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Trades of the living dead: Style differences, style persistence and performance of currency fund managers

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ABSTRACT

We make use of a new database on daily currency fund manager returns over a three-year period, 2005–2008. This higher frequency data allows us to estimate both alpha measures of performance and beta style factors on a yearly basis, which in turn allows us to test for persistence. We find no evidence to support alpha persistence; a manager's alpha in one year is not significantly related to his alpha in the prior year. On the other hand, there is substantial evidence for style persistence; funds that rely on carry, trend or value trading or with a long/short bias toward currency volatility are likely to maintain that style in the following year. In addition, we are able to examine the performance of managers that survive through the entire sample period, versus those that drop out. We find significant differences in both the investment styles of living versus deceased funds, as well as their realized alpha performance measures. We conjecture that both style differences and ineffective market timing, rather than market conditions, have impacted performance outcomes and induced some managers to close their funds.

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1. Introduction

A large number of academic and professional studies support the notion that various types of currency trading strategies can be quite profitable.[1] Knowing that currency alpha can be easily transported into a wide range of investment products, the asset management industry is naturally very interested in currency as an asset class.

However, recent performance of currency managers has been disappointing. For example, both the Parker FX index and the Barclay Currency Traders Index (BCTI), which track the performance of currency managers, have underperformed cash (risk-free returns) over the three years ending March 2008 (see Table 1).[2] Performance over a three-year term is an important measure as it sometimes is associated with the "average life" of an investment mandate.[3]

In part, these lacklustre returns may reflect the disappointing performance of various well-known currency strategies such as carry trading, trend following, and value investing. Fig. 1 shows the performance of three examples of these currency trading strategies for the three years between April 2005 and March 2008. The carry strategy showed essentially zero return over the first 18 months, and then exhibited a strong run up until June 2007. But carry has given back its gains since the U.S. credit crunch began in summer 2007. As expected, the spike in currency volatility (Fig. 2) coincides with the underperformance of carry trades. Returns from trend following moved mostly sideways throughout the period, although trend started to perform well in 2008. The value trading strategy oscillated between 100 and 110 but closed the period as the worst performing strategy of the three with a slightly negative return. This may not be a surprise given the climb in the spot EUR/USD rate towards 1.60, presumably further away from its "fair" value.

In earlier research, Pojarliev and Levich (PL, 2008) show that a significant part of the variation of the returns of professional currency managers can be explained by these three trading strategies and an indicator of currency volatility. PL redefine the alpha in currency management as only that portion of the excess returns which cannot be explained by these four factors. In this paper, we take a closer look at the returns of professional currency managers by estimating their alpha performance measures and style betas over successive annual intervals. We are interested in the following questions: First, is past performance any indication for future performance (are alphas persistent)? Second, are investment styles (beta exposure) persistent? Third, what differences in performance are there between funds that survive throughout the sample period and those that do not? And finally, what explains difference in performance between funds that survive and those that do not?

To address these questions, we rely on data for 80 currency managers for three years between April 2005 and March 2008. We estimate alpha performance measures and style betas using the four-factor model proposed in PL (2008) which allows us to investigate style difference across managers and test for style persistence. We use higher frequency, weekly return data to obtain efficient parameters estimates for annual periods. Moreover, our database includes "dead funds" which allows us to correct for backfill and survivorship bias, and examine differences between living and deceased funds.

Overall, the results are quite illuminating. We find no alpha persistence. Past performance by an individual manager seems to offer no indication for his future performance. However, we detect significant style persistence indicating that managers have a tendency to stick to the same investment style (or strategy). This may be good as it raises investor confidence that managers will stick with their original or mandated strategy. But at the same time, persistence suggests that managers are less willing to exploit market timing or reallocate their positions when other strategies look more promising.

[1] Research has focused on three types of trading strategies. The carry trade or forward rate bias strategy relies on the general tendency for currencies with high interest rates to appreciate. See Froot and Thaler (1990) for a survey and Burnside, et al. (2006) for a recent study. Technical trend-following strategies rely on persistent movements in spot exchange rates. See Park and Irwin (2007) and Neely et al. (2009) for surveys. Value investing strategies based on mean reversion to long run PPP exchange rates offer another approach. Studies prepared at Citibank (2003) and Deutsche Bank (2007) suggest that simple value trading strategies have been profitable.

[2] Some alternative currency managers' indices (the CTA Equal Weighted Currency Index and the CTA Asset Weighted Currency Index prepared by the Centre for International Securities and Derivatives Markets) show a positive return over this period. Nevertheless, opinion in the currency management industry remains strong that average returns have been poor in this period.

[3] Recently, 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.

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Table 1
Cumulative excess returns of currency indices.

	FoF portfolio DB FXSelect	Parker FX index reported	Parker FX index scaled returns	Barclay currency traders index
1 year, April 2007–March 2008	4.08%	2.44%	0.77%	1.23%
2 years, April 2006–March 2008	3.54%	0.00%	−0.70%	−1.51%
3 years, April 2005–March 2008	4.66%	−0.49%	−1.42%	−3.29%

The FoF portfolio is compromised of equally-weighted positions in each of the funds available on the Deutsche Bank FXSelect platform on every Wednesday over the sample period. These are gross returns before taking fees into account. Source: Deutsche Bank.
Parker FX index reported excess returns are the net of fees returns on the FX Parker Index less the risk-free rate. As a proxy for the risk-free rate we use 1-month LIBID (LIBOR less 12.5 bps). Source: Parker Global Strategies, LLC and Bloomberg.
Parker FX Index scaled returns are the net of fees returns on the Parker FX index, in excess of short term interest rates and scaled to a 5% volatility. Source: Parker Global Strategies, LLC.
Barclay Currency Traders Index returns are the net of fees returns on the Barclay Currency Traders Index less the risk-free rate. As a proxy for the risk-free rate we use 1-month LIBID (LIBOR less 12.5 bps). Source: BarclayHedge, British Bankers Association and Bloomberg.

Because consultants usually "penalize" managers who do not stick to the same investment style, some style persistence may be an attempt by managers to enhance credibility with investment consultants.

We also find some important differences between managers who perform well (and survive) versus managers who perform poorly (and drop out of the database). Not surprisingly, the set of funds that died over our sample achieved a significant negative alpha and an alpha significantly less than for funds that survived until the ending date. Moreover, the surviving or live funds showed greater association (in terms of *R*-squared) with the four style factors than those funds that performed poorly and eventually died. Furthermore, contrary to the presumption of the market that underperformance of the trend-

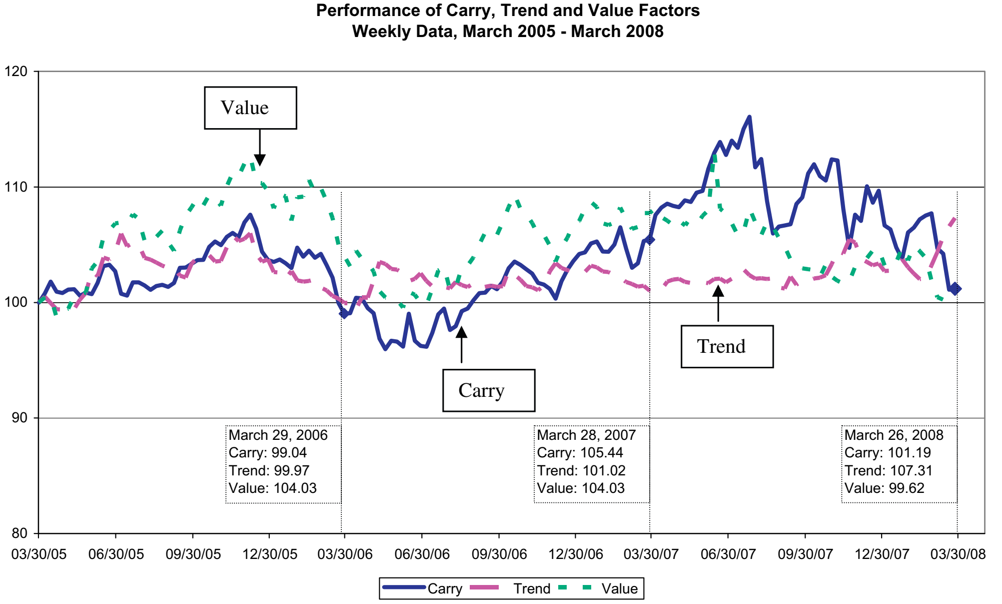

Fig. 1. Cumulative excess returns of currency trading strategies. The Carry Index return is represented by the Deutsche Bank G10 Harvest Index as the proxy for the returns of a carry strategy. This index reflects the return of being long the 3 high-yielding currencies against being short the 3 low-yielding currencies within G10 currency universe. The index is rebalanced quarterly. The Trend Index return is represented by the AFX Currency Management Index. The AFX Index is based on trading in seven currency pairs (EUR–USD, USD–JPY, USD–CHF, GBP–USD, EUR–JPY, EUR–GBP, and EUR–CHF) 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). The Value Index return is represented by the Deutsche Bank FX PPP Index. The average daily spot rate over the last three months is divided by the PPP exchange rate as published annually by the OECD and ranked. This 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. Source: Deutsche Bank, Bloomberg, Liverpool John Moores University

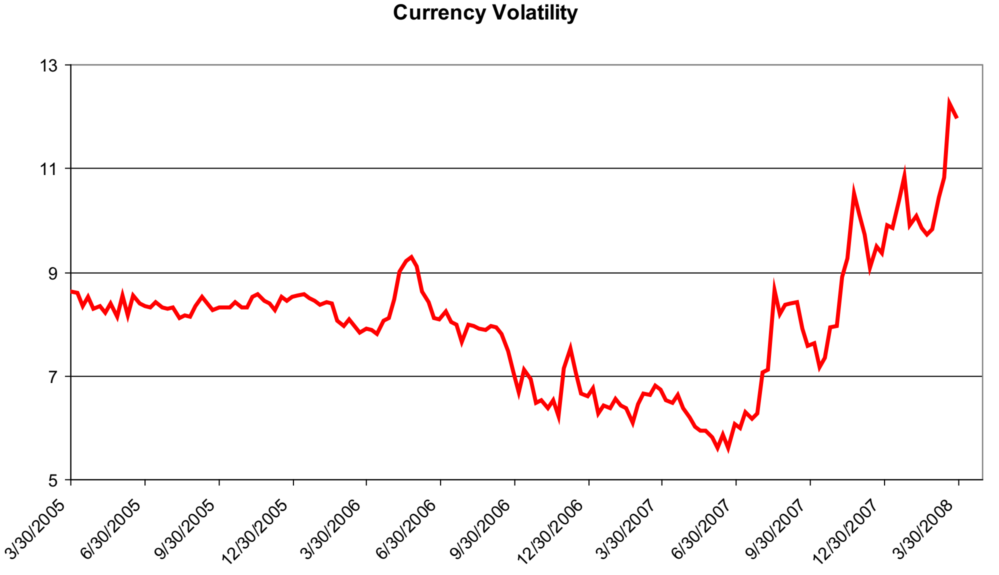

Fig. 2. Currency volatility. The Deutsche Bank Currency Volatility Index as the proxy for foreign exchange volatility. This index is calculated as the weighted average of 3-month implied volatility for nine major currency pairs (EUR–USD, USD–JPY, USD–CHF, USD–CAD, AUD–USD, GBP–USD, EUR–JPY, EUR–GBP, and EUR–CHF) as provided by the British Bankers Association with weights based on trading volume in the BIS surveys. Source: Deutsche Bank, Bloomberg.

following rule has been responsible for the diminishing returns of professional currency managers, we find that the strong performance of the carry strategy until the credit crunch in the summer of 2007 was devastating for many managers, who apparently were betting on liquidation of carry trades.

In the next section of the paper, we layout our methodology for relating currency fund returns to style factors and describe the data in our study. In Section 4, we report our empirical evidence on currency fund performance over the entire three-year period for indices constructed to represent various groups of managers, including those who survive through the entire data sample (the "live" funds) and those who drop out (the "dead" funds). In Section 5, we examine the empirical evidence for individual managers over the three-year period and over one-year intervals and report our results for persistence in alpha (i.e. performance) and persistence in beta (i.e. style). Conclusions and implications of our findings are in the final section.

