

On the Use of Currency Forwards: Evidence from International Equity Mutual Funds*

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Abstract

Using a novel, hand-collected, dataset of currency forward positions we undertake the first comprehensive investigation into currency management at U.S. international equity mutual funds. While funds actively manage currency exposure via currency overlay, we find funds more commonly construct separate currency portfolios of long and short derivative positions, often involving currencies not in the underlying equity portfolio. Across the industry we find, however, that both approaches have limited impact on investment performance, which we ascribe to sub-optimal use of currency forwards. Moreover, we find substantial investment gains could have been achieved among non-users of currency derivatives through dynamic currency hedging.

Keywords: currency hedging, currency derivatives, mutual funds

JEL Classification: F31, G11, G15, G23

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1 Introduction

Investing in overseas equity markets has increased rapidly over the past 30 years, consistent with investors taking advantage of international diversification (Solnik, 1974; Eun et al., 2008; Du and Huber, 2024). A primary way that investors gain exposure to foreign equities is by investing in international equity mutual funds. Indeed, the assets under management at U.S.-based international equity mutual funds have expanded rapidly since the early 1990s, growing from \$100 billion to almost \$3 trillion—around one-quarter of the entire U.S. equity mutual fund industry (see Figure 1).

Managers at these funds face a critical question: what role should *currency* play in the portfolio? Because international equity returns are driven, in part, by exchange rate returns, they are inherently exposed to exchange rate risk. Indeed, the decision as to how best to manage currency exposure has been shown to have a substantial impact on the investment performance of an international portfolio over time (Campbell et al., 2010; Opie and Riddiough, 2020). Given the additional value that currency management can offer international equity portfolios, it is critical to understand how fund managers actually manage currency exposure in practice.

In this paper, we therefore undertake the first comprehensive investigation into the management of currency exposure at U.S. international equity mutual funds by hand-collecting a unique dataset of over 55,000 net currency forward positions that were outstanding at funds' quarter ends, over a 15-year window, from the holdings reports of 1,279 funds.¹ Using these data we address three primary research questions: What determines the use of currency forwards? Do currency forwards impact funds' investment performance? And, to what extent can the current industry practice be viewed as optimal?

Ex-ante, it is unclear how exchange rate risk should be managed by international equity fund managers. While the textbook recommendation for international *fixed income* portfolios is universal—exchange rate risk should be fully hedged to reduce volatility and enhance investment performance—there is no clear recommendation for equity portfolios.² This ambiguity reflects the similarity in performance of unhedged and fully hedged equity portfolios, which is driven primarily by the natural hedges offered by various currencies that are lost when their exposure

¹In each case, we ensure that the use of currency forwards is not mechanical: all the funds have unhedged equity benchmarks, no fund has a mandate to hedge currency exposure, and no fund offers an equivalent currency-hedged portfolio to investors. The decision to use currency forwards is therefore made at the discretion of the fund manager.

²For example, Eun and Resnick (2018) state that “empirical evidence regarding bond markets suggest that it is essential to control exchange rate risk to enhance the efficiency of international bond portfolios.”

	International Bond		International Equity	
	Unhedged	Hedged	Unhedged	Hedged
<i>Avg return (%)</i>	4.06	4.66	6.51	6.48
<i>Std (%)</i>	5.50	2.70	15.2	13.7
<i>Sharpe ratio (%)</i>	0.73	1.73	0.43	0.47

Exhibit 1: Hedging Currency Risk in International Equity and Bond Portfolios.

The table presents the average annualized monthly returns, standard deviations, and Sharpe ratios of international equity and bond portfolios that are fully hedged or unhedged against currency movements. The equity portfolio is the MSCI All Country World Index. The bond portfolio is the Bloomberg Global Aggregate Index. The sample is from Jan 1999 to Dec 2019.

is hedged. As an example, in Exhibit 1, we present the investment performance of hedged and unhedged international equity and fixed income portfolios. The impact of fully hedging currency risk in the Bloomberg Global Aggregate Bond index is striking—the Sharpe ratio more than doubles through the reduction in volatility. In stark contrast, the unhedged and fully hedged MSCI World indices generate almost identical Sharpe ratios over the equivalent period. Given the similarity in performance, it raises the question: does currency management matter for international equity funds?³

The answer is *yes*. But to enhance the investment performance of an international equity portfolio requires a more nuanced approach than full hedging, which is often prescribed for bond portfolios. Fortunately, the extant literature has identified two primary methods for equity managers that outperform full hedging. The first approach, known as “currency overlay,” allows currency exposure to vary across currencies, and is typically undertaken through the use of mean-variance optimization (see, e.g. Campbell et al., 2010; Opie and Riddiough, 2020). The second approach constructs a separate currency portfolio, which is then subsequently combined with the underlying equity portfolio (Kroencke et al., 2014). Both approaches have been found to add substantial value to international equity portfolios, either through generating higher returns or lowering volatility, and therefore increasing the overall Sharpe ratio of the portfolio.

To explore how funds use currency forwards in practice, we initially split our sample into two groups: users and non-users. A user is defined as a fund which has an outstanding currency forward contract at the end of at least one quarter in the sample. Based on this initial screening, we find that 471 funds were users of currency forwards during our sample period. We focus on

³The average returns are similar between a fully hedged and unhedged portfolio when the base currency earns a low average currency excess return. Indeed, the “dollar” portfolio is known to earn a low average return that is not statistically different from zero (Lustig et al., 2011). Moreover, unlike for bond portfolios, fully hedging currency exposure removes natural hedges offered by safe haven currencies (Campbell et al., 2010).

these funds in the main body of the analysis, while in further analyses we turn our attention to funds not using currency forwards to assess the extent to which they are leaving money-on-the-table through their inaction.

Comparing users and non-users, we find differences in fund characteristics across the two groups. Users tend to be slightly older, larger, and more active funds—users have annual turnover ratios of over 70%, relative to around 55% for non-users. Moreover, users tend to hold a slightly larger fraction of their portfolio in G9 currencies, although both groups invest just over 80% of their total portfolio in foreign securities.⁴ But while we find differences in fund characteristics, we find no differences in the investment performance of the two groups. Average net returns, volatility of returns, benchmark adjusted returns, and tracking errors are almost identical across both groups, which is particularly puzzling given the enhancement to investment performance that currency forwards have been shown to offer.

To begin our investigation into how funds use currency forwards, we construct a standard measure in the literature—the hedge ratio, which reflects the percentage of currency exposure offset through the use of currency forwards. We find that around one-in-seven users hedge a significant portion of exchange rate risk, although we find that only two funds fully hedge each quarter. The majority of funds, however, adopt a hedge ratio close to zero, indicating that hedging, in the sense of simply removing currency exposure, is unlikely to be the main purpose for using currency forward contracts.

Indeed, while hedge ratios are typically low, we find many funds adopt large *absolute* currency forward positions (i.e., the sum of non-signed forward positions), which often exceed 20% and reach as high as 60% of total net assets (TNA). International equity mutual funds therefore commonly enter both long and short currency forward contracts (in different currencies) to build, essentially, separate currency portfolios. We find these currency portfolios frequently contain currencies that are not part of the underlying equity portfolio but provide exposure to various sources of currency excess returns, including carry and momentum. Moreover, these positions can be viewed as “shadow” portfolios, since they are not reported in the funds’ total asset position but add, sometimes substantially, to a fund’s total risky asset position.

Across the industry, funds have therefore undertaken currency overlay but have more typically sought to build separate currency portfolios. Given the different approaches, we categorize

⁴The term “G10” refers to the most actively traded developed market currencies: the U.S. dollar, Eurozone euro, Japanese yen, British pound, Swiss franc, Australian dollar, Canadian dollar, New Zealand dollar, Swedish krona, and Norwegian krone. We refer to the “G9” as the G10 currencies excluding the U.S. dollar.

and investigate funds' behavior across distinct "styles." The first style, that we label "exposure management," selectively reduces currency exposure through currency overlay. Funds in this group have non-trivial hedge ratios, typically above 25%. The second style, that we label "portfolio building," constructs a separate currency portfolio. These funds have low average hedge ratios at the fund level, close to 0% on average, but large average absolute forward positions—typically above 10% of their TNA. Finally, funds that exhibit both low average hedge ratios and low absolute forward positions trade less frequently and in fewer currencies, potentially for short-term hedging or speculative motives. Since currency forwards have relatively limited impact on these funds, we choose to study them as a separate group of "occasional users."

We explore how exposure managers and portfolio builders choose their currency forward positions using fixed-effects panel regressions. The literature on optimal currency management has emphasized the role of currency risk factors and sources of currency excess returns, such as carry, value, and momentum, as a means to enhance investment performance. And indeed, we find strong evidence that currency carry, momentum, and volatility, are all important factors in determining funds' currency forwards strategies across both styles of currency management. But while this evidence is partially favourable to funds adopting methods consistent with those proposed in the literature, a substantial amount of variation in forward positions remains unexplained, indicating a substantial idiosyncratic component to funds' use of currency forwards that does not appear to add significant investment value relative to non-user funds.

We build on this analysis by investigating fund behavior and investment performance within each style of management. Across exposure managers, we identify a mix of both passive (low variation in hedge ratios) and active (high variation in hedge ratios) approaches to the management of currency exposure. Investigating within these groups, we find that the most active fund managers do exhibit some evidence of market timing in their hedge ratios and did enhance their overall portfolio performance through the use of currency forwards relative to not hedging—indicating that funds have generated superior performance from actively managing currency. Nonetheless, we find that even stronger investment performance could have been obtained if funds had adopted a dynamic approach to managing currency exposure to exploit well-known sources of currency risk. Indeed, excess fund returns and Sharpe ratios would have been economically and statistically higher, particularly among passive exposure managers.

Across the universe of portfolio builders, we find currency portfolios generated low returns, around 1% per annum, and Sharpe ratios close to zero (0.08 on average), consistent with the

earlier finding that users and non-users exhibit similar investment performance. Yet, across portfolio builders, we find significant variation in the investment performance of the underlying currency portfolios. Grouping funds based on the information ratio of their currency portfolio returns, we find a spread in returns between the highest and lowest quintiles of around 10% per annum. In fact, the Sharpe ratio of the best performing funds was over 0.70, compared to -0.62 for the worst performing. For many of the best performing funds, however, the size of their currency portfolio was still relatively small compared to total net assets, reducing the potential gains that the currency portfolio could provide and, in further analysis, we highlight the potential gains funds could achieve through allocating a higher weight to currency portfolios. Furthermore, we find evidence that supports a skill-based interpretation: funds which formed the best (worst) performing currency portfolios were also the best (worst) stock pickers, generating the highest (lowest) excess return, Sharpe ratio, and information ratio in the equity-specific component of their portfolio.

In the final part of our analysis we investigate non-user funds. We compare the actual performance of each fund relative to alternatives, in which we hypothetically manage the funds' currency exposure using either currency overlay or through the addition of a separate currency portfolio. We find that in all cases the funds' return volatility would have been significantly reduced and Sharpe ratios and certainty-equivalent returns are typically higher, especially when exploiting dynamic currency factor hedging, which is found to statistically improve the investment performance across the industry in periods of both U.S. dollar strength and weakness.

Related literature. The paper is closely related to the literature studying derivative use at mutual funds. Various benefits have been attributed to using derivatives, including to utilize information better, manage risk, and reduced transaction costs.⁵ Koski and Pontiff (1999) study derivative use among equity mutual funds and find only 21% of funds use derivatives, and that the risk exposure and return performance of users and non-users is similar. In contrast, Kaniel and Wang (2020) study derivative usage around the Covid-19 crisis and find users significantly outperformed non-users of derivatives.⁶ Our granular data on derivative positions help to provide more nuanced insights on the relation between fund performance and derivative use.

⁵Deli and Varma (2002) study the option to allow fund advisors to invest in derivative securities and find the decision is driven by increased efficiency rather than to opportunistically manipulate risk, while Almazan et al. (2004) consider the economic rationale for mutual fund investment restrictions and find patterns consistent with an optimal contracting equilibrium.

⁶Aragon and Martin (2012) also find that hedge funds using option contracts deliver higher benchmark-adjusted portfolio returns and lower risk than those of non-users.

For example, while we generally find little difference in the investment performance of users and non-users, we do find evidence of superior performance in pockets of the industry, either when dynamically hedging currency exposure or when constructing a separate currency portfolio.

Kubitza et al. (2024) find that deviations from covered interest rate parity (CIRP) are an important determinant of currency hedging, although Du and Huber (2024) find that institutional investors outside of the United States substantially increased their demand for currency hedges in spite of the higher costs associated with CIRP deviations and that the currency hedge ratios of these global institutions often deviate from mean-variance implied hedge ratios. Our evidence supports the finding on the sub-optimal use of currency forwards, while we also highlight the potential investment gains that both users and non-users could obtain from optimizing their use of currency forwards.⁷

Sialm and Zhu (2022) is an important complementary study that investigates the use of currency derivatives at *fixed income* funds. As noted, the prescription for the management of currency at bond and equity funds is quite different—bond funds can enjoy a significant enhancement to their investment performance by simply removing foreign exchange exposure that equity funds do not and, indeed, the authors find that over 90 percent of fixed income funds use currency forwards.⁸ For this reason, studies often choose to study a single industry. Liao and Zhang (2024), for example, investigate fixed income funds, dropping equity portfolios given the less salient hedging among equity funds. Indeed, portfolio building, the key strategy used by equity funds to manage currency exposure, is not observed at fixed income funds.

Finally, the paper contributes to a broader literature investigating the impact of exchange rates on mutual funds' decision making. Massa et al. (2016) find that funds under-weighting risky currencies in their equity portfolio tend to underperform due to self-imposed portfolio constraints, while Camanho et al. (2022) show that foreign exchange returns impact the extent of portfolio rebalancing. Burger et al. (2018) and Maggiori, Neiman, and Schreger (2020) both highlight that mutual funds' selection of international investments is also heavily influenced by their currency of denomination. Our study contributes to this literature by providing the first exploration into the use of derivative contracts in the management of exchange rate exposure by U.S. international equity mutual funds. The study enables us to shed new light on the range of

⁷Liao and Zhang (2024) document a channel by which currency hedging demand is related to countries' external imbalances, while Ben Zeev and Nathan (2024) find that global equity market valuation shocks drive demand for U.S. dollar hedges. Furthermore, Brauer and Hau (2023) show that hedging is important for determining exchange rates, with as much as 30% of monthly exchange rate variation explained by fluctuations in the net hedging positions of institutional investors.

⁸The average hedge ratio was found, however, to be surprising low, at only 18%.

approaches used in currency management, the main determinants of currency forward positions, and the broader implications of exchange rates for mutual funds' investment performance.

The remainder of the paper is structured as follows: in Section 2 we describe the data and present initial summary evidence. In Section 3 we provide details of our methodology for categorizing funds' according to their "style" of currency forward usage. In Section 4 we present results from our main empirical analysis. In Section 5 we turn to non-users and consider their hypothetical performance from using currency forwards. In Section 6 we conclude. An Online Appendix contains additional results and full details regarding the construction of our dataset.

2 Data and Summary Evidence

We obtain data on U.S. international equity mutual funds from CRSP and Morningstar. The dataset initially includes all international (including global) equity mutual funds at the intersection of the two datasets. Merging the two databases is primarily undertaken to obtain accuracy in the final dataset. CRSP and Morningstar define international equity funds in slightly different ways, and we find inconsistencies in the classification of certain funds. We therefore only consider funds that are classified as an international fund by *both* CRSP and Morningstar. Moreover, through the extensive data merging process we are able to undertake various intermediate checks using a similar procedure to that adopted by Berk and van Binsbergen (2015) and Pástor et al. (2015).⁹ The Morningstar dataset also offers important fund characteristics that are not available via CRSP. In particular, we obtain funds' stated benchmarks, to determine if a fund is targeting a currency-hedged benchmark, as well as the portfolio weight denominated in each currency, enabling us to calculate funds' hedge ratios.

Portfolio holdings data are available from CRSP from 2003 onwards. However, the data on currency derivatives for U.S.-based international mutual funds only became available in 2010 and contain significant errors when compared with the portfolio holdings disclosed by funds to the SEC.¹⁰ To ensure data accuracy, we therefore hand-collect data on funds' open currency forward positions directly from their SEC filings, obtained via the SEC's EDGAR database.¹¹ The sample starts in 2004, the year the SEC mandated quarterly reporting by mutual funds

⁹Full details of the procedure are documented in the Online Data Appendix.

¹⁰For example, we find situations in which currency forwards reported in CRSP are not held by the fund or vice-versa, find no evidence of currency forwards in the CRSP dataset when the fund was an active user. We contacted various funds for which CRSP reports currency forward contracts that are not reported to the SEC. Those funds confirmed the error is in the CRSP dataset and could not account for the values reported in CRSP.

¹¹We find that only a handful of funds ever used other currency derivatives, such as futures or option contracts. For this reason, we focus our analysis on funds' use of currency forward contracts.

using forms N-Q and N-CSR. We end our sample in the second quarter of 2019, when funds begin to file monthly reports, using form N-Port, through the SEC’s EDGAR system.

Figure 2 presents an example of the forward positions we collect. It shows an extract from an N-CSR report filed by AB International Value Fund, for the reporting period ending May 31, 2019. There is no standard format when reporting open forward contracts, however funds typically report: the notional amount in foreign currency and U.S. dollars (USD), the settlement date, the counter-party to the contract, and the unrealised gains/losses in USD. The notional value of the contracts is required to calculate hedge ratios and currency portfolio weights. For cross-currency forward contracts, we convert each leg into a forward position against the USD. We also aggregate long and short positions to obtain a net forward position for each fund-currency-quarter.¹² Determining a fund’s hedge ratio also requires information on the currency exposure stemming from the underlying equity portfolio. We obtain this information from Morningstar, using the percentage of each funds’ TNA invested across 48 countries.¹³

We merge the quarterly data on open currency forward contracts with monthly fund-level data from CRSP and Morningstar. The initial sample has 157,117 fund-month observations across 1,620 funds, of which 519 funds reported open currency forward positions.¹⁴ As part of our sample selection, we drop fund-month observations in which: (i) the sum of country weights (including the U.S.) is greater than 101% or less than 0%; (ii) the sum of the country weights (excluding the U.S.) is less than 25%; or (iii) the TNA is less than \$15 million in 2019 dollars.¹⁵ We also require funds to have at least four quarters of available data, to not use a currency-hedged benchmark, and to not have a benchmark denominated in foreign currency.

The remaining sample consists of 55,615 net open forward positions and 1,279 funds, of which 471 funds have open currency forward contracts during the sample. The average net forward position has a notional value of minus \$13.2m (i.e., a short position in foreign currency), 62% of the positions are on G9 currencies, and less than 3% of positions are in cross-currency forwards, i.e., *not* involving the USD. We also consider if funds are restricted from using

¹²Some funds invest solely in a master portfolio. In these cases, we collect the fund’s percentage ownership in the master portfolio and use this percentage to calculate the fund’s share of currency forward positions held within the master portfolio. If the information is missing, we use the fund’s dollar investment in the master portfolio, combined with the master portfolio’s net assets, to calculate the ownership percentage.

¹³We aggregate across Euro-zone countries to obtain funds’ euro exposure. When country weights are not available on a monthly frequency we backward- and forward- fill weights if available within a two-quarter period.

¹⁴Fund reports are filed at fiscal quarter-ends, not calendar quarter-ends. We follow Wermers et al. (2012) and assume that portfolio positions reported at a fiscal quarter-end are valid at the subsequent calendar quarter-end.

¹⁵We implement these filters since: (i) an aggregate portfolio weight that exceeds 101% or is less than 0% is likely a data error; (ii) CRSP requires a global fund to invest at least 25% of its portfolio in foreign equities; and (iii) consistent with Pástor et al. (2015), small funds often generate extreme and uninformative outcomes.

currency forwards by checking if funds' prospectuses (form N-1A) mention the use of currency forwards.¹⁶ We find that 97% of the funds state explicitly that they *may* use currency forwards for hedging and (sometimes) speculation purposes. The remaining funds make no mention of currency forwards within their prospectus, and thus we find no evidence that any of the funds in our sample outright prohibit the use of currency forward contracts.

2.1 U.S. international equity mutual funds

In Figure 3, we present time-series information on the final sample of funds. The top figure shows the total number of funds each year, split by users and non-users. The percentage of funds using currency forward contracts is displayed above each bar. We see that the number of funds increases over time, from 491 in 2004 to 892 in 2019. Of these funds, the share using currency forward contracts fluctuates over the sample, beginning at 12.8% in 2004 but increasing to over 31% during the global financial crisis (GFC). Following 2008, the proportion of funds using currency forward contracts dropped, falling below 20% by the end of the sample.

These industry-wide patterns coincide with broad U.S. dollar movements. Between 2004 and 2011, the U.S. dollar experienced a significant depreciation against a broad basket of currencies, before generally appreciating in the latter part of the sample. In an environment of dollar weakness, funds may choose to lock-in exchange rates in anticipation of future asset purchases or hedge in anticipation of a reversal in currency value. Moreover, funds may have sought to gain exposure to currencies offering higher expected currency excess returns. Indeed, various currency strategies, including the currency carry trade, generated high returns in the years leading up to the GFC. Following 2011, these broad trends reversed—the U.S. dollar strengthened and global interest rates converged towards zero—limiting the profitability of currency trading.

In the bottom figure we present a similar pattern in the net sales and absolute positions of the outstanding currency forward contracts. The net sales represent the total notional value of forward positions (the sum of both short and long positions) relative to total net assets, such that a positive value indicates that exchange rate exposure was reduced across the industry. The absolute position sums the modulus of the notional long and short positions. We find that net sales were typically low—less than 4% of total net assets—suggesting that equity funds do not, in general, remove exposure to foreign currencies when using currency forwards. Moreover,

¹⁶Figure A.1 provides an example statement on currency forward usage extracted from the fund's prospectus.

we observe large differences between net sales and absolute forward positions, particularly before and during the global financial crisis, indicating that funds *increase* their exchange rate exposure during the sample, consistent with a prominent speculative motive.

