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

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Abstract

We undertake the first comprehensive investigation into the use of currency forwards at international equity mutual funds. Using a unique hand-collected dataset spanning 15 years and over 1,200 US mutual funds, we identify three distinct styles to the use of currency forwards, spanning liquidity, hedging, and speculation motives. Funds frequently construct separate currency portfolios of both long and short positions that often contain exposure to currencies not in the underlying equity portfolio. These currency portfolios can be large, reaching as high as 60% of the fund's total net assets. Furthermore, we find that forward usage is related to exchange rate momentum, carry, and volatility, and that funds with better currency-picking capabilities are also superior stock pickers. Among the group of non-user funds, we show that a dynamic approach to currency forward contract usage would have generated substantially stronger investment performance.

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 the diversification gains it can offer (Solnik, 1974; Eun et al., 2008; Opie and Riddiough, 2020). A primary way that investors gain exposure to foreign equities is through international equity mutual funds. Since the early 1990s, the assets under management across U.S.-based international equity mutual funds have expanded rapidly from \$100 billion to almost \$3 trillion. Indeed, these funds now account for around 25% of the entire U.S. equity mutual fund industry, up from 15% in the early 1990s (see Fig 1).

Fund managers at international equity mutual funds face a critical question that domestic equity fund managers do not: what role should currency play in the portfolio? International equity returns are affected by exchange rate returns, generating a source of exchange rate risk. Yet the currency management decision is not a simple question as to whether that risk should be hedged or not. While managers can selectively reduce exposure to certain currencies through the use of currency derivative contracts, they can also target higher risk-adjusted returns by judiciously expanding their exposure to other currencies. In fact, currency management can be undertaken at arms-length from the underlying equity portfolio, such that the currency composition of the derivative and equity portfolios can be largely unrelated.

A growing body of literature documents that currency management matters—an international portfolio's investment performance is materially affected by the choice of currency management, no matter whether this is undertaken using passive hedging (Campbell et al., 2010), dynamic hedging (Opie and Riddiough, 2020; Barroso et al., 2022), or by building a separate currency portfolio at arms-length from the equity portfolio (Kroencke et al., 2014; Pojarliev and Levich, 2014). But despite this importance, we have little evidence on the ways in which currency risk is managed in practice by international equity fund managers and whether the approaches used are optimal. This paper aims to fill this gap in the literature.[1]

Using the quarterly holdings reports of 1,279 international equity funds, we hand-collect fund-level details on over 55,000 net currency forward positions, from Q1 2004 to Q2 2019.[2] In

[1]Given recent evidence that US domestic equity funds experience diminishing returns to scale as the industry grows in size (Pástor et al., 2015), international investing is poised to become an avenue through which US active fund managers can add value. Indeed, Berk and van Binsbergen (2015) find that active funds that invest more in international stocks add more value. They also show that the fraction of TNA managed by active domestic-equity-only funds has almost halved over the last few decades. As international investing become more common place, how best to manage currency exposure is increasingly critical to investment outcomes.

[2]Currency forward contracts are the derivative of choice for the management of currency exposures at mutual funds. We observe only a handful of funds using alternatives such as options or futures contracts and therefore

no case is the use of currency forwards mechanical: the funds we study all have unhedged equity benchmarks, they have no underlying mandate to hedge currency exposure, and in no case is an otherwise equivalent currency-hedged portfolio offered to investors. Analysing these data, we contribute to the funds management literature by: (i) providing the first categorization of international equity mutual funds according to the way they use currency forwards; (ii) documenting the determinants of currency forward usage; (iii) investigating the impact of the use of currency forwards on fund performance; (iv) studying the relationship between currency-picking and stock-picking capabilities, and (v) exploring the potential investment performance of non-user funds from alternative currency management strategies.

In the empirical analysis, we initially split our sample into two groups: users and non-users. A user is defined as any 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 these funds in the main body of the analysis, while in further analyses we consider the impact that using currency forwards could have made on non-user funds.

To determine funds' main purpose for using currency forwards, we first look at a standard measure used in the currency hedging literature—the hedge ratio, which measures the percentage of currency exposure being offset by the use of currency forwards. We find that around 14% of funds hedge a significant portion of exchange rate risk, although only two funds could be considered "full" (100%) hedgers. Instead, the majority of funds adopt a hedge ratio close to zero. In fact, over 80% of the funds have an average fund-level hedge ratio between −5% and +5%, indicating that hedging is unlikely to be the main purpose for using forward contracts.

Exploring further, we find that while hedge ratios are typically low, many funds adopt large *absolute* currency forward positions (i.e., the sum of all absolute currency forward positions), which often exceed 20% and reach as high as 60% of their total net assets (TNA). Put differently, funds frequently enter a mix of long and short currency forward contracts on different currencies in order to construct a separate currency portfolio. Given the low hedge ratios, vast majority of these portfolios are approximately dollar-neutral, but are large in absolute terms relative to the size of the underlying equity portfolio—indicating a desire to use currency markets for an additional source of investment performance. Indeed, we find that many of the forward positions are entered in currencies that are not part of the underlying equity portfolio. These

focus our attention on currency forward contracts.

portfolios can be viewed as "shadow" portfolios—the positions are not reported as part of the funds' total asset position, and yet amplify funds' total risky asset positions.

Funds have therefore adopted a range of approaches to managing currency exposure. We choose to categorize this behavior into three distinct "styles." The first style, labelled "exposure management" (66 funds), involves entering short currency forward contracts to reduce currency exposure. Funds in this group have non-trivial hedge ratios, above 25% on average. The second style, which we labelled "portfolio building" (202 funds) involves the construction of a separate currency portfolio. These funds have low average hedge ratios (around 0% on average) but large average absolute forward positions (above 10% of their TNA on average). Finally, funds with both low average hedge ratios and absolute forward positions, likely trading on a tactical basis for shorter-term liquidity needs, are classified as "occasional users" (203 funds).

To make the categorization clear, in Fig 2, we present examples of each style 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 US 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 the main empirical analyses we focus on the behavior of exposure managers and portfolio builders to document the properties and determinants of currency forward use in each case. For exposure managers, we find a clear cost motive: currency forwards are typically used to hedge only a handful of positions in the portfolio that relate to the largest currency exposures and mainly the currencies of developed economies. We also find evidence that funds may use forwards to target returns using momentum and carry signals: hedge ratios are lower for both recently appreciated currencies and those with the highest interest rates. In addition, funds reduce the volatility in their underlying equity portfolio by hedging currencies with the highest levels of volatility. Moreover, consistent with the recommendation to dynamically hedge currency exposure, we find the largest increases in investment performance are observed for the most active exposure managers—those exhibiting the highest volatility of hedge ratios both over time and within the portfolio.

Among portfolio builders, we investigate the determinants of currency portfolio weights to understand why a currency is chosen as an investment or funding currency in a given quarter. We find evidence that currencies exhibiting either higher short-term momentum or higher volatility-adjusted carry are attractive investment currencies, although we find no evidence that currency value is a significant driver of forward usage. We find that a large driver of "funding" positions (i.e., negative currency portfolio weights) are the weights in the underlying equity portfolio and hence funds often "hedge" currencies such as the euro, Japanese yen, and British pound, while simultaneously increasing exposure in currencies that could enhance investment performance. Building on this analysis, we investigate the investment performance of the currency portfolios. We observe large cross-sectional variation: across five groups sorted by investment performance, we find the Sharpe ratios of the currency portfolios range from -0.62 in the lowest group to 0.73 in the highest group. Moreover, funds with the strongest currency investment performance also deliver the highest information ratios in the underlying equity portfolio measured in local currency, indicating that investment skills may manifest across multiple asset classes.

We extend our analysis by considering the 808 funds that did not use currency forward contracts during the sample period. Opie and Riddiough (2020) find that an unhedged international equity portfolio generated the weakest investment performance for a US fund manager between 1997 and 2017, when compared with a large set of alternative approaches to managing currency exposure. Indeed, relative to a fully hedged portfolio or a portfolio hedged using "dynamic currency factor" (DCF) hedging, the Sharpe ratio of the unhedged portfolio would have been between 0.09 and 0.25 lower over the period. Given this prior finding, we explore the potential gains that US international mutual fund managers could have obtained through utilizing currency forward contracts in the portfolio.

We find that across the entire sample both the fully hedged and DCF-hedged approaches would have delivered substantially higher Sharpe ratios, for which risk-averse investors would have been willing to pay up to 2% per annum to obtain. One concern, however, is that the US dollar appreciated strongly post-2011, implying stronger performance for the fully hedged position. Nonetheless, when we split our sample, we find that full hedging and DCF hedging produced superior performance to not hedging during the period of US dollar appreciation, but also a similar level of performance prior to 2011—reinforcing the potential benefits from using currency derivatives within an international equity portfolio.

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.[3] 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.[4] Our granular data on derivative positions help to provide more nuanced insights on the relation between fund performance and derivative use. According to our findings, the use of currency derivatives by an "occasional user" is notably different, and has contrasting objectives, to that of an "exposure manager" or "portfolio builder." For example, we find evidence that exposure managers exhibit lower portfolio volatility but higher tracking error than non-users, which would not have been evident from a direct comparison between users and non-users.

Ex-ante, it is not clear how international equity mutual funds will use currency forwards, if they even do so at all. While the textbook treatment of international *bond* portfolios typically recommends fully hedging currency exposure to remove unwanted volatility (i.e., a 100% 'hedge ratio'),[5] there is no clear-cut recommendation for international equity portfolios. If currency exposure only increases volatility without impacting returns, then a 100% hedge ratio is thought to be optimal for international equity portfolios. Perold and Schulman (1988) argue in favour of this approach, describing it as a "free lunch" for portfolio managers. In contrast, Froot (2019) argues that a hedge ratio closer to zero is optimal in the long run, since hedging only reduces volatility over short horizons. Indeed, if a country's currency and equity market are negatively correlated, then currency exposure can provide a natural hedge.[6] If agents are

[3] Deli 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.

[4] Aragon 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.

[5] See, e.g. Campbell et al. (2010). Eun and Resnick (2018) note that "empirical evidence regarding bond markets suggest that it is *essential to control exchange rate risk* to enhance the efficiency of international bond portfolios" (emphasis added).

[6] The evidence on historical stock-currency correlations suggests, however, that the correlation is close to zero (see Cenedese et al., 2016, for details).

subject to "regret risk" that arises from choosing an extreme hedging option that subsequently underperforms, then a hedge ratio between 50% and 100% becomes optimal (Michenaud and Solnik, 2008). Other authors have contended, however, that existing currency exposures should be managed selectively. Campbell et al. (2010) for example, argue that equity managers should only partially hedge currencies that negatively correlate with world equity markets, while Black (1990) incorporates expected returns from Siegel's paradox and finds that a "universal hedge" ratio is less than 100%.[7] Glen and Jorion (1993) and Opie and Riddiough (2020) find that conditional hedging strategies can substantially improve an international equity portfolio's performance when hedge ratios are dynamically updated. An alternative perspective is to view currency as an *independent* source of investment performance. Kroencke et al. (2014) and Pojarliev and Levich (2014) take this viewpoint and show benefits from fully hedging currency exposure in the underlying equity portfolio, while simultaneously allocating part of the fund's capital to a separate currency portfolio.[8]

Sialm and Zhu (2022) is an important complementary study that investigates the use of currency derivatives at US international *fixed income* mutual funds.[9,10] The authors find that most funds use currency forwards, with the average hedge ratio being 18%. Moreover, hedging is related to the degree of foreign currency exposure and known sources of currency premia, including carry and momentum. In contrast, we show that the behavior of international equity funds displays striking differences—exposure hedging is rarer at equity mutual funds, while portfolio building is not observed at fixed income funds. Our study also offers benefits from additional features in the data. We can rule out the possibility that benchmarks influence fund behavior by focusing only on funds without a hedged benchmark, and study the implications from not using currency forwards. Sialm and Zhu (2022) find that funds using currency forwards earn higher returns than those not using currency forwards. As the authors note, however, this finding could be biased by their shorter sample in which the US dollar was mainly appreciating. In contrast, our study almost doubles the sample period, allowing us to study different phases

[7]Black (1989) finds plausible values for the universal hedge ratio equal to 30% and 77%. Solnik (1993) argues, however that the universal hedge ratio is driven entirely by wealth and risk aversion.

[8]A fundamental reason for this perspective stems from the beneficial diversification properties of currencies due to the observed low correlation between currency market "factors" and equity market index returns. See, e.g. Burnside et al. (2011). Glen and Jorion (1993) find, however, little benefit from adding currencies to a pre-determined equity portfolio.

[9]A larger literature exists studying the use of currency derivatives at corporations. See, e.g. Geczy et al. (1997), Allayannis and Weston (2001), and Brown (2001).

[10]Maggiori et al. (2020) have documented that investors have a preference for investing in bonds denominated in their home currency, however unlike bond markets, equity markets are denominated universally in the local currency.

of both US dollar appreciation and depreciation.

Finally, the paper contributes to a broader literature investigating the impact of exchange rates on mutual fund's 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 fund's selection of international investments is also heavily influenced by its 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 US international equity mutual funds. The study enables us to shed new light on the range of 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 US international equity mutual funds from CRSP and Morningstar, and select all international (including global) equity mutual funds at the intersection of the two datasets. Merging the two databases serves three purposes: first, CRSP and Morningstar have slightly different definitions of international equity funds, and there are inconsistencies in the classification of certain funds. We only consider funds that are classified as international funds by *both* CRSP and Morningstar. Second, we undertake an extensive data merging and checking process, similar to that adopted by Berk and van Binsbergen (2015) and Pástor et al. (2015), to help ensure the accuracy of the data. Full details of the procedure are documented in the Online Data Appendix. Third, Morningstar provides performance benchmarks extracted from funds' prospectuses, which enable us to determine if a fund has a currency-hedged benchmark. Finally, Morningstar records the percentage portfolio weight denominated in each currency, which we use in the calculation of funds' hedge ratios.

Portfolio holdings data are available from CRSP from 2003 onward. However, we find 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.[11] To ensure data accuracy, we therefore manually collect data on the mutual funds' currency forward positions from SEC filings via the SEC's EDGAR database. The sample starts in 2004, the year in which the SEC mandated quarterly reporting by mutual funds 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.

Our primary data are funds' open forward foreign exchange forward contracts. Figure 3 presents an example of the forward positions we hand-collect from funds' SEC filings. It shows an extract from the 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 some or all of the following: the notional amount of the contract in foreign currency and US dollars (USD), the market value in USD on the reporting date, the settlement date, the counter-party to the contract, and the unrealised gains/losses in USD.

