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Detecting Crowded Trades in Currency Funds

Momtchil Pojarliev, CFA, and Richard M. Levich

Investors and regulators suspect that crowded trades may pose a special risk. The authors propose a methodology to measure crowded trades and apply it to currency managers. This methodology offers useful insights regarding the popularity of certain trades among hedge funds and provides regulators with another tool for monitoring markets.

Over the last 20 years, institutional investors have increasingly directed their allocations to alternative investments like hedge funds and away from traditional assets like equities and bonds. For example, a recent survey conducted by the National Association of College and University Business Officers (2008) found that U.S. university endowments larger than $1 billion allocated more than 20 percent of their assets to hedge funds. This strategy was partly the result of conventional beliefs that diversification is the key to successful investing and that returns on alternative assets have little or no correlation with returns on traditional investments.

The transfer of substantial assets under management to hedge funds, however, 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 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 crowded trades was realized during the global financial crisis.

In turbulent periods, "positioning" and being aware of crowded trades become crucial because 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 because everyone is rushing to exit a "burning house." In order to leave a burning house, however, reaching the exit is not enough; you must persuade someone from the outside to take your place (i.e., to take the other side of the trade). Not surprisingly, therefore, positioning and the concentration—the popularity, the crowded nature—of certain trades and trading styles are much-discussed topics among investment managers.[2]

To understand the importance of positioning, note that some banks, as part of their periodic foreign exchange research commentaries, have introduced U.S. Commodity Futures Trading Commission data on market positioning in currency futures.[3] These analyses focus on the positioning of the noncommercial or speculative accounts. Custodians are also able to take advantage of their proprietary equity flow data in order to gauge positioning. For example, State Street Bank and Trust is said to make use of its proprietary flow data to gauge positioning across different currencies.[4] To date, however, no single measure that captures the crowdedness of a trade or trading style has been developed. Identifying crowded trades is challenging because of the large number of asset classes that hedge funds can invest in. Furthermore, given that most databases collect monthly returns, such data would allow gauging crowdedness only over the long term.

In our study, we used a new database of daily data on currency funds to develop a new approach for detecting positioning and identifying crowded trades. Because currency funds have a clearly defined investment universe, they offer a good laboratory for developing an approach for detecting crowded trades. Moreover, the high-frequency data in our sample allowed us to develop measures of crowdedness over economically relevant horizons.[5] Although we applied our approach to currencies, the methodology 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

Momtchil Pojarliev, CFA, is a director and senior portfolio manager at Hathersage Capital Management LLC, New York City. Richard M. Levich is professor of finance at New York University Stern School of Business.

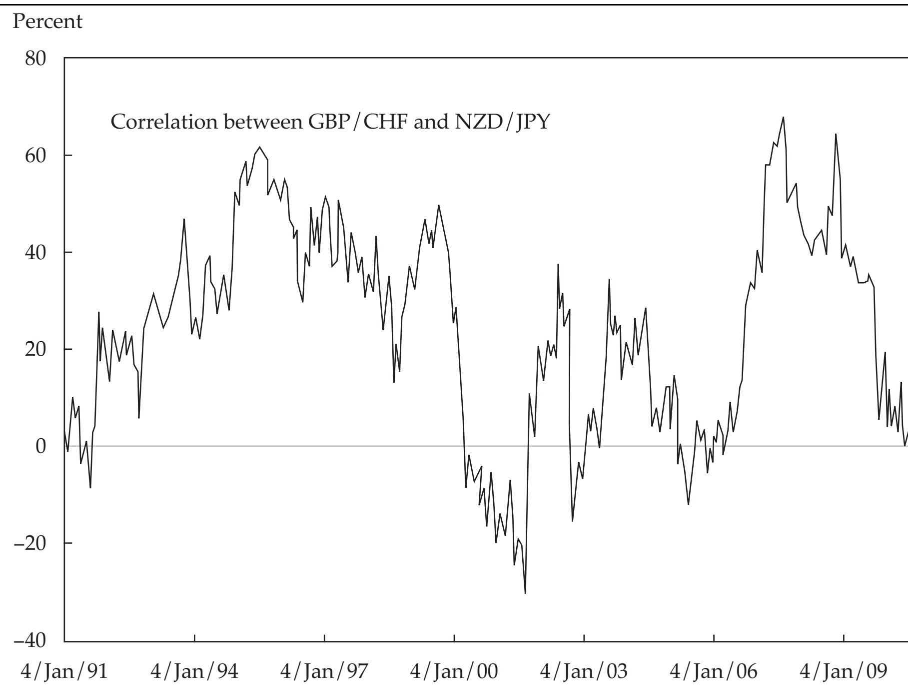
to expect a high correlation between currency returns on the GBP/CHF cross and the NZD/JPY cross. A carry trader who established a long position in high-yielding currencies by taking a short position in low-yielding currencies, however, could very likely have been long the two crosses (long GBP versus CHF and long NZD versus JPY) over much of the last 20 years because interest rates in New Zealand and the United Kingdom were generally higher than interest rates in Japan and Switzerland.[6] The increasing popularity of the carry trade could account for the greater correlation of these two crosses in recent years (**Figure 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 dropping sharply in the first half of 2009, after a massive liquidation of carry trades in late 2008.[8]

Analyzed in this way, currency traders appear to be focused more on exposure to a particular risk factor or trading strategy and less on exposure to particular currencies. A large short JPY exposure might be offset by a long CHF exposure because 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 currency pair seems preferable, which is a property that our technique can exploit.

Previous research (see Pojarliev and Levich 2008a) has shown that four factors (or styles), which represent the return on several well-known currency trading strategies, and 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 useful way to gauge the popularity or crowdedness of a trading strategy.[9]

In this study, we defined style crowdedness as the percentage of funds with significant positive exposure to a given style less the percentage of funds with significant negative exposure to the same style ("contrarians").[10] To estimate crowdedness, we relied on data for 107 currency managers that covered the period April 2005–June 2010, a little more than five years.[11] We estimated style betas by using the four-factor model proposed in Pojarliev and Levich (2008a). We used high-frequency weekly return data to obtain efficient parameter estimates for rolling 26-week periods.

Figure 1. Rolling Yearly Correlation of Returns on Two Cross Rates' Weekly Data, 4 January 1991–30 July 2010



Notes: Correlations were computed by using a rolling sample of 52 weekly observations. The first correlation measure is for 4 January 1991. Currency returns were computed from 12 January 1990 to 30 July 2010.

Sources: Bloomberg; authors' calculations.