2.2 Comparing users and non-users

Table 1 presents the mean and standard deviation of various fund characteristics and investment performance metrics for users and non-users of foreign exchange forward contracts. The column “Obs” reflects the number of fund-quarter observations, while the final two columns report the differences in the mean values between the two groups. The associated p -values are obtained via permutation tests with 1,000 resamples.¹⁷

Comparing users and non-users, we note that both groups have a similar proportion of international securities—just over 80% of assets under management are held overseas—although users have a slightly higher weight in G9 countries. Cost potentially plays an important role in the decision to use foreign exchange forward contracts, and thus the difference offers an early indication that holding assets denominated in less liquid currencies may disincentivize the use of forward contracts. Moreover, while both sets of funds hold assets from around 16 countries on average, the range is wide: the sample includes country funds that focus on a single economy as well as funds with a broad geographical focus across both developed and emerging markets.

Other differences are observed in the fund characteristics across users and non-users. Users tend to be more active funds: their average annual turnover ratio is 70%, compared to 55% for non-users. Users also tend to be older (13 years versus 10 years), and have more assets under management (total net assets are typically around \$1 billion higher). Furthermore, consistent with the higher costs potentially arising from the use currency forward contracts, we find that the expense ratio of users is approximately 0.07% per annum higher than for non-users.

Prior studies have investigated the differences in investment performance across users and non-users of derivatives securities, with mixed findings. Koski and Pontiff (1999), for example, finds no difference in investment performance, while Kaniel and Wang (2020) find evidence that derivative users outperformed non-users during the COVID-19 pandemic. In the lower panel of Table 1, we build on these prior findings by presenting evidence on the differences in investment performance between users and non-users of currency forward contracts during our

¹⁷For each variable, we randomly regroup the funds into two groups, in equal size to the original groups, and construct a new estimate of the mean value. Each fund appears once in each resample. Consistent with the null hypothesis of no difference in the mean between users and non-users, the p -value equals the proportion of resampled test statistics that exceed the original test statistic.

sample. Supporting the findings of Koski and Pontiff (1999), we find no statistical difference in net returns, volatility of net returns, benchmark adjusted returns, or tracking error of the two groups. This finding is surprising. Extensive evidence indicates that currency forwards should be used to optimize an international equity portfolio (Perold and Schulman, 1988; Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020; Barroso et al., 2022), and our earlier evidence suggests that funds may have speculative timing motives when using currency forwards, further highlighting the importance of understanding how the funds have undertaken currency management in practice.

3 Currency Management Styles

In this section, we begin our investigation into the use of currency forward contracts at U.S. international equity mutual funds. We initially categorize funds by their style of currency management using funds' hedge ratios and absolute forward positions, before making initial observations on the use of currency forwards across each currency management style.

3.1 Hedge ratios

To gauge the extent by which funds reduce currency exposure, we begin our investigation by studying the distribution of fund-level hedge ratios. The fund-level hedge ratio is the proportion of a fund's total foreign exchange rate exposure, stemming from its underlying assets, that is offset through currency forward contracts. Specifically, the fund-quarter hedge ratio for fund i at time t is calculated as:

$$HR_{i,t} = \sum_j \frac{\tilde{f}_{i,j,t}}{w_{i,j,t}} \quad (1)$$

where $\tilde{f}_{i,j,t} = f_{i,j,t}/tna_{i,t}$, is the U.S. dollar value of the net forward position of fund i in currency j at time t ($f_{i,j,t}$) scaled by the fund's total net assets on that date ($tna_{i,t}$). We measure the net forward position as the difference in the values of short and long forward contracts in currency j at time t . Therefore, a positive value reflects a net short forward position in currency j (i.e., a reduction in foreign exchange exposure). The denominator equals fund i 's portfolio weight in currency j at time t .

In Figure 4a, we present a histogram of fund-level hedge ratios, in which each observation equals a fund's average fund-level hedge ratio over the sample. We make three observations: (i) average fund-level hedge ratios tend to cluster around zero (the mean value is 2.4%); (ii)

over 100 funds tended to increase exposure to foreign exchange rates; and (iii) only around 20 funds typically hedged over 20% of their foreign currency exposure.

From this initial evidence we conclude that most funds using currency forwards are not primarily aiming to remove currency exposure. This fact would be surprising for fixed-income funds, but is consistent with equity funds either using dynamic currency overlay (in which hedge ratios vary across currencies and time) or constructing separate currency portfolios. Indeed, a separate currency portfolio that is neutral to the U.S. dollar would generate an average hedge ratio of zero. Moreover, the fact that many funds increase exposure to foreign currency is consistent with a speculation motive. To better understand the underlying behaviour we therefore construct a second measure—the “absolute forward position.”

3.2 Absolute forward position

If a fund-level hedge ratio is close to zero, it could indicate one of two underlying conditions. The fund may be entering small currency forward contracts relative to their total foreign exchange exposure. Alternatively, the fund may enter a mix of long and short currency forward contracts. Since hedge ratios are signed, the average value of these hedge ratios could be low, even if they are large in absolute terms at the individual currency level. Moreover, funds may enter forward positions on currencies that are not part of the underlying equity portfolio, and thus the hedge ratio is not defined. To better understand the approach funds are taking, we form a measure of each fund i 's absolute forward position at time t , by summing across the absolute value of each individual currency's standardized forward position:

$$AFP_{i,t} = \sum_j |\tilde{f}_{i,j,t}|. \quad (2)$$

In Figure 4b, we present a scatter plot of funds' average hedge ratios against their average absolute forward positions.¹⁸ We observe that many funds operate large absolute forward positions, in some instances summing to over 50% of TNA. In the figure, we highlight funds with average absolute forward positions over 2% with red crosses. To be clear, a fund with a zero average hedge ratio but an average absolute forward position over 50% of TNA is essentially entering an equal mix of long and short currency forward contracts on different currencies. These positions net to zero, in the sense of generating no additional U.S. dollar exposure, but

¹⁸We calculate these fund-level averages using the quarters in which a fund uses currency forwards. For clarity, we present the scatter plot for funds with average fund-level hedge ratios between -20% and $+20\%$.

are large in U.S. dollar magnitude—summing to over half the fund’s total net assets.¹⁹ Since these funds combine a mix of long and short positions on foreign currency, they can be viewed as effectively constructing separate currency portfolios using currency forward contracts. From the figure we also observe that a cluster of funds exhibit both low average hedge ratios *and* average absolute forward positions. We denote these funds with blue diamonds. These funds all had average absolute forward positions below 2% and average hedge ratios between -5% and $+5\%$.

From the preceding analysis we thus observe three broad types of currency forward user. First are funds that build a separate currency portfolio of forward positions. For these funds, forward contracts do not remove exchange rate exposure at the fund level, and may even slightly increase it. We refer to these funds as “portfolio builders.” Second are funds that selectively reduce their foreign exchange rate exposure, across currencies or time. These “exposure managers” are funds marked by having the highest fund-level hedge ratios. Third are funds that enter relatively small or infrequent currency forward contracts, potentially to hedge short-term transactions in the underlying portfolio or obtain liquidity for an upcoming equity purchase. These funds have low average hedge ratios and absolute forward positions and we refer to them as “occasional users.” Each “style” of currency management has possibly different underlying motives, and thus potentially different determinants of forward usage and implications for a fund’s investment performance. For that reason, we choose to assign each user fund to a specific currency management style and investigate each group separately. In the next section, we describe our procedure for assigning funds to each of the three currency management styles.

3.3 Assigning currency management styles

We assign funds using three indicator variables: (i) the percentage of quarters in which the fund uses currency forwards; (ii) the average hedge ratio over the quarters in which the fund uses currency forwards; and (iii) the average absolute forward position over the quarters in which the fund uses currency forwards. The first variable allows us to identify infrequent users of currency forwards, while the second and third variables allow us to differentiate between whether a fund is primarily constructing a separate currency portfolio or is aiming to remove foreign currency exposure. We classify a fund as an exposure manager if it uses currency forwards in at least

¹⁹For example, suppose a \$100 million international equity fund has two equal-weighted equity positions in Japan and Australia. If the fund had two net currency forward contracts outstanding against the U.S. dollar: a \$25 million short position on Japanese yen, and a \$25 million long position on Australian dollars, then the fund-level hedge ratio would equal zero, but the absolute forward position would equal 50%.

10% of quarters, and has an average hedge ratio of at least 10% during those quarters. Instead, we classify a fund as a portfolio builder if it uses forwards in at least 10% of quarters, has a hedge ratio below 10%, and its average absolute forward position is at least 2%. The remainder of the funds are classified as occasional users that either enter currency forwards infrequently, or enter contracts that are, in aggregate, small relative to the fund overall. In total, we identify 66 exposure managers, 202 portfolio builders, and 203 occasional users.²⁰

To make the categorization clear, in Figure 5 we present examples of each type of fund. The exposure manager (Evermore Global Value Fund) is presented in the top panel. We see that Evermore targeted a hedge ratio of around 100% across the sample and never entered long forward contracts (i.e., never sought to obtain *more* exposure to a given currency). In the middle panel, we present a portfolio builder (J.P. Morgan International Value Fund). The fund adopted a hedge ratio close to zero but entered long and short currency forward positions vis-à-vis the U.S. dollar, and therefore constructed a separate currency portfolio that had an absolute notional value of \$786 million, equivalent to 20% of its total net assets (TNA), at its peak in 2014. Finally, in the bottom panel, we see an occasional user (Threadneedle International Opportunity Fund), which periodically entered small currency forward positions (relative to the fund’s TNA) and thus had little impact on the fund’s overall performance.

In Figure 6, we present each fund’s average foreign currency exposure across different styles. The horizontal axis measures each fund’s average portfolio weight in foreign currency, highlighting that the majority of funds have substantial foreign equity holdings (over 80% of the portfolio).²¹ The vertical axis measures each fund’s average currency exposure, arising from the combination of the underlying equity positions plus currency forward contracts. A fully hedged fund would therefore lie on the horizontal axis, while funds that do not on average reduce currency exposure would lie on the 45-degree line.²² Confirming our classification scheme, exposure managers are clearly funds with the largest average reduction in currency exposure while, in contrast, portfolio builders and occasional users are all concentrated around the 45-degree line,

²⁰The classification scheme we adopt is simple and transparent, capturing the various approaches to currency management that we observe. Nonetheless, it is also inherently subjective and the classification of funds would change as the thresholds we select change. For that reason, in further analyses, we undertake an extensive robustness exercise in which we re-estimate all the main tables using varying thresholds. Moreover, we also implement a more sophisticated machine learning algorithm to classify funds. Overall, we find no evidence that our qualitative findings are reliant upon a specific threshold or categorization scheme.

²¹A group of funds allocate a smaller proportion of weight to foreign equities, equal to around 40%-60% of the total portfolio. We find these funds are mainly classified as “world funds” and present additional information on the breakdown of the different types of funds in the Online Appendix.

²²A fund that never used forwards would also lie on the 45-degree line.

since their currency exposure remains essentially unchanged after the use of currency forwards.

3.4 Currency forwards across management styles

In Table 2, we present statistics on currency forward usage across exposure managers, portfolio builders, and occasional users. Consistent with our definition of occasional users, we find they only hold forward positions in around one-third of quarter ends, in contrast to exposure managers and portfolio builders that tend to have outstanding forward positions around twice as often. Moreover, exposure managers and portfolio builders tend to hold forward contracts on more currencies (4.8 and 6.6, respectively, relative to 2.9 for occasional users) and for around twice the fraction of currencies to which the equity portfolio generates exposure. Indeed, we find that exposure managers typically seek to reduce currency exposure for around one-third of currencies in their equity portfolio, adopting an average fund-level hedge ratio of 27.7%. Consistent with the prior analysis, portfolio builders and occasional users adopt fund-level hedge ratios close to zero (0.1 and -0.1 , respectively). The absolute forward position for portfolio builders is, however, far higher, at 12.4%, relative to just 1.5% for occasional users. In other words, portfolio builders' currency positions typically incorporate both a long and short leg with notional values in each leg summing to just over 6% of the fund's total net assets.

Across the three styles of currency management, we obtain data on 55,615 net outstanding forward positions. Of these positions, 68% (37,564) are held by portfolio builders, of which just over 50% (19,730) are long forward positions that increase funds' foreign currency exposure. Occasional users also enter a significant number of long forward positions, which may also point towards a speculative motive, although may reflect occasional users' desire to obtain foreign currency prior to an equity market purchase. Indeed, occasional users only obtain exposure to currencies that are not held in the underlying equity portfolio in around 2% of cases, which contrasts with over 11% among portfolio builders. In fact, just under 90% of positions that are not on a currency in the underlying equity portfolio belong to portfolio builders, consistent with these funds using currency as an independent source of investment performance. Moreover, the direction of net forward positions further confirms our definition of exposure managers, since over 85% of their outstanding forward positions reduce exchange rate exposure.

In Table A.2 of the Online Appendix, we list the number of forward positions held across management styles for each currency. Currencies are ordered based on their total number of net forward positions in the dataset, which aligns closely with measures of currency turnover, in

which the euro, yen, pound sterling, and other major developed market currencies are dominant (see, e.g., BIS (2022)). We also observe a sizeable number of contracts in more speculative emerging market currencies, including the Korean won, South African rand, Brazilian real, and Mexican peso. Indeed, we observe more positions in each of these currencies than in the New Zealand dollar—a major G10 currency. Interestingly, many of the portfolio builders’ currency positions that are not held in the underlying equity portfolio have a strong carry trade flavour—generating exposure to high interest rate currencies, including the Australian dollar, New Zealand dollar, Norwegian krone, and Israeli shekel.

In Figure 7, we extend the analysis by presenting the average currency-level positions of exposure managers and portfolio builders over time. For exposure managers we present information on “abnormal” hedge ratios, defined as the difference between the hedge ratio for the currency ($HR_{i,j,t}$) and the hedge ratio for the fund ($HR_{i,t}$). In the plots, the size of each square represents the relative frequency in which forwards for that currency are obtained. We make two observations. First, there is persistence in positions: the euro, for example, typically has the largest abnormal hedge ratio among exposure managers, while the Australian dollar is typically held in the long-leg of portfolio builders’ currency portfolios. Moreover, the carry dynamic suggested by Table A.2 is again observed for portfolio builders. Long positions are entered in the Australian dollar, New Zealand dollar, and Canadian dollar, while the euro and Japanese yen are generally included in the short leg.

Second, we observe differences between the two groups. Exposure managers, for example, held relatively few positions prior to the GFC, but far more after 2011 when the U.S. dollar experienced a period of appreciation. In contrast, portfolio builders were more active between 2006 and 2014, when active currency investing was particularly profitable. Indeed, since the GFC many well-known currency strategies have experienced weaker performance (Ranaldo and Somogyi, 2021), which may partly account for the reduced size of these portfolios.

4 Exposure Managers and Portfolio Builders

In this section, we investigate the behavior of exposure managers and portfolio builders. In each case, we investigate the determinants of their currency forward usage and the impact that currency forwards have on their fund overall. In doing so, we aim to address whether the current management of currency at U.S. international mutual funds can be viewed as optimal.

4.1 Exposure managers

We investigate the determinants of funds' currency-level hedge ratios using fixed-effects panel regressions, in which the dependent variable is fund i 's hedge ratio in quarter t for currency j ($HR_{i,j,t}$).²³ The model we estimate takes the form

$$HR_{i,j,t} = \mathbf{b}'\mathbf{X}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t}, \quad (3)$$

and thus we estimate a vector of coefficients (\mathbf{b}) on a set of lagged currency-specific determinants ($\mathbf{X}_{j,t-1}$) that we describe below. The purpose of the model is to understand the cross-sectional dynamics behind why exposure to certain currencies is reduced more than for others. We therefore include fund \times quarter fixed effects ($\gamma_{i,t}$) to explore cross-currency hedge ratio variation within each fund-quarter. Moreover, since funds may avoid hedging emerging market currencies due to the lower liquidity and higher transaction costs, we include an emerging market dummy variable (δ_{em}).²⁴ We cluster standard errors at the fund \times currency level.

We present results in Table 3. In columns (1) to (8), each specification includes a single time-varying explanatory variable, while column (9) combines all variables. From column (1) we see that funds primarily reduce exposure for currencies to which they have the largest underlying exposure within their equity portfolio. This finding is intuitive and helps account for why hedge ratios are typically lower for emerging market currencies. Furthermore, the effect is similar when all variables are included in the model. The coefficient in the full model suggests that if a country changed its allocation to a country from 20% to 50%, a 30% increase, its hedge ratio on the currency would increase by around 20% ($0.701 \times 30\%$), holding all else equal.

In columns (2) to (4) we include three variables known to predict cross-sectional currency excess returns: lagged exchange rate returns (Asness et al., 2013; Menkhoff et al., 2012), the forward discount (Lustig et al., 2011), and the real exchange rate (Asness et al., 2013; Menkhoff et al., 2017). These predictors have been shown to have important implications for optimal currency management, indicating that Sharpe ratio maximization can be best achieved through conditioning on this information (see, e.g. Glen and Jorion, 1993; Opie and Riddiough, 2020). Reassuringly, we find that stronger momentum (the one-quarter exchange rate return) and carry (the one-quarter forward discount) both have statistically significant relations with the next-period hedge ratio and in the direction required for Sharpe ratio maximization. For currency

²³We winsorize the hedge ratios at the 1% and 99% levels to mitigate the impact of outliers.

²⁴The dummy variable is set equal to 1 if a currency is classified as an emerging market according to Morgan Stanley Capital International (MSCI).

value, however, we find that currencies that are comparatively more under-valued, tend to be hedged more—not less, as expected.²⁵ Nonetheless, the relationship with currency value is not statistically different from zero in the full model, and therefore shorter-term carry and momentum signals appear to have a stronger influence on managers’ decision making.

We investigate the cost of hedging in columns (5) and (8). In column (5), we include the bid-ask spread, while in column (8) we include the emerging market dummy variable. We find that a wider bid-ask spread is associated with a reduced incidence of hedging, and we observe lower hedge ratios for emerging market currencies in general—the hedge ratio of an emerging market currencies is over 4.6% lower than for otherwise identical developed market currency. When controlling for all other determinants, however, the coefficient on the bid-ask spread is found to be statistically indistinguishable from zero and thus short-term variation in currency-specific liquidity does not appear to be a major driver of quarterly hedging demand.

A natural rationale for using currency forward contracts is to reduce portfolio volatility.²⁶ Funds may therefore choose to adopt larger hedge ratios when a currency has higher underlying volatility. Indeed, this is precisely what we observe, although the economic magnitude is relatively modest. From column (6), we see that if a currency’s annualized volatility increases by 10%—a substantial increase—it leads to an average increase in its hedge ratio by only 4.3%. Finally, we test if country-level equity returns are important for currency hedging. Ben Zeev and Nathan (2024) find that equity market movements can impact hedging demand, as stronger foreign returns increase FX exposure and thus the demand for currency forward contracts. From column (7), we see, however, that the coefficient is essentially zero and thus foreign equity returns do not appear to be a strong influence on funds’ decision in the cross-section. This finding is consistent with the mechanism in Camanho et al. (2022), in which funds undertake portfolio rebalancing at quarter end, without need to adjust their hedging demand.

In sum, we find evidence that exposure managers decide on their currency forward positions by considering their underlying equity exposures, in combination with cost, return, and volatility motives. Loading on currency carry and momentum provides some early evidence that funds, in aggregate, do undertake actions consistent with optimal currency management. But despite finding clear correlations in the data, we also note that the majority of variation in

²⁵We measure currency value following the procedure of Asness et al. (2013)).

²⁶Campbell et al. (2010) suggest that funds should leave unhedged their exposure to currencies that offer a natural hedge. These “safe haven” currencies tend to appreciate when global stock markets fall in value, and thus provide natural protection against global bad times. We find, however, that because funds typically hedge their largest exposures and given the U.S. dollar typically appreciates during these periods, that a safe haven dummy variable has a positive correlation with funds’ hedge ratios. Results available upon request.

hedge ratios remains unexplained. In the following analysis we therefore turn to the question of optimal choice in hedge ratios by considering the extent to which alternative approaches may have been superior.

4.1.1 The optimality of currency forward usage among exposure managers

We begin our investigation into the optimality of currency forward usage among exposure managers by assessing how currency forwards actually impact their investment performance. To do so, we compare the actual performance of the fund against the performance that would have been obtained had the fund not used currency forwards. The prior literature on optimal currency management within international equity portfolios, has highlighted the need to dynamically vary hedge ratios—over time and across currencies (e.g., Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020). We therefore investigate the contrast in actual performance relative to an unhedged benchmark, across different types of exposure manager, grouped based on the extent to which they use dynamic versus passive hedge ratios.

We initially split the sample in two, based on the volatility of funds’ average hedge ratios over time, i.e., the standard deviation of hedge ratios at the fund level. We refer to this measure as the time series (*ts*) volatility. Funds with low volatility are defined as “passive,” while those with high volatility are denoted as “active.” Then, within these groups, we again split the funds into two groups based on the average *within* portfolio hedge ratio variation. To measure this variation, we calculate the quarterly standard deviation of hedge ratios across currencies within a fund, and then obtain the fund-level value by calculating the average standard deviation over the sample. We refer to this measure as the cross-sectional (*cs*) volatility.

We present results for the four groups in Table 4. Consistent with the definitions, time series volatility is found to be almost three-times higher for active funds, while we observe similar cross-sectional volatility among the two groups with low cross-sectional volatility (12.1% and 8.8%) and in the two groups with high cross-sectional volatility (32.7% and 33.1%). Across the four groups, realized excess returns and Sharpe ratios are similar, averaging between 4.9% and 5.4% for excess returns, and between 0.35 and 0.43 for Sharpe ratios.

We compare the actual excess return and Sharpe ratio with an unhedged version of each funds’ portfolio by excluding the impact of currency forwards on the fund.²⁷ Across the four

²⁷The calculation involves subtracting the return on the fund’s portfolio of currency forwards from the net return of fund as a whole. The net return of fund i (with forwards) at time $t+1$ can be decomposed as $R_{i,t+1}^{with} = R_{i,t+1}^{without} + R_{i,t+1}^{for}$. The total return on fund i ’s forward positions at time $t+1$ is calculated as $R_{i,t+1}^{for} = \sum_j (\widetilde{nf}_{i,j,t} \times ExR_{j,t+1}^{for})$, where $\widetilde{nf}_{i,j,t}$ is the net forward position in foreign currency j observed at time t normalised by the

groups, we find that excess returns and Sharpe ratios would all have been lower had the funds *not* used currency forwards, indicating an important role for the use of currency forwards in enhancing investment performance of exposure managers. Moreover, consistent with the largest gains being more likely to arise from active management, we observe the biggest impact on Sharpe ratios (0.03) among active funds. Supporting this finding, we also find that active funds display greater market timing ability, as measured by the percentage of hedge ratio changes that predicted the subsequent quarter’s currency excess return.²⁸

While currency forwards generally appear to have helped improve the investment performance of exposure managers, the earlier results in Table 3 indicated a substantial idiosyncratic component in the choice of currency hedge ratios. In other words, across the industry, exposure managers appear to have followed approaches outside of those suggested by the prior literature. It is therefore important to understand how different the performance of the funds would have been had a previously identified optimal approach been followed. We define optimal as the *ex-ante* maximization of the portfolio’s Sharpe ratio—the common benchmark in the literature, and the one that investor flows appear to be most sensitive.²⁹ To assess the potential inefficiency of the adopted methods, we therefore overlay each fund’s equity portfolio with its own individually optimized set of currency forwards, following the dynamic currency factor (DCF) methodology of Opie and Riddiough (2020).