2. Methodology and data description

To measure the systematic components of currency returns (the betas) and isolate the portion due to skill, we follow the approach used in PL (2008) and adopt a standard factor model of the form:

$$R_t = \alpha + \sum_i \beta_i F_{i,t} + \epsilon_t \tag{1}$$

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. Our empirical proxies for these factors are based on data for the major currencies that make up the vast bulk of foreign exchange trading volume.[4]

[4] The April 2007 survey of global foreign exchange turnover conducted by the Bank for International Settlements in 2007 shows that the G10 currencies accounted for an average 90.1% of all currency turnover.

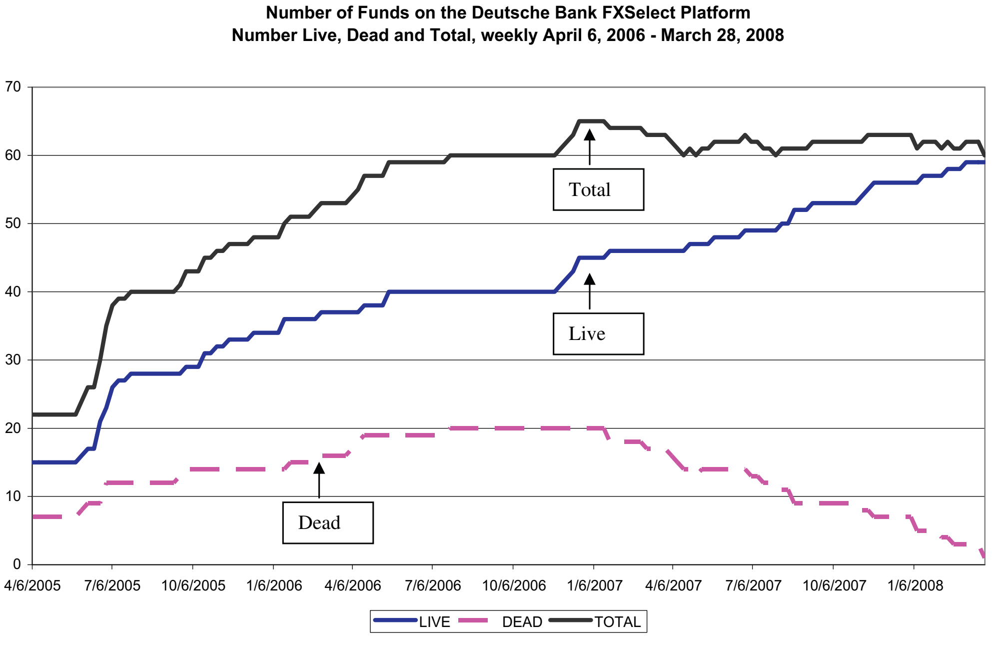

Fig. 3. Number of funds on the Deutsche Bank FXSelect platform. "Live" funds are those on the platform in week *t* and still active and on the platform in April 2008. "Dead" funds are those on the platform in week *t* but inactive and no longer on the platform as of April 2008. "Total" is the sum of "Live" and "Dead" funds on the platform in week *t*. Source: Deutsche Bank and authors calculations.

While estimating (1) allows us to gain knowledge about a manager's investment style, the beta coefficients are not known ex-ante and so the alpha estimates may be biased downward. Put differently, without knowledge of the betas, (1) is not an investable strategy that managers could mimic even if desired. One intuitive solution is to form a single-index model based on an equally-weighted combination of possible currency investment strategies as representative of a naïve investment strategy. If a manager then outperforms this measure of beta, even by simply re-weighting the styles, this would constitute alpha. To address this possibility, we estimate a single-index model where the index (I_t) is an equally-weighted average of the available currency strategies. As an empirical matter, our estimates of alpha and inferences are essentially unchanged when based on the single-index model.[5]

While the four-factor model could underestimate alpha, the single-index model could, in some cases, overestimate alpha.[6] For example, suppose a manager has publicized his intention of mimicking a single strategy (e.g. carry) for which he earns a positive return. Evaluating this manager's returns against a single-index combining many strategies would leave some returns unexplained and labelled as alpha, when in fact they were beta returns wholly related to a single strategy.

2.1. *Currency manager returns*

In this study, we aim to estimate alphas of currency managers over annual periods. Thus, using monthly data is not an option as twelve observations are not enough to obtain robust estimates. It is

[5] As expected, the *R*-squared measures are somewhat larger using the four-factor model. The estimated alphas are somewhat larger using the single-index model, but again not significantly different than zero. At the level of individual funds, using the single-index model there is one additional fund that appears to have a significant alpha. Otherwise, there is no change in the inferences about individual funds. More details are in the empirical section.

[6] The four-factor model could also overstate alpha if part of the return stems from omitted risk factors, such as from a simple trend-following strategy in emerging market currencies.

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challenging to obtain higher frequency data for the returns of professional currency managers as hedge fund data providers usually collect monthly performance data. In this study, we make use of a new database of currency managers who are part of the Deutsche Bank (DB) FXSelect platform.[7] 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 on 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% maximum drawdown over the last 12 months
c) Assets under management must be at least 15 million USD
d) Satisfactory criminal and regulatory searches on key individuals

While FXSelect is a new venture, the platform is presumably 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.[8] Most importantly for this study, daily returns data on the FXSelect platform are available, thus providing us with sufficient data to conduct an analysis of 12-month periods.

Deutsche Bank provided daily returns data (gross of fees) for all managers who were actively trading on the platform since its exception. To correct for accounting errors and eliminate outliers, we transformed the daily returns into weekly returns by using Wednesday observations.[9] Weekly data provide 52 observations for each 12-month period, which is sufficient to obtain reasonably efficient parameter estimates with a four-factor model.

2.2. Backfill and survivorship biases

Performance evaluation needs to control for the usual biases affecting databases. In particular, backfill and survivorship biases might be severe. As indicated earlier, managers were required to submit at least 18 months of performance data before being considered for the platform. As a manager could choose the time when to approach Deutsche Bank, waiting for the “best” 18 months of past performance would have been possible. To correct for backfill bias, we use returns after a manager has actually joined the platform and started trading. Also, during our sample period, many managers have joined and exited the platform due to a poor performance. We label these managers “dead” funds. Fig. 3 shows the number of “dead” funds (as of April 2008), the number of “live” funds and the total number of funds from April 2005 until March 2008. Fig. 3 illustrates the magnitude of the survivorship bias. While 22 funds started in the platform in April 2005, only 15 of these funds (68%) survived until April 2008. Almost 1/3 of the funds exited the platform within three years after listing, as we show later most likely due to poor performance. This highlights the necessity of including the performance of dead funds in the analyses.[10] We obtained data for 80 funds in total, but only 15 of these funds had a complete 3-year track record.

[7] 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.

[8] Many (about 25%) of the managers in the FXSelect database are also included in other well-known hedge fund databases (CISDM and TASS). As another example for the visibility of the platform, Deutsche Bank recently launched the Mercer Currency Manager Index – a multimanager product based on managers from the FXSelect platform chosen by Mercer Investment Consulting.

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

[10] Not correcting for backfill and survivorship biases resulted in significant alpha estimates for the average manager in 2001, 2002, 2003, 2004, 2005 and 2006. The average alpha for 2007 was also estimated to be positive, but was not significantly different from zero. These results contrast strongly with the reported results after correcting for backfill and survivorship biases, where none of the annual periods average alphas was found to be significantly different from zero. This highlights the value of this database as other databases often do not allow for correction of backfill and survivorship bias.

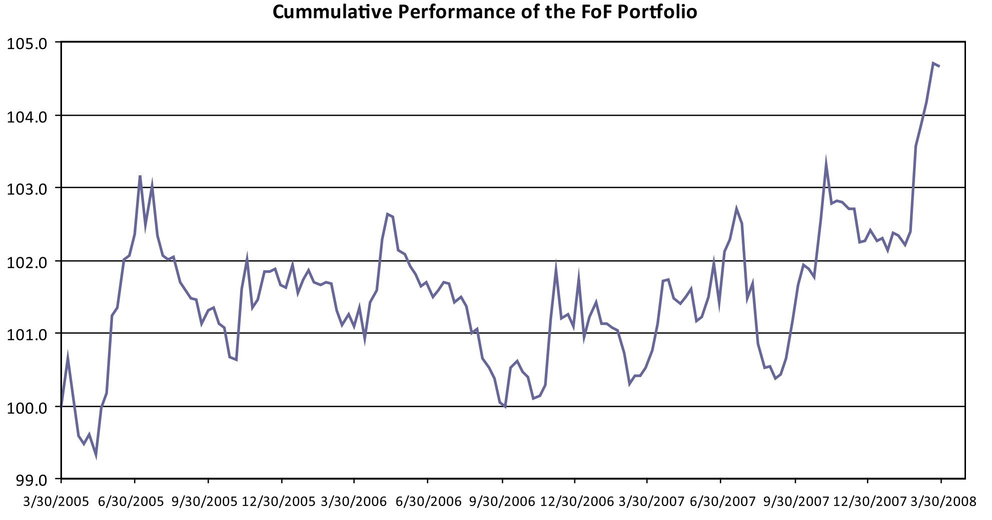

Fig. 4. Cumulative performance of the "FoF" Portfolio. This portfolio is an equally-weighted portfolio of all funds on the Deutsche Bank FXSelect platform, rebalanced weekly with newly listed funds added and dead funds excluded from the portfolio. Source: Deutsche Bank and authors calculations.

2.3. *Data for risk factors*

2.3.1. *Carry factor*

We use the Deutsche Bank G10 Harvest Index as the proxy for the returns of a carry strategy.[11] 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.

2.3.2. *Trend factor*

As a proxy for the trend-following factor, we use the AFX Currency Management Index.[12] 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).[13] Earlier research by Lequeux and Acar (1998) showed that this measure was a good proxy for a trend-following style among professional managers. The AFX Index is a well established proxy for trend-following strategies. It has been used for a number of years in various research papers, and therefore is known to researchers in this field.

2.3.3. *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

[11] In this paper, we were not able to use the same proxies for risk factors as in PL (2008) as the Citi indices were provided to us only on a monthly base. On the other hand, the Deutsche Bank indices are available as daily data in Bloomberg. To check the validity of using different indices for proxies of the risk factors, we redid the regressions reported in PL (2008) for the period, which overlaps with this study, using indices from Deutsche Bank. There was essentially no difference in the empirical results whether we used Deutsche Bank or Citi factors as right hand side variables.

[12] Monthly data for this index are available at the AFX web site (http://www.ljmu.ac.uk/LBS/93557.htm). We are grateful to Jason Laws from the Liverpool John Moore University for providing daily data. We transformed the daily returns into weekly returns by using the Wednesday observations.

[13] The seven currency pairs are EUR–USD, USD–JPY, USD–CHF, GBP–USD, EUR–JPY, EUR–GBP, and EUR–CHF.