We require the market value of funds' forward currency contracts for the calculation of hedge ratios and currency portfolio weights. If the market value of the contract is not reported, we use the notional value of the contract, in conjunction with spot exchange rate data, to calculate the market value. To do so, we obtain daily bid, mid, and ask WMR spot and forward exchange rate data from Datastream. For cross-currency forward contracts, we convert each leg of the contract into a forward position against the USD. We also aggregate long and short positions for the *same* foreign currency within a given reporting period to arrive at a net forward position for each fund-currency-quarter.[12] Determining hedge ratios also requires information on the magnitude of funds' currency exposure arising from the underlying equity portfolio. To derive these exposures, we use data provided by Morningstar on the percentage of each funds' TNA invested across 48 countries.[13]

[11] For 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 they were unable to account for the CRSP values.

[12] Some funds utilize an investment structure in which the fund invests solely in a master portfolio. In these cases, we collect the fund's percentage ownership in the master portfolio. If that 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. We then use this percentage to calculate the fund's share of currency forward positions held within the master portfolio.

[13] We aggregate euro-zone countries to obtain each funds' euro exposure. Country weights are available on a monthly frequency for some funds and on a quarterly or semi-annual frequency for others. We backward- and

We merge the quarterly data on currency forward contracts with the 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 US) is greater than 101% or less than 0%; (ii) the sum of the country weights (excluding the US) 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 resulting sample consists of 55,615 net forward positions and 1,279 funds, of which 471 (37%) have open currency forward contracts during the sample. The average net forward position has a notional value of minus US $13.2m (i.e., a short position in foreign currency) and 62% of the positions are written on G9 currencies. We find that less than 3% of the positions are in cross-currency forwards, i.e., *not* involving the USD. Given the majority of funds did not have open currency forward contracts, we check if funds are restricted by mandates from using currency forwards. We do so by studying the funds' prospectuses (form N-1A) for any mention of currency forwards (see Figure 4 for examples of the use of currency forward contracts, extracted from funds' filings with the SEC). 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 outright prohibit the use of currency forward contracts.

2.1 US International Equity Mutual Funds

Table 1 reports descriptive statistics on the US international equity mutual funds we study. We initially report statistics for all funds in the sample, and then later turn to the split between users and non-users of foreign exchange forward contracts. In each case, the column "Obs" refers to number of fund-quarter observations in the sample.

Confirming that the funds we study are internationally focused in their investment activity, we observe that 83% of their assets held are, on average, issued by firms outside of the United

forward- fill weights if available within a two-quarter period.

[14]Fund reports are filed at fiscal quarter-ends, not calendar quarter-ends. A fund can end its fiscal year in any month, and it can change its fiscal cycle over time. We bring the SEC data to calendar quarter-ends for consistency. Following Wermers et al. (2012), we assume that portfolio positions reported at a fiscal quarter-end are valid at the subsequent calendar quarter-end.

[15]We 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.

States. Moreover, 50% of the assets are issued by G9 developed market firms, and hence around one-third of assets are held outside the United States in either small developed market or emerging market countries.[16] We also observe that the funds typically hold assets from a large set of countries, with funds investing, on average, in over 16 different countries. The range is, however, large: the sample includes country funds that focus on a single economy and funds with a broad geographical focus across both developed and emerging markets.

Considering the remaining descriptive statistics for all funds, we note that the average quarterly net return is 1.9% and is in line with the funds' benchmark index return. Indeed, the average fund return, adjusted for the benchmark index return, is essentially zero (-0.01% on average). Furthermore, we find that funds' average expense ratios, turnover ratios, and total net assets, are all in line with prior studies of global equity funds (see, e.g. Busse et al., 2014).

Turning to the split between user and non-user funds, we report the same set of descriptive statistics for each group and, in the final two columns of Table 1, report the differences in the mean values between the two groups and associated p-values. To obtain the p-values, we conduct permutation tests with 1,000 simulations on the fund-average value of each fund characteristic.[17] Comparing the values across user and non-user funds, we first note that the funds are similar in terms of their investment focus: both types of funds hold over 80% of their assets outside the United States, with user funds holding marginally more G9 assets. Cost potentially plays an important role in the decision to hedge foreign exchange exposure, and thus funds holding assets of smaller developed economies or emerging economies may be less inclined to enter less liquid, and thus more costly, currency forward contracts.

Prior studies have focused on the differences in investment performance of users and non-users of derivatives securities, with mixed findings (e.g., Koski and Pontiff, 1999; Kaniel and Wang, 2020). Supporting the earlier finding of Koski and Pontiff (1999), we observe no statistical difference in net returns, volatility of net returns, or benchmark adjusted returns of the two groups. In part, this result is surprising: hedging currency exposure should in principal reduce return volatility, unless currencies exhibit a natural hedge, for which the prior evidence has

[16] The "G10" is a common reference in currency markets to the most actively traded developed market currencies. These include the US 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 US dollar.

[17] For each characteristic, we randomly regroup the funds into two groups of the same size as the two original groups, consistent with the null hypothesis of no difference between users and non-users. Each fund appears once in each resample. We calculate the test statistic for each resample and construct its distribution. The p-value is the proportion of resampled test statistics that exceed the original test statistic.

largely failed to support.[18] We return to explore this observation further, when investigating currency management styles in Section 3.

While we fail to observe differences in investment performance, we do find that user funds tend to be more active funds. Indeed, their annual turnover ratio is 70% on average, compared to 55% for non-user funds. User funds also tend to be more established: they are older (13 versus 10 years on average), manage more assets (total net assets are around $1 billion higher on average), and have lower changes in funds under management (1.3% vs 3.6% average fund flow). Furthermore, consistent with higher costs arising from currency forwards, we note that the fund expense ratio of user funds is 0.07% per annum higher than that of non-user funds.

In Figure 5, we present time-series evidence on the breakdown of user- and non-user funds. In the top panel, we show the total number of funds in the sample by year (the height of each bar), split by users and non-users. The percentage of funds using currency forward contracts in that period is denoted above each bar. We see that the number of mutual funds trends higher across the sample, beginning at 491 in 2004 and increasing to 892 in 2019. Of these funds, the share using currency forward contracts changes substantially across the sample, displaying an inverted-V shape pattern.

In 2004, only 12.8% of funds used currency forwards. This value quickly increased over the following years, reaching a high of 31.6% in 2008. Following the global financial crisis, however, the proportion of funds using currency forward contracts began to steadily fall, dropping below 20% by the end of the sample in 2019. These industry-wide patterns in user fund levels coincide closely with broad movements in the US dollar and global interest rates. Indeed, between 2004 and 2011, the US dollar experienced a significant depreciation against a broad basket of other currencies.[19] A depreciating US dollar generates higher returns for funds with *unhedged* foreign assets and thus more use of forwards may seem surprising.

However, there are three main reasons why funds would have chosen to use currency forwards during this period spanning liquidity, hedging, and speculation rationales. First, in terms of liquidity, in an environment of dollar weakness, some funds may have chosen to lock-in exchange

[18]See, for example, Cenedese et al. (2016) who find that the correlation between a country's equity market return and its foreign exchange return is typically close to zero. There are, however, a handful of currencies that do display natural hedge tendencies, including the Japanese yen and Swiss franc. Prior studies have considered the drivers of this "safe haven" status (Ranaldo and Söderlind, 2010; Habib and Stracca, 2013) and how it potentially affects optimal currency hedging (Campbell et al., 2010).

[19]This depreciation continued a trend following the collapse of the dot-com bubble, in which the US Dollar Index (DXY, a measure of US dollar strength against a basket of developed market currencies), fell from around 120 to less than 80 in 2011. Only during the global financial crisis did the dollar experience a significant, but short lived, appreciation due to heightened safe-haven flows.

rates early in anticipation of future asset purchases, prior to any further dollar weakness. Second, during the period the US dollar became undervalued relative to PPP against most currencies and thus funds may have begun hedging in anticipation of mean-reversion in value. Finally, the period witnessed high returns for currency hedge funds, driven in large part to high carry trade returns in 2005, 2006, and 2007 when global interest rates were high. Funds may have sought to gain exposure to this source of returns during this part of the sample. Following 2011, these broad trends have reversed—the US dollar has strengthened and global interest rates converged towards zero, limiting the profitability of the currency carry trade. The liquidity, hedging, and speculation motivation for using currency forwards have thus reversed during the second half of the sample.

Consistent with these observations on the number of user funds, in the lower panel of Figure 5 we find a similar pattern in the notional amounts of forward usage across the sample. The figure present the net sales and absolute position of currency forwards across the sample of user funds. The net sales represent, for user funds as a whole, the total notional value of forward positions (the sum of short and long positions) relative to their total net assets. A positive value indicates that the user funds in aggregate have removed exchange rate exposure, whereas a negative value indicates that they have obtained additional exposure. We make two primary observations from the figure, which we expand upon in Section 3. First, the average net sales are typically low—less than 4% of total net assets, suggesting that funds are not, in general, hedgers of foreign exchange exposure. Second, there are large differences between the net sales and absolute forward positions, especially around the global financial crisis. This second observation suggests that funds may increase, rather than reduce, exchange rate exposure, indicating possible liquidity or speculative motives for using currency forwards. In the next section, we build upon these observations by investigating and categorizing the alternative approaches funds use in their management of currency exposure.

3 Currency Management Styles

In this section, we begin our investigation into the approaches that US international equity mutual funds use when managing their currency exposure. Our analysis is focused, therefore, entirely on the activities of user funds. We categorize user funds by their style of currency management and make initial observations on their investment performance and decisions relating to which currency forward contracts they enter.

3.1 Hedge Ratios

To gauge the extent of currency hedging activity, we first explore the distribution of fund-level hedge ratios. The fund-level hedge ratio is the proportion of a fund's aggregate foreign exchange rate exposure (from foreign equity investments) that is offset by short currency forward positions. Precisely, the fund-quarter hedge ratio for fund i at time t is calculated as:

$$hr_{i,t} = -\frac{\sum_j \widetilde{nf}_{i,j,t}}{\sum_j w^{na}_{i,j,t}} \tag{1}$$

where $\widetilde{nf}_{i,j,t} = \frac{nf_{i,j,t}}{TNA_{i,t}}$ is the net forward position of fund i in currency j at time t, normalised by the fund's TNA at time t. We measure the net forward position as the difference in the US dollar values of long and short contracts in currency j at time t. Therefore, a negative value represents a net short forward position in currency j. Furthermore, $w^{na}_{i,j,t}$ is the weight of the fund's TNA denominated in foreign currency j at time t.

For each user fund, we calculate their average fund-quarter hedge ratio over time and present the histogram of these averages in left-hand panel of Figure 6. We make three primary observations: (i) average fund-level hedge ratios tend to cluster around zero; (ii) over 100 funds *obtained* new exposure to foreign currencies through net long currency forward contracts; and (iii) only around 20 funds hedged, on average, more than 20% of their entire foreign currency exposure. Indeed, among user funds, the average fund-level hedge ratio is only 2.4%. Overall, therefore, this initial evidence indicates that only a small fraction of the mutual funds in our sample can be viewed as a "currency hedger" in a traditional sense.

3.2 Absolute Forward Positions

While a textbook currency hedger would enter primarily short currency forward contracts, we observe that most users instigate a mix of both long and short forward contracts across a range of foreign currencies, suggesting a quite different approach to currency management. To better understand this dimension of funds' activity in the forward foreign currency market, we measure funds' *gross* forward positions (i.e., as opposed to the hedge ratio that captures a *net* position). Specifically, we define fund i's absolute forward position (normalised by fund TNA) at time t as:

$$f^{abs}_{i,t} = \sum_j |\widetilde{nf}_{i,j,t}| \tag{2}$$

where $|\widetilde{nf}_{i,j,t}|$ is the absolute net forward position in foreign currency j observed at time t normalised by the fund's TNA at time t. In the right-hand panel of Figure 6, we present the scatter plot of funds' average hedge ratios against their absolute currency forward positions.[20] While the initial analysis highlighted that most funds have near-zero fund-level hedge ratios, by extending the analysis we see that many funds form large aggregate currency positions—often above 2% of their TNA (highlighted in red in Figure 6). In fact, some fund even adopt absolute positions above 50% of their TNA. To be clear, a fund with an approximately zero average hedge ratio but an absolute forward position above 50% is, in effect, running a separate currency portfolio that is neutral to the US dollar (hence the zero hedge ratio) but is amplifying the risk exposure of the entire fund by over 50%.

We make two additional observations relating to the scatter plot. First, for a small number of funds, both the absolute forward position and the hedge ratio are high and comparable in size (bottom-right quadrant of the figure). These funds are, either exclusively or predominantly, entering short forward positions and thus reducing foreign exchange rate exposure.[21] Second, a large cluster of funds have both low hedge ratios *and* low absolute forward positions. We denote these funds by blue diamonds in the plot. These funds all have absolute forward positions lower than 2% of TNA and hedge ratios between −5% and +5%, and therefore trade forwards in both directions but in small quantities relative to their total assets.

3.3 Exposure Managers, Portfolio Builders, and Occasional Users

From the preceding analysis, it is clear that funds use currency forwards in different ways and with different objectives. Indeed, three broad types of currency forward user (or currency management "styles") emerge from the preceding analysis. The first are funds that build a currency portfolio that is sizable relative to the fund's total net assets. The forward contracts used by these funds have negligible hedging effect (at the fund level) and may actually increase the fund's overall currency exposure. We refer to these funds as "portfolio builders," and conjecture that the principal aim of this group is to use currency markets to enhance the investment performance of the fund. The second group of users are those primarily reducing

[20] We calculate these fund-level averages over the quarters that a fund uses forwards. Some funds use currency forwards sparingly, and therefore we only consider the quarters that a fund uses forwards to remove the impact of hedging frequency. Furthermore, for presentation, we present only funds with average fund-level hedge ratios between −20% and +20%.

[21] For a fund that only takes short forward positions, the fund hedge ratio is either equal to or greater than the fund's absolute forward positions (normalized by TNA), depending on whether the fund is fully or partially invested in assets denominated in foreign currencies. The smaller the portfolio weight in foreign assets, the bigger the gap between the two measures.

their foreign exchange rate exposure. These funds have the most substantial hedge ratios and absolute forward positions. We denote this second group as "exposure managers." Exposure managers may principally intend to passively reduce foreign exchange volatility or they may adopt more dynamic setups, which intend to also capture positive currency excess returns. The third group take relatively small positions in currency forward contracts. These positions do not hedge significant underlying exposure and have little-to-no impact on a fund's overall investment performance. We refer to this group as "occasional users." Various motives may explain the use of currency forwards among this final group, but we view the most likely rationales to include hedging short-term transactions in the underlying portfolio or obtaining liquidity for an upcoming equity purchase. In the next sub-section, we provide details of our approach for categorizing funds into these three styles of currency management.