We report results in the lower panel of Table 4. We observe that across each group, excess returns and Sharpe ratios would have increased had the DCF methodology been applied when determining hedge ratios. In each case, the increase is both statistically and economically significant. The average increase in portfolio excess returns ranges from 36 to 74 basis points per annum, while Sharpe ratios would have been on average over 20% higher among passive funds. In line with the prior result, we observe smaller overall gains from DCF hedging among active funds, consistent with these funds seeking to exploit time-varying currency predictability.

In sum, we document evidence that supports the argument that exposure managers enhance their overall investment performance through their currency management practice. The largest

fund’s TNA at time t , and $ExR_{j,t+1}^{for}$ is the return on a long forward on foreign currency j at time $t+1$.

²⁸A fund may have market timing if they hedge more (less) prior to a negative (positive) excess return on the currency. We create a dummy variable equal to 1 if a decrease (increase) in the hedge ratio from time $t-1$ to time t in currency j is accompanied by a positive (negative) currency excess return at time $t+1$. We exclude observations with two or more consecutive quarters of zero hedge ratios.

²⁹Ben-David et al. (2022) find that Morningstar ratings, that are highly correlated with Sharpe ratios are the primary driver of investors’ flows to equity funds, while Duong Dang et al. (2022) show that Sharpe ratios are the most important factor determining fund flows into corporate bond funds.

gains being observed for the exposure managers with the most active hedging style. But despite these gains, the findings also point to even more substantial gains that were not exploited by funds. In this regard, the disparity in performance may reflect an alternative objective that funds pursue rather than Sharpe ratio maximization. Moreover, the DCF methodology was developed subsequent to the sample’s end. To be clear, the purpose of this final exercise is to assess the potential magnitude of available gains and thus to understand whether similarities in investment performance between users and non users may be due to funds’ approach to currency management, rather than a general irrelevance of currency forwards. The analysis does not suggest that the DCF approach is optimal, or the only alternative available to managers.³⁰

4.2 Portfolio builders

The size of portfolio builders’ currency portfolios vary and many forward contracts relate to currencies not in the underlying equity portfolio. It is therefore uninformative to study the hedge ratios of these funds. Instead, we look within the currency portfolio to study the determinants of the portfolio weight a fund i allocates to currency j in quarter t ($W_{i,j,t}$). To enable comparability across funds we standardize the notional currency forward positions by first calculating two values, the absolute sum of long forward positions and short forward positions. We then use the maximum of these two values to normalize the forward position in each currency and it is this normalized value that defines each currency’s portfolio weight. We treat the U.S. dollar as the balancing position, such that weights across all currencies, including the U.S. dollar, sum to zero.

We study the cross-sectional decision of funds to understand why particular currencies command higher positive or negative portfolio weights. The model we estimate takes the same functional form that we adopted when studying the hedge ratios of exposure managers:

$$W_{i,j,t} = \mathbf{b}'\mathbf{X}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t}, \quad (4)$$

where $\gamma_{i,t}$ reflects a fund \times quarter fixed effect, allowing us to study the determinants of portfolio weights within each fund-quarter. All determinants are lagged by one quarter and we again include an emerging market dummy variable (δ_{em}). Coefficient estimates and standard errors are presented in Table 5. We present results for each independent variable separately in

³⁰Future research should seek to better understand the underlying objective function of fund managers when using currency forwards and to assess whether learning takes place as fund managers adopt newly proposed methods for currency management in their daily practice.

columns (1) to (7), and include all variables in column (8).

Our first observation is that the weights in the underlying equity portfolio are statistically significantly associated with currency portfolio weights. An increase in the equity weight of 50% corresponds, on average, to around a 25% lower portfolio weight. The short (or funding) leg of the currency portfolio is therefore likely to include currencies held in the equity portfolio. At least two reasons may motivate this behaviour. First, by removing currency exposure, the fund may seek to reduce its overall level of return volatility stemming from existing exposures, before obtaining new exposure where risk-return trade-offs are more attractive. This practice is consistent with the conclusions of Pojarliev and Levich (2014) and Kroencke et al. (2014), that funds should hedge foreign exchange exposure from the underlying portfolio, before obtaining new currency exposure in a separate portfolio. Second, the largest underlying equity positions are often in developed market currencies that offer low interest rates, including the euro and Japanese yen. These currencies are known to generate lower currency excess returns, making short positions more attractive (Lustig et al., 2011). Moreover, these currencies also offer higher levels of liquidity, lowering the transaction costs associated with entering forward contracts.

The recent foreign exchange literature has identified various strategies that generate significant cross-sectional spreads in currency returns and impressive risk-return properties, such as carry, value, momentum, and liquidity.³¹ Portfolio builders may therefore seek exposure to these strategies when forming their currency portfolio, especially as these strategies are known to offer favourable diversification gains to equity market investors (Kroencke et al., 2014). We present evidence on the relationship between the signals underlying these strategies and the currency portfolio weights in columns (2) to (6).

In columns (2) to (4) we observe that momentum and carry are both positively related to portfolio weights—currencies with stronger exchange rate momentum or higher interest rates command higher portfolio weight. The effect for momentum is, however, economically modest. A 4% increase in the quarterly exchange rate return is associated with around a 1% higher weight in the currency portfolio. But we observe far larger effects for carry (column 3) and, especially, risk-adjusted carry (column 4). Currency value and liquidity, on the other hand, do

³¹Menkhoff et al. (2012) find that short-term exchange rate returns (i.e., momentum over one-to-three months) generate large cross-sectional spreads, especially for emerging market currencies. Lustig et al. (2011) show that high interest rate currencies earn higher excess returns, while more recent papers have shown these carry returns are often enhanced by risk-adjusting using exchange rate volatility (e.g., Dupuy, 2021; Maurer et al., 2023). Furthermore Asness et al. (2013) and Menkhoff et al. (2017) show that undervalued currencies—measured relative to a purchasing power parity based metric—tend to outperform overvalued currencies, while Mancini et al. (2013) find that less liquid currencies earn higher currency returns than highly liquid currencies.

not appear to be a major driver of the portfolio weights. This behaviour is broadly consistent with that observed for exposure managers, indicating that momentum, carry, and volatility are the primary considerations when entering forward contracts across the mutual fund industry.³²

As we observed for exposure managers, by gaining exposure to momentum and risk-adjusted carry, the mutual fund industry is showing indication of behaving in a way that is consistent with normative prescriptions. Once again, however, our ability to explain the choice of portfolio weights remains modest, suggesting a large idiosyncratic component to the decision. Moreover, the lack of exposure to known sources of currency return, including from currency value, is an early indication that the industry may have generated further gains from their currency portfolios with different choices. To better understand the magnitude of these potential gains, we investigate the underlying investment performance of funds' currency portfolios.

4.2.1 The investment performance of currency portfolios

In the top panel of Table 6, we present statistics on the investment performance of the funds' currency portfolios at the industry level. We find that the annualized Sharpe ratios and mean returns of the currency portfolios are only 0.08 and 0.99 on average, which are substantially below the levels documented by many recent studies that optimize the investment performance of currency portfolios, either by combining strategies (see, e.g. Jordà and Taylor, 2012; Asness et al., 2013; Kroencke et al., 2014), enhancing existing strategies (Bakshi and Panayotov, 2013), or mean-variance optimizing across individual currencies (Maurer et al., 2023). The range in the returns is, however, large. Indeed, the inter-quartile range stretches from an average currency portfolio loss of -1.05% per year, to an average gain of 2.88% , indicating substantial disparity in the investment performance across funds.

We investigate this disparity in performance and present results in the lower panel of Table 6. To do so, we begin by sorting funds into one of five groups (G1 to G5) according to the information ratio generated by their currency portfolio.³³ In keeping with the sorting procedure, we observe that currency portfolio returns and Sharpe ratios increase monotonically, when moving from G1 to G5. This improvement in the investment performance is driven entirely

³²The emerging market dummy variable is statistically significant in the full model but not when entering individually. This is because developed market currencies typically having larger absolute weights than emerging market currencies, which is not evident until controlling for country weights in the underlying equity portfolio.

³³To compute the information ratio, we construct a currency benchmark portfolio which invests in the three long/short portfolios on carry, value, and momentum with equal weights. A fund's information ratio is then calculated as the annualized average quarterly benchmark adjusted return divided by the annualized standard deviation of the benchmark adjusted return.

by rising returns—the portfolio standard deviations are similar across the groups. In fact, the Sharpe ratio of the G5 funds is high (0.73), and in line with some of the best performing currency strategies, including the currency carry trade. But the performance across other groups is much weaker. Indeed, the average Sharpe ratios are found to be negative across G1 to G3 portfolios, hinting towards a sub-optimal approach to the construction of currency portfolios. Moreover, we find the stronger performance among G5 funds is unrelated to the portfolio size: G1 and G5 funds have, on average, similar sized currency portfolios relative to the funds' TNA.

The evidence suggests that, while a pocket of funds construct currency portfolios with positive information ratios and substantial Sharpe ratios, the majority do not. As with exposure managers, we therefore choose to explore if there is evidence that the funds could have generated stronger investment performance for their entire portfolios through adopting alternative approaches when building currency portfolios. There are many potential alternative approaches, and therefore the evidence is indicative of the potential gains that remain available.

We consider three alternatives. First, we scale the existing currency portfolio to 20% of the underlying equity portfolio. This choice normalizes the currency size across groups and highlights the potential gains, particularly to G5 funds, from allocating a higher weight to their currency portfolio. Doing so, we see that the funds' would have enjoyed a 0.04 lift in their Sharpe ratio from the higher allocation to the currency portfolio, while for G1 funds, the Sharpe ratio would have fallen by 0.02 on average. The two other alternatives involve adding a currency portfolio that combines carry, value, and momentum with equal weights, and a DCF time series portfolio that takes long or short currency positions based on the sign of the expected currency returns.³⁴ We find that, relative to the actual fund performance, Sharpe ratios across all five groups are lower with the addition of the combo portfolio. This weaker performance reflects the general under-performance of currency investment strategies since the global financial crisis (Rinaldo and Somogyi, 2021) and highlights, in particular, the out-performance of G5 funds. However, as with exposure managers, we find that conditioning on exchange rate predictability through a DCF time series portfolio could have increased the Sharpe ratio across all five groups. Indeed, relative to their own currency portfolios, this increase ranges from 0.03 for G5 funds, through to a substantial 0.10 increase for G1 funds—highlighting the potential gains available.

In the final four rows of Table 6, we present the investment performance of the groups' equity

³⁴To implement these portfolios, we first remove the impact of currency forwards from actual fund returns and then allocate a weight of 80% to the adjusted fund returns and a weight of 20% to either the combo or DCF time series portfolio.

portfolios in *local* currencies, and therefore the performance prior to adjusting for exchange rate movements.³⁵ We do so to assess whether the apparent investor skill in currency selection is supported through the managers’ skill in their core investment activity. And looking across the five groups, we do observe a similar pattern: excess returns increase monotonically when moving from G1 to G5. Indeed, the G5 funds generate Sharpe ratios that are, on average, over 2.5 times higher than those generated by G1 funds.

One potential concern, however, is that G5 funds adopt benchmarks that outperformed during our sample period. To control for this possibility, we also report the benchmark-adjusted net returns and information ratios.³⁶ Once again, the investment performance increases across the groups. Benchmark adjusted returns increase from -0.31% per annum to 0.54% per annum, when moving from G1 to G5 funds, and information ratios increase from -0.18 to 0.09 . In sum, the apparent ability of some funds to form currency portfolios with strong investment performance is supported by the performance of their underlying stock picking ability, which also generates the strongest relative investment performance.

5 Non-user Funds

The decision to not use currency forward contracts is an active choice—the fund effectively decides to accept a particular form of returns—one that is driven, in part, by foreign exchange rate movements. In this section, we investigate how the investment performance of non-user funds could have been affected through the use of currency forwards. Our approach therefore builds on the earlier analysis of exposure managers and portfolio builders and serves to highlight the potential gains, rather than to champion a particular alternative method. To keep the analysis consistent, we again implement the DCF approach of Opie and Riddiough (2020) as part of a currency overlay strategy and as a separate currency portfolio. We complement this analysis by also comparing against a full currency hedge and by adding a combination currency

³⁵We estimate the local-currency return of fund i at time $t+1$ as $R_{i,t+1}^{local} = R_{i,t+1}^{with} - R_{i,t+1}^{for} - R_{i,t+1}^{cur}$. $R_{i,t+1}^{with}$ is the observed net return (with forwards) for fund i at time $t+1$. The total return on fund i ’s forward positions at time $t+1$ is calculated as $R_{i,t+1}^{for} = \sum_j (\widetilde{nf}_{i,j,t} \times ExR_{j,t+1}^{for})$, where $\widetilde{nf}_{i,j,t}$ is the net forward position in foreign currency j observed at time t normalised by the fund’s TNA at time t , and $ExR_{j,t+1}^{for}$ is the return on a long forward on foreign currency j at time $t+1$. The currency return on fund i ’s foreign equity positions at time $t+1$ is calculated as $R_{i,t+1}^{cur} = \sum_j w_{i,j,t}^{na} \times CuR_{i,j,t+1}$, where $CuR_{i,j,t+1}$ is the exchange rate return on foreign currency j at time $t+1$.

³⁶Morningstar classifies international funds into 17 categories based on funds’ portfolio holdings and assigns a composite equity index from MSCI as the benchmark for each fund category. We collect the daily local-currency net return of the 17 indices from Datastream and calculate the benchmark-adjusted net return for each fund in local currency. The information ratio in local currency is the average benchmark-adjusted return divided by the standard deviation of the benchmark-adjusted return.

portfolio that includes carry, value, and momentum signals.

To investigate the impact of currency forwards, we use the monthly currency weights reported by Morningstar for each fund, in combination with the fund’s total net assets. For example, if at the end of a month, a \$100 million fund held 5% of its assets in Japan, we would enter a hypothetical one-month forward contract to sell the equivalent of \$5 million of yen when overlaying with a full hedge and scale the position accordingly for other approaches.³⁷

We present the hypothetical performance in Table 7. In the top panel (2004 to 2019), we show the change relative to the actual fund performance across the full sample for both currency overlay and when adding a separate currency portfolio. Turning first to currency overlay, we find that the funds would have generated substantially stronger investment performance had they either fully hedged or adopted the dynamic hedging strategy. Average Sharpe ratio increases by 0.10 or more, stemming from both higher returns of between 60bps and 80bps per annum and lower portfolio volatility. Indeed, based on the certainty-equivalent return, risk-averse investors would be willing to forgo substantial return to switch to a hedged portfolio.³⁸ The addition of a separate currency portfolio is also seen to offer substantial diversification gains, as evidenced by the reduction in portfolio volatility. The weaker performance of the combination strategy, however, results in a slight decrease in the Sharpe ratio, whereas the DCF time series approach continues to enhance the investment performance.

A natural concern, however, is the short sample and that an unhedged portfolio will underperform during a period of U.S. dollar appreciation. To address this concern, we split the sample into two periods: 2004 to 2011 and 2012 to 2019. The first period reflects a period of U.S. dollar weakness, in which the U.S. dollar index (the DXY) fell from 87.4 to 80.2. From 2012 to 2019, the trend was reversed and the U.S. dollar index climbed back to 96.5. We report separate results for these two sub-periods in the lower panels of Table 7.

During the latter period, the fully hedged approach is clearly superior—returns are higher, volatility is substantially reduced, and the Sharpe ratio is economically and statistically higher than for the unhedged portfolio. DCF hedging also generates statistically significantly higher

³⁷To overlay with DCF hedging necessitates initially calculating a hedge ratio for each currency within the portfolio, which requires the estimation of fund-specific covariance matrix each month. We limit the hedge ratios to fall between 0 and 1 (inclusive), and thus funds can neither “over” hedge nor seek to gain additional exposure to a currency.

³⁸The certainty-equivalent return is calculated as $\mu - \frac{1}{2}\lambda\sigma$ where μ and σ are the mean and standard deviation of the excess return and λ is the investor risk aversion coefficient, which we set to 3. To calculate the statistical significance of each difference, we perform permutation tests with 1,000 resamples. In each resample, we randomly assign funds into hedged and unhedged groups under the null that there is no difference between the two groups. We then calculate the p -value based on the distribution of the test statistic.

average Sharpe ratios and certainty-equivalent returns but not to the same magnitude as the full hedge. In contrast, between 2004 and 2011 the full hedge led to significantly lower average excess returns that were not offset by a reduction in portfolio volatility. Thus, during this earlier period the full hedge was the worst performing method. DCF hedging, however, continued to deliver stronger performance, as measured by the Sharpe ratio and certainty-equivalent return, than the unhedged approach.

For the separate currency portfolios, we observe a significant reduction in volatility under both alternative approaches during the two sub-periods due to the lower volatility of the currency portfolios relative to funds' equity portfolios. However, adding the combination portfolio also generated lower average excess returns relative to not using currency forwards, hence resulting in significantly lower average Sharpe ratios over all three time periods. In contrast, adding the DCF time series portfolio proves to be beneficial, generating significantly higher average Sharpe ratio and certainty-equivalent returns. Although this approach generated lower average excess return between 2012 and 2019, this reduction is more than offset by the fall in volatility, and hence the average Sharpe ratio is consistently higher relative to not using currency forwards.

In sum, fully hedging currency exposure is, just like no hedging, an extreme. In periods of dollar appreciation the approach provides a high benchmark. But during dollar weakness, it is likely to offer some of the weakest performance. This finding echoes the starting point for this study. The recent normative literature on currency management has stressed the need to move beyond the extremes of either fully hedging or not hedging currency exposure. We highlight one potential middle ground, that employs the predictability of currency excess returns, identified in recent years, as part of either a currency overlay or separate currency portfolio. The evidence indicates that non-user funds may have investment opportunities available to them through exploiting these recent advances in the international finance literature, that would offer gains across periods of both U.S. dollar weakness and strength.

6 Conclusions

U.S. investors are increasingly diversifying their wealth in international equity markets. One of the main avenues for investing in foreign equities is via internationally focused equity mutual funds, which today have almost \$3 trillion assets under management. When funds are invested in international equities, the portfolio is inherently exposed to foreign exchange movements,

which introduces a new source of risk and return that is known to be of critical importance to a portfolio's overall investment performance. How currency is managed can therefore have a material impact on investors' lifetime wealth creation.

This paper seeks to understand the behavior of these fund managers by undertaking the first comprehensive study on currency management at U.S. international equity mutual funds. We find that among the funds using currency forwards, there are two primary styles of currency management based on currency overlay (exposure managers) and, more commonly, the construction of a separate currency portfolio (portfolio builders). Exposure managers use forwards to reduce foreign exchange exposure—either in an effort to increase returns or reduce volatility, whereas portfolio builders construct a separate currency portfolio, frequently in currencies not held within the underlying equity portfolio.

At the industry level, the use of currency forwards is found to have a limited impact on fund performance—the investment performance of users and non-users is essentially the same. But we find the industry averages mask important pockets of out-performance within the industry, both within the group of exposure managers and portfolio builders. Overall, however, our evidence points towards a sub-optimal use of currency forwards across the mutual fund industry as a whole. Users and non-users could both enhance their investment performance by dynamically exploiting the return predictability known to exist in foreign exchange markets.