Data Description and Definition of Crowdedness

To measure exposure to styles, we followed the approach used in Pojarliev and Levich (2008a) and used a standard factor model of the form

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

where

R = 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 = a measure of active manager skill

F = a beta factor that requires a systematic risk premium in the market

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

ε = a random error term

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

We used the same database that was used in Pojarliev and Levich (2008b)—that is, daily return data for currency managers listed on the Deutsche Bank FXSelect trading platform.[12] Although FXSelect is a relatively 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 way to assess performance in the currency management industry.[13] Because investors who use FXSelect may buy and sell positions continuously, daily prices of funds are available, which allowed us to measure crowdedness over short intervals. Our sample included daily data on returns for 107 funds between April 2005 and June 2010.[14] Only 10 of the funds had a complete 63-month track record. But 18 funds had more than five years of data, and 48 funds had at least three years of data. To correct for accounting errors and eliminate data outliers, we converted the daily returns into 156 weekly returns by using Wednesday observations.[15] The FXSelect database was especially useful because it provided us with high-frequency returns and allowed for the correction of backfill and survivorship bias.[16]

Data for Risk Factors. For risk factors, we used the same proxies as in Pojarliev and Levich (2008b).

- *Carry factor.* We used the Deutsche Bank Currency Harvest G10 Index as the proxy for the returns of a carry strategy. This index reflects the return of being long the three high-yielding currencies against being short the three low-yielding currencies among the G–10 currencies. The index is rebalanced quarterly. Every quarter, the currencies are reranked according to their current three-month LIBOR. The Bloomberg code for this factor is DBHVG10U.
- *Trend factor.* We used the AFX Currency Management Index as a proxy for the trend-following factor.[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 used the Deutsche Bank G10 Valuation 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 purchasing power parity (PPP) exchange rate as published annually by the Organisation for Economic Co-Operation and Development. The Deutsche Bank G10 Valuation Index reflects the return of being long the three currencies with the highest rank (undervalued currencies) against being short the three currencies with the lowest rank (overvalued currencies) among the G–10 currencies. The Bloomberg code for this factor is DBPPPUSF.
- *Currency volatility factor.* We used the Deutsche Bank Currency Volatility Index as the proxy for foreign exchange volatility. This index is calculated as the weighted average of three-month implied volatility for nine major currency pairs (as provided by the British Bankers' Association), with weights based on trading volume in surveys by the Bank for International Settlements.[19] The Bloomberg code for this factor is CVIX. We used the first difference for this factor in Equation 1 because it is not a trading strategy. For the previous three factors, we used returns.

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

$$C_{F,t} = a_{F,t} - b_{F,t}, \quad (2)$$

where

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

$b_{F,t}$ = the percentage of funds with significant negative exposure to risk factor F over the period $t-25$ through t

For both positive and negative exposures, we used a standard 95 percent confidence level and a t-value with an absolute value greater than or equal to 1.96 to identify significant exposure.

By restricting our measure to only those funds with significant style betas, we intended to exclude funds whose point estimate of exposure, although nonzero, might not be meaningful. To check for robustness, we used several other measures of crowdedness that are based on only the magnitude of style betas regardless of their significance.

Empirical Results

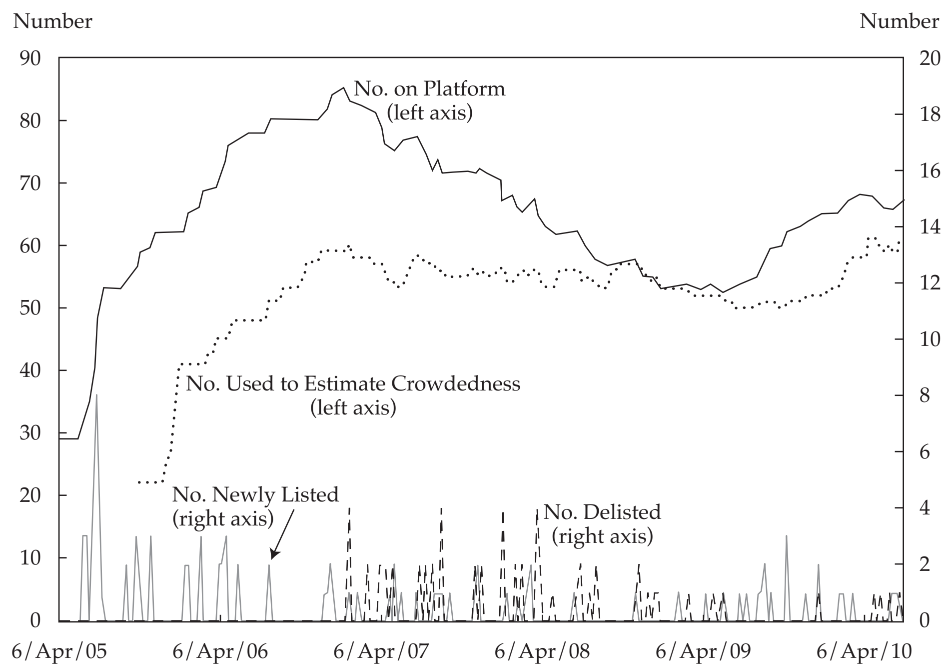
We present our results for the time variation in carry, trend, and value crowdedness. We also present evidence regarding the determinants of crowdedness, including robustness checks that rely on alternative measures of crowdedness.

Time Variation in Crowdedness. To determine which funds had significant exposure to each trading strategy, we estimated Equation 1 by using a rolling sample of 26 weekly observations over the sample period of 63 months (274 weeks), 6 April 2005–30 June 2010. Thus, we were able to estimate crowdedness on 249 dates, from 28 September 2005 to 30 June 2010. We excluded from our analysis any funds that were on the platform for less than 26 weeks.[20]

The number of funds that we used to estimate crowdedness varied from week to week as new funds joined the platform and some funds exited the platform. **Figure 2** plots the number of funds that we used to estimate crowdedness. The number of funds was lowest (22) at the beginning of the sample; it then rose steadily toward 60 in late 2006 as funds joined the platform and then oscillated between 50 and 60 for the remainder of the sample as funds were listed and delisted. Delisted funds tended to outnumber newly listed funds between January 2007 and the spring of 2009, when net new listings resumed for the remainder of the sample.

