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

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Abstract

Using a novel, hand-collected dataset of over 55,000 net currency forward positions, we provide the first large-scale empirical study of currency management in US international equity mutual funds. Although some funds hedge currency exposure, many construct separate "shadow" currency portfolios with long- and short-derivative positions, often in currencies unrelated to their equity holdings. Surprisingly, we find that both approaches have a limited impact on overall fund performance, largely due to suboptimal implementation. Furthermore, non-user funds could have materially improved risk-adjusted returns through dynamic currency hedging. Our findings highlight inefficiencies in currency management and offer insight into optimizing portfolio performance.

Keywords: currency hedging, currency derivatives, mutual funds

JEL Classification: F31, G11, G15, G23

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1 Introduction

Investing in international equity markets has grown substantially in the past 30 years, driven by the benefits of diversification and facilitated by the lower cost of investing overseas (Solnik, 1974; Eun et al., 2008; Du and Huber, 2024). One of the primary ways investors gain exposure to foreign equities is through international equity mutual funds. Assets under management (AUM) in US-based international equity mutual funds have expanded significantly since the early 1990s, rising from $100 billion to nearly $3 trillion, now comprising approximately one-quarter of the entire US equity mutual fund industry (see Figure 1).

Managers of international equity mutual funds face a critical question: What role should currency play in the portfolio? Since international equity returns are partially driven by exchange rate movements, these funds are inherently exposed to currency risk. Research has shown that efficient management of this exposure can have a substantial positive impact on portfolio performance over time (Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020). Given the potential value that effective currency management can provide, it is essential to understand how fund managers actually approach this challenge in practice.

In this paper, we provide the first comprehensive analysis of currency exposure management in international equity mutual funds in the United States. We do so using a unique, hand-collected dataset of more than 55,000 net currency forward positions, over a 15-year period, from the holding reports of 1,279 funds. Our study addresses three key research questions: What determines the use of currency forwards among international equity mutual funds? How do currency forwards affect these funds' overall investment performance? And how efficient is the mutual fund industry in its current practice of currency management?

Optimal currency management is not well established for international equity fund managers. The ambiguity in best practice is driven by the similarity in performance between fully-hedged and unhedged portfolios. Exhibit 1 illustrates this characteristic of markets by presenting the investment performance of hedged and unhedged versions of the MSCI All Country World Equity Index, which yield nearly identical investment performance over a 20-year period.[1]

[1]The average returns between fully hedged and unhedged portfolios are similar when the base currency earns a low absolute average excess return. In fact, the "dollar" portfolio is known to earn an average return that is not statistically different from zero (Lustig et al., 2011). Volatility in hedged and unhedged equity portfolios is often similar because currency hedging can, paradoxically, increase volatility when a hedged currency negatively correlates with the equity market. Currencies that exhibit this property are often referred to as "safe haven" currencies (see, e.g. Ranaldo and Söderlind, 2010).

	International Equities		International Bonds	
	Unhedged	Hedged	Unhedged	Hedged
Avg return (%)	6.51	6.48	4.06	4.66
Std (%)	15.2	13.7	5.50	2.70
Sharpe ratio (%)	0.43	0.47	0.73	1.73

Exhibit 1: Hedging Currency Risk in International Equity and Bond Portfolios. The table presents the average annualized monthly returns, standard deviations, and Sharpe ratios of international equity and bond portfolios that are fully hedged or unhedged against currency movements. The equity portfolio is the MSCI All Country World Index. The bond portfolio is the Bloomberg Global Aggregate Index. The sample is from January 1999 to December 2019.

This lack of clarity contrasts with the unambiguous textbook recommendation for international *fixed-income* managers. Since fixed-income volatility is typically low, embedded currency risk tends to increase portfolio volatility and should thus be hedged, most commonly using currency forward contracts, to improve portfolio efficiency.[2] Indeed, in Exhibit 1, we observe the striking impact of full hedging on the Bloomberg Global Aggregate Bond Index, for which the Sharpe ratio more than doubles due to reduced volatility. Campbell et al. (2010) also show that an almost complete hedge is optimal for risk minimizing bond investors, while Sialm and Zhu (2024) find that 90% of fixed-income mutual funds hedge using currency forwards, which tends to enhance funds' investment performance.

Fortunately, the academic literature has identified two general methods to efficiently manage currency exposure within international equity portfolios. But unlike for international fixed-income investing, these efficient methods are nuanced and dynamic in nature.

The first involves dynamically adjusting hedges across currencies, often through mean-variance optimization (see, e.g., Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020). The second involves constructing an entirely separate currency portfolio, which is then added to the global equity portfolio (Kroencke et al., 2014). Both methods exploit conditional information about expected currency returns and covariances. Moreover, both methods have been found to enhance the performance of international equity portfolios, beyond full hedging or not hedging, either by increasing returns or reducing volatility.[3] Yet whether funds adopt either method in practice remains an open empirical question that we seek to address.

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

[3]Other recent studies that highlight gains to international equity funds from conditionally entering currency forwards contracts include Boudoukh et al. (2019) and Barroso et al. (2022).

To examine how funds use currency forwards in practice, we begin by categorizing them into two groups: users and non-users. A *user* fund is defined as one that holds an outstanding currency forward contract at the end of at least one quarter in the sample. Based on this classification, we identified 471 funds as users of currency forwards during our sample period. The main body of our analysis focuses on these funds, while in further tests we examine non-user funds to assess whether their inaction results in missed investment opportunities.

Comparing users and non-users, we find notable differences in fund characteristics. User funds tend to be slightly older, larger in terms of AUM, and more active, with annual turnover ratios exceeding 70%, compared to around 55% for non-users. User funds also tend to have a lower fraction of institutional ownership, pointing towards a possible clientele effect. Furthermore, users allocate a slightly larger share of their portfolios to the more liquid G9 currencies, although both groups invest, on average, over 80% of their total portfolio in foreign securities.[4]

Surprisingly, and in contrast to Sialm and Zhu (2024), we find that despite these differences in fund characteristics, investment performance is remarkably similar, on average, between the two groups. Net returns, benchmark-adjusted returns, and tracking errors are nearly identical, while Sharpe ratios are *lower* for users, on average, due to higher portfolio volatility. The similarity in returns is not attributable to differences in fund fees, as we find no significant differences in management fees or *gross* returns between user and non-user funds. The comparative underperformance of user funds is particularly striking in light of previous studies showing that currency forwards can substantially enhance the investment performance of international equity portfolios.

To further investigate the use of currency forwards by funds, we construct their "hedge ratio," a widely adopted measure in the literature that quantifies the percentage of currency exposure offset through forward contracts. We find that approximately one in seven user funds hedge a significant portion of their exchange rate risk, although only two funds can be considered to nearly fully hedge their currency exposure every quarter. The majority of funds, instead, maintain hedge ratios close to zero, implying that eliminating currency exposure is not the primary motivation for using currency forward contracts.

Although hedge ratios are typically low, we find that many funds hold large *absolute* currency forward positions, that is, the sum of non-signed forward positions. These positions

[4] The term "G10" refers to the most actively traded developed market currencies: the US dollar (USD), euro (EUR), Japanese yen (JPY), British pound (GBP), Swiss franc (CHF), Australian dollar (AUD), Canadian dollar (CAD), New Zealand dollar (NZD), Swedish krona (SEK), and Norwegian krone (NOK). We refer to the "G9" as the G10 currencies excluding the US dollar.

often exceed 20% and sometimes reach as high as 60% of a fund's total net assets (TNA). This suggests that international equity mutual funds frequently enter long and short currency forward contracts, in different currencies, to essentially construct a *separate* currency portfolio. Notably, these portfolios often include currencies absent from the equity portfolio and provide exposure to well-documented sources of currency excess returns, such as currency momentum.[5] Moreover, the positions function as "shadow" portfolios—a source of portfolio leverage that is unreported in a fund's TNA, but that increases their risky position. Thus, some funds not only retain, but deliberately expand, their foreign currency exposure for speculative purposes.

To capture these varying approaches to currency management, we categorize funds into three distinct styles. The first, *exposure management*, selectively reduces currency exposure within the equity portfolio. Funds in this group maintain non-trivial hedge ratios, typically exceeding 25%. The second, *portfolio building*, involves the construction of a separate currency portfolio. These funds exhibit low average hedge ratios, close to 0%, but hold large absolute forward positions that typically exceed 10% of TNA. Finally, funds with both low hedge ratios and low absolute forward positions trade less frequently and in fewer currencies, likely using currency forwards for short-term hedging or speculative purposes—such as hedging an upcoming dividend receipt. Given the relatively limited impact of currency forwards on these funds, we classify them as *occasional users* and analyze them separately.

We analyze how exposure managers and portfolio builders select their currency forward positions using fixed-effects panel regressions. The literature on optimal currency management highlights the importance of currency risk factors, such as carry, in enhancing investment performance. Consistent with this, we find strong evidence that currency carry, momentum, and volatility play a significant role in shaping currency management in both styles. However, while these findings suggest some alignment with established theories, a substantial portion of variation in currency forward positions remains unexplained, indicating a large idiosyncratic component to fund managers' use of currency forwards.

Based on this analysis, we examine fund behavior and investment performance within each management style. Among exposure managers, we identify both *static* (low time-series variation in hedge ratios) and *dynamic* (high time-series variation in hedge ratios) approaches to currency exposure management. We find that funds that are more active in their hedging exhibit some market timing in their hedge ratios and enhance their overall portfolio performance

[5] See, e.g., Menkhoff et al. (2012) and Asness et al. (2013).

by using currency forwards. Thus, active currency management has *partly* aided investment performance. However, much larger investment gains could have been achieved if funds had adopted an easily implementable, alternative, approach to currency exposure, based on a naive carry trade (Glen and Jorion, 1993; Lustig et al., 2011) or a minimum-variance hedge (Campbell et al., 2010). Indeed, excess fund returns and Sharpe ratios would have been both economically and statistically higher across all exposure managers, on average, but especially so for static exposure managers.

Among portfolio builders, we find that currency-specific portfolios generated low returns, averaging around 1% per annum, and Sharpe ratios close to zero (0.08 on average). This aligns with our earlier finding that user and non-user funds exhibit similar investment performance. However, there is significant variation in performance between portfolio builders. Sorting funds by the Sharpe ratio of their currency-specific portfolio, we observe a return spread of over 10% per annum between the highest and lowest quintiles. However, despite their strong performance, many top performing funds maintained small currency portfolios relative to their TNA, limiting the contribution of the currency portfolio to their overall performance. However, we find little evidence of persistence in the performance of the best performing funds or learning among the poorer performing funds, underscoring the inefficiency we observe in currency management across the mutual fund industry. Indeed, in further analysis, we highlight the significant gains that even the best performing funds could have achieved through allocating weight to alternative currency portfolios, such as a naive carry trade.

In the final part of our analysis, we assess non-user funds by comparing their actual performance to their performance under alternative scenarios, in which their portfolios are overlaid with various currency hedging strategies. Across all approaches, return volatility is significantly reduced, while Sharpe ratios and certainty-equivalent returns improve. The benefits are especially notable when adopting the minimum-variance hedging approach of Campbell et al. (2010) for which Sharpe ratios increase, on average, during both periods of US dollar strength and weakness. In additional analysis, we find similar or even stronger performance gains when augmenting non-user portfolios with independent currency portfolios.