3.4 Categorizing Funds

We classify forward users into three groups—namely exposure managers, portfolio builders, and occasional users—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. The first variable allows us to identify funds that use currency forwards only infrequently, while the second and third variables allow us to disentangle between the primary motives, i.e. whether to construct a separate currency portfolio or to reduce foreign currency exposure. A fund is classified as an exposure manager if it uses forwards in at least 10% of quarters, and has an average hedge ratio of at least 10% during those quarters. We classify a fund as a portfolio builder if it uses forwards in at least 10% of quarters, and its absolute forward position is at least 2% 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 10% of quarters, or whose absolute forward position is, on average, less than 2% of their TNA.

Naturally, any classification scheme requires subjective choices. Indeed, there is no well-defined point at which a fund with a zero hedge ratio and small, but non-zero, absolute forward position, is constructing a currency portfolio rather than simply obtaining liquidity for equity transactions. For that reason, we choose a categorization scheme that is simple and transparent, but that captures the spirit of the various approaches to currency management we observe. Nonetheless, in further analyses, we undertake robustness around these cut-off points and also implement a machine learning algorithm to classify funds, in order to highlight that the main findings in our paper are in no way reliant upon a specific approach to categorization.

After employing our classification scheme, we obtain a sample of 66 exposure managers, 202 portfolio builders, and 203 occasional users. In Figure 7, we present a measure of each fund's foreign currency exposure, split by the user type. On the horizontal axis, we plot each fund's weight in foreign currencies. The majority of funds are heavily weighted (over 80%) in foreign equities, although we also find a second cluster with around 40% to 60% foreign exposure (which are mainly "world funds" as we show in the Online Appendix). On the vertical axis, we plot the fund's average currency exposure, arising from both underlying equity positions and currency forward positions. A fund that fully hedges currency exposure using currency forwards would therefore have a value around zero on this dimension. We also include a 45-degree line and a (+/−) 5% band. Funds on the 45-degree line have effectively the same exposure to currency following the use of currency forwards, as they did before their use.[22]

We note that exposure managers are observed across funds with both the highest and lowest shares of foreign assets in the portfolio. Nonetheless, some of the biggest reductions in exposure are among funds with the lowest overall shares in foreign assets. In part, this could be because it is less costly to significantly reduce foreign currency exposure in the portfolio. But it could also reflect an effort to better align with peer funds, if these exposure managers happen to be relatively underweight in US dollar assets. Portfolio builders and occasional users are, as would be expected, almost entirely concentrated around the 45-degree line—their exposure is effectively unchanged through the use of currency forward contracts.

In Table 2, we present additional statistics, split by the three styles of currency management. In the top panel, we provide further details on the use of currency forwards across groups. Exposure managers and portfolio builders use currency forwards in the majority of quarters, whereas occasional users have outstanding currency forward contracts only around one-third of the time. In part this is mechanical, since funds using forwards in less than 10% of quarters are automatically designated as occasional users, however it also indicates that many funds are regular users, but in small quantities and typically for fewer currencies. The other statistics in the top panel confirm our categorization procedure. The average hedge ratio for exposure managers is over 25%, whereas it is only 0.1% and −0.1% for portfolio builders and occasional users. Moreover, the average absolute value of fund forwards (as a percentage of TNA) jumps

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

to 12.4% for portfolio builders but remains low, at only 1.5%, for occasional users.

In the lower panel of Table 2, we begin our investigation of the investment performance of funds across the three styles of currency management. We focus on three primary measures of performance: benchmark adjusted returns, return volatility, and tracking error. For each metric, we report the average and standard deviation across funds, as well as the difference in the average value relative to non-users. Our first finding, consistent with the earlier work by Koski and Pontiff (1999), is that none of the groups generated superior benchmark adjusted returns. This result is less surprising for exposure managers and occasional users, since the latter trades in small quantities, likely for liquidity reasons, while the former may principally be seeking to remove foreign exchange risk. Indeed, we find that exposure managers *do* reduce a statistically significant proportion of portfolio risk relative to non-users. The result is more surprising for portfolio builders, since the rationale for obtaining an additional currency portfolio is, presumably, to improve the portfolio's overall risk-return profile. Yet, we find that benchmark adjusted returns are lower, and volatility is higher, than for non-users—a topic we return to explore more deeply in the next section.

The cost of removing foreign exchange exposure for exposure managers is an increased tracking error—since the benchmark is unhedged, removing exchange rate volatility creates an immediate asymmetry with the returns of the benchmark portfolio. In contrast, we see that portfolio builders have lower overall tracking error compared to the non-user funds. Indeed, one possible alternative motive for portfolio builders is to realign their portfolio to more closely match the composition of currencies held in the benchmark portfolio.

3.5 Foreign Exchange Forwards by Currency Management Style

In Table 3, we focus on exposure managers and portfolio builders to begin our investigation into *which* currency forward contracts they instigate. In total, we obtain data on over 55,000 net forward positions (i.e., while a fund many have multiple forward contracts outstanding on a given currency pair at quarter-end, we net the positions to obtain a single outstanding position, and hence the number of positions we report is smaller than the total number of contracts outstanding). Over two-thirds of these currency forward positions are held by portfolio builders, while exposure managers held around 15%.

We list the currencies in descending order based on their total number of net positions in the dataset. Unsurprisingly, the list matches closely with those compiled in the triennial surveys of the Bank for International Settlements (BIS, see e.g. BIS (2022)), in which currencies are ranked by daily turnover, with the euro, yen, pound sterling, and other major developed market currencies being dominant. 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 these currencies than for the New Zealand dollar, a major G10 currency. The evidence in the table also confirms the classification of exposure managers: for almost every currency, the proportion of positions that hedge over 25% of the underlying exposure (column headed % HR>25%) is substantial—typically between 70% and 100%.

For both exposure managers and portfolio builders we report the number of positions in which the fund had no underlying position (NUP) in the equity of that country. Put differently, while the positions could potentially have cross-hedged a third currency, they were not *directly* hedging any underlying exposure. We observe that just over 93% of these positions were held by portfolio builders, consistent with these funds using currency as an independent source of investment performance. Indeed, we find that some of the largest NUP currencies have a carry trade flavour—offering especially high or low interest rates, including the Australian and New Zealand dollars, Norwegian krone, Israel shekel, Danish krone, and Singapore dollar. In the column denoted % long, we present the proportion of positions in which the fund obtains *more* exposure to that currency, i.e. the currency is effectively long in the portfolio. Within the G10, we observe especially high values for the Australian dollar and Swedish krone, while in emerging market space, the Malaysian ringgit and Indian rupee are the most prominent currencies. In contrast, the euro is only in the long-side of the currency portfolios 41% of the time.

In Figure 8, we build upon this analysis to highlight which currencies exposure managers tend to hedge more of, and which currencies portfolio builders tend to hold long or short. Moreover, the figure provides a time-series dimension, allowing for a comparison across years. The size of each square represents the relative frequency of currency forward positions held by that particular group of user. We make two primary observations relating to the figure. First, there is typically consistency in the positions over time. The euro, for example, is the currency most likely to receive an abnormally high hedge ratio or to be in the short-leg of a currency portfolio,[23] particularly following the global financial crisis (GFC) when interest rates in the euro-area fell to zero. Moreover, the carry dynamic hinted at in Table 3, is again observed for

[23] We define the abnormal hedge ratio for currency j in fund i at time t as the difference between the hedge ratio for the currency $hr_{i,j,t}$ and the hedge ratio for the fund $hr_{i,t}$.

portfolio builders: long currencies typically include the Australian, New Zealand, and Canadian dollars, while the euro and Japanese yen are the most likely to be included in the short leg.

Second, we notice that the number of net forward positions change in different ways across time for the two groups. For exposure managers, we see relatively small number of positions in the lead up to the GFC, but much larger number of positions following 2011—a period in which the US dollar underwent a significant appreciation. In contrast, we observe that portfolio builders were more active during the period between 2006 and 2014, when active currency managers enjoyed some of their most profitable years, prior to a subsequent drop in performance. Indeed, in the years since the GFC, many well-known currency strategies have experienced weakened performance, limiting the gains from currency investing (Ranaldo and Somogyi, 2021), which may account, at least in part, for the reduction in the use of currency forwards observed earlier in Figure 5.

4 Exposure Managers and Portfolio Builders

In this section, we investigate the currency management styles of exposure managers and portfolio builders. We begin by studying exposure managers to identify the different levels of hedging activity within this style of management, before exploring the main determinants of funds' currency-level hedge ratios. We then turn to portfolio builders, to assess the investment performance of the funds' currency portfolios, and to investigate if there is a relationship between the investment performance of the currency portfolio and the underlying equity portfolio. Finally, we investigate the determinants of portfolio weights in portfolio builders' currency portfolios.

4.1 Exposure Managers

In Table 4, we present initial evidence on the use of currency forward contracts by exposure managers. From Table 1, we learned that user funds typically hold assets in a wide range of countries—the average number of countries invested is over 16. We observe in Table 4, however, that the number of currencies for which currency forward contracts are obtained is much lower. The average is less than five, while the interquartile range is narrow—stretching from 2.0 to 6.3. In fact, only around one-third of currencies held by exposure managers are hedged. Even at the 75th percentile, less than 50% of currencies are hedged. We attribute this outcome to a cost motivation: hedging of smaller developed and emerging market currencies is more expensive and, if those currencies form a relatively small weight in the portfolio, hedging costs may be prohibitively high. Indeed, when exposure managers do hedge, they tend to hedge a significant proportion of the underlying currency exposure (47.3% on average), and therefore the average hedge ratio at the fund level (in quarters when forward contracts are outstanding) is almost 30%.

As highlighted in the earlier discussion of related literature, various alternatives have been proposed for optimal currency hedging. In some approaches, the hedge ratio is constant across time and currencies (e.g., Perold and Schulman, 1988). But at the other extreme, dynamic hedging advocates for varying the hedge ratio at regular intervals over time, while also adopting different hedge ratios across currencies (e.g., Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020). In the final two rows of Panel A in Table 4, we report the distribution of hedge ratio volatility over time (time-series, ts) and across currencies (cross-section, cs). To measure the time-series volatility, we calculate the standard deviation of the hedge ratio at the fund level. To measure the cross-sectional volatility, we calculate the quarterly standard deviation of hedge ratios across currencies within a fund, and then obtain the fund-level value by calculating the mean cross-sectional volatility over time. We find the values display a considerable range across the exposure managers in our sample. The time-series volatility is 16.3% on average but the series is positively skewed—one-quarter of funds exhibit volatility at or below 9.4%, and thus select relatively static hedge ratios. Moreover, cross-sectional volatility is also high for many funds (the average is 21.1%), but the series is once again positively skewed, and thus the choice to adopt similar hedge ratios across currencies is common across the sample.

In Panel B of Table 4, we investigate the different approaches to exposure management to learn how the differences impact investment performance. To do so, we first split funds into two groups based on their hedge ratio volatility (ts). We label these two groups "passive" and "active." Within these two groups, we then split again into two new groups based on their hedge ratio volatility (cs). We label these groups "low" and "high." Hence we construct four groups in total (two passive groups and two active groups). The average values of hedge ratio volatility within each group are reported in the first two rows of Panel B, confirming the sorting procedure. In the next four rows, we present the funds' average excess returns, Sharpe ratios and equivalent values *without* currency forward contracts.

To exclude the impact of currency forwards from the calculation of funds' returns we subtract the return on the funds' portfolio of forwards from the net return of funds.[24] We note that for all

[24]The net return of fund i (with forwards) at time t+1 can be decomposed as $R^{with}_{i,t+1} = R^{without}_{i,t+1} + R^{for}_{i,t+1}$. The total return on fund i's forward positions at time t+1 is calculated as $R^{for}_{i,t+1} = \sum_j (\widetilde{nf}_{i,j,t} \times ExR^{for}_{j,t+1})$,

groups, the funds slightly increase their Sharpe ratios, on average, from using currency forward contracts. This increase is not only through a reduction in volatility. In fact, we find that each group generates a slightly higher average excess return, which is around 0.25% per annum for active funds, and 0.13% per annum for passive funds. Indeed, one of the primary motivations for adopting a more active approach to currency exposure management is to take advantage of changing expected returns. Consistent with this view, we find that one in five active funds displays statistically significant market timing in their hedging activity—more than twice the level of passive funds.[25]

4.1.1 On the Determinants of Hedge Ratios

We investigate the determinants of funds' currency-level hedge ratios by estimating a set of fixed-effects panel regressions, in which the dependent variable is fund i's hedge ratio in quarter t for currency j, which we denote $hr_{i,j,t}$. We winsorize the hedge ratios at the 1% and 99% levels to mitigate the impact of outliers. The model we estimate takes the form:

$$hr_{i,j,t} = \mathbf{B}'\mathbf{X}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t} \tag{3}$$

The purpose of the model is to uncover why certain currencies tend to be hedged more-or-less than others in a given quarter. Thus, while the data has a time-series dimension, our focus is on the cross-sectional decision making of funds. To answer this question we therefore include fund × quarter fixed effects ($\gamma_{i,t}$) to explore the within fund-quarter determinants of hedge ratios. The set of K determinants we consider are time-varying, currency-specific, and lagged by one quarter. We thus estimate a vector ($\mathbf{B}$) of coefficients using the K-dimensional vector of determinants ($X_{j,t-1}$). Since funds may avoid hedging emerging market currencies due to the lower liquidity and higher cost, we also include an emerging market dummy variable (δ_{em}), equal to 1 if the currency is classified as an emerging market according to Morgan Stanley Capital International (MSCI). We cluster standard errors at the fund × currency level.

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 $ExR^{for}_{j,t+1}$ is the return on a long forward on foreign currency j at time t+1.

[25] A fund may have market timing if they hedge less (more) prior to a positive (negative) excess return on the currency, and hence increase the return from hedging. To explore, we create a dummy variable equal to 1 if an increase (decrease) in the hedge ratio from time t-1 to time t in currency j is accompanied by a negative (positive) currency excess return at time t+1. We exclude observations with two or more consecutive quarters of zero hedge ratios. For each fund, we calculate the percentage of observations with correct market timing and report the group average in the row labeled Avg % correct hedge ratio timing. We apply the market timing test of Henriksson and Merton (1981) for each fund, and reject the null hypothesis of no market timing at the 10% significance level (using the critical value of 1.28 for a one-tailed test).

