Currency-Hedged Funds: Performance and Fund Flows

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Abstract

Measuring fund manager skill by factor model alphas, the factors should capture the returns of known strategies, such as investing in small or value stocks. A known strategy of funds not captured by common factor models is the currency hedging of currency-hedged funds. We show how factor models can account for the hedging success of these funds with a hedging designation by introducing a currency hedging return factor, which helps to generate a more reasonable alpha at the portfolio and individual fund level. In our empirical analysis, we use a sample of "twin share classes" that have the same underlying portfolio but differ in their hedging behavior: One has a currency hedging designation, while the other does not. We show that this factor is able to capture the returns from currency hedging. Studying fund flows, we also find indication that the part of the return of currency-hedged funds that can be attributed to the hedging success drives fund flows in addition to the manager's skill.

Keywords: factor models, currency hedging, fund flows, mutual funds

JEL classification: G11, G12, G23

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1 Introduction

For funds that invest in international regions other than their base currency region, currency risk must be considered. For this reason, some funds offer share classes that hedge the fund's currency risk, hereafter simply referred to as hedging. Similar to a fund that invests small or value stocks, this is a known strategy impacting fund returns and might not be interpreted as fund manager skill. Using factor models to assess fund performance, the factors should capture the returns of these known strategies. Thus, an outperformance indicated by the factor model, i.e. an alpha, can be interpreted as the fund manager's skill. Therefore, the fund manager should not be rewarded (or penalized) for positive (or negative) returns that are generated by the fund's known investment strategy. So factor models evaluating the skill of the manager should not reward (or penalize) the returns from hedging with a positive (or negative) alpha when measuring the performance of currency-hedged funds.

To get a first impression whether currency hedging could potentially influence fund performance measured, Figure 1 shows rolling one-factor alphas over 36-month windows of a passive investment in two indexes in Panel A: The standard TOPIX (blue) and the U.S. dollar-hedged TOPIX (red). The used basic one-factor model by Jensen (1968) has the market excess return as the only explanatory variable. The excess returns of the Japanese market are downloaded from Kenneth R. French's homepage.[1] Panel B shows the average monthly exchange rate return in the respective 36-month window. All returns are in U.S. dollars, i.e. from the perspective of a U.S. investor.

[Figure 1 about here.]

As the TOPIX is a broad index covering Japanese stocks, the results when looking at the rolling alpha of the standard TOPIX are not surprising. The market as the explanatory variable is able to explain most of the excess returns of the TOPIX, resulting in an estimated alpha close to 0 for all windows. As the TOPIX focuses mainly on stocks in the Prime segment of the Tokyo Stock Exchange[2], i.e. it does not

[1] see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] see Index Guidebook, available at https://www.jpx.co.jp/english/markets/indices/topix/tvdivq00000030ne-att/e_cal2_30_topix.pdf.

include all stocks of the Japanese market, small divergences from 0 are not unusual, as shown by Cremers et al. (2012). Also the precision of the estimation seems quite good, as the 95% confidence interval is quite narrow. A different impression emerges when looking at the currency-hedged TOPIX, as the coefficient estimate fluctuates quite a lot around 0 and the confidence interval is much wider. The estimate over time is almost inverted to the average exchange rate return in Panel B, indicating that most of the exchange rate changes are reflected in the (unexplained) returns of the hedged TOPIX with the opposite sign, thus reflecting the currency hedging. So this example shows that a different measured performance of currency-hedged equity mutual funds may not be due to skill, but to the returns from hedging, especially in times of substantial exchange rate fluctuations.

To address this problem, we first propose a new factor that captures the returns of a simple hedging strategy. In our empirical analysis, we apply our new "currency hedging return factor" to equity mutual funds that invest in Japanese equities and have the U.S. dollar as their base currency, i.e., they are exposed to the risk of changes in the exchange rate of the U.S. dollar to the Japanese yen. We use a set of "twin share classes", i.e., two share classes of the same fund whose main difference is their hedging behavior: One fund is fully hedged, while the other has no hedging designation. We show, first at the portfolio level and then at the level of individual funds over the entire sample period and over time, that this new factor is very much able to capture the returns from hedging. Thus, it provides a more accurate performance evaluation of currency-hedged funds.

Building on our results from the factor model analysis, we focus in a second empirical analysis on currency-hedged funds and examine their fund flows. We find indication that the measured performance based on standard one-factor model has a stronger relation to the investor's decision than the one using the factor model including our newly proposed currency hedging return factor. Using an approach similar to Barber et al. (2016), we also find that the returns from hedging have a significant impact on fund flows.

We contribute to the existing literature in two ways. First, we extend the literature on the performance analysis of stocks and equity funds based on factor models by introducing a currency hedging return factor designed to capture the returns from currency hedging. There are widely accepted standard models, starting with the one-factor model of Jensen (1968) with the excess returns of the market factor as the only explanatory variable. This model was extended by Fama and French to their well-known three-factor model by adding the size and value factors (Fama and French, 1993). Later, Carhart (1997) introduced the four-factor model including the momentum factor, and Fama and French (2015) added the investment and the profitability factor to their original three-factor model. Fama and French also combined these factors to a six-factor model (Fama and French, 2018). These standard models have been subject of previous studies focusing on explaining the returns of the Japanese stock market. Fama and French (2017) themselves find a strong relation between book-to-market ratio and the stock returns for the Japanese market, which is captured by their three-factor model. In line with these results, Maeda et al. (2017) find the three-factor model to be more appropriate for the Japanese stock market than the q-factor model of Hou et al. (2015), which does not include a value factor, and Kubota and Takehara (2018) as well as Roy and Shijin (2019) find that the two additional factors of the Fama-French five-factor model do not add much explanatory power when looking at Japanese stock returns. However, the latter also find that the Carhart four-factor model or the Fama-French five-factor model outperform the three-factor model (among others) for differently sorted portfolios of Japanese stocks. Therefore, we focus our analysis on the six-factor model, in addition to the one-factor model, to evaluate the performance of funds. Other authors consider additional factors, sometimes for specific asset classes, such as Hübel and Scholz (2020), who introduce ESG risk factors, or Lustig et al. (2011), who derive common risk factors in currency markets. To our knowledge, we are the first to introduce a currency hedging factor for equity funds.

We also contribute to the literature that examines the relationship between fund performance and fund flows. Early work from Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), and in a more recent study Sialm et al. (2015) show that fund flows are sensitive to the fund's prior returns. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find this relationship to be convex, i.e. stronger for positive inflows after positive returns than vice versa. With respect to abnormal returns calculated using factor models, both Barber et al. (2016) and Berk and Van Binsbergen (2016) find that the alpha of the one-factor model is the most relevant for an investor's decision, i.e. the fund flows. Agarwal et al. (2018) find a similar result for hedge funds. Because of these results, we also focus on the one-factor alpha as a measure of performance in our fund flow analysis. In contrast, Ben-David et al. (2022) find that the unadjusted return is more relevant rather than the one-factor alpha. But as both Barber et al. (2016) and Ben-David et al. (2022) use a similar approach, we build on it to test whether the hedging success is a driver of fund flows.

The remainder of the paper is organized as follows. Section 2 focuses on the performance analysis, as we introduce our newly proposed currency hedging return factor and justify its validity through empirical analyses. Section 3 focuses on the fund flow analysis. Section 4 concludes.

2 Factor Models and Performance Analysis

In this section, we show the results of the performance analysis when using standard factor models and factor models that account for currency hedging by an explicit factor. We begin with the model description and the introduction of our newly proposed factor, then explain the data used and the summary statistics, before showing the results, first for the performance analysis over the entire sample period, and then for the development of some coefficients over time.