Related literature. The paper is closely related to the literature studying derivative use in mutual funds, which has attributed various benefits to derivative use, including improved information efficiency, risk management, and lower transaction costs.[6] Koski and Pontiff (1999)

[6]See, for example, Deli and Varma (2002) and Almazan et al. (2004).

analyze derivative use among equity mutual funds, finding that only 21% of the funds use derivatives and that risk exposure and return performance are similar between users and non-users. More recently, Kaniel and Wang (2025) examine the use of mutual fund derivatives during and after the COVID-19 pandemic, finding that users did not outperform non-users during the pandemic and even underperformed in its aftermath.[7] Our granular data on derivative positions provide a more nuanced perspective on the relationship between fund performance and derivative use. We identify a source of inefficiency in the use of derivative contracts and document the size of this inefficiency relative to simple benchmarks for currency management. The inefficiencies we identify have implications for best practice within international equity funds and suggest a need for additional forms of monitoring and performance evaluation among mutual fund investors.

Sialm and Zhu (2024) provide an important complementary study on the use of currency derivatives in fixed income funds. Although bond funds benefit from fully hedging foreign exchange risk, equity funds do not experience the same straightforward performance gains. Reflecting this, almost all fixed income funds use currency forwards, although the average hedge ratio is surprisingly low, at only 18%. Unlike fixed-income funds, equity portfolios typically exhibit high volatility, and certain currencies provide natural hedges for equity risk, making optimal currency management more complex and not a simple binary choice between hedging and not hedging. In addition, Goldstein et al. (2017) find that fixed income and equity mutual funds exhibit different flow-to-performance relationships, with equity fund flows displaying a convex shape—being less sensitive to poor performance but highly responsive to strong performance, thereby creating distinct incentives for equity funds.[8]

Studying international equity funds is thus different but also equally important due to the distinct risk-return characteristics of the asset class and the different relationship with currency risk. We also document key empirical differences with respect to fixed income funds. For example, portfolio building, the dominant currency management strategy among international equity mutual funds, is largely absent among international fixed income funds. Our results also align with Goldstein et al. (2017), as we show that, unlike fixed income funds, portfolio builders do not respond to weaker past performance when adjusting their currency positions.

Recent deviations from covered interest rate parity (CIRP) create opportunities and con-

[7]In contrast, in the hedge fund literature, Aragon and Martin (2012) find that hedge funds using option contracts delivered higher benchmark-adjusted portfolio returns and lower risk than non-users.

[8]Since bond funds display a concave flow-performance relationship, in which investor flows are more responsive to *poor* past performance, it may further incentivize these funds' to lower volatility through hedging.

straints for currency hedging, influencing the cost and availability of forward contracts.[9] Kubitza et al. (2024) find that CIRP deviations are a key determinant of currency hedging over time, while Du and Huber (2024), studying institutional investors outside the US, document a decrease in demand for currency hedges when the cost of hedging associated with CIRP deviations increases in the cross section of currencies. Similarly, we find that CIRP deviations influence hedging activity of funds inside the US, particularly among exposure managers, who also hedge less those currencies that are associated with higher hedging costs.[10]

Finally, the paper contributes to the broader literature on how exchange rates influence mutual fund decision making. Massa et al. (2016) find that funds under-weighting risky currencies in their equity portfolios tend to underperform, while Camanho et al. (2022) show that foreign exchange returns shape portfolio rebalancing decisions. Burger et al. (2018) and Maggiori, Neiman, and Schreger (2020) further highlight that the international investment choices of mutual funds are heavily influenced by their currency of denomination. Our study extends this literature by providing the first detailed exploration of how equity mutual funds use foreign exchange derivative contracts and the impact it has on their investment performance.

Overall, the paper contributes through the introduction of a novel, granular data set that sheds new light on the styles of currency management adopted by US international equity mutual funds. We provide initial evidence on the determinants of currency forward usage between these funds and are the first to quantify the magnitude of inefficiency in their currency management. The paper therefore provides new insights for fund managers seeking to better manage currency and for investors wishing to better assess fund managers' investment performance.

The remainder of the paper is structured as follows. Section 2 describes the data and presents the initial summary evidence. Section 3 outlines our methodology for categorizing funds based on their style of currency forward usage. Section 4 presents results of our main empirical analysis. Section 5 examines non-user funds and evaluates their hypothetical performance under alternative currency strategies. Section 6 describes the results from further analyses we have performed. Section 7 concludes. Additional results and full details on dataset construction are provided in the Online Appendix.

[9] See Du et al. (2018) and Cenedese et al. (2016) for empirical evidence on CIRP deviations.

[10] Currency hedging can also feed into the determination of exchange rates and CIRP deviations. Brauer and Hau (2023) find that institutional hedging can explain up to 30% of monthly exchange rate variation, while Aldunate et al. (2023) find that mandated institutional hedging was associated with larger deviations from the CIRP in the Chilean peso.

2 Data and Summary Evidence

In this section, we describe our sample of international equity mutual funds and the construction of our unique data set of currency forward positions. We begin by describing data sources, merging procedures, and sample filters. A comprehensive step-by-step description is provided in Section C of the accompanying Online Appendix. We then explore trends in currency forward usage across time and compare the characteristics and investment performance between funds that we classify as users and non-users of currency forwards.

2.1 International equity mutual funds

We construct our sample of US international equity mutual funds by merging data from *CRSP* and *Morningstar*. The initial data set includes all international equity mutual funds at the intersection of the two data sources. We primarily merge data sets to improve classification accuracy, as *CRSP* and *Morningstar* define international equity funds in slightly different ways and occasionally classify the same fund inconsistently. To ensure accuracy, we retain only funds classified as international by both *CRSP* and *Morningstar*.

The merging process also enables us to perform intermediate consistency checks, following a procedure similar to Berk and van Binsbergen (2015) and Pástor et al. (2015). Moreover, *Morningstar* provides several important characteristics at the fund level that are not available in *CRSP*. The most notable include, first, funds' benchmark indices, which allow us to verify whether a fund targets a currency-hedged index, and second, detailed portfolio weights by currency, which we use later to construct currency-level hedge ratios for each fund every quarter.[11]

2.2 Currency forward positions

Data for fund portfolio holdings are available from *CRSP* from as early as 2003. Information on currency derivatives, however, only become available in 2010 and exhibit significant discrepancies relative to funds' SEC filings.[12] To ensure data accuracy, we therefore hand collect data on funds' open currency forward positions from their quarterly SEC filings, obtained through the

[11] *Morningstar* reports the percentage of each fund's TNA allocated across 48 countries. We aggregate across eurozone countries to calculate a fund's euro exposure. When country weights are not reported at a monthly frequency, we forward and backward fill the available values within a two-quarter window.

[12] For example, we identify numerous cases where currency forward positions in *CRSP* are not observed in SEC filings, and vice versa. In several instances, we contacted mutual funds directly to query the discrepancy. The funds we contacted always confirmed that the *CRSP* reported positions are erroneous.

EDGAR database. Our sample begins in 2004, the year the SEC mandated quarterly reporting via forms N-Q and N-CSR, and ends in the second quarter of 2019, just before the introduction of monthly filings using form N-Port. Although some funds use other currency derivatives, such as futures or options, these instances are rare, and we focus exclusively on forwards.

Figure 2 provides an example of the currency forward positions we collect. It shows an extract from the N-CSR filing of AB International Value Fund, for the reporting window ending on 31 May 2019. Each row corresponds to a distinct currency forward contract outstanding on that date. Although there is no standardized format for disclosing open forward contracts, funds typically report the notional contract size in both the foreign currency and US dollars (USD), the settlement date, the counterparty, and any unrealized gain or loss on the forward contract in USD. The notional value is essential for calculating hedge ratios and currency portfolio weights. For cross-currency forward contracts, which do not involve the US dollar, we convert each leg into a forward position against the USD. We aggregate long and short positions for each period to compute funds' *net* currency forward position by currency and quarter.[13]

We merge the hand-collected forward contract data with monthly fund-level characteristics from *CRSP* and *Morningstar*. The initial merged sample includes 157,117 fund-month observations in 1,620 funds, of which 519 reported open currency forward positions at some point during the sample period and are therefore classified as "user" funds.[14]

2.3 Filtering the dataset

To refine our sample, we apply several filters. First, we drop fund-month observations where (i) the sum of country weights (including the US) exceeds 101% or falls below 0%; (ii) the sum of foreign (non-US) country weights is below 25%; or (iii) total net assets are less than $15 million in 2019 dollars.[15] We further restrict the sample to funds with at least four quarters of available data and exclude funds that either track a currency-hedged benchmark or use a benchmark denominated in a foreign currency. We also examine the prospectus of each fund (form N-1A)

[13]Some funds invest only in a master portfolio. In these cases, we collect the fund's ownership percentage and apply it to the master portfolio's forward positions. If the ownership share is not reported, we calculate it based on the dollar investment of the fund relative to the net assets of the master portfolio. Our results are unaffected when funds invested in a master portfolio are excluded. These additional results are available on request.

[14]Fund reports are filed at fiscal quarter-ends rather than calendar quarter-ends. Following Wermers et al. (2012), we assume that a portfolio position reported at the end of a fiscal quarter reflects the fund's holdings as of the nearest calendar quarter end.

[15]These filters address: (i) likely data errors in aggregate country weights; (ii) *CRSP*'s requirement that global funds allocate at least 25% to non-US securities; and (iii) the tendency of very small funds to produce extreme, uninformative outcomes (Pástor et al., 2015).

for language related to currency derivatives. We find that 97% of the funds explicitly state that they may use currency forwards for hedging–and, in some cases, speculative–purposes.[16] The remaining funds do not mention currency forwards. Furthermore, we also verify that no fund offers a currency-hedged equivalent portfolio to investors. No fund in the sample, therefore, is either explicitly prohibited from using forward contracts or is mechanically required to hedge or not hedge currency exposure—the use of currency forward contracts is discretionary.

Our final sample includes 55,615 net open forward positions in 1,279 funds, of which 471 report using currency forwards during the sample period. The average net forward position has a notional value of −\$13.2 million, indicating a short position in foreign currency. Sixty-two percent of forward contracts are in G9 currencies, while fewer than 3% are cross-currency.

2.4 Exchange rate and other data

We complement our main data set with daily data on spot and forward exchange rates from *WM/Reuters*, Eurocurrency deposit rates from the *Financial Times*, and country equity indexes (net return with dividends reinvested after withholding tax) from *MSCI*. All additional data are sourced from *Datastream*.

With the final sample defined, we now turn to key descriptive patterns associated with our primary data set of currency forward positions, beginning with the overall adoption of currency forwards across funds and time.

2.5 Currency forward usage over time

We begin by examining the time series evolution of the currency forward usage in our sample. Figure 3 presents annual data on the total number of funds, split into users and non-users of currency forwards. The percentage of user funds is displayed above each bar. The total number of funds increases steadily from 491 in 2004 to 892 in 2019. However, forward usage fluctuates throughout the sample period. Although only 12.8% of the funds report using forwards in 2004, that share increases to above 31% during the global financial crisis (GFC), before declining to below 20% at the end of the sample.

These industry-wide patterns in forward usage coincide with broad movements in the US dollar. From 2004 to 2011, the dollar depreciated significantly against a broad basket of currencies, before generally appreciating over the remainder of the sample. During periods of

[16] Figure A.1 in the Online Appendix shows statements from funds' prospectuses that illustrate these alternative uses.

dollar weakness, funds can use forwards to lock in favorable exchange rates ahead of foreign asset purchases or hedge potential reversals. In addition, some funds may have sought to profit from currency strategies that offered high expected excess returns—such as the currency carry trade—which delivered strong performance in the years leading up to the GFC. After 2011, as the US dollar strengthened and global interest rates converged toward zero, the profitability of currency trading decreased, potentially contributing to a decline in forward usage.