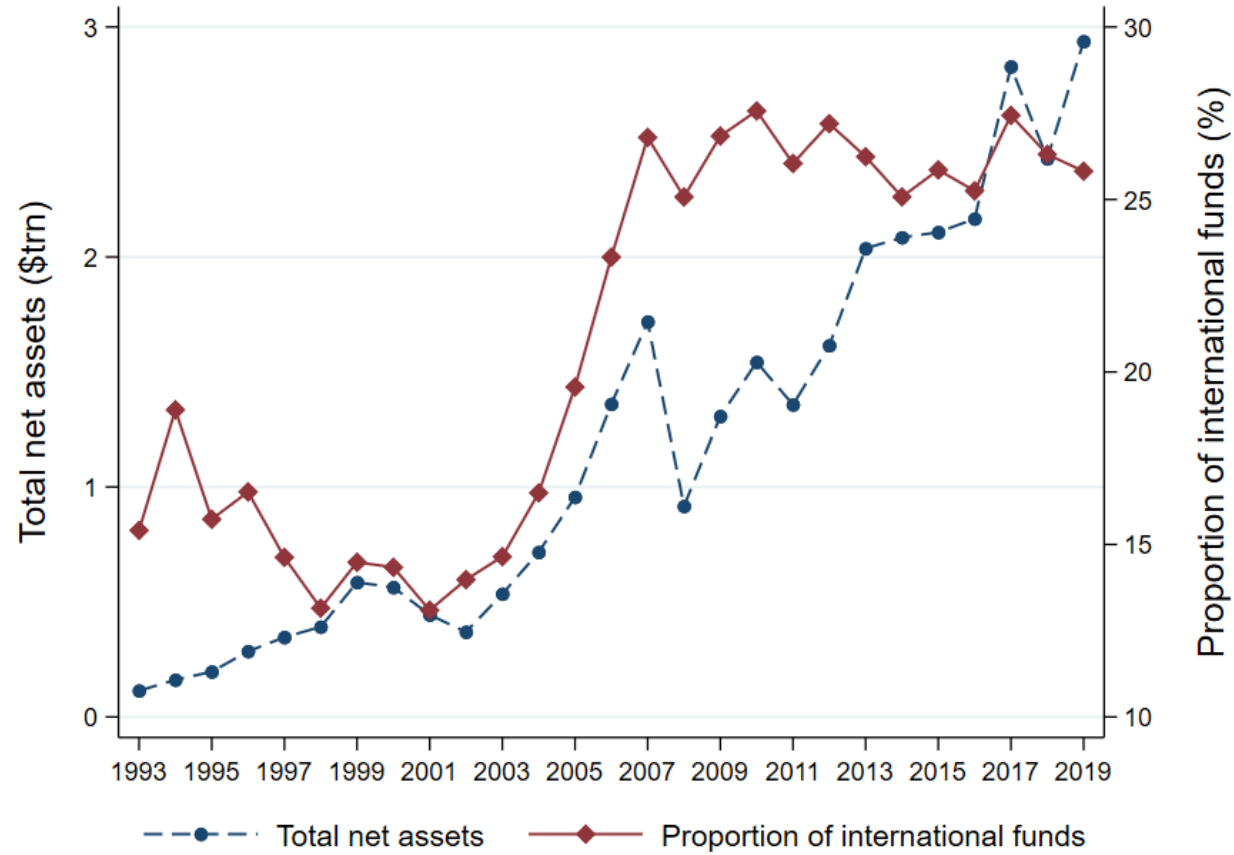
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Figure 1: The Growth of U.S. International Equity Mutual Funds



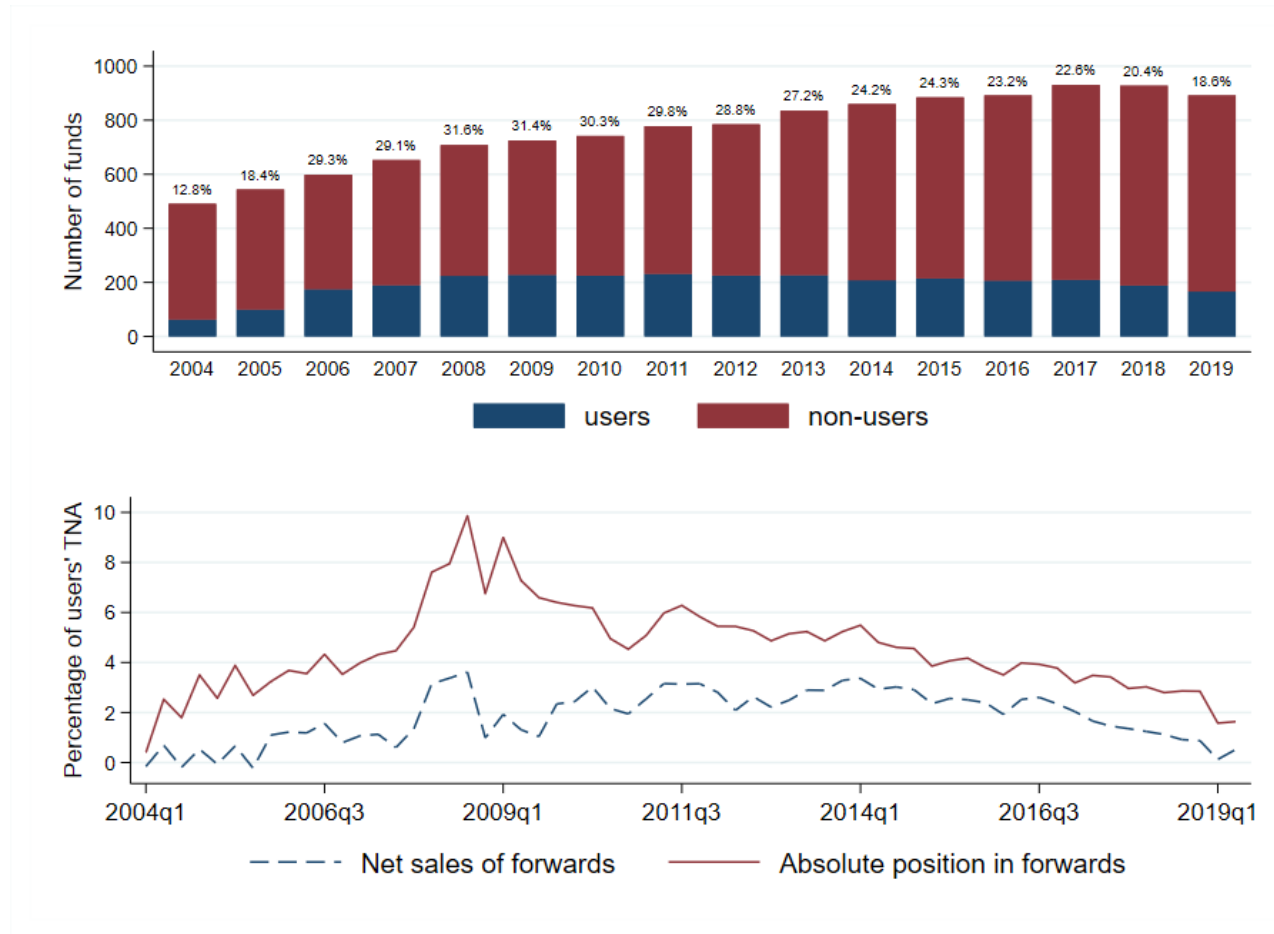
The figure presents the total net assets (in \$trillions) of U.S.-domiciled equity mutual funds as well as the proportion of the assets managed by international equity funds. Data source: Investment Company Institute (ICI) Fact Book.

Figure 2: Extract of Currency Forward Positions for AB International Value Fund

Counterparty	Contracts to Deliver (000)	In Exchange For (000)	Settlement Date	Unrealized Appreciation/ (Depreciation)
HSBC Bank USA	USD 2,502	SGD 3,374	6/17/19	\$ (45,882)
HSBC Bank USA	USD 1,855	CNY 12,537	7/25/19	(43,495)
JPMorgan Chase Bank, NA	GBP 1,077	USD 1,426	6/17/19	63,026
JPMorgan Chase Bank, NA	NOK 16,984	USD 1,958	6/17/19	16,768
JPMorgan Chase Bank, NA	USD 560	GBP 434	6/17/19	(11,226)
JPMorgan Chase Bank, NA	USD 555	JPY 61,169	6/17/19	9,925
Morgan Stanley & Co., Inc.	BRL 9,378	USD 2,371	6/04/19	(19,146)
Morgan Stanley & Co., Inc.	USD 2,340	BRL 9,378	6/04/19	49,481
Morgan Stanley & Co., Inc.	EUR 1,826	USD 2,068	6/17/19	25,835
Morgan Stanley & Co., Inc.	JPY 164,617	USD 1,490	6/17/19	(30,929)
Morgan Stanley & Co., Inc.	USD 939	EUR 831	6/17/19	(9,737)
Morgan Stanley & Co., Inc.	USD 519	JPY 57,540	6/17/19	12,657
Morgan Stanley & Co., Inc.	BRL 7,846	USD 1,949	7/02/19	(45,583)
Morgan Stanley & Co., Inc.	KRW 780,901	USD 658	8/26/19	(737)
Morgan Stanley & Co., Inc.	USD 222	KRW 262,398	8/26/19	(512)
Natwest Markets PLC	USD 935	EUR 817	6/17/19	(20,541)
Natwest Markets PLC	USD 952	CLP 663,798	7/12/19	(17,122)
Natwest Markets PLC	EUR 725	USD 818	9/13/19	1,600
Standard Chartered Bank	BRL 3,528	USD 893	6/04/19	(5,817)
Standard Chartered Bank	USD 895	BRL 3,528	6/04/19	3,822

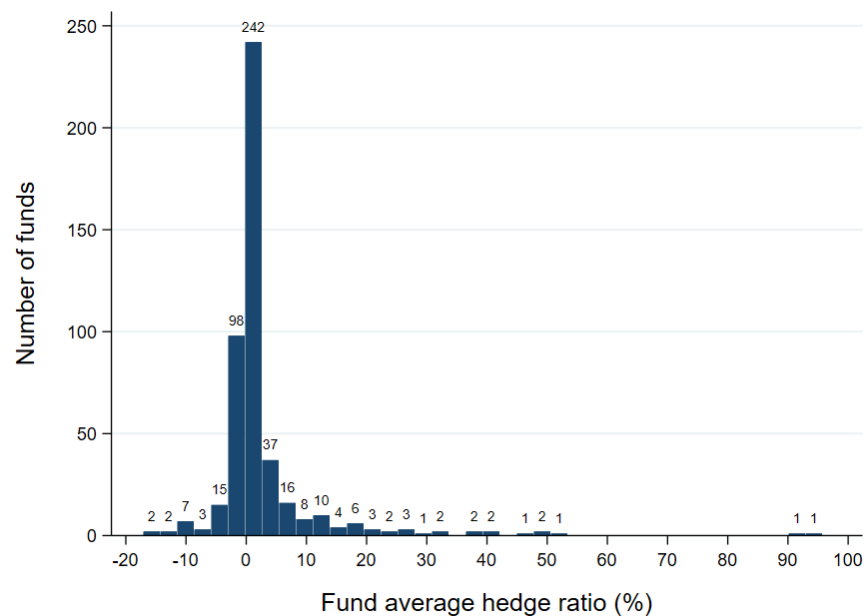
The figure presents an extract of the foreign currency forward contracts held by AB International Value Fund as of May 2019. The extract displays the dealer name (counterparty), the amount and currency the fund has contracted to deliver (Contracts to Deliver), the amount and currency the fund has contracted to receive (In Exchange For), the settlement date, and the current U.S. dollar gain or loss on the contract (Unrealized Appreciation/(Depreciation)).

Figure 3: The Time Series of Currency Forward Usage

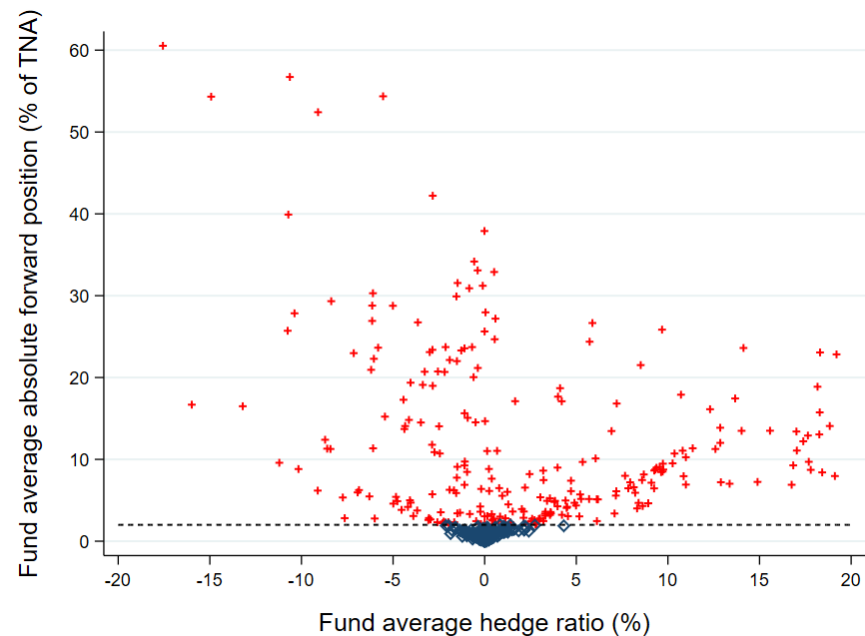


The top graph presents the total number of funds in the sample each year, split between funds that used currency forward contracts during the year (users) and those which did not use currency forward contracts (non-users). The bottom graph presents two time series: (i) the total notional amount of currency forward contracts (expressed as the net short position) relative to the funds' total TNA (dashed blue line) and (ii) the total absolute position in forwards, which sums the absolute notional values of both short and long currency forward contracts vis-a-vis the U.S. dollar, relative to the funds' total TNA (red line). The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure 4: Hedge Ratios and Absolute Currency Forward Positions



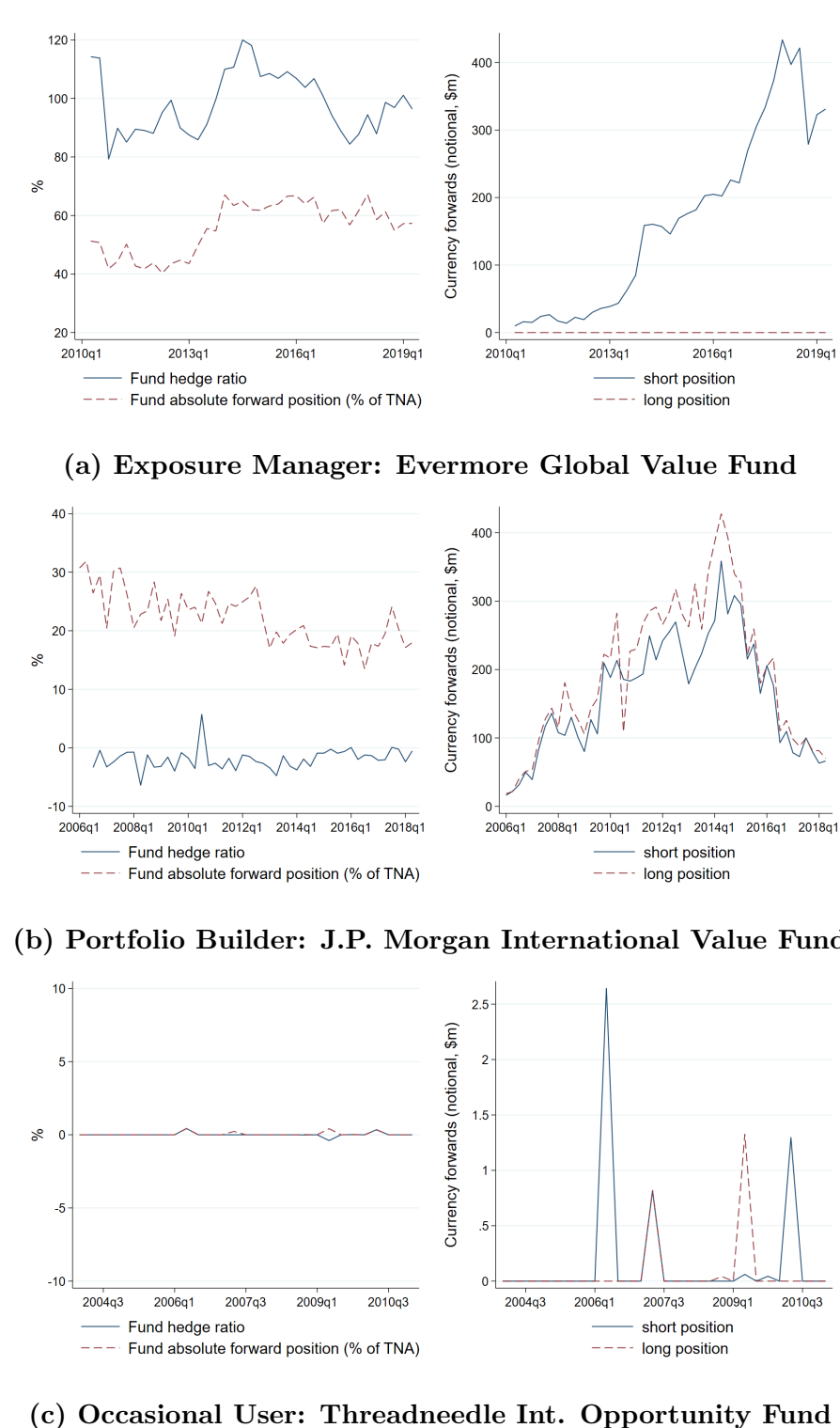
(a)



(b)

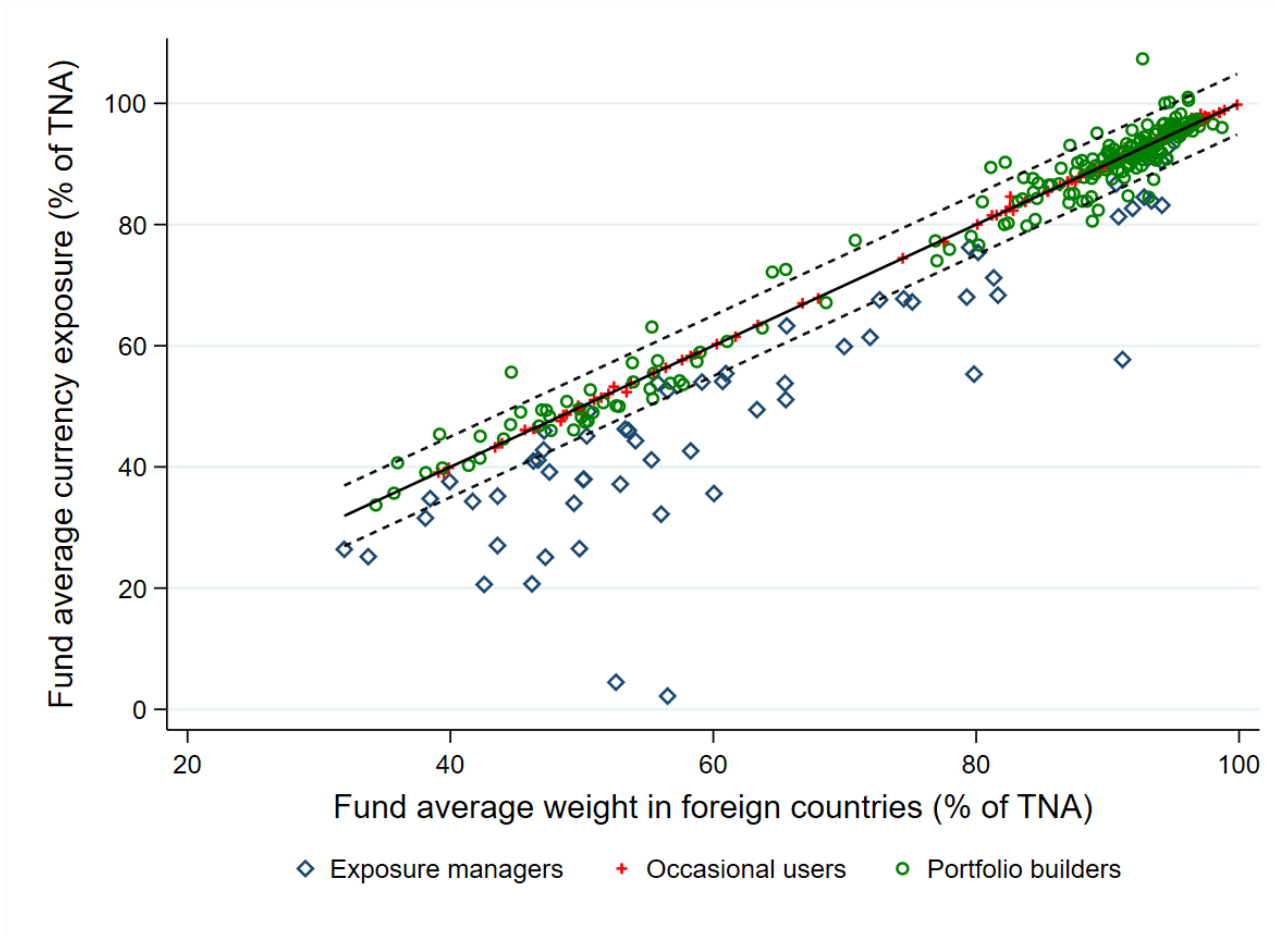
The left-hand graph presents the histogram of average hedge ratios across funds that used currency forward contracts. The right-hand graph presents a scatter plot of funds' average absolute forward positions (y -axis) against their average hedge ratios (x -axis), calculated over the quarters in which the funds held outstanding forward contracts. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure 5: Examples of Currency Management Styles



The figure presents the time series of hedge ratios and the total notional dollar values (\$million) of long and short currency forward contracts for three funds: Evermore Global Value Fund (top graph, the “Exposure Manager”); J.P. Morgan International Value Fund (middle graph, the “Portfolio Builder”); and Threadneedle International Opportunity Fund (bottom graph, the “Occasional User”). The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure 6: Currency Exposure Across Currency Management Styles



The figure presents a scatter plot of funds' average weight in foreign countries (x-axis) plotted against their average currency exposure (y-axis). The plot includes a 45-degree solid line with dashed-lines indicating a (+/-) 5% boundary. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure 7: The Use of G10 Currency Forwards by Exposure Managers and Portfolio Builders



38

The left-hand graph presents a heat plot showing the average abnormal hedge ratios for G10 currencies (the difference between the hedge ratio for the currency and the average hedge ratio for the fund) across the group of exposure managers. The currencies are ordered from the highest to the lowest average abnormal hedge ratios. The size of each square reflects the number of contracts entered by exposure managers. The right-hand graph presents the average portfolio weights for G10 currencies across the group of portfolio builders. The currencies are ordered from highest to lowest average portfolio weights (i.e., from investment currencies to funding currencies). The size of each square reflects the number of contracts entered by portfolio builders. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 1: The Characteristics of User and Non-User Funds

	Users (471 Funds)			Non-Users (808 Funds)			Difference	
	Obs	Mean	Std	Obs	Mean	Std	U-NU	<i>p</i> -val
<i>Fund Characteristics</i>								
<i>Portfolio weight outside U.S. (%)</i>	17,188	82.2	18.9	23,786	83.0	19.2	-0.82	0.65
<i>Portfolio weight in G9 (%)</i>	17,188	54.1	30.6	23,786	47.0	33.2	7.20	0.00
<i>No. countries invested</i>	17,188	16.8	6.95	23,786	16.0	7.46	0.78	0.00
<i>Fund turnover ratio (annual, %)</i>	17,517	70.4	53.8	22,610	55.2	48.1	15.2	0.00
<i>Fund expense ratio (annual %)</i>	17,573	1.25	0.46	22,749	1.19	0.49	0.07	0.03
<i>Fund age (years)</i>	19,107	12.6	8.52	25,594	10.2	8.28	2.39	0.00
<i>Fund TNA (\$ millions)</i>	18,320	2,096	10,097	24,473	1,192	3,007	904	0.00
<i>Family TNA (\$ millions)</i>	18,901	18,177	51,104	25,228	24,443	44,703	-6,266	0.05
<i>Investment Performance</i>								
<i>Net return (%)</i>	18,495	1.85	9.42	24,522	1.93	9.31	-0.07	0.79
<i>Stdev net return (%)</i>	17,494	7.66	3.82	22,863	7.62	3.81	0.04	0.13
<i>Benchmark adj return (%)</i>	18,250	-0.06	2.62	24,207	0.02	2.66	-0.08	0.39
<i>Tracking error (%)</i>	17,243	2.20	1.28	22,570	2.26	1.35	-0.06	0.06