The estimates from these regressions are presented in Table 5. In columns (1) to (8), we present results in which we include a single explanatory variable to clearly observe the individual relations. In the final column, we combine the variables to estimate the main model described above to take account of the cross-determinant correlations. In column (1) we observe that funds choose to primarily hedge currencies in which they have the largest underlying exposure—confirming earlier observations that relatively lower weights in the equity portfolio, likely of smaller developed or emerging market countries, are more likely to remain unhedged. The magnitude of this effect is only slightly reduced when all variables are included and indicates that a country with a 30% higher weight in the underlying equity portfolio, will have around a 20% higher hedge ratio (0.701 $\times$ 30%), holding all else equal.

We next consider three determinants known to be potential drivers of currency returns: momentum (Menkhoff et al., 2012), carry (Lustig et al., 2011), and value (Menkhoff et al., 2017), which are potentially important factors in a dynamic currency hedging strategy that targets a higher Sharpe ratio (Glen and Jorion, 1993; Opie and Riddiough, 2020). We find that all three variables have a statistically significant relation with next-period hedge ratios at the 5% significance level, and that the signs of the coefficients are broadly in the direction anticipated when seeking higher returns. Specifically, stronger momentum (the one-quarter exchange rate return) or carry (the forward discount relative to the US dollar) predict a lower hedge ratio, consistent with an attempt to capture momentum or carry returns. We find, however, that under-valued currencies (measured following Asness et al. (2013), as the deviation from the real exchange rate) are more likely to be hedged, although only momentum and carry remain highly statistically significant in the full model.

In columns (5) and (8), we turn to the cost of hedging, conjecturing that a higher cost reduces the incentive to hedge foreign exchange exposure. In column (5), we consider a direct cost: the bid-ask spread on the three-month forward exchange rate. Instead, in column (8), we present the coefficient on the emerging market dummy variable. As anticipated, a wider bid-ask spread, and emerging market currencies in general, are found to reduce the incidence of hedging. Once controlling for all possible determinants, we find the bid-ask spread is rendered insignificant and that, from a cost perspective, funds appear to generally favour hedging developed economy currencies—the hedge ratio of an emerging market currency is found to be over 4.5% lower than that of an otherwise identical developed market currency.

One of the most natural rationales for using currency forward contracts is to reduce portfolio volatility stemming from unwanted foreign exchange risk.[26] Funds may thus choose to adopt a higher hedge ratio for currencies with higher underlying exchange rate volatility, which is precisely what we observe. In column (6), we note that a 1% higher level of exchange rate volatility, calculated using the past 12-months of returns, increases the hedge ratio by 0.43%, which is essentially unchanged in the broader model.

Finally, we test if country-level equity returns are important for currency hedging, since a relatively high equity return increases a fund's exposure to that country's currency. Camanho et al. (2022) find that equity market movements can have a relation with exchange rates, as funds rebalance their portfolio—selling the currencies of recently outperforming equity markets. Instead, we test if funds increase their hedge ratios of these currencies by including the equity return as a determinant variable in the model. We find, however, that the coefficient is effectively zero and thus does not appear to be important in funds' decision making. This finding is also consistent with the mechanism of Camanho et al. (2022), in that funds may undertake all of their rebalancing at the end of the quarter, and therefore do not require additional currency forward contracts if their foreign exchange exposure is unaffected.

In sum, the preceding analysis has shown that exposure managers choose hedge ratios in quite different ways—ranging from passive funds that maintain relatively similar hedge ratios over time and for all currencies, to those funds adopting active approaches. Within the portfolio, funds tend to hedge higher proportions of currencies that occupy a larger component of the underlying equity portfolio. Doing so offers a means to reduce portfolio volatility and often comprises currencies that are highly liquid and thus less costly to hedge. Moreover, we find evidence that developed market currencies, and those currencies exhibiting higher volatility, tend to have higher hedge ratios. But we also find a clear expected return motivation, with momentum and carry both important in driving funds' hedge ratios.

4.2 Portfolio Builders

We next turn to investigate portfolio builders. Portfolio builders construct currency-specific portfolios, consisting of both long and short currency forward contracts. We ask three questions about these currency portfolios: (i) what is the investment performance? (ii) Is there a link

[26] Campbell et al. (2010) suggest that funds leave exposure in currencies which offer a natural hedge. These "safe haven" currencies will tend to appreciate when stock markets fall in value, and thus provide some protection against downside risk. We find, however, that because funds typically hedge their largest exposures and perhaps also because the US dollar tends to appreciate during global "bad times" due to flight-to-safety flows, that a safe haven dummy variable has a positive correlation with funds' hedge ratios. These results are available upon request.

between better currency picking abilities and the investment performance of the underlying equity portfolio? And (iii) what factors determine the portfolio weights?

4.2.1 The Investment Performance of Currency Portfolios

In Table 6, we present statistics on the investment performance of the currency portfolios constructed by portfolio builders. Across all portfolio builders, the annualized Sharpe ratio of the portfolio is found to equal 0.08, which is substantially below the level documented by many recent studies that optimize the investment performance of currency portfolios, either by combining various strategies (see, e.g. Jordà and Taylor, 2012; Asness et al., 2013; Kroencke et al., 2014), enhancing existing strategies (Bakshi and Panayotov, 2013), or through mean-variance optimization (Maurer et al., 2023). Consistent with this result, we find a mildly positive average annualized "alpha" of 27 basis points across funds, after controlling the returns for carry, momentum, and value.[27] Therefore, it appears that currency portfolios do not contribute significantly to returns, yet they may still provide diversification benefits, due to the low correlation of currencies with equity markets (Burnside et al., 2011; Cenedese et al., 2016).

Across the entire set of portfolio builders, the range of average currency portfolio returns is large. Indeed, the interquartile range stretches from an average loss of −1.05% per year, to a gain of 2.88%. We further explore this distribution of performance in the lower panel of Table 6. To do so, we initially sort funds into one of five groups (G1 to G5) according to the information ratio of the currency portfolio.[28] Differences in values between the extreme portfolios are denoted under the column G5−G1 and p-values associated with the null hypothesis that the difference equals zero, are presented in the final column.[29]

We find the size of the portfolio is unrelated to the outperformance of the G5 funds. In

[27]We form long/short currency portfolios based on carry, value, and momentum signals for G10 currencies (excluding the USD). Each quarter, we rank currencies based on each of the three signals (i.e., the interest rate differential, the extent of currency undervaluation, and the exchange rate return) from the previous quarter, each long/short portfolio then buys the top three currencies and shorts the bottom three currencies based on the ranking for each signal. We generate the average alpha across funds by regressing fund currency portfolio returns on carry, value, and momentum portfolio returns in a panel regression with fund fixed effects. We note that, from unreported results, the alpha is slightly higher if we construct the long/short portfolios using all currencies with floating exchange rates (25 including both developed and emerging market currencies).

[28]To 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.

[29]We perform permutation tests with 1,000 resamples. In each resample, we randomly regroup funds in the original groups 1 and 5 into two new groups of the same size. Each fund appears once in each resample. We calculate the p-value as the proportion of resampled test statistics (difference in the groups' mean) that exceeds the original test statistic.

fact, both G1 and G5 have the smallest overall currency portfolios—around 8% of total net assets, which is around half the size of the portfolios held, on average, by funds in G2 to G4. Furthermore, we find 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. We find these higher risk-adjusted returns are driven entirely by higher portfolio returns rather than lower portfolio volatility. Indeed, the volatility of the G5 currency portfolios is higher, on average, than the volatility of portfolios among funds in G1 to G4.

We next turn to address whether there is any relation between currency portfolio performance and funds' underlying stock-picking abilities. We undertake the analysis by continuing to study the same five groups of funds, sorted by the information ratio of their currency portfolios. In the final four rows of Table 6, we present the performance of their underlying international equity portfolio. The first two rows reflect the performance of these portfolios in *local* currencies, and hence are uncontaminated by exchange rate movements.[30] The excess returns of these groups are not perfectly monotonic, but there is a clearly increasing pattern from G1 to G5, with the annualized difference being 2.94% (p-val = 0.02), which is also reflected in the Sharpe ratios (difference of 0.24, p-val = 0.00). We find the strength of these results are driven by the extremes of the distribution—the Sharpe ratios of G2 to G4 fall in a relatively narrow range.

One potential concern is that the results are driven by G5 funds adopting benchmarks, and hence associated strategies, that happened to outperform during our sample period. To control for this possibility, we report the benchmark adjusted returns and benchmark adjusted information ratios in local currencies.[31] Once again, we find a close relation with currency investment performance. The difference in benchmark adjusted returns is 1.18% per annum (p-val = 0.05) and the difference in benchmark adjusted information ratios (which monotonically increase across groups) is 0.32 (p-val = 0.01). Overall, therefore, we find significant differences in the performance of currency portfolios across funds, and that the outperformance correlates

[30] We estimate the local-currency return of fund i at time t+1 as $R^{local}_{i,t+1} = R^{with}_{i,t+1} - R^{for}_{i,t+1} - R^{cur}_{i,t+1}$. $R^{with}_{i,t+1}$ 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 $R^{for}_{i,t+1} = \sum_j (\widetilde{nf}_{i,j,t} \times ExR^{for}_{j,t+1})$, 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 $ExR^{for}_{j,t+1}$ 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 $R^{cur}_{i,t+1} = \sum_j w^{na}_{i,j,t} \times CuR_{i,j,t+1}$, where $CuR_{i,j,t+1}$ is the exchange rate return on foreign currency j at time t+1.

[31] Morningstar 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 gross benchmark-adjusted return for each fund in local currency by adding back the management fee. The information ratio in local currency is the average benchmark-adjusted return divided by the standard deviation of the benchmark-adjusted return.

with stronger investment performance in the underlying equity portfolio.

4.2.2 On the Determinants of Portfolio Weights

Since the size of currency portfolios vary and, given that many currency forward contracts are held in currencies with no underlying equity position, it is uninformative to study the determinants of currency hedge ratios. Instead, we study the determinants of currency portfolio weights ($w^{cp}_{i,j,t}$) for fund i in currency j at quarter t. To enable comparability of currency portfolio weights across funds of different sizes, we take the following steps to standardize the notional forward positions: first, we calculate the sum of fund i's long forward positions and the sum of the absolute value of its short forward positions. Second, we normalize the forward positions of fund i using the maximum of the two values calculated in step 1. Third, we treat the USD as the balancing position, such that the long and short forward positions sum to 0.

Consistent with our study of hedge ratios among exposure managers, we choose to study the cross-sectional choices of funds—i.e., we explore why certain currencies command higher positive weights, while others are effectively "funding" currencies that reduce the portfolio's net US dollar exposure. In the recent foreign exchange literature, various currency strategies have been documented that generate, often large, cross-sectional spreads in currency returns. A major part of this investigation is, therefore, to assess the extent to which these approaches are adopted by funds in practice.

The model we estimate takes the same functional form as that for hedge ratios:

$$w^{cp}_{i,j,t} = \mathbf{B}'\mathbf{X}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t} \tag{4}$$

where $\gamma_{i,t}$ reflects a fund $\times$ quarter fixed effect, allowing us to study within each fund-quarter the determinants of the cross-sectional spread in funds' portfolio weights. All determinants are lagged by one quarter and we include an emerging market dummy variable (δ_{em}). The coefficient estimates, and associated standard errors, are presented in Table 7. As before, the results are initially shown separately for each independent variable, prior to presenting the full model that controls for interdependencies among the factors.

Interestingly, we find that weights in the underlying equity portfolio are significant predictors of currency portfolio weights. Indeed, if a country increases it's equity weight by 50% it would, on average, lead to around a 25% reduction in the currency weight. In other words, short forward contracts, which reduce currency exposure, are partly chosen in consideration of the underlying equity portfolio. This decision is likely driven by a few motivating factors. First, while we consider portfolio builders as funds that invest in a separate currency portfolio, most likely for return generation, it is possible that these funds also use forwards for hedging purposes. This practice is consistent with earlier recommendations by Pojarliev and Levich (2014) and Kroencke et al. (2014) to hedge the foreign exchange rate exposure in the underlying equity portfolio, while obtaining new currency exposure in a separate portfolio. Second, the largest equity positions are often in developed market currencies, which are less costly to hedge. Third, those developed markets are often low interest rate economies, such as the Eurozone or Japan, which are known to generate lower currency excess returns (Lustig et al., 2011).

We consider four main determinants of currency portfolio weights that arise from the literature on cross-sectional currency returns: (i) momentum, (ii) carry, (iii) value, and (iv) liquidity. Menkhoff 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.

As was observed for exposure managers, we find clear evidence that momentum and carry are important factors in the decision-making process. Currencies with stronger exchange rate momentum command a higher weight in the portfolio. The effect of momentum is, however, relatively modest. A 4% increase in the exchange rate return over the quarter translates into just over a 1% higher weight in the currency portfolio. We observe larger effects for carry and, especially, risk-adjusted carry. Both variables display statistically significant and positive relationships with portfolio weights, but only risk-adjusted carry remains significant in the final model, presented in column (8). Indeed, a currency whose risk-adjusted carry increases by 1 (the measure equals 1 if the interest rate differential relative to the United States is the same as the exchange rate volatility vis-à-vis the US dollar), would command almost 4% higher weight in the currency portfolio.

We find no effect on average, however, for currency value or the liquidity of currencies, while the emerging market dummy variable is also not significant individually, although becomes so in full model. This final observation is the result of 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. Overall, therefore, the drivers of portfolio weights are found to be similar to those influencing the hedge ratio decisions of exposure managers—weights in the underlying equity portfolio, momentum, carry, and volatility (or risk-adjusted carry) are highly statistically significant predictors of forward positions for both styles of currency management.

5 Non-user Funds

Having studied the two principal users of currency forward contracts, exposure managers and portfolio builders, we now turn our attention to non-user funds. The decision to not use currency forward contracts is still an active choice—the fund is effectively deciding to accept a particular form of returns—one that is driven, in part, by foreign exchange rate movements. Recent evidence has found, however, that an unhedged approach to managing currency exposure would have generated the weakest overall investment performance for US international funds (Opie and Riddiough, 2020). Indeed, Opie and Riddiough (2020) find that an alternative, "dynamic currency factor" (DCF), approach to hedging would have generated substantially stronger investment performance. In this section, we therefore reconsider the investment performance of non-user funds by assessing how this performance would have been affected by using currency forwards. There are, of course, multiple alternative approaches to currency management. However, given the success of the DCF approach, we consider that strategy as one alternative approach.[32] The second approach we consider is to simply engage in a full hedge, in which all foreign exchange exposure is eliminated each period.