The bottom panel of Figure 3 presents analogous trends in the net and absolute notional values of the outstanding currency forward contracts. We define net sales as the net notional value of forward positions (short minus long) scaled by TNA. A positive value therefore indicates an industry-wide reduction in foreign exchange exposure. The absolute position captures the sum of absolute long and short positions, scaled by TNA. Net sales are typically modest, less than 4% of TNA, suggesting that equity funds do not, on average, hedge substantial foreign currency exposure. However, the absolute positions are substantially larger, especially in the years preceding and during the GFC. This gap between net and absolute exposure suggests that funds can actively enter both long and short positions with the intention of increasing currency exposure and pursuing speculative strategies.

To better understand which types of funds use currency forwards, we now turn to compare the characteristics and investment performance of user and non-user funds.

2.6 Comparing users and non-users of currency forwards

Table 1 reports the mean and standard deviation of various fund characteristics and performance metrics for users and non-users of currency forward contracts. The column labeled "Obs" shows the number of fund-quarter observations, while the final two columns report the difference in means and associated p-values.[17]

Comparing users and non-users, we find that both groups allocate a similar share of assets—just over 80%—to international securities. However, users tend to have slightly higher exposure to G9 currencies. This difference is economically meaningful and may be tied to forward usage: Forward contracts are more readily available and less expensive to trade in liquid currencies, suggesting that funds with greater exposure to less liquid currencies may be disincentivized

[17] We obtain p-values using permutation tests on average fund characteristics with 1,000 resamples. Specifically, for each variable, we randomly assign funds into two groups, which have the same size as the original sample (i.e., the same number of users and non-users), and recalculate the difference in means. Each fund appears once in each resample. The null hypothesis is that there is no difference in means between users and non-users. The p-value represents the proportion of simulated test statistics that exceed the observed test statistic.

from using forwards. Although both groups invest in equity securities from around the world (16 countries, on average, for both groups), the dispersion is large. In fact, our sample includes a mix of narrowly focused country-specific funds and globally diversified funds with broad exposure to developed and emerging markets.

Users also differ from non-users in several other key fund characteristics. They are more active, with an average annual equity turnover ratio of 70%, compared to 55% for non-users. Additionally, users tend to have slightly higher expense ratios—about 0.07 percentage points per year more—potentially reflecting the cost of currency forward contracts. Since hedging costs likely influence the decision to use forward contracts, the scale of the fund may be important. Indeed, we find that users are typically older (13 years versus 10 years) and have more assets under management, with total net assets typically $1 billion higher relative to non-user funds.

If economies of scale are important, one might expect user funds to be associated with larger fund families. However, we find that users are typically from smaller fund families, whether measured by assets under management or the number of funds, possibly reflecting the greater flexibility afforded to funds within smaller families. Finally, we consider a potential clientele effect: institutional investors, who are better able to directly engage in currency forward contracts, may reduce the need for fund managers to do so. Indeed, we find that funds using forwards tend to have a lower proportion of institutional share ownership compared to non-users.[18]

In the lower panel of Table 1, we turn to explore differences in the average investment performance of user and non-user funds. Consistent with previous studies on mutual funds, which explore differences in average performance between users and non-users of derivatives securities more generally (Koski and Pontiff, 1999; Kaniel and Wang, 2025), we do not detect statistically significant differences between users and non-users across a range of investment performance metrics, including net returns, benchmark-adjusted returns, or tracking error. Across each metric, the average value is almost indistinguishable between the two groups. The finding is not driven by higher fees among users: gross returns and management fees are also not different, on average, between the two groups. Moreover, we find that users delivered *lower* Sharpe ratios, on average, than non-users funds due to higher portfolio volatility.

This result is particularly surprising given the large body of evidence suggesting that cur-

[18] Our sample also includes funds that target a specific index. Although we ensure that none of the funds in the sample track a currency-hedged index, we do *not* find evidence that "index funds" are less likely to use currency forwards.

rency forwards can reduce volatility and improve risk-adjusted performance when investing in international equities. Furthermore, our earlier findings on the size of currency forward contracts indicate that many funds may be using forwards in more speculative ways. This raises a critical question: Why has the use of currency forwards not led to significantly improved performance? To answer this, we turn to investigate the micro-level implementation of currency forwards in practice, their impact on funds' investment performance, and whether our initial findings do indeed indicate inefficiency in currency management.

3 Currency Management Styles

In this section, we begin our investigation of *how* US international equity mutual funds use currency forwards. We classify funds into distinct styles of currency management based on two key metrics: the hedge ratio, which captures the extent to which funds offset currency exposure using currency forwards, and the absolute size of forward positions relative to total net assets. This classification enables us to distinguish between funds that tend to reduce a material fraction of their currency exposure, those that build separate currency portfolios within the equity fund, and those that use forwards only occasionally. We document key descriptive patterns across each group to provide an initial lens into the heterogeneity of currency management practices.

3.1 Hedge ratios

To gauge the extent to which funds reduce currency exposure, we begin by examining the distribution of fund-level hedge ratios. The hedge ratio measures the proportion of the total foreign exchange exposure of a fund arising from its underlying assets that is offset through forward currency contracts. Specifically, for fund i in quarter t, we define the hedge ratio as:

$$\mathrm{hr}_{i,t} = \frac{\sum_j \tilde{f}_{i,j,t}}{\sum_j w_{i,j,t}} \tag{1}$$

where $\tilde{f}_{i,j,t} = f_{i,j,t}/TNA_{i,t}$ is the US dollar value of the net forward position in currency j, scaled by the fund's TNA in that quarter. The net forward position $f_{i,j,t}$ is calculated as the difference between the nominal values of the short- and long-forward contracts in currency j. Thus, a positive value reflects a net short forward position, i.e., a reduction in foreign exchange exposure. The denominator, $w_{i,j,t}$, is the portfolio weight of foreign currency j in the fund's equity holdings.

Figure 4a presents a histogram of the average hedge ratios at the fund level over the sample period. Three patterns emerge: (i) hedge ratios tend to cluster around zero—the mean is just 2.4%; (ii) more than 100 funds, on average, increased their exposure to foreign exchange risk (i.e., had *negative* fund-level hedge ratios); and (iii) only around 20 funds typically hedged more than 20% of their foreign currency exposure.

These results suggest that most funds using currency forwards do not primarily attempt to eliminate currency risk. Although such a behavior would be surprising for fixed income funds, it is consistent with a fund that implements a time-varying conditional approach to currency exposure. For example, a fund may selectively increase and reduce their level of currency exposure over time, or construct a separate currency portfolio, through combining long- and short-forward positions. In fact, a neutral currency portfolio with respect to the US dollar would also result in a *fund-level* hedge ratio of zero. Moreover, the fact that many funds increase their exposure to currencies supports the hypothesis that currency forwards are often used for speculative purposes. To investigate this possibility more directly, we introduce a second measure: the *absolute forward position.*

3.2 Absolute forward positions

A fund-level hedge ratio close to zero can reflect two distinct behaviors. The fund may simply be taking small currency forward positions relative to its total foreign exchange exposure, either because the notional values of the contracts are low or because the fund so infrequently engages in these contracts. Alternatively, the fund may hold a mix of long- and short-currency forward contracts, in different currencies, which offset each other when aggregated at the portfolio level. For example, an international equity fund with \$100 million under management, invested equally in Japan and Australia, could take a \$25 million short forward position in yen and a \$25 million long forward position in AUD. The aggregated hedge ratio for the fund would be zero, but the absolute value of the position—essentially a separate currency carry trade portfolio—would be 50% of TNA.

To better understand the nature of forward usage, we therefore further define each fund i's *absolute* forward position (afp) at time t as the sum of the absolute values of its standardized currency forward positions:

$$\mathrm{afp}_{i,t} = \sum_{j} |\tilde{f}_{i,j,t}|. \tag{2}$$

It may be wondered why we do not directly investigate funds' absolute hedge ratios. The answer, as will be seen, is that funds frequently enter forward contracts in currencies that are *not* part of their underlying equity portfolio. For those currencies, the hedge ratio is undefined and therefore this alternative measure captures both the spirit of the absolute hedge ratio, while also being defined for all currency forward positions.

Figure 4b plots the average hedge ratio of each fund against its average absolute forward position.[19] The plot reveals a striking pattern: Many funds operate with large absolute forward positions, sometimes exceeding 50% of TNA, despite having average hedge ratios near zero. These cases represent funds that simultaneously enter large offsetting long- and short-forward positions. Although these contracts net out toward zero in their US dollar exposure, they significantly increase the scale of currency bets embedded in the fund. We highlight in red (+ markers) those funds with average afp above 2%.

Put differently, these funds are engaging in an activity that is analogous to constructing a separate "shadow" currency portfolio; it increases the leverage of the fund but is not part of a fund's formal list of investments. Instead, the positions are only reported in the notes to the fund's investment statements. However, at the other end of the scale, we also identify a group of funds that exhibit both low average hedge ratios and low absolute forward positions (denoted by blue $\diamond$ markers). These funds typically use currency forwards in small size or infrequently, most likely for short-term hedging (e.g., of an upcoming dividend receipt or equity purchase), tactical speculation, or liquidity management.

These patterns motivate us to form a natural classification of currency forward users into three distinct styles of currency management:

1. **Portfolio builders:** Funds that actively construct separate currency portfolios using long and short positions. Their hedge ratios are close to zero, but their absolute forward positions are large.

2. **Exposure managers:** Funds that use forward contracts to reduce significant currency exposure over time. These funds exhibit high hedge ratios, but rarely enter speculative long-forward contracts.

3. **Occasional users:** Funds that participate in small or infrequent forward transactions. Both hedge ratios and absolute forward positions are low, and thus forward contracts do

[19] We compute averages over quarters in which the fund reports using currency forwards. To aid in interpretation, we restrict the plot to funds with average hedge ratios between −20% and +20%.

not have a material impact on the funds' overall investment performance.

Each style likely reflects different goals and skill sets, with distinct implications for performance and fund behavior. We assign each user fund to one of these three currency management styles and analyze their characteristics and performance in the sections that follow.

3.3 Assigning currency management styles

We assign funds to one of the three currency management styles using three indicators: (i) the percentage of quarters in which a fund uses currency forwards, (ii) the average hedge ratio during those quarters, and (iii) the average absolute forward position during those quarters. The first variable identifies infrequent users, while the second and third differentiate between funds that aim to remove currency exposure and those seeking to build separate currency portfolios.

A fund is classified as an exposure manager if it uses currency forwards in at least 10% of the quarters and has an average hedge ratio of at least 10%. A fund is classified as a portfolio builder if it also uses forwards in at least 10% of the quarters, but its hedge ratio is below 10% and its average absolute forward position exceeds 2% of TNA. The remaining funds are labeled occasional users, either because they use forwards infrequently or because their forward positions are small in aggregate. Applying this classification yields 66 exposure managers, 202 portfolio builders, and 203 occasional users. We keep our classification system purposely simple, designed to transparently reflect the diversity of currency management behaviors observed in the data. In robustness tests, we apply alternative classification systems, including a machine learning approach, and find that our core results are robust to these alternative approaches. See Section 6.1 for details.