The table presents summary statistics for the international equity mutual funds in the sample. For each fund characteristic, we present the number of fund-quarter observations (Obs), the average (Mean), and the standard deviation (Std). The statistics are split across funds that use currency forward contracts during the sample (Users) and those which do not (Non-Users). The difference between the average fund characteristics for user and non-user funds is calculated and presented in the column headed U-NU. Each *p*-value is calculated using a permutation test with 1000 resamples. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 2: The Use of Currency Forward Contracts Across Currency Management Styles

	Exposure Managers (66 Funds)		Portfolio Builders (202 Funds)		Occasional Users (203 Funds)	
	Mean	Std	Mean	Std	Mean	Std
<i>Fund quarters using currency forwards (%)</i>	67.5	27.8	59.8	27.1	33.3	28.2
<i>Average number of currencies with forward contracts</i>	4.8	4.3	6.6	5.3	2.9	2.1
<i>Ratio of forward currencies to equity currencies (%)</i>	34.2	22.6	37.9	31.2	18.1	12.6
<i>Average fund hedge ratio (%)</i>	27.7	19.6	0.1	6.4	-0.1	2.6
<i>Average absolute value of fund forwards as % of TNA</i>	18.7	12.1	12.4	11.8	1.5	3.0
<i>No. of net forward positions</i>	7,963		37,564		10,088	
<i>No. of net long forward positions</i>	1,147		19,730		6,106	
<i>No. of no underlying positions (NUP)</i>	300		4,274		193	

The table presents summary statistics on the use of currency forward contracts across exposure managers, portfolio builders, and occasional users. The total number of funds in each group is shown in parentheses. For each characteristic, we present the average (Mean) and standard deviation (Std) across funds. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 3: The Determinants of Hedge Ratios Among Exposure Managers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Country weight</i>	0.816*** (0.082)								0.701*** (0.082)
<i>Momentum</i>		-0.084** (0.037)							-0.139*** (0.037)
<i>Carry</i>			-0.729*** (0.117)						-0.378*** (0.125)
<i>Value</i>				0.068*** (0.025)					-0.018 (0.024)
<i>Bid-ask spread</i>					-0.061*** (0.022)				0.023 (0.019)
<i>Volatility</i>						0.428*** (0.099)			0.472*** (0.107)
<i>Equity return</i>							-0.012 (0.021)		-0.001 (0.021)
<i>EM dummy</i>								-8.489*** (1.102)	-4.637*** (1.243)
Observations	27,527	28,524	28,412	28,524	28,413	28,524	28,524	28,525	27,425
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.303	0.267	0.273	0.268	0.268	0.271	0.267	0.286	0.315

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is the hedge ratio of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, the 12-month currency return volatility, the MSCI equity index return for country j , and a dummy variable equal to 1 if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 4: The Hedging Behaviour of Exposure Managers

Hedging Style: CS variation in hedge ratios:	Passive		Active	
	Low	High	Low	High
<i>Number of funds</i>	14	13	16	15
<i>Hedge ratio volatility (ts)</i>	9.1	9.7	22.7	25.4
<i>Hedge ratio volatility (cs)</i>	12.1	32.7	8.8	33.1
<i>Excess return (%)</i>	4.93	5.23	5.42	4.87
<i>Sharpe ratio</i>	0.37	0.43	0.35	0.40
Unhedged portfolio (relative to actual performance)				
<i>Excess return</i>	-0.19**	-0.08	-0.34***	-0.15
<i>Sharpe ratio</i>	-0.02**	-0.01	-0.03***	-0.03***
<i>Avg % correct hedge ratio timing</i>	50.2	49.0	53.3	52.8
DCF hedged portfolio (relative to actual performance)				
<i>Excess return</i>	0.60***	0.74***	0.58***	0.36**
<i>Sharpe ratio</i>	0.08***	0.12***	0.06***	0.06**

The table presents statistics on the hedging behavior of exposure managers, split into four groups based on the volatility of their hedge ratios. Hedge ratio volatility (*ts*) is the time-series standard deviation of the fund’s hedge ratio (measured across all currencies hedged). Hedge ratio volatility (*cs*) is the average cross-sectional standard deviation of hedge ratios (i.e., the within fund standard deviation each quarter) measured across hedged currencies. Funds are initially split based on their hedge ratio volatility (*ts*) into two groups: low (“Passive”) and high (“Active”). Within those groups, the funds are again split based on their hedge ratio volatility (*cs*). Avg % correct hedge ratio timing indicates the percentage of times a change in a currency hedge ratio in one quarter resulted in a positive return on the forward over the following quarter. DCF hedged portfolio uses the Dynamic Factor Hedging approach in Opie and Riddiough (2020). The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 5: The Determinants of Portfolio Weights Among Portfolio Builders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Country weight</i>	-0.498*** (0.069)							-0.532*** (0.071)
<i>Momentum</i>		0.236*** (0.034)						0.256*** (0.037)
<i>Carry</i>			0.240*** (0.093)					0.162 (0.137)
<i>Volatility adjusted carry</i>				2.321*** (0.840)				3.805*** (1.179)
<i>Value</i>					-0.024 (0.026)			0.038 (0.026)
<i>Bid-ask spread</i>						0.009 (0.015)		-0.014 (0.0211)
<i>EM dummy</i>							-1.037 (1.075)	-5.066*** (1.172)
Observations	32,923	36,411	36,211	36,208	35,944	36,211	36,411	32,864
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.146	0.120	0.119	0.119	0.118	0.118	0.119	0.152

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is the currency portfolio weight of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the forward discount adjusted by the prior three months' volatility of the exchange rate (*Volatility adjusted carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, and a dummy variable equal to $\mathbf{1}$ if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 6: The Investment Performance of Portfolio Builders

	SR	Mean	Median	p25	p75
<i>All portfolio builders</i>	0.08	0.99	0.85	-1.05	2.88
	G1	G2	G3	G4	G5
	<i>Currency Portfolios (Actual)</i>				
<i>Information ratio</i>	-0.75	-0.17	0.01	0.23	0.68
<i>Portfolio return (%)</i>	-3.90	-0.61	0.79	2.71	6.10
<i>Stdev portfolio return (%)</i>	7.69	7.05	7.54	7.75	8.39
<i>Sharpe ratio</i>	-0.62	-0.14	-0.10	0.35	0.73
<i>Portfolio size (% of TNA)</i>	7.83	17.4	13.8	14.3	7.78
<i>The impact of increasing the currency portfolio size on the overall fund performance</i>					
Δ <i>Sharpe ratio using own currency portfolio</i>	-0.02***	-0.01***	-0.01	0.01	0.04***
Δ <i>Sharpe ratio using currency combo</i>	-0.01	-0.02***	-0.02***	-0.03***	-0.04***
Δ <i>Sharpe ratio using DCF time series</i>	0.08***	0.07***	0.07***	0.06***	0.07***
	<i>International Equity Portfolio</i>				
<i>Excess return in local currencies (%)</i>	3.08	3.89	4.13	5.15	7.06
<i>Sharpe ratio in local currencies</i>	0.24	0.37	0.34	0.36	0.61
<i>Benchmark adjusted net return in local currencies (%)</i>	-0.31	-0.34	-0.36	0.72	0.54
<i>Inf. ratio of benchmark adj. return in local currencies</i>	-0.18	-0.11	-0.07	0.09	0.09

44

The table presents statistics on the investment performance of portfolio builders. The first row presents aggregate summary statistics across all portfolio builders pertaining to their currency-specific portfolio of currency forward contracts. The values include the average Sharpe ratio (**SR**), mean, median, 25th and 75th percentiles of the return distribution. In the lower panel, funds are split into five equally sized groups based on their sample currency portfolio information ratio from low (G1) to high (G5). Investment performance is presented for the five groups for their currency portfolio and international equity portfolio (excluding all currency considerations). Performance gain relative to the fund's actual performance is reported when combining funds' equity portfolio with a separate currency portfolio with weights of 80%/20%. The currency combo portfolio is an equally weighted portfolio of carry, value, and momentum long/short portfolios constructed using G10 currencies, and the DCF time series portfolio is constructed following the approach in Opie and Riddiough (2020). Significance of Δ *Sharpe ratio* at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table 7: The Potential Performance Gains from Using Currency Forwards

	Currency Overlay		Currency Portfolio	
	Full	DCF	Combo	DCF
	<i>2004 to 2019</i>			
<i>Mean excess return (%)</i>	0.60***	0.79***	-1.35***	-0.24***
<i>Std excess return (%)</i>	-2.56***	-1.63***	-3.16***	-3.46***
<i>Sharpe ratio</i>	0.14***	0.10***	-0.03***	0.06***
<i>Certainty-equivalent return</i>	1.73***	1.54***	0.29***	1.53***
	<i>2004 to 2011</i>			
<i>Mean excess return (%)</i>	-2.81***	0.08	-1.17***	0.79***
<i>Std excess return (%)</i>	-4.46***	-2.15***	-4.57***	-4.86***
<i>Sharpe ratio</i>	-0.05***	0.04***	-0.02***	0.08***
<i>Certainty-equivalent return</i>	-0.06	1.52***	2.06***	4.21***
	<i>2012 to 2019</i>			
<i>Mean excess return (%)</i>	1.42***	1.00***	-1.48***	-0.67***
<i>Std excess return (%)</i>	-2.13***	-1.53***	-2.42***	-2.72***
<i>Sharpe ratio</i>	0.21***	0.13***	-0.03***	0.06***
<i>Certainty-equivalent return</i>	2.24***	1.61***	-0.52***	0.38***

The table presents the portfolio performance gains from various approaches to currency management for non-user funds. The full sample includes 800 funds that have at least 12 monthly returns. The second and third columns present performance gain from implementing a 100% full hedge and a Dynamic Currency Factor (DCF) hedge via a currency overlay. The last two columns present performance gain from combining funds' equity portfolio and a separate currency portfolio in the weights of 80%/20%. The currency combo portfolio is an equally weighted portfolio of carry, value, and momentum long/short portfolios constructed using G10 currencies. The DCF time series portfolio and the DCF hedge are implemented following the procedure in Opie and Riddiough (2020). Significance of the performance difference at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Results for the full sample are reported in Panel A. Results for two sub-samples are presented in Panel B (Q1 2004 to Q4 2011) and Panel C (Q1 2012 to Q2 2019). Further details on the funds and data sources can be found in Section 2.

Online Appendix

On the Use of Currency Forwards: Evidence from International Equity Mutual Funds

Not for publication

Contents

SECTION A: Further Tables and Analysis

Table A.1: Variable Definitions

A list of variables used in the empirical analysis and their descriptions.

Table A.2: Currency Forward Usage by Currency and Management Style

Statistics on the currency forward contracts in the sample.

Figure A.1: Example statements on currency forward usage from fund reports

Extracts from fund prospectuses.

Figure A.2: The Split Between Active and Index Equity Mutual Funds

Pie charts showing the breakdown in currency hedging styles across active and index U.S. equity mutual funds.

Figure A.3: The Split Between Types of International Equity Mutual Funds.

Pie charts showing the breakdown in currency hedging styles across foreign funds, world funds, emerging market funds, and regional funds.

Figure A.4: Currency Exposure

Reproduction of Figure 6 differentiating by the type of fund.

SECTION B: Alternative Categorization Schemes

Description of the alternative categorization schemes.

Table B.1: Currency Management Styles.

Replicating the top panel of Table 2 using the alternative categorization schemes.

Table B.2: The Determinants of Exposure Managers' Hedge Ratios

Replicating the results in Table 3 using the alternative categorization schemes.

Table B.3: The Determinants of Portfolio Builders' Portfolio Weights

Replicating the results in Table 5 using the alternative categorization schemes.

Table B.4: The Determinants of Occasional Users Hedge Ratios

Replicating the results in Table 3 using the alternative categorization schemes for occasional users.

Table B.5: The Determinants of Occasional Users Portfolio Weights

Replicating the results in Table 5 using the alternative categorization schemes for occasional users.

SECTION C: Data Appendix

Description of how the dataset was constructed.

Table A.1: Variable Definitions

Variable	Description
Portfolio weight outside U.S. (%)	Sum of non-U.S. country weights from Morningstar.
Portfolio weight in G9 (%)	Sum of country weights in countries with G9 currencies.
No. of countries invested in	No. of unique foreign currencies that a fund's investments are denominated in. Morningstar has weights for 47 unique countries (including the U.S.) plus "other countries". We count Eurozone countries as one country in this calculation.
Net Return (%)	Quarterly fund return net of fees and expenses.
Std. Net Return (%)	Standard deviation of monthly net returns over a 12-month period scaled to quarterly.
Benchmark adj. return (%)	Net return minus the return on the benchmark index specified in fund prospectus. We report quarterly return in Tables 1 and 2, and annualized return in Tables 6 and 8.
Tracking error (%)	Standard deviation of monthly benchmark-adjusted returns over a rolling 12-month period. Values are quarterly in Tables 1 and 2. Table 8 reports the annualized standard deviation of monthly benchmark-adjusted returns calculated over the entire sample.
Fund Flow (%)	Fund flow equals $\frac{AUM_t - AUM_{t-1} \times (1 + \text{GrossReturn}_{t-1})}{AUM_{t-1}}$, where <i>GrossReturn</i> is the quarterly net return plus 1/4 of the annual expense ratio.
Fund turnover ratio (% annual)	Minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund as reported by CRSP.
Fund expense ratio (% annual)	Ratio of total investment that shareholders pay for the fund's operating expenses as reported by CRSP
Fund age (Years)	Fund age in years calculated using the earliest inception date of all share classes of a fund.
Fund TNA	Total asset under management of a fund at quarter end.
Family TNA	Total asset under management of a fund family at quarter end.

Fund forwards as % of TNA	Total net forward currency positions in USD as a percentage of TNA.
Absolute value of fund forwards as % of TNA	Total absolute value of forward positions in USD as a percentage of TNA.
Fund hedge ratio (%)	Total net forward currency sale positions as a percentage of total investment in foreign currencies.
Fund exposure as % of TNA	Country weights in foreign currencies as a percentage of TNA minus forward hedge positions as a percentage of TNA.
Volatility (%)	Realised volatility for a currency constructed as the square root of the sum of squares of daily log changes in the exchange rate against the USD over a year.
Country weight (%)	Proportion of a fund's TNA invested in a country.
Momentum (%)	Rate of change in the value of a foreign currency from a U.S. perspective.
Carry (%)	The annualized forward discount calculated as the difference between the log of spot and forward exchange rates.
Volatility adjusted carry	Carry divided by annualised currency realised volatility.
Value (%)	Deviation from the real exchange rate as constructed by Asness et al. (2013). It is the negative of the 5-year return on the exchange rate from 4.5 to 5.5 years ago divided by the spot exchange rate today minus the log difference in the change in consumer price index (CPI) in the foreign country relative to the U.S. over the same period.
Bid-ask spread (%)	The difference between the bid- and ask- price of a foreign currency (in USD) divided by the mid-price.
Equity return (%)	Quarterly return on MSCI country indices in local currencies.
EM dummy	Dummy variable =1 for currencies of economies classified as emerging by MSCI.
CEQ return (%)	Mean (excess return)-1/2 investor risk aversion coefficient \times Variance (excess return).

Foreign fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: “U.S. Fund Foreign Large Value,” “U.S. Fund Foreign Large Blend,” “U.S. Fund Foreign Large Growth,” “U.S. Fund Foreign Small/Mid Value,” “U.S. Fund Foreign Small/Mid Blend,” and “U.S. Fund Foreign Small/Mid Growth.”
World fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: “U.S. Fund World Large Stock” and “U.S. Fund World Small/Mid Stock.”
Emerging market fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: “U.S. Fund Diversified Emerging Mkts,” “U.S. Fund Latin America Stock,” “U.S. Fund China Region,” and “U.S. Fund India Equity.”
Regional fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: “U.S. Fund Diversified Pacific/Asia,” “U.S. Fund Europe Stock,” “U.S. Fund Pacific/Asia ex-Japan Stock,” “U.S. Fund Japan Stock,” and “U.S. Fund Miscellaneous Region.”
Index fund	Dummy variable = 1 if a fund is an index fund.

Table A.2: Currency Forward Usage by Currency and Management Style

Currency	Total	Exposure Managers		Portfolio Builders		Occasional Users	
	Positions	Positions	NUP	Positions	NUP	Positions	NUP
EUR	6,279	1,181	20	3,746	95	1,352	16
JPY	5,914	1,004	2	3,531	75	1,379	2
GBP	5,378	939	4	3,214	11	1,225	10
AUD	4,177	547	39	2,701	254	929	13
CHF	3,785	757	7	2,444	86	584	0
CAD	2,846	498	14	1,980	158	368	15
SEK	2,792	346	18	2,009	267	437	5
HKD	2,775	235	18	1,777	110	763	43
NOK	2,392	346	32	1,788	376	258	10
SGD	2,265	307	13	1,586	412	372	16
DKK	1,586	253	7	1,107	325	226	11
KRW	1,376	259	24	943	53	174	0
ZAR	1,358	120	9	849	126	389	2
BRL	1,173	148	3	799	39	226	1
MXN	1,156	138	9	805	136	213	4
NZD	1,080	143	36	885	397	52	6
ILS	939	93	9	772	321	74	1
TWD	757	85	1	581	52	91	0
INR	751	81	5	559	50	111	3
TRY	727	57	1	526	57	144	4
CNY	617	124	6	488	9	5	0
PLN	617	24	17	514	124	79	2
THB	585	26	3	432	39	127	3
IDR	570	43	1	423	70	104	4
MYR	561	66	1	401	117	94	5
HUF	467	23	0	364	38	80	4
CZK	465	0	0	397	91	68	1
RUB	463	56	0	385	68	22	0
PHP	461	21	1	388	61	52	2
CLP	319	20	0	276	128	23	4
COP	229	0	0	224	74	5	3
PEN	192	0	0	189	49	3	1
Other	563	23	0	481	6	1	0
Total	55,615	7,963	300	37,564	4,274	10,088	193

The table presents statistics on the currency forward contracts in the sample. The second column reports the total number of net forward contracts against the USD (i.e., if a fund had multiple outstanding forward contracts on the same foreign currency at quarter-end, they are netted and recorded as a single contract). The remaining columns present the number of net forward contracts (Positions) and the number of net contracts without underlying equity positions (NUP). The data are quarterly, beginning in Q1 2004 and ending in Q2 2019.

Figure A.1: Funds' Stated Use of Currency Forward Contracts

1. Derivative Financial Instruments

The Fund may use derivatives in an effort to earn income and enhance returns, to replace more traditional direct investments, to obtain exposure to otherwise inaccessible markets (collectively, "investment purposes"), or to hedge or adjust the risk profile of its portfolio.

The principal type of derivative utilized by the Fund, as well as the methods in which they may be used are:

- **Forward Currency Exchange Contracts**

The Fund may enter into forward currency exchange contracts in order to hedge its exposure to changes in foreign currency exchange rates on its foreign portfolio holdings, to hedge certain firm purchase and sale commitments denominated in foreign currencies and for non-hedging purposes as a means of making direct investments in foreign currencies, as described below under "Currency Transactions".

A forward currency exchange contract is a commitment to purchase or sell a foreign currency at a future date at a negotiated forward rate. The gain or loss arising from the difference between the original contract and the closing of such contract would be included in net realized gain or loss on forward currency exchange contracts. Fluctuations in the value of open forward currency exchange contracts are recorded for financial reporting purposes as unrealized appreciation and/or depreciation by the Fund. Risks may arise from the potential inability of a counterparty to meet the terms of a contract and from unanticipated movements in the value of a foreign currency relative to the U.S. dollar.

(a) AB International Value Fund

The Fund may enter into forward foreign currency exchange contracts, which are a type of derivative. A forward foreign currency exchange contract is an agreement to buy or sell a country's currency at a specific price on a specific date, usually 30, 60, or 90 days in the future. In other words, the contract guarantees an exchange rate on a given date. Managers of funds that invest in foreign securities can use these contracts to guard against unfavorable changes in currency exchange rates. These contracts, however, would not prevent the Fund's securities from falling in value during foreign market downswings. Note that the Fund will not enter into such contracts for speculative purposes. Under normal circumstances, the Fund will not commit more than 20% of its assets to forward foreign currency exchange contracts.

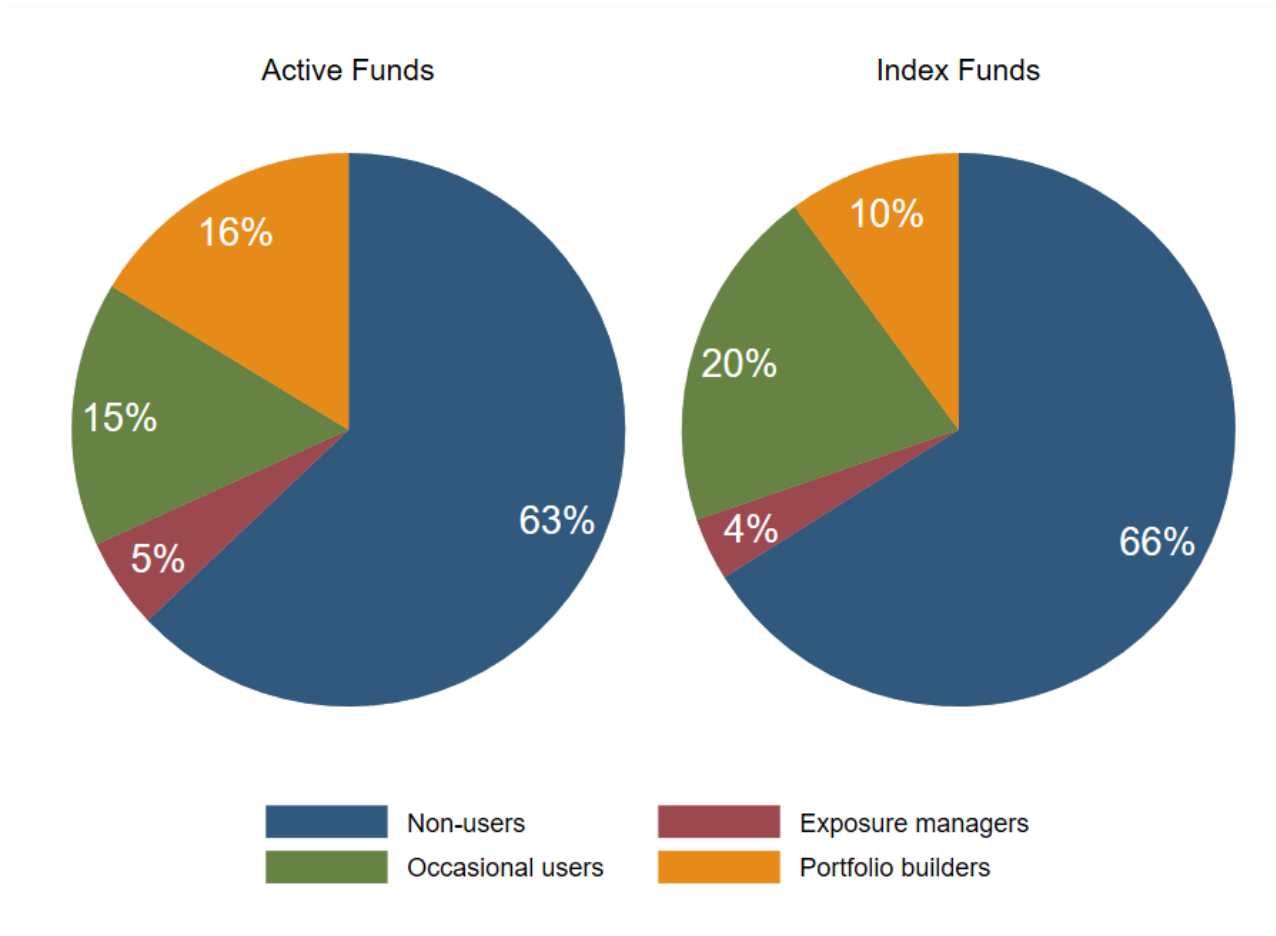
(b) Vanguard Global Equity Fund

Non-Hedging Foreign Currency Trading Risk. The Fund may engage in forward foreign currency transactions for both hedging and non-hedging purposes. The Investment Adviser may purchase or sell foreign currencies through the use of forward contracts based on the Investment Adviser's judgment regarding the direction of the market for a particular foreign currency or currencies. In pursuing this strategy, the Investment Adviser seeks to profit from anticipated movements in currency rates by establishing "long" and/or "short" positions in forward contracts on various foreign currencies. Foreign exchange rates can be extremely volatile and a variance in the degree of volatility of the market or in the direction of the market from that anticipated by the Investment Adviser may produce significant losses to the Fund. Some of these transactions may also be subject to interest rate risk.