To illustrate the methodology, **Figure 3** plots the estimated t-statistics for the alphas and betas of Fund #6 (indicating Fund #6 in the database). This fund had a track record of slightly more than three years (170 weeks) from the launch of the trading platform until Fund #6 was delisted, on 25 June 2008. Using a rolling window of 26 weeks with this sample, we obtained t-statistics for 144 weeks. Figure 3 shows that over the entire sample period,

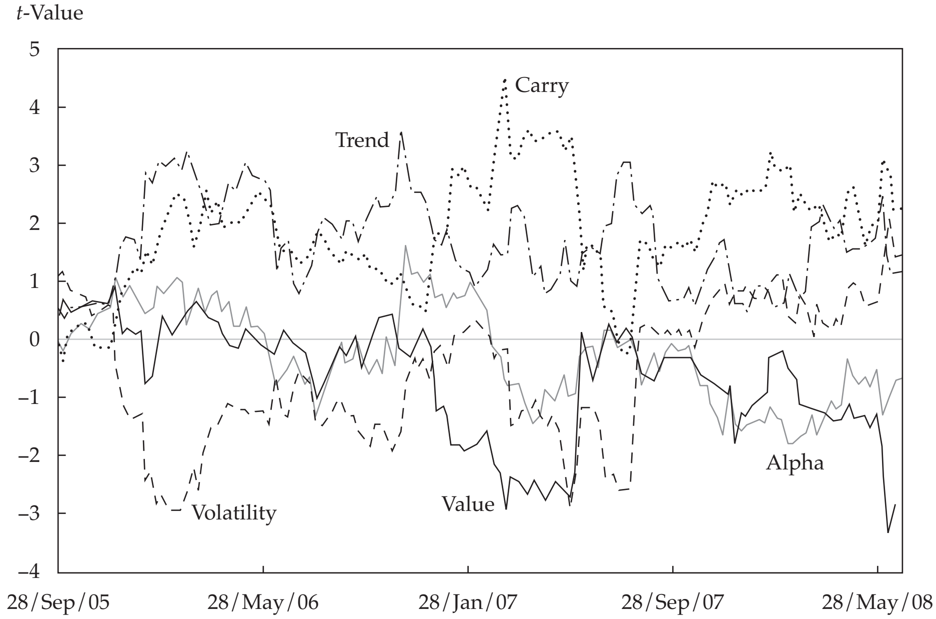
Figure 2. Number of Funds on Deutsche Bank FXSelect Platform, Number Used to Estimate Crowdedness, and Number Newly Listed and Delisted, 6 April 2005–30 June 2010



Notes: This figure plots the number of active funds on the platform between weeks t and $t-25$ that were used to estimate crowdedness for week t. For example, the 22 funds that were active between 6 April and 28 September 2005 were used to estimate crowdedness for 28 September 2005. Funds with a track record of less than 26 weeks (half a year) were not used to estimate crowdedness.

Sources: Deutsche Bank; authors' calculations.

Figure 3. Estimated *t*-Values for Alpha and Beta Coefficients for Fund #6, 28 September 2005–25 June 2008



Notes: This figure plots the rolling regression results for $R_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$, where R = the returns of Fund #6; i = carry, trend, value, and volatility; and $t = 1, \ldots, 26$ weekly observations. The first regression is estimated with 26 weekly observations from 6 April 2005 to 25 June 2008 (when Fund #6 left the platform). The last regression is estimated with 26 weekly observations from 2 January to 25 June 2008. The sample contains 144 rolling windows.

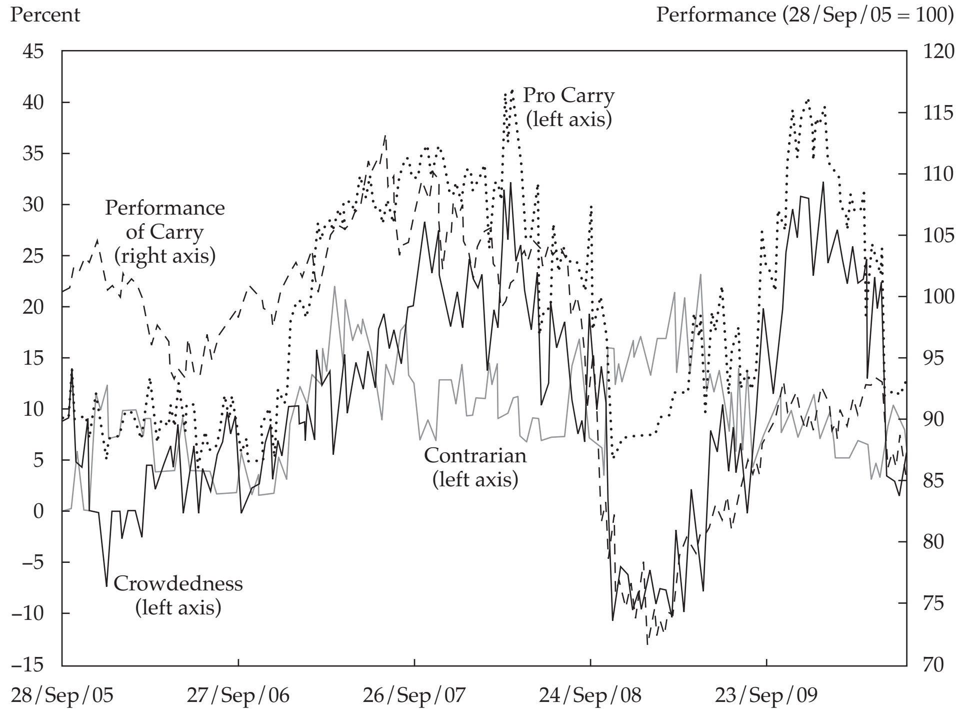
Fund #6 never achieved a significant alpha. It generally had positive exposures to carry and trend and negative exposures to value and volatility.[21] These exposures, however, were not consistently significant throughout the entire sample period (i.e., the *t*-statistics of the factor loadings were not constantly above 1.96 or below –1.96).[22] For example, although the exposure to value was not significant most of the time, the manager of Fund #6 exhibited strong contrarian value positioning (i.e., the *t*-statistics of the value factor were between –2 and –3) at the beginning of 2006 and toward the middle of 2007. Thus, the manager of Fund #6 apparently had 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 estimated crowdedness by using Equation 2 for three of the four factors (i.e., carry, value, and trend). Because the fourth risk factor does not represent return on a trading strategy but simply the first difference of the implied foreign exchange volatility, we did not estimate crowdedness for volatility.

Carry crowdedness. **Figure 4** plots our measure for carry crowdedness between 28 September 2005 and 30 June 2010. It also plots $a_{carry,t}$ and $b_{carry,t}$, which represent the percentage of funds with significant positive exposure to carry and the percentage of funds with significant negative exposure to carry (the contrarians) and include the performance of the carry strategy.