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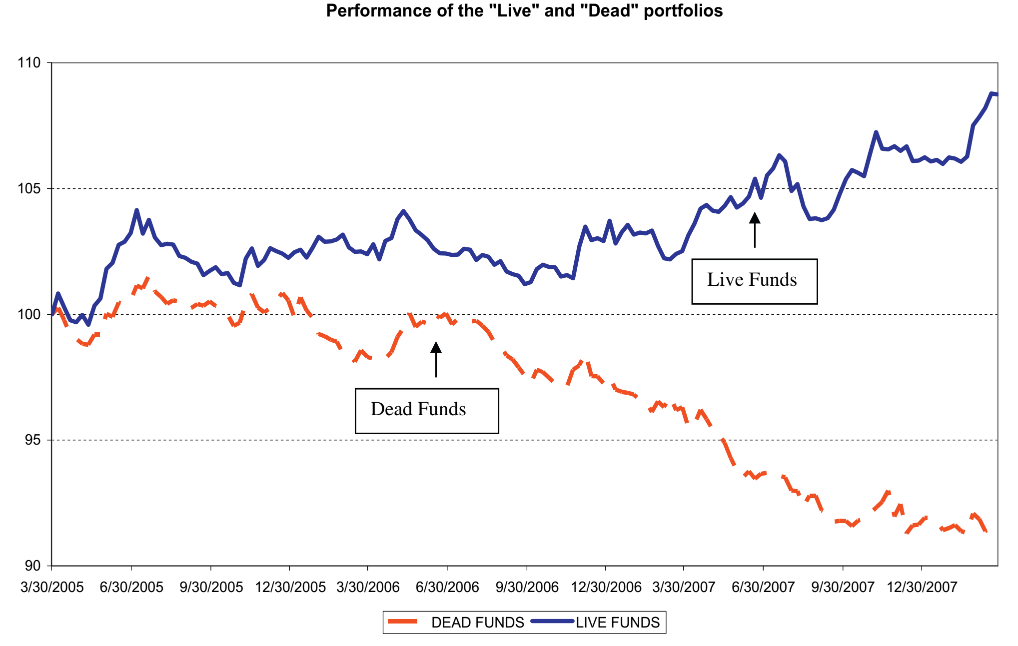

Fig. 5. Cumulative performance of the "Live" and "Dead" portfolios. Cumulative performance on two portfolios of funds listed on the Deutsche Bank FXSelect platform. One portfolio consists only of "dead" funds, i.e. the funds which were no longer on the platform in April 2008, and a second portfolio consists of "live" funds, i.e. those that were still active as of April 2008. Source: Deutsche Bank and authors calculations.

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.

2.3.4. 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 weights based on trading volume in the BIS surveys.[14] The Bloomberg code for this factor is CVIX Index. Our volatility factor is the arithmetic difference between volatility at time t and volatility at time $t-1$.[15] Even though it is not an investable strategy, including a volatility factor allows us to measure the sensitivity of a manager's performance to the volatility environment.

3. Empirical results on currency return indices

3.1. Grouping managers into fund-of-funds

To measure the overall returns for managers included on DB FXSelect, we construct several portfolios representing all available funds and certain subsets of funds. The first "fund-of-funds" (FoF) portfolio is compromised of equally-weighted positions in each of the funds available on the platform on every Wednesday over the sample period. The return on this index can be defined as:

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

[15] Because our volatility factor is not a return-based style factor in the sense of Sharpe (1992), we also estimate equation (1) using only the three investable strategies. The results for the three-factor and four-factor models are essentially identical.

$$R_{FOF,t} = \sum_{j=1}^{n_t} R_{j,t}/n_t \tag{2}$$

where $R_{j,t}$ is the weekly return for manager j at time t; and n_t is the number of managers available on the platform at time t.

This portfolio is rebalanced weekly with newly listed funds added and "dead" funds excluded from our fund-of-funds portfolio. As a result, every one of the 80 managers who were on the platform between April 2005 and March 2008 is included in our fund-of-funds index during their active period on the platform. From Fig. 3, we see that n_t ranges from a low of 22 funds in April 2005 rising steadily to a high of 65 funds in December 2006 and then levelling off. The FoF portfolio is our primary gauge of performance of managers on the DB FXSelect platform and represents an investable index.

Fig. 4 plots the cumulative performance of the FoF portfolio. The performance is positive, highlighting the attraction of currency as an alternative asset class.[16] However, almost all of the performance is generated in the last 12 months. This performance pattern is consistent with the performance of the Parker FX index and the BCTI (see Table 1).[17]

To gain additional perspective on the performance of funds on the DB FXSelect platform, we construct two other portfolios, one consisting only of "dead" funds, i.e. the funds which were no longer on the platform in April 2008, and a second portfolio of "live" funds, i.e. those that were still active as of April 2008. The returns on these two funds are defined in an analogous way to our FoF, namely

$$R_{D,t} = \sum_{j=1}^{n_{D,t}} R^D_{j,t}/n_{D,t} \tag{3}$$

$$R_{L,t} = \sum_{j=1}^{n_{L,t}} R^L_{j,t}/n_{L,t} \tag{4}$$

where $R^D_{j,y}$ is the weekly return for manager of dead fund j at time t; $R^L_{j,y}$ is the weekly return for manager of live fund j at time t; $n_{D,t}$ is the number of managers classified as dead as of April 2008 but available on the platform at time t; and $n_{L,t}$ is the number of managers classified as living as of April 2008 and available on the platform at time t.

For example, the dead portfolio would have invested in 7 funds as of April 2005, increasing to 20 at the end of 2006 and consisting of only one manager in March 2008 (see Fig. 3). The number of living funds reached 59 in March 2008, Compared to the investable FoF index, our "Dead" and "Live" portfolios represent an "in-sample" experiment, which could be conducted only by looking backwards as we did not know which funds are going to die or remain on the platform. The cumulative performance of these two portfolios as shown in Fig. 5 clearly differs and we will analyze this more closely in the next section.

3.2. Regression results on return indices

Following the approach in PL (2008), we estimate equation (1) using 156 weekly observations over the 3-year sample period, April 2005–March 2008. We regress the returns of these 3 portfolios (FoF, Live and Dead) on the four risk factors described in the previous section. Alpha is the estimated intercept term, i.e. that portion of excess returns not explained by the four-factor model, or

[16] The annualized Sharpe ratio of the FoF portfolio is 0.56, comparable with the Sharpe ratios of the S&P 500 index (0.30), MSCI World index (0.71) and the Lehman Global Aggregate bond index (0.75) during this period. Furthermore, the attraction of currencies as an alpha source is visible trough the low correlation with the other asset classes. The correlation of the returns on the FoF portfolio with the returns on the S&P 500, MSCI World and Lehman Global Aggregate indices is −0.4%, 12% and 23%, respectively. The Sharpe ratio is computed as the average excess annualized monthly return (including dividends) divided by the annualized standard deviation of the excess returns. We use the 1-month LIBID (LIBOR less 12.5 bps) as the risk-free rate.

[17] The correlation over this 3-year period between the monthly returns on the FoF portfolio and the monthly returns on the Parker FX index and the returns on the BCTI is 67% and 65%, respectively. This suggests that the DB FXSelect database may be a reasonable proxy for the currency management industry. Over a longer period, from February 1987 to April 2008, the correlation between the returns on the Parker FX index and the returns on the BCTI is 90%.

Table 2
Regression results for "Fund-of-Funds" portfolios, April 2005–March 2008.

Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \epsilon_{j,t}$ for portfolios $j = 1, \ldots 3$; $t = 1, \ldots$ 156 weekly observations, 4/06/2005–3/26/2008

Panel A: four-factor model

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	Beta volatility	*T*-stat	*R*-square	F-stat	D–W
"FoF"	0.00001	0.31	0.14	**6.03**	0.40	**10.88**	−0.08	**−3.85**	0.12	1.53	0.534	43.30	2.21
"Live"	0.00027	1.16	0.19	**7.21**	0.45	**10.70**	−0.10	**−4.25**	0.15	1.74	0.550	46.24	2.27
"Dead"	−0.00064	**−2.31**	−0.06	**−2.12**	0.23	**4.57**	0.02	0.75	−0.01	−0.15	0.183	8.48	2.41

Regression Results for $R_{j,t} = \alpha_j + \beta_j I_t + \epsilon_{j,t}$ I is an equally-weighted combination of Carry, Trend and Value factors

Panel B: single-index model (equal weights on Carry, Trend and Value factors)

	Alpha	*T*-stat	Beta	*T*-stat	*R*-square	F-stat	D–W
"FoF"	0.00026	0.92	0.17	**4.17**	0.101	17.41	1.92
"Live"	0.00049	1.53	0.23	**4.73**	0.127	22.45	2.01
"Dead"	−0.00055	**−1.80**	−0.01	−0.18	0.000	0.03	2.29

Panel C: three-factor model (volatility factor omitted)

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	*R*-square	F-stat	D–W
"FoF"	0.00001	0.40	0.11	**6.26**	0.42	**12.20**	−0.07	**−3.59**	0.526	56.44	2.23
"Live"	0.00029	1.26	0.16	**7.55**	0.48	**12.05**	−0.09	**−3.95**	0.541	59.83	2.30
"Dead"	−0.00065	**−2.33**	−0.06	**−2.49**	0.22	**4.85**	0.02	0.73	0.18	11.37	2.41

The Deutsche Bank G10 Harvest Index is 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 G10 currency universe. The index is rebalanced quarterly. Every quarter the currencies are re-ranked according to their current 3-month Libor rate. Source: Deutsche Bank and Bloomberg.
The AFX Index reflects returns on a trend-following strategy involving three moving average rules applied to seven currency pairs, weighted by the volume of turnover in the spot market. Monthly data are available at http://cwis.livjm.ac.uk/AFE/AFE_docs/AFX_Monthly.xls. Source: Liverpool John Moores University.
The Deutsche Bank FX PPP Index is the proxy for the returns of a Value strategy. The average daily spot rate over the last three months is divided by the PPP exchange rate as published annually by the OECD and ranked. This 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. Source: Deutsche Bank and Bloomberg.
The Deutsche Bank Currency Volatility Index (CVIX index) is the proxy for the foreign exchange volatility. It is calculated as the weighted arithmetic average of the 3 months level of implied volatility for all major currency pairs (provided by BBA) and weighted by traded market volume. Source: Deutsche Bank and Bloomberg. Numbers in bold indicate statistical significance at the 5% level.

$$\widehat{\alpha} = R_t - \sum_i \widehat{\beta}_i F_{i,t} \tag{5}$$

Overall, the results in Table 2 support the four-factor model of currency trading returns. The model explains roughly 53% of the variability of the "FoF" portfolio returns. Trend appears to be the most significant factor. The trend coefficient is 0.40, larger than for any other factor and highly significant. On average, the managers on the FXSelect platform seem to rely on trend-following. The trend factor alone explains 40% of the variability of the excess returns of the "FoF" portfolio (we have regressed the returns of "FoF" portfolio on each individual factor, but do not report the results). The carry coefficient is also positive and significant. The value coefficient is significant but negative, indicating that on average managers were positioned to profit from further deviations from PPP. The volatility coefficient is positive but not significant at the 10% level in a 2-tail test.[18]

Our point estimate for alpha in the "FoF" portfolio is zero and not significant. This result implies that managers included in the FXSelect platform were not able to generate alpha on average between April

[18] In Panel B, we show the results for the single-index model. As expected, the *R*-squared for the single-index model is smaller than when we use four explanatory variables. But the F-statistic confirms that the regression is significant for the "FoF" portfolio and the "Live" portfolio. The single-index model produces an insignificant *R*-squared for the "Dead" portfolio.

Table 3
Market timing model. Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \sum_i \gamma_{i,j} F_{i,t}^2 + \mu_{j,t}$. Based on 156 weekly observations, 4/06/2005–3/26/2008

	Alpha[a]	*T*-st.	β Carry	*T*-st.	β Trend	*T*-st.	β Value	*T*-st.	β Vol.	*T*-st.
"Live"	-2.7bps	-0.85	0.18	**6.70**	0.40	**9.02**	-0.09	**-4.01**	0.07	0.72
"Dead"	-9.0 bps	**-2.41**	-0.09	**-2.91**	0.15	**3.03**	0.04	1.40	0.01	0.09

γ Carry	*T*-st.	γ Trend	*T*-st.	γ Value	*T*-st.	γ Vol.	*T*-st.	R^2	F-Stat	D–W
-0.24	-0.21	13.29	**3.02**	0.99	1.05	3.30	0.31	0.581	25.54	2.36
-1.23	-0.95	17.09	**3.35**	0.79	0.72	-20.2	**-1.65**	0.278	7.09	2.43

See notes to Table 2 for explanation of factors.
[a] In decimal form, the alphas are −0.00027 and 0.00090 for live and dead funds respectively. Numbers in bold indicate statistical significance at the 5% level.