We present the investment performance of these alternatives in Table 8. In the top panel (2004 to 2019), we show the investment performance across the entire sample. The first column shows the realized performance of the non-user funds. Unlike in Table 1, we present results here at the fund-level, i.e., the mean excess return is the average return across all non-user funds, irrespective of the number of periods in which they are part of the sample. The funds generated

[32]Full details of the approach can be found in Opie and Riddiough (2020). The essence of the approach is to utilize the predictability of the "dollar" and "carry" currency risk factors, in order to generate a conditional set of expected currency returns each month. The approach thus extends the ideas of Campbell et al. (2010) to allow for time-varying returns, which gives rise to a set of time-varying hedge ratios at the currency level.

an average Sharpe ratio of 0.35 but typically failed to beat the benchmark—the benchmark adjusted return was -0.24%, on average. These values serve as a comparison for the overall investment performance had currency forward contracts been used.

To investigate how currency forward contracts would have impacted the investment positions of non-user funds, we make use of the currency weights reported by Morningstar at the end of each month, in combination with the total net assets of the fund. For the full hedge, we evaluate the impact from entering a one-month forward contract that fully covers the exchange rate exposure. 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 in one month. The DCF approach to hedging involves initially calculating a hedge ratio for each currency within the portfolio, which requires the estimation of fund-specific covariance matrix each period. We follow Opie and Riddiough (2020) and 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. In the above example, if the hedge ratio, according to DCF hedging, was equal to 25% for the Japanese yen, then the fund would be assumed to enter a forward contract to sell the equivalent of \$1.25 million of yen in one month.

The investment performance of the funds from fully hedging or from using the DCF approach to currency hedging, are presented in the subsequent columns. For each statistic, we also present the difference relative to the unhedged approach (in the column Diff) as well as the statistical significance of that difference.[33] Comparing across the two alternative approaches to using currency forwards, we observe that in almost every case, the funds could have generated substantially stronger investment performance from using currency forwards. The average Sharpe ratio increases to over 0.40, stemming from both higher returns and lower volatility, while the benchmark-adjusted returns turn positive. Indeed, the benchmark-adjusted returns are between 40 and 60 basis points per annum higher with currency hedging, for which risk-averse investors would require substantially higher certainty-equivalent returns relative to the unhedged portfolio.[34] Intuitively, since the funds use unhedged benchmarks, the tracking error of the portfolio also increases following the introduction of currency forward contracts.

A natural concern is that an unhedged portfolio appears to underperform simply because of

[33]To calculate the statistical significance, 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.

[34]The 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.

broad moves in the US dollar. Indeed, in an environment of US dollar strength, an unhedged position will be inherently a weak strategy, whereas when the trend reverses, the unhedged strategy may prove to be one of the strongest options. Without any currency predictability, it is feasible to conclude that either an unhedged position or a fully hedged position is reasonable, with returns ultimately balancing in the long run. Indeed, it is for this reason that a 50% hedge rule is an alternative strategy and, while not widely observed in our dataset, it was seen more prominently by Sialm and Zhu (2022) for bond funds.

To explore this concern, we split the sample into two periods: 2004 to 2011 and 2012 to 2019. The first period reflects a period of US dollar weakness, in which the US dollar (DXY) index fell from 87.4 to 80.2. From 2012 to 2019, the trend was reversed and the US dollar index climbed back to 96.5. Naturally, we would anticipate that the unhedged strategy would perform better during the first half of the sample and underperform during the second. We are primarily interested, however, in whether no hedging statistically outperforms *both* fully hedging and DCF hedging during the first period. Indeed, there is reason to believe that DCF hedging would not underperform, since the approach directly attempts to predict US dollar movements, and thus, to the extent that the US dollar is predictable, should generally reduce hedge ratios during the first half of the sample and increase them during the second.

Before turning to the earlier period, we first consider the period from 2012 to 2019 in which the US dollar appreciated strongly. In this environment, the fully hedged approach is superior—returns are substantially higher, volatility is the lowest and thus the Sharpe ratio is 0.15 higher on average than for the unhedged portfolios. Nonetheless, while the fully hedged version is superior, we also find that DCF hedging generates a statistically significantly higher average Sharpe ratio, benchmark adjusted return, and certainty-equivalent return relative to not using currency forward contracts.

For the earlier period, between 2004 and 2011, we do observe an improvement in the overall performance from not using currency forward contracts. Interestingly, the performance is, however, not generally statistically significant, even relative to fully hedging. Indeed, the reduction in volatility from fully hedging offsets the reduction in the excess return, such that the Sharpe ratios of the unhedged and fully hedged portfolios are similar. Only the benchmark adjusted return is found to be statistically significantly lower (63 basis points per annum) when fully hedging. In contrast, DCF hedging generates slightly *stronger* performance than the unhedged portolios—returns are marginally higher and volatility is lower.

In sum, the earlier evidence from Opie and Riddiough (2020), on the under-performance from not hedging foreign exchange exposure is confirmed in this setting. Fully hedging the exposure or time-varying the hedge ratios using DCF hedging, both provide statistically significant improvements in the overall investment performance. This outperformance is stronger during periods of US dollar strength, but we also find no notable deterioration, and even modestly stronger performance using DCF hedging, during a period of US dollar weakness.

6 Conclusions

US investors are increasingly seeking to diversify their wealth in foreign markets. One potential avenue for investing overseas is via internationally focused mutual funds. Indeed, almost $3 trillion is now held in US international equity mutual funds. Whenever funds are invested internationally, it exposes the portfolio to foreign exchange risk, which introduces a potential source of return but also additional portfolio volatility. How this currency exposure is managed is thus of critical importance to a portfolio's overall investment performance and can have a material impact on investors' lifetime wealth creation.

This paper provides the first comprehensive study on the management of currency at US international equity mutual funds. Covering a 15 year period, we study over 1,200 mutual funds, and over 55,000 net forward currency contracts, to address a set of first-order questions. We find that among the international mutual funds using currency forwards, three approaches are most commonly adopted that span liquidity, hedging, and speculation motives. While many funds use currency forwards sporadically, and most likely for short-term liquidity requirements, we find that the majority adopt a more substantial foreign currency policy that we label as either "exposure management" or "portfolio building."

Exposure managers use forwards to reduce foreign exchange exposure—either in an effort to increase returns or reduce volatility, whereas portfolio builders effectively construct a "dollar neutral" portfolio, taking long and short positions, frequently in currencies not within the underlying equity portfolio. While the approaches are quite different conceptually, we find common drivers of the positions in both cases: funds typically seek more exposure to currencies with higher interest rates, stronger short-term momentum, and lower volatility.

Furthermore, we document that portfolio builders who generate the strongest currency investment performance also have the strongest performance in their equity portfolio—offering a potential new avenue for exploration in the literature on mutual fund performance. Moreover, the study highlights that non-users are potentially leaving "money on the table" through not incorporating currency forwards in the portfolio. Understanding the extent to which this is an inefficient approach to currency management, or an equilibrium outcome driven by underlying economic frictions, offers a fruitful direction forward for both theoreticians and empiricists alike.

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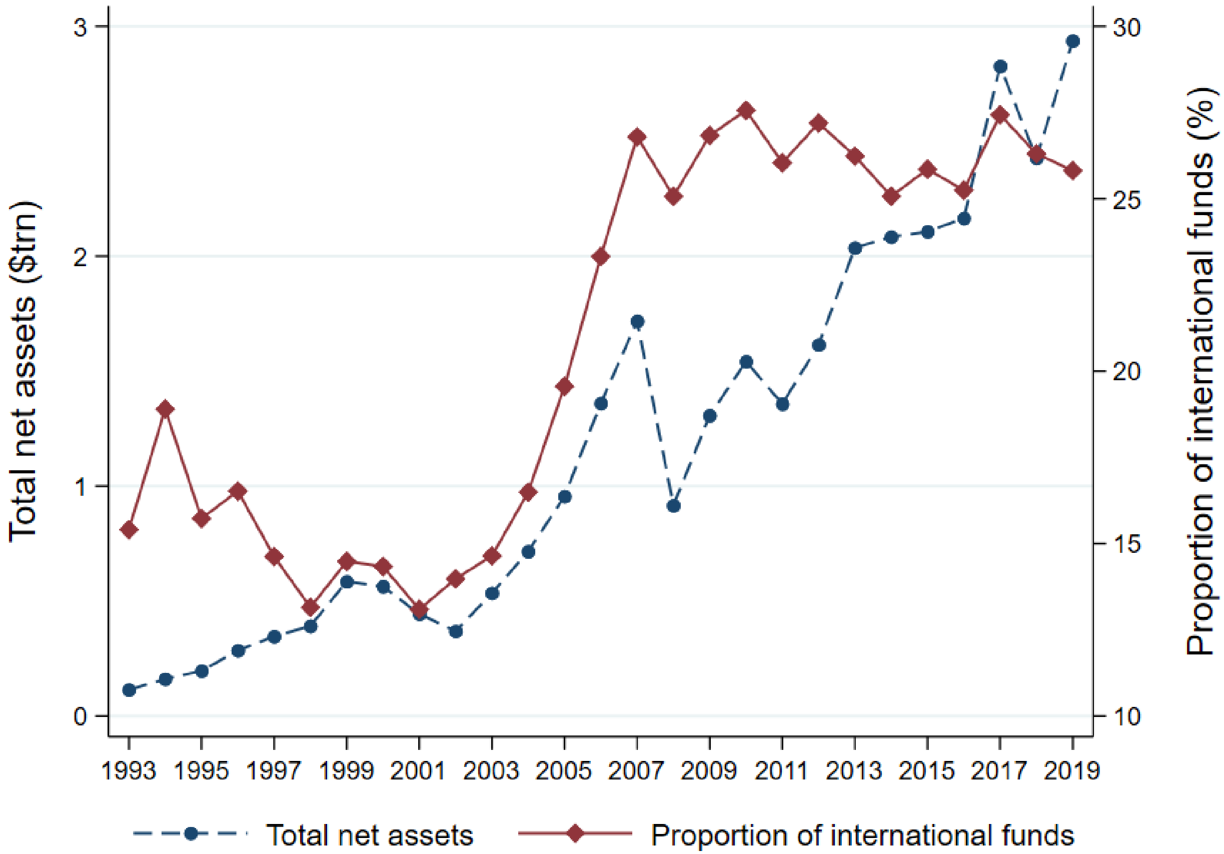
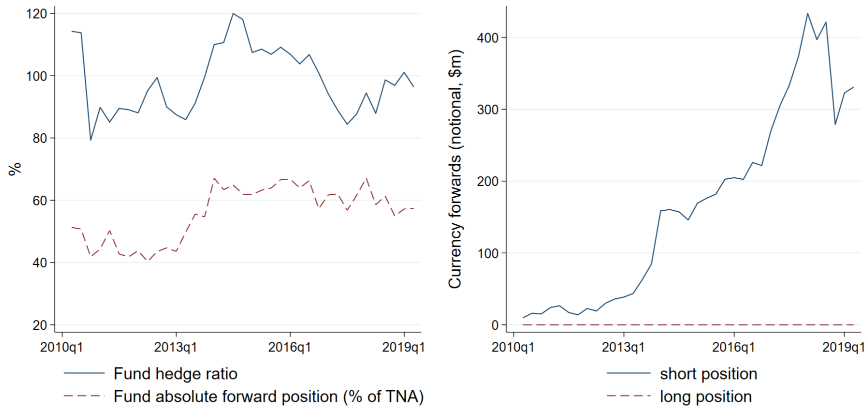
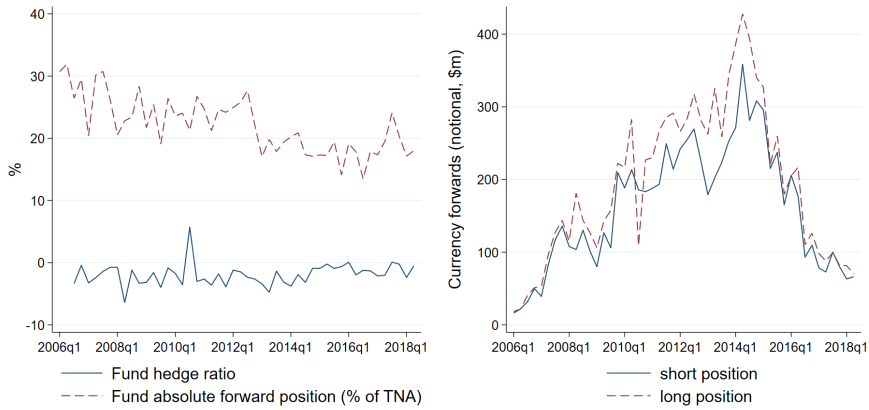


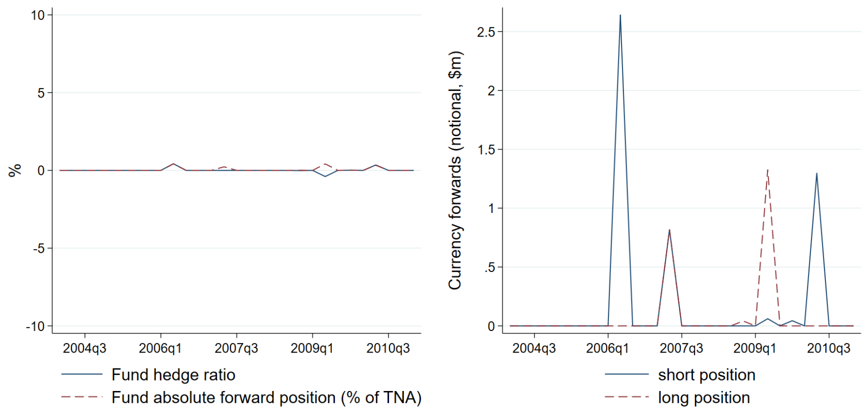
Figure 1: The Growth of International Mutual Funds. The figure presents the total net assets (in $trillions) of US-domiciled equity mutual funds and the proportion of the assets managed by international equity funds. Data source: Investment Company Institute (ICI) Fact Book.



(a) Exposure Manager: Evermore Global Value Fund



(b) Portfolio Builder: J.P. Morgan International Value Fund



(c) Occasional User: Threadneedle Int. Opportunity Fund

Figure 2: Categorizing the Use of Currency Forwards. The figure presents the time series of fund hedge ratios and total notional dollar value ($M) of long and short currency forward contracts for three funds. In the top panel, the figures is for the Evermore Global Value Fund (the "Exposure Manager"). In the middle panel, the figure is for the J.P. Morgan International Value Fund (the "Portfolio Builder"). In the bottom panel, the figure is for the Threadneedle International Opportunity Fund (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.