(c) Goldman Sachs Total Emerging Markets Income Fund

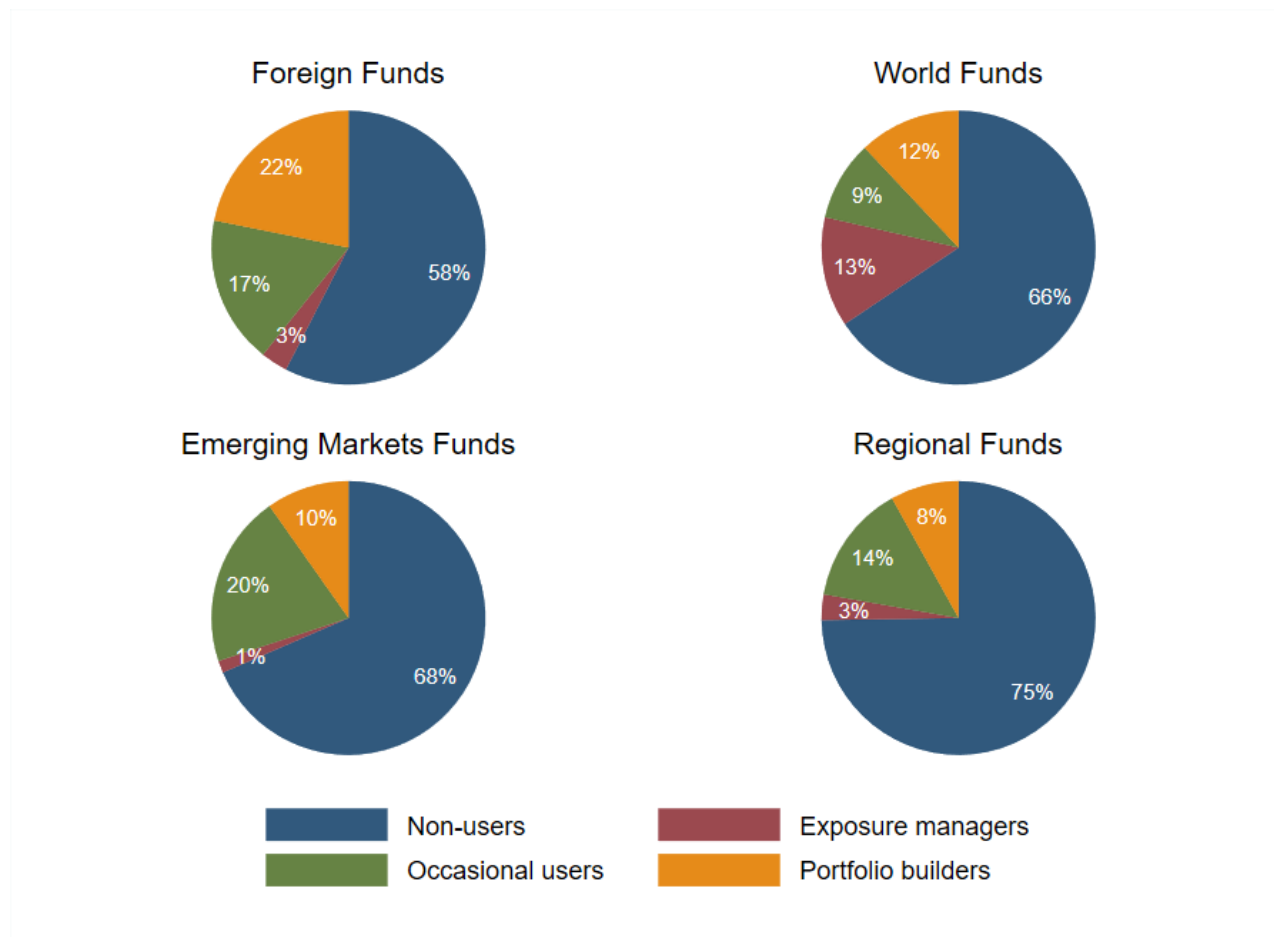
The figure presents extracts from fund reports and prospectuses concerning their potential use of foreign currency forward contracts. Panel A is extracted from the May 2019 N-CSR form of AB International Value Fund, Panel B is extracted from the prospectus (form N-1A) of the Vanguard Global Equity Fund, and Panel C is extracted from the prospectus (form N-1A) of Goldman Sachs Total Emerging Markets Income Fund.

Figure A.2: The Split Between Active and Index Equity Mutual Funds



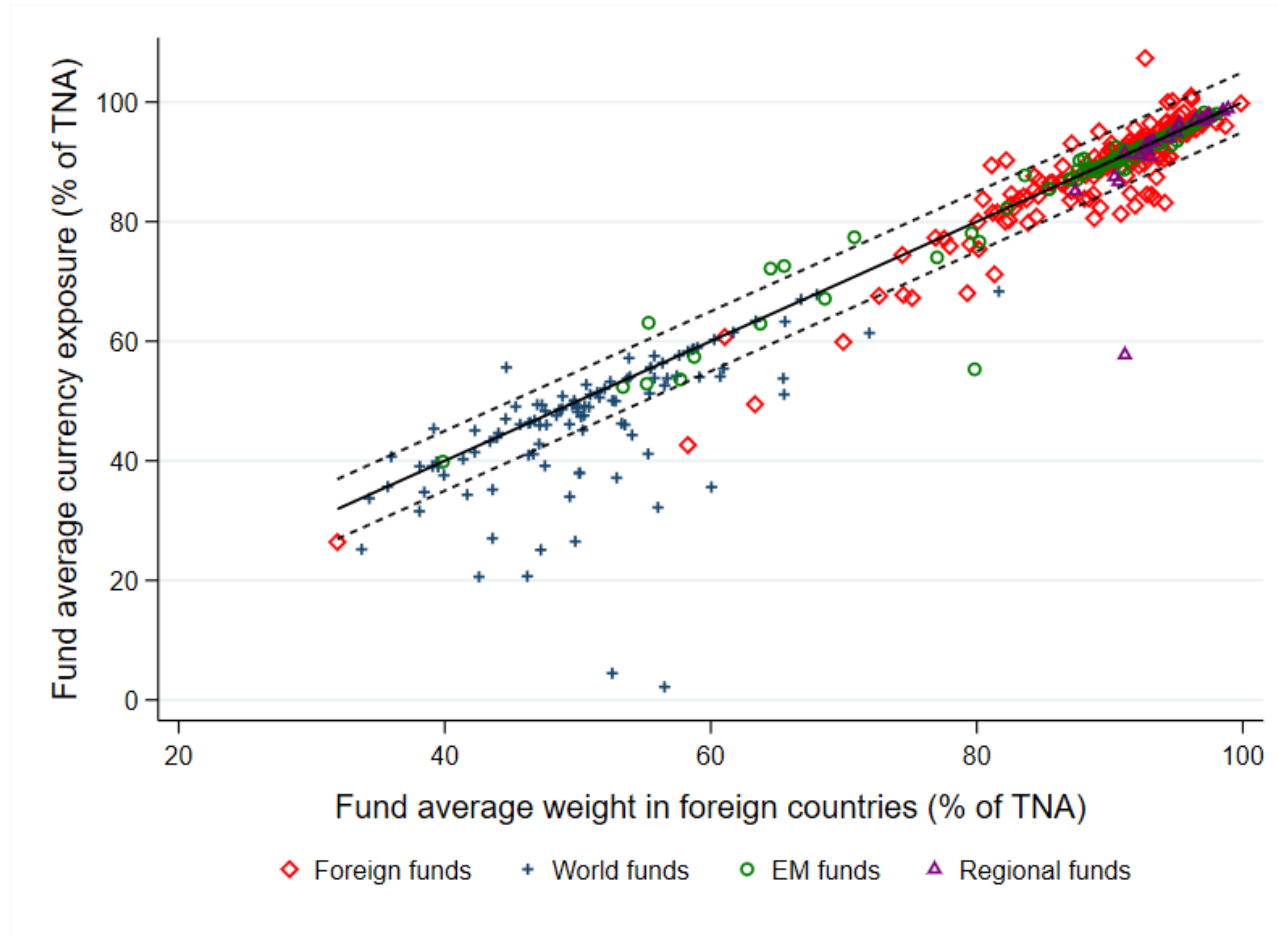
The figure presents pie charts that split the active and passive funds in our sample between users and non-users of currency forward contracts. Within the group of user funds, the funds are split between exposure managers, portfolio builders, and occasional users. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure A.3: The Split Between Types of International Equity Mutual Funds



The figure presents pie charts that split users and non-users of currency forward contracts across the different types of international equity mutual funds: foreign funds, world funds, emerging market funds, and regional funds. For each type of fund, the group of user funds are split between exposure managers, portfolio builders, and occasional users. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure A.4: Currency Exposure Across Different Types of Mutual Funds



The figure presents a scatter plot of funds' average weight in foreign countries (x-axis) plotted against their average currency exposure (y-axis). The plot includes a 45-degree solid line with dashed-lines indicating a (+/-) 5% boundary. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Section B: Alternative Categorization Schemes

As specified in the main body of the paper, we classify forward users into three groups based on three indicator variables: (i) the percentage of quarters in which the fund uses currency forwards; (ii) the average hedge ratio over the quarters in which the fund uses currency forwards; and (iii) the absolute forward position averaged over the quarters in which the fund uses currency forwards. A fund is classified as an exposure manager if it uses forwards in at least $x\%$ of quarters, and has an average hedge ratio of at least $a\%$ during those quarters. We classify a fund as a portfolio builder if it uses forwards in at least $x\%$ of quarters, and its absolute forward position is at least $b\%$ of TNA, when averaged over those quarters. We treat the remainder of the user funds as occasional users, which either use forwards in less than $x\%$ of quarters, or whose absolute forward position is, on average, less than $b\%$ of their TNA. We have the following variations of the cut-off values for x , a , and b :

- **v1:** $x=50$; $a=10$; $b=2$
- **v2:** $x=25$; $a=10$; $b=2$
- **v3:** $x=20$; $a=10$; $b=2$
- **v4:** $x=20$; $a=10$; $b=5$
- **v5:** $x=10$; $a=10$; $b=2$ (the version adopted in the main-body of the paper)
- **v6:** $x=10$; $a=10$; $b=5$

As an additional robustness check, we also cluster funds into three groups in a two-step procedure using the k-means machine learning algorithm (**v7**).³⁹ In each step, the funds are partitioned into six clusters based on their similarities in terms of two indicator variables. In step one, we use (as indicator variables) fund average hedge ratios calculated, respectively, over the entire sample and over the quarters that a fund used forwards. In step two, we use (as indicator variables) fund average absolute forward positions calculated, respectively, over the entire sample and over the quarters that a fund used forwards. We then assign funds in the resulting clusters to three groups based on the clusters' average hedge ratios and average absolute forward positions. Specifically, exposure managers consist of clusters with high average fund hedge ratios, portfolio builders consist of clusters with low or negative average fund hedge ratios but high average absolute forward positions, and occasional users consist of clusters that are low on both measures.

³⁹Kmeans is a partition cluster-analysis method which breaks the observations into a distinct number of non-overlapping groups. It follows an iterative process to cluster observations into k groups based on how close each observation is to the group mean. The process stops when no observation changes group.

Table B.1: Currency Management Styles

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
	<i>Exposure Managers</i>						
<i>Number of funds</i>	48	59	59	59	66	66	34
<i>Fund quarters with currency forwards (%)</i>	82.0	73.7	73.7	73.7	67.5	67.5	77.2
<i>Average number of currencies with forward contracts</i>	5.6	5.0	5.0	5.0	4.8	4.8	6.1
<i>Average fund forwards as % of TNA</i>	-17.1	-16.2	-16.2	-16.2	-16.5	-16.5	-22.5
<i>Average fund hedge ratio</i>	28.9	27.7	27.7	27.7	27.7	27.7	39.8
<i>Average absolute value of fund forwards as % of TNA</i>	20.0	18.7	18.7	18.7	18.7	18.7	25.4
	<i>Portfolio Builders</i>						
<i>Number of funds</i>	135	169	181	122	202	132	191
<i>Fund quarters with currency forwards (%)</i>	75.7	68.2	65.1	68.9	59.8	64.7	59.1
<i>Average number of currencies with forward contracts</i>	7.9	7.2	6.9	8.6	6.6	8.2	6.8
<i>Average fund forwards as % of TNA</i>	0.1	0.1	-0.0	0.5	-0.3	0.2	-1.3
<i>Average fund hedge ratio</i>	-0.4	-0.4	-0.3	-1.2	0.1	-0.8	1.7
<i>Average absolute value of fund forwards as % of TNA</i>	14.7	13.5	13.0	17.8	12.4	17.2	14.7
	<i>Occasional Users</i>						
<i>Number of funds</i>	288	243	231	290	203	273	246
<i>Fund quarters with currency forwards (%)</i>	31.7	30.5	31.0	36.3	33.3	37.7	38.1
<i>Average number of currencies with forward contracts</i>	3.1	3.0	3.0	3.1	2.9	3.0	3.0
<i>Average fund forwards as % of TNA</i>	-1.1	-0.8	-0.7	-0.8	0.1	-0.2	-0.5
<i>Average fund hedge ratio</i>	1.7	1.1	1.0	1.1	-0.1	0.4	0.6
<i>Average absolute value of fund forwards as % of TNA</i>	3.8	2.7	2.5	2.6	1.5	1.9	1.5

The table presents summary statistics for international equity mutual funds that use currency forward contracts during the sample. Each column reflects a different approach to identifying exposure managers, portfolio builders, and occasional users. The three panels split the funds based on their style of currency forward usage. For each characteristic of currency usage, we present the average (Mean) across funds. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table B.2: The Determinants of Hedge Ratios Among Exposure Managers

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
<i>Country weight</i>	0.903*** (0.116)	0.776*** (0.093)	0.776*** (0.093)	0.776*** (0.093)	0.701*** (0.082)	0.701*** (0.082)	1.316*** (0.129)
<i>Momentum</i>	-0.148*** (0.048)	-0.144*** (0.042)	-0.144*** (0.042)	-0.144*** (0.042)	-0.139*** (0.037)	-0.139*** (0.037)	-0.209*** (0.061)
<i>Carry</i>	-0.436** (0.180)	-0.397** (0.155)	-0.397** (0.155)	-0.397** (0.155)	-0.378*** (0.125)	-0.378*** (0.125)	-0.687*** (0.235)
<i>Value</i>	-0.020 (0.032)	-0.028 (0.028)	-0.028 (0.028)	-0.028 (0.028)	-0.018 (0.024)	-0.018 (0.024)	0.008 (0.040)
<i>Bid-ask spread</i>	0.027 (0.026)	0.023 (0.023)	0.023 (0.023)	0.023 (0.023)	0.023 (0.019)	0.023 (0.019)	0.074** (0.036)
<i>Volatility</i>	0.567*** (0.144)	0.506*** (0.124)	0.506*** (0.124)	0.506*** (0.124)	0.472*** (0.107)	0.472*** (0.107)	0.709*** (0.180)
<i>Equity return</i>	0.001 (0.028)	-0.003 (0.024)	-0.003 (0.024)	-0.003 (0.024)	-0.001 (0.021)	-0.001 (0.021)	-0.000 (0.035)
<i>EM dummy</i>	-5.607*** (1.644)	-4.830*** (1.425)	-4.830*** (1.425)	-4.830*** (1.425)	-4.637*** (1.243)	-4.637*** (1.243)	-8.296*** (1.995)
Observations	20,016	23,983	23,983	23,983	27,425	27,425	14,189
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.300	0.300	0.300	0.300	0.315	0.315	0.355

The table presents coefficient estimates from fixed effects panel regressions. Each column reflects a different approach to identifying exposure managers. The dependent variable is the hedge ratio of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, the 12-month currency return volatility, the MSCI equity index return for country j , and a dummy variable equal to **1** if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table B.3: The Determinants of Portfolio Weights Among Portfolio Builders

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
<i>Country weight</i>	-0.542*** (0.076)	-0.545*** (0.072)	-0.535*** (0.071)	-0.651*** (0.074)	-0.532*** (0.071)	-0.647*** (0.074)	-0.618*** (0.073)
<i>Momentum</i>	0.264*** (0.038)	0.257*** (0.037)	0.260*** (0.037)	0.269*** (0.040)	0.256*** (0.037)	0.260*** (0.039)	0.243*** (0.038)
<i>Carry</i>	0.121 (0.143)	0.160 (0.139)	0.169 (0.138)	0.205 (0.151)	0.162 (0.137)	0.207 (0.149)	0.176 (0.149)
<i>Volatility adjusted carry</i>	3.866*** (1.218)	3.964*** (1.175)	4.034*** (1.174)	4.894*** (1.306)	3.805*** (1.179)	4.657*** (1.311)	4.522*** (1.286)
<i>Value</i>	0.054** (0.027)	0.045* (0.026)	0.041 (0.026)	0.041 (0.029)	0.038 (0.026)	0.038 (0.029)	0.042 (0.027)
<i>Bid-ask spread</i>	-0.012 (0.023)	-0.019 (0.022)	-0.020 (0.022)	-0.032 (0.024)	-0.014 (0.021)	-0.027 (0.024)	-0.029 (0.024)
<i>EM dummy</i>	-4.425*** (1.220)	-5.010*** (1.188)	-5.078*** (1.180)	-6.184*** (1.227)	-5.066*** (1.172)	-6.235*** (1.221)	-6.107*** (1.226)
Observations	30,292	32,259	32,528	27,740	32,864	27,935	30,920
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.146	0.149	0.150	0.105	0.152	0.107	0.191

The table presents coefficient estimates from fixed effects panel regressions. Each column reflects a different approach to identifying portfolio builders. The dependent variable is the currency portfolio weight of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the forward discount adjusted by the prior three months' volatility of the exchange rate (*Volatility adjusted carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, and a dummy variable equal to $\mathbf{1}$ if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table B.4: The Determinants of Hedge Ratios Among Occasional Users

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
<i>Country weight</i>	0.028*** (0.006)	0.005** (0.003)	0.005** (0.002)	0.007* (0.004)	-0.000 (0.002)	0.003 (0.004)	0.008* (0.004)
<i>Momentum</i>	-0.016*** (0.006)	-0.006 (0.004)	-0.007** (0.004)	-0.010** (0.005)	-0.007** (0.003)	-0.011** (0.005)	-0.011** (0.005)
<i>Carry</i>	-0.029*** (0.011)	-0.026*** (0.006)	-0.021*** (0.006)	-0.019** (0.008)	-0.012** (0.005)	-0.013 (0.009)	-0.011 (0.009)
<i>Value</i>	0.007** (0.003)	0.002 (0.002)	0.002 (0.001)	0.002 (0.002)	-0.001 (0.001)	0.001 (0.002)	-0.003 (0.002)
<i>Bid-ask spread</i>	0.001 (0.002)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.002 (0.001)
<i>Volatility</i>	0.006 (0.010)	0.022*** (0.006)	0.025*** (0.006)	0.022*** (0.008)	0.014*** (0.004)	0.013 (0.008)	0.025*** (0.007)
<i>Equity return</i>	0.003 (0.003)	-0.001 (0.002)	0.000 (0.002)	0.003 (0.002)	0.001 (0.002)	0.003 (0.002)	0.002 (0.002)
<i>EM dummy</i>	0.557*** (0.125)	0.189** (0.085)	0.165** (0.077)	0.082 (0.134)	0.136** (0.056)	0.045 (0.134)	-0.070 (0.131)
Observations	162,441	141,772	135,577	171,956	115,827	161,029	144,574
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.084	0.144	0.181	0.095	0.014	0.021	0.017

The table presents coefficient estimates from fixed effects panel regressions. Each column reflects a different approach to identifying occasional users. The dependent variable is the hedge ratio of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, the 12-month currency return volatility, the MSCI equity index return for country j , and a dummy variable equal to $\mathbf{1}$ if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table B.5: The Determinants of Portfolio Weights Among Occasional Users

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
<i>Country weight</i>	-0.051 (0.114)	0.204** (0.100)	0.195* (0.103)	0.132 (0.085)	0.220** (0.107)	0.142 (0.086)	0.021 (0.094)
<i>Momentum</i>	0.071 (0.078)	0.063 (0.087)	0.047 (0.089)	0.102 (0.068)	0.060 (0.090)	0.122* (0.069)	0.099 (0.074)
<i>Carry</i>	0.004 (0.235)	-0.040 (0.235)	-0.075 (0.235)	-0.095 (0.191)	0.013 (0.248)	-0.080 (0.198)	0.033 (0.195)
<i>Volatility adjusted carry</i>	1.135 (2.047)	-0.126 (2.186)	-0.422 (2.205)	-0.994 (1.755)	0.249 (2.152)	-0.558 (1.711)	-0.484 (1.784)
<i>Value</i>	-0.001 (0.036)	0.023 (0.036)	0.037 (0.036)	0.033 (0.030)	0.054 (0.036)	0.042 (0.030)	0.060* (0.032)
<i>Bid-ask spread</i>	-0.008 (0.027)	-0.018 (0.031)	0.011 (0.031)	0.008 (0.026)	-0.040 (0.032)	-0.005 (0.026)	-0.003 (0.026)
<i>EM dummy</i>	-3.032* (1.830)	-0.136 (2.052)	0.374 (2.104)	1.864 (2.176)	0.355 (2.170)	2.151 (2.213)	2.254 (2.082)
Observations	11,368	9,122	8,853	13,641	8,358	13,287	12,065
Fund \times Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.199	0.209	0.207	0.234	0.198	0.230	0.206

The table presents coefficient estimates from fixed effects panel regressions. Each column reflects a different approach to identifying occasional users. The dependent variable is the currency portfolio weight of fund i for currency/country j in quarter t . The independent variables include fund i 's portfolio's weight in country j , the exchange rate return (*Momentum*), the forward discount (*Carry*), the forward discount adjusted by the prior three months' volatility of the exchange rate (*Volatility adjusted carry*), the deviation from the real exchange rate (*Value*), the bid-ask spread, and a dummy variable equal to $\mathbf{1}$ if the currency is issued by an emerging market economy (*EM dummy*). All independent variables are lagged by one quarter and each regression includes fund \times quarter fixed effects. Standard errors clustered at the fund \times currency level are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Section C: Data Appendix

Following Pastor, Stambaugh, and Taylor (2015), hereafter PST (2015), we use the intersection of CRSP and Morningstar data on international (including global) equity funds in our study. We only consider funds that are classified as international funds by both CRSP and Morningstar. We require data on funds' currency forward positions to determine their currency management activities. Portfolio holdings data are available from CRSP since 2003, but we find the data on currency derivatives for U.S.-based international funds only became available in 2010, and they contain significant errors when compared with portfolio holdings that funds disclose to the SEC.¹ To ensure data accuracy, we manually collect data on currency forwards from funds' SEC filings starting from 2004, the year the SEC decided to adopt quarterly reporting requirements for mutual funds. Our sample therefore spans the period from January 2004 to June 2019. Below we detail our procedure for collecting, cleaning, and merging data from various sources.