2005 and March 2008. This confirms the presumption in the market that this period has been extremely challenging for currency managers. It is also consistent with previous research (PL, 2008) that as a group, currency managers were not able to generate significant alpha returns over the long run (between 1990 and 2006). The returns in our sample are gross of fees, which means that the average alpha would be negative after management fees. Managers often charge a 2% per annum management fee and 20% performance fee, but fees do vary.[19]

As the population of funds in the FXSelect platform changed over the 3-year period, it is interesting to explore differences in the performance of Live versus Dead funds, as defined by equations (3) and (4). Fig. 5 reveals that live funds achieved a cumulative value of 108.7 far better than dead funds where value sank to only 91.6 after 3 years. Put differently, the live funds earned about 2.8% per annum (with an information ratio of 0.91) compared to dead funds which earned −2.8% per annum (with an information ratio of −1.21).[20] We examine the performance of live and dead funds more closely with various regression tests. Several observations stand out in Table 2.

First, the alpha for the "Live" portfolio is quite high at almost 3 bps per week (or 1.4% per year). Although, not significant, this alpha suggests that this group of managers might have at least roughly covered their management fees. The alpha for the "Dead" portfolio is negative and significant. The "dead" managers lost about 6.5 bps per week (or roughly 3.3% per year). A t-test for the equality of the alphas of the "Live" and the "Dead" portfolio rejects the null hypothesis of equal means at the 95% confidence level (p-value = 0.0107). This may well explain why the "dead" funds exited the trading platform.

Second, using the single-index model (Panel B), we observe that 'live' managers had a positive and significant exposure to the composite factor while "dead" managers did not. With the four-factor model (Panel A), we can delve deeper and observe that the "live" managers have a positive and significant carry coefficient, but the "dead" managers have a negative and significant carry coefficient. Both groups are significantly exposed to trend, although the "live" managers have almost twice as much trend exposure as the "dead" managers. This is a noteworthy result as it suggests that "betting against carry" was an important reason why the "dead" managers underperformed. There has been a presumption in the market, that the recent underperformance of trend-following rules (the AFX is roughly flat in the period under consideration) has been the main reason for the disappointing performance of professional currency managers. Our results suggest that this presumption may be misplaced. Our results show that the strong performance of carry (up to the beginning of the credit crunch in July 2007) had a substantial impact on managers who were betting against the carry strategy. Ironically, although some managers might have been punished due to heavy exposure to carry after July 2007 (e.g. NZD/JPY dropped 23% between July 24, 2007 and August 16, 2007), many managers seem to have suffered heavy losses prior to that by betting against carry.

[19] In Panel B, point estimates for alpha with the single-index model are slightly higher than for the four-factor, but the alphas remain insignificant for the "FoF" and "Live" funds. The alpha for the "Dead" portfolio becomes marginally significant in the single-index model (a T-stat of −1.80 corresponds to a p-value of 7.2% in a two-tailed test) whereas in the four-factor model, the alpha on the "Dead" portfolio is highly significantly negative. In Panel C, we also report results for a three-factor model, omitting the volatility factor. These results are essentially the same as with the four-factor model in Panel A.
[20] An information ratio is the ratio of excess returns divided by their standard deviation.

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Table 4
Summary statistics of alpha performance measures for bootstrap simulations of 1000 trials over 156 weeks.

α	$N > 0$	$N\,[t(\alpha) > t^{*}(\alpha = 0)]$	Percent of 1000
0.01%	686	73	7.30%
0.02%	829	191	19.10%
0.03%	943	360	36.00%
0.04%	976	556	55.60%
0.05%	998	746	74.60%
0.06%	1000	872	87.20%
0.07%	1000	954	95.40%
0.08%	1000	989	98.90%
0.09%	1000	1000	100.00%
0.10%	1000	1000	100.00%

Notes:
These ten simulations are based on the procedure described in Kosowski et al. (2007). We use the estimated residuals from our "FoF" equation in Table 2 and take repeated samples, with replacement, to generate 1000 samples of 156 observations each. We then calculate a new series of returns using equation (6) which imposes the null hypothesis that $\alpha = 0$. We take each series of bootstrapped returns and run regression (1) to obtain the empirical distribution of α and its t-statistic. We then augment each alpha estimate by a fixed amount representing $\alpha = 1$ up to 10 basis points per week, implying an annualized true α ranging from 0.52% up to 5.33%. Using t^{*}, the bootstrapped t-statistic from a 5% test against the null that $\alpha = 0$, we can calculate how frequently this boundary is exceeded conditional on true α values ranging from 1 to 10 basis points per week.

Third, the "live" managers have a negative and significant exposure to the value factor and the "dead" managers have a positive, but not significant value coefficient. Betting against PPP and for continuation of departures from fair value seems to have helped the surviving managers to remain on the platform.

Finally, the 55% R-square for the "live" managers is much higher than the 18% R-square for "dead" managers. Anson (2008) theorizes that there is a trade-off between beta style returns and alpha returns. In short, strategies that mimic an index cannot earn returns that lead to outperformance. In an earlier study (PL, 2008), we found evidence supporting Anson's conjecture, namely that currency managers with high R-square tend to have lower alpha, and vice versa. In the DB FXSelect sample which includes live and dead funds, our results suggest that live managers tended to track the four factors more closely, earning beta returns, which should have helped them remain in operation. And indeed the live managers in our sample earned positive (although not significant) alpha as well. With weaker linkages to the four style factors, the dead managers were positioned to execute "pure" alpha seeking strategies. Unfortunately, in this instance, the dead managers realized significant negative alpha.

So while being an alpha manager is good in the sense that it would justify active management fees, it is good only as long as the managers are able to deliver positive returns. Beta chasers might find it more difficult to justify alpha fees, but sticking close to the benchmark (the four trading strategies) has apparently helped them to stay in business. This result is consistent with a common strategy in the asset management industry. The bulk of assets under management are allocated close to the benchmark as large deviations from the benchmark expose the manager to significant business risk in case of underperformance.

To better understand this anomaly of high (low) R-square and high (low) alpha, we re-estimated the regressions for "live" and "dead" funds in Table 2 including quadratic terms for each factor to test for market timing.[21] The results for "live" managers show positive and significant timing ability with respect to the trend-following factor (see Table 3). Once this effect is included, the point estimate for alpha for live managers drops to -2.7 bps per week from $+2.7$ bps per week, suggesting that all of their alpha could be accounted for by timing skills in trend following.[22]

The "dead" managers also have positive timing skill in trend, but on the other hand, they exhibit negative timing skills for volatility.[23] The actual returns of "dead" managers were made worse by

[21] Lo (2007) proposes a quadratic term as a way to detect market timing skills.

[22] Having estimated the alpha of the live managers with the 4-factor model and with the market timing model (8-factors) we were able to test for equality in the alphas. A t-test rejects the null hypothesis of equal means at the 90% confidence level (p-value $= 0.0866$). Thus, market timing has significantly contributed to the superior returns of the live managers.

[23] The coefficient of the squared volatility term is significant only at the 10% level. However, in an alternative specification of the market timing model, which omits the volatility factor, the dead managers exhibit a significant negative market timing ability in the carry strategy at the 5% level.

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taking positions that faltered when volatility increased. Overall, our analysis suggests that market timing skills had no significant positive impact on the returns of dead managers.[24]

3.3. Short sample bias, non-normality and simulation results

While the empirical analysis so far suggests some meaningful findings about the performance of "live" versus "dead" funds and how differences in trading styles may have contributed to that performance, our results could be influenced by the relatively short sample period and tendency toward non-normality in hedge fund returns. One concern is whether the lack of alpha for the "Live" managers and the negative alpha for the "Dead" managers is simply due to chance (being unlucky) during this 3-year period. To investigate this possibility, we undertake a bootstrap simulation following an approach discussed in Kosowski et al. (2007).

To begin, we use the time series of estimated residuals from the regressions in Table 2, Panel A ($\widehat{\epsilon}_{j,t}$ where $j = 1, 2, 3$ equations and $t = 1, 2 \ldots 156$) as a baseline for drawing samples, with replacement, to create $b = 1, 2 \ldots B$ time series of residuals each with 156 observations. Because the estimated residuals have mean zero by construction, the expected value of each drawing will also be zero, but (a) their variability will reflect the empirical distribution of residuals from our sample, and (b) the actual mean of any bootstrapped series can be non-zero. Then, for each bootstrap iteration (we set $B = 1000$) we calculate a new series of returns using the appropriate $\widehat{\beta}_i$ estimates and style factors in the formula

$$\widehat{R}_{j,t,b} = \sum_i \widehat{\beta}_i F_{i,t} + \widehat{\epsilon}_{j,t,b} \tag{6}$$

which in effect imposes the null hypothesis that the true performance measure $\alpha = 0$, or equivalently that the t-statistic of α is zero. Finally, we take each series of bootstrapped returns from (6), and run regression equation (1) to generate new estimates of α (and the t-statistic of α). These 1000 bootstrapped estimates generate an empirical distribution of alpha and its t-statistic which we can use for drawing inferences about our results.

In Table 2, Panel A, our initial estimates of alpha for the "FoF" and "Live" portfolios were small and not significant in the OLS regressions, and not surprisingly this was confirmed with the bootstrap simulations. The alpha for the "Dead" portfolio of funds was −6.4 basis points per week and significant using a conventional t-test. Our bootstrap simulation for "Dead" funds suggests that its t-value of −2.31 corresponds to a 1.3% p-value, and still highly significant. Thus, we can conclude that the negative alpha for the "Dead" managers results from lack of skill and not due to being "unlucky." Therefore, the difference in performance between "Live" and "Dead" funds in our sample remains highly significant even in the bootstrap test.

A second issue, however, is whether the sample period itself is too short for managers to demonstrate significant alpha even when they have trading skill. To examine this possibility, we utilize the empirical distribution of α and its t-statistic obtained through the bootstrap analysis described above. We then augment each alpha estimate by a fixed amount representing $\alpha = 1$ up to 10 basis points per week. Compounded over 52 weeks, this implies an annualized true α ranging from 0.52% up to 5.33%. Using the bootstrapped t-statistic from a 5% test against the null that $\alpha = 0$, we can calculate how frequently this boundary is exceeded in the 1000 bootstrapped samples conditional on true α values ranging from 1 to 10 basis points per week. The results in Table 4 suggest that when α is only 2 basis points per week (1.05% per annum), there is a relatively small chance (less than 1 in 5) that a sample of 156 weeks will produce a significant α estimate. However, if α were 4 basis points per week (or 2.10% per annum), the chance of finding a significant α rises to about 55%. And if α were 8 basis points per week or higher, we would have been almost certain to observe it in a sample of 156 weeks.

These simulations suggest that if managerial skill is modest and in the range of 2–4 basis point per week, there is a reasonable chance that a researcher would not find a significant result in a short sample. However, if managerial skill were greater, our 156 week sample would have been sufficient to document

[24] A t-test for the equality of the alphas estimated with the 4-factor model and with the market timing model did not rejects the null hypothesis of equal means for the dead managers. Market timing did not improve the returns of the dead managers as the positive market timing in trend was offset with negative market timing in volatility.

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Table 5
Regression results for individual currency managers, April 2005–March 2008.

Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \epsilon_{j,t}$ for managers $j = 1, \ldots 15$; t = 1, … 156. Weekly observations, 4/06/2005–3/26/2008

Panel A: four-factor model

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	Beta volatility	*T*-stat	*R*-square	F-stat	D–W
“Index”	0.00040	1.27	0.10	**2.89**	0.51	**9.03**	−0.12	**−3.58**	0.08	0.69	0.411	26.37	2.07
L6	−0.00057	−0.50	0.55	**4.23**	1.07	**5.15**	−0.04	−0.35	−0.10	−0.22	0.271	14.09	2.16
L10	−0.00001	−0.05	−0.01	−0.32	0.09	1.32	−0.01	−0.39	0.26	1.80	0.074	3.04	1.85
L15	−0.00092	−0.76	0.17	1.29	0.97	**4.44**	−0.42	**−3.31**	0.15	0.34	0.174	7.99	2.17
L28	0.00116	1.85	−0.00	−0.07	0.09	0.87	−0.08	−1.26	0.38	1.57	0.057	2.31	1.80
L29	0.00321	1.56	−0.48	**−2.08**	−0.68	−1.84	0.06	0.30	1.24	1.57	0.105	4.43	2.23
L30	0.00001	0.09	−0.05	−0.57	0.08	0.53	0.21	**2.21**	0.32	0.94	0.055	2.21	2.41
L35	0.00026	0.21	0.07	0.54	0.21	1.00	−0.08	−0.65	−1.00	**−2.15**	0.059	2.37	2.29
L42	0.00194	1.47	−0.94	**−6.31**	−0.24	−1.01	0.21	1.50	−0.42	−0.84	0.268	13.84	2.09
L46	0.00036	0.67	0.07	1.18	0.19	**2.06**	−0.10	−1.83	0.47	**2.34**	0.104	4.40	1.95
L47	0.00036	0.89	−0.15	**−3.37**	0.03	0.45	−0.31	−0.73	−0.05	−0.32	0.134	5.88	2.25
L49	0.00079	1.64	−0.05	−1.04	0.23	**2.65**	−0.05	−1.05	0.36	1.96	0.167	7.57	2.20
L50	−0.00086	−0.64	0.29	1.95	1.77	**7.34**	−0.23	−1.64	1.28	**2.50**	0.360	21.25	1.92
L52	0.00080	0.68	0.67	**5.08**	2.05	**9.65**	−0.35	**−2.86**	−0.47	−1.05	0.464	32.75	2.45
L53	0.00018	0.13	0.66	**4.30**	1.44	**5.85**	−0.47	**−3.28**	−0.53	−1.02	0.294	15.75	2.54
L58	−0.00077	−1.07	0.75	**9.26**	0.37	**2.89**	−0.37	**−4.93**	−0.64	**−2.32**	0.535	43.45	2.13

Panel B: single-index model (equal weights on Carry, Trend and Value factors)

Regression results for $R_{j,t} = \alpha_j + \beta_j I_t + \epsilon_{j,t}$ for managers $j = 1, \ldots 15$.
I is an equally-weighted combination of the $F(i)$, where $i = 1, \ldots 3$ factors (Carry, Trend and Value)

	Alpha	*T*-stat	Beta	*T*-stat	*R*-square	F-stat	D–W
“Index”	0.00065	1.62	0.11	1.80	0.020	3.24	1.81
L6	−0.00024	−0.19	1.02	**5.55**	0.166	30.77	2.13
L10	0.00009	0.23	−0.05	−0.88	0.004	0.77	1.88
L15	−0.00040	−0.31	−0.08	−0.40	0.001	0.16	2.11
L28	0.00133	**2.09**	−0.14	−1.48	0.013	2.18	1.78
L29	0.00330	1.58	−0.94	**−2.99**	0.054	8.91	2.26
L30	0.00016	0.18	0.17	1.24	0.009	1.54	2.42
L35	0.00012	0.09	0.18	0.97	0.006	0.93	2.30
L42	0.00184	1.31	−1.1	**−5.15**	0.147	26.54	1.95
L46	0.00057	1.04	−0.04	−0.51	0.002	0.25	2.04
L47	0.0004	0.98	−0.25	**−4.05**	0.096	16.44	2.30
L49	0.00101	1.94	−0.14	−1.82	0.021	3.32	2.20
L50	0.0002	0.12	0.4	1.61	0.016	2.59	1.81
L52	0.00153	1.03	1.08	**4.83**	0.131	23.33	2.38
L53	0.00067	0.43	0.77	**3.26**	0.064	10.65	2.34
L58	−0.00080	−0.84	0.77	**5.36**	0.157	28.74	1.94

Panel C: three-factor model (volatility factor omitted)

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	*R*-square	F-stat	D–W
“Index”	0.00041	1.32	0.08	**3.04**	0.53	**9.97**	−0.11	**−3.52**	0.409	35.11	2.07
L6	−0.00060	−0.52	0.57	**5.36**	1.06	**5.45**	−0.05	−0.41	0.271	18.88	2.14
L10	0.00002	0.06	−0.06	−1.66	0.14	**2.10**	0.00	−0.01	0.054	2.91	1.91
L15	−0.00090	−0.75	0.15	1.34	1.00	**4.91**	−0.42	**−3.33**	0.174	10.67	2.17
L28	0.00123	**1.95**	−0.07	−1.19	0.16	1.54	−0.06	−0.95	0.042	2.23	1.82
L29	0.00342	1.65	−0.70	**−3.64**	−0.48	−1.37	0.14	0.66	0.09	5.02	2.24
L30	0.00014	0.16	−0.11	−1.38	0.14	0.94	0.23	**2.47**	0.049	2.64	2.42
L35	0.0001	0.08	0.24	**2.16**	0.05	0.24	−0.14	−1.12	0.030	1.57	2.31
L42	0.00187	1.42	−0.87	**−7.14**	−0.32	−1.42	0.19	1.36	0.264	18.25	2.13
L46	0.00044	0.81	−0.01	−0.19	0.28	**3.08**	−0.08	−1.34	0.071	3.92	1.98
L47	0.00036	0.88	−0.15	**−3.91**	0.02	0.36	−0.03	−0.83	0.134	7.84	2.24
L49	0.00086	1.75	−0.12	**−2.64**	0.29	**3.57**	−0.03	−0.65	0.145	8.64	2.23

(*continued on next page*)

Table 5 (*continued*)

Panel C: three-factor model (volatility factor omitted)

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	*R*-square	F-stat	D–W
L50	−0.00066	−0.48	0.08	0.61	2.00	**8.69**	−0.16	−1.12	0.333	25.36	1.99
L52	0.00073	0.62	0.76	**6.96**	1.98	**9.94**	−0.39	**−3.17**	0.460	43.25	2.47
L53	0.00010	0.07	0.75	**5.98**	1.35	**5.88**	−0.51	**−3.59**	0.289	20.64	2.53
L58	−0.00088	−1.20	0.86	**12.79**	0.27	**2.17**	−0.41	**−5.48**	0.518	54.55	2.14

"Index" represents an equally-weighted portfolio consisting of all managers in this table. L6, L10 etc. stand for returns the managers, who were live (still on the platform) as of April 2008. Numbers in bold indicate statistical significance at the 5% level. See notes to Table 2 for explanation of factors.

it. In other words, if alpha was economically significant, we would have been very likely to observe it and it would also have been statistically significant in the 3-year sample.[25] The results in Table 4 apply symmetrically for managers with negative alpha. Recall that our point estimate of alpha for "Dead" managers was −6.4 basis points per week (see Table 2a). As our simulations suggest, managers having such extreme performance have nearly a 90% chance of being uncovered even in a sample of our size.

Furthermore, even if three years might be too short a sample period to detect significant alpha from a statistical point of view, it is often long enough from an economic point of view, i.e. managers with a negative 3-year track record are likely to lose their mandate.[26] In Table 5, Panel A shows that 2/3 of the managers have positive alpha over the 3-year sample and 1/3 of the managers delivered negative alpha. This suggests a similar survivor ratio as the one demonstrated in Fig. 3, i.e. while 22 funds started in the platform in April 2005, only about 2/3 of these (15 funds) survived after three years.

4. Empirical results for individual managers

4.1. Full three-year sample period

Table 5 summarizes the results for the individual currency managers with a track record spanning the entire 3-year period. We include three panels to show results for the four-factor model, the three-factor model with volatility omitted, and the single-index model. The first row of each panel shows the results for an equally-weighted portfolio ("Index" portfolio) consisting of all 15 managers. As in the case of the "Live" and "Dead" portfolios, this is a backward looking exercise as we did not know which managers who were on the platform in April 2005 would remain until March 2008.

For the 15 individual managers, panel A in Table 5 shows that trend was the most important factor over the 3-year period. Trend is significant for more than half of the managers (8). Carry is significant for 7 managers, but three of the managers had a significant negative exposure to carry. It seems that while 25% of the managers were exhibiting carry exposure, a similar number were betting on liquidation of carry trades. Value was significant only for 5 managers and four of these managers had a negative exposure to value, i.e. they were betting for further deviation from PPP. Volatility was significant for 4 managers – two managers would have benefited from falling volatility environment (the volatility coefficient was negative and significant) and two managers would have benefited from rising volatility environment (positive and significant volatility beta).

Finally, none of the managers was able to deliver significant alpha as defined by our four-factor model. Manager L28 was the best of all with alpha estimated at 12 bps per week (about 6.0% per year) and significant at the 90% confidence level. If we examine Manager L28 using the three-factor model, alpha is slightly higher, but the significance level reaches the 95% confidence level. In Panel B, Manager L28 shows a slightly higher alpha with a slightly higher *t*-statistic. In Panel B, Manager L49 also shows a positive alpha (about 10 bps per week) with a significant t-statistic. The likelihood that more managers can outperform the naïve single-index standard is confirmed in this table.

[25] It is worth repeating that our returns data do not account for management fees. An alpha of 2–4 basis points per week would be needed to offset management fees of 1–2 per cent per annum.

[26] Recently, 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.

Table 6
Performance of individual currency managers.

Manager	Average excess annual return	Std. dev.	IR	Rank	Average annual alpha	Tracking error	IR*	Rank*	Max. drawdown	Scaled max. drawdown	Rank scaled max. drawdown
Carry									−13.2%	−15.2%	
Trend									−6.4%	−14.8%	
Value									−12.5%	−16.2%	
“Index”									−4.2%	−11.7%	
L6	−0.08%	11.957%	−0.01	13	−3.01%	10.20%	−0.30	12	−23.1%	−19.3%	12
L10	0.40%	3.532%	0.11	10	−0.11%	3.40%	−0.03	11	−6.0%	−16.8%	10
L15	−2.18%	11.828%	−0.18	14	−4.82%	10.75%	−0.45	14	−23.8%	−20.2%	14
L28	6.73%	5.732%	1.17	1	6.08%	5.56%	1.09	1	−7.9%	−13.8%	7
L29	16.10%	19.282%	0.83	3	16.74%	18.24%	0.92	3	−17.9%	−9.3%	3
L30	1.03%	8.123%	0.13	9	0.46%	7.90%	0.06	10	−13.0%	−16.0%	9
L35	0.80%	11.084%	0.07	12	1.36%	10.75%	0.13	8	−10.2%	−9.2%	2
L42	8.34%	13.654%	0.61	5	10.10%	11.68%	0.86	4	−30.9%	−22.6%	15
L46	2.93%	4.972%	0.59	6	1.87%	4.71%	0.40	7	−4.9%	−9.9%	4
L47	1.79%	3.844%	0.47	7	1.89%	3.58%	0.53	5	−5.9%	−15.5%	8
L49	5.07%	4.693%	1.08	2	4.14%	4.28%	0.97	2	−2.7%	−5.8%	1
L50	1.49%	14.800%	0.10	11	−4.49%	11.84%	−0.38	13	−18.7%	−12.7%	6
L52	9.16%	14.253%	0.64	4	4.21%	10.43%	0.40	6	−24.9%	−17.5%	11
L53	4.34%	14.380%	0.30	8	0.97%	12.08%	0.08	9	−16.4%	−11.4%	5
L58	−3.30%	9.307%	−0.35	15	−4.02%	6.35%	−0.63	15	−18.1%	−19.5%	13
Average	3.51%		0.37		2.09%		0.24		−14.96%	−14.63%	

IR = $R_j/\sigma(R_j)$, where R_j is the annualized average excess return and $\sigma(R_j)$ is its annualized standard deviation.
IR* = $\alpha_j/\sigma(\alpha_j)$, where α_j is the average annual alpha estimated from equation (1) and $\sigma(\alpha_j)$ is its annualized standard deviation, or tracking error.

We make additional calculations to determine how manager performance ranks once various risk measures are taken into account. Table 6 reports the annualized excess returns, standard deviations and information ratios for these 15 managers. The average excess annual return is positive, ranging from −3.30% (L58) to 16.10% (L29) and the volatility ranges from 3.53% (L10) to 19.28% (L29). The average information ratio is 0.37. However, this average information ratio overstates the performance of the average manager during this challenging period as it is not adjusted for survivorship bias. The fourth column of Table 6 ranks the managers by their information ratio. Manager L28 is ranked first (IR equals 1.17) and manager L58 is ranked last (fifteen) with an information ratio of −0.35.