To illustrate the classification, Figure 5 presents examples of each style of currency management. Figure 5a shows an exposure manager, *Evermore Global Value Fund*, which maintained a hedge ratio near 100% and never entered long forward positions. Figure 5b features a portfolio builder. *J.P. Morgan International Value Fund*, which maintained an average hedge ratio near zero but entered large long and short currency positions—basically constructing a US-dollar-neutral currency portfolio that reached $786 million in notional value, or around 20% of TNA, at its peak in 2014. Figure 5c shows an occasional user, *Threadneedle International Opportunity Fund*, who only sporadically entered forward positions, with almost no impact on its overall currency exposure.

In Figures A.2 and A.3 of the Online Appendix, we provide further details on the breakdown of funds across the different styles of currency management. In Table 1, we observed that index funds were not less likely to be users of currency forwards, despite choosing not to target a currency-hedged index. Figure A.2 presents the split between currency management styles in active and index funds. The two splits are similar, although index funds are slightly more likely to be occasional users and less likely to be a portfolio builder or exposure manager, consistent with these funds aiming to avoid forward contracts having a material impact on their fund's overall performance. In Figure A.3, we divide funds according to their type, as defined by *Morningstar*.[20] The funds are broadly grouped into one of four types: *foreign funds* that allocate the majority of their assets outside of the United States, *world funds* that may still retain a material US asset exposure, *emerging market funds*, and *regional funds*, which may be single-country funds. We observe that the funds most likely to be portfolio builders are *foreign funds*, which arguably have the broadest range of investments. *World funds* are the most likely to be exposure managers, possibly because they already have a large US dollar asset portfolio and wish to substantially reduce their foreign currency exposure. In fact, we find only a small number of exposure managers in the other types of funds.

In Table 2, we present statistics on currency forward usage among exposure managers, portfolio builders, and occasional users. Validating our definition of occasional users, we find that they only hold forward positions at the end of around one-third of quarters. In contrast, exposure managers and portfolio builders tend to have outstanding forward positions in at least 60% of the quarter ends. Moreover, exposure managers and portfolio builders tend to hold forward contracts in more currencies (4.8 and 6.6, respectively), relative to occasional users (2.9 currencies) and in around twice the fraction of currencies to which the equity portfolio generates exposure. In fact, exposure managers typically seek to reduce exposure to around a third of currencies in their equity portfolio, adopting an average hedge ratio at the fund level of 28%. Instead, portfolio builders and occasional users maintain fund-level hedge ratios near zero (0.1% and –0.1%, respectively) but for portfolio builders the average absolute forward notional is around 12% of TNA—far higher than the 1.5% observed for occasional users.[21]

[20]Detailed classifications can be found in Table A.1 of the Online Appendix.

[21]Table A.2 in the Online Appendix reports results from logit regressions in which we analyze the determinants of currency forward usage across the different styles of currency management. Consistent with our findings in Table 1, we find that funds using currency forwards tend to invest in more countries, have higher portfolio turnover and expense ratios, are older, and have more assets under management. However, the table adds to these results by highlighting which type of currency management style drives each finding. For example, older and more active funds using forwards tend to be portfolio builders or occasional users, while fund size plays a

We find that 68% (37,564) of net forward positions are held by portfolio builders, of which 11% are in currencies *not* in the underlying equity portfolio (NUP). Just over 50% (19,730) of these positions are in *long* forward contracts that increase funds' foreign currency exposure. In contrast, more than 85% of the forward positions reduce exchange rate exposure for exposure managers. We also find occasional users enter a significant number of long forward positions, which may also point to a speculative motive, although could also reflect occasional users' desire to obtain foreign currency prior to an equity market purchase. In fact, occasional users only obtain exposure to currencies that are not held in the underlying equity portfolio in around 2% of cases. Indeed, almost all (around 90%) of the forward positions that are not related to a currency in the underlying equity portfolio are held by portfolio builders, consistent with these funds using currency forwards as an independent source of investment performance.[22]

In Figure 6, we further validate these classifications by comparing the average foreign asset weight of each fund (horizontal axis) with its average exposure to foreign currencies (vertical axis), where currency exposure includes the impact of forward contracts. A fully hedged fund would lie on the horizontal axis, while a fund that never adjusts its currency exposure would lie on the 45-degree line.[23] As expected, exposure managers show the largest reductions in currency exposure and lie well below the 45-degree line. In contrast, portfolio builders and occasional users are clustered along the 45-degree line, confirming that currency forwards do not substantially alter their *net* foreign exchange exposure.

3.4 Currency forwards across management styles

As noted in Section 2.3, we obtain data on 55,615 net outstanding currency forward positions. In Table 3, we present a breakdown of these positions in the three styles of currency management. The currencies are ordered on the basis of their total number of net forward positions in the data set. The ranking is closely aligned with measures of currency turnover, in which the euro, yen, pound sterling, and other major developed market currencies dominate (see, e.g., BIS (2022)). However, we also observe a high number of contracts in emerging market currencies

more prominent role for exposure managers. We also find that, unlike Table 1, the institutional share does not appear to have predictive power on forward usage, while the results on family size are mixed.

[22]Table A.3 of the Online Appendix, reports the sensitivity of flows to exposure managers and portfolio builders following either a negative or positive benchmark-adjusted return. In line with earlier literature on flow-performance sensitivity, we find that flows to international equity mutual funds are more sensitive after positive returns, in contrast to the higher sensitivity in flows after negative returns for fixed income funds (Goldstein et al., 2017). Moreover, portfolio builders are found to be unresponsive in their currency portfolio to past weak investment performance, but adjust based on past stronger performance. That behavior is opposite to exposure managers and international fixed income funds documented by Sialm and Zhu (2024).

[23]A fund that *never* uses currency forwards would also lie on the 45-degree line.

that typically carry a higher interest rate, including the South African rand, the Brazilian real, and the Mexican peso. Indeed, many of those currencies are not held in the underlying equity portfolio, indicating a possible carry trade motivation. In that theme, we observe that 45% of portfolio builders' positions in the New Zealand dollar, a high-yielding G10 currency, are entered *without* an investment in New Zealand equities.

In Figure 7, we extend the analysis by presenting the average currency-level positions of exposure managers and portfolio builders over time. For exposure managers, we show their average "abnormal" hedge ratios across currencies, i.e., the deviation from the fund's average hedge ratio, which allows us to isolate discretionary tilts away from its typical behavior. For portfolio builders, we show the weights of the currency portfolio. The size of each square represents the relative frequency with which currency forwards are used for that currency. We make two observations. First, there is persistence in the positions: the euro, for example, typically has the largest abnormal hedge ratio among exposure managers, while the Australian dollar is typically held in the long leg of the currency portfolio for portfolio builders. Moreover, the carry dynamic hinted at in Table 3 is again observed for portfolio builders. Long positions are typical in the Australian dollar, the New Zealand dollar, and the Canadian dollar, while the euro and Japanese yen are the most common funding currencies.

Second, we observe key differences between the two styles of currency management. Exposure managers, for example, held relatively few positions before the GFC, but far more in the years following 2011, a period in which the US dollar experienced a period of strong appreciation. In contrast, portfolio builders were more active between 2006 and 2014, when active currency investing was particularly profitable. In fact, since the GFC many well-known currency strategies have experienced a weaker performance (Ranaldo and Somogyi, 2021), which may partly explain the reduced size of these currency-specific portfolios.

In sum, the shift in activity over time suggests that funds responded to macro conditions and the evolving profitability of currency strategies, highlighting the discretionary and opportunistic nature of currency management in the industry. In the next section, we study the determinants of these positions, assess whether they align with known approaches to managing currency exposure, and evaluate their overall impact on investment performance.

4 Exposure Managers and Portfolio Builders

In this section, we analyze the behavior of the two most active styles of currency management: exposure management and portfolio building. For each style, we examine the determinants of currency forward usage and assess how their currency forward positions affect overall fund performance. By doing so, we aim to evaluate whether current practices in currency management at US international equity mutual funds reflect efficient decision making, or whether they reveal missed opportunities.

4.1 Exposure managers: The determinants of hedge ratios

We examine the determinants of currency-level hedge ratios using fixed-effects panel regressions. The dependent variable is the hedge ratio of the fund i in quarter t for the currency j, $\mathrm{hr}_{i,j,t}$. Explanatory variables include equity portfolio weights; factors associated with higher currency excess returns, including exchange rate momentum, carry, and value; the bid-ask spread, a measure of the cost associated with currency hedging; exchange rate volatility—an inherent drag on the risk-return of the portfolio; as well as equity market returns, to capture potential portfolio rebalancing motives.[24]

Specifically, we estimate the model

$$\mathrm{hr}_{i,j,t} = \mathbf{b}'\mathbf{x}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t}, \tag{3}$$

where $\mathbf{x}_{j,t-1}$ is a vector of lagged currency-level characteristics and $\mathbf{b}$ is the vector of associated coefficients that we estimate. To isolate cross-currency variation within funds, we include fund-by-quarter fixed effects, $\gamma_{i,t}$, allowing us to study why a fund chooses to hedge one currency relatively more than another. An additional dummy variable for the emerging market, δ_{em}, captures the impact of systematically lower liquidity and higher trading costs among these currencies. Standard errors are two-way clustered by fund and currency.[25]

Table 4 reports regression estimates. Columns (1) to (8) include each explanatory variable separately, while column (9) presents the complete model. Intuitively, we find that funds tend to hedge more aggressively those currencies with larger equity portfolio weight, consistent with those currencies increasing portfolio risk the most. The coefficient in the full model indicates that increasing the portfolio weight of a currency by 10% increases the associated hedge ratio

[24] We provide a description of variables used in the empirical analysis in Table A.1 of the Online Appendix.

[25] We also winsorize the hedge ratios at the 1st and 99th percentiles to mitigate the impact of outliers.

by approximately seven percentage points.

In columns (2) to (4), we present results for three well-documented sources of cross-sectional currency excess returns: exchange rate momentum, forward discount (carry), and currency value.[26] The results are largely consistent with anticipated efficient behavior. We find that funds, for example, typically reduce the size of their currency hedges on currencies that have appreciated strongly or offer higher yields—suggesting exposure is varied in ways consistent with targeting higher expected returns, as recommended in academic studies (e.g., Boudoukh et al., 2019; Opie and Riddiough, 2020). The estimated coefficients for currency carry and momentum are both statistically significant at the 1% level of significance in the full model. In contrast, we find that the coefficient on currency value is not statistically significantly different from zero, providing a potential source of inefficiency given the known diversification gains from conditioning on value, especially when combined with information on currency momentum (Asness et al., 2013) and currency carry (Jordà and Taylor, 2012).

Column (5) addresses the role of transaction costs. We observe that wider bid-ask spreads are associated with lower hedge ratios, consistent with a cost-based disincentive to hedging. However, once we control for all variables, this effect becomes statistically insignificantly different from zero. In contrast, the emerging market dummy variable, which captures the systematically higher cost and lower liquidity of trading these currencies, is highly statistically significant at the 1% level of significance (column 9). In fact, hedge ratios for emerging market currencies are, on average, 4.7 percentage points lower than those for developed market currencies[27]

Column (6) explores the critical role of the volatility of the exchange rate. Since exchange rate volatility typically increases the volatility of an international portfolio, it is often necessary to hedge currencies that exhibit the highest volatility to minimize volatility, as suggested by Campbell et al. (2010).[28] Consistent with this volatility motive, we find a strongly positive

[26]Exchange rate momentum is measured as the rate of return in the exchange rate over the past quarter, the forward discount is measured as the log difference between the three-month forward and spot rates, while we measure currency value following the procedure of Asness et al. (2013). See Lustig et al. (2011) and Menkhoff et al. (2012, 2017) for background on the theoretical foundations of currency carry, momentum, and value.