I. Raw CRSP database clean-up and merge

We download the raw CRSP data files from the WRDS server. We start our data filtering process with the `fund_summary` dataset which contains quarterly data on CRSP fund share-class.

1. The CRSP style code classifies funds into different categories such as Foreign Equity and Domestic Equity. We first back-fill and forward-fill the CRSP style code (`crsp_obj_cd`) using the closest observation for each CRSP fund share-class (`crsp_fundno`). We keep only foreign equity funds, which are identified by CRSP style codes starting with "EF". We further differentiate international funds from global funds using Lipper objective codes (`lipper_obj_cd`). The CRSP style code is based on Lipper objective codes starting from 1998. Lipper classifies Global Funds as funds that invest at least 25% of their portfolio in securities traded outside of the United States. Around 30% of observations are for global funds.

2. The CRSP portfolio number (`crsp_portno`) is a unique identifier for a security or a group of securities held in the fund's portfolio. A portfolio may be held by one or many different funds. The CRSP class group (`crsp_cl_grp`) associates different classes with a fund and therefore, for any given date, each `crsp_cl_grp` corresponds to one `crsp_portno`. Across time, the same fund share class (`crsp_fundno`) or `crsp_cl_grp` can be associated with different `crsp_portno`. We require `crsp_portno` to later merge with CRSP's holdings dataset. We drop observations for which both `crsp_cl_grp` and `crsp_portno` are missing. We replace any missing `crsp_cl_grp` with the next available `crsp_cl_grp` for the same `crsp_fundno`, but only if the `crsp_portno` for both observations are consistent. Following this procedure, no observation is missing its `crsp_cl_grp`. If `crsp_portno` is missing, we look to see if another fund share class (`crsp_fundno`) within the same class group (`crsp_cl_grp`) has a non-missing `crsp_portno`. If so, we replace with that `crsp_portno`. In situations when multiple `crsp_fundno`, belonging to the same `crsp_cl_grp`, have different `crsp_portno` at a given point in time, we set the `crsp_portno` to missing for all the `crsp_fundnos` of that group in that month. Following this procedure, each `crsp_cl_grp` corresponds to only one `crsp_portno` in any given month.

¹ Schwarz and Potter (2016) document that CRSP equity portfolio holdings data (for U.S. domestic equity funds) only became reliable in the last quarter of 2007 when CRSP switched its data provider from Morningstar to Lipper. We find that CRSP holdings data on currency derivative securities still contain significant errors, and the same is also true of the Morningstar holdings data. In Section V of this Data Appendix, we provide a few examples of the various errors we have observed.

3. We merge *fund_summary* data with data on monthly returns and dividends. To address the incubation bias documented by Evans (2010), we remove observation before a fund's first offer date (*first_offer_dt*).² We also remove observations that are after a fund's termination date (*end_dt*). Finally, we drop observations for which both the monthly return (*mret*) and total net assets (*mtna*) are missing.³ The merged dataset has 857,269 monthly observations and we verify there are no duplicate *crsp_fundno* during the same month.

4. There are 91,921 observations with an empty *ticker*. As in Berk and van Binsbergen (2015), hereafter BV (2015), we back-fill and forward-fill empty *ticker* with the most recent *ticker* available for each *crsp_fundno*. If an observation has a non-empty *ticker*, but which is not the same as the last non-empty *ticker* used by the fund, we replace it with the last *ticker*. In cases in which a *ticker* is associated with more than one *crsp_fundno* for a given month, we change the *ticker* to missing for all observations of the *crsp_fundnos* associated with that *ticker*. Following these procedures, each *ticker* only corresponds to one *crsp_fundno* in any given month, and each *crsp_fundno* corresponds to only one *ticker* over the sample period (unless *ticker* is empty). Therefore, the variables *ticker*, *year*, and *month* can uniquely identify an observation if the *ticker* field is non-empty. However, a *ticker* can be associated with multiple *crsp_fundnos* over time, this is because *tickers* are sometimes re-used. We find a *ticker* is never used more than three times in this database, and we create a variable *ticker_reuse* to indicate whether a ticker is being used for the first, second, or third time. There are 82,527 observations with an empty *ticker* following this procedure, we replace the *ticker* of these observations with the *crsp_fundno*.

5. Following PST (2015), we check for extreme reversals in total net assets that are likely decimal-place mistakes (CRSP sometimes reports -99 under total net assets, we set these values to missing). We first calculate the fractional change in total net assets over a month, $dtna = (tna - lag_tna) / lag_tna$. We then create a reversal variable to capture the reversal pattern, $reversal = (lead_tna - tna) / (tna - lag_tna)$. The reversal variable will be approximately -1 if it is a reversal (e.g. 20m, 2m, 20m). Lastly, we assign missing values to both *tna* and *dtna* if $abs(dtna) \geq 0.5$, $-0.75 > reversal > -1.25$, and $lag_tna > 10m$. No changes are made to our sample following this procedure.

Our final CRSP dataset has 857,269 monthly observations for 9,753 fund share classes of 3,707 funds that are associated with 4,879 unique portfolios from Jan 2004 to June 2019.

II. Raw Morningstar database clean-up and merge

We download data on fund summary information, Morningstar category, benchmark return, dividend, annual expense ratio, annual turnover ratio, monthly returns, net assets, net asset value, ratings, and country weights from Morningstar Direct. We include only funds that are under the Morningstar category "International Equity", which includes both international and global mutual funds domiciled in the US.

1. Morningstar country weight reports the percentage (as a percentage of asset under management) of non-cash equity assets held by the fund on a monthly basis. We manually checked the country weights of a number of funds in the funds' N-Q and N-CSR filings from EDGAR. We observe that Morningstar country weights are fairly accurate representations of the actual filings of the funds we checked. On some occasions, Morningstar has monthly weights while funds only disclose quarterly holdings to the SEC (this could be voluntary disclosure to Morningstar), on other occasions, Morningstar's reporting dates do not align with

² This approach is consistent with Amihud and Goyenko (2013) and Solomon et al. (2014). Unlike Evans (2010) who finds that a fund can have multiple first offer date, we find *first_offer_dt* is always the same for the same fund.

³ Observations reporting a value of -99 for *mtna* are set to missing.

the funds' reporting dates in EDGAR (nor the filing dates), but the holdings are nevertheless the same, Morningstar calculate market values based on the month the weights are reported in Morningstar. For funds that invest in other mutual funds, those investments are not recognised as part of common equity hence are not included in the country weights. We conclude that Morningstar data on country weight are reasonably accurate for the month they are reported and form the basis for the hedge ratio calculations in the main paper.

2. We merge the datasets together and remove all observations before the *inception date* to address incubation bias. We delete observations with share class type “Load Waived” as in Kim (2019). This share class type has tickers ending with “.lw” which are not found in CRSP. Also, total net assets for this share class type are always missing in Morningstar. Finally, we drop observations where both *return* and *net_assets* are missing. There are 603,591 observations for the period January 2004 to June 2019, of which 124,963 do not have a ticker. Following BV (2015), we verify that each fund share-class (*secid*) either corresponds to a unique non-empty ticker for the entire sample, or to an empty ticker, but never to both. There are no cases in our sample for which two *secids* are associated with the same non-empty ticker during the same year and month, therefore the variables *ticker*, *year*, and *month* can identify a unique observation if the ticker is non-empty. There is one ticker that is associated with two *secids* over the sample period, we create a variable *ticker_reuse* to indicate the ticker is being used for a second time.

3. Following PST (2015), we check for extreme reversals in total net assets that are likely decimal-place mistakes. We first calculate the fractional change in total net assets over a month, $dtna = (tna - lag_tna) / lag_tna$. We then create a reversal variable to capture the reversal pattern, $reversal = (lead_tna - tna) / (tna - lag_tna)$. The reversal variable will be approximately -1 if it is a reversal (e.g. 20m, 2m, 20m). Lastly, we assign missing value to both *tna* and *dtna* if $abs(dtna) \geq 0.5$, $-0.75 > reversal > -1.25$, and $lag_tna > 10m$. No changes are made to our sample following this procedure.

4. The variable *morningstar_category* contains category assignments by Morningstar based on funds' previous 3 years' portfolio holdings. There are missing values for different share classes of the same fund and for the same fund over time. As all share classes of the same fund hold the same portfolio (hence belong to the same category), we forward- and backward-fill data on *morningstar_category* if there is data available for any share class of a fund (based on *fundid*) at any point in time.⁴ As a result of forward and backward filling, 3,795 empty *morningstar_category* observations are replaced.

The Morningstar Category classifications assign a benchmark index for each category under *morningstar_category*. For example, the benchmark index for category “Foreign Large Value” is “MSCI ACWI Ex USA Value NR USD”. Since all funds in our database are classified as ‘International Equity’ by Morningstar, each fund is mapped to one of 17 “International Equity” benchmark indices as follows:

International Equity	Category index
1. Foreign Large Value	MSCI ACWI Ex USA Value NR USD
2. Foreign Large Blend	MSCI ACWI Ex USA NR USD
3. Foreign Large Growth	MSCI ACWI Ex USA Growth NR USD
4. Foreign Small/Mid-Value	MSCI World Ex USA SMID NR USD
5. Foreign Small/Mid-Blend	MSCI World Ex USA SMID NR USD
6. Foreign Small/Mid-Growth	MSCI World Ex USA SMID NR USD

⁴ On occasions in which a fund's category changes during our sample period, the change is applied to all fund share classes in that month.

7. World Large Stock	MSCI ACWI Large Cap NR USD
8. World Small/Mid Stock	MSCI ACWI SMID NR USD
9. Diversified Emerging Markets	MSCI EM NR USD
10. Diversified Pacific/Asia	MSCI Pacific NR USD
11. Miscellaneous Region	MSCI ACWI Ex USA NR USD
12. Europe Stock	MSCI Europe NR USD
13. Latin America Stock	MSCI EM Latin America NR USD
14. Pacific/Asia ex-Japan Stock	MSCI AC Far East Ex Japan NR USD
15. China Region	MSCI China NR USD
16. India Equity	MSCI India NR USD
17. Japan Stock	MSCI Japan NR USD

We find this mapping does not always hold. Occasionally, the *morningstar_category* contains categories belonging to category groups other than “International Equity”, such as “US Equity” or “Allocation” (see table below). This occurs because Morningstar makes changes to a fund’s category classification over time following changes to the portfolio holdings. Since we rely on the Morningstar Category classifications to select our sample of international equity funds, we remove 410 observations for which the *morningstar_category* is empty, and 14,970 observations for which the *morningstar_category* is not one of those listed under “International Equity”.⁵

Our final Morningstar dataset has 588,211 monthly observations for 6,996 fund share classes of 2,005 funds from January 2004 to June 2019.

III. Merging CRSP and Morningstar databases

1. We first merge CRSP and Morningstar by *ticker*, *year*, and *month* at the share-class level. 450,485 observations are matched in this process. Following PST (2015), we check matching quality by comparing data on funds’ monthly returns and total net assets (TNA) from CRSP and Morningstar. A fund share class (identified by *secid* in Morningstar) is “well matched” if and only if:

- 1) the 60th percentile of the absolute difference between CRSP and Morningstar monthly returns is less than 5 basis points, and
- 2) the 60th percentile of the absolute different between CRSP and Morningstar monthly TNA is less than \$100,000.

A fund (identified by *fundid* in Morningstar) is “completely matched” if all the share classes of the fund are well matched. A fund is “partially matched” if some, but not all, share classes are well matched. We find that 4,871 share classes (49.9% of 9,753 CRSP share classes, and 69.6% of 6,996 Morningstar share classes) are well matched by ticker. 1,079 funds (53.8% of 2,005 Morningstar *fundids*) are completely matched, 388 (19.4%) are partially matched, and 538 (26.8%) are not matched at all.

⁵ Changes to a fund’s classification also occur in the CRSP dataset. In the rare event that CRSP and Morningstar disagree on whether a fund is international, we choose to follow the Morningstar category classification.

Table 1: Breakdown of Funds' Monthly Classifications by Morningstar Category

morningstar_category	Freq.	Percent	Cum.
US Fund Allocation--50% to 70% Equity	260	0.04	0.04
US Fund Allocation--70% to 85% Equity	366	0.06	0.10
US Fund Allocation--85%+ Equity	255	0.04	0.15
US Fund Bear Market	7	0.00	0.15
US Fund China Region	12,042	2.00	2.14
US Fund Diversified Emerging Mkts	94,259	15.63	17.77
US Fund Diversified Pacific/Asia	6,698	1.11	18.88
US Fund Emerging Markets Bond	308	0.05	18.93
US Fund Equity Energy	590	0.10	19.03
US Fund Europe Stock	19,131	3.17	22.20
US Fund Financial	145	0.02	22.23
US Fund Foreign Large Blend	133,310	22.10	44.33
US Fund Foreign Large Growth	52,588	8.72	53.05
US Fund Foreign Large Value	54,565	9.05	62.09
US Fund Foreign Small/Mid Blend	11,810	1.96	64.05
US Fund Foreign Small/Mid Growth	21,352	3.54	67.59
US Fund Foreign Small/Mid Value	10,638	1.76	69.35
US Fund India Equity	2,917	0.48	69.84
US Fund Intermediate Core Bond	6	0.00	69.84
US Fund Japan Stock	7,023	1.16	71.00
US Fund Large Blend	4,826	0.80	71.80
US Fund Large Growth	2,367	0.39	72.19
US Fund Large Value	2,750	0.46	72.65
US Fund Latin America Stock	4,369	0.72	73.37
US Fund Long Government	5	0.00	73.38
US Fund Long-Short Equity	242	0.04	73.42
US Fund Market Neutral	213	0.04	73.45
US Fund Mid-Cap Blend	431	0.07	73.52
US Fund Mid-Cap Growth	459	0.08	73.60
US Fund Mid-Cap Value	340	0.06	73.65
US Fund Miscellaneous Region	2,572	0.43	74.08
US Fund Miscellaneous Sector	100	0.02	74.10
US Fund Natural Resources	49	0.01	74.11
US Fund Pacific/Asia ex-Japan Stk	13,477	2.23	76.34
US Fund Small Blend	114	0.02	76.36
US Fund Small Growth	584	0.10	76.46
US Fund Tactical Allocation	123	0.02	76.48
US Fund Technology	310	0.05	76.53
US Fund Utilities	309	0.05	76.58
US Fund World Allocation	889	0.15	76.73
US Fund World Bond	40	0.01	76.73
US Fund World Large Stock	121,144	20.08	96.82
US Fund World Small/Mid Stock	19,198	3.18	100.00
Total	603,181	100.00	

The table presents the breakdown of funds by Morningstar category. Categories associated with “International Equity” are highlighted in yellow. All observations associated with non-“International Equity” categories (14,970 in total) are dropped from the sample.

2. Next, we map a Morningstar *fundid* to a corresponding *crsp_cl_grp* if at least one share class belonging to the fund is matched by *ticker* in the previous step.⁶ For *fundids* that have unmatched share classes but non-empty *crsp_cl_grp*, we match the share classes under the same *fundid* by a text-based search. First, we extract the keyword of each fund share class name from Morningstar and CRSP respectively. The Morningstar keyword is often the last word of the fund name in Morningstar. The CRSP keyword is separated by comma in the CRSP fund name, we remove non-essential words or symbols such as “class”, and “share”, as well as hyphens, to enable matching with Morningstar keywords. For example, “Class B

⁶ A fund share class is identified by *crsp_fundno* in CRSP and by *secid* in Morningstar. Different classes of the same fund are associated by *crsp_cl_grp* in CRSP and by *fundid* in Morningstar.

Share” in CRSP is replaced with “B” in the matching procedure. Second, we standardize variations of the same share-class name in both Morningstar and CRSP as specified in the table below:

Morningstar Keyword	CRSP Keyword	Replaced by Keyword
Adm/Admin/Admiral/Admr	Administrator	Administrative
Adviser/Adv/Consultant	Adviser/Consultant	Advisor
Equity R6		R6
FdmlInt'lSmCpInst/Ins/Inst/Instl/RsrchInstl/DivInst		Institutional
Intl		International
Inv/Investment/Invmt	Investment	Investor
Prem/Premier	Advantage	Premium
Sel		Select
Svc		Service
Retire/Retiremt/R	R	Retirement
Retl		Retail

Third, we remove observations that belong to the same *fundid* and have the same keyword for a given year and month. Therefore *fundid*, *year*, *month*, and *keyword* can identify a unique observation following this procedure. We merge data from CRSP and Morningstar by *fundid*, *year*, *month*, and *keyword* and find 48,727 additional matched observations.

3. For the remaining observations that have both *fundid* and *crsp_cl_grp* but are not matched in step 2 (due to non-standard fund share-class names), we perform a search based on TNA and monthly return within each fund group, then manually check whether a match can be made. Specifically, we identify a potential match between two observations that belong to the same *fundid* in the same *year* and *month* in which returns differ by less than 5 bps and TNA differ by less than \$100,000. Following manual inspection, 1,249 additional observations are matched.⁷ We find 546 additional well-matched share classes following steps 2 and 3.

4. For observations that cannot be merged by *ticker* and cannot be linked at the fund level in step 2, we perform a search based on TNA and monthly returns similar to that undertaken by BV (2015). For each unmatched observation from Morningstar, we search in the unmatched observations from CRSP in the same year and month, a match is made if and only if the following 5 criteria are satisfied:

- 1) the absolute return difference between CRSP and Morningstar is less than 5bps
- 2) the absolute TNA difference between CRSP and Morningstar is less than \$100,000
- 3) the first word of Morningstar fund name must be found in CRSP fund name
- 4) the Morningstar share class name must match the CRSP share class name by the keyword
- 5) the matching based on the above four criteria must be 1-to-1

We extract a keyword from the fund share class name, following step 2 of this section, and standardize slight variations in the share-class names within Morningstar and CRSP, as specified in Table XYZ.

Morningstar Keyword	CRSP Keyword	Replaced by Keyword
Adm/Admin/Admiral/Admr/ Administrator	Administrator/Admiral	Administrative
Adviser/Adv/Consultant	Adviser/Consultant	Advisor

⁷ For example, “ING Investors Trust: ING VP Index Plus International Equity Portfolio; Service Class Shares” from CRSP is matched with “ING Index Plus Intl Equity Port S” from Morningstar.

Ins/Inst/Instl/EquityInstl	Institutional/ Institutional/ Inst/Instl	Institutional
Intl		International
Inv/Investment/Invmt	Inv/Investment	Investor
	Advantage	Premium
Sel		Select
Svc	Svc	Service
	Service 2	S2
Retire/Retiremt/R	R	Retirement
Retl		Retail
Stndrd	Std	Standard

There are cases where a *secid* is matched with multiple *crsp_fundnos*. For example, “Nuveen Tradewinds Emerging Markets A” from Morningstar is matched with both “Nuveen Investment Trust II: Nuveen Tradewinds Global Resources Fund; Class A Shares” and “Nuveen Investment Trust II: Nuveen Tradewinds Emerging Markets Fund; Class A Shares” from CRSP (in different months). We manually check all such cases and remove the matches that were made incorrectly (4 observations). We keep the matches if a multiple match is made due to changes in *crsp_fundno* for what appears to be the same fund share class. For example, “Transamerica Funds: Transamerica International Value Opportunities; Class I2 Shares” has *crsp_fundno* 42301 (*crsp_cl_grp* 2013567) from September 2008 to August 2012 but *crsp_fundno* 56397 from October 2012 (*crsp_cl_grp* 2018922) onwards, whereas the *secid* (FOUSA07XWU) for the share class remains unchanged.⁸

5. By definition, all observations matched in step 4 are well matched cases due to the matching criteria, hence the same match should also hold in the time-series as well. BV (2015) require more than 60% of the Morningstar observations to be matched to CRSP observations before accepting the match in the time-series. We observe that many Morningstar share classes are partially matched to CRSP share classes in step 4 because of missing data in CRSP. Manual inspection shows that the matching quality is very high following step 4, we therefore do not apply the 60% rule.⁹ Therefore, if a fund share class identified by *secid* is matched to a *crsp_fundno* in any month, we assign the same *crsp_fundno* to all observations with the same *secid*. Overall, 55,698 additional observations are matched following steps 4 and 5, and we find 850 well-matched share classes and 248 completely matched funds.