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

Figure 3: Currency Forward Positions of AB International Value Fund. 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 currency and amount that the fund is obliged to deliver (Contracts to Deliver), the currency and amount the fund is contracted to receive (In Exchange For), the settlement date, and the current US dollar gain or loss on the contract (Unrealized Appreciation/(Depreciation)).

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

Figure 4: On the Use of Currency Forwards. 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.

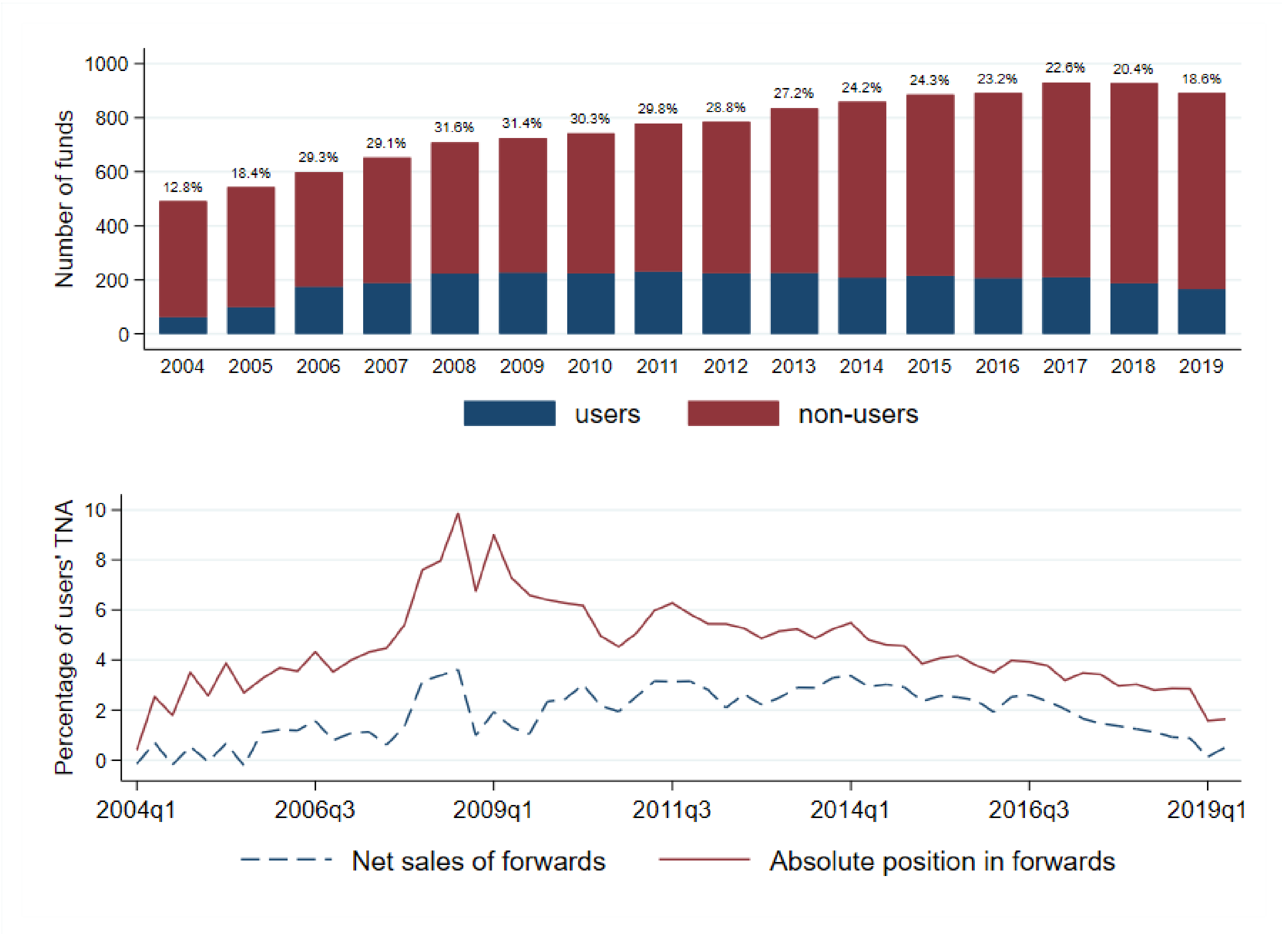


Figure 5: The Time Series of Currency Forward Usage. The top figure presents the total number of funds in the sample each year split between funds that used currency forward contracts during the year (users) and those which did not use currency forward contracts (non-users). The bottom panel shows the total notional amount of currency forward contracts (expressed as net short positions) relative to the funds' total TNA (blue line) and the total absolute position in forwards, which sums the absolute notional values of both short and long currency forward contracts vis-a-vis the US 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.

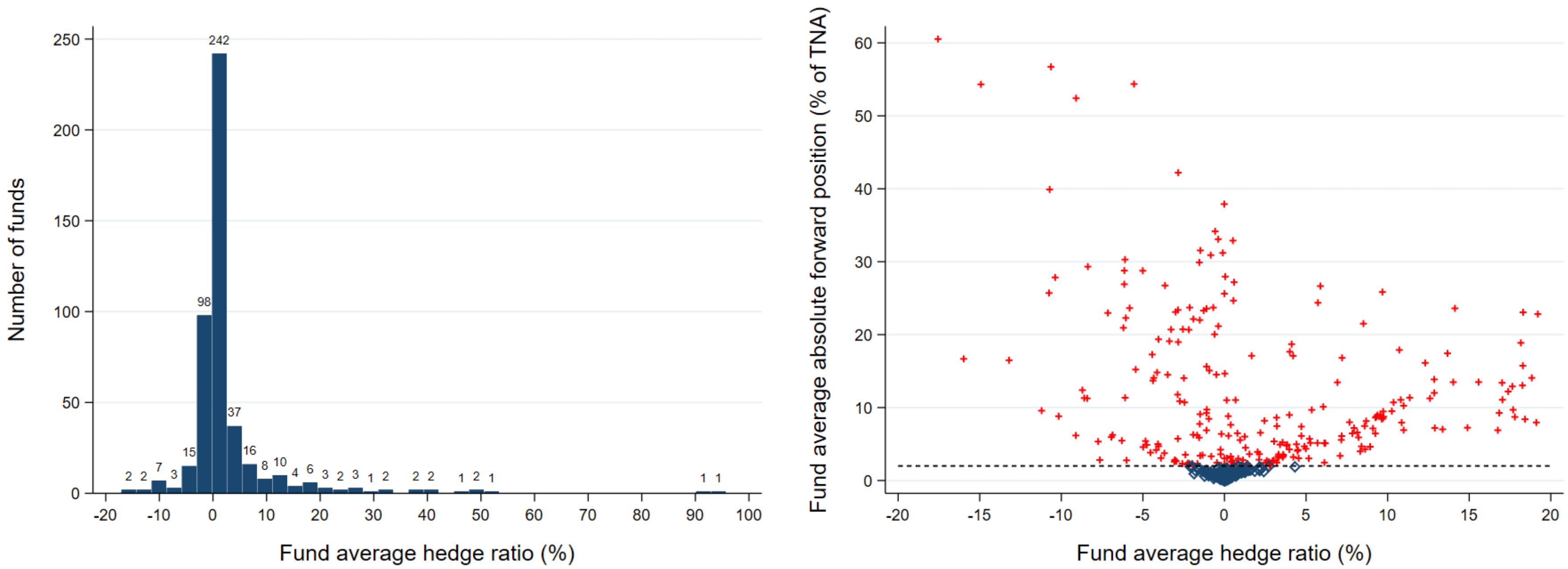


Figure 6: Hedge Ratios and Absolute Currency Forward Positions. The left-hand figure presents the histogram of average hedge ratios across funds that used currency forward contracts. The right-hand figure presents a scatter plot of funds' average absolute forward positions (y-axis) plotted against their average hedge ratio (x-axis), both of which calculated over the quarters that funds used forwards. Each point in the plot therefore reflects a separate fund in the sample. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

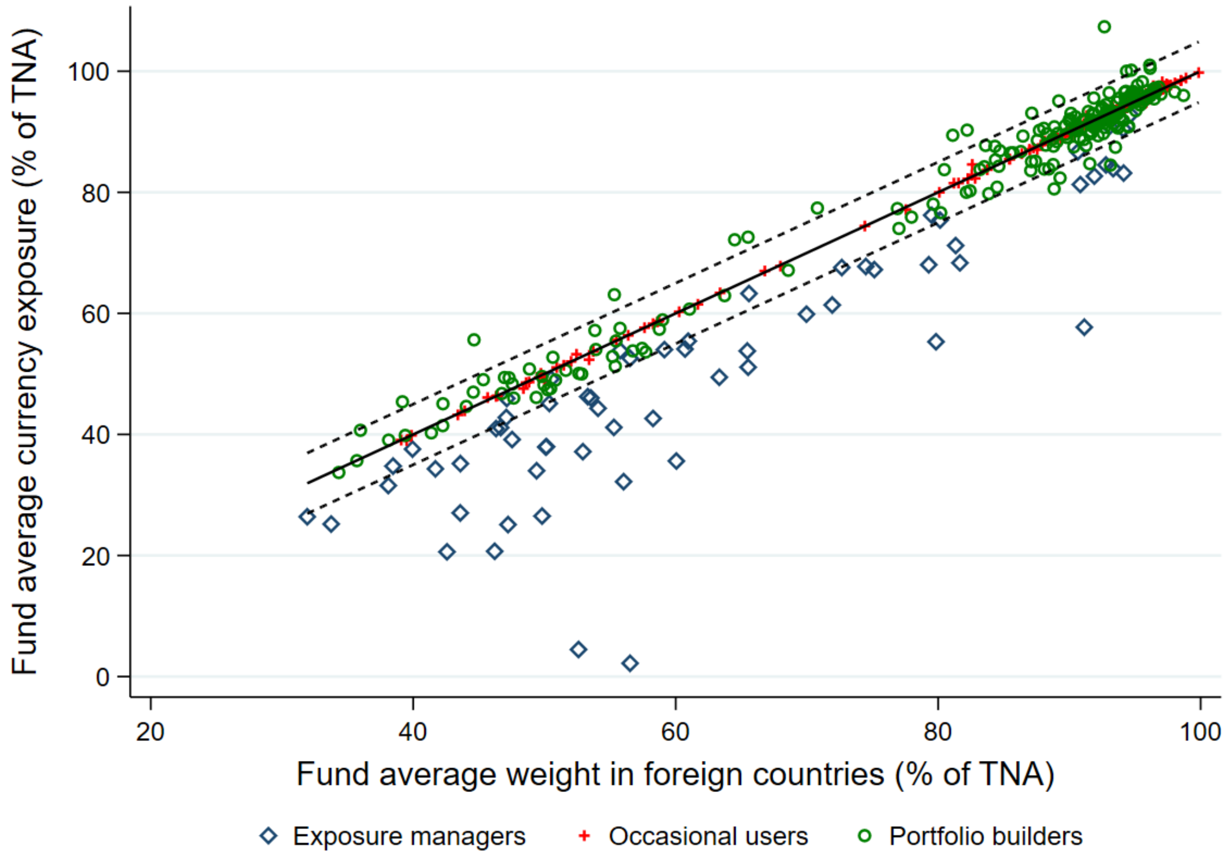


Figure 7: Currency Exposure. The figure presents a scatter plot of funds' average weight in foreign countries (x-axis) plotted against their average currency exposure (y-axis). The plot includes a 45-degree solid line with the dashed-lines to either side indicating a (+/-) 5% boundary. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Figure 8: The Use of G10 Currency Forwards by Exposure Managers and Portfolio Builders. The left-hand figure presents a heat plot showing the average abnormal hedge ratios for G10 currencies (i.e., the difference between the hedge ratio for a currency and the 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 in that currency entered by exposure managers. The right-hand figure 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 in that currency 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.

	All Funds			Non-Users			Users			Difference	
	Obs	**Mean**	**Std**	**Obs**	**Mean**	**Std**	**Obs**	**Mean**	**Std**	**U–NU**	***p*-val**
Portfolio weight outside US (%)	40,974	82.7	19.1	23,786	83.0	19.2	17,188	82.2	18.9	–0.82	0.65
Portfolio weight in G9 (%)	40,974	50.0	32.3	23,786	47.0	33.2	17,188	54.1	30.6	7.20	0.00
No. countries invested	40,974	16.3	7.26	23,786	16.0	7.46	17,188	16.8	6.95	0.78	0.00
Net return (%)	43,017	1.89	9.36	24,522	1.93	9.31	18,495	1.85	9.42	–0.07	0.79
Stdev net return (%)	40,357	7.64	3.81	22,863	7.62	3.81	17,494	7.66	3.82	0.04	0.13
Benchmark adj return (%)	42,457	–0.01	2.64	24,207	0.02	2.66	18,250	–0.06	2.62	–0.08	0.39
Tracking error (%)	39,813	2.24	1.32	22,570	2.26	1.35	17,243	2.20	1.28	–0.06	0.06
Fund flow (%)	37,305	2.61	16.1	20,979	3.59	17.2	16,326	1.34	14.5	–2.25	0.00
Fund turnover ratio (annual, %)	40,127	61.8	51.2	22,610	55.2	48.1	17,517	70.4	53.8	15.2	0.00
Fund expense ratio (annual %)	40,322	1.22	0.48	22,749	1.19	0.49	17,573	1.25	0.46	0.07	0.03
Fund age (years)	44,701	11.3	8.47	25,594	10.2	8.28	19,107	12.6	8.52	2.39	0.00
Fund TNA ($ millions)	42,793	1,579	7,001	24,473	1,192	3,007	18,320	2,096	10,097	904	0.00
Family TNA ($ millions)	44,129	21,759	47,651	25,228	24,443	44,703	18,901	18,177	51,104	–6,266	0.05

Table 1: Summary Statistics. 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). Summary statistics are also 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 Users and Non-Users is calculated and presented in the column headed U-NU. We calculate the p–val using permutation tests 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.