[27]Another cost associated with currency hedging stems from covered interest rate parity violations, otherwise known as the cross-currency basis (Du et al., 2018). We calculate the cross-currency basis using eurocurrency rates. Since these rates are not widely available across emerging markets, we choose to evaluate the impact of the cross-currency basis separately for developed market currencies and report our findings in Table A.4 of the Online Appendix. We find that a higher cross-currency basis, indicative of higher hedging costs for US investors, is associated with significantly lower hedging demand, consistent with hedging demand being sensitive to cost. We find that this relationship is maintained when the model is extended to include all other explanatory variables.

[28]The volatility of a foreign currency denominated international portfolio is directly increased by exchange rate volatility, but this can be offset if the covariance between the exchange rate and the foreign asset is negative, i.e., if the foreign asset is a "natural hedge" against foreign exchange risk and vice versa.

relationship in which a 10 percentage point increase in the volatility of a currency (annualized) tends to result in the hedge ratio increasing by 4.3 percentage points, and thus we find evidence of funds seeking to target higher returns while also eliminating unwanted, and potentially unrewarded, sources of exchange rate risk.

In column (7), we test whether foreign equity returns drive hedging behavior. Ben Zeev and Nathan (2024) show that stronger foreign equity performance increases foreign currency exposure, which, through a portfolio rebalancing channel, leads to increased hedging demand. We do not observe this relationship, and the coefficient we estimate is close to zero and is statistically insignificant. However, this finding is also consistent with the work of Camanho et al. (2022), who find that international funds rebalance their equity portfolios at quarter-end, limiting the need for contemporaneous hedging adjustments and thus breaking the link between equity returns and hedging demand.

Taken together, the evidence from this initial analysis indicates that exposure managers, on average, consider a mix of expected returns, volatility, and structural characteristics, such as liquidity and existing portfolio weights, when choosing their hedge ratios. Given the evidence that expected returns play an important role in determining hedge ratios, the evidence suggests a dynamic component to the decision. To better understand the timing component of the decision, in column (10), we extend the model to include fund-by-currency fixed effects.

The inclusion of these fixed effects allows us to explore active timing versus persistence in the hedge ratio. Following the inclusion of fixed effects, we find that previously significant factors, including carry and volatility, become insignificantly different from zero, highlighting that these factors are associated with the static components of interest rates and volatility, that is, exploiting the property that certain currencies *tend to* have persistently higher interest rates and volatility than others. In contrast, momentum and country weights remain highly statistically significant, and thus, from one quarter to the next, changes to hedging demand are driven most by the composition of the equity portfolio and recent exchange rate movements.

Although rebalancing based on currency momentum has been found to be an important source of expected return and helpful when managing currency exposure (Kroencke et al., 2014), other approaches in the literature have highlighted the benefits of conditioning on additional sources of information (Glen and Jorion, 1993; Opie and Riddiough, 2020). The findings in this section therefore raise the natural question as to whether funds are optimally incorporating sufficient information into their hedging decision process. To address this question, we assess the implications for investment performance of the hedge ratio decision by comparing the realized investment performance of the funds with the investment performance that *would* have been obtained if alternative hedge ratios had been adopted, based on other simple and easy-to-implement approaches to currency management.

4.2 Exposure managers: The optimality of hedge ratios

We begin our investigation into the optimality of currency forward usage among exposure managers by assessing how currency forwards actually impact their investment performance. The prior literature on optimal currency management within international equity portfolios has highlighted the need to dynamically vary hedge ratios (e.g., Glen and Jorion, 1993; Campbell et al., 2010; Opie and Riddiough, 2020). We therefore split our investigation based on whether a fund is principally "static" or "dynamic" in their approach to currency forward usage. We define a fund as being "static" or "dynamic" based on the time-series volatility of their hedge ratio. Funds below the median level of volatility are labeled as static, while those above the median are labeled as dynamic.

Table 5 reports results. Consistent with the sorting method, we see that the volatility of the time series (ts) hedge ratio is almost three times higher for dynamic funds (24% versus 9%). Within each group, we compute the average volatility of currency-level hedge ratios, which we refer to as "cross-sectional" (cs) volatility. Comparing across the two groups, we observe similar values (22% and 21%) indicating that the degree of variation in currency hedge ratios across currencies is similar in static and dynamic funds. At the fund level, static funds tended to generate higher average excess returns of 5.2% versus 4.8% for dynamic funds, which translated into a higher average Sharpe ratio of 0.41 versus 0.36.

One of the main reasons dynamic currency forward usage is considered to be optimal relative to a static implementation is that currency returns have a predictable component that can be exploited through dynamic hedging. Consistent with this, we find evidence of market timing ability among dynamic funds. Specifically, we find they are more likely to adjust hedge ratios in the correct direction ahead of a subsequent currency excess returns. We define a timing indicator equal to one when a reduction (increase) in the hedge ratio from $t-1$ to t is followed by a positive (negative) currency excess return in $t+1$. For dynamic funds, we find that they make adjustments in the direction of the next quarters market movement 51.4% of the time, relative to 49.2% for static funds, hinting towards a beneficial impact from their approach.[29]

In the lower panels of Table 5, we compare each exposure manager's actual excess return and Sharpe ratio with a counterfactual version of their portfolio. In the first case, we consider the impact of *excluding* currency forward positions, that is, an unhedged portfolio. To obtain these values, we subtract the return on fund i's currency forward positions from its total net return. That is,

$$R_{i,t}^{unhedged} = R_{i,t}^{hedged} - R_{i,t}^{for},$$

where $R_{i,t}^{for} = \sum_j \widetilde{nf}_{i,j,t} \times ExR_{j,t+1}^{for}$ is the return on the currency forward portfolio, $\widetilde{nf}_{i,j,t}$ is the net forward position (long minus short) in currency j scaled by TNA at time t, and $ExR_{j,t+1}^{for}$ is the return on a long forward in currency j. Across both groups, we find that both the excess returns and Sharpe ratios would have been lower had currency forward contracts not been used. This initial finding highlights that currency forwards helped improve investment performance for exposure managers. The largest average gain, an additional 24bps in excess return per annum and an increase of 0.02 in Sharpe ratio, is observed for the dynamic funds, consistent with the more dynamic approach having a more significant impact on fund performance.

In the remaining panels, we assess the optimality of the funds' approach to currency management. To do so, we start from the unhedged position and then overlay the portfolio with an alternative approach to currency management based on one of three easily implementable and widely understood methods. The first is to follow the typical approach suggested for bond funds and fully hedge the portfolio (Perold and Schulman, 1988), the second approach is to exploit information in interest rates for currency excess returns by fully hedging currencies with lower interest rates than in the United States, but leave currencies with higher interest rates unhedged (Glen and Jorion, 1993), while the final approach is to implement a dynamic hedge ratio that aims to minimize the variance of the portfolio (Campbell et al., 2010).

To be clear, other approaches are also available. For example, the dynamic currency factor approach of Opie and Riddiough (2020) is a method that incorporates additional sources of predictability. However, since this technology was not available prior to the start of our sample, we instead chose to concentrate on approaches that would have been available and easily implemented. Although the mean-variance approach of Campbell et al. (2010) was published after the start of the sample, the use of mean-variance approaches to currency hedging has long been established and reviewed in the practitioner space in Jorion (1994). It seems reasonable,

[29] We exclude cases with two or more consecutive quarters of zero hedge ratios.

therefore, to believe that the funds had relevant information to minimize variance.[30]

To assess the efficiency of a fund's approach, we compare its actual performance versus that which *would* have been obtained under alternative approaches to currency management that we rebalance on a monthly basis. We choose to define efficiency as the *ex-ante* maximization of the portfolio's Sharpe ratio—a widely accepted benchmark in the academic literature and closely related to investor behavior. Ben-David et al. (2022), for example, find that *Morningstar* ratings, which are almost perfectly correlated with Sharpe ratios, are the *primary* driver of investor flows into equity funds. Similarly, Duong Dang et al. (2022) find that Sharpe ratios, specifically, are the most important determinant of flows into corporate bond funds.

Here, a discussion is warranted. Clearly, we do not observe the objective function of management and acknowledge that a myriad of other reasons may exist for a mutual fund's investment decisions beyond maximizing assets under management. Indeed, it may be argued that a mutual fund's investors *want* the fund's managers to behave in a way consistent with a lower Sharpe ratio. Our results should therefore be viewed as evidence regarding the degree of inefficiency in currency management, *if* the principal aim of the fund is to maximize the assets under management, which, given the incentive systems within the industry, we feel is a reasonable and often used benchmark.[31]

Turning to the results, we find that applying any of the alternative approaches we consider would have generated significantly higher excess returns and Sharpe ratios. These improvements are both statistically and economically significant. The average increase in annualized excess returns ranges from 34 to 58 basis points per year, while the Sharpe ratios would have been more than 20% higher on average. In each case, we find that the largest benefits would have been obtained for the most static funds in terms of hedging style, consistent with at least some of the dynamic hedging funds already incorporating elements of the alternative, time-varying, approaches in their hedging strategies.

[30] We estimate the asset-currency covariances using a 60-month rolling window. In unreported results, we also find that strong investment gains would have been available if some of the more recently developed technology, such as in Opie and Riddiough (2020) had been used. Results are available upon request.

[31] An exciting avenue for future research is to better understand the objective functions guiding fund managers' use of currency derivatives and to examine the extent to which learning and adaptation occur as new methods for currency management become available. Furthermore, we add a caveat about the incremental performance we document: The analysis does not account for certain frictions that could weaken the hypothetical performance. We do not, for example, incorporate transaction costs or consider the liquidity risk that fund managers may incorporate into their decision making around currency management. Moreover, the currency forward data we obtain are at quarter ends—we cannot observe any changes in forward positions between reporting dates. Thus, our estimation of fund forward returns is based on the implicit assumption that the positions are fixed during each quarter and the contracts are quarterly.

Interestingly, the full hedge provides some of the largest gains. This is consistent with the fact that a large portion of the sample overlaps with a period of appreciation of the US dollar, in which a full hedge performs well. As we will see in our later results, the full hedge is not always superior and can significantly underperform the unhedged position when the US dollar is weakening. Nonetheless, the evidence strongly supports the primary takeaway that hedging matters and can have a significant implication for funds' overall investment performance.

In sum, while exposure managers improved their investment performance through the use of currency forwards, with the largest benefits flowing to those pursuing the most dynamic hedging strategies, substantial unrealized gains remain. This performance gap may reflect alternative objectives beyond the maximization of the Sharpe ratio and assets under management. However, to the extent that this is *not* the case, the evidence contains practical insights for investors and fund managers. Funds can seek alternative approaches to currency hedging that could improve risk-adjusted returns, especially for those currently adopting the most passive approaches. Investors, on the other hand, may push for greater transparency on the use of currency forwards to assess the impact of these contracts relative to natural benchmarks, just as they would for the equity component of the investment portfolio.

4.3 Portfolio builders: The determinants of currency portfolio weights

Portfolio builders construct separate currency portfolios that exhibit considerable heterogeneity in terms of portfolio size relative to TNA. Moreover, as discussed previously, these currency-specific portfolios often include forward contracts on currencies that are not held in the underlying equity portfolio. Due to these portfolio characteristics, fund-level hedge ratios are less meaningful as a comparison metric for this style of currency management. Instead, therefore, we examine the composition of the currency portfolios directly by investigating the determinants of the currency *weights* in each funds' currency portfolio, to understand why a fund chooses to invest in certain currencies while using other currencies to "fund" the portfolio.