2.1 Model Description - Factor Model Approaches

To analyze the performance of the funds, we look at U.S dollar-denominated equity funds that invest in Japanese equities and combine them into two different portfolios depending on their hedging designation. We use two different factor models to explain the monthly excess returns of both of these two portfolios: One is the standard one-factor model from Jensen (1968) in equation (1) and the other is the six-factor model from Fama and French (2018) in equation (2). All fund and factor returns are in U.S. dollars, i.e. from the perspective of a U.S. investor.

$$R_{i,t} - r_{f,t} = \alpha_i^{1F} + \beta_i^{1F-RMRF} RMRF_t + \epsilon_{i,t} \tag{1}$$

$$\begin{aligned} R_{i,t} - r_{f,t} = \alpha_i^{6F} + \beta_i^{6F-RMRF} RMRF_t + \beta_i^{6F-SMB} SMB_t + \beta_i^{6F-HML} HML_t \\ \beta_i^{6F-WML} WML_t + \beta_i^{6F-RMW} RMW_t + \beta_i^{6F-CMA} CMA_t + \eta_{i,t} \end{aligned} \tag{2}$$

The dependent variable is the return of the evaluated portfolio i at month t, $R_{i,t}$, minus the risk-free rate $r_{f,t}$. α_i can be interpreted as the abnormal return of portfolio i. $RMRF_t$ is the excess return of the market and SMB_t, HML_t, RMW_t, CMA_t, and WML_t indicate the Fama and French (2018) factors. $\epsilon_{i,t}$ and $\eta_{i,t}$ are the error terms.

We refer to these two models as the standard factor models. For both models, we expect $RMRF$ to have a coefficient of about one, since a portfolio of many funds, which themselves contain many stocks, should be a good approximation of the market. In addition, because of this relationship, the explanatory power of the standard factor models should be high at least for the portfolio of funds without hedging designation.

Since hedging is not reflected in any of the standard factor models, there is a potential omitted variable bias when trying to evaluate the performance of a hedged fund portfolio. We present a possible solution to this problem by adding an additional factor to account for the hedging success. We call this factor the currency hedging return factor CHR, which is calculated using the spot exchange rate s_t at the end of month t and the one-month forward exchange rate at the end of the prior month S_{t-1}, both in U.S. dollars (USD) per Japanese yen (JPY):

$$CHR_t = \frac{S_{t-1} - s_t}{S_{t-1}} \tag{3}$$

This formula captures the return of a monthly currency hedging strategy which fully hedges the fund's assets at the end of each month using one-month forward contracts. For example, if the USD appreciates relative to the JPY, s_t would sink and an unhedged investor would receive less in USD for his investment in JPY. If this appreciation is larger than anticipated in the forward exchange rate and the hedged investor has secured the (higher) forward exchange rate S_{t-1}, he or she does not suffer from the sunk spot exchange rate and therefore has a positive hedging success, i.e. CHR is positive.

This currency hedging return factor is added to both the one-factor and the six-factor model, extending them to a two-factor and a seven-factor model, respectively. This results in the following regression equation for the two-factor model:

$$R_{i,t} - r_{f,t} = \alpha_i^{2F} + \beta_i^{2F-RMRF} RMRF_t + \beta_i^{2F-CHR} CHR_t + \upsilon_{i,t} \tag{4}$$

And the seven-factor model is estimated via the following equation:

$$\begin{aligned} R_{i,t} - r_{f,t} = \alpha_i^{7F} &+ \beta_i^{7F-RMRF} RMRF_t + \beta_i^{7F-SMB} SMB_t + \beta_i^{7F-HML} HML_t \\ &+ \beta_i^{7F-WML} WML_t + \beta_i^{7F-RMW} RMW_t + \beta_i^{7F-CMA} CMA_t \\ &+ \beta_i^{7F-CHR} CHR_t + \iota_{i,t} \end{aligned} \tag{5}$$

$\upsilon_{i,t}$ and $\iota_{i,t}$ are the respective error terms. If the hedging practice of a fully hedged fund is properly approximated by CHR, the coefficient estimates from the regressions should be about 1.

2.2 Data and Summary Statistics for Original Sample

We use a sample of "twin share classes", i.e. two share classes of the same fund that differ in their hedging behavior: One is hedged and the other has no hedging designation. We divide our sample into two groups according to this hedging designation and construct two equally weighted portfolios. Per the construction of our sample, the fund share classes in both portfolios contain the same underlyings, thus, the return from hedging is the main difference in the performance of the funds.

We use Morningstar Direct to find the fund share classes for our study. All funds used in this study are U.S. dollar-denominated equity funds with at least 90% of their assets invested in Japanese equities. Enhanced index funds, index funds and funds of funds are excluded from the sample, which after this initial search contains 852 funds. These are then manually matched to pairs of two from the same fund share class. The funds in each pair differ in their hedging practices - one is designated as "fully" hedged, while its twin has no hedging designation. We obtain the monthly Total Return Indices (RI) for these funds from Refinitiv Datastream over the sample period from September 2012 to September 2022, i.e. ten years. The RI includes both dividends and price changes, so it is not influenced by the distribution policy of a fund. The fund's discrete return is then calculated as the percentage change in the RI from one month-end to the next. Funds with less than 24 RIs were dropped from the sample. Thus, non-survivoring funds are part of the final original sample consisting of 170 funds, i.e. 85 pairs of one hedged fund share class and its twin without a hedging designation. This results in a total of 12,296 fund-month observations. The average number of funds per month in the sample is 101.65, with a minimum of 14, or seven pairs, and a maximum of 148, or 74 pairs. The development of the number of funds, which grows rapidly in the first months of the sample period, can be seen in figure 2.

[Figure 2 about here.]

The data for the monthly returns of the standard model factors for the Japanese market and the risk-free rate are downloaded from the data library from Kenneth R. French's homepage.[3] Since the factors are already in U.S. dollars, the same currency as the fund returns, no currency conversion is necessary. The monthly spot exchange rates and one-month forward exchange rates, both in USD per JPY, used to calculate the currency hedging return factor are obtained from Refinitiv Datastream. Table 1 shows the summary statistics for our original sample used for the factor model analysis.

[Table 1 about here.]

[3] see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The currency-hedged funds have a higher mean monthly excess return by 0.5 percentage points at both the individual fund and the portfolio level. Their excess return is 3.5 times the excess return of the individual funds and on a portfolio basis twice the excess return of the portfolio of unhedged funds. This trend can also be seen when looking at the quantiles. Since both portfolios consist of the same underlings and the mean exchange rate return is exactly this difference, it is plausible to think of the hedging success as the main driver of the higher return of the hedged funds. In terms of risk, the two groups of funds are about the same both at the individual fund and the portfolio level. So it seems necessary to take a closer look at the performance evaluation of hedged funds with and without consideration of the hedging success.

Table 2 shows the mean and standard deviation of the explanatory factors as well as their variance inflation factor (VIF) and the correlations.

[Table 2 about here.]

Special focus is on the summary statistics of CHR. With an average monthly return of 0.6% it is almost as large as the (negative) exchange rate return, suggesting that most of the exchange rate changes could be unexpected relative to the forward exchange rate. The factor has significant correlations with HML (positive) as well as with WML and RMW (negative), but they are quite low. Looking at the VIF of the factors, all are below 5. Thus multicollinearity should not be an issue. The only factor close to 5 is HML, which could stem from the characteristics of the Japanese equity returns in terms of the relationship between stock returns and HML, as stated e.g. in Fama and French (2017).

