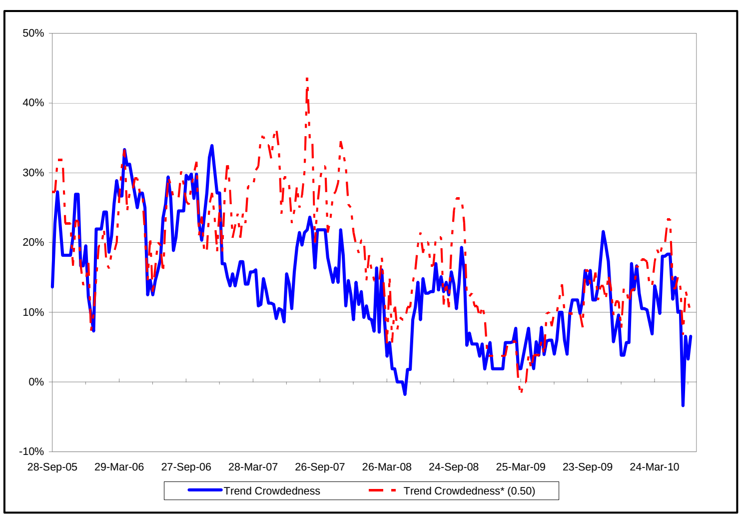
Exhibit 7: Original Crowdedness Measure (C) and Alternative Crowdedness Measure (C*) for X=0.50

Rolling regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \varepsilon_{j,t}$ for manager *j* active on the platform at least from week *t-25* onwards. The number of managers varies according to Exhibit 2. Crowdedness measure (C) is defined as in Equation 2. Details of the calculation are in the notes to Exhibits 4, 5, and 6. Crowdedness measure (C*) is defined as in Equation 3. We use the identical rolling regression method based on active managers. C* tracks the number of funds with β>0.5 less the number of funds with β<-0.5 regardless of whether or not the β coefficients are significant.

Panel A: Carry Crowdedness



Panel B: Trend Crowdedness



Panel C: Value Crowdedness

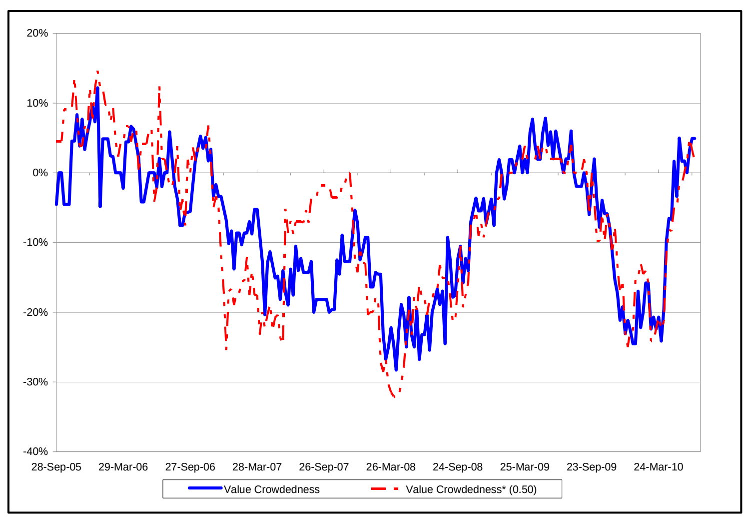


Table 1: Characteristics of Funds at High and Low Points of Crowdedness by Style of Strategy

Crowdedness (date)	# funds on the platform	# funds with significant exposure	# funds with significant negative exposure (contrarian)	# funds with no significant exposure
Panel A: Carry				
-7.31% (Dec 28, 2005)	41	2	5	34
32.08% (Apr 9, 2008)	53 (25, 28, NA) *	22 (12, 1, 9)	5 (2, 2, 1)	26 (11, 13, 2)
-10.52% (Nov 5, 2008)	57 (9, 48, NA)	3 (1, 0, 2)	9 (4, 1, 4)	45 (4, 20, 21)
32.08% (Jan 13, 2010)	53 (7, 46, NA)	21 (3, 2, 16)	4 (1, 1, 2)	28 (3, 22, 3)
1.64% (June 16, 2010)	61 (11, 50, NA)	7 (3, 4, 0)	6 (1, 1, 4)	48 (7, 23, 18)
Panel B: Trend				
33.9% (Dec 6, 2006)	59	21	1	37
-1.64% (May 14, 2008)	56 (16, 40, NA)	2 (1, 0, 1)	3 (2, 0, 1)	51 (13, 22, 16)
21.57% (Nov 4, 2009)	51 (10, 41, NA)	13 (3, 0, 10)	2 (0, 0, 2)	36 (7, 27, 2)
-3.39% (June 9, 2010)	59 (12, 47, NA)	4 (1, 0, 3)	6 (1, 0, 5)	49 (10, 24, 15)
Panel C: Value				
12.20% (Jan 18, 2006)	41	6	1	34
-28.30% (April 9, 2008)	53 (25, 28, NA)	2 (1, 0, 1)	17 (8, 0, 9)	34 (16, 16, 2)
7.84% (May 20, 2009)	51 (11, 40, NA)	4 (1, 0, 3)	0	47 (10, 24, 13)
-24.53% (Jan 13, 2010)	53 (5, 48, NA)	1 (0, 0, 1)	14 (1, 0, 13)	38 (4, 30, 4)
5.00% (May, 19, 2010)	60 (9, 51, NA)	5 (1, 1, 3)	2 (1, 0, 1)	53 (7, 34, 12)

Each triple of numbers (a, b, c) indicates (a) The number of new funds since the previous date in the table (upper left column); (b) The number of funds with the same style also at the previous date in the table (upper left column); and (c) The number of existing funds (active also at the previous date in the table) which switched style. For example, a fund with no significant carry exposure on one date, but with significant carry exposure on the following date is counted as having switched style.

Table 2: Correlations of Crowdedness Measures with Lagged Performance of Trading Strategies

Crowdedness for each style factor is defined as in Equation #2. The first measure for crowdedness is estimated as of 9/28/2005 with 26 weekly observations from 4/06/2005 until 9/28/2005. Performance of each trading strategy is measured over the prior 26-week period. The first measure for lagged performance is for the period 10/13/2004 until 04/06/2005. Entries in the table are the correlation of crowdedness for each style factor with its own lagged performance.

Sample Periods	Carry-Crowdedness	Trend-Crowdedness	Value-Crowdedness
Sept 28, 2005 – June 30, 2010 (249 weekly observations)	41%	-16%	23%
Feb 13, 2008 – June 30, 2010 (124 weekly observations)	47%	-6%	29%
Sept 28, 2005 – Feb 13, 2008 (125 weekly observations)	41%	2%	19%

Table 3: Correlation between Original Measure of Crowdedness (C) and Alternative Measures of Crowdedness (C*) for Alternative Beta Values

The original measure of crowdedness (C) is defined in equation #2. An alternative measures of crowdedness (C*) based on the percentage of managers with styles betas greater than or equal to a given cut-off value is defined in equation #3. Both measures of crowdedness are estimated on 26-week periods from 4/6/2005 until 6/30/2010. The sample contains 249 rolling windows.

	Carry	**Trend**	**Value**
	Crowdedness	Crowdedness	Crowdedness
Crowdedness* (0.25)	83%	63%	84%
Crowdedness* (0.50)	78%	68%	81%
Crowdedness* (0.75)	56%	68%	71%
Crowdedness* (1.00)	34%	63%	55%