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CURRENCY HEDGE FUNDS**

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Carry Trades and the Performance of Currency Hedge Funds*

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Abstract

We investigate the performance and risk of currency hedge funds using a large and unique consolidated currency hedge fund dataset. We find that a substantial number of hedge funds generate returns that exceed foreign exchange risk premia obtained through carry trades. The best alpha-generating funds exhibit a performance that persists over a one-year horizon. This performance persistence is mostly due to compensation for currency risk-taking as there is no strong evidence of remuneration for active management. The results are robust to biases affecting hedge fund returns, alternative carry trade benchmarks and different methodologies used to correct for sample variability.

Keywords: Hedge Funds, Foreign Exchange, Asset Allocation, Funds Performance Evaluation

JEL Classification: F31, F37

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1. Introduction

In recent years the carry trade investment strategy has been under the scrutiny of the empirical research. In fact, this popular foreign exchange trading strategy, which involves borrowing in currencies with low interest rates and investing in currencies with high interest rates, has proved profitable over the past decades. However, its positive record violates the dictates of uncovered interest parity (UIP), which states that if investors are risk neutral and form their expectations rationally, the interest rate differential across countries should be fully offset by exchange rate returns.¹ The profitability of the carry trade strategy is also associated with another stylized feature of exchange rates: their dynamics are close to a random walk (RW). In fact, if exchange rates are unpredictable and follow closely a RW, deviations from UIP *must* be predictable by means of interest rate differentials (see, *inter alia*, Bacchetta and van Wincoop, 2007 and the references therein). Hence, the overwhelming evidence recording the lack of predictability of exchange rates suggests that the profitability of the carry trade strategy is not surprising.²

The academic literature has proposed various explanations for the existence of UIP violations and the profitability of carry trade strategies, including time-varying risk premia (Engel 1984; Fama, 1984; Lustig *et al.*, 2011; Menkhoff *et al.*, 2012a, and the references therein), but the growing popularity of the carry trade strategy and its well-known profitability have led to substantial growth of currency products designed to generate additional returns, or alphas, to investors. Among those investment vehicles, currency hedge funds (i.e., the ones whose main investment strategies involve exclusively directional trading on the price of currencies) experienced a rapid growth.³

Nevertheless, the profitability of currency hedge funds has been recently questioned. Jylhä and Suominen (2011) documented that hedge funds actively engage in currency speculation and the profitability of the carry trade strategy tends to decrease as the number of hedge funds engaging in carry trades increases. These findings corroborate the conclusions of Pojarliev and Levich (2008; 2010), who showed that professional currency managers generate returns that are mostly, if not exclusively, associated with passive currency-trading strategies, and the performance of currency hedge funds deteriorated during the past decade. Some of these results are not novel *per se*, since they have been documented in other contexts. In fact, earlier studies showed that the best-performing hedge funds outperform their benchmarks occasionally, their performance does not persist over time, and a large proportion of hedge fund returns is associated with market-related factors (see, *inter alia*,

¹ A non-exhaustive list of studies investigating the UIP condition and its implications includes Hansen and Hodrick (1980; 1983), Fama (1984), Engel (1984; 1996), Lustig and Verdelhan (2007), Burnside *et al.* (2011a,b), Lustig *et al.* (2011), Clarida *et al.* (2009), Menkhoff *et al.* (2012a), Ang and Chen (2010) and the references therein.

² On the lack of predictability of nominal exchange rates, see Meese and Rogoff (1983), Obstfeld and Rogoff (2000), Cheung *et al.* (2005a,b), Engel and West (2005), Sarno and Valente (2009) and the references therein.

³ For example, the total assets under management of the funds constituting the Barclay Currency Traders Index, a major benchmark in the foreign exchange industry, increased by a factor of 7.5 during the period 1999-2007 (see <http://www.barclayhedge.com/> for further information). For an excellent overview of the main features of active currency management programs, see Pojarliev and Levich (2012).

Fung and Hsieh, 1997; 1999; 2001; 2004; 2011; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004 and the references therein). As a corollary, hedge funds fees seem to provide compensation for risk-taking rather than for exploiting glaring profitable opportunities (Fung *et al.*, 2008).

In this paper we combine these two somewhat separate strands of the literature and investigate whether the returns generated by currency hedge funds are simply due to foreign exchange risk premia obtained through carry trades, by assuming that exchange rates follow a RW, or include a compensation for genuine active management skills. Specifically, we use a mean-variance analysis and consider the returns that an investor could generate by constructing a portfolio of international bonds dynamically rebalanced assuming that the agent adopts RW expectations (the RW strategy), therefore by neglecting potential exchange rate movements. Such expectations are common among market practitioners and are routinely used in executing carry trade strategies (Bacchetta and van Wincoop, 2007).

We focus on two key questions. First, we ask whether the performance of the RW strategy is better than the one exhibited by a sample of hedge funds using a large and unique consolidated currency hedge funds database. Second, when the previous exercise suggests evidence of incremental performance beyond the RW strategy over the full sample period, we investigate the performance persistence of currency hedge funds over time. We then provide a decomposition of hedge fund performance continuation in terms of exposures to currency risk-related factors and active management skills.

Our results are as follows. First, we find that the RW strategy is able to deliver positive net-of-all-fees returns which are similar in size to the net returns of the average currency hedge fund (i.e. 1.14 percent on a monthly basis). Second, some, but not all, currency hedge funds perform better than the RW strategy. For instance, although the fund at the top 10th percentile delivers an average monthly alpha of 1.96 percent, there is evidence of negative alphas over the same sample period for a nonnegligible fraction of currency hedge fund managers, with a monthly alpha of -0.58 percent for the fund at the bottom 10th percentile. Third, the performance of the best funds against the RW strategy tends to persist over time. Specifically, the funds that perform better than the RW strategy during any past year also outperform the RW strategy during the subsequent year. Fourth, these extra returns generated by currency hedge funds over time co-move with a set of currency risk-related factors but for all funds there is no evidence of a remuneration for active management skills. Fifth, the outperformance with respect to the RW strategy is slightly larger for small funds but there is no clear support for the argument that small funds better manage the trade-off between size and management costs.

Two important related papers are the studies by Pojarliev and Levich (2008; 2010). They investigate the performance of currency hedge funds and find that their returns are mostly correlated with popular foreign exchange rate strategies. They also find little evidence of performance persistence, which is concentrated only in the fund managers' investment style.

Our work differs from theirs in several important respects. First, our goal is to compare the performance of currency hedge funds with respect to a simple benchmark that only captures foreign exchange risk premia obtained by assuming that investors adopt RW expectations, a benchmark used in the exchange rate literature since the study by Meese and Rogoff (1983) (see, *inter alia*, Sarno and Valente, 2009, and the references therein). Second, we use a large and unique consolidated dataset of individual "live" and "defunct" currency hedge funds spanning more than 10 years of monthly data to investigate both how funds perform over the full sample period and conditionally over time.⁴ Pojarliev and Levich (2008) investigate the performance of the Barclay Currency Trader Index (BCTI) *vis-à-vis* a set of foreign exchange strategies. They also analyze individual currency managers on the basis of the only 34 individual currency funds that survived over the full sample period. Furthermore, Pojarliev and Levich (2010) analyze the performance persistence of about 60 live and defunct currency hedge funds over a 3-year period. Our paper investigates the risk and return characteristics of currency hedge funds using a dataset that spans more than 700 currency live and defunct funds over a 10-year period. This allows us to draw robust conclusions based on a longer sample period and a larger number of hedge funds that does not suffer from survivorship bias. Third, on the methodological side, we improve on the analyses of Pojarliev and Levich (2008, 2009) in that we evaluate the currency hedge funds performance with a bootstrap approach recently proposed by Kosowski *et al.* (2006; 2007). This methodology is particularly well suited in this context given the non-normality of individual-fund alpha distributions and the heterogeneity in terms of strategy and risk-taking across currency funds.⁵ Fourth, unlike Pojarliev and Levich (2008; 2010), we decompose the performance continuation (with respect to the RW strategy) generated by our universe of currency hedge funds in terms of currency-related risk factors and a remuneration for active management skills, and investigate the role of a fund's size to determine its performance.