We define the weight allocated by fund i to currency j in quarter t, as $w_{i,j,t}$. To calculate the weight, we first normalize the forward position of each currency by the total gross notional exposure of the fund. Specifically, we calculate the absolute notional values of the fund's long and short forward positions, and divide each forward position by the largest of the two values. This approach preserves directional exposure while ensuring that all weights are defined on a consistent scale between funds. We treat the US dollar as the balancing currency so that the currency portfolio weights, including the US dollar, sum to zero.

Adopting the same method that we used to investigate the hedge ratios of exposure managers, we estimate the model

$$w_{i,j,t} = \mathbf{b}'\mathbf{x}_{j,t-1} + \delta_{em} + \gamma_{i,t} + \varepsilon_{i,j,t}, \tag{4}$$

where $\mathbf{x}_{j,t-1}$ is a vector of lagged currency-level characteristics and $\mathbf{b}$ is the vector of associated coefficients that we estimate. Once again we include fund-by-quarter fixed effects, $\gamma_{i,t}$, to study the cross-sectional dimension of currency portfolio weights and include an emerging market dummy variable, δ_{em}, to capture the systematically lower level of liquidity and higher trading costs among those currencies. Standard errors are two-way clustered by fund and currency.

Table 6 presents the coefficient estimates and standard errors. Columns (1) through (6) report univariate regressions for each independent variable, column (7) includes all variables jointly, while column (8) adds additional fund-by-currency fixed effects to assess the extent to which managers dynamically adjust positions in response to changing currency-level characteristics.

Our first observation is that currency portfolio weights are significantly and negatively associated with country weights in the equity portfolio. A ten-percent increase in the equity portfolio weight is consistent with a five-percent reduction in the currency weight, and hence funds typically hedge the largest exposures in the equity portfolio and extend them elsewhere. There are at least two potential motivations for this pattern.

First, funds may hedge currency exposures derived from their equity holdings to reduce return volatility before adding currency exposure with more attractive risk-return properties. This practice would align with Pojarliev and Levich (2014) and Kroencke et al. (2014), who argue that funds should separate hedging from alpha-seeking currency trades. Second, the highest equity exposures are often in larger developed markets, which are more central to the global trade network and offer lower interest rates, such as in the eurozone or Japan. Because these countries are associated with lower currency excess returns, they are typically held as funding currencies in a currency carry trade (see, e.g., Hassan, 2013; Richmond, 2019).

Previous studies have identified multiple currency strategies that generate large cross-sectional risk adjusted returns based on carry, value, momentum, and liquidity.[32] Given these

[32]Menkhoff et al. (2012) find that short-term momentum (one- to three-month exchange rate returns) generates substantial cross-sectional spreads, particularly among emerging market currencies. Lustig et al. (2011) show that high interest rate currencies earn higher excess returns. In addition, Asness et al. (2013) and Menkhoff

findings, portfolio builders can rationally seek to gain exposure to these sources of return when constructing their currency portfolios. In columns (2) to (5), we present evidence on the relationship between the choice of currency weights and the signals underlying these strategies.

The momentum of the currency, measured as the previous one-quarter return, and the carry, captured by the forward discount, are seen to be positively associated with the weights of the currency portfolio, consistent with an attempt to capture higher returns. For momentum, a 1% exchange rate return during the quarter is associated with around a 0.27% increase in its currency portfolio weight. The effect for carry is larger, especially in the full model, for which a 1% higher interest rate is associated with a 0.36% higher portfolio weight.[33] By comparison, currency value and liquidity do not appear to influence portfolio weights meaningfully on average. This pattern is broadly consistent with the behavior observed among exposure managers and again suggests that funds may be overlooking important sources of currency excess return when forming their currency portfolio. Finally, the emerging market dummy is statistically significant and negative in the full model, reflecting the decision of the funds to assign less weight to these currencies, offsetting the higher weight they would typically be assigned by offering higher yields.[34]

When we add fund-by-currency fixed effects, we again see, consistent with exposure managers, the carry variable become statistically indistinguishable from zero, consistent with funds assigning a higher currency weight to currencies that offer a *persistently* higher interest rate, i.e., capturing the permanent component of interest rate differentials. Furthermore, momentum and the country weight in the equity portfolio remain important drivers of the currency weights. The finding mirrors that observed for exposure managers and implies that adjustments to the currency portfolio are largely based on underlying equity tilts and recent fluctuations in exchange rate markets.[35]

et al. (2017) document that undervalued currencies, measured relative to purchasing power parity benchmarks, tend to outperform, while Mancini et al. (2013) show that illiquid currencies earn higher returns than their more liquid counterparts.

[33]Practitioners often consider risk-adjusted carry by investing in a carry trade in which interest rates are scaled by the volatility of the exchange rate (e.g., Dupuy, 2021; Maurer et al., 2023). In Table A.5 of the Online Appendix, we explore this alternative measure of carry and find an even stronger effect, supporting the perspective that volatility-adjusted carry has a more pronounced impact on the formation of currency portfolios.

[34]As with exposure managers, we also study the impact of the cross-currency basis on portfolio builders. We report our findings in Table A.6 of the Online Appendix. Once we include all explanatory variables, we find that currency portfolio weights are not responsive to CIRP deviations.

[35]It may be wondered why exposure managers and portfolio builders appear to respond to the same sources of information. One explanation is that certain factors, such as carry, are widely known and thus common information. An alternative explanation is that mutual funds outsource currency decisions to a specialized currency manager and therefore many decisions appear similar because they are being made by a smaller set of these managers. In fact, for this reason we cannot study the characteristics of managers, since we cannot observe

We now turn to assess the impact of the separate currency portfolio on funds' overall investment performance. The fact that funds appear to only partially gain exposure to key sources of risk-adjusted currency returns hints toward a source of inefficiency in the decision-making process. In the next section, we quantitatively evaluate the magnitude of these potential inefficiencies by comparing each fund's performance with alternative currency portfolios.

4.4 Portfolio builders: The optimality of currency portfolio weights

We begin by analyzing the distribution of returns and the investment performance of the currency portfolios constructed by portfolio builders. Table 7 reports the results. Across all portfolio builders, the average annualized return of the currency portfolio is 0.95% per annum. The median is similar at 0.88% per annum. The range of average returns is wide and the middle 50% of the observations is between −1.15% and 2.84%. Put differently, a quarter of all portfolio builders generated *negative* average currency portfolio returns below −1.15%. Given the substantial returns of the currency portfolio that are often reported in academic studies, especially when combining various currency investment strategies, the returns are surprisingly low if the main objective is to enhance investment performance.[36]

We investigate the dispersion in investment performance by sorting each fund into one of five groups (G1 to G5), based on the Sharpe ratio of their currency portfolio. The average Sharpe ratios for G1 and G5 funds are −0.75 and 0.77, highlighting the wide range of performance observed in the industry. However, when focusing only on funds from G1 to G4, we find that the average Sharpe ratio is negative (−0.09), and thus in the industry the currency portfolio appears to be highly inefficient from a Sharpe ratio maximization perspective.[37]

Portfolio returns are seen to increase monotonically from G1 to G5, indicating that higher Sharpe ratios are not driven by lower portfolio volatility. In fact, we find volatility tends to rise from G1 to G5, hinting at slightly less risk in the portfolio for G1 funds. The performance differential is also not driven by scale. In fact, we find that the G1 and G5 funds hold similar sized currency portfolios, around 10% of their TNA, which are the smallest average values—funds in G3 typically constructed currency portfolios equivalent to around 15% of their TNA.[38]

whether the fund hires an external manager to make the final decision about currency forward contracts.

[36]See, for example, Jordà and Taylor (2012), Asness et al. (2013), Bakshi and Panayotov (2013), Kroencke et al. (2014), Maurer et al. (2023) and Riddiough and Zhang (2025) for evidence on the potential investment performance of currency portfolios that combine various sources of information.

[37]In additional tests, we split the sample to test if funds which generated the strongest investment performance during the first half of the sample continue to do so during the second half. However, we find no evidence for this type of persistence in skills. Results are available upon request.

[38]We investigate whether there are systematic differences in the main currencies that different groups use

Given the observed performance of currency portfolios, we seek to quantify the magnitude of their inefficiency. We do so by assessing the impact on funds' overall investment performance if they had incorporated other easily implementable currency investment strategies. As in the case of exposure managers, we begin by first stripping out the impact of currency forwards on the overall investment performance. In the lower panel, we report the average change in funds' Sharpe ratios by not including a currency portfolio. Interestingly, we find a relatively small effect. Unsurprisingly, G1 funds would have generated slightly higher Sharpe ratios, and G5 funds would have generated slightly lower Sharpe ratios from not incorporating the currency portfolios. But in both cases, the effect is just a 0.01 change in the Sharpe ratio.

The reasons are twofold. First, the sizes of currency portfolios are typically too small to have a material impact on fund performance. In fact, studies that recommend a separate currency portfolio generally advocate for a larger notional weighting on the currency portfolio of around 33%, with the remaining 67% allocated to the portfolio of stocks and bonds (see, e.g., Kroencke et al., 2014). Although funds typically construct currency portfolios with far lower weights, they also refrain from building currency portfolios in some quarters (the size of the currency portfolio we report is based on the quarters in which a fund *holds* a currency portfolio). Failing to hold a currency portfolio in some quarters naturally reduces the impact of currency forwards on total investment performance when averaged across the entire sample. The generally weak performance of funds' currency portfolios, combined with the lack of material impact on total performance across the industry, raises the pertinent question for the entire industry: What *could* the impact of a currency portfolio have been, had a strategy been consistently implemented by funds over the entire sample?

We consider three alternative currency portfolios. The first two are based on the currency carry trade, which exploits cross-sectional violations of the uncovered interest parity condition, resulting in large currency excess returns for the highest interest rate currencies (Glen and Jorion, 1993; Lustig et al., 2011; Hassan and Mano, 2019). We consider two versions of this strategy. The first takes positions only in the G9 currencies. Specifically, each month, we form the strategy by going long the three currencies with the highest interest rates and short the

as investment and funding currencies. We report the top five investment currencies and the top five funding currencies for each group in Table A.7 of the Online Appendix. In general, all groups display similar behavior, tending to be long the Australian dollar and Swedish krone, and short the Japanese yen and euro. In support of a carry-based trade, G5 funds are more likely to invest in emerging market currencies, such as the Indian rupee and the Mexican peso. In contrast, G1 funds tend to invest in low-yielding currencies, including the euro and Swiss franc, and fund in higher-yielding currencies, such as the Norwegian krone, South Korean won, and Israeli shekel.

three currencies with the lowest interest rates. The second version broadens the currency set to include emerging markets currencies. In total, we consider 25 currencies with floating exchange rates in this second version (the G25) and construct a portfolio that is long the five currencies with the highest interest rates and short the five currencies with the lowest interest rates.[39] For each portfolio builder, we add the resulting portfolios to their fund, after removing their existing currency portfolios and applying a full hedge.

In each case, we scale the currency portfolios so that a weight of 20% is allocated to the currency portfolio and the remaining 80% is allocated to their existing equity portfolio. In the lower panel of the table, we see a notable increase in the Sharpe ratios of the portfolios. Adding just the G9 carry trade portfolio tends to increase the funds' overall Sharpe ratios in magnitude by 0.05 to 0.06, equivalent to an increase of over 20% in the overall Sharpe ratio.[40]

The magnitude of this effect grows far larger, however, when also incorporating emerging market currencies given the higher interest rates typically on offer among these currencies. In this case, Sharpe ratios are seen to increase between 0.12 and 0.14 on average across the five groups. The greatest increase is, as expected, for the G1 funds, but *all* funds would have observed a significant increase in their investment performance through the incorporation of a carry strategy. For half of the funds in the portfolio builders sample, these increases would have resulted in an increase in the Sharpe ratio of more than 48%.