We also report the annualized alpha return, the standard deviation of alpha returns (tracking error) and the alternative information ratio (IR*) as defined in PL (2008).[27] Rank* is therefore the ranking of the managers by their IR*. Note that manager L35 experiences the largest improvement in ranking; he jumps to 8th place from 12th place. This is not a surprise as his *R*-square was the second smallest (see Table 3). Less than 6% of the variability of his returns could be explained by exposure to the four factors.

The average IR* is smaller (0.24) than the average IR (0.37). This suggests that significant part of the returns of the average manager could be attributed to exposure to the four risk factors and it is not pure alpha.

It could be argued that although some managers do not deliver alpha, they might offer a better return profile than the simple investable strategies by, for example, limiting the maximum drawdown (MDD) over an investment period.[28] As managers may operate with different volatility profiles, comparisons without adjusting for volatility would not be appropriate. Therefore, we adjust returns (up or down) so that they exhibit 10% per annum volatility. We then compute the maximum drawdown for scaled returns and report these measures in Table 6.

[27] The information ratio (IR) is defined as the ratio of excess returns to their standard deviation. If we assume that all returns are excess returns, then IR = $R_j/\sigma(R_j)$, where R_j is the annualized average excess return and $\sigma(R_j)$ is its annualized standard deviation. Using equation (1) to estimate alpha, PL define the alternative information ratio as IR* = $\dot{\alpha}_j/\sigma(\dot{\alpha}_j)$.

[28] Maximum drawdown is defined as the largest cumulative loss from a market peak to the following trough. It proxies how large a sustained loss can become.

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The average scaled MDD for the 15 individual funds is −14.6%, about the same as any of the three investable strategies although a bit smaller than 15.0%, the figure for the single-index model. Thus, as a group, these managers did not realize better drawdown results than the naïve strategies.

While the lowest MDD (−5.8%) belongs to a manager (L49) with one of the highest IR* measures, the second and fourth lowest MDD measures were achieved by managers with more mediocre IR* results. The rank correlation between scaled MDD and IR* is about 0.45 suggesting that the two measures capture different aspects of risk and performance and are complementary in this sample of managers.

4.2. Successive one-year samples

To investigate performance and style persistence, we estimate equation (1) using 52 weekly observations on successive one-year periods. Tables 7–9 show the results for three periods: April 2005–March 2006, April 2006–March 2007 and April 2007–March 2008. For each sub-period, we include those managers who have a full performance track record in the respective period. We start with 22 funds in the first sub-period. Twenty-one of these managers have also a full performance history in the second sub-period (manager D10 exited the platform in January 2007 – after a total return of −12% since entering) and is not included in the second sub-period. An additional 31 managers joined the platform between May 2005 and April 2006 and have a full track record available through the second sub-period. Thus, the total number of managers with a performance track record between April 2006 and March 2007 rises to 52. The last sub-period contains 46 currency managers. Twenty-one managers did not make it through the last 12 months after joining the platform sometime before

Table 7

Regression results for individual currency managers, April 2005–March 2006. Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \epsilon_{j,t}$ for managers $j = 1, \ldots 22$. Based on 52 weekly observations, 4/06/2005–3/29/2006.

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	Beta volatility	*T*-stat	*R*-square	F-stat	D–W
“Index”	0.00026	0.58	−0.05	−0.68	0.36	**4.60**	0.07	1.18	0.27	0.92	0.500	11.76	2.04
L6	0.00019	0.08	0.54	1.45	0.83	**2.14**	0.15	0.46	0.54	0.37	0.269	4.34	2.44
L10	0.00043	0.62	−0.13	−1.10	0.04	0.39	0.04	0.38	1.00	**2.19**	0.150	2.09	2.07
L15	−0.00206	−0.81	−0.12	−0.29	0.33	0.74	0.51	1.40	1.58	0.96	0.147	2.04	2.28
L28	0.00104	1.11	0.03	0.21	0.13	0.84	−0.09	−0.69	−0.69	−1.14	0.036	0.45	1.11
L29	0.00511	1.10	−0.39	−0.50	−0.75	−0.92	−0.47	−0.69	2.10	0.69	0.104	1.37	2.13
L30	−0.00064	−0.33	−0.01	−0.05	−0.19	−0.57	0.41	1.47	0.29	0.23	0.079	1.02	2.50
L35	0.00092	0.78	0.21	1.09	0.22	1.09	−0.40	**−2.35**	0.13	0.17	0.117	1.56	1.45
L42	0.00193	1.64	−0.53	**−2.70**	−0.70	**−3.41**	0.15	0.91	1.05	1.37	0.342	6.12	1.64
L46	0.00029	0.37	0.20	1.59	0.38	**2.83**	−0.31	**−2.70**	−0.10	−0.20	0.181	2.61	2.44
L47	0.00001	0.05	−0.14	−1.04	0.26	1.84	−0.22	−1.86	0.33	0.62	0.250	3.93	2.44
L49	0.00082	1.04	−0.07	−0.59	0.38	**2.76**	−0.04	−0.41	0.73	1.43	0.254	4.01	2.21
L50	−0.00119	−0.63	−0.48	−1.54	1.53	**4.64**	−0.10	−0.36	2.72	**2.22**	0.500	11.77	1.94
L52	0.00101	0.53	0.38	1.21	2.06	**6.26**	0.43	1.57	−1.30	−1.06	0.661	22.92	1.99
L53	0.00047	0.18	−0.26	−0.63	1.09	**2.50**	0.71	1.95	−1.15	−0.71	0.331	5.82	2.14
L58	−0.00169	−1.12	0.66	**2.62**	0.11	0.42	−0.20	−0.92	−1.82	−1.84	0.213	3.18	1.96
D3	0.00001	0.01	−0.24	−0.79	−0.69	**−2.11**	0.24	0.90	−0.28	−0.23	0.106	1.40	2.03
D5	−0.00134	−0.99	−0.12	−0.54	1.19	**5.06**	0.62	**3.18**	−1.81	**−2.07**	0.641	21.01	2.22
D6	−0.00001	−0.15	0.11	1.10	0.34	**3.31**	−0.15	−1.78	0.42	1.09	0.250	3.93	1.58
D10	−0.00164	−0.55	−0.18	−0.36	0.30	0.58	0.43	0.99	−0.63	−0.33	0.061	0.77	2.84
D14	−0.00030	−0.24	−0.39	−1.92	0.91	**4.34**	0.07	0.41	0.80	1.02	0.450	9.63	2.10
D15	0.00143	1.04	−0.11	−0.50	0.23	0.98	−0.17	−0.89	1.67	1.87	0.157	2.19	1.54
D21	0.00100	1.45	−0.06	−0.55	−0.14	−1.22	0.09	0.95	0.34	0.76	0.037	0.46	1.78

Numbers in bold indicate statistical significance at the 5% level. See notes to Table 2 for explanation of factors.

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Table 8
Regression results for individual currency managers, April 2006–March 2007. Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \epsilon_{j,t}$ for managers $j = 1, \ldots 52$. Based on 52 weekly observations, 4/05/2006–3/28/2007.

	Alpha	*T*-stat	Beta carry	*T*-stat	Beta trend	*T*-stat	Beta value	*T*-stat	Beta volatility	*T*-stat	*R*-square	F-stat	D–W
"Index"	−0.00017	−0.53	0.14	**2.62**	0.35	**4.96**	−0.12	−1.88	0.39	**2.79**	0.613	18.63	2.45
L1	−0.00031	−0.15	0.44	1.27	−0.37	−0.84	−0.18	−0.44	0.80	0.91	0.074	0.95	2.06
L2	0.00043	0.41	0.11	0.60	1.11	**4.79**	0.93	**4.40**	−0.98	**−2.13**	0.691	26.33	1.74
L3	−0.00244	−0.78	0.59	1.07	−0.43	−0.61	−0.54	−0.85	3.67	**2.63**	0.184	2.66	2.34
L6	−0.00124	−0.71	0.97	**3.18**	1.32	**3.38**	−0.59	−1.64	−1.69	**−2.18**	0.332	5.86	2.11
L10	−0.00048	−0.76	0.10	0.95	0.13	0.97	−0.09	−0.72	0.36	1.29	0.128	1.74	1.79
L12	−0.00099	**−2.75**	0.02	0.38	−0.11	−1.38	−0.07	−1.07	0.00	0.02	0.077	0.98	2.45
L13	−0.00038	−0.57	−0.18	−1.60	0.23	1.60	0.07	0.54	−0.40	−1.35	0.140	1.92	1.89
L14	−0.00076	−0.37	0.69	1.92	0.98	**2.13**	−1.00	**−2.40**	0.57	0.63	0.281	4.61	1.97
L15	−0.00019	−0.13	0.29	1.16	0.52	1.65	−1.23	**−4.23**	0.37	0.59	0.548	14.26	1.94
L21	−0.00001	−0.07	0.13	0.68	0.73	**2.90**	−0.26	−1.15	0.28	0.57	0.294	4.91	1.94
L22	−0.00026	−0.45	−0.16	−1.63	0.08	0.65	0.19	1.64	0.09	0.36	0.078	1.00	2.32
L23	0.00232	0.77	0.93	1.76	1.93	**2.85**	−1.73	**−2.80**	0.71	0.53	0.390	7.53	1.89
L24	−0.00093	−1.85	−0.06	−0.74	0.00	0.05	−0.13	−1.28	−0.41	−1.83	0.204	3.03	1.98
L27	−0.00072	−0.38	1.12	**3.32**	0.45	1.06	−0.43	−1.11	0.82	0.97	0.297	4.98	2.28
L28	0.00331	**2.26**	−0.33	−1.31	−0.27	−0.83	0.27	0.90	1.55	**2.38**	0.159	2.23	1.88
L29	0.00037	0.16	−1.08	**−2.80**	−0.56	−1.15	0.72	1.61	1.88	1.93	0.236	3.63	2.47
L30	0.00028	0.18	−0.28	−1.06	0.28	0.82	0.28	0.91	−0.07	−0.11	0.043	0.53	2.27
L32	0.00059	0.38	0.46	1.69	0.32	0.92	0.25	0.80	0.52	0.75	0.273	4.43	1.98
L33	−0.00160	−0.70	−0.30	−0.76	−0.75	−1.48	0.66	1.42	1.67	1.64	0.092	1.20	1.92
L34	−0.00042	−0.76	0.03	0.38	0.07	0.58	0.07	0.64	−0.02	−0.10	0.067	0.85	1.41
L35	−0.00120	−0.69	0.44	1.44	1.14	**2.92**	−0.44	−1.24	−1.27	−1.64	0.173	2.47	2.22
L38	0.00078	0.62	0.11	0.49	0.43	1.54	−0.10	−0.39	0.28	0.50	0.101	1.32	1.84
L41	−0.00107	−0.80	0.36	1.53	0.78	**2.61**	−0.10	−0.37	−0.21	−0.35	0.189	2.75	2.16
L42	−0.00051	−0.42	−0.35	−1.67	−0.18	−0.66	−0.01	−0.04	1.58	**2.95**	0.376	7.10	1.68
L43	−0.00060	−0.77	0.01	0.13	0.07	0.45	−0.15	−0.96	0.53	1.54	0.192	2.81	1.47
L45	0.00119	0.52	1.23	**3.06**	0.73	1.43	−0.80	−1.71	0.04	0.04	0.212	3.18	2.18
L46	−0.00001	−0.03	0.10	0.81	0.44	**2.62**	−0.10	−0.67	0.03	0.09	0.185	2.68	1.63
L47	0.00135	**2.20**	0.22	**2.05**	−0.15	−1.12	−0.42	**−3.40**	0.02	0.08	0.248	3.89	1.67
L49	0.00106	1.10	0.12	0.72	0.23	1.07	−0.16	−0.84	0.83	**1.93**	0.221	3.35	2.27
L50	−0.00057	−0.26	0.35	0.93	2.37	**4.90**	−0.45	−1.03	1.04	1.09	0.508	12.13	2.34
L51	0.00045	0.31	−0.06	−0.25	0.00	0.02	−0.33	−1.14	−0.61	−0.96	0.106	1.40	2.09
L52	−0.00216	−1.17	0.35	1.08	1.53	**3.70**	0.05	0.15	1.11	1.35	0.378	7.16	2.68
L53	−0.00110	−0.51	0.23	0.62	0.15	0.32	−0.28	−0.64	1.02	1.07	0.069	0.88	2.56
L54	−0.00020	−0.33	0.16	1.44	0.41	**2.93**	−0.12	−0.99	0.04	0.14	0.230	3.52	1.93
L55	0.00054	0.25	0.64	1.68	0.16	0.34	0.72	1.61	−0.66	−0.68	0.451	9.66	2.11
L56	−0.00028	−0.20	0.12	0.49	1.82	**5.81**	−0.24	−0.83	1.80	**2.91**	0.674	24.34	1.76
L58	−0.00030	−0.38	0.34	**2.46**	0.67	**3.78**	−0.01	−0.10	−0.31	−0.89	0.381	7.25	2.65
D1	−0.00126	**−2.35**	−0.05	−0.59	0.02	0.22	−0.06	−0.55	0.11	0.50	0.117	1.57	2.35
D2	−0.00181	−1.08	−1.00	**−3.40**	−0.19	−0.51	0.66	**1.93**	1.27	1.70	0.293	4.87	2.27
D3	0.00364	1.34	0.13	0.27	−0.97	−1.59	−0.06	−0.10	0.43	0.35	0.064	0.82	2.38
D4	−0.00001	−0.55	−0.01	−0.46	−0.02	−0.66	0.03	1.09	0.13	**1.91**	0.082	1.05	1.90
D5	−0.00240	−1.55	0.45	1.68	1.36	**3.93**	−0.05	−0.17	0.03	0.05	0.339	6.04	1.81
D6	0.00034	0.46	−0.17	−1.33	0.39	**2.39**	0.10	0.67	0.19	0.61	0.253	3.99	2.05
D7	−0.00152	−0.73	−0.31	−0.87	−0.00	−0.01	−0.04	−0.10	−0.03	−0.03	0.062	0.79	2.14
D11	−0.00160	−0.83	0.18	0.54	−0.47	−1.09	−0.45	−1.15	0.39	0.45	0.065	0.83	2.44
D12	0.00161	1.17	0.12	0.52	0.14	0.47	−0.18	−0.63	0.71	1.16	0.087	1.13	2.14
D14	−0.00040	−0.40	0.00	0.03	1.10	**4.80**	0.00	0.01	−0.13	−0.29	0.396	7.73	1.80
D15	−0.00028	−0.27	−0.13	−0.73	0.52	**2.23**	0.04	0.19	0.75	1.63	0.312	5.34	1.80
D17	−0.0001	−0.21	0.06	0.85	−0.10	−1.08	−0.05	−0.61	0.61	**3.25**	0.227	3.47	2.33
D19	0.00054	0.36	0.08	0.32	−0.23	−0.69	−0.04	−0.15	0.65	0.99	0.025	0.31	2.36
D20	−0.00038	−0.51	0.27	**2.12**	0.52	**3.15**	−0.22	−1.49	0.63	**1.94**	0.414	8.32	1.76
D21	0.00109	1.33	0.18	1.29	0.18	1.00	−0.29	−1.74	−0.11	−0.32	0.089	1.16	2.03