Another closely related paper is Jylhä and Suominen (2011), who propose a two-country general equilibrium model with partially segmented financial markets where hedge funds emerge endogenously. Their paper documents that hedge funds actively engage in currency speculation by means of a carry trade strategy, which is similar to the RW strategy adopted in this paper. Using aggregate index data over the past 30 years, they find that the carry trade strategy explains more than 16 percent of overall hedge fund returns. Our study differs from theirs in at least three ways. First, we compare the performance of the RW strategy against the performance of individual funds, rather than aggregate indices. Second, unlike Jylhä and Suominen (2011), we investigate only the subsample of hedge funds whose main investment strategies involve exclusively directional trading on the price of currencies, hence avoiding the potential contamination of strategies generally found in the global macro sector of hedge funds. Third, the main goal of this study is to explore the features of currency hedge funds' performance over and above the RW strategy, whereas Jylhä and Suominen (2011)

⁴ Full details of the databases used in the empirical analysis are discussed in Section 3.

⁵ In a subsequent version of their paper, Pojarliev and Levich (2010) extended their sample period to three years and implemented a similar bootstrap technique to assess whether the lack of alpha for the live managers and the negative alpha of the defunct managers is due to chance. We thank Richard Levich and Momtchil Pojarliev for pointing out this to us.

investigate the contemporaneous co-movement between hedge fund aggregate returns and those from the carry trade strategy.⁶

The remainder of the paper is organized as follows. Section 2 briefly outlines the framework used to derive the net-of-all-fees returns of the RW benchmark in a mean-variance setting, and Section 3 describes the dataset and some key institutional details of the currency hedge fund industry. Section 4 provides the main empirical results. In Section 5 we discuss an extensive set of robustness checks and the Section 6 concludes.

2. The RW Strategy

In this section we describe the framework for measuring the net-of-all-fees returns of an international asset allocation strategy based on the forecasts of a RW model of exchange rates. In particular, we assume that investors in the foreign exchange market adopt RW expectations when forming their portfolios, thereby neglecting potential exchange rate movements. This strategy can be interpreted as an "optimized" carry trade where agents optimally use both returns and risk from investing in the various currencies rather than ordering currencies solely on the basis of their expected returns (see Menkhoff *et al.*, 2012b and the references therein).

Specifically, consider a US investor who allocates her wealth on the basis of a dynamically rebalanced portfolio by maximizing the conditional expected portfolio return subject to a given volatility target (Della Corte *et al.*, 2009; Thornton and Valente, 2012). The investor allocates her wealth between a domestic bond with yield i_t and N foreign bonds with yields \mathbf{i}_t^* expressed in local currency, where \mathbf{i}_t^* is a $N \times 1$ vector of bond yields. The foreign bond yields are converted into USD by using the prevailing exchange rate S_{t+1} , expressed as the domestic price of foreign currency. At each period t the investor faces the following constrained maximization problem

$$\begin{aligned} \max_{\mathbf{w}_t} E_t(r_{p,t+1}) &= \mathbf{w}_t' E_t(\mathbf{r}_{t+1}) + (1 - \mathbf{w}_t' \mathbf{1}) i_t \\ \text{s.t. } (\sigma_p^*)^2 &= \mathbf{w}_t' \Sigma_{r,t} \mathbf{w}_t \end{aligned} \quad (1)$$

where \mathbf{w}_t is the $N \times 1$ vector of weights on the foreign bonds, $\mathbf{1}$ is a $N \times 1$ vector of ones,

$$E_t(\mathbf{r}_{t+1}) = E_t \left\{ \left[\left(\mathbf{1} + \mathbf{i}_t^* \right) \frac{\mathbf{S}_{t+1}}{\mathbf{S}_t} - \mathbf{1} \right] \right\}, \text{ a } N \times 1 \text{ vector of USD returns from investing in foreign bonds,}$$

⁶ Other related papers are Cumby and Glen (1990) and Brown *et al.* (1999), who investigate the performance of internationally diversified mutual funds and off-shore hedge funds, respectively. Our study differs from these in at least two ways: First we focus only on currency hedge funds; therefore, we do not consider funds that adopt currency overlay structures or those that invest in international equities. Second, Cumby and Glen (1990) and Brown *et al.* (1999) do not consider the comparison with an international benchmark capturing foreign exchange risk premia obtained by means of carry trades, which is the main goal of our paper.

$\Sigma_{\mathbf{r},t}$ is the conditional variance-covariance matrix of \mathbf{r}_{t+1} , and σ_p^* is the volatility target of the portfolio returns.⁷

The solution to the constrained maximization problem (1) is

$$\mathbf{w}_t = \frac{\sigma_p^*}{\sqrt{C_t}} \Sigma_{\mathbf{r},t}^{-1} [E_t(\mathbf{r}_{t+1}^*) - \iota i_t] \quad (2)$$

where $C_t = [E_t(\mathbf{r}_{t+1}^*) - \iota i_t]' \Sigma_{\mathbf{r},t}^{-1} [E_t(\mathbf{r}_{t+1}^*) - \iota i_t]$

Assuming that the investor rebalances the portfolio at the end of each month and adopts RW expectations,

$$\frac{S_{t+1}}{S_t} = 1 + \boldsymbol{\varepsilon}_{t+1} \quad \text{and} \quad \boldsymbol{\varepsilon}_{t+1} \sim NIID[\mathbf{0}, \Sigma_{\boldsymbol{\varepsilon},t}] \quad (3)$$

then equation (2) simplifies to

$$\mathbf{w}_t^{RW} = \frac{\sigma_p^*}{\sqrt{C_t^{RW}}} \Sigma_{\boldsymbol{\varepsilon},t}^{-1} [\mathbf{i}_t^* - \iota i_t] \quad (4)$$

since $E_t(\mathbf{r}_{t+1}) = \mathbf{i}_t^*$ and $C_t^{RW} = [\mathbf{i}_t^* - \iota i_t]' \Sigma_{\boldsymbol{\varepsilon},t}^{-1} [\mathbf{i}_t^* - \iota i_t]$. Once the weights \mathbf{w}_t^{RW} are obtained, the realized portfolio returns of the RW strategy (4) are computed as

$$\begin{aligned} r_{p,t+1}^{RW} &= \mathbf{w}_t^{RW} \left[\left(1 + \mathbf{i}_t^*\right) \frac{S_{t+1}}{S_t} - 1 \right] + (1 - \mathbf{w}_t^{RW} \iota) i_t = \\ &= \mathbf{w}_t^{RW} \mathbf{r}_{t+1} + (1 - \mathbf{w}_t^{RW} \iota) i_t \end{aligned} \quad (5)$$

To account for transaction costs, bid and ask prices are applied to equation (5) as follows:

⁷ Returns in the maximization problem (1) have been expressed in discrete terms to allow for a direct comparison with the actual returns reported by currency hedge funds.

$$r_{p,t+1}^{RW,n} = \begin{cases} \mathbf{w}_t^{RW} \mathbf{r}_{t+1}^n + (1 - \mathbf{w}_t^{RW} \mathbf{1}) i_t^a & \text{if } (1 - \mathbf{w}_t^{RW} \mathbf{1}) < 0 \\ \mathbf{w}_t^{RW} \mathbf{r}_{t+1}^n + (1 - \mathbf{w}_t^{RW} \mathbf{1}) i_t^b & \text{if } (1 - \mathbf{w}_t^{RW} \mathbf{1}) > 0 \end{cases} \quad (6)$$

where the superscripts a and b denote ask and bid rates, respectively, and the net returns for currency j , $r_{t+1}^{j,n}$ included in the vector \mathbf{r}_{t+1}^n are equal to $(1 + i_t^{j,b}) \frac{S_{t+1}^{j,b}}{S_t^{j,b}} - 1$ if $w_t^j > 0$ and to

$(1 + i_t^{j,a}) \frac{S_{t+1}^{j,a}}{S_t^{j,a}} - 1$ if $w_t^j < 0$. Finally, to make the returns from the RW strategy comparable with the

ones reported by the hedge funds in our sample, we also deduct realistic management fees computed as a fixed 20 percent of the annual returns generated by the RW strategy, net of transaction costs.