Figure 4 suggests an interesting story. At the beginning of our sample, carry crowdedness was minimal (around 5 percent) because only about 10 percent of the funds in our analysis were significantly exposed to carry and the contrarians were about 5 percent. 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 strong performance of the carry strategy, whereas the second group was betting that carry was overbought. Because the first group was only slightly larger than the second, carry crowdedness increased steadily, to about 15 percent. In the summer of 2007, the contrarians started to "die out" as the performance of the carry strategy accelerated.[23] As a result, carry crowdedness reached a peak of 32 percent in early April 2008 as the contrarians either gave up or were forced out of the market. Interestingly, the carry strategy exhibited a substantial decline just a few months later. Although the popular press attributed 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

Figure 4. Carry Crowdedness, 28 September 2005–30 June 2010



Notes: This figure plots the rolling regression results for $R_{j,t} = \alpha_j + \Sigma_i \beta_{i,j}, F_{i,t} + \varepsilon_{j,t}$ for manager j active on the platform at least from week $t - 25$ on. The number of managers varies according to Figure 2. Carry crowdedness is defined as in Equation 2. The first measure of crowdedness is estimated as of 28 September 2005 with 26 weekly observations from 6 April to 28 September 2005. The last measure of crowdedness is estimated as of 30 June 2010 with 26 weekly observations from 6 January to 30 June 2010. The sample contains 249 rolling windows. Crowdedness measures are on the left-hand y-axis, and performance measures are on the right-hand y-axis.

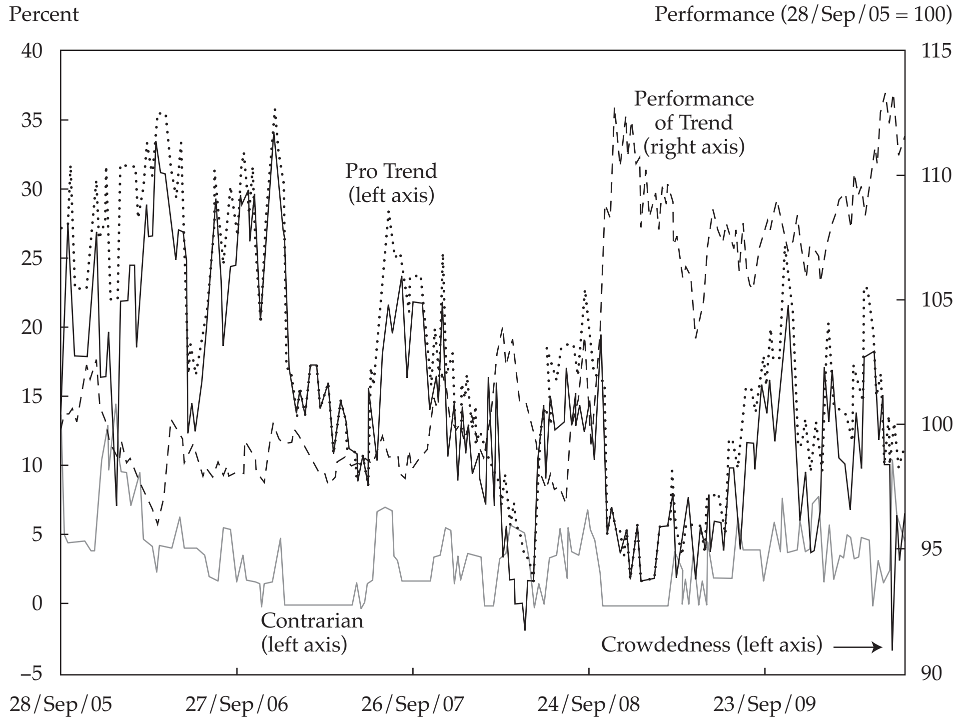
that the strategy had become crowded. This explanation is consistent with the "liquidity spiral" story suggested by Pedersen (2009) and the shrinking hedge fund asset base discussed in Jylhä and Suominen (2009).

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 relatively safe assets with low interest rates. By the spring of 2009, after a decline of nearly 30 percentage points, the performance of carry resumed an upward trend; in late 2009, crowdedness in the carry trade again advanced to 32 percent. Crowdedness subsided in early 2010 but dropped precipitously (along with performance) after the "flash crash" of May 2010.

■ *Trend crowdedness.* **Figure 5** plots our measure for trend crowdedness. In contrast to carry crowdedness, trend crowdedness was a relatively crowded strategy at the beginning of our sample period. Some 25–35 percent of the funds had significant positive trend exposure, and only a very small percentage were contrarian. Because most of the currency research in the 1990s (see, e.g., Levich and Thomas 1993) advocated trend-following strategies, this finding is not surprising. Over time, as trend failed to deliver returns, crowdedness declined to near zero or slightly negative (contrarian) by May 2008. This change was the result not of a rise in the number of contrarians but, rather, of trend followers apparently "giving up." Ironically, the trend strategy began to deliver excellent performance a few months later, in the fall and winter of 2008. In the midst of this favorable performance, trend crowdedness increased before returning to single-digit levels by the fall of 2008 and undergoing a 10 percentage point correction through the summer of 2009. Trend crowdedness rebounded, reaching 21.6 percent in November 2009, and after following a jagged course, returned to near zero or slightly negative at the end of our sample period.

■ *Value crowdedness.* **Figure 6** plots our measure for value crowdedness. Although the pattern is different from that of carry and trend crowdedness, the main story bears a strong similarity to our interpretation for carry crowdedness. The

Figure 5. Trend Crowdedness, 28 September 2005–30 June 2010



Notes: This figure plots the rolling regression results for $R_{j,t} = \alpha_j + \Sigma_i \beta_{i,j,}F_{i,t} + \varepsilon_{j,t}$ for manager *j* active on the platform at least from week t – 25 on. The number of managers varies according to Figure 2. Trend crowdedness is defined as in Equation 2. The first measure of crowdedness is estimated as of 28 September 2005 with 26 weekly observations from 6 April to 28 September 2005. The last measure of crowdedness is estimated as of 30 June 2010 with 26 weekly observations from 6 January to 30 June 2010. The sample contains 249 rolling windows. Crowdedness measures are on the left-hand *y*-axis, and performance measures are on the right-hand *y*-axis.