In column 1, bold indicates the fund was operating in April 2005–March 2006. Other numbers in bold indicate statistical significance at the 5% level. See notes to Table 2 for explanation of factors.

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Table 9
Regression results for individual currency managers, April 2007–March 2008. Regression results for $R_{j,t} = \alpha_j + \sum_i \beta_{i,j} F_{i,t} + \epsilon_{j,t}$ for managers $j = 1, \dots 46$. Based on 52 weekly observations, 4/04/2007–3/26/2008

	Alpha	T-stat	Beta carry	T-stat	Beta trend	T-stat	Beta value	T-stat	Beta volatility	T-stat	R-square	F-stat	D–W
"Index"	0.00047	1.17	0.22	**6.15**	0.37	**4.76**	−0.12	**−3.51**	0.15	1.17	0.673	24.27	2.20
L1	−0.00186	−0.96	0.06	0.39	0.20	0.53	0.02	0.17	0.46	0.73	0.036	0.44	1.74
L2	0.00001	0.01	0.80	**3.16**	0.99	1.82	0.34	1.43	0.55	0.61	0.339	6.04	1.77
L3	0.00042	0.12	0.57	1.82	0.73	1.08	−0.42	−1.38	2.44	**2.15**	0.185	2.67	2.18
L6	−0.00205	−0.93	0.57	**2.84**	1.19	**2.78**	−0.18	−0.96	0.30	0.42	0.329	5.77	1.92
L8	−0.00008	−0.34	1.41	**6.45**	0.96	**2.06**	−1.05	**−5.04**	0.82	1.04	0.672	24.14	2.63
L9	0.00026	0.20	1.05	**8.75**	0.62	**2.45**	−0.33	**−2.94**	−0.31	−0.73	0.813	51.20	1.99
L10	0.00019	0.27	−0.06	−0.93	0.06	0.44	0.00	0.04	0.04	0.19	0.069	0.88	1.70
L12	−0.00021	−0.28	−0.02	−0.29	−0.07	−0.53	0.03	0.52	−0.26	−1.05	0.068	0.86	1.68
L13	−0.00001	−0.03	−0.06	−1.06	−0.04	−0.31	−0.05	−0.95	0.08	0.37	0.107	1.41	1.80
L14	0.00236	1.22	0.04	0.28	0.69	1.85	−0.40	**−2.37**	−0.11	−0.18	0.206	3.06	1.91
L15	−0.00035	−0.17	0.19	1.02	1.02	**2.55**	−0.48	**−2.69**	−0.15	−0.23	0.293	4.89	1.97
L17	0.00112	0.73	0.32	**2.32**	−0.18	−0.60	−0.30	**−2.23**	0.52	1.04	0.172	2.45	2.17
L19	−0.00083	−0.83	−0.18	**−1.98**	0.38	1.95	−0.08	−0.98	−0.73	**−2.23**	0.194	2.84	2.02
L20	0.00199	1.32	0.30	**2.20**	0.90	**3.06**	0.02	0.18	0.08	0.17	0.290	4.81	2.11
L21	0.00040	0.21	0.09	0.52	0.01	0.04	−0.40	**−2.45**	−0.42	−0.67	0.186	2.70	1.74
L22	0.00022	0.20	−0.20	**−2.06**	−0.13	−0.62	0.02	0.31	−0.09	−0.25	0.150	2.08	2.37
L23	0.00647	**1.93**	0.24	0.80	−0.08	−0.13	−0.59	**−2.03**	−1.43	−1.30	0.255	4.04	2.28
L24	−0.00018	−0.15	−0.08	−0.72	0.28	1.20	0.10	1.02	−0.11	−0.29	0.061	0.76	1.97
L25	−0.00001	−0.04	−0.15	−1.19	0.41	1.53	0.03	0.26	0.57	1.25	0.306	5.19	1.55
L27	−0.00004	−0.25	0.91	**5.60**	0.77	**2.22**	−0.29	−1.91	−0.11	−0.19	0.628	19.86	2.14
L28	−0.00059	**−0.82**	0.02	0.33	0.25	1.80	−0.08	−1.37	0.33	1.43	0.230	3.53	2.20
L29	0.00590	1.56	−0.46	−1.34	−0.01	−0.01	0.58	1.75	0.45	0.36	0.169	2.40	2.14
L30	0.00032	0.25	0.00	0.06	0.08	0.32	0.15	1.35	0.52	1.25	0.142	1.96	1.94
L32	−0.00026	−0.11	1.12	**5.53**	1.06	**2.46**	−0.14	−0.76	−0.26	−0.35	0.627	19.79	2.38
L33	0.00107	0.50	−0.68	**−3.53**	−0.01	−0.03	0.32	1.71	0.96	1.37	0.542	13.92	1.91
L34	0.00159	0.54	0.85	**3.24**	−0.10	−0.19	−0.56	**−2.22**	2.13	**2.24**	0.211	3.16	1.36
L35	0.00251	0.81	−0.09	−0.33	−0.07	−0.12	0.23	0.87	−1.77	−1.74	0.132	1.79	2.37
L36	−0.00117	−1.33	−0.11	−1.47	−0.07	−0.44	−0.06	−0.89	0.23	0.81	0.203	3.00	2.78
L38	0.00070	0.40	−0.12	−0.78	0.64	1.88	−0.09	−0.59	0.27	0.47	0.193	2.82	2.19
L39	−0.00374	−1.43	0.05	0.21	−0.53	−1.04	0.80	**3.50**	0.11	0.13	0.274	4.45	1.90
L41	0.00039	0.33	0.46	**4.27**	0.52	**2.28**	−0.03	−0.29	−0.10	−0.27	0.505	12.01	2.24
L42	0.00683	**2.00**	−1.77	**−5.69**	0.57	0.86	0.55	1.85	−3.65	**−3.27**	0.426	8.72	2.03
L43	−0.00077	−0.85	0.00	0.03	0.13	0.76	−0.20	**−2.57**	−0.32	−1.10	0.215	3.23	2.11
L44	−0.00530	**−2.01**	0.22	0.92	−0.63	−1.24	−0.11	−0.51	1.76	2.03	0.097	1.27	1.52
L45	0.00012	0.07	1.08	**7.55**	0.36	1.18	−0.45	**−3.33**	0.56	1.09	0.702	27.69	2.42
L46	0.00070	0.55	0.10	0.92	−0.01	−0.07	−0.10	−0.92	0.77	1.85	0.097	1.27	1.84
L47	0.00011	0.22	−0.23	**−5.03**	0.11	1.10	0.09	**2.19**	−0.35	**−2.07**	0.420	8.52	2.69
L49	0.00103	1.35	−0.15	**−2.16**	−0.09	−0.60	−0.08	−1.22	0.11	0.46	0.268	4.31	2.00
L50	−0.00035	−0.12	0.54	**2.08**	1.67	**2.98**	0.10	0.42	1.47	1.56	0.303	5.13	1.79
L51	−0.00097	−0.95	0.19	**2.05**	0.32	1.62	−0.00	−0.04	0.77	**2.32**	0.237	3.66	2.17
L52	0.00351	1.76	0.67	**3.68**	1.08	**2.80**	−0.88	**−5.09**	−0.26	−0.40	0.597	17.43	2.18
L53	0.00001	0.00	0.95	**4.81**	1.34	**3.17**	−0.89	**−4.73**	0.17	0.24	0.624	19.55	2.38
L54	0.00097	1.58	0.33	**6.04**	0.50	**4.25**	−0.18	**−3.45**	0.08	0.43	0.677	24.68	2.42
L55	0.00258	1.55	0.49	**3.26**	0.03	0.12	0.13	0.95	0.11	0.20	0.351	6.38	1.87
L56	0.00044	0.24	0.29	1.77	1.11	**3.11**	−0.40	**−2.54**	1.31	**2.19**	0.406	8.03	1.54
L58	−0.00043	−0.32	0.86	**7.04**	0.30	1.16	−0.37	**−3.20**	−0.41	−0.93	0.758	36.86	1.92

In column 1, bold indicates the fund was operating in April 2005 - March 2006. Other numbers in bold indicate statistical significance at the 5% level. See notes to Table 2 for explanation of factors.

April 2007. This illustrates again the magnitude of the survivorship bias and the necessity to include the performance of the "dead" funds in the analyses.

Several results stand out from the analysis. First, the data continue to support the four-factor model over shorter periods, specifically for these three one-year sub-periods. To gauge the explanatory power of the model on an index level, we have proceeded as in the section above and constructed three equally-weighed portfolios, which consist of the managers with a full history in the respective sub-period. These portfolios/indices are in the row labelled "Index." In the three 12-month periods ending March 2006,

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Table 10
Fraction of managers with significant betas.