We denote the net-of-all-fees returns from the RW strategy as $r_{p,t+1}^{RW,all}$ and use it throughout this paper.

We construct and use this strategy, instead of other indices representing pure beta returns in the context of currency markets, since our aim is to isolate the net-of-all fees returns that accrue to investors whose main strategy is to pick foreign exchange rate risk premia by assuming that exchange rates follow a mere RW. Hence, this strategy is consistent with the benchmark used in the exchange rate literature since the study by Meese and Rogoff (1983). Other currency indices would certainly represent reasonable alternatives to our strategy, but their returns would contain compensation for risk exposures other than the one we are trying to assess in this paper.

Constructing the portfolio weights of the RW strategy requires the current values of interest rate differentials between the US and 9 foreign countries⁸, $\mathbf{i}_t^* - \mathbf{i}_t$, and estimates of the conditional variances and covariances of the 9 bilateral USD exchange rate changes, $\Sigma_{e,t}$. In our empirical investigation we compute the conditional variances and covariances as the previous 12-month realized variances and covariances respectively.^{9, 10}

We also set a monthly volatility target, σ_p^* , equal to 5.38 percent, which is the average cross-sectional monthly volatility exhibited by the full universe of currency hedge funds over the sample

⁸ The 9 currencies and further details on the data used in the empirical investigation are reported in Section 3.

⁹ In particular, for each US dollar exchange rate, we computed the realized monthly variance as the monthly average of the daily quantity $[(S_t^j/S_{t-1}^j) - 1]^2$, where S_t^j is the level of the end-of-day spot bilateral exchange rate. Similarly, for each pair of exchange rates j and h we computed the monthly realized covariance as the monthly average of the daily quantity $[(S_t^j/S_{t-1}^j) - 1] \cdot [(S_t^h/S_{t-1}^h) - 1]$

¹⁰ We also performed some robustness checks using 1) different windows of past observations to compute realized variances and covariances and 2) a different way to estimate conditional variances and covariances by using the sample monthly variance and covariance using daily data over each month. The results of these robustness (available upon request) show that the findings reported in the following Sections do not hinge on how we estimate conditional variances and covariances.

period (reported in Table 1) to make the returns from the RW strategy fairly comparable, in terms of their overall risk, with the average currency hedge fund.

3. Data and Summary Statistics

The hedge fund data used in this paper are provided by BarclayHedge, a data provider specializing in hedge funds. To the best of our knowledge, BarclayHedge is the only data provider that supplies information on funds whose main investment strategies involve *exclusively* directional trading on the price of currencies (in both the spot and the derivative markets). BarclayHedge also publicizes the Barclay Currency Traders Index (BCTI), a proprietary hedge fund index and one of the major benchmarks in the foreign exchange industry. All currency hedge funds used in the empirical investigation exhibit at least 12 months of history.

Hedge funds are private investment vehicles typically organized as limited partnerships, in which investors and managers are limited and general partners, respectively. Among this group of funds, currency funds are structured as hedge fund partnerships and are managed by commodity trading advisors (CTAs). CTAs are firms or individuals who handle customer funds or provide advice for trading futures contracts or options on futures contracts. CTAs often conduct transactions in the over-the-counter security markets, especially in derivative instruments (i.e. currency futures and options). The universe of currency hedge funds in our study consists mostly of CTA-managed funds. This is not a limitation since the growth of financial derivatives in the past decades has blurred the distinction between traditional hedge funds and CTA-managed funds (Fung and Hsieh, 1999). Moreover, the growth of the futures market globally has driven futures contracts as one of the main instruments of risk management for hedge funds managers.

Since survivorship bias is one of the first issues any study of hedge funds alpha and persistence of alpha must address, we construct our dataset by consolidating the data reported in the Barclay Currency Database (BCD), i.e. the funds "live" at the end of each date, with the currency hedge funds reported in the Barclay Graveyard Database (BGD) which includes funds that are no longer reporting or have decided not to be included in the BCD, i.e. the "defunct" funds. After this consolidation, the sample of funds in our study covers 724 currency funds over the period January 1999-January 2009. The number of funds available ranges between a minimum of 154 in January 1999 and a maximum of 443 funds in July 2005. Although it is difficult to quantify the size of the currency hedge fund sector within the hedge fund industry, to the best of our knowledge, the consolidated database exhibits one of the best coverages of currency managers. For example, the overall total of the funds' assets under management (AUM) exhibits a value of about 40 USD billion at the end of 2007. Although the total amount of capital devoted to currency hedge funds is likely to be larger, since the consolidated database used in this paper does not include the complete universe of currency hedge funds, the

figures reported at the end of 2007 are nearly twice the size of the fixed-income arbitrage sector investigated in recent studies (Duarte *et al.*, 2006).¹¹

The two Barclay datasets contain monthly returns for all funds net of all fees; 94 percent of the funds report their returns in USD and the remaining 6 percent of funds report returns in other currencies. To avoid potential biases related to conversion of foreign currency returns into USD, our baseline estimations are carried out eliminating the funds that report their returns in currencies other than the USD.

The empirical analysis in the paper also uses monthly data for the 9 most-liquid currencies as reported in the triennial survey of the Bank for International Settlements (2007), namely, the euro, the Japanese yen, the British pound, the Swiss franc, the Canadian dollar, the Australian dollar, the New Zealand dollar, the Swedish krona, the Norwegian krone. Over the same sample period, we use end-of-month spot USD exchange rates and 1-month eurodeposit rates obtained from the Reuters Datastream database.¹²

Table 1 reports the descriptive statistics for the monthly excess returns exhibited by the sample of currency hedge funds and the RW strategy, computed as the difference between the net returns exhibited by currency funds or $r_{p,t+1}^{RW,all}$ and the 1-month US deposit rate. The reported figures for currency funds are cross-sectional measures of the individual statistics computed for each fund over the full sample period. The cross section of currency hedge funds shows an average monthly excess return of 0.93 percent over the sample period; this is associated with a monthly standard deviation (SD) of 5.38 percent. The cross section of currency funds also exhibits an average monthly Sharpe ratio of 0.20. The cross-sectional distribution of currency fund Sharpe ratios is positively skewed and exhibits fat tails. This suggests that although the average cross-sectional Sharpe ratio is equal to 0.20, there is a substantial fraction of currency funds that can deliver a better performance than the average fund. Similar cross-sectional statistics are reported for the size of the funds in terms of AUM. The average cross-sectional AUM over the sample period is about USD 56 million. The cross-sectional distribution of the average AUM is also positively skewed and exhibits substantial fat tails. This result is not surprising since it is well known that currency funds can exhibit average AUM larger than USD 300 million, and the size of AUM by a few funds can be substantial.¹³

¹¹ Among the 724 currency funds analyzed, 81 percent disclose some details of their strategies. 34 percent of those funds indicate that their trades are based on fundamentals, while the remaining 66 rely on technical rules. Furthermore, 64 percent of all funds also report details of their second strategy. Among these funds, more than 50 percent use systematic rules likely based on algorithm trading: the remaining funds are equally split among funds that rely on the currency manager's discretion and funds that use other technical rules. In all cases, the funds explicitly or implicitly state that they use models or rules based on exchange rate forecasts (for spot and derivatives) to inform their trading.

¹² In the empirical investigation we use a fixed group of 9 developed currencies. Although this may be seen as a limitation, since profit arbitrage for these currencies decreased over the past years, it is in line with the common practice adopted by hedge fund managers of focusing on liquid currencies. From informal conversations we had with currency fund managers and major foreign exchange dealers, we gauged that very few other currencies are usually considered in addition to the ones investigated in this paper.

¹³ The largest fund in our sample exhibits an average AUM of USD 1.65 billion.

The RW strategy records an average monthly excess return of 1.14 percent associated with a monthly standard deviation of 6.19 percent and the portfolio composition results very stable over time.¹⁴ The monthly Sharpe ratio of the RW strategy, reported in the last column of Table 1, suggests that the average currency fund performs in line with a carry trade strategy even when all fees and transaction costs are taken into account.