2.3 Empirical Factor Model Analysis

Since there appears to be a noticeable difference in the performance between the funds with and without hedging designation and most of the exchange rate returns seem to be unexpected relative to the forward exchange rate, we now analyze the effect of the hedging success on the performance evaluation using factor models. Since an abnormal return, shown via an alpha in a factor model, signals a manager's skill, he or she should not be rewarded (or penalized) for the returns of the fund's overall strategy, such as investing in small cap stocks or, in our case, being hedged against exchange rate changes relative to the forward exchange rate. We run a total of six factor model analyses at the portfolio level: Two for the portfolio of funds without hedging designation using the standard factor models from equations (1) and (2) and four for the portfolio of hedged funds, using the standard factor models and the two- and seven-factor model with CHR from equations (4) and (5). The results are shown in Table 3. As a first step, we analyze portfolio returns rather than returns of individual funds to use diversification benefits to identify common drivers and to mitigate possible noise from individual outliers. To focus on the main results, we first look at columns (1) and (2) of Table 3, where the excess returns of the equally weighted portfolio of funds without hedging designation are explained by the standard factor models. This is our "base case".

[Table 3 about here.]

The results are not surprising. Since a portfolio of many funds, each holding various stocks, can be viewed as an approximation for the market index, the coefficient of $RMRF$ is close to 1 and highly statistically significant in both models. The other factors in the six-factor model, except for CMA, are not statistically significant and no significant alpha can be detected. The adjusted R^2 is very high at well over 90% in both the standard one-factor and six-factor model.

Next, we look at the results when using the standard factor models to explain the excess return of the equally-weighted portfolio of currency-hedged funds in columns (3) and (4) of Table 3. Since both portfolios have the same underlying stocks and hedging is a known strategy of these funds, the results should not differ that much if hedging either has no effect on the performance or is already properly accounted for in the standard factor models. The results are very different from the base case. Although $RMRF$ still has a highly significant coefficient of about 1, both models show a statistically significant positive abnormal return of 55 basis points, significant at the 10% level, for the one-factor model or even 69 basis points, significant at the 5% level, for the six-factor model, respectively. Also the R^2 decreases by both models by about 31 percentage points (one-factor model) and 22 percentage points (six-factor model). There are also differences when looking at the other factors in the six-factor model, as RMW now has a statistically significant coefficient and the significant coefficient of CMA is now about 3.5 times as high as in the base case.

So in our sample using the standard factor models to analyze the returns of currency-hedged funds leads to an indication of a positive abnormal return. Looking at the summary statistics, this can be driven by the negative exchange rate return and thus a likely positive hedging success. Since this part of the returns of currency-hedged funds seems to be substantial, the lower explanatory power could also originate from this. Therefore, we look at the possible solution, i.e. the models that account for the hedging success via the currency hedging return factor CHR. The results are shown in columns (5) and (6) of Table 3.

Again, the coefficient of $RMRF$ is about 1 and highly significant. The explanatory power increases very much to about 97% for each of the models, indicating that the additional factor can explain almost all of the variation in the hedged portfolio's excess returns that cannot be explained by the standard factor models shown in columns (3) and (4) of Table 3. Using an F-test, we can determine that the increase in R^2 for the six-factor model, i.e. the improvement in explanatory power, is highly statistically significant at the 1% level with an F-statistic of 1,237.2. This indicates an omitted variable bias when the hedging success is not taken into account. New to the results is a negative alpha for both models of 15 basis points, which is significant at the 5% level. This is different from the base case, but in line with the findings from Fama and French (2010). It can be partly explained by the indication of higher costs for hedged funds when looking at the summary statistics for the fund flow analysis in Table 5. Other explanations are that there are hidden costs for the hedging of the hedged funds, or that the funds without hedging designation nevertheless hedged some of their exposure to the Japanese yen, as it was on average profitable over the observation period. If this is the case, the managers of the funds without hedging designation should be rewarded with a higher, i.e. non-negative, alpha, since this part of the return can be attributed to pure skill. However, a negative alpha is a common finding in the literature for actively managed funds. We can also detect an at the 10% level significant coefficient of HML, which is in line with previous studies for the Japanese market (e.g., Kubota and Takehara, 2018). Overall, the newly introduced factor CHR seems to approximate the hedging strategy at the portfolio level quite well. For both models, its coefficient is around 1.1, which is still close to our expectation of 1. Since funds can employ various other hedging strategies, e.g., using options or shorter- and longer-term forwards, this little divergence from 1 does not seem unusual.

To take an interim summary, our newly introduced currency hedging return factor CHR does seem to be able to properly account for the hedging success of the portfolio and by that allowing investors to determine an alpha that better reflects the true skill of the fund manager after costs. In further analyses, our main results remain the same when using a synthetic hedged market factor, i.e. adding the estimated return from hedging to $RMRF$, and when calculating value-weighted portfolios. To further evaluate the validity of our results, we also replace $RMRF$ from the standard factor model with an actual hedged index. We use two hedged indices, i) the hedged Nikkei 225 as the best known stock index for Japanese stocks, and ii) the more broader hedged TOPIX. The main results still hold.[4]

Next, we examine whether these results hold for individual funds, to address the concern that offsetting effects when aggregating them to a portfolio may impact our results. We take all individual funds with at least 36 months of return data, which results in a total of 76 for both hedged funds and funds without hedging designation, and run the factor model analysis for each of them. We focus on the six-factor and seven-factor model, respectively, because they have higher values for the adjusted R^2 at the portfolio level than the one-factor and two-factor model, respectively. Table 4 shows the mean, standard deviation, median, 25% quantile, and 75% quantile for the regression coefficient estimates, as well as the number of at the 5% level significant coefficient estimates of the 76 regressions when the standard six-factor model and the seven-factor model, respectively.

[4]Detailed results for these additional tests are available upon request.

[Table 4 about here.]

Panel A of Table 4 shows the results for the individual funds without hedging designation. The results of the performance evaluation are consistent with our findings at the portfolio level. A total of nine funds have a statistically significant alpha, of which four have a positive coefficient and five have a negative coefficient. So most of the funds do not have a (positive or negative) abnormal return. The explanatory power is still high with a mean of about 87% and little variation. The estimated betas for $RMRF$ are all statistically significant at the 1% level with a mean of about 1 and also little variation So overall, the results obtained at the portfolio level hold at the individual fund level, which is no surprise for the standard six-factor model used to explain the excess return of the funds without hedging designation. These results again provide perspective for the analysis of the individual hedged funds in Panels B and C of the table.

Looking at Panel B of the table, i.e. the results for individual currency-hedged funds using the standard six-factor model, it can be seen that the mean alpha is positive and also significant at the 5% level for more than a third of them. No fund has a statistically significant alpha with a negative coefficient. Thus, the positive performance evaluation when using the standard six-factor model also holds at the individual level. This again suggests that these results are driven by the positive hedging success. The adjusted R^2 is relatively low with an average of about 72% and seems to be quite stable across the funds. $RMRF$ is still quite close to one and significant at the 1% level for all funds. So the main results at the portfolio level also hold when looking at each fund individually.

To check whether this is also true for the model including CHR, the results for the 76 regressions using the seven-factor model are shown in Panel C of Table 4. In contrast to the results using the standard six-factor model, the mean alpha is negative. The underperformance is also statistically significant for 19 funds, i.e. a quarter of all funds. Only one fund remains with a significantly positive alpha. This result is more common and is in line with the possible explanations above, i.e. the indication of higher costs for hedged funds, the hidden costs of hedging, or the possible hedging of funds without hedging designation. The mean R^2 also rises to about 92% and seems to be stable across the funds. All coefficients of $RMRF$ and CHR are statistically significant at the 1% level and have a mean coefficient of about 1 across all funds. The standard deviations and quantiles indicate that this result is also quite stable across the funds. In addition, all of the coefficient estimates for the other factors go towards zero relative to the coefficient estimates when using the standard six-factor model.