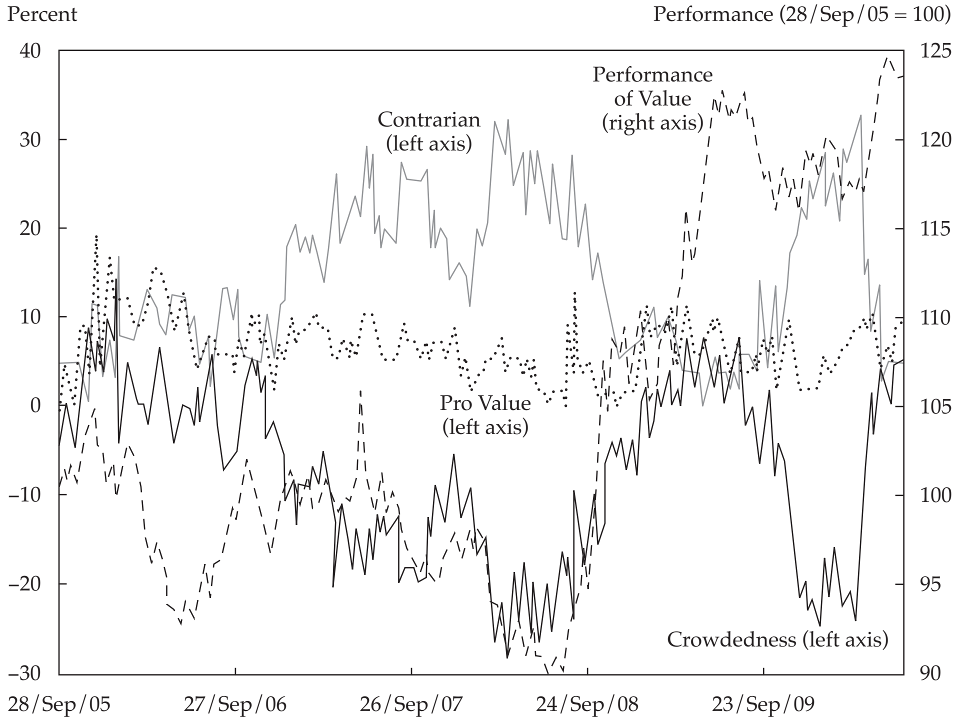
percentage of funds with significant positive exposure to value was relatively small and constant, around 10 percent. But the percentage of contrarians (funds with significant negative value exposure) rose steadily through the spring of 2008 and became progressively more crowded, peaking at 32 percent. A few months later, in the summer of 2008, the financial crisis intensified and undervalued currencies rose, resulting in substantial losses for 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 percent in May 2009. The performance of value was stunning, with the factor rising from 90 (in the summer of 2008) to more than 120 (in the summer of 2009).

The contrarian value trade re-emerged in the summer of 2009 and continued into the fall, peaking at 30 percent in January 2010. Value crowdedness reached a low of about –24.5 percent that lasted into March. In the spring of 2010, concern over Greece's external debt coincided with a flight toward undervalued currencies. The value trade earned a quick 8 percent return, which led value contrarians to exit their positions. Once again, crowdedness in a trading strategy proved unrewarding for those holding the relatively popular trading position. At the end of the sample period, both pro-value and contrarian traders were a small percentage of the managers on the platform and crowdedness was nearly zero.

Determinants of Crowdedness. As we can see from Figures 4, 5, and 6, our measure of crowdedness can vary considerably. For example, carry crowdedness varied between a low of –10 percent and a high of 32 percent. Trend crowdedness ranged from –3 percent to 34 percent, and value crowdedness moved from a high of about 12 percent early in the sample to a low of around –28 percent. Selected extreme values of crowdedness for each of the trading strategies are summarized in the first column of **Table 1**.

In considering the question of what drives crowdedness, we looked at two channels that affect the crowdedness of a trading strategy: (1) existing managers who adopt or abandon a strategy and (2)

Figure 6. Value Crowdedness, 28 September 2005–30 June 2010



Notes: This figure plots the rolling regression results for $R_{j,t} = \alpha_j + \Sigma_i\beta_{i,j,}F_{i,t} + \varepsilon_{j,t}$ for manager j active on the platform at least from week $t - 25$ on. The number of managers varies according to Figure 2. Value crowdedness is defined as in Equation 2. The first measure of crowdedness is estimated as of 28 September 2005 with 26 weekly observations from 6 April to 28 September 2005. The last measure of crowdedness is estimated as of 30 June 2010 with 26 weekly observations from 6 January to 30 June 2010. The sample contains 249 rolling windows. Crowdedness measures are on the left-hand y-axis, and performance measures are on the right-hand y-axis.

managers who enter or exit the trading platform, which determined the number of funds in our data sample. Table 1 summarizes the composition of our universe of managers at the peaks and troughs of crowdedness for each style.

On 28 December 2005, carry crowdedness was at a trough. At that point, 41 funds were active on the platform (only 16 of those funds [40 percent] 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 9 April 2008. At that point, 53 funds were active on the platform (with a track record of at least 26 weeks). Of those 53 funds, 28 were active as of 28 December 2005 and 25 were new funds. Of the new funds, 12 (48 percent) had significant carry exposure. Furthermore, a significant proportion of the existing funds with no carry exposure (nine funds, or 22 percent) acquired 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 carry crowdedness seems to be 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 dropped to –10.5 percent on 5 November 2008, reflecting that 9 funds (out of 57) held contrarian styles, only 3 funds had positive carry exposure, and fully 45 funds had no exposure. The increase in funds with no exposure—from 26 to 45 over the interval—is largely attributable to 21 funds that switched their style betas and to 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 percent on 13 January 2010 and reaching a trough of 1.6 percent on 16 June 2010—mimicked the previous two descriptions. The rise in crowdedness is the result of a few new funds (3) that followed a carry strategy joining the platform and a larger number of existing funds (16) switching to a positive carry strategy. The decline in crowdedness is also the result of a few new funds (7) with no exposure to carry joining

Table 1. Characteristics of Funds at High and Low Points of Crowdedness by Style of Strategy, 28 September 2005–30 June 2010

Crowdedness (date)	No. Funds on Platform	No. Funds with Significant Positive Exposure	No. Funds with Significant Negative Exposure (contrarian)	No. Funds with No Significant Exposure
A. Carry				
–7.31%	41	2	5	34
(28 Dec. 2005)	—	—	—	—
32.08%	53	22	5	26
(9 Apr. 2008)	(25, 28, na)	(12, 1, 9)	(2, 2, 1)	(11, 13, 2)
–10.52%	57	3	9	45
(5 Nov. 2008)	(9, 48, na)	(1, 0, 2)	(4, 1, 4)	(4, 20, 21)
32.08%	53	21	4	28
(13 Jan. 2010)	(7, 46, na)	(3, 2, 16)	(1, 1, 2)	(3, 22, 3)
1.64%	61	7	6	48
(16 June 2010)	(11, 50, na)	(3, 4, 0)	(1, 1, 4)	(7, 23, 18)
B. Trend				
33.9%	59	21	1	37
(6 Dec. 2006)	—	—	—	—
–1.64%	56	2	3	51
(14 May 2008)	(16, 40, na)	(1, 0, 1)	(2, 0, 1)	(13, 22, 16)
21.57%	51	13	2	36
(4 Nov. 2009)	(10, 41, na)	(3, 0, 10)	(0, 0, 2)	(7, 27, 2)
–3.39%	59	4	6	49
(9 June 2010)	(12, 47, na)	(1, 0, 3)	(1, 0, 5)	(10, 24, 15)
C. Value				
12.20%	41	6	1	34
(18 Jan. 2006)	—	—	—	—
–28.30%	53	2	17	34
(9 Apr. 2008)	(25, 28, na)	(1, 0, 1)	(8, 0, 9)	(16, 16, 2)
7.84%	51	4	0	47
(20 May 2009)	(11, 40, na)	(1, 0, 3)	—	(10, 24, 13)
–24.53%	53	1	14	38
(13 Jan. 2010)	(5, 48, na)	(0, 0, 1)	(1, 0, 13)	(4, 30, 4)
5.00%	60	5	2	53
(19 May 2010)	(9, 51, na)	(1, 1, 3)	(1, 0, 1)	(7, 34, 12)