It is noteworthy that the distribution of currency funds and the RW strategy returns are quite different. In fact, the currency funds excess returns exhibit a positive skewness, while the RW strategy excess returns are mildly negatively skewed. The positive skewness for currency funds may be related to their use of currency derivatives to reduce the impact of downside risk or it may simply reflect possible biases in reporting funds returns (Aiken *et al.*, 2012).¹⁵

4. Empirical Results

4.1 Performance Evaluation Over the Full Sample Period

In this section, we evaluate the ability of currency hedge funds to deliver extra returns beyond the benchmark represented by the returns of the RW strategy. We regress the monthly excess returns of each currency fund k on the excess returns earned by the RW strategy, denoted as

$$R_{k,t} = \alpha_k + \beta_k R_{p,t}^{RW,all} + e_{k,t}, \quad (7)$$

where $R_{k,t} = r_{k,t} - i_t$ and $R_{p,t}^{RW,all} = r_{p,t}^{RW,all} - i_t$ denote returns of the hedge fund k and the RW strategy in excess of the 1-month USD risk free rate, i_t . The parameters α_k and β_k denote the alpha performance measure and the loading parameter of the currency fund k on the RW benchmark, respectively. A positive intercept α_k can be interpreted as the average abnormal performance over and above the RW strategy. The larger (and more statistically significant) α_k is, the better the performance of the currency fund k with respect to the RW strategy. The parameter β_k captures the co-movement between the actual returns exhibited by the currency fund k and those of the RW strategy. Following previous studies, we also use the measure t_{α_k} , the t -statistics of $\hat{\alpha}_k$, since the it

¹⁴ The portfolio weights associated with individual currency change very slowly over the sample period. The stability of the portfolio weights is also corroborated by the value of their first-order autocorrelation coefficients, which range between 0.94 and 0.98 across currencies over the full sample period. These results are in line with Della Corte *et al.* (2009) who document a similar pattern for an international portfolio strategy comprising only three major currencies. They are also consistent with the notion that carry trade strategies, based on persistent interest rate differentials, imply weights which do not change frequently over time.

¹⁵ The robustness of our results to various biases affecting hedge funds returns is investigated in Section 5.

has been shown to provide a robust correction for outliers by normalizing the estimated α_k by means of its estimated precision (Kosowski *et al.*, 2006; 2007).

Equation (7) is routinely used in the literature on funds performance evaluation; several studies have suggested that it is difficult to make a correct inference on the performance parameter α_k using conventional statistical theory (Kosowski *et al.*, 2006, and the references therein). In fact, individual hedge fund returns (and hedge fund alphas) are generally non-normal and characterized by large cross-sectional variation. Furthermore, fund returns time series are generally available over short periods and the heterogeneity in terms of strategy and risk-taking across currency funds makes the choice of a single benchmark somewhat difficult. Incorrect benchmarks and short sample availability result in potential model mis-specifications and small-sample biases.

To account for these econometric problems, we adopt the bootstrap approach proposed by Kosowski *et al.* (2006; 2007). In essence, we seek to determine whether any fund's abnormal performance over and above the RW strategy is due to genuine management skills or is just an artifact of luck. In the latter case, any recorded positive abnormal performance arises solely due to sample variability. The bootstrap approach proposed by Kosowski *et al.* (2006; 2007) allows us to control for sample variability without imposing specific parametric distributions for fund returns. Hence, this methodology is flexible enough to take into account the statistical difficulties in hedge fund returns and provides an adequate inference on the performance parameter α_k .¹⁶ Specifically, we compare the realized performance of currency hedge funds with the simulated performance of the same funds where the cross-sectional variability in fund performance is due to sample variability or luck.^{17, 18}

The results of the performance evaluation for the full sample period are reported in Table 2.¹⁹ We rank the currency funds in terms of $\hat{\alpha}_k$ (Panel A) and the t-statistics of $\hat{\alpha}_k, \hat{t}_{\hat{\alpha}_k}$ (Panel B). The results are displayed for funds at the 10th, 20th and 30th percentiles on both ends of the $\hat{\alpha}_k, \hat{t}_{\hat{\alpha}_k}$ spectra, as well as the median. The results in Panel A show that the magnitude of abnormal performance with respect to the RW strategy is heterogeneous in the cross section of currency hedge funds. The estimated

¹⁶ See also Pastor and Stambaugh (2002) for a Bayesian treatment of the potential biases in funds performance evaluation.

¹⁷ For further details, see the online Appendix, Section B.

¹⁸ The bootstrap procedure used in this section is one of the possible methodologies that can be used to mitigate the effect of sample variability in fund performance evaluation. We check the robustness of our results to the alternative methodology proposed by Barras *et al.* (2010) in Section 5.

¹⁹ Before the estimation of equation (7), we also tested for normality, heteroskedasticity, and serial correlation of the currency fund residuals $e_{k,t}$. The results indicate that fund residuals are non-normal, heteroskedastic and moderately serially correlated. This, in turn, corroborates the fact that currency fund residuals $e_{k,t}$ are characterized by complex non-normal distributions: therefore, an evaluation of equation (7) based on conventional inference may lead to an incorrect interpretation of the estimated $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$.

average monthly alphas range between -0.586 percent (bottom 10th percentile) and 1.960 percent (top 10th percentile). Furthermore, almost 70 percent of the currency funds under investigation generate positive $\hat{\alpha}_k$. These results are confirmed in Panel B, which reports estimated t -statistics of $\hat{\alpha}_k$ that range between -0.997 (bottom 10th percentile) and 2.182 (top 10th percentile).

The second row of each panel reports the p -values for the null hypothesis that $\hat{\alpha}_k = 0$ (or $\hat{t}_{\hat{\alpha}_k} = 0$) using Kosowski *et al.* (2006) cross-sectional bootstrap procedure previously outlined. When the estimates are assessed using the inference provided by the bootstrap, most of the $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ are statistically significant at the conventional statistical level, with the exception of the funds at the lowest percentiles. Overall, the results suggest that, on the one hand, the funds located in the upper tail of the distributions of $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}_k}$ substantially outperform the RW strategy while, on the other, the funds located in the lower tail exhibit a performance that, albeit negative, is not different from the one achievable as a mere outcome of bad luck. The negative, but not statistically significant, $\hat{\alpha}_k$ for the fund at the lowest percentile suggests that the currency manager of this fund is able to generate returns close to those of the RW strategy but insufficient to offset its management fees. For comparison we also compute, and report in the last row of each panel in Table 2, the p -values for the null hypothesis that $\hat{\alpha}_k = 0$ (or $\hat{t}_{\hat{\alpha}_k} = 0$) using the standard t -statistic critical values. In line with existing studies (see, *inter alia*, Kosowski *et al.*, 2006; Barras *et al.*, 2010 and the references therein), the results without luck-correction are somewhat different from the ones obtained by bootstrap. For instance, without luck-correction, only the fund at the top 10th percentile exhibits $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ that are statistically significant at conventional level. This finding reinforces the argument that when assessing the performance of funds, it is important to take explicitly into account the role of luck (or sample variability) to control for potential biases that arise from an ex post sort.

Overall, the evidence reported in Table 2 suggests that there is evidence of abnormal performance of currency hedge funds above that recorded by the RW strategy. However, some, but not all, funds are able to outperform the benchmark if transaction costs and management fees are explicitly included in the computation of returns. Stated differently, the evidence of outperformance of currency funds over and above the RW strategy over the full sample period cannot be attributed to mere luck or sample variability. Indeed, there is clear evidence that a fraction of hedge funds in our sample is generating returns that are higher than foreign exchange risk premia obtained simply through carry trades.²⁰

²⁰ The results reported in this section are not due to transaction costs and/or the relatively quick rebalancing period chosen in the baseline estimations. In fact if we disregard transaction costs and/or choose a longer rebalancing period the results are qualitatively and quantitatively similar to the ones reported above.

4.2 Performance Persistence

This section examines whether successful past-performing funds also continue to outperform the RW strategy in the following years.