	Exposure Managers (66 Funds)		Portfolio Builders (202 Funds)		Occasional Users (203 Funds)	
	Mean	Std	Mean	Std	Mean	Std
			Currency Forwards			
Fund quarters using currency forwards (%)	67.5	27.8	59.8	27.1	33.3	28.2
Average number of currencies with forward contracts	4.8	4.3	6.6	5.3	2.9	2.1
Average fund forwards as % of TNA	–16.5	10.7	–0.3	4.3	0.1	2.2
Average fund hedge ratio (%)	27.7	19.6	0.1	6.4	–0.1	2.6
Average absolute value of fund forwards as % of TNA	18.7	12.1	12.4	11.8	1.5	3.0
	Mean	Std	Mean	Std	Mean	Std
			Investment Performance			
Benchmark adjusted return (%)	–0.08	0.62	–0.09	0.52	–0.05	0.56
Difference relative to non-users	–0.05		–0.05		–0.01	
p-value	[0.62]		[0.33]		[0.81]	
Std net returns (%)	6.53	1.99	7.53	1.50	7.74	1.70
Difference relative to non-users	–0.78		0.23		0.43	
p-value	[0.01]		[0.14]		[0.00]	
Tracking error (%)	2.72	1.02	2.07	0.85	2.18	1.09
Difference relative to non-users	0.39		–0.27		–0.16	
	[0.01]		[0.00]		[0.08]	

Table 2: Currency Management Styles. The table presents summary statistics for international equity mutual funds that use currency forward contracts during the sample. The funds are split based on their style of currency forward usage between "Exposure Managers," "Portfolio Builders," and "Occasional Users." The total number of funds in each group is shown in parentheses. For each characteristic of currency usage, we present the average (Mean) and the standard deviation (Std) across funds. In the bottom panel, we report funds' net returns adjusted by their performance benchmark, which is identified in their prospectus. The difference between each user type and non-users are reported under the Mean for each group, and the p-val is calculated using permutation tests with 1,000 re-samples. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Currency	Total Positions	Exposure Managers Positions	% HR>25%	NUP	Portfolio Builders Positions	% long	NUP
EUR	6,279	1,181	74	20	3,746	41	95
JPY	5,914	1,004	74	2	3,531	50	75
GBP	5,378	939	68	4	3,214	49	11
AUD	4,177	547	76	39	2,701	75	254
CHF	3,785	757	69	7	2,444	51	86
CAD	2,846	498	75	14	1,980	49	158
SEK	2,792	346	63	18	2,009	66	267
HKD	2,775	235	67	18	1,777	54	110
NOK	2,392	346	83	32	1,788	52	376
SGD	2,265	307	68	13	1,586	71	412
DKK	1,586	253	78	7	1,107	57	325
KRW	1,376	259	87	24	943	44	53
ZAR	1,358	120	90	9	849	53	126
BRL	1,173	148	79	3	799	52	39
MXN	1,156	138	71	9	805	56	136
NZD	1,080	143	91	36	885	61	397
ILS	939	93	87	9	772	60	321
TWD	757	85	83	1	581	47	52
INR	751	81	74	5	559	73	50
TRY	727	57	20	1	526	51	57
CNY	617	124	93	6	488	34	9
PLN	617	24	100	17	514	54	124
THB	585	26	75	3	432	36	39
IDR	570	43	97	1	423	64	70
MYR	561	66	78	1	401	76	117
HUF	467	23	0	0	364	48	38
CZK	465	0	-	0	397	31	91
RUB	463	56	0	0	385	56	68
PHP	461	21	100	1	388	48	61
CLP	319	20	84	0	276	66	128
COP	229	0	-	0	224	62	74
PEN	192	0	-	0	189	62	49
Other	563	23	-	0	481	70	6
Total	**55,615**	**7,963**		**300**	**37,564**		**4,274**

Table 3: Breakdown of Currency Forward Contracts. 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) for exposure managers and portfolio builders. We also report, for exposure managers, the percentage of forward positions representing a hedge ratio greater than 25% (%HR>25%) for each foreign currency and, for portfolio builders, the percentage of forward positions that are long in each foreign currency (% long). The data are quarterly, beginning in Q1 2004 and ending in Q2 2019.

Panel A: All Exposure Managers

	Mean	Med	25^{th} Pct	75^{th} Pct
Number of currencies hedged	4.8	3.0	2.0	6.3
% of currencies hedged	34.3	28.4	16.6	44.3
Hedge ratio (fund level)	29.3	21.7	10.3	39.3
Hedge ratio (hedged currencies)	47.3	50.5	25.3	85.7
Hedge ratio volatility (ts)	16.3	13.1	9.4	19
Hedge ratio volatility (cs)	21.2	17.0	10.5	24.2

Panel B: Exposure Managers by Type

	Passive		Active	
	Low	High	Low	High
Hedge ratio volatility (ts)	9.1	9.7	22.7	25.4
Hedge ratio volatility (cs)	12.1	32.7	8.8	33.1
Excess return	5.00	5.85	5.87	5.00
Sharpe ratio	0.38	0.47	0.38	0.41
Excess return without currency forwards	4.80	5.78	5.58	4.80
Sharpe ratio without currency forwards	0.36	0.46	0.36	0.37
Avg % correct hedge ratio timing	50.2	49.0	53.3	52.8
% funds with significant market timing	7	8	19	20

Table 4: The Hedging Behaviour of Exposure Managers. The table presents statistics on the hedging behavior of exposure managers. In Panel A, summary statistics are presented for all exposure managers. 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. Panel B presents investment performance of exposure managers, split into four groups based on the volatility of their hedge ratios. 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. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country weight	0.816***								0.701***
	(0.082)								(0.082)
Momentum		–0.084**							–0.139***
		(0.037)							(0.037)
Carry			–0.729***						–0.378***
			(0.117)						(0.125)
Value				0.068***					–0.018
				(0.025)					(0.024)
Bid-ask spread					–0.061***				0.023
					(0.022)				(0.019)
Volatility						0.428***			0.472***
						(0.099)			(0.107)
Equity return							–0.012		–0.001
							(0.021)		(0.021)
EM dummy								–8.489***	–4.637***
								(1.102)	(1.243)
Observations	27,527	28,524	28,412	28,524	28,413	28,524	28,524	28,525	27,425
Fund × 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

Table 5: The Determinants of Exposure Managers' Hedge Ratios. 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 × quarter fixed effects. Standard errors clustered at the fund × 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.

	Average			Returns (%)			
Currency Portfolios	**SR**	**Alpha (%)**		**Mean**	**Med**	**25^{th} Pct**	**75^{th} Pct**
All portfolio builders	0.08	0.27		0.99	0.85	–1.05	2.88
	G1	**G2**	**G3**	**G4**	**G5**	**G5−G1**	***p*-val**
				Currency Portfolio			
Information ratio	–0.75	–0.17	0.01	0.23	0.68	1.43	0.00
Portfolio size (% of TNA)	7.83	17.39	13.78	14.34	7.78	–0.05	0.98
Portfolio return (%)	–3.90	–0.61	0.79	2.71	6.10	10.0	0.00
Stdev portfolio return (%)	7.69	7.05	7.54	7.75	8.39	0.70	0.34
Sharpe ratio	–0.62	–0.14	–0.10	0.35	0.73	1.35	0.00
				International Equity Portfolio			
Excess return in local currencies (%)	3.09	4.28	3.36	4.28	6.03	2.94	0.02
Sharpe ratio in local currencies	0.21	0.31	0.24	0.29	0.45	0.24	0.00
Benchmark adjusted return in local currencies (%)	–0.06	0.70	0.13	1.32	1.12	1.18	0.05
Inf. ratio of benchmark adj. return in local currencies	–0.01	0.13	0.04	0.27	0.31	0.32	0.01

Table 6: The Investment Performance of Portfolio Builders. 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**), portfolio alpha (generated by regressing fund currency portfolio returns on carry, value, and momentum long/short portfolio returns in a panel regression with fund fixed effects), 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 (exluding all currency considerations). The column G5−G1 presents the difference between values in G5 and G1, while the column p-val is the p-value from testing the hypothesis that the value in G5−G1 is equal to zero. We calculate the p-val using permutation tests with 1,000 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country weight	–0.498***							–0.532***
	(0.069)							(0.071)
Momentum		0.236***						0.256***
		(0.034)						(0.037)
Carry			0.240***					0.162
			(0.093)					(0.137)
Volatility adjusted carry				2.321***				3.805***
				(0.840)				(1.179)
Value					–0.024			0.038
					(0.026)			(0.026)
Bid-ask spread						0.009		–0.014
						(0.015)		(0.0211)
EM dummy							–1.037	–5.066***
							(1.075)	(1.172)
Observations	32,923	36,411	36,211	36,208	35,944	36,211	36,411	32,864
Fund × 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

Table 7: The Determinants of Portfolio Builders' Portfolio Weights. 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 **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 × quarter fixed effects. Standard errors clustered at the fund × 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.

	Unhedged	Full Hedging		DCF Hedging	
	Mean	Mean	Diff	Mean	Diff
		2004 to 2019			
Mean excess return (%)	5.18	5.76	0.58***	5.60	0.42
Std excess return (%)	16.21	15.29	–0.91***	15.63	–0.58**
Sharpe ratio	0.35	0.43	0.08***	0.40	0.05***
Certainty-equivalent return	0.95	1.94	0.99***	1.63	0.68**
Benchmark adj. return (%)	–0.24	0.34	0.58***	0.17	0.41***
Tracking error	4.92	5.95	1.03***	5.54	0.62***
		2004 to 2011			
Mean excess return (%)	3.87	3.25	–0.63	3.91	0.04
Std excess return (%)	21.78	20.46	–1.32***	21.12	–0.66**
Sharpe ratio	0.20	0.18	–0.02	0.21	0.01
Certainty-equivalent return	–3.63	–3.48	0.15	–3.18	0.45
Benchmark adj. return (%)	–0.00	–0.63	–0.63***	0.035	0.04
Tracking error	5.55	6.69	1.14***	6.06	0.50***
		2012 to 2019			
Mean excess return (%)	6.25	7.44	1.19***	6.87	0.63**
Std excess return (%)	13.45	12.62	–0.83***	12.84	–0.61***
Sharpe ratio	0.49	0.64	0.15***	0.57	0.08***
Certainty-equivalent return	3.45	4.94	1.49***	4.30	0.85***
Benchmark adj. return (%)	–0.28	0.92	1.20***	0.34	0.62***
Tracking error	4.48	5.57	1.09***	5.25	0.77***

Table 8: The Potential Performance Gains from Using Currency Forwards. The table presents portfolio investment performance, measured across various benchmarks, for funds which did not use currency forward contracts during the sample The full sample includes 800 funds that have at least 12 monthly returns. The column "Unhedged" indicates the funds' actual performance. The column "Full Hedging" indicates the hypothetical performance had the fund implemented a 100% full hedge of its G10 currency holdings. The column "DCF Hedging" indicates the hypothetical performance had the fund implemented a Dynamic Currency Factor hedge following the procedure in Opie and Riddiough (2020). The difference in performance between not hedging and the alternative approaches is given in the columns headed "Diff." Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. We calculate the p–val using permutation tests with 1000 resamples. The sample period is from Q1 2004 to Q2 2019. Results for the full sample are reported in Panel A. Results 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

Variable	Description
Portfolio weight outside US (%)	Sum of non-US 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 US) 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 $\frac{AUM_t - AUM_{t-1} \times (1+GrossReturn_{t-1})}{AUM_{t-1}}$, where $GrossReturn$ 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 US 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 US 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: "US Fund Foreign Large Value," "US Fund Foreign Large Blend," "US Fund Foreign Large Growth," "US Fund Foreign Small/Mid Value," "US Fund Foreign Small/Mid Blend," and "US Fund Foreign Small/Mid Growth."
World fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: "US Fund World Large Stock" and "US Fund World Small/Mid Stock."
Emerging market fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: "US Fund Diversified Emerging Mkts," "US Fund Latin America Stock," "US Fund China Region," and "US Fund India Equity."
Regional fund	Dummy variable = 1 if a fund belongs to any of the following Morningstar categories: "US Fund Diversified Pacific/Asia," "US Fund Europe Stock," "US Fund Pacific/Asia ex-Japan Stock," "US Fund Japan Stock," and "US Fund Miscellaneous Region."
Index fund	Dummy variable = 1 if a fund is an index fund.

Table A.1: Variable Definitions

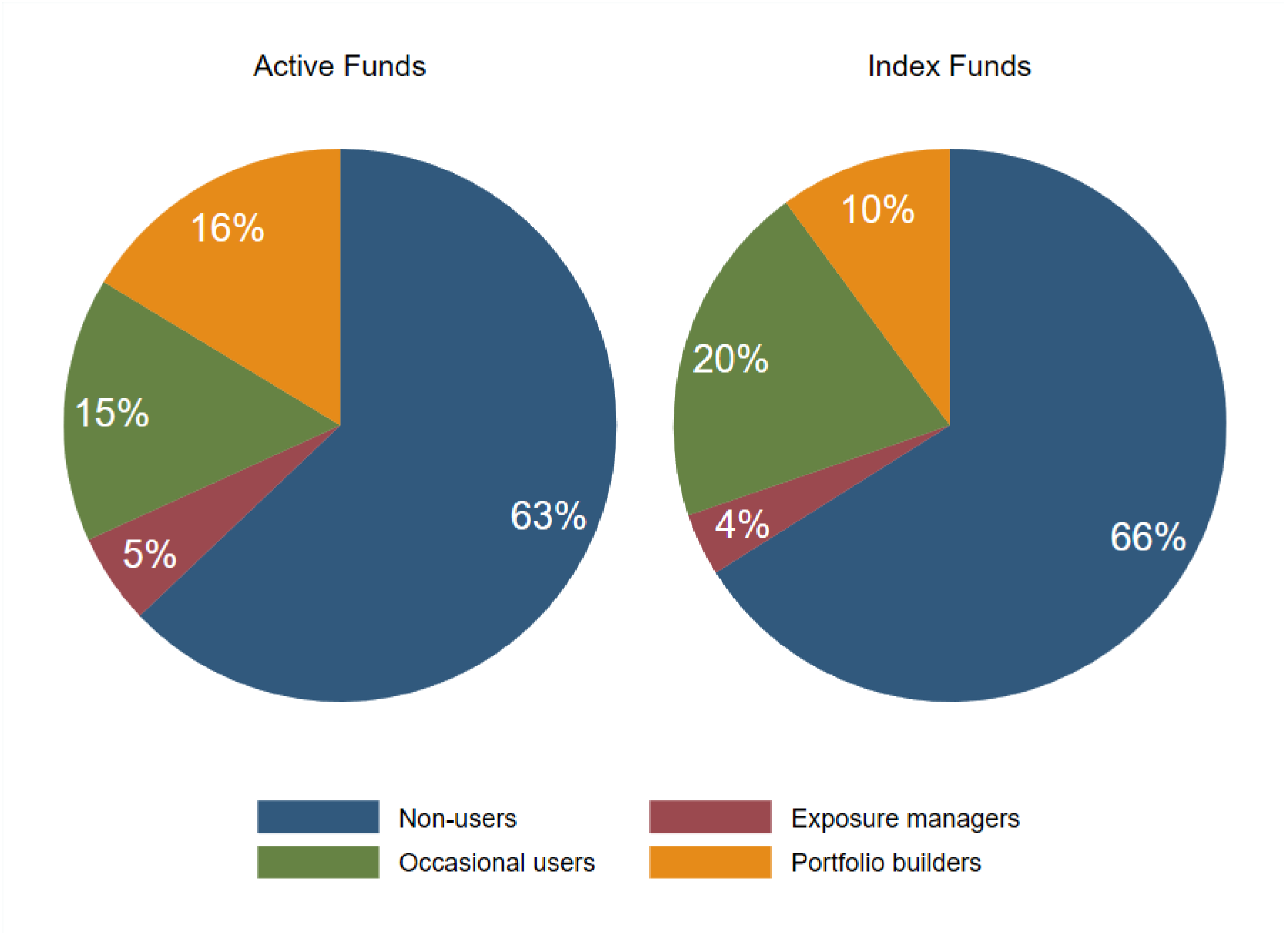


Figure A.1: The Split Between Active and Index Equity Mutual Funds. The figure presents pie charts that disaggregate the active and passive funds in our sample between users and non-users of currency forward contracts. Within the group of user funds, the funds are split between exposure managers, portfolio 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.