Following this 5-step procedure, we observe 1,620 completely matched funds (5,709 well-matched share classes), 146 partially matched funds, and 239 unmatched funds. We keep only the completely matched funds.

⁸ This fund share class is marked as being liquidated in CRSP (dead fund). *crsp_fundno* 42301 has *end_dt* of August 2012, and *crsp_fundno* 56397 has *end_dt* of November 2013. Both have *first_offer_dt* of September 2008. CRSP has monthly return data for *crsp_fundno* 42301 from September 2008 to August 2012, and for *crsp_fundno* 56397 from October 2012 to November 2013. In the fund_summary data file, the share class has *crsp_fundno* 42301 for March and June of 2012, and *crsp_fundno* 56397 for December 2012, March, June, and September 2013, all the while with the same fund share class name. Judging from these, we decide to side with Morningstar and consider these two *crsp_fundnos* as belonging to the same fund share class.

⁹ There are only 6 observations that are incorrectly matched. For example, on one occasion, “Ashmore Funds: Ashmore Emerging Markets Equity Opportunities Fund; Class A Shares” from CRSP is matched with “Ashmore Emerging Markets Active Eq A” rather than “Ashmore Emerging Markets Eq Opps A” from Morningstar. We remove these matches before applying the time-series match.

6. Using the *secid - crsp_fundno* mapping created in step 5, we perform the following steps to merge CRSP and Morningstar data. First, we create a dataset of completely matched funds from CRSP and from Morningstar, respectively, using the *secid - crsp_fundno* link.¹⁰ The CRSP dataset contains 504,196 observations and the Morningstar dataset contains 496,308 observations. Second, we use the Morningstar dataset as the master file and merge in the matched observations from CRSP. The merged dataset contains 496,304 observations for 5,709 share classes and 1620 funds (80.8% of 2,005 Morningstar *fundids*).

IV. Other Screenings and Fixes

1. Fixing Expense Ratio, Management Fee, and Turnover Ratio

Both CRSP and Morningstar report annual expense ratios for a fund's fiscal year. We mainly use the expense ratio reported by CRSP since CRSP is more precise about its timing. Morningstar reports the last month of a fund's fiscal year based on the most recent observation. We observe in our sample that some funds changed their fiscal calendar. If the fiscal year end information is missing for a fund share class in CRSP, we first fill in the fiscal year end information from another share class of the same fund if available. We then take the following steps to supplement CRSP data with Morningstar data: 1) if a fund never had fiscal year end information in CRSP, when available, we fill in the missing information using Morningstar data. 2) If a fund did not change its fiscal year end and the expense ratio is missing in some months but not all, we fill in the missing value using Morningstar data. 3) If a fund changed its fiscal year end, and the expense ratio is missing in some months but not all, we fill in the missing value using Morningstar data only if the last month of the fiscal year reported by CRSP matches that from Morningstar. We apply the same procedure to fix data on turnover ratio from CRSP.

We set the expense ratio/management fee to missing if its value reported by CRSP is negative, and we set the turnover ratio to missing if its reported value is -99. We find that 8.9% (21.8%) of the 496,304 observations have a missing expense ratio (management fee), and 9.17% of the observations have a missing turnover ratio.

2. Return Fix

487,142 observations (98.2%) of the merged sample have return data from both CRSP and Morningstar. Of these observations, 1,979 (0.4%) have inconsistent returns, defined as those differing by more than 10 basis points. We follow BV (2015) to correct these returns using data on dividend and net asset value from both CRSP and Morningstar. Following steps 1 and 2 on pages 16-18 of their data appendix (included in section VII of this data appendix), we reduce the number of inconsistent returns to 184 (0.04% of the 487,142 observations).¹¹ We set the 184 inconsistent returns to missing and use the CRSP reported return for consistent observations between CRSP and Morningstar. Following this procedure, 486,958 observations (98.1% of the merged sample of 496,308 observations) remain with non-missing return data.

3. Total Net Assets Fix

¹⁰ We observe that the mapping between *secid* and *crsp_fundno* is not always 1-to-1, this is because Morningstar and CRSP do not always agree on whether a fund share class is dead, as we have shown in section III.4 about *Transamerica Funds*. There are 8 *secids* that fall into this category.

¹¹ There are 26 observations where the return reported by CRSP and Morningstar equal their respective calculated return and we are not able to determine whether CRSP or Morningstar made a mistake, we set the return of these observations to CRSP's return.

We use total net assets (TNA) as reported by Morningstar. We do so because Morningstar reports TNA to the nearest dollar, whereas CRSP reports TNA to the nearest million dollars. A more precise TNA allows us to calculate currency hedge ratios with higher degree of accuracy. We set TNA to missing if either CRSP or Morningstar reports a missing value. We also set TNA to missing if the difference between the values reported by CRSP and Morningstar is greater than \$100,000 and the difference is at least 5% of the TNA reported by Morningstar. Following this procedure, 487,309 observations (98.2% of the merged dataset of 496,308 observations) remain with non-missing TNA.

4. Identifying Index Funds

We create a dummy variable *index_fund_dummy* following a two-step procedure:

1) A fund is designated as an index fund if either CRSP or Morningstar classifies it as an index fund. That is, if the CRSP *index_fund_flag* is not empty or if the value for Morningstar's *index_fund* or *enhanced_index* equals "Yes".

2) A fund is also deemed as an index fund if the fund name in either CRSP or Morningstar contains the word "Index".

Following this procedure, 139 funds (8.6% of 1620 funds) in our sample are identified as index funds.

5. Grouping Subclasses

We aggregate data from the share class level to the fund level using the *fundid* reported by Morningstar. Monthly TNA at the fund level is the sum of the TNA of all share classes with the same *fundid* in that *month*. We set TNA at the fund level to missing in months in which any share class within the fund has a missing TNA. When aggregating monthly returns, expense ratios, turnover and management fees, we take the lagged-TNA-weighted average of the values across all share classes without missing data.

V. Extracting Holdings Data

1. Merging with CRSP Holdings Data

The portfolio holdings of mutual funds are available from CRSP from 2003, these including data on derivative positions. We merge our final dataset with CRSP holdings data using *crsp_portno*, *year*, and *month* and extract data on currency derivatives and cash denominated in foreign currencies based on keywords in *security_name*. Most currency derivative positions involve foreign currency forward contracts, but a small number of funds also used currency futures, options, and swaps.

We perform random checks on the accuracy of CRSP reported currency forward positions against funds' SEC filings. Since 2004, US mutual funds are required to disclose their portfolio holdings on a quarterly basis using SEC forms N-Q, and N-CSR.¹² These reports are available online from the SEC's EDGAR database. We find various inconsistencies and summarize the main issues in the following examples:

i) *Ambiguous Data Items*

We find data items in CRSP correspond to different types of data depending on the fund/report. For example, the market value (*market_val*) of a currency forward position sometimes corresponds to the market value (in USD) in SEC filings but may also reflect the unrealised appreciation/depreciation of the currency

¹² Form N-Q was replaced by form N-PORT in 2019.

forward. We also find instances in which values cannot be reconciled. The same issues are also observed for the number of shares (*nbr_shares*) item in CRSP.

Example 1 Dreyfus International Value Fund

Report date: 28 February 2011

For this fund, the *market_val* of the forward contracts from CRSP matches with Value (\$) in the SEC filing, and *nbr_shares* matches with Foreign currency amounts (to be purchased).

Data from CRSP

report_dt_~s	security_name	nbr_shares	market_val
28feb2011	AUD FORWARD CONTRACT	268001	272866.2
28feb2011	USD FORWARD CONTRACT	-1048167	-588157.75
28feb2011	EUR FORWARD CONTRACT	96903	133722.02
28feb2011	HKD FORWARD CONTRACT	620590	79685.41
28feb2011	GBP FORWARD CONTRACT	62673	101884.12

Data from SEC filing

Forward Foreign Currency Exchange Contracts	Foreign Currency Amounts	Cost (\$)	Value (\$)	Unrealized Appreciation(\$)
Purchases:				
Australian Dollar, Expiring 3/1/2011	268,001	272,348	272,866	518
British Pound, Expiring 3/1/2011	62,673	100,745	101,884	1,139
Euro, Expiring 3/1/2011	96,903	133,264	133,722	458
Hong Kong Dollar, Expiring 3/1/2011	620,590	79,681	79,685	4
				2,119

Example 2 Evermore Global Value Fund

Report date : 30 June 2015

For this fund, the CRSP *market_val* matches with “Net unrealized Appreciation (Depreciation)” in the SEC filing rather than with the Fair value (market value), although the *nbr_shares* still matches with the amount of foreign currency (to be delivered).

Data from CRSP

report_dt_~s	security_name	nbr_shares	market_val
30jun2015	JPY/USD FORWARD CONTRACT	-896200000	-110423.12
30jun2015	CHF/USD FORWARD CONTRACT	-6761000	19553.34
30jun2015	JPY CASH	4102990	33525.27
30jun2015	RON CASH	676224.2	168476.91
30jun2015	SEK/USD FORWARD CONTRACT	-173809600	83627.37
30jun2015	SGD/USD FORWARD CONTRACT	-6400000	-9712.68
30jun2015	NOK/USD FORWARD CONTRACT	-171004000	233016.79
30jun2015	EUR/USD FORWARD CONTRACT	-99967600	947106.03
30jun2015	EUR CASH	596635.88	665160.74
30jun2015	CHF CASH	.02	.02
30jun2015	RON/USD FORWARD CONTRACT	-11380000	49979.57

Data from SEC filing

FORWARD FOREIGN CURRENCY CONTRACTS at June 30, 2015 (Unaudited)

As of June 30, 2015, the Fund had the following forward currency contracts outstanding with Morgan Stanley:

Currency to be Received	Amount of Currency to be Received	Settlement Date	Currency to be Delivered	Amount of Currency to be Delivered	Fair Value	Net Unrealized Appreciation (Depreciation)
USD	7,272,740	9/14/15	CHF	6,761,000	\$ 7,253,187	\$ 19,553
USD	120,488,305	9/14/15	EUR	106,967,600	119,383,260	1,105,045
USD	7,219,832	9/14/15	JPY	896,200,000	7,330,255	(110,423)
USD	22,004,176	9/14/15	NOK	171,004,000	21,771,159	233,017
USD	3,096,830	9/14/15	RON	12,230,000	3,043,105	53,724
USD	21,084,332	9/14/15	SEK	173,809,600	21,000,704	83,627
USD	4,736,892	9/14/15	SGD	6,400,000	4,746,604	(9,712)
EUR	7,000,000	9/14/15	USD	7,970,424	7,812,485	(157,939)
RON	850,000	9/14/15	USD	215,244	211,500	(3,745)
Net Value of Outstanding Forward Currency Contracts					\$ 192,552,259	\$ 1,213,147

Example 3 BlackRock GA Enhanced Equity Fund

Report date: 30 April 2014

For this fund, both *market_val* and *nbr_shares* from CRSP match with “Net unrealized Appreciation (Depreciation)” in the SEC filing.

Data from CRSP

report_dt_~s	security_name	nbr_shares	market_val
31oct2017	USD/EUR FORWARD CONTRACT	810	810
31oct2017	GBP/USD FORWARD CONTRACT	993	993
31oct2017	USD/JPY FORWARD CONTRACT	-111	-111
31oct2017	AUD/USD FORWARD CONTRACT	-144	-144

Data from SEC filing

Forward Foreign Currency Exchange Contracts

Currency Purchased		Currency Sold		Counterparty	Settlement Date	Unrealized Appreciation (Depreciation)
GBP	92,000	USD	121,515	UBS AG	1/22/18	\$ 993
USD	215,003	EUR	183,000	Goldman Sachs International	1/22/18	810
						1,803
AUD	43,000	USD	33,030	Goldman Sachs International	1/22/18	(144)
CAD	109,000	USD	85,065	Goldman Sachs International	1/22/18	(502)
USD	361,419	JPY	40,935,000	UBS AG	1/22/18	(111)
						(757)
						\$ 1,046
Net Unrealized Appreciation						

ii) Inconsistent portfolio report dates and unaccountable forward positions

The reports checked in EDGAR are not always available in CRSP, and CRSP sometimes reports for months that are inconsistent with EDGAR filings. Schwarz and Potter (2016) report the same issue and attribute the additional reports in CRSP to voluntary reporting by mutual funds. We are thus unable to verify the CRSP reported currency positions for reports with inconsistent report dates.

Example 1 AQR Emerging Core Equity Fund

CRSP recorded forward positions for the fund for August, September, and October of 2014, but only a report for the quarter ending September is filed with the SEC and it shows no open forward position for the fund for the reporting period.

Example 2 Fidelity Diversified International K6 Fund

The fund has forward data in CRSP in almost every month. The fund files reports to the SEC for the periods ending January, April, July and October. CRSP's record shows that the fund had 4 open forward positions in April 2018. But the SEC report shows no forward position under Schedule of Investments and no unrealized gain/loss in the statement of Assets and Liabilities. The same can be said for the July 2018 N-Q report.

Example 3 Wells Fargo Factor Enhanced International Fund

CRSP records multiple forward positions for the fund in August 2018. SEC report for the same period shows that the fund invests solely in a master portfolio – Wells Fargo Factor Enhanced International Portfolio, and the portfolio had no outstanding currency forward contracts in August 2018.

Example 4 FundVantage Trust: Formula Investing International Value Select Fund

The fund has an SEC filing with a report date of 30 April 2012. The closest report date we found for the fund in CRSP is 31 March 2012.

iii) *Cash Positions in Foreign Currency*

CRSP reports data on funds' foreign cash positions. These positions cannot be found in the funds' SEC filings. Instead, we observe the total (USD denominated) cash positions.

2. Checking Holdings Data from Morningstar

We also randomly check the quality of currency derivatives data in Morningstar and find a large number of inconsistencies with reported positions in SEC filings. In view of the various data errors associated with currency forwards that we observe in both CRSP and Morningstar, we choose to manually collect data on currency forwards from SEC forms N-Q and N-CSR for the funds in our merged sample.

VI. Data from Fund Prospectus

We check in fund prospectus (form N-1A) whether funds are allowed to use currency forwards. Based on the information we find, we create the following two dummy variables:

1. Allow to use forward foreign currency contracts
=1 if the prospectus states that the fund may use forward currency contracts for any purposes, such as hedging or non-hedging purposes.
=0 if no information regarding forward currency contracts can be found

2. Forward foreign currency contracts for speculative purposes
=1 if the prospectus makes any of the following comments about the use of derivatives:
 - speculative purposes
 - derivatives for speculative purposes (but not specific to forwards)
 - foreign currency transactions for speculative purposes (but not specific to forwards)
 - gain exposure to a currency
 - increase exposure to a currency
 - increase income
 - increase return
 - intended to profit from anticipated currency exchange fluctuation
 - investment purposes
 - non-hedging purposes
 - take advantage of certain inefficiencies in the currency exchange market

=0 if the prospectus contains no information regarding using forwards for speculative purposes, or if it includes any of the following statement about the use of derivatives:

- not for speculative purposes
- Not for leveraging purposes
- hedging purpose only

VII. Excerpts from Berk and Van Binsbergen (2011) Data Appendix

Pages 16-18:

Correction of Monthly Returns

There is a significant number of observations for which the monthly return reported by Morningstar and the monthly return reported by CRSP differ. The combined database contains a total of 4525081 observations, of which 2357848 observations have both *mret* and *totretlmo* reported. Of these, 60831 observations (2% of total observations) have *mret* (the CRSP reported monthly return) and the *totretlmo* (Morningstar reported monthly return) differ significantly (more than 10 basis points). Details on the differences between *totretlmo* and *mret* can be found in the table below:

Difference between <i>mret</i> and <i>totretlmo</i>	# of observations	% of observations
Do not differ	2152604	91%
1 basis point	4057	0.2%
2-10 basis points	140356	6.1%
11-100 basis points	40755	1.7%
> 100 basis points	20076	1.0%

In this section, we use the terms "differing significantly" or "inconsistent" when the absolute difference in the monthly return reported by Morningstar and by CRSP is bigger than 10 basis points (for example, one number is 2.03% and the other number is 2.14%). To ensure accuracy in our database, we decided to make corrections on these 60831 observations. Our correction mechanism in this section can be divided into four steps.

Step One

We apply several automated correction mechanisms to these inconsistent monthly returns. First, we recognize that both CRSP and Morningstar report funds' net asset values (NAV) and sometimes also report dividend values. From these NAVs, we can compute two additional sets of monthly returns, one from the NAV reported by Morningstar and one from the NAV reported by CRSP, which we will now call *ms_ret* and *crsp_ret*, respectively. More specifically, they are calculated as:

$$crsp_ret_{i,t} = \frac{crsp_nav_{i,t} + crsp_dividend_{i,t} - crsp_nav_{i,t-1}}{crsp_nav_{i,t-1}}$$

$$ms_ret_{i,t} = \frac{ms_nav_{i,t} + ms_dividend_{i,t} - ms_nav_{i,t-1}}{ms_nav_{i,t-1}}$$

The dividend value is missing. We apply the following set of rules to fill in the dividend values as best as we can:

- 1) If dividend is missing in one database (either CRSP or Morningstar), but not the other, then we fill in the dividend value for that database using the dividend value of the other database.
- 2) If (1) cannot resolve the missing dividend problem for an observation, we assume the dividend paid for that observation is 0.
- 3) If under the assumption in (2), we find that the difference between *mret* and *crsp_ret* is equivalent to the difference between *totretlmo* and *ms_ret*, then we can infer that the difference is caused by dividends and since the two differences are consistent, the inferred dividends of the two databases are consistent, and we fill in the difference as the dividend ratio. In the following example, note although dividends are missing, the difference between *crsp_ret* and *mret* and the difference between *ms_ret* and *totretlmo* are both 0.07, indicating that the dividend ratio is 0.07.

Before:					
Mret	totretlmo	crsp_ret	ms_ret	crsps_dividend	ms_dividend
0.17	0.18	0.10	0.11	.	.
After:					
mret	totretlmo	crsp_ret	ms_ret	crsps_dividend	ms_dividend
0.17	0.18	0.10	0.11	0.07	0.07

Next, for a given observation with a monthly return inconsistency, we apply the following set of rules:

1. If *mret* is consistent with both *crsp_ret* and *ms_ret*, then we accept *mret* as the correct monthly return
2. If *totretlmo* is consistent with both *crsp_ret* and *ms_ret*, then we accept *totretlmo* as the correct monthly return
3. If *mret* is consistent with *crsp_ret* but not with *ms_ret*, and *totretlmo* is not consistent with *ms_ret*, we accept *mret* as the correct monthly return
4. If *totretlmo* is consistent with *ms_ret* but not with *crsp_ret*, and *mret* is not consistent with *crsp_ret*, we accept the *totretlmo* as the correct monthly return.
5. This set of rules allows us to correct for 11319 return inconsistencies in the database.

Step Two

One major reason why there are still significant inconsistencies remaining is because there are many cases where the computed *crsp_ret* is consistent with *mret*, and the computed *ms_ret* is consistent with *totretlmo*, but the returns are inconsistent across the two databases. An example of such a case is presented below:

Year	month	Ticker	mret	totretlmo	crsp_ret	ms_ret
1997	7	ABESX	1.66	1.85	1.66	1.85

Consequently, we apply another set of rules to correct for the remaining return inconsistencies. To understand how this mechanism works, consider the following example.

year	month	Ticker	Mret	totretlmo	crsp_ret	ms_ret
2002	8	UGSBX	-3.22	-3.22	-3.22	-3.22
2002	9	UGSBX	4.01	4.01	4.01	4.01
2002	10	UGSBX	0.74	1.94	0.74	1.94
2002	11	UGSBX	1.33	1.33	1.33	0.13
2002	12	UGSBX	-1.07	-1.07	-1.07	-1.07

In this case, in 10/2002, *mret* is consistent with *crsp_ret*, *totret1mo* is consistent with *ms_ret*, but *totret1mo* is not consistent with *mret*. This means that any correction mechanism described so far will fail to correct this inconsistency. This also means that in 10/2002, either CRSP or Morningstar must have reported both an incorrect net asset value and an incorrect return. So instead of finding which of the two databases reported an incorrect return, we search for which one of the two reported an incorrect NAV, and from it infer which return reported is mistaken. To do so, we sort the fund's data chronologically, and look above and below the observation with the inconsistency to see which database has inaccurately reported the NAV. Is *crsp_ret* consistent with *mret* at (t-1) or (t+1)? Is *ms_ret* consistent with *totret1mo* at (t-1) or (t+1)? In the example, *crsp_ret* and *mret* are consistent but *ms_ret* and *totret1mo* are inconsistent at 11/2002 (i.e. t+1). From this we deduce that *mret* is accurate in 10/2002.

What if consecutive months contain errors in NAV? We need to search above and below for more than one month, until we resolve the inconsistency or we are sure that the inconsistency cannot be resolved using this method. An example of such a case is given below:

year	month	ticker	mret	totret1mo	crsp_ret	ms_ret
1999	1	TECFX	4.41	4.41	4.41	4.41
1999	2	TECFX	-1.11	-1.11	-1.11	-1.11
1999	3	TECFX	7.26	7.26	7.26	5.26
1999	4	TECFX	1.73	0.73	1.73	0.73
1999	5	TECFX	0.26	-0.77	0.26	-0.77
1999	6	TECFX	3.71	3.71	3.71	3.71
1999	7	TECFX	-6.69	-6.69	-6.69	-6.69

Note that in both 4/1999 and 5/1999, *mret* is consistent with *crsp_ret* and *totret1mo* is consistent with *ms_ret*, but *mret* is not consistent with *totret1mo*. Using the approach we just described using the earlier example, we look above and below. Using what we have in 3/1999, we judge that Morningstar made a mistake in recording its NAVs on 3/1999. Consequently, we accept that *mret* is the correct monthly return for both 4/1999 and 5/1999. Using this mechanism as illustrated in the two examples above, we were able to correct an additional 17730 return inconsistencies.