Persistence in funds performance has been largely investigated in various contexts (see, *inter alia*, Lynch and Musto, 2003; Cohen *et al.*, 2005; Mamaysky *et al.*, 2008 and the references therein). Carhart (1997) proposes an empirical framework to determine whether the performance of funds above a given benchmark persists over a 1- to 3-year period. We adopt this approach in that we sort all currency funds k in January of each year into five equally-weighted portfolios, $q = 1, \dots, 5$, based on alphas estimated from equation (7) over the previous year ($\hat{\alpha}_{k,y-1}$) and then track the performance of these portfolios over the next year y as follows²¹:

$$R_{q,y} = \alpha_{q,y} + \beta_{q,y} R_{p,y}^{RW,all} + \eta_{q,y} \quad q = 1, \dots, 5, y = 2000, \dots, 2009, \quad (8)$$

where $R_{q,y}$ denotes the excess return from portfolio q over the test year y , and we impose that portfolio $q = 1$ contains currency funds with low estimated $\hat{\alpha}_{k,y-1}$ (i.e. the previous year "losers"), while portfolio $q = 5$ contains currency funds with high estimated $\hat{\alpha}_{k,y-1}$ (i.e. the previous year "winners"). Equation (8) is estimated to obtain portfolio alphas $\hat{\alpha}_{q,y}$ over each test year $y = 2000, \dots, 2009$ and, for each portfolio q , we take the average of the resulting alphas over the full period. A bootstrap procedure consistent with Kosowski *et al.* (2006; 2007) is also implemented to carry out the inference on the estimated portfolio alphas.²²

The results of this exercise are shown in Table 3. The performance of the top portfolio ($q = 5$) is clearly positive and statistically significant at the conventional statistical level. In fact, the top-ranked portfolio generates monthly alphas of 0.84 percent and t-statistics of alpha of 4.37, values that are more than four times larger the ones exhibited by the subsequent two portfolios. These numbers are significant when using the cross-sectionally bootstrapped p -values. The other portfolios, with the exception of portfolio $q = 3$, exhibit alpha estimates that are positive but statistically not significantly different from zero at 5 percent level. These results are also qualitatively confirmed when the p -values are computed using the standard critical values.

²¹ In Section 5 we also report results where funds are sorted into portfolios according to their past-two-year $\hat{\alpha}_{k,y-2}$ and their future performance is monitored over the subsequent year.

²² For further details, see the online Appendix, Section B.

Overall, this evidence suggests that the positive performance of some currency funds over and above the RW strategy, reported in Table 2, is generally complemented by performance persistence over time. However, the evidence in Table 3 also suggests that only the best-performing funds are able to deliver a sizable and consistent performance above the RW strategy over time.

4.3 Risk/skill Performance Attribution

The results thus far have shown that a non-negligible portion of currency hedge funds can generate returns that exceed foreign exchange risk premia obtained through carry trades. Furthermore, the performance of the best funds tends to persist over a one-year horizon. An important question still remains: What is the source of the alpha returns exhibited by the best currency funds over time? In order to address this question, we investigate whether the performance continuation over and above the RW strategy generated by the best-performing funds is simply the result of a given exposure to risk factors, or it also contains a remuneration for active management skills, or a combination of both.

We use the excess returns generated by the 5 portfolios obtained by sorting funds on the basis of their previous alphas, and assess whether their dynamics are associated with various currency-related risk factors and, perhaps, contain a remuneration due to the value of active management. In line with Ferson and Schadt (1996), Avramov and Werner (2006), Mamaysky *et al.* (2008) and Patton and Ramadorai (2012), we use the following linear factor model:

$$R_{q,t} = \alpha_{S,q} + \sum_{m=1}^M \beta_{q,m} F_{m,t} + \varepsilon_{q,t} \quad q = 1, \dots, 5, \quad (9)$$

where $R_{q,t}$ denotes the time series of portfolio q 's excess returns formed using the procedure discussed in Subsection 4.2, $F_{m,t}$ is the risk factor m , $\beta_{q,m}$ is the exposure to the risk factor m , and $\alpha_{S,q}$ denotes the active management skill component of portfolio q 's excess returns.

A distinctive feature of hedge funds is their dynamic management of their exposures according to economic conditions and market dynamics (Bali *et al.*, 2011; 2012). Therefore, it is important to identify, prior to the estimation of equation (9), a set of currency-related risk factors that may affect the time-variation of risk of currency hedge funds. A recent growing strand of literature documents that the cross section of foreign exchange excess returns is associated with several factors. Lustig *et al.* (2011) show that the average dollar excess return, RX_t , explains about 70 percent of the common variation of currency excess returns, while a second factor, labeled HML_t^{FX} , measuring the component of the stochastic discount factor that is common across countries, explains an additional 12 percent. In a similar fashion, Menkhoff *et al.* (2012a) document that a global volatility factor explains more than 90 percent of the return spread in carry trade portfolios. This evidence is complemented by Mancini *et al.* (2012) who find that an illiquidity factor can successfully explain both the time-series and the cross-

sectional variation of currency excess returns. Furthermore, Patton and Ramadorai (2012) also document that systematic risk exposures are associated with liquidity dynamics. Finally, Pojarliev and Levich (2008) show that currency momentum strategies returns are strongly correlated with hedge fund returns and Burnside *et al.* (2011b) and Menkhoff *et al.* (2012b) suggest that currency momentum returns have very different properties from carry trade returns and they are not explained by traditional risk factors.

In line with these recent studies, we select a set of five risk factors that includes 1) the average dollar excess return RX_t , 2) a slope excess return factor, HML_t^{FX} , 3) a global volatility factor, $GVOL_t$, 4) an illiquidity factor, $ILLIQ_t$, and 5) a currency momentum factor, MOM_t .²³ As a control variable, we also add a proxy for the leverage of US financial intermediaries, LEV_t , in line with Adrian *et al.* (2009) who find that it is able to explain the dynamics of foreign exchange returns, and Patton and Ramadorai (2012) that note that the systematic risk exposures of hedge funds depend upon the level of leverage they choose.

Some of the selected risk factors, namely $GVOL_t$, $ILLIQ_t$ and LEV_t , are not expressed in terms of returns and are non-tradable, hence it is difficult to interpret the estimated $\alpha_{s,q}$ in equation (9) as remuneration for active management. To account for this issue, we follow Ang *et al.* (2006) and Menkhoff *et al.* (2012a) and construct mimicking portfolios of these factors. We compute innovations to the relevant time series by filtering $GVOL_t$, $ILLIQ_t$ and LEV_t by means of a AR(12) process. The residual from the estimated AR models are then projected onto the six currency excess return portfolios, rx_t^h , $h = 1, \dots, 6$ as in Lustig *et al.* (2011)²⁴

$$\Delta X_t = a + \sum_{h=1}^6 b_h \cdot rx_t^h + e_t, \quad (10)$$

where $\Delta X_t = \Delta GVOL_t, \Delta ILLIQ_t$ or ΔLEV_t and the operator Δ denotes the innovations of the original time series. The returns from the volatility, illiquidity and leverage-mimicking portfolios are given by the mean of the traded portfolio $\hat{a} + \sum_{h=1}^6 \hat{b}_h \cdot rx_t^h$ and are denoted by $\Delta G\hat{V}OL_t$, $\Delta \hat{I}LLIQ_t$ and $\Delta \hat{L}EV_t$, respectively. In order to maximize the correlation between the factor innovations and the

²³ Full details of the risk factor data construction are provided in the online Appendix, Section A.

²⁴ A detailed description of the construction of the carry trade portfolio returns is provided in the online Appendix, Section A.

resulting mimicking portfolio returns we estimate equation (10) recursively using a constant rolling window of 12 month.²⁵

It is instructive to explore the characteristics of the mimicking portfolios in order to interpret the empirical results from the following estimations. As in Menkhoff *et al.* (2012a), the factor-mimicking portfolio for volatility innovation loads positively on the returns of the currency excess return portfolio rx_t^1 . This portfolio is the one comprising currencies with the lowest interest rates (or smallest forward discounts) and was shown to provide a hedge against volatility innovations. Furthermore the loading on rx_t^6 , i.e. the portfolio comprising currencies with the largest interest rates (or largest forward discounts), is instead negative. Both portfolio loadings are statistically significant at conventional level. Hence, this mimicking portfolio can be interpreted as a *hedging* portfolio against global volatility shocks.