na = not applicable.

Notes: Each triplet of numbers (a, b, c) indicates (a) the number of new funds since the previous date in the table, (b) the number of funds with the same style (also on the previous date), and (c) the number of existing funds (also active on the previous date) that switched styles. 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 styles.

the platform and a larger number of existing funds (18) switching to a neutral carry strategy.

Emulating many of the same patterns, trend crowdedness was at its peak (33.9 percent) on 6 December 2006. At that point, 59 funds were active on the platform (23 of those funds [39 percent] did not survive until the end of our time horizon). Of the 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 percent) on 14 May 2008. At that point, 56 funds were active on the platform (with a track record of at least 26 weeks). Of those 56 funds, 40 were active as of 6 December 2006 and 16 were new funds. Of the new funds, 13 (81 percent) had no significant trend exposure. Moreover, of the 21 funds with positive trend exposure, 16 (76 percent) exited the trend style (i.e., had no exposure to trend as of the end of the time horizon). Of the 21 managers with trend-following exposure during the peak in trend crowdedness, only 1 manager exhibited trend exposure during its trough. Thus, the decline in trend crowdedness seems to be driven by (1) new funds with no trend exposure joining the platform and (2) a large number of the initial trend followers abandoning trend.

In the subsequent cycles of trend crowdedness—which reached a peak of 21.6 percent on 4 November 2009 and dropped to a low of –3.4 percent on 9 June 2010—the changes in crowdedness seem to be driven by a similar pattern. The rise (fall) in crowdedness is the result of a large number of existing funds adopting (abandoning) the trend strategy and a number of new funds with significant positive (contrarian) positions.

Further emulating this pattern, value crowdedness peaked on 18 January 2006. At that point, 41 funds were active on the platform, and only 16 of those funds (39 percent) survived until the end of our time horizon. Of the 41 funds, 6 had significant value exposure, 1 was betting against value, and 34 had no significant value exposure. Of the six funds with positive value exposure, four abandoned the value style and two exited the platform. None of the funds that followed value as of 18 January 2006 remained positively exposed to value as of 9 April 2008, when value crowdedness reached an interim trough. At that point, 53 funds were active on the platform (with a track record of at least 26 weeks). Of those 53 funds, 28 were active as of 18 January 2006 and 25 were new funds. Of the new funds, eight (32 percent) had significant negative value exposure (contrarian). The decline in value crowdedness seems to be driven by (1) new funds that bet against value joining the platform and (2) a large number of the existing funds (nine) adopting a value contrarian strategy.

In the subsequent cycles of value crowdedness—which reached a peak of 7.8 percent on 20 May 2009 and a trough of –24.5 percent on 13 January 2010—the changes in crowdedness seem to be driven by a similar pattern. The rise (fall) in crowdedness is again the result of a large number of existing funds adopting (abandoning) the value strategy and a number of new funds with significant positive (contrarian) positions.

One general conclusion that we can draw from Table 1 is that the change in crowdedness across the different styles is driven not only by the change in styles of the existing managers but also by the different styles of the new managers on the platform. What could 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 also rises. Specifying the formation of expected returns, however, is always problematic. We considered two possibilities. First, managers could form expected returns on the basis of 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 carry and value crowdedness responded to expected returns modeled in this way.[25]

A second possibility is to model the expected returns on a strategy as a direct function of past returns on that strategy. If managers form expectations in this way, we would expect to observe herding—that is, positive returns on a strategy attract newcomers and negative returns on a strategy encourage managers to abandon the strategy. Because we measured crowdedness over 26 weeks, we also cumulated the performance of the various strategies over 26 weeks. Our methodology for ascertaining whether managers are following a particular strategy relies on estimating betas and requires a number of weeks before we can determine whether managers have shifted their allocations in response to higher expected returns on any strategy. So, there is a lag of 26 weeks between when returns on a strategy first appear and when we can identify a statistically significant relationship, or style beta. Therefore, we must lag the cumulative past performance of the strategies by 26 weeks to explore the link with our measure of crowdedness.

Table 2 summarizes the correlations between our measure of crowdedness and the lagged performance of the trading strategies. The first row contains results for the whole sample period. The second and third rows 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. We found weaker support for herding in the value strategy and no support for herding in the trend strategy.

Table 2. Correlations of Crowdedness Measures with Lagged Performance of Trading Strategies, 6 April 2005–30 June 2010

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

Notes: This table presents the correlations of crowdedness for each style factor with its own lagged performance. Crowdedness for each style factor is defined as in Equation 2. The first measure for crowdedness is estimated as of 28 September 2005 with 26 weekly observations (6 April 2005–28 September 2005). Performance of each trading strategy is measured over the prior 26-week period. The first measure for lagged performance is for 13 October 2004–6 April 2005.

Several factors may account for this weak evidence. First, not all managers have discretionary authority to allocate to a given currency strategy, even when it appears to be profitable. For instance, a fund that specializes in trend following—and has stated so in an investment mandate—cannot 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. For example, we should not expect every manager in any sample to follow carry when carry is profitable because some of those managers are trend followers or value managers by design or choice. So, not all the managers in our sample had the ability to shift. Second, managers might be constrained in joining the platform; a fund needs an 18-month track record to be listed on FXSelect. Therefore, even if a new carry manager might be keen to join the platform (because she expects future carry returns to be high), she would have to wait for the appropriate track record before joining. Finally, a strategy's past returns might not be the best proxy for what managers think regarding a strategy's future expected returns.