The third strategy we consider also includes all G25 currencies, but this time combines an equal mix of currency carry, value, and momentum, which we call the "combo" trade. The value and momentum of the currency are known to generate large returns in the currency markets and to offer useful diversification benefits to international equity investors (Kroencke et al., 2014). Since value and momentum have generated lower returns than currency carry, on average, over the sample period, the overall impact on the fund's return profile is smaller than when only incorporating the carry trade. However, this lower-risk alternative would have also offered large benefits to portfolio builders, somewhere in magnitude between the G9 and G25 carry trades, with an increase of between 0.07 and 0.09, on average, to the Sharpe ratio across the five groups.

The findings for portfolio builders indicate that fund managers pursuing the construction

[39]The 25 currencies include the G9 plus the currencies of Brazil (BRL), Chile (CLP), Colombia (COP), Indonesia (IDR), Iceland (ISK), Israel (ILS), South Korea (KRW), Mexico (MXN), Malaysia (MYR), Philippines (PHP), Poland (PLN), Russia (RUB), Singapore (SGD) Thailand (THB), Turkey (TRY), South Africa (ZAR). Note that we do not have forward exchange rate data for ISK.

[40]The average fund-level Sharpe ratios of portfolio builders is 0.22.

of a separate currency portfolio could significantly enhance the performance of their investment portfolios by (i) increasing the size of their currency-specific portfolio, (ii) maintaining a currency-specific portfolio in all quarters, and (iii) incorporating well-known sources of currency excess returns within their portfolio. Our results indicate that funds could see a substantial boost in performance by allocating weight to currency carry, value, and momentum and, given the growth in the literature documenting alternative ways to build currency portfolios that offer alternative sources of value (Lustig et al., 2014; Colacito et al., 2020; Riddiough and Zhang, 2025), even larger gains may be available today.

In sum, fund managers could have significantly improved the performance of their international equity funds by adopting a more dynamic and diversified approach to currency management. In Figure 8, we highlight the gains across the industry for user funds. The figure presents the average return and standard deviation of every user fund (denoted by red diamonds). We then add to the plot the average return and standard deviation for each fund, when an alternative approach to currency management is applied (denoted by blue circles). For portfolio builders, we add the G25 carry trade portfolio, while for exposure managers and occasional users, we overlay their portfolio with the minimum-variance portfolio approach of Campbell et al. (2010).[41] We fit a quadratic polynomial to both sets of data to more clearly highlight the discrepancy in investment performance. Through the inclusion of the alternative forms of currency management, the fitted line under the alternative approach shifts clearly lower, indicating a reduced level of portfolio volatility for a given average return, and hence an improvement in the ex-post risk-return profile of the portfolio.

Thus, by integrating known sources of currency excess returns, scaling currency portfolios, and dynamically adjusting hedge ratios, managers can better align with efficient currency management practices. In addition, by exploring emerging methodologies and sources of currency predictability, funds can further optimize their currency exposures, ultimately enhancing their overall risk adjusted returns.

5 Non-user Funds

If a fund does not use currency forward contracts, it has still made an active decision: Non-user funds optimize their portfolio by accepting a return profile in which foreign exchange rate fluctuations are central. Implicit in the approach, therefore, is the view that currency forwards

[41] We discuss occasional users further in Section 6.2.

are not value additive. The perspective stands in contrast, however, to the body of literature highlighting the potential investment performance gains to international equity funds, through taking a more active approach to managing currency exposure.

In this final section, we therefore investigate the potential impact of incorporating currency forwards on the investment performance of non-users. In our main analysis, we overlay each non-user fund's portfolio with the three alternative approaches discussed in the analysis of exposure managers. We therefore consider the impact on the funds from fully hedging their currency exposure, tilting hedging based on currency carry, and adopting a mean-variance approach that seeks to minimize the portfolio's variance.

To overlay the funds' portfolios with currency forwards using the three approaches, we begin by calculating each fund's total exposure across currencies each month. We do so by obtaining the monthly currency weights reported by *Morningstar* for each fund, in combination with the TNA of the fund. As an example, if a fund has \$100 million in TNA and holds 5% of its assets in Japanese equities, this implies a \$5 million exposure to the Japanese yen. To fully hedge this exposure, we enter a one-month forward contract to sell the equivalent of \$5 million yen and scale the position accordingly for the other strategies. To avoid over-hedging or *increasing* currency exposure, when applying the minimum-variance approach of Campbell et al. (2010), we limit all hedge ratios to lie between 0 and 1 (inclusive).

Table 8 reports results. We divide the findings into three time periods. The first period is for the entire sample, ranging from Q1 2004 to Q2 2019. The second period is from Q1 2004 to Q4 2011 and the final period is from Q1 2012 to Q2 2019. The sample is split to highlight the impact of different approaches to currency management in periods of appreciation and depreciation of the US dollar. From 2004 to 2011, the US dollar weakened—the DXY index, a broad measure of the US dollar's movements, fell from 87.4 to 80.2. In contrast, from 2012 to 2019, the DXY index rebounded to 96.5. If the US dollar is strengthening, it naturally favors full-currency hedging. In contrast, a period of weakness for the US dollar will tend to show stronger investment performance for an unhedged portfolio.

The first column of the table reports the actual performance of the non-user funds. The remaining columns report the incremental performance of (i) overlaying the portfolio with a full hedge, in which currency exposure is completely removed using currency forwards; (ii) a carry approach, in which only currencies with lower interest rates than in the US are fully hedged and other currencies remain unhedged; and (iii) the minimum-variance hedge of Campbell et al.

(2010). Statistical significance of incremental performance is obtained from a permutation test with 1,000 resamples, generating p-values based on the distribution of the test statistic.

We turn first to the full sample. Non-users delivered an average Sharpe ratio of 0.39, certainty-equivalent return of 1.9%, and a benchmark-adjusted return of -0.56.[42] In contrast, all three alternative approaches are seen to substantially increase these values. Sharpe ratios increase, on average, by more than 20%, benchmark adjusted returns increase on average by up to 78 bps per annum—turning positive after incorporating currency forwards—while, according to the certainty-equivalent return, a risk-averse investor would typically be willing to pay as much as 1.81% per annum to switch to an international equity portfolio whose currency component is actively managed.

We also note, however, that in each case the tracking error increases significantly. Thus, an unwillingness on the part of funds' managers to deviate too far from an existing benchmark, due to career concerns associated with generating returns substantially different from competition, may offer one possible explanation for why currency management is not more actively pursued.

Turning to the period between 2004 and 2011, we observe that full hedging would have significantly *underperformed* the actual values obtained from not incorporating currency forwards—the Sharpe ratio and benchmark-adjusted return would have been substantially lower. This observation may partially account for fund managers choosing not to engage with currency forwards, as it appears that they may outperform in some time periods but not in others, averaging towards a similar level of performance over time. Indeed, at the outset of this study, we highlighted the similar performance of the hedged and unhedged versions of the MSCI All Country World Equity Index, implying that neither the unhedged nor fully hedged position is likely to be optimal over a long horizon. We find, however, that even during this period that naturally favored the unhedged approach, the minimum-variance hedge of Campbell et al. (2010) would have *still* increased the Sharpe ratio and certainty-equivalent return, and reduced portfolio volatility.

During the period 2012 to 2019, when the US dollar strengthened, the full hedge performed best, generating higher returns, lower volatility, and a substantially higher Sharpe ratio compared to the unhedged portfolios. However, risk-averse investors would have been willing to pay a substantial premium to switch to *any* of the alternative currency managed portfolios, as

[42]The certainty-equivalent return is calculated as $\mu - \frac{1}{2}\lambda\sigma^2$, where μ is the mean excess return, σ^2 is the variance of excess returns, and λ is the investor's risk-aversion coefficient that we set equal to 3. We calculate benchmark-adjusted return using the benchmark assigned to each fund by *Morningstar*.

Sharpe ratios and benchmark adjusted returns would have always been statistically significantly higher, and portfolio volatility would have been reduced.[43]

In summary, we find evidence that non-users could have substantially enhanced their overall investment performance by managing their currency exposure using currency forwards. Across the entire sample, simple alternative strategies would have all offered substantial improvement in standard performance metrics. However, tracking errors would have been higher and the improvement would have been less extreme during periods of US dollar weakness.

A natural recommendation that emerges, therefore, is for fund managers to go beyond the extreme of either a full hedge or an unhedged portfolio, and instead consider alternative approaches that condition on more information about the current state of the economic environment. For investors, the finding highlights the need for greater transparency in currency management, given the apparent inefficiency in the current practice that appears to be leaving money on the table.

6 Further Analyses

In this section, we briefly review further analyses that we undertake and document in the Online Appendix. These analyses address two additional questions. First, to what extent are the main results affected by our particular choice of classification scheme when identifying currency management styles? And second, what are the main determinants of currency forward usage for occasional users? All results are reported in Section B of the Online Appendix.

6.1 Alternative categorization schemes

We describe our approach to assigning currency management styles in Section 3.3. The approach is based on selecting thresholds in funds' hedge ratios, absolute forward positions, and the proportion of quarters in which funds use currency forwards. We investigate whether the results on the determination of hedge ratios, among exposure managers, and the determination of currency portfolio weights, among portfolio builders, are affected when changing categorization scheme.

In total, we consider seven alternative approaches. The first six are based on changing threshold values. We vary the required proportion of active quarters from 10% to 50% and

[43] In Table A.8 of the Online Appendix, we extend the analysis to investigate the impact of including a separate currency portfolio, using the alternative strategies described in Section 4.4 for portfolio builders. We find a similar improvement in performance across the samples.

set the absolute forward position at 2% or 5%. The final categorization scheme is based on a two-step procedure using the k-means machine learning algorithm, which provides a way to cluster funds into three groups that is free from an arbitrary threshold decision.

Table B.1 reports the breakdown of funds across currency management styles for the seven different categorization schemes. We tend to find that there is more stability in the classification of funds as exposure managers. This is unsurprising given that an exposure manager is a fund with a high hedge ratio that regularly uses currency forwards. Changing the thresholds makes relatively little difference in this categorization. The machine learning approach stands out as being stricter, requiring an even higher hedge ratio to define an exposure manager—the average hedge ratio for this classification is 40%, relative to around 28% for the threshold-based approach. The biggest switches take place between portfolio builders and occasional users. These two styles can look similar: Although some funds clearly operate large long-short positions, other funds may simply be engaging in larger liquidity trades. For that reason, we see significant movement between the two categories. Indeed, being especially conservative, such that the currency portfolio is required to be at least 5% of the fund's TNA, we observe a switch of around 90 funds from being classified as portfolio builders to occasional users. Using these alternative categorization schemes, we repeat the full-specification analysis documented in Tables 4 and 6.

Tables B.2 and B.3 report results. Across the two tables, we see qualitatively identical results to those observed in the main tables. For exposure managers, no matter the classification approach, country weights, momentum, carry, volatility, and the emerging market dummy variable are always highly statistically significant. We find virtually no evidence of any other variable being important in the alternative specifications. The same pattern is observed for the portfolio builders, and, moreover, the coefficient estimates based on the machine learning categorized funds are almost identical to those we observe for the main sample and all other alternative categorizations.