The weights of the factor-mimicking for illiquidity innovations are similar in sign to the ones of the volatility portfolio but smaller in size and statistically insignificant at conventional level. The similarities between the volatility and illiquidity portfolios are not surprising since volatility and illiquidity have been shown to be positively correlated in several existing studies (see, *inter alia*, Bandi *et al.*, 2008 and the references therein). Even in this case, the illiquidity-mimicking portfolio can be interpreted as a hedging portfolio against illiquidity shocks. The weights of the factor-mimicking portfolio for leverage innovations are generally negative on both extreme currency portfolios, rx_t^1, rx_t^6 , but statistically insignificant which make the interpretation of the portfolio returns less clear.

The estimates of equation (9) for all five portfolios of currency hedge funds are reported in Table 4. The empirical results show some interesting patterns. First, all portfolios show a positive and statistically significant exposure to $\Delta GVOL_t$, RX_t and MOM_t . While the loadings on $\Delta GVOL_t$, RX_t are generally increasing as q increases, the loadings on MOM_t are decreasing as q increases. The other risk factors are overall statistically insignificant at conventional level. The statistical significance of all factors is confirmed as the p -values of the null hypothesis of $\alpha_{q,S} = 0$ and $\beta_{q,m} = 0$, computed by parametric bootstrap²⁶, are all below the conventional statistical level.

Overall, these findings suggest that the hedge funds that consistently improve upon the RW strategy hedge more against global volatility shocks (or exhibit larger exposures to the hedging volatility portfolio), are more exposed to currency risk (as represented by the RX_t factor) and are less exposed to momentum strategies. On the contrary, funds that generally do not improve upon the RW

²⁵ It is also worthwhile noting that the correlations between $\Delta GVOL_t, \Delta ILLIQ_t, \Delta LEV_t$ and the returns from the mimicking portfolios are equal to 0.90, 0.74 and 0.73, respectively.

²⁶ The details of the bootstrap algorithm are reported in the online Appendix, Section B.

strategy hedge less against global volatility shocks, are less exposed to currency risk and more exposed to momentum strategies.

Finally, the skill components $\alpha_{S,q}$ are statistically insignificant at 5 percent significant level for all portfolios, indicating that the source of outperformance of many hedge funds *vis-à-vis* the carry trade strategy is due to compensation for risk rather than remuneration for active management skills. The only mild exception is represented by the portfolio of best-performing funds $q = 5$, where the skill component is significant at 10 percent level. We gauge some further insights by computing $\alpha_{S,q}$ over time using a 24-month rolling window, as in Avramov *et al.* (2011). The results (plotted in Figure 1) show that most of the portfolios are not able to generate consistent and significant positive alpha over time. As in Table 4, the only exception is represented by portfolio $q = 5$ that exhibits a substantial positive trend from the end of 2005 reaching a monthly alpha of 1.2% at the end of the sample. Nonetheless, the overall alpha of the same portfolio is dampened, and found marginally statistically significant in Table 4, by the fact that during the period 2001-2005 its recorded $\alpha_{S,q}$ was generally negative and highly volatile.

5. Robustness

This section checks the robustness of the baseline results reported in Section 4. More specifically, we test whether our results are sensitive to 1) existing biases in funds returns (i.e. incubation and backfill biases), 2) alternative bootstrapping resampling procedures, which takes into account the short-term serial correlation of funds returns and the joint resampling of residuals and benchmark, 3) a different sample window used to construct currency fund portfolios and assess the funds' performance persistence, 4) different returns from alternative carry trade strategies and 5) a different methodology used to account for luck when assessing the performance of the various funds. We show that our main results are robust to all these issues. Finally, we also refine our baseline results by investigating the relationship between the size of currency hedge funds and their performance.

5.1 Biases in Currency Fund Returns

Our first robustness check relates to biases peculiar to hedge fund returns: incubation and backfill biases. Hedge funds often incubate their funds with their own money before seeking outside investors. Hedge funds also tend to report returns from periods before their inclusion in the database; this is more likely when returns are positive and large in magnitude. Since the inclusion of hedge funds in databases occurs on a voluntary basis, funds with a poor performance have no incentive to report their performance. Both biases act similarly and overweight positive returns, especially during the first part of the sample of each individual fund's records. To test for the presence of incubation and backfill biases, we exclude the first 12 months of data for each fund and repeat a fraction of the empirical analysis reported in Subsection 4.1. The results of this exercise (reported in Table D1 of the online

Appendix), confirm that incubation and backfill biases do not affect quantitatively and qualitatively the results reported in Subsection 4.1.

5.2 Bootstrap Amendments

On the methodological side, we perform two additional robustness checks to test the effect of time-series dependence in the residuals from equation (7) and the importance of sampling residuals and benchmark contemporaneously. To address the first issue, we implemented a variant of the block bootstrap (Politis and Romano 1994; Politis *et al.* 1999). More specifically, during any iteration $b = 1, 2, \dots, B$ of the bootstrap procedure the resampling of the residuals occurs in blocks of a certain length. This block bootstrap allows the preservation of the time-series properties of the residuals, especially their serial correlation.²⁷ The results of this exercise (reported in Table D2 of the online Appendix) show that the serial correlation present in the residuals from equation (7) does not affect the findings of the baseline results reported in Subsection 4.1.

We also implemented a variant of the cross-sectional bootstrap described in Section 4.1 to allow for the possibility of joint resampling of $\hat{\beta}_k \cdot R_{p,t}^{RW,all}$ and $\hat{e}_{k,t}$ during any iteration $b = 1, 2, \dots, B$ of the bootstrap procedure. The results of this additional exercise, not reported here but available upon request, are also qualitatively and quantitatively similar to those reported in Subsection 4.1.

5.3 Performance Persistence: Alternative Fund Sorting

As a further check we investigate the robustness of the baseline results to a different choice of sample windows to evaluate the performance persistence of currency funds. In Section 4 we sorted all currency funds into five portfolios based on $\hat{\alpha}_k$ estimated over the previous year and then tracked the performance of these portfolios over the next year. In this subsection, we investigate the performance of the five currency hedge fund portfolios constructed using the estimated $\hat{\alpha}_k$ over the past two years and evaluated over the next year.

The results of this exercise are reported in Tables D3 and D4 of the online Appendix. Even when portfolios are sorted and evaluated on a two-year basis, the evidence discussed in Subsections 4.2 and 4.3 is qualitatively confirmed. In fact, the values of the estimated $\hat{\alpha}_q$ and \hat{t}_{α_q} are similar to the ones reported in Tables 3 and the results of the risk-skill attribution confirm and corroborate the findings reported in Table 4.

²⁷ The length of each block is computed according to the procedure introduced by Politis and White (2004). We thank Andrew Patton for making available the computer code to carry out the automatic block-length selection procedure.

5.4 Other Carry Trade Strategies

Throughout the paper, we use returns from the carry trade strategy proposed in Section 2 as a benchmark to compare against the returns from currency funds. However, it is important to check whether the baseline results reported in Section 4 are robust to other carry trade strategies commonly used in the literature. To this aim, as alternative benchmarks, we select the returns from two popular carry trade strategies proposed in Brunnermeier *et al.* (2008) and Lustig *et al.* (2011), respectively.^{28,29}

The results of this robustness exercise are reported in Table D5 of the online Appendix. The use of the other two benchmarks does not change the results reported in Table 2. In fact, even over a slightly shorter sample period through which all three strategies are available, the estimated $\hat{\alpha}_q$ and \hat{t}_{α_q} are similar to the ones discussed in Subsection 4.1.³⁰

5.5 Alternative Correction for Sample Variability

As a further robustness check, we also assess the sensitivity of our baseline results to the empirical approach used in the paper to correct for luck, or sample variability in fund performance. We employ a recent methodology proposed by Barras *et al.* (2010) which controls for false discoveries. In essence, the approach allows for the identification of funds with skills from the ones with zero or no skills, even with dependencies in cross-funds estimated alphas.³¹

We apply this methodology to our population of currency funds and the results are reported in Table D6 of the online Appendix. Panel A shows that the proportion of skilled funds in population is close to 20 percent. This figure is not too far away from the top 30 percent of funds that record statistically significant alphas in Table 2.³² Furthermore, in line with our baseline results, there is no evidence of funds that significantly underperform the benchmark. In fact, the proportion of unskilled funds is close to zero in population. It is also worthwhile noting that, similar to Barras *et al.* (2010), we estimate that 79 percent of currency fund managers exhibits skills that are just sufficient to cover trading costs and other expenses (Berk and Green, 2004).