Robustness Checks. To check for robustness, we calculated several alternative crowdedness measures that are based on the difference in the percentages of those funds with betas above a certain positive cutoff and those with betas below a certain negative cutoff, regardless of whether the *t*-statistics are significant. Thus, we defined an alternative measure of crowdedness of style F at time t ($C^*_{F,t}$) as the percentage of funds with F beta greater than X minus the percentage of funds with F beta less than $-X$:

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

where

$a^*_{F,t}$ = the percentage of funds with beta of risk factor F greater than X over the period $t - 25$ through t (i.e., we used rolling windows of 26 weeks to estimate the exposures to the risk factors in Equation 1)

$b^*_{F,t}$ = the percentage of funds with beta of risk factor F less than $-X$ over the period $t - 25$ through t

Figure 7 plots our original measure of crowdedness for carry, trend, and value and the alternative measure of crowdedness for a 0.50 cutoff (X = 0.50). The correlation between the two measures for carry and value is high—78 percent and 81 percent, respectively. For trend, the correlation is smaller (68 percent) but still positive and significant.[26] We calculated the alternative measure of crowdedness for the cutoff values X = 0.25, 0.50, 0.75, and 1.00. **Table 3** summarizes the correlations between our original and alternative measures of crowdedness.

Table 3. Correlation between Original Measure of Crowdedness (*C*) and Alternative Measure of Crowdedness (*C) for Alternative Beta Values, 28 September 2005–30 June 2010**

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

Notes: The original measure of crowdedness (*C*) is defined in Equation 2. The alternative measure of crowdedness (*C**), based on the percentage of managers with style betas greater than or equal to a given cutoff value, is defined in Equation 3. Both measures of crowdedness are estimated for 26-week periods from 28 September 2005 to 30 June 2010. The sample contains 249 rolling windows.

Figure 7 shows that both the original and the alternative measures of crowdedness behave quite similarly for our sample. The relationship is very strong for carry and value, whereas there is an apparent break for trend during parts of 2007. From January to May 2007, trend crowdedness declined, from 17 percent to 9 percent, and the alternative measure increased, from 19 percent to 36 percent. For most of the remainder of the sample, however, the generally close association between *C* and *C** for trend held.

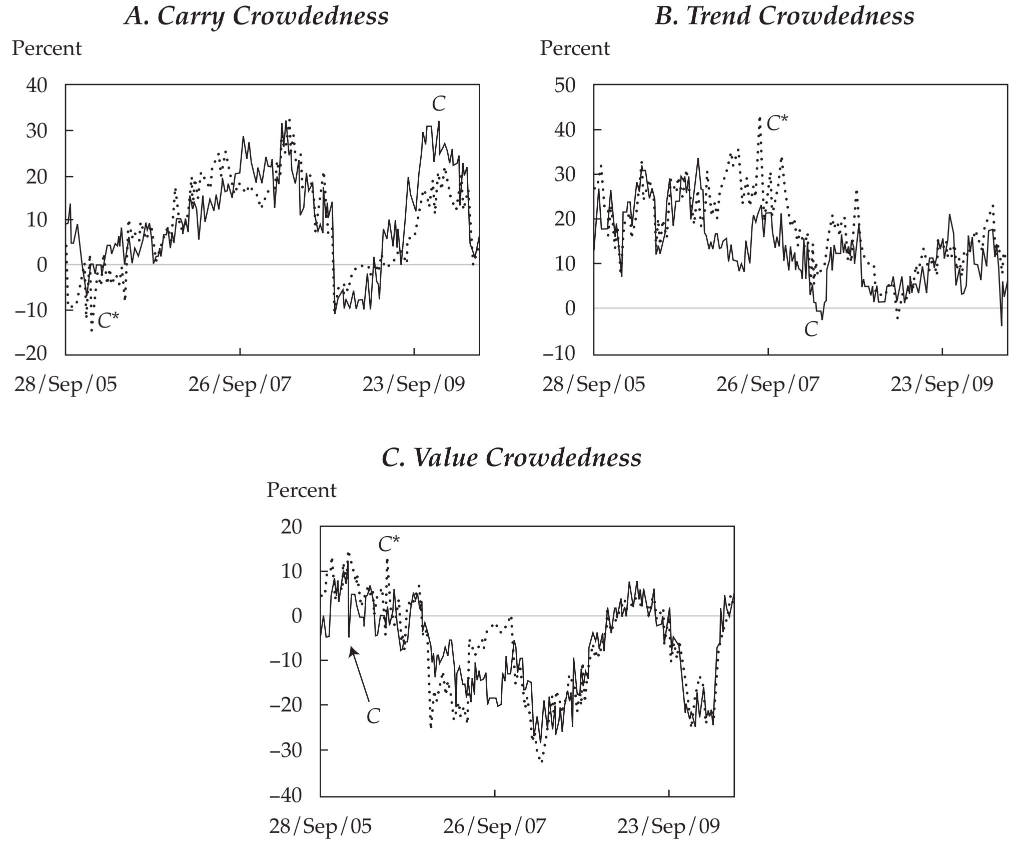
Overall, the alternative measures (*C**) show patterns similar to those of our original measure (*C*) for much of the sample, with only a small number of instances where the measures move in opposite directions for an extended period.

Conclusion

The financial crisis of 2008 highlighted the importance of detecting crowded trades because of the risks they pose to the stability of both the global financial system and the global economy. Crowded trades, however, are perceived as difficult to identify.[27] To date, no single measure that captures the crowdedness of a trade or trading style has been developed.

Using a unique database of professional foreign exchange manager returns, we proposed and estimated a new measure for style crowdedness. Our measures of crowdedness offer additional perspective on events in currency markets during

Figure 7. Original Crowdedness Measure (*C*) and Alternative Crowdedness Measure (*C) for *X* = 0.50, 28 September 2005–30 June 2010**



Notes: This figure plots the rolling regression results for $R_{j,t} = \alpha_j + \Sigma_i \beta_{i,j} F_{i,t} + \varepsilon_{j,t}$ for manager *j* active on the platform at least from week $t - 25$ on. The number of managers varies according to Figure 2. The crowdedness measure *C* is defined as in Equation 2. Details of the calculation are in the notes to Figures 4, 5, and 6. The crowdedness measure *C** is defined as in Equation 3. We used the identical rolling regression method based on active managers. *C** tracks the number of funds with $\beta > 0.5$ less the number of funds with $\beta < -0.5$, regardless of whether the β coefficients are significant.

the financial crisis. In the first quarter of 2008, the data show that a higher-than-usual percentage of funds were significantly exposed to carry and those 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 funds bet significantly against value. Later in 2008, however, 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 simply led to flat performance for the trend strategy during this period. After managers gave up on the trend strategy, it delivered strong performance, which led to opportunity costs but no actual losses.