In summary, hedging success can lead to inaccurate performance evaluations of hedged funds if not correctly captured in factor models. This can lead to incorrect evaluations and thus to incorrect buying signals for some individual funds. The addition of the currency hedging return factor CHR seems to be able to account for this hedging success. These findings hold at the portfolio level as well as at the individual fund level. But because the exchange rate return was especially adverse at the beginning and at the end of our sample period, as indicated in Panel B of Figure 1, the results may be influenced by funds that existed only during these periods and thus are likely to have a high hedging return and a higher unexplained portion of their returns. To address the concern that our results are driven by time effects we want to verify in the following section whether our findings also hold over time.

2.4 Development of Relevant Factors over Time

This section shows the development of alpha and the coefficient of CHR for individual funds over time. All results are gathered using either the standard six-factor model or the seven-factor model including CHR, over rolling 36-month windows. The left side of Figure 3 shows the development of alphas of individual funds, and the right side shows the number of significant alphas at the 5% level. The red line indicates coefficient estimates with a positive sign, whereas the green dashed line indicates coefficients with a negative sign. Panel A presents the results for funds without hedging designation, again using the standard six-factor model as the "base case". The coefficient is close to 0 for almost all funds with only a few outliers. In general, all funds tend to have more or less the same development over time. This is not surprising as most of the funds in the sample have a TOPIX benchmark. Also, there are only a few significant coefficient estimates for most of the windows, which is consistent with the previous findings.

[Figure 3 about here.]

The rolling alpha of the hedged portfolio using the standard six-factor model is shown in Panel B of Figure 3. The abnormal return has a positive coefficient for all currency-hedged funds in the windows at the beginning and at the end of the observation period. The graphs are nearly reversed to the rolling exchange rate return in Panel B of Figure 1, indicating again that this is mostly driven by the hedging success. In line with the development of the alphas, despite the precision of the estimation is likely to be worse, there are many positive and significant coefficient estimates at the beginning and especially at the end of the observation period. These outcomes change when including CHR in the factor model, for which the results are shown in Panel C of Figure 3. They align better with the expectation. The estimated alphas are near 0 across all windows, but appear slightly lower than the coefficients in Panel A, which is consistent with our previous results. We also observe some negative coefficient estimates for the most part of the observation period, while also having positive significant alphas at the end of the observation period. So when looking at the alphas over time, we come to the same conclusion as in the previous analysis: Without accounting for the hedging success, the performance evaluation of the hedged portfolio is biased upwards. Our proposed solution with the introduced factor CHR seems to deliver results that are stable over time.

As the final part of this section, we look at the individual coefficients for CHR over time using the seven-factor model. The results are displayed in Figure 4. The lines show that the individual coefficients are mostly around 1, but there are some outliers. This is an indication that hedging should be represented by an additional factor rather than a hedged market factor or index, as this allows to capture different hedging strategies by the different coefficients. Using a hedged market index as one single factor combines the effects from both the market factor and the currency hedging return factor into one coefficient, which can be potentially problematic for an individual fund if its factor loadings on the two factors differs largely. For the funds in our sample, this difference can be up to 0.4, which can lead to incorrect performance evaluations when both effects are united into a single hedged market index.

[Figure 4 about here.]

3 Fund Flow Analysis

In this section, we want to examine whether the performance measurement using a standard factor model, i.e., without taking the hedging success into account, or the measurement using a model including CHR, has a greater impact on an investor's decision. We first describe our model, the data used, and the summary statistics of the subsample before presenting the results.

3.1 Model Description - Fund Flow Analysis

The dependent variable in all regressions in this section are the monthly fund flows received by each currency-hedged fund, i.e. we are dealing with panel data. Following the prior literature on fund flows, we assume that a fund receives all its flows at the end of a month, so that the fund flows of fund i in month t can be calculated using its total net assets (TNA) as:

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \cdot (1 + R_{i,t})}{TNA_{i,t-1}} \tag{6}$$

In order to test whether the hedging success, i.e. a portion of the return that is actually not generated by the skill of the fund manager but by the strategy of the share class, has an impact on fund flows, we estimate two different monthly alphas for each hedged fund per month. One alpha is generated using the standard one-factor model (1F), and the other alpha is estimated using the two-factor model with CHR (2F). So the first alpha is calculated using the model with the hedging success as an omitted variable, while the second alpha is the one not including the hedging success and therefore the more accurate measure of the fund manager's skill according to our results in Section 2. We focus on the one-factor model (and its extension including CHR) because on the one hand it is the most relevant factor model alpha for an investor's decision according to Barber et al. (2016) and Berk and Van Binsbergen (2016) and on the other hand we can also determine by comparing the estimated coefficients for the alphas of each model whether the hedging success as part of the overall return has an impact on the fund flows, which would be in line with Ben-David et al. (2022). In both cases, for our sample we expect a higher coefficient for the one-factor alpha that is not corrected for the hedging success.

We calculate each monthly alpha using a similar approach to Barber et al. (2016), which Ben-David et al. (2022) also pick up in a part of their paper, by taking the excess return of a fund in month t minus its beta times the factor return in month t, resulting in the following equation for the two-factor model:

$$\hat{\alpha}_{i,t}^{2F} = R_{i,t} - r_{f,t} - [\hat{\beta}_{i,t}^{2F-RMRF} RMRF_t + \hat{\beta}_{i,t}^{2F-CHR} CHR_t] \tag{7}$$

When estimating the alpha of the standard one-factor model, the CHR part of equation (7) is dropped. In case of the betas, the subscript t indicates that this parameter is used in month t, but they are estimated over the 24 months prior to t.

We then use the estimated alphas of model j, i.e. the one-factor or the two-factor model, respectively, from equation (7) and include them as lagged explanatory variables with lag h in a fund flow regression. We use each lagged $\hat{\alpha}_{i,t}^{j}$ individually up to lag H as a measure of the fund's performance. This results in the following regression:

$$Flows_{i,t} = b_0 + \sum_{h=1}^{H} b_{t-h} \hat{\alpha}_{i,t-h}^{j} + \gamma' X + \kappa_t + \nu_{i,t} \tag{8}$$

As a result, we get two regression outputs, one for each model j and its differently calculated lagged $\hat{\alpha}_{i,t}^{j}$. This allows us to see which alpha has a higher estimated coefficient and therefore a greater impact on the fund flows of the hedged funds given the same abnormal return. As mentioned before, based on the prior literature on which performance measure drives fund flows, we expect the hedging returns to have an impact on the fund flows. We determine the number of lags H by running regressions including lagged alphas for up to the last twelve months and selecting the regression with the highest adjusted R^2. As a result, we include alphas with a lag up to $H = 3$ for both models. In all regressions, X is a vector of controls that includes the log of the fund's TNA in the prior month, the fund's total expense ratio (TER), the standard deviation of the fund's monthly returns over the previous 12 months, and the log of the fund's age in months. Fund flows, TNA, and age are winsorized at the 1% and 99% level. We also include month-fixed effects (κ_t). $\nu_{i,t}$ is the error term.