²⁸ It is worthwhile noting that the two strategies are different from the RW strategy proposed Section 2. More specifically, they differ in terms of their returns' standard deviations which are unconstrained for the two alternative benchmarks, but set equal to the average cross-sectional standard deviation of currency fund returns, for the RW strategy. In order to make a meaningful comparison among benchmarks, we normalize the standard deviation of carry trade returns from the two alternative benchmarks to the value exhibited by the RW strategy over the same sample period.

²⁹ We obtain the carry trade returns relative to the strategy proposed in Lustig *et al.* (2011) from Hanno Lustig's website (<https://sites.google.com/site/lustighanno/data>). The carry trade returns from the strategy proposed by Brunnermeier *et al.* (2008) have been kindly provided by Stefan Nagel.

³⁰ For the sake of completeness, we have also carried out the results of the persistence analysis as in Table 3 using the two additional benchmarks. The results, not reported to save space but available from the authors upon request, are qualitatively and quantitatively similar to the ones reported in Table 3 of the main text.

³¹ The details of the procedure adopted to implement this methodology are reported in the online Appendix, Section C.

³² The remaining 20 percent of funds that is found significant in Table 2 is associated with fairly small and positive alphas that, in population, may not differ from zero.

The similarities between the results reported in Table 2 and the ones in Table D6 are further strengthened by the evidence reported in Panel B where we show the proportion of significant alpha funds in the right tail of the distribution of $\hat{\alpha}$, for four significance levels of $\hat{t}_{\hat{\alpha}_k}$. In fact, although the percentage of funds exhibiting positive alphas is relatively high, ranging between 13 and 26 percent, the proportion of lucky zero-alpha funds is also relatively sizable, ranging between 2 and 8 percent. Nevertheless, in line with the results reported in Table 2, we cannot reject that some of the right tail funds have truly skilled managers (the estimated \hat{T}_γ^+ , i.e. the percentage of managers which record positive $\hat{\alpha}$ corrected for luck, are larger than 10 percent at all significance levels) and the average alpha for those top-performing funds is close to the one exhibited by the fund at top 10th percentile reported in Table 2.

We have also carried out a comparison using the two different methodologies with regards to the performance persistence of currency funds. More specifically, we have compared the performance of the portfolio $q = 5$ constructed as in Subsection 4.2, with the one exhibited by a portfolio that explicitly accounts for the location of the skilled funds by using the False Discovery Rate in the right tail of the distribution of fund alphas, as in Barras *et al.*, 2010; Section III.C (labelled as FDR10%).³³ The results of this robustness check are reported in Table D6, Panel C. Even in this case, the results exhibited by the two methodologies are very similar. In fact, the average alphas computed against the RW strategy for both portfolios are comparable in sign and size (0.84 and 0.86 percent per month, respectively) and both are statistically significant at conventional level, as documented by the large t-statistics.

Overall, the results reported in this subsection confirm that a different methodology used to assess the fund performance, and account for luck (or sample variability), does not affect quantitatively and qualitatively the results reported in Subsections 4.1 and 4.2.

5.6 Does Size Matter?

Finally, as a refinement of our baseline results, we perform the performance evaluation described in Subsection 4.1 distinguishing between small and large currency hedge funds. Recent studies have highlighted the issue of capacity constraints in the mutual and hedge fund industry (see, *inter alia*, Teo, 2009, and the references therein). Hedge funds exploit limited investment opportunities by strategies that involve a correct mix of speed, leverage and execution cost management. Diseconomies of scale, which occur when the size of the AUM of hedge funds reaches a certain level, might prevent hedge funds from achieving and maintaining a satisfactory level of returns. The relationship between fund size and performance has been investigated in earlier studies with mixed results. Some contributions find a positive relationship between size and future performance (Getmansky, 2005) whereas others document an explicit or implicit inverse relationship (Goetzmann *et al.*, 2003; Naik *et al.*, 2007; Fung

³³ The details of the procedure adopted to implement this methodology are reported in the online Appendix, Section C.

et al., 2008; Teo, 2009). To check whether our baseline results are driven by funds of a certain size, we split the universe of funds into two groups: the large funds, identified by average AUM >USD 14 million, and the small funds, with average AUM \leq USD 14 million. We chose USD 14 million as a threshold since it is equal to the median AUM recorded for all funds whose AUM >USD 1 million over the full sample period. This selection rule allocates 284 funds to each size group. We then follow the evaluation procedure described in Subsection 4.1 for both groups. The results of this exercise are reported in Tables D7 (large funds) and D8 (small funds) of the online Appendix. The estimated $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ for big (small) currency funds are slightly smaller (bigger) than those in Table 2. However small funds seem to generate better alphas than large funds, when their performance is positive but suffer a larger negative alphas than large funds when their performance is negative. This suggest that 1) both small and large currency funds can outperform the RW strategy on average, the small funds group exhibits a slightly better overall performance, 2) there is no clear evidence supporting the fact that small funds are systematically better than large funds. This conclusion is visually corroborated by the kernel densities of estimated $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ for both large and small funds plotted in Figure D1 in the online Appendix.³⁴ Small-size funds exhibit a slightly better performance than large-size funds in that the densities of the small-size funds record a larger mass in the right tail than the densities of the large-size funds. In any case the difference is fairly small and becomes less pronounced for the estimated $\hat{t}_{\hat{\alpha}_k}$, rather than $\hat{\alpha}_k$, as the standardization mitigates the effects of outliers. Overall, the results do not seem to support the notion that that small funds better manage the trade-off between size and management costs.

6. Conclusions

In this paper we study the performance and risk of currency hedge funds over the period January 1999-January 2009 using a large consolidated dataset of currency hedge funds. We investigate whether currency hedge fund returns represent only foreign exchange risk premia obtained through carry trades, by assuming that exchange rates follow a RW, or include the compensation for genuine active management skills.

We find a host of interesting results. First, we document that the simple RW strategy is able to deliver positive net-of-all-fees returns which are similar to the ones recorded for the average hedge fund in our sample. Second, some but not all currency hedge funds perform better than the RW strategy. Third, the performance of the best funds persists over a one-year horizon. Fourth, the performance continuation of currency hedge fund, over a horizon of one year, seems to be only due to compensation for exposures to currency-related risk factors and hedge fund excess returns do not contain a clear remuneration for active management. Fifth, there is no strong evidence supporting the

³⁴ The smoothed kernel densities shown in Figure D1 were computed with the bandwidth parameter selected as in Silverman (1986). For further details, see Pagan and Ullah (1999, Ch. 2).

argument that small funds perform better than large funds since the magnitude of the performance against the RW strategy is fairly similar for both small and large funds. The results are robust to biases affecting hedge fund returns, alternative carry trade benchmarks and different methodologies used to correct for fund returns sample variability.

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Table 1. Summary Statistics

The table shows the summary statistics of net-of-fees monthly excess returns for the sample of currency hedge funds (foreign exchange funds) and net-of-all-fees monthly excess returns for the RW strategy, respectively. $\overline{R}_{k,t}$, $\sigma_{r_{k,t}}$ and $SR_{k,t}$ denote the time-series average and standard deviation of currency fund returns, and their Sharpe ratio, respectively. $\overline{AUM}_{k,t}$ and $\sigma_{AUM_{k,t}}$ denote the time-series average and standard deviation of currency fund AUM, respectively. AUM are expressed in USD million. $R_{p,t}^{RW,all}$ denotes net-of-all fees excess returns from the RW strategy computed as in equation (6) of the text. Mean, SD, Skew and EKurt denote the cross-sectional monthly average, standard deviation, skewness, and excess kurtosis of the different variables. Time-series averages are computed over the sample period January 1999- January 2009. Mean and SD of returns are expressed as monthly percentage points. SR are expressed on a monthly basis.