Updating our sample from March 2008 to June 2010 (when data became available), we confirmed our hypotheses. Following carry's strong performance in 2009, it 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 our earlier findings.

Our results suggest that our measure of crowdedness deserves closer scrutiny. In our short sample period, the anecdotal evidence shows that crowdedness may provide useful signals regarding the future performance of a given strategy. Although our sample period was 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. We hope that our study will stimulate 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 U.S. dollar interest rates remained close to zero during 2009, commentators asserted that a surging U.S. dollar–based carry trade had developed that would have dire consequences once it began to unwind.[28] This prediction was realized during the European sovereign debt crises in the spring of 2010 as the U.S. dollar index rose 15 percent between January and June. Additional data would allow researchers to document when our measure of crowdedness reveals any unwinding and whether changes in crowdedness correlate with exchange rate movements.[29]

In 2009, the U.S. House Financial Services Committee considered proposals for a "systematic risk regulator" that could take into account, among other things, that crowded trades pose a risk to the financial system because crowding is itself a source of instability. As some observers have noted, however, "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 applied our approach to currencies, it could easily be extended to other asset classes. Further research in this area could yield useful findings for investors, managers, and regulators.

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This article qualifies for 1 CE credit.

Notes

1. Remarks by Timothy F. Geithner before the Economic Club of New York (27 May 2004).
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 because some areas had become so overcrowded that they were no longer profitable (Laurence Fletcher, "Quant Hedgies Must Fish in Fresh Waters—Goldman," Reuters [1 December 2009]).
3. See Deutsche Bank (2009).
4. See Froot and Ramadorai (2005, 2008) for analyses that rely on the State Street Bank and Trust equity flow data.
5. Gross (2005) suggested that the "average life" of investment firms is three to four years (i.e., the time span before an average client will leave if performance disappoints).
6. See Froot and Thaler (1990) for a survey of the carry trade.
7. The USD/JPY spot rate fell from more than 145 to almost 100 during this period.
8. This rolling correlation could be interpreted as a simple measure of carry crowdedness until the end of 2008. Indeed, from September 2005 until the end of 2008, the correlation between this measure of crowdedness and our measure was 49 percent. But it dropped to –72 percent from January 2009 to June 2010, a period in which the Swiss National Bank intervened massively to stem the appreciation of the Swiss franc. Between 2009 and mid-2010, the Swiss National Bank sold Swiss francs valued at roughly USD200 billion, including USD73 billion in May 2010 alone. These calculations suggest that the Swiss franc was no longer considered a funding currency after 2008 as investors sought safety and preferred to own Swiss francs.
9. These factors are specific to the currency funds. Clearly, when measuring crowdedness for various types of hedge funds (e.g., global macro), a researcher should use various factors (e.g., those identified in Fung and Hsieh 2002).
10. Alternatively, managers could be weighted by their assets under management (AUM). Jylhä and Suominen (2009) found that AUM at hedge funds are significantly related to contemporaneous and expedited future returns from a risk-adjusted carry trade. Unfortunately, we did not have data on AUM for the managers in our sample and were thus unable to experiment with this alternative measure.
11. In an earlier draft, we used only a three-year sample (6 April 2005–26 March 2008). We expanded our sample as more data became available. The post–26 March 2008 results can be interpreted as out of sample and highlight the usefulness of our framework for measuring crowded trades.
12. Launched in March 2005, FXSelect is an open platform that allows clients of Deutsche Bank to allocate their funds to various currency managers. Currency managers can apply for registration in the platform and be accepted if they satisfy the following criteria: (1) They must be able to provide a daily track record for at least the last 18 months verified by a third party, (2) they cannot have had more than a 20 percent performance drawdown over the last 12 months, (3) their assets under management must be at least USD15 million, and (4) key individuals and the firms themselves must undergo satisfactory criminality and regulatory searches conducted by Mercer Investment Consulting. More information about FXSelect can be found in the Deutsche Bank brochure "The FXSelect Platform" (2005), available at www.pamfx.de/fileadmin/publikationen/FX_Select_Brochure.pdf.
13. Many (about 25 percent) of the managers in the FXSelect database are also in other well-known hedge fund databases (e.g., the CISDM Hedge Fund/CTA Database and the Lipper TASS database). In our initial three-year sample, the correlations between the monthly returns on a "fund-of-funds" portfolio comprising 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 Currency Traders Index) were 67 percent and 65 percent, respectively. As another example of 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 its website, FXSelect has attracted $3.5 billion in AUM from pension funds, funds 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 used Wednesday observations because fewer bank holidays fall on Wednesdays than on other days of the week. Managers were based in various locations (the United States, the United Kingdom, Australia, Switzerland, Monaco, Spain, Sweden, Germany, Ireland, and Canada).
16. For more information, see Pojarliev and Levich (2008b).
17. Monthly data for this index are available at the AFX Index website (www.ljmu.ac.uk/LBS/102316.htm). We converted 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.
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.
20. Seven funds on the platform had a track record of less than 26 weeks.
21. This positive carry exposure might explain the delisting of Fund #6 during the period of massive underperformance of carry trades.
22. We are referring to the results of the rolling regressions. Pojarliev and Levich (2008b) showed that Fund #6 exhibited significant positive exposure to carry and trend and no significant exposure to value and volatility over a three-year period (6 April 2005–26 March 2008).
23. Pojarliev and Levich (2008b) showed 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 who bet too early on the liquidation of carry trades.
24. This low survivorship rate highlights the importance of including dead funds in our analysis.
25. For trend, most simple trend-following rules indicate only the future trend and not the magnitude of future exchange rate developments; therefore, we cannot readily test whether conditions are more or less favorable for managers to shift in or out of this style.
26. In testing the significance of the correlation coefficient between C and C^*, we found that all correlations are highly significant, with p-values < 0.00001.
27. For example, in attempting to measure the extent of carry trade activity, Galati, Heath, and McGuire (2007) analyzed various banking and capital flow data. They did not offer numerical estimates. They concluded that "growth in carry trades funded in yen and Swiss francs has probably contributed to increased activity in these currencies . . . [but] the available data do not allow for a more refined measurement of the size of carry trade positions" (p. 40). In their analysis of carry trading and currency movements in 2008, McCauley and McGuire (2009) observed that "carry trades always defy measurement" (p. 92). Note that our approach does not provide a quantitative estimate of the volume of carry trades outstanding.
28. Nouriel Roubini, "Mother of All Carry Trades Faces an Inevitable Bust," *Financial Times* (1 November 2009).
29. Data on currency managers' returns are usually available to plan sponsors on a daily basis. 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* (2 March 2009).

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