With the regression from equation (8) we can determine which alpha has a larger coefficient and therefore a larger impact on the fund flows. But to determine whether the hedging success has a statistically significant impact on fund flows, we continue to take a similar approach to Barber et al. (2016) and regress the fund flows on the alpha from the two-factor model including CHR, i.e. the alpha corrected for hedging success of each fund, and add the estimated hedging success $HedgeSuccess$ for each fund as an additional explanatory variable to the model. We do this by estimating $\hat{\beta}_{i,t-h}^{CHR-2F}$ for each fund i over the 24 months prior to $t-h$ and multiplying the estimated coefficient by the factor return of CHR of the corresponding period. Thus, for each period $t-h$ the hedging success of fund i is calculated by the following equation:

$$HedgeSuccess_{i,t-h} = \hat{\beta}_{i,t-h}^{2F-CHR} CHR_{t-h} \tag{9}$$

Analogue to the lagged alphas, we include each estimated lagged hedging success up to lag H individually in the regression. So equation (8) is further developed to:

$$Flows_{i,t} = b_0 + \sum_{h=1}^{H} b_{t-h}\hat{\alpha}_{i,t-h}^{2F} + \sum_{h=1}^{H} c_{t-h} HedgeSuccess_{i,t-h} + \gamma' X + \kappa_t + \epsilon_{i,t} \tag{10}$$

We expect a positive and significant impact of the hedging success on the fund flows, similar to the results from Barber et al. (2016) and Berk and Van Binsbergen (2016) as well as from Ben-David et al. (2022).

3.2 Data and Summary Statistics for Subsample of Currency-Hedged Funds

We collect data for the fund's TNA from both Morningstar Direct and Refinitiv Datastream to ensure that we have as much data as possible. The TER and inception date for each fund, which is used to calculate its age, are from Refinitiv Datastream. Since these data are not available for all funds in our original sample, we construct a second fund flow sample, which is a subsample of our original sample and consists of a total of 78 hedged funds. The number of fund-month observations varies depending on the maximum lag of the alphas, but per fund we lose at least 24 observations due to the calculation of the $\hat{\alpha}^{j}_{i,t-h}$ from equation (7). Using alphas with lags of up to three months results in 2,675 fund-month observations per regression. For perspective in the summary statistics, we also obtain the additional data for funds without hedging designation, if available, which results in a total of 72. But since our focus is on the influence of the hedging success on the fund flows, we do not conduct further analysis with these funds. Table 5 shows the summary statistics for the subsample used for the fund flow analysis. All data points are per month, and we report $\hat{\alpha}^{1F}_{i,t-h}$, i.e., the abnormal return from the standard one-factor model, for reasons of comparability between the hedged funds and the funds without hedging designation.

[Table 5 about here.]

On average, hedged funds are smaller and receive fewer inflows than unhedged funds. As in the original sample, hedged share classes have higher returns and also a higher $\hat{\alpha}^{1F}_{i,t}$ than the ones without hedging designation, while having about the same risk. So, judging by the summary statistics, the subsample seems comparable to the original sample. Regarding the remaining controls, hedged funds have a higher TER, i.e. higher costs, are younger and smaller.

3.3 Fund Flow Analysis

In this section, we want to determine whether the better performance based on the standard one-factor model in our observation period due to the hedging success has an impact on the decision of an investor, in which funds he or she invests. First, we check which estimated $\hat{\alpha}^j$ from which model j has the greater impact on this decision. The results are shown in Table 6. The first column shows the results using $\hat{\alpha}^{1F}$ from the standard one-factor model, i.e. the performance evaluation with the hedging success as an omitted variable. Again, we include lagged alphas of the last three months in our regressions, as they have the highest adjusted R^2 relative to other regressions with up to twelve months lagged alphas.

[Table 6 about here.]

The performance estimated with the standard one-factor model has a statistically significant impact at the 1% level for the one-month lagged alpha and at the 10% level for the two-month lagged alpha, while the three-month lagged alpha has no significant estimate. The two significant estimated coefficients have about the same amount. Looking at the controls, there are two significant coefficients, namely the negative one for the one-month lagged AUM, which is highly statistically significant, and the positive one for the standard deviation of the fund's returns over the previous twelve months, which has a positive coefficient at the 10% level. This suggests that investors have a certain risk appetite.

So the results in the first column indicate an influence of the upwardly biased performance measurement with the one-factor model on the fund flows. How the effect changes when the performance is approximated with the better fitting two-factor model is shown in the second column of Table 6. Only the coefficient of the one-month lagged alpha is still statistically significant, while the other coefficients, including the previously significant two-month lagged alpha, do not have significant estimates. There are also differences in the level of significance of the one-month lagged alpha, which is only significant at the 5% level. In addition, the magnitude of the estimated coefficient for the abnormal return decreases noticeably by more than 30% compared to the corresponding coefficient in the first column. With respect to the controls, the coefficients do not differ much to the results when using the one-factor model, except for the coefficient of the standard deviation, which is no longer significant. So overall, it can be stated that the abnormal return of a fund from both the one-factor and the two-factor model have significant coefficients, but the number of significant coefficients, their magnitude, and their significance level is higher for the alpha when using the one-factor model, i.e. the one with the hedging success as an omitted variable. This leads to the suspicion that the hedging success in the past is rewarded by the investors through higher inflows and that not the pure skill of the fund manager is relevant for the investment decision.

To further test whether the hedging success has a significant effect on the investor's decision, in the third column of Table 6 we take the alpha from the two-factor model, i.e. the approximation of the abnormal return without the hedging success and therefore also the approximation for the manager's skill, and add the lagged approximated hedging success $HedgeSuccess_{i,t-h}$ as additional explanatory variables to the model. A positive and significant coefficient for the approximated hedging success would indicate that the hedging success is indeed driving fund flows. The results are shown in the third column of Table 6. Indeed, the one-month lagged estimated hedging success has a positive and at the 5% level significant coefficient. This means that there is evidence that the hedging success, which does not capture the fund manager's skill, leads to additional inflows beyond the flows for the return that can be assigned to the manager skill. Looking at the lagged alphas, the one-month lagged and two-month lagged alphas are both significant and have higher coefficients relative to the estimation without hedging success in the second column, but remain lower than the coefficients in the first column using the one-factor model.

Overall, our results suggest that the hedging success has at least a short-term effect, i.e., investors do not allocate their investments according to the pure skill of the fund manager. Our results remain stable when we use the mean of the lagged monthly alphas instead of each lagged alpha individually and when we include the lagged estimated market returns as additional explanatory variables in the regression. The results further support that hedging success has an impact on the fund flows in addition to the pure manager's skill[5]. Our results are in line with both Barber et al.

[5]Detailed results are available on request.

(2016) and Berk and Van Binsbergen (2016), as the one-factor alpha seems to have a higher impact on the fund flows, as well as with Ben-David et al. (2022), as the hedging success as part of the overall return of a fund has a significant coefficient.

4 Conclusion

We introduce a new currency hedging return factor that extends the existing standard factor models and captures the returns from currency hedging. Using a set of "twin share classes" that differ in terms of their hedging behavior, we find that standard factor models fail to explain the hedging portion of the returns of fully hedged funds, leading to problematic performance evaluations. By extending the standard factor models with the currency hedging return factor, we can better evaluate the true skill of the fund manager, i.e. the part of the performance that he or she actually can influence. Our results hold on a portfolio level and for individual funds as well as over time for rolling windows of 36 months.

Examining the impact of the different performance evaluations on the fund flows into hedged funds, we find that the standard one-factor alpha has a greater impact on the investor's decision which to invest. By adding the estimated hedging success of a fund as an explanatory variable, we find an indication that this part of the return, which is dictated by the fund and not the fund manager, is indeed a driver of fund flows. Our results are in line with both Barber et al. (2016) and Berk and Van Binsbergen (2016), as the standard one-factor alpha seems to have the greater impact relative to the two-factor alpha, as well as with Ben-David et al. (2022), as the hedging success as part of the overall return has an impact on the fund flows.

Overall, our results highlight the importance of correctly evaluating the performance of a mutual fund, as some portions of the past returns can be driven by factors that are are not influenced by the fund manager. This should be taken into account by investors when choosing a fund to invest in.