	Mean	SD	Skew	EKurt	SR
Foreign Exchange Funds					
$\overline{R}_{k,t}$	0.93	1.83	5.00	40.19	—
$\sigma_{R_{k,t}}$	5.38	4.93	2.98	14.71	—
$SR_{k,t}$	0.20	0.41	12.52	243.34	—
$\overline{AUM}_{k,t}$ (USDmln)	55.80	166.11	6.38	47.65	—
$\sigma_{AUM_{k,t}}$ (USDmln)	37.10	123.70	7.33	63.47	—
$R_{p,t}^{RW,all}$	1.14	6.19	-0.13	0.07	0.18

Table 2. Performance of Currency Funds

The table shows the estimated $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ for the sample of currency hedge funds over the period January 1999- January 2009. Currency funds are ranked according to their $\hat{\alpha}_k$ (Panel A) and the $\hat{t}_{\hat{\alpha}_k}$ (Panel B) with respect to the RW strategy. The first row of Panel A reports the OLS estimates of $\hat{\alpha}$ expressed as monthly percentage points, while the first row of Panel B reports the estimates of $\hat{t}_{\hat{\alpha}}$. The other two rows show the p -value of the null hypothesis that $\hat{\alpha} = 0$ (or $\hat{t}_{\hat{\alpha}} = 0$) based on the cross-sectionally bootstrapped p -values of the null hypothesis that $\hat{\alpha} = 0$ (or $\hat{t}_{\hat{\alpha}} = 0$) as described in Section 4.1 of the text and in the online Appendix, section B (p -value boot) and the asymptotic p -values of the same null hypothesis (p -value param), respectively. For each panel the first column reports results for the marginal fund at the bottom 10th percentile, while the last column reports results for the marginal fund at the top 10th percentile of the statistics of interest ($\hat{\alpha}$ or $\hat{t}_{\hat{\alpha}}$). The cross-sectionally bootstrapped p -values are computed using 1,000 bootstrap replications. $\hat{\alpha}_k$ and $\hat{t}_{\hat{\alpha}_k}$ are computed using heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987).

Panel A: Currency hedge funds, $\hat{\alpha}_k$

	bottom				top		
	10%	20%	30%	median	30%	20%	10%
$\hat{\alpha}$	-0.586	-0.222	-0.025	0.260	0.631	1.084	1.960
p -value (boot)	0.99	0.99	0.99	<0.01	<0.01	<0.01	<0.01
p -value (param)	0.44	0.22	0.50	0.21	0.29	0.13	0.01

Panel B: Currency hedge funds, $\hat{t}_{\hat{\alpha}}$

	bottom				top		
	10%	20%	30%	median	30%	20%	10%
$\hat{t}_{\hat{\alpha}}$	-0.997	-0.459	-0.047	0.562	1.175	1.542	2.182
p -value (boot)	0.99	0.99	0.99	<0.01	<0.01	<0.01	<0.01
p -value (param)	0.16	0.32	0.48	0.28	0.12	0.06	0.02

Table 3. Performance Persistence

The table shows the results of the persistence tests on the performance of currency funds over the period January 2001-January 2009. In January of each year, currency funds are sorted to five portfolios ($q = 1, \dots, 5$) on the basis of their alpha (with respect to the RW strategy) estimated over the previous year. Portfolio 1 (Portfolio 5) contains the funds with the lowest (highest) estimated alpha over the previous year. In each portfolio, funds are included on an equal-weight basis. ER (%) and SD (%) denote the monthly average excess returns and their standard deviation respectively. $\hat{\alpha}_q$ and $\hat{t}_{\hat{\alpha}_q}$ denote the estimated alpha and t -alpha for each portfolio $q = 1, \dots, 5$. $\hat{\alpha}_q$ values are expressed as monthly percentage points. The last two columns report the bootstrapped p -values of the null hypothesis that $\hat{\alpha}_q \leq 0$ computed as in Kosowski *et al.* (2006) (p -value boot) and asymptotic p -values of the same null hypothesis (p -value param), respectively. Bootstrapped p -values are calculated using 1,000 replications. See also the online Appendix, Section B.

q	ER (%)	SD (%)	$\hat{\alpha}_q$	$\hat{t}_{\hat{\alpha}_q}$	p -value (boot)	p -value (param)
1	0.34	0.78	0.10	0.50	0.34	0.32
2	0.20	0.37	0.03	0.24	0.45	0.41
3	0.36	0.30	0.24	2.10	0.06	0.04
4	0.38	0.55	0.18	1.09	0.20	0.16
5	0.97	0.49	0.84	4.37	0.01	<0.01

Table 4. Risk/Skill Attribution

The table shows the parameter estimates $\hat{\alpha}_{s,q}$, $\hat{\beta}_{q,m}$ of the regression $R_{q,t} = \alpha_{s,q} + \sum_{m=1}^6 \beta_{q,m} F_{m,t} + \varepsilon_{q,t}$, $q = 1, \dots, 5$ where $R_{q,t}$ has been constructed using the performance of each fund during the past year and tested over the next year. The regressions are estimated over the period January 2000-January 2009. The risk factors included are 1) global volatility factor ($\Delta G\hat{V}OL_t$) of Menkhoff *et al.* (2012a); 2) an illiquidity factor ($\Delta \hat{L}LIQ_t$); 3) the USD level (RX_t) and slope factor (HML_t^{FX}) as in Lustig *et al.* (2011); 3) the currency momentum factor (MOM_t) as in Menkhoff *et al.* (2012b); and 4) a leverage factor ($\Delta \hat{L}EV_t$) as in Adrian *et al.* (2009). Data sources and details of the construction of the risk factors are reported in the online Appendix (Section A) and in Subsection 4.3, respectively. $\hat{\alpha}_{s,q}$ are expressed as monthly percentage points. Values in brackets denote bootstrapped p -values computed under the null hypothesis that $\beta_{q,m} = 0$ while values in parentheses denote bootstrapped p -values computed under the null hypothesis that $\alpha_{s,q} = \beta_{q,m} = 0$, and \bar{R}^2 denotes the adjusted coefficient of determinations. The bootstrapped p -values are computed using 1,000 bootstrap replications. See also notes to Table 3.

	$q = 1$		$q = 2$		$q = 3$		$q = 4$		$q = 5$						
$\alpha_{s,q}$	-0.23	[0.27]	(0.16)	-0.15	[0.17]	(0.22)	-0.03	[0.41]	(0.41)	-0.21	[0.21]	(0.13)	0.54	[0.37]	(0.08)
$\Delta G\hat{V}OL_t$	5.59	[0.04]	(0.04)	3.34	[0.06]	(0.05)	4.39	[0.01]	(0.01)	5.39	[0.01]	(0.01)	6.47	[0.06]	(0.05)
$\Delta \hat{L}LIQ_t$	0.48	[0.35]	(0.35)	0.13	[0.44]	(0.43)	-0.03	[0.47]	(0.48)	-0.80	[0.21]	(0.22)	-0.29	[0.44]	(0.42)
$\Delta \hat{L}EV_t$	1.97	[0.33]	(0.35)	0.34	[0.46]	(0.45)	-0.34	[0.46]	(0.45)	0.73	[0.42]	(0.42)	-1.26	[0.42]	(0.42)
RX_t	0.65	[< 0.01]	(< 0.01)	0.33	[< 0.01]	(< 0.01)	0.45	[< 0.01]	(< 0.01)	0.71	[< 0.01]	(< 0.01)	0.67	[< 0.01]	(< 0.01)
HML_t^{FX}	-0.02	[0.39]	(0.37)	0.05	[0.24]	(0.22)	0.02	[0.38]	(0.37)	0.03	[0.36]	(0.35)	0.05	[0.34]	(0.34)
MOM_t	0.39	[< 0.01]	(< 0.01)	0.17	[< 0.01]	(< 0.01)	0.21	[< 0.01]	(< 0.01)	0.19	[0.01]	(0.01)	0.19	[0.07]	(0.09)
\bar{R}^2	0.28			0.15			0.28			0.27			0.11		

Figure 1. Active Managerial Skills, Rolling 24-Month Alpha