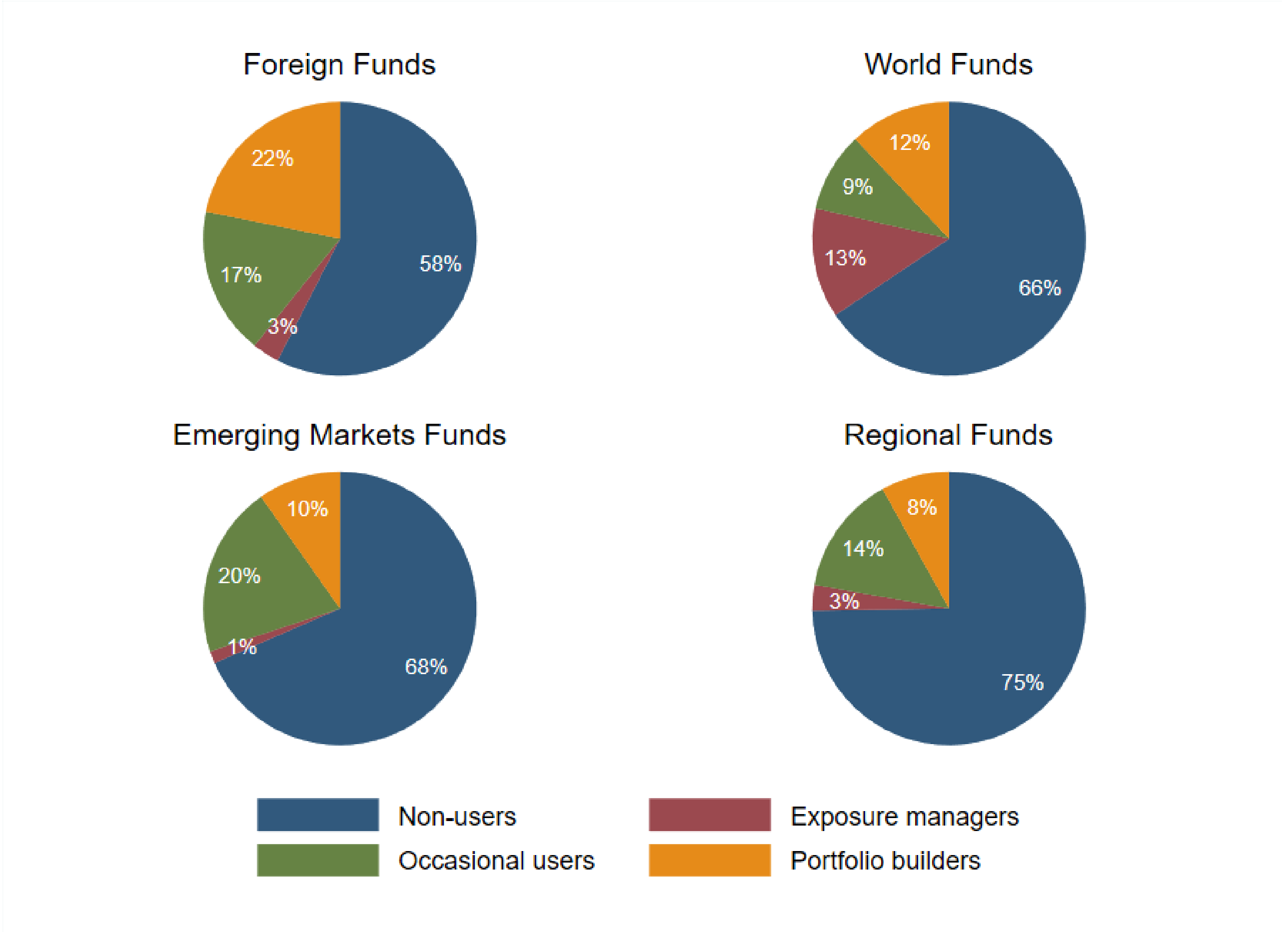


Figure A.2: The Split Between Types of International Equity Mutual Funds. The figure presents pie charts that disaggregate between users and non-users of currency forward contracts across the different types of international equity mutual funds: foreign funds, world funds, emerging market funds, and 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.

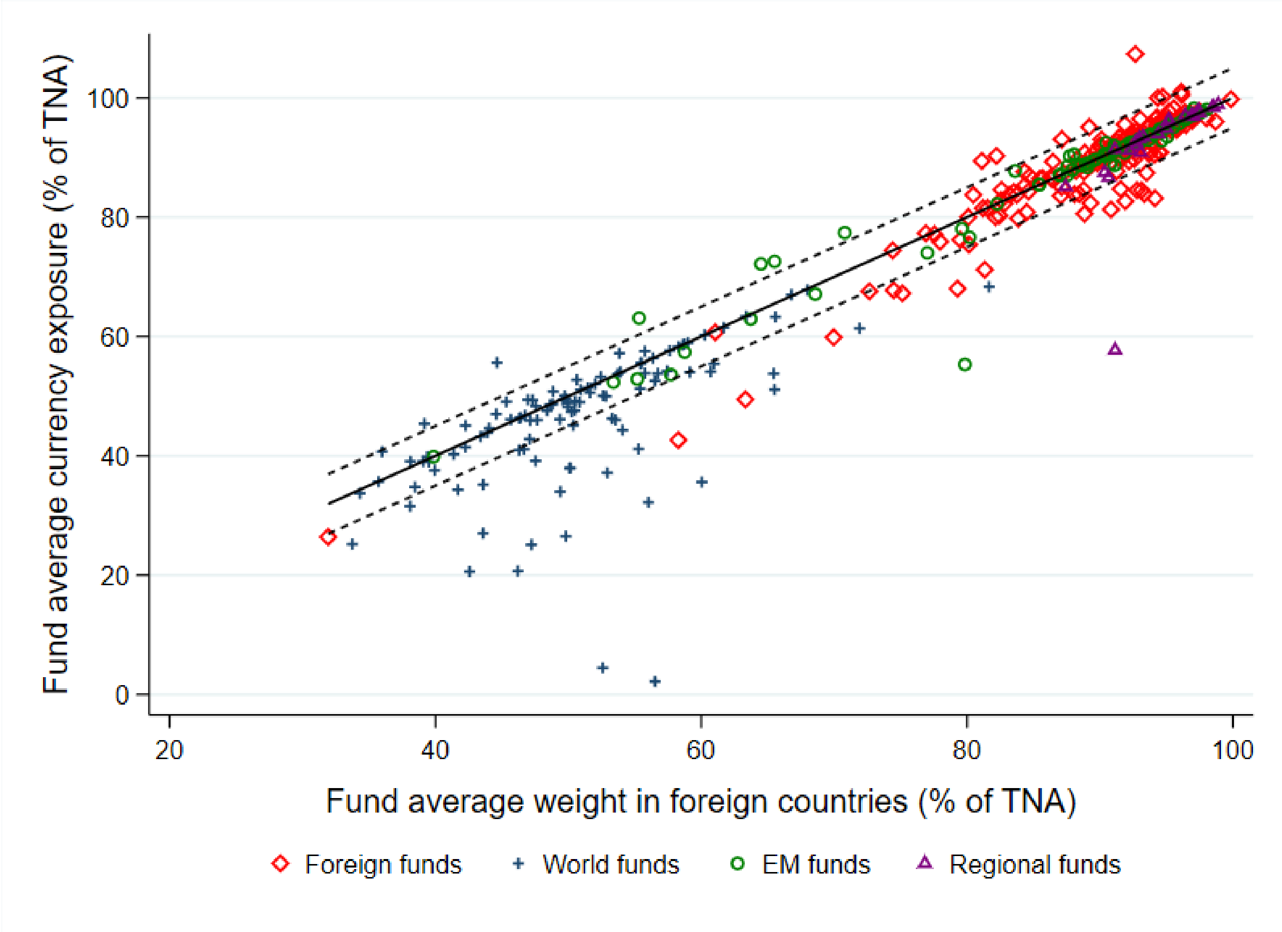


Figure A.3: Currency Exposure. The figure presents a scatter plot of funds' average weight in foreign countries (x-axis) plotted against their average currency exposure (y-axis). The plot includes a 45-degree solid line with the dashed-lines to either side indicating a (+/-) 5% boundary. The sample period 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**).[35] 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.

[35]Kmeans 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.

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

Table B.1: Currency Management Styles. 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.

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

Table B.2: The Determinants of Exposure Managers' Hedge Ratios. 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 × quarter fixed effects. Standard errors clustered at the fund × 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.

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

Table B.3: The Determinants of Portfolio Builders' Portfolio Weights. 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 **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 × quarter fixed effects. Standard errors clustered at the fund × 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.

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
Country weight	0.028***	0.005**	0.005**	0.007*	–0.000	0.003	0.008*
	(0.006)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)
Momentum	-0.016***	-0.006	-0.007**	-0.010**	-0.007**	-0.011**	-0.011**
	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)
Carry	–0.029***	–0.026***	–0.021***	–0.019**	–0.012**	–0.013	–0.011
	(0.011)	(0.006)	(0.006)	(0.008)	(0.005)	(0.009)	(0.009)
Value	0.007**	0.002	0.002	0.002	-0.001	0.001	–0.003
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Bid-ask spread	0.001	–0.000	–0.001	–0.001	0.000	–0.001	–0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	0.006	0.022***	0.025***	0.022***	0.014***	0.013	0.025***
	(0.010)	(0.006)	(0.006)	(0.008)	(0.004)	(0.008)	(0.007)
Equity return	0.003	-0.001	0.000	0.003	0.001	0.003	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EM dummy	0.557***	0.189**	0.165**	0.082	0.136**	0.045	–0.070
	(0.125)	(0.085)	(0.077)	(0.134)	(0.056)	(0.134)	(0.131)
Observations	162,441	141,772	135,577	171,956	115,827	161,029	144,574
Fund × 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

Table B.4: The Determinants of Occasional Users' Hedge Ratios. 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 **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 × quarter fixed effects. Standard errors clustered at the fund × 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.

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

Table B.5: The Determinants of Occasional Users' Portfolio Weights. 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 **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 × quarter fixed effects. Standard errors clustered at the fund × 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.

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
Excess return in local currencies (%)	1.819	2.437	3.037	1.723	2.940	1.909	2.342
	[0.102]	[0.083]	[0.045]	[0.224]	[0.018]	[0.134]	[0.109]
Sharpe ratio in local currencies	0.207	0.220	0.259	0.179	0.237	0.180	0.196
	[0.015]	[0.014]	[0.008]	[0.077]	[0.002]	[0.045]	[0.043]
Benchmark adjusted return in local currencies (%)	0.824	1.082	1.220	0.980	1.180	1.153	1.264
	[0.237]	[0.117]	[0.066]	[0.165]	[0.048]	[0.099]	[0.064]
Inf. ratio of benchmark adj. return in local currencies	0.218	0.318	0.353	0.323	0.319	0.363	0.279
	[0.141]	[0.026]	[0.018]	[0.027]	[0.009]	[0.014]	[0.049]

Table B.6: The Equity Investment Performance of Portfolio Builders. The table presents equivalent statistics to those in the bottom panel of Table 6 for the difference between values in G5 and G1. Each column reflects a different approach to identifying portfolio builders. We present p-values in brackets. The p-value is obtained from testing the hypothesis that the value is equal to zero and is calculated using permutation tests with 1,000 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.

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)>=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)>=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	Isntitutional/ Insttitutional/ 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 reminds 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).

<u>Data from CRSP</u>

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

<u>Data from SEC filing</u>

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	Settle-ment 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

<u>Data from SEC filing</u>

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)
Net Unrealized Appreciation						$ 1,046

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 *totret1mo* reported. Of these, 60831 observations (2% of total observations) have *mret* (the CRSP reported monthly return) and the *totret1mo* (Morningstar reported monthly return) differ significantly (more than 10 basis points). Details on the differences between *totret1mo* and *mret* can be found in the table below:

Difference between mret and totret1mo	# 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 totret1mo 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 *totret1mo* are both 0.07, indicating that the dividend ratio is 0.07.

Before:					
Mret	totret1mo	crsp_ret	ms_ret	crsps_dividend	ms_dividend
0.17	0.18	0.10	0.11	.	.
After:					
mret	totret1mo	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 *totret1mo* is consistent with both *crsp_ret* and *ms_ret,* then we accept *totret1mo* as the correct monthly return
3. If *mret* is consistent with *crsp_ret* but not with *ms_ret*, and *totret1mo* is not consistent with *ms_ret*, we accept *mret* as the correct monthly return
4. If *totret1mo* is consistent with *ms_ret* but not with *crsp_ret*, and *mret* is not consistent with *crsp_ret*, we accept the *totret1mo* as the correct monthly return.
5. This set of rules allows us to correct for 11319 return inconsistencies in the database.

<u>Step Two</u>

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 *totret1mo*, but the returns are inconsistent across the two databases. An example of such a case is presented below:

Year	month	Ticker	mret	totret1mo	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	totret1mo	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 deduct 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.