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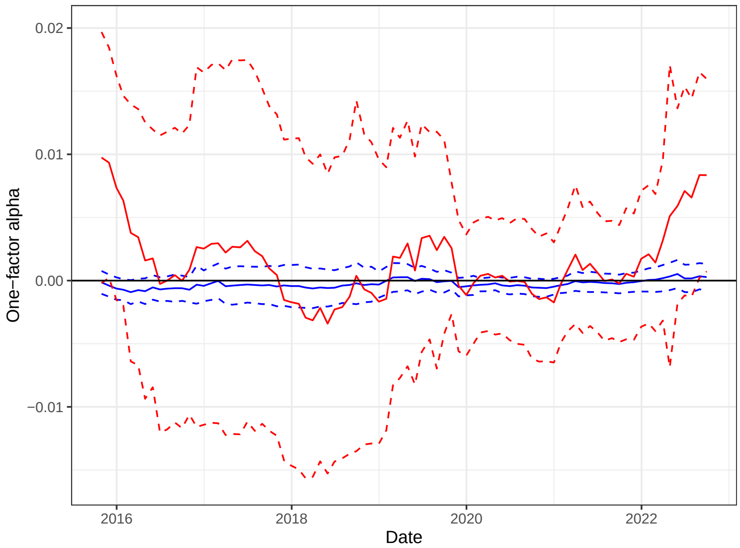
Figures

Panel A: Rolling one-factor alpha with 95% confidence interval for TOPIX (blue) and hedged TOPIX (red)



Panel B: Rolling exchange rate return

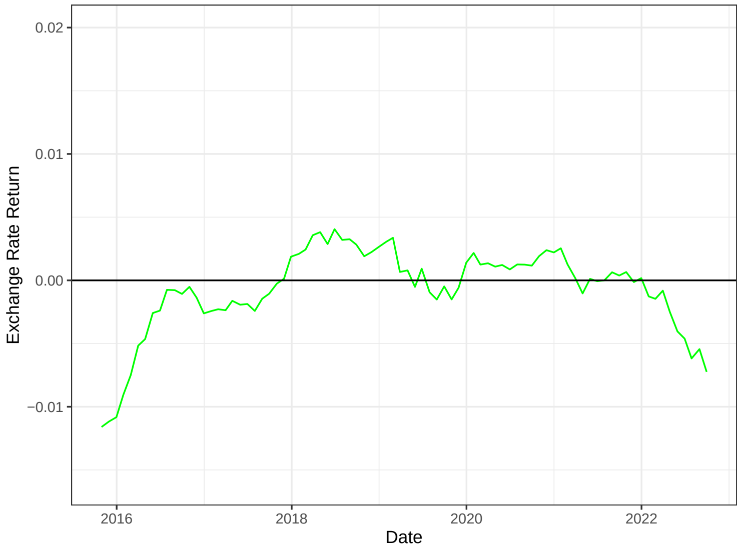


Figure 1: Rolling one-factor alpha of TOPIX and hedged TOPIX and rolling exchange rate return Panel A shows the rolling one-factor alpha of a passive investment in the TOPIX (blue) and the hedged TOPIX (red) when explaining their returns using the Fama-French market factor as the only explanatory variable and the 95% confidence interval. Panel B shows the rolling average monthly exchange rate return. Alphas, confidence intervals, and exchange rate returns are calculated using rolling 36-month windows from September 2012 to September 2022. All returns are in U.S. dollars. The last month of each window is indicated on the x-axis. In Panel A, confidence intervals are calculated using standard errors as proposed by Newey and West (1987) with a lag of 4, as suggested as best practice in Greene (2020), to adjust for autocorrelation and heteroskedasticity.

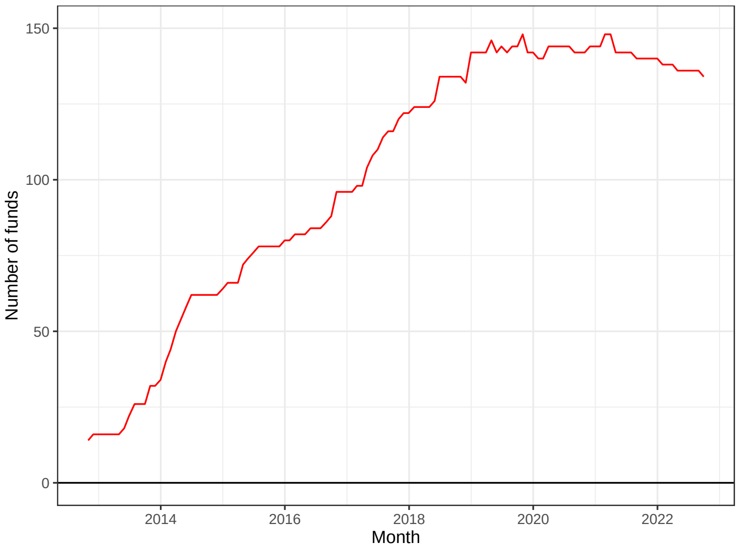
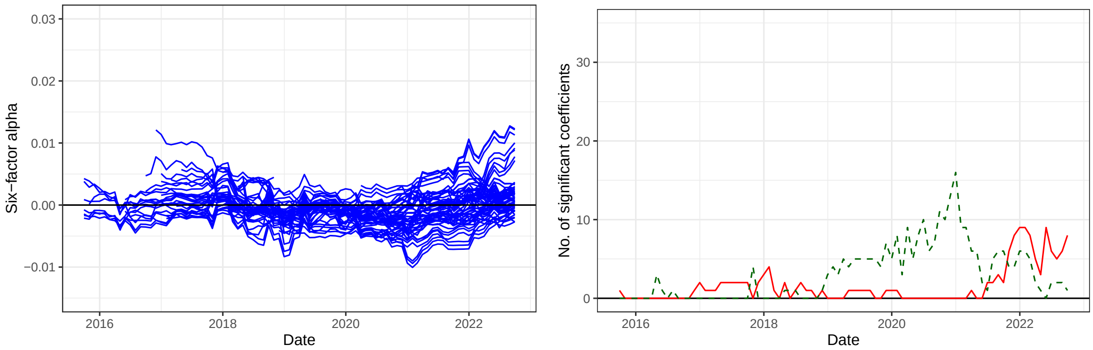
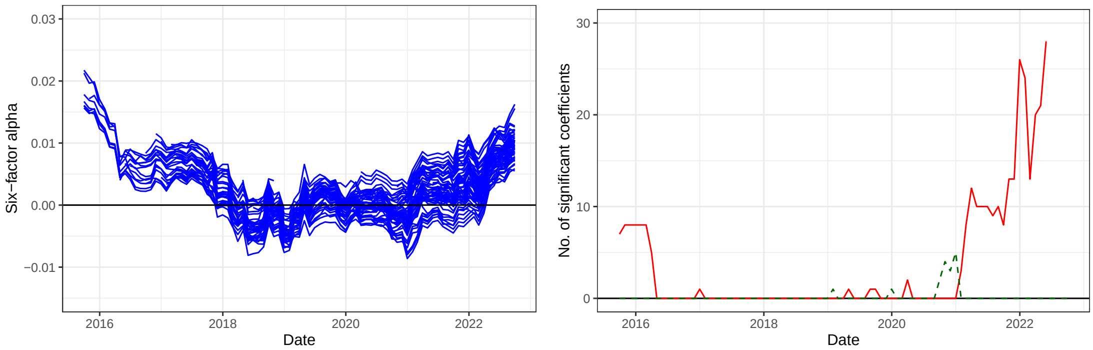


Figure 2: Number of funds in the sample per month
This figure shows the development of the number of individual funds in the sample. To get to the number of "twin fund" pairs, the total number has to be divided by two. The month is indicated on the x-axis.