	Carry beta	Trend beta	Value beta	Volatility beta
April 2005–March 2006	9%	50%	14%	14%
April 2006–March 2007	15%	35%	10%	13%
April 2007–March 2008	50%	28%	37%	17%

March 2007 and March 2008, the four factors explain 50.0%, 61.3% and 67.3% respectively of the variability of the returns in these portfolios. Looking at individual managers, the median *R*-squares are 19.7%, 20.8% and 26.2% over the three successive periods. On a year-by-year basis, between 10–25% of individual managers exhibit an *R*-square exceeding 50% (the highest *R*-square, 81%, was recorded for manager L9 in the third sub-period), while roughly the same fraction produce an *R*-square under 10%.

Second, the importance of trend seems to be declining while the importance of carry seems to be rising and exceeded trend in the last sub-period. Table 10 shows the fraction of the managers with significant exposure to each individual factor for the different sub-periods. While trend was the most important factor between April 2005 and March 2006 with 50% of the managers significantly exposed to it, trend was only second to last in terms of importance between March 2007 and April 2008 with only 28% of the managers significantly exposed to it. Ironically, this was also the period where trend started to perform well again as a strategy. Trend yielded 0.1% in the first sub-period, 1.11% in the second sub-period and 6.12% in the last sub-period. Carry shows a similar picture: it yielded its worst performance (−3.4%) in the third sub-period, where 50% of the managers were significantly exposed to it (18 with positive coefficient and 5 with a negative coefficient). This suggests a reason to avoid not only "crowded" trades, but also "crowded" styles as well. When a trading style becomes "crowded" it appears as if performance in that style declines.[29]

Third, only a small fraction of managers (10–17%) were significantly exposed to value and volatility with the exception of the last sub-period in which value was the second most important factor (after carry) with 37% of the managers exhibiting significant value beta. However, while half of these managers were betting for mean reversion towards the PPP exchange rate, the other half was betting for further deviation from PPP.

4.3. Performance persistence

To investigate the question of whether managers who have been performed well in the past continue to perform well in the future, we follow Aggarwal and Jorion (2010) and report the results for the following regression

$$\alpha_{jt} = \delta_0 + \delta_1 \alpha_{jt-1} + \mu_{jt} \tag{7}$$

where α_j is the excess return for fund manager *j* that is not explained by the four factors, or

$$\widehat{\alpha}_j = R_{j,t} - \sum_i \widehat{\beta}_{i,j} F_{i,t} \tag{8}$$

Table 11 presents the results. We have 21 funds in the second sub-period, which were also active in the first sub-period and 37 in the third sub-period, which were also active in the second sub-period. Neither regression yields a significant coefficient on the previous year's alpha. This result suggests that past excess performance as measured by alpha is not related to future performance. Although, δ_1 is positive, it is not significantly different from zero.

As an alternative way to gauge performance persistence, we form portfolios based on performance quartiles. The performance of the best performing (ranked by alpha return, performance in the first quartile Q1) managers in the first sub-period is aggregated by constructing an equally-weighted portfolio, labelled the Q1 portfolio. We also aggregate the performance of the bottom quartile managers into a Q4 portfolio. Comparing the performance of the Q1 and the Q4 portfolio in the second

29 The relationship between crowding and performance is a topic we leave for future research.

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Table 11
Alpha regressions. This exhibit presents the results of cross-sectional regressions of: $\alpha_{jt} = \delta_0 + \delta_1 \alpha_{jt-1} + \mu_{jt}$.

	Number of funds	Intercept	*T*-stat	Coefficient, Alpha Year $t-1$	*T*-stat	*R*-square
April 2006–March 2007	21	−0.00001	−0.01	0.11	0.53	0.015
April 2007–March 2008	37	0.00085	**2.53**	0.16	0.53	0.008

Note: Numbers in bold indicate statistical significance at the 5% level.

sub-period is a way to gauge persistence.[30] The average weekly alpha for the Q1 portfolio in the second sub-sample was 1.4 bps (or 0.7% annualized), higher than the average weekly alpha of the Q4 portfolio −11 bps (or −5.8% annualized). This is an indication for some persistence. However, a *t*-test for the difference in the means does not reject the hypothesis of equal average alpha.

We performed the same exercise for the third sub-period (comparing the performance of managers who were in the top quartile in the second sub-period with the performance of the managers who were in the bottom quartile in the second sub-period). Again, there is no evidence of performance persistence. The average alpha for the Q4 portfolio was even higher (3.6 bps or 1.88% annualized) than the average alpha of the Q1 portfolio (2.8 bps or 1.46% annualized). Thus, the managers who were in the bottom quartile (ranked on alpha) between April 2006 and March 2007 outperformed during the following 12 months those managers who were in the top quartile between April 2006 and March 2007. Again, a t-test for the difference in the means did not reject the hypothesis of equal average alpha.

Note, that the methodology in equation (7) estimates the average persistence (from year t to year $t+1$) for a cross section of managers rather than the persistence over time for a specific manager.[31] Thus, our rejection of persistence does not mean that not a single manager is able to deliver persistent performance. Indeed, in a previous study Levich and Pojarliev (2008) report that of the 8 managers with significant alpha over a 3-year period (2001–2003), fully 7 managers continued to make positive alpha in the following 3-year period (2004–2006).[32] No manager showed significant alpha in the second period who did not produce alpha in the first sub-period. Although, the average manager does not show persistence, some skilled managers do.

4.4. Style persistence

To check for style persistence, we perform regressions similar to (7) estimating cross-sectional regressions for each one of the four betas. Table 12 reports the results.

The results indicate strong persistence for the trend factor and carry factor. The coefficients for both carry and trend for year $t-1$ are positive and highly significant. This suggests that managers who are exposed to carry in period $t-1$ are likely to maintain significant carry exposure in period t. The same result is valid for the trend factor. Value is persistent only from the second into the third sub-period, but not from the first into the second sub-period. We do not detect persistence for volatility, which is also consistent with the finding that this is the least important factor.

Style persistence can be interpreted as either good or bad news. It is good news, since an investor might expect that his currency manager will continue to follow the same investment style. This would allow endowment and pension fund sponsors to issue mandates that diversify their style exposure. On

[30] Managers who did not survive during the following 12 months are included as long as they are on the platform. Although Carpenter and Lynch (1999) recommend comparing top and bottom decile portfolios, because of our small sample size, we follow Aggarwal and Jorion (2010) and compare top and bottom quartile portfolios

[31] The later would require many estimates of alpha for manager j over successive periods to estimate that manager's δ_1 persistence factor.

[32] We should caution that in this paper our tests for performance persistence rely on performance measured over only one year. The one-year period may be too short to accurately access underlying performance. The differences between performance persistence when estimating performance over different periods (1-year, 3-years and 5-years) is a topic we leave for a future research. In addition, we examine only two intervals, which may be too few to detect persistence especially if persistence is weak. As one final cautionary note, if our alpha estimates are biased due to an omitted factor[6] this could induce bias against finding persistence. See Carhart (1997).

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Table 12
Beta Regressions. This exhibit presents the results of cross-sectional regressions of: $\beta_{jt}^{k} = \lambda_0 + \lambda_{t-1}\beta_{jt}^{k} + \epsilon_{it}$, for $k = 1, \ldots 4$ (carry, trend, value, volatility).

Panel A: carry	Number of funds	Intercept	*T*-stat	Coefficient, beta carry year $t-1$	*T*-stat	*R*-square
April 2006–March 2007	21	0.13	1.66	0.68	**2.70**	0.278
April 2007–March 2008	37	0.04	0.54	0.74	**4.50**	0.369
Panel B: trend	**Number of funds**	**Intercept**	***T*-stat**	**Coefficient, beta trend year $t-1$**	***T*-stat**	***R*-square**
April 2006–March 2007	21	0.17	1.50	0.88	**6.12**	0.663
April 2007–March 2008	37	0.26	**3.16**	0.34	**3.40**	0.248
Panel C: value	**Number of funds**	**Intercept**	***T*-stat**	**Coefficient, beta value year $t-1$**	***T*-stat**	***R*-square**
April 2006–March 2007	21	−0.10	−1.22	−0.26	−1.01	0.051
April 2007–March 2008	37	−0.07	−1.41	0.34	**3.75**	0.287
Panel D: volatility	**Number of funds**	**Intercept**	***T*-stat**	**Coefficient, beta vol. year $t-1$**	***T*-stat**	***R*-square**
April 2006 – March 2007	21	0.32	1.64	0.15	0.95	0.045
April 2007–March 2008	37	0.02	0.11	0.22	1.32	0.047

Note: Numbers in bold indicate statistical significance at the 5% level.

the other hand, it is bad news, since style persistence would indicate less market timing ability, i.e. switching between styles when one style fails to perform well.

5. Conclusions

In this paper, we estimate cross-sectional annual alphas for professional currency managers for the three years between April 2005 and March 2008. With data for all managers on the DB FXSelect platform since inception, even those who eventually exit, we can control for survivorship and backfill bias. We estimate the alphas using a four-factor model based on several available currency trading strategies – carry, trend and value – and a currency volatility factor. Empirical results based on only the three investable strategies or a single-index using fixed weights are not materially different. The multi-factor model, however, allows us to examine cross-sectional investment style differences and changes in style over time (persistence).

The results in this paper confirm results from our earlier study, namely that four factors representing the returns of well–known currency trading strategies and currency volatility explain a significant part of returns of professional currency managers. We extend those results by demonstrating that the relationship is present in a different time period (2005–2008 versus 2001–2006 in the earlier study) and for shorter intervals of 3 years and 1 year. More importantly, obtaining annual alphas and style betas allows us to test for performance and style persistence. We find no indication of performance persistence, but we do find statistically significant evidence of style persistence.

These results have important implications for the investment management industry. Plan sponsors should be careful when selecting currency managers based only on past performance data. As in other venues of investment management, in this sample of currency managers it appears that past performance is no indication for future performance. On the other hand, style persistence indicates that choosing currency managers with different styles makes sense as they are likely to maintain their style, and thus continue to offer a diversification benefit. Plan sponsors usually seek to hire more than one currency manager with different styles to obtain diversification benefits. From this perspective, our evidence for style persistence is welcome. However, style persistence may imply that individual managers are less able to exploit market timing ability.

In addition, we document some significant differences between managers who did not survive our three-year sample and managers who were still alive and active in April 2008. Not surprisingly, we find that surviving managers produced alpha that was higher than exiting managers, and with a difference

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of about 9.5 bps per week (or nearly 5% per year), the difference is both statistically and economically significant. Our analysis suggests that living mangers generally tracked our four factors more closely (with a higher *R*-square) than managers that would eventually die. Sticking closer to the "benchmarks" has helped some managers to stay in business. Components of their investment strategies, as evidenced by the sign of factor coefficients, varied as well. Contrary to the presumption in the market that the recent underperformance of trend-following strategies was the main reason for the lacklustre performance of currency managers over the last three years, we found that "betting for liquidation of carry strategies" caused more damage for some managers. Additional tests suggest that live managers owe some of their success to timing skills in the trend-following strategy, whereas dead managers demonstrated negative timing with respect to volatility.

Overall, our results lend further support to the notion that style factors explain a substantial part of returns for indices composed of professional currency fund managers. While the track records of individual managers – their strategies and performance, as well as their longevity – vary considerably, managers appear to have two things in common – a lack of performance persistence and a tendency for style persistence.

Our results are subject to the limitation that we analyzed only the currency managers listed on the DB FXSelect platform. Furthermore, since the platform was launched in March 2005, the available data cover a relative short period of 3 years (2005–2008). Our simulations revealed that in a sample of this length the likelihood of finding significant alpha can be small when the true alpha is less than around 4 basis points per week. However, when the true alpha is larger and economically significant, the likelihood of finding it in our sample would be high. In this study, the small sample did not preclude us from observing significant negative alpha among dead funds, and a significant difference between the alpha in living and dead funds.

The sample period covers the beginning of the sub-prime crisis, an important structural break in markets, which might contribute to the lack of alpha persistence. Further research based on longer time series may help to evaluate alpha persistence of individual managers.

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