Panel A: Six-factor alphas for individual funds without hedging designation



Panel B: Six-factor alphas for individual hedged funds



Panel C: Seven-factor alphas for individual hedged funds

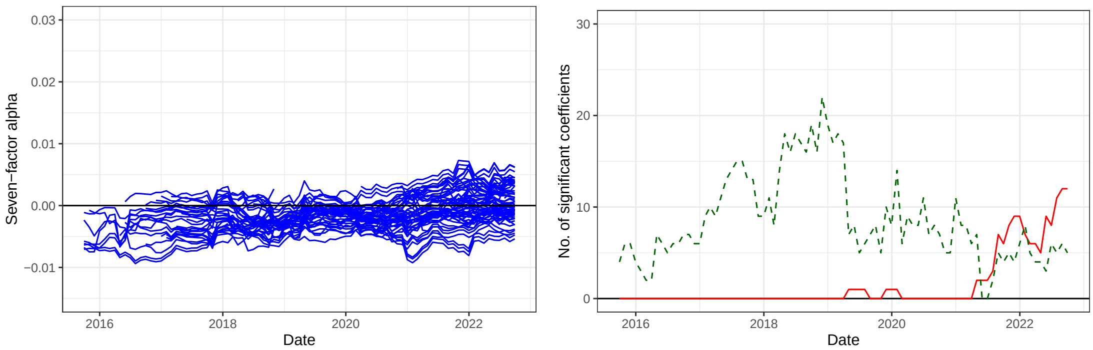


Figure 3: Rolling six- and seven-factor alpha of individual funds
This figure shows on the left the development of rolling six- and seven-factor alphas for individual funds and on the right the number of coefficient estimates that are significant at the 5% level in each window with a positive sign (red) and with a negative sign (green and dashed). Panel A shows the six-factor alpha for individual funds without hedging designation. Panel B shows the six-factor alpha for individual currency-hedged funds. Panel C shows the seven-factor alpha for individual currency-hedged funds. All coefficients are calculated over rolling windows of 36 months. The last month of each window is indicated on the x-axis. Significance is determined with standard errors following Newey and West (1987) to adjust for autocorrelation and heteroskedasticity using a lag of $T^{\frac{1}{4}}$ depending on the number of time series observations T per fund following Greene (2020).

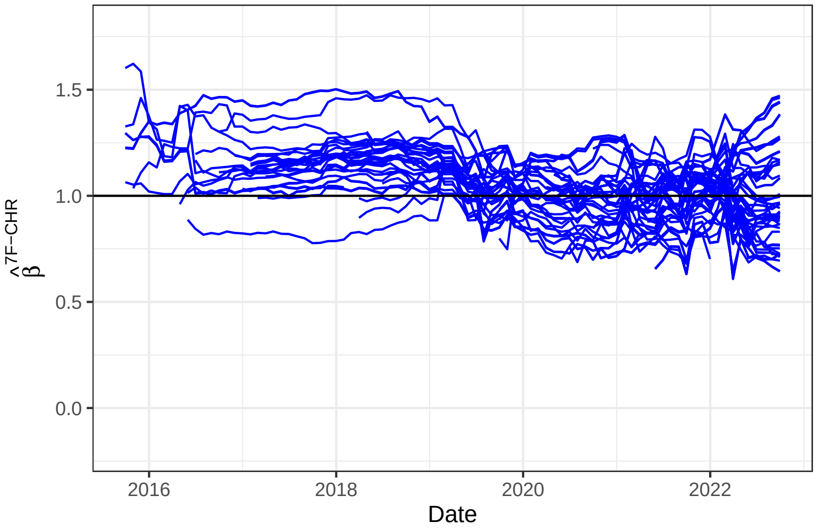


Figure 4: Rolling coefficient estimated of CHR for individual funds
This figure shows the development of the coefficient estimated of CHR for individual hedged funds using the seven-factor model. All coefficients are calculated over rolling windows of 36 months. The last month of each window is indicated on the x-axis.

Tables

Table 1: Summary statistics of original sample

	Mean	Sd	Median	0.25 Q.	0.75 Q.
			Hegded - Individual funds ($N = 85$)		
Mean of monthly ER	0.007	0.003	0.006	0.005	0.008
Sd of mean monthly ER	0.050	0.006	0.049	0.047	0.054
			Unhedged - Individual funds ($N = 85$)		
Mean of monthly ER	0.002	0.004	0.002	-0.0001	0.004
Sd of mean monthly ER	0.048	0.008	0.047	0.043	0.052
			Hedged - Portfolio ($T = 120$)		
Monthly ER	0.010	0.048	0.013	-0.017	0.042
			Unhedged - Portfolio ($T = 120$)		
Monthly ER	0.005	0.041	0.008	-0.015	0.024
			Exchange Rate USD/Yen ($T = 120$)		
Monthly return	-0.005	0.024	-0.001	-0.017	0.007

This table shows the summary statistics for the original sample of funds used in the factor model analysis. ER refers to the excess return of the funds. Sd refers to the standard deviation. The evaluation period is September 2012 to September 2022. The sample is divided into currency-hedged funds and funds without hedging designations at both the individual fund and portfolio level. The funds without hedging designation are referred to as unhedged funds. All fund data points are derived from monthly excess returns. Also the monthly exchange rate return is displayed.

Table 2: Summary statistics of factors

	Mean	Sd	VIF	Correlation					
				RMRF	SMB	HML	WML	RMW	CMA
RMRF	0.46	0.039	1.16						
SMB	0.15	0.021	1.24	0.04					
HML	−0.10	0.032	4.92	−0.22**	−0.38***				
WML	−0.08	0.031	1.56	−0.03	0.31***	−0.47***			
RMW	0.21	0.016	3.00	0.12	0.21**	−0.79***	0.29***		
CMA	0.00	0.017	2.56	−0.32***	−0.15	0.68***	−0.06	−0.61***	
CHR	0.60	0.024	1.22	−0.09	−0.16	0.27***	−0.21**	−0.30***	0.01

This table shows summary statistics for the monthly explanatory factors. The evaluation period is from September 2012 to September 2022. Means are reported in percent. Sd refers to the standard deviation of monthly returns. VIF refers to the variance inflation factor. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively, for the correlations.

Table 3: Factor model analysis of equally weighted portfolios

	Unhedged portfolio		Hedged portfolio			
	(1)	(2)	(3)	(4)	(5)	(6)
RMRF	1.0422***	1.0376***	0.9983***	0.9833***	1.0603***	1.0685***
	(0.0315)	(0.0347)	(0.0929)	(0.0927)	(0.0212)	(0.0216)
SMB		−0.0232		−0.0580		0.0191
		(0.0537)		(0.1331)		(0.0400)
HML		0.1095		0.2785		0.1035*
		(0.0801)		(0.2007)		(0.0583)
WML		−0.0291		−0.0435		−0.0275
		(0.0327)		(0.0880)		(0.0304)
RMW		−0.0622		−0.4754*		0.0779
		(0.1294)		(0.2823)		(0.1112)
CMA		−0.1990**		−0.6481***		−0.0342
		(0.0893)		(0.2002)		(0.0797)
CHR					1.1286***	1.1034***
					(0.0333)	(0.0323)
α	0.00001	0.0003	0.0055*	0.0069**	−0.0015**	−0.0015**
	(0.0008)	(0.0008)	(0.0031)	(0.0033)	(0.0006)	(0.0007)
Obs.	120	120	120	120	120	120
R^2	0.9384	0.9474	0.6497	0.7200	0.9741	0.9768
Adj. R^2	0.9378	0.9446	0.6467	0.7052	0.9736	0.9753

This table presents regression coefficient estimates from time series regressions of the excess return of equally weighted fund portfolios (dependent variable) using factor models. Columns (1) and (2) show the results for the portfolio of funds without hedging designation using the standard factor models. For brevity reasons this portfolio is referred to as "unhedged portfolio" in the table. Columns (3) and (4) show the results for the portfolio of currency-hedged funds using the standard factor models. Columns (5) and (6) show the results for the portfolio of currency-hedged funds using the two- and seven-factor model, i.e., the models including CHR. Standard errors are in parentheses and are calculated following Newey and West (1987) with a lag of 4, as suggested as best practice in Greene (2020), to adjust for autocorrelation and heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 4: Summary of coefficients from regressions using individual funds

	Mean	Sd	Median	0.25 Q.	0.75 Q.	# sign. > 0	# sign. < 0
	Panel A: Funds without hedging designation - six-factor model						
α	0.0003	0.0021	0.0001	−0.0012	0.0013	4	5
RMRF	1.0306	0.0855	1.0374	0.9854	1.0961	76	0
SMB	0.0635	0.2927	−0.0221	−0.1397	0.1454	17	10
HML	0.1624	0.3365	0.2132	−0.0461	0.4020	27	7
WML	−0.0293	0.1772	−0.0352	−0.1379	0.0840	5	21
RMW	0.0171	0.3536	0.0909	−0.0862	0.2123	2	4
CMA	−0.2241	0.2031	−0.0.2031	−0.3797	−0.0708	2	14
Adj. R^2	0.8716	0.0857	0.8924	0.8621	0.9296	–	–
	Panel B: Hedged Funds - six-factor model						
α	0.0055	0.0029	0.0055	0.0038	0.0074	28	0
RMRF	0.9195	0.1097	0.9297	0.8607	0.9865	76	0
SMB	0.1331	0.3561	0.0328	−0.0922	0.2673	16	4
HML	0.3715	0.3293	0.3845	0.1967	0.6122	35	1
WML	−0.1332	0.2020	−0.1274	−0.2356	−0.0054	0	20
RMW	−0.3054	0.2861	−0.2841	−0.4622	−0.1259	0	3
CMA	−0.7278	0.2475	−0.7179	−0.8767	−0.5858	0	64
Adj. R^2	0.7244	0.0666	0.7340	0.6797	0.7689	–	–
	Panel C: Hedged Funds - seven-factor model						
α	−0.0010	0.0018	−0.0009	−0.0024	0.0004	1	19
RMRF	1.0611	0.0760	1.0710	1.0228	1.1073	76	0
SMB	0.0794	0.2877	−0.0185	−0.1047	0.2104	19	7
HML	0.1645	0.3124	0.1864	−0.0034	0.3943	35	7
WML	−0.0251	0.1679	−0.0261	−0.1340	0.0832	11	19
RMW	0.1398	0.2596	0.1798	0.0078	0.2750	7	3
CMA	−0.0840	0.2370	−0.0799	−0.1852	0.0307	5	8
CHR	1.0638	0.1230	1.0648	0.9714	1.1171	76	0
Adj. R^2	0.9200	0.0309	0.9231	0.8926	0.9423	–	–

This table shows the distribution parameters of coefficients and adjusted R^2 from factor model regressions for 76 individual funds. Panel A shows the results for individual funds without hedging designation using the standard six-factor model. Panel B shows the results for individual currency-hedged funds using the standard six-factor model. Panel C shows the results for individual currency-hedged funds using the seven-factor model including CHR. Sd refers to the standard deviation of the 76 coefficient estimates for each factor. The last two columns indicate how many of the estimated coefficients are statistically significantly different from 0 at the 5% level and have a positive or negative sign. Significance levels are computed using standard errors following Newey and West (1987) with a lag of 4, as suggested as best practice in Greene (2020), to adjust for autocorrelation and heteroskedasticity.

Table 5: Summary statistics of subsample for fund flow analysis

	Mean	Sd	Median	0.25 Q.	0.75 Q.
			Hedged		
Fund flows	0.006	0.320	-0.0003	-0.038	0.001
TNA	34,192,429	75,280,494	5,490,045	759,953.8	26,647,989
$\hat{\alpha}^{1F}_{i,t-h}$	0.003	0.033	0.003	-0.016	0.024
Returns	0.006	0.049	0.012	-0.019	0.039
Sd of returns	0.048	0.016	0.047	0.035	0.059
TER (%)	1.371	0.513	1.290	0.970	1.790
Age	67.217	27.108	64	44	87
			Unhedged		
Fund flows	0.021	0.296	-0.0002	-0.033	0.013
TNA	68,913,983	157,784,340	14,225,000	2,016,860	64,133,792
$\hat{\alpha}^{1F}_{i,t-h}$	-0.001	0.023	0.001	-0.011	0.013
Returns	0.002	0.048	0.005	-0.023	0.030
Sd of returns	0.044	0.015	0.043	0.032	0.054
TER (%)	1.355	0.545	1.290	0.950	1.770
Age	126.974	94.638	92	54	182

This table shows the summary statistics for the subsample of currency-hedged funds used for the fund flow analysis. In addition, the data for funds without hedging designation are also provided for perspective. We refer to them as unhedged funds. TNA refers to the total net assets of the funds. Sd refers to the standard deviation of a fund's monthly returns over the prior twelve months. TER refers to the total expense ratio of the funds. The evaluation period is September 2012 to September 2022.

Table 6: Fund flow regressions

	1F	2F	2F
$\hat{\alpha}^{j}_{i,t-1}$	0.9527***	0.6554**	0.8219***
	(0.2877)	(0.2626)	(0.2767)
$\hat{\alpha}^{j}_{i,t-2}$	0.9557*	0.9164	0.9372**
	(0.5485)	(0.5919)	(0.4634)
$\hat{\alpha}^{j}_{i,t-3}$	0.1012	0.2736	0.2033
	(0.3127)	(0.3299)	(0.2805)
$HedgeSuccess_{i,t-1}$			3.3007**
			(1.4096)
$HedgeSuccess_{i,t-2}$			0.4979
			(0.5981)
$HedgeSuccess_{i,t-3}$			−0.5731
			(0.8489)
log(AUM)	−0.0138***	−0.0145***	−0.0137***
	(0.0041)	(0.0042)	(0.0043)
TER	0.0111	0.0119	0.0112
	(0.0201)	(0.0204)	(0.0203)
Sd	2.1196*	2.2278	2.0808*
	(1.2481)	(1.3387)	(1.2079)
log(Age)	−0.0236	−0.0194	−0.0232
	(0.0246)	(0.0236)	(0.0257)
Observations	2,675	2,675	2,675
Month-FE	Yes	Yes	Yes
R^2	0.0597	0.0573	0.0626
Adjusted R^2	0.0337	0.0312	0.0355

This table presents the regression coefficient estimates from panel regressions of percentage fund flow of currency-hedged funds (dependent variable) on different measures of abnormal performance. The header of each column indicates the model used to calculate the alphas, where "1F" indicates the standard one-factor model and "2F" indicates the two-factor model including CHR. The first column shows the results when the individual lagged alphas calculated using the standard one-factor model are used as explanatory variables. The second column shows the results when the individual lagged alphas calculated using the two-factor model including CHR are used as explanatory variables. The third column shows the results when the individual lagged alphas calculated using the two-factor model including CHR and the estimated hedging success are used as explanatory variables. Standard errors are in parentheses and double-clustered by fund and month following Petersen (2008). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.