In sum, the additional analyses confirm that our main results are not highly sensitive to the choice of categorization scheme, and thus the determinants of currency forward usage that we concluded to be important in the main analysis continue to remain so following these tests.

6.2 Occasional users

Occasional users enter currency forward contracts infrequently or on notional values that are small relative to their fund's TNA. Given the magnitude of these positions, we anticipate that their use is more idiosyncratic in nature and that the determinants we explored in the main analysis would explain a smaller fraction of the behavior. In Table B.4 we investigate the determinants of their hedge ratios across the seven alternative approaches to fund categorization, while in Table B.5 we turn to study currency portfolio weights—*as if* these occasional users had purposefully built separate currency portfolios.

Unlike exposure managers and portfolio builders, we find little robustness in the results for occasional users, other than for the *lack* of relationship observed between hedge ratios, currency portfolio weights and the determining factors we consider. We do find some evidence that country weights, momentum, carry, and volatility play a role in determining hedge ratios, but these results are not consistently observed across categorization schemes and the amount of variation we explain in hedge ratios is a fraction of what we observe for exposure managers. Moreover, turning to their currency portfolio weights, we find that virtually every coefficient is statistically indistinguishable from zero, highlighting a clear disparity with portfolio builders.[44]

Overall, therefore, these findings provide supportive evidence in favor of our categorization of these funds as entering currency forward contracts infrequently and for idiosyncratic reasons. Their forward positions are either too small or too infrequent to materially impact the funds' overall investment performance. These positions are therefore most likely to reflect one-off liquidity or hedging requirements than a systematic attempt to manage currency exposure.

7 Conclusions

As US investors increasingly turn to international equity markets as a source of portfolio diversification, internationally focused equity mutual funds, managing nearly $3 trillion in assets, are becoming increasingly attractive. However, these funds also expose investors to the risks and returns associated with foreign exchange movements. Given the significant impact that currency exposure can have on portfolio performance, how funds manage currency risk can

[44]Given the limited impact that currency forwards are likely to have on the investment performance of occasional users, it is anticipated that adding alternative currency forward strategies to their portfolios should improve their investment performance, much as it did for non-user funds. Indeed, when we replicate the analysis on non-user funds, presented in Table 8, for occasional users, we find qualitatively identical results. These results are reported in Table B.6 of the Online Appendix.

have profound implications for investors' long-term wealth creation. This paper explores how currency is managed by international equity mutual funds, how this usage impacts fund performance, and whether current industry practice can be viewed as efficient.

Using a unique, hand-collected data set of over 55,000 net currency forward positions, this study serves as the first comprehensive analysis of currency management in US international equity mutual funds. We categorize funds as adopting one of two primary currency management strategies: Exposure management, in which funds use currency forwards to adjust their existing foreign exchange exposure, in an effort to reduce risk or enhance returns, and portfolio building, in which funds create separate speculative currency portfolios, often incorporating currencies not represented in the underlying equity portfolio. Although both approaches could help to enhance overall investment performance, our findings indicate that neither approach has made a significant impact on funds' performance, on average. Users and non-users of currency forwards have shown similar levels of investment performance over time.

Although we uncover evidence that funds utilize information thought to be useful for currency management, such as exchange rate momentum and currency carry, the findings more generally point towards substantial levels of inefficiency in the usage of currency forwards. We quantify this inefficiency, in particular, by measuring the incremental Sharpe ratio that would have been obtained under alternative approaches to currency management. Many of these alternatives, both for exposure managers and portfolio builders, would have resulted in Sharpe ratio improvements between 20% and 50%. We document similar, and often larger, missed opportunities among funds choosing not to use currency forwards.

The findings of the paper point to concrete actions for investors and managers of international equity mutual funds. Investors should seek to measure and benchmark currency management to help elevate the investment performance of international equity funds, while fund managers should seek to engage more actively and optimally with this underlying portfolio exposure, aiming to reduce uncompensated sources of return volatility while also remaining open to the potentially large benefits that currency can offer to the portfolio.

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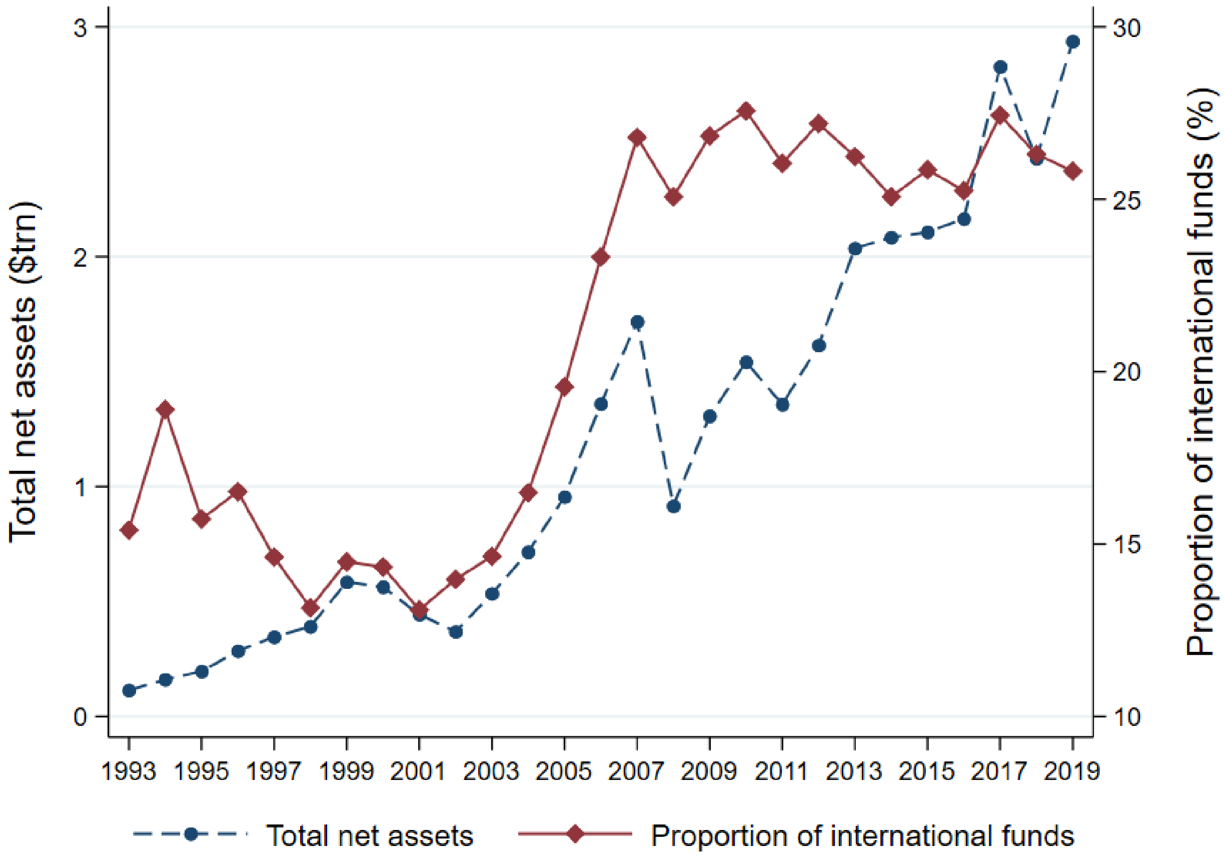
Figure 1: The Growth of US International Equity Mutual Funds



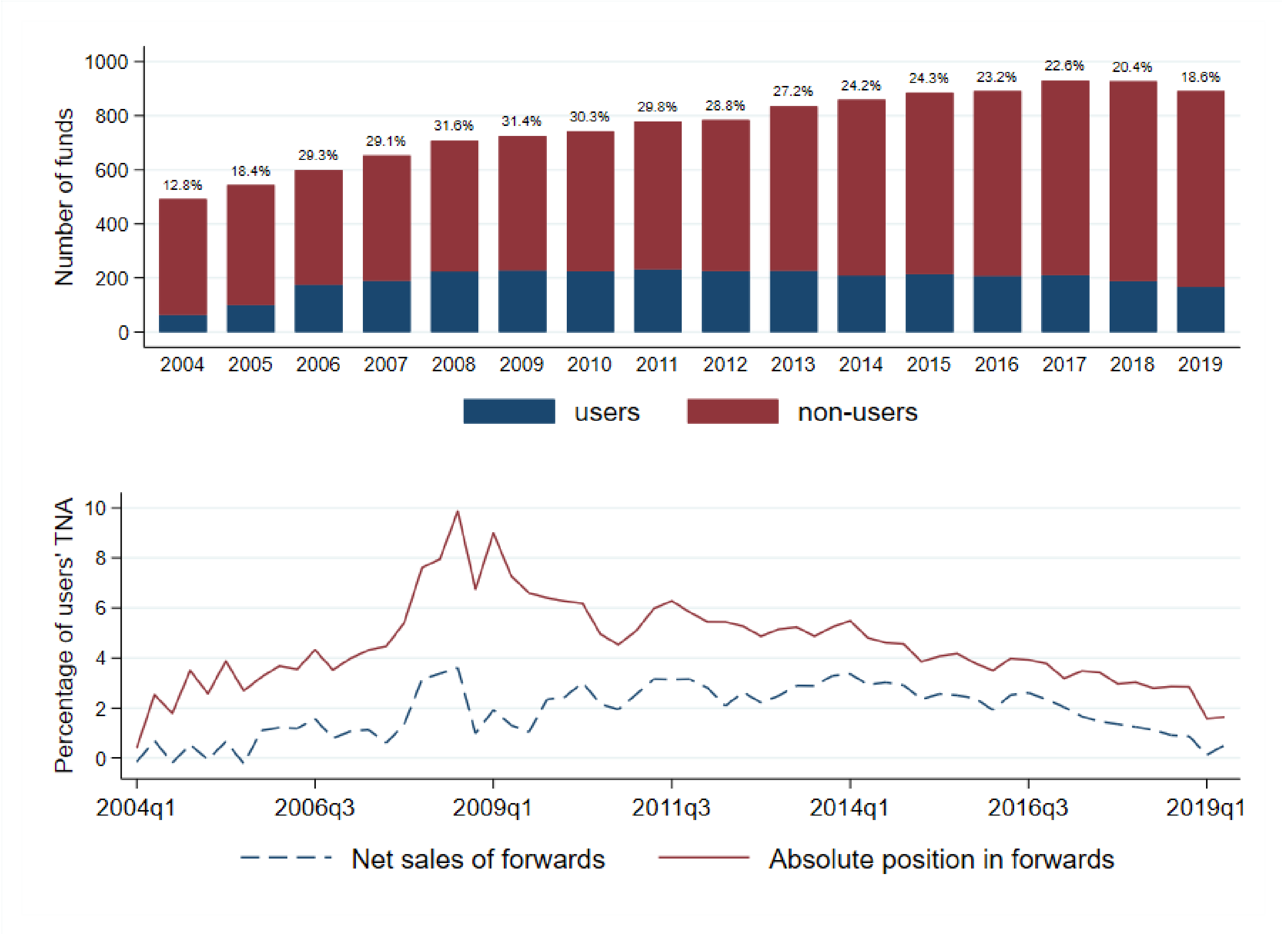
The figure presents the total net assets (in $trillions) of US-domiciled international mutual funds and their share in the assets managed by all equity mutual funds. Data source: Investment Company Institute (ICI) Fact Book.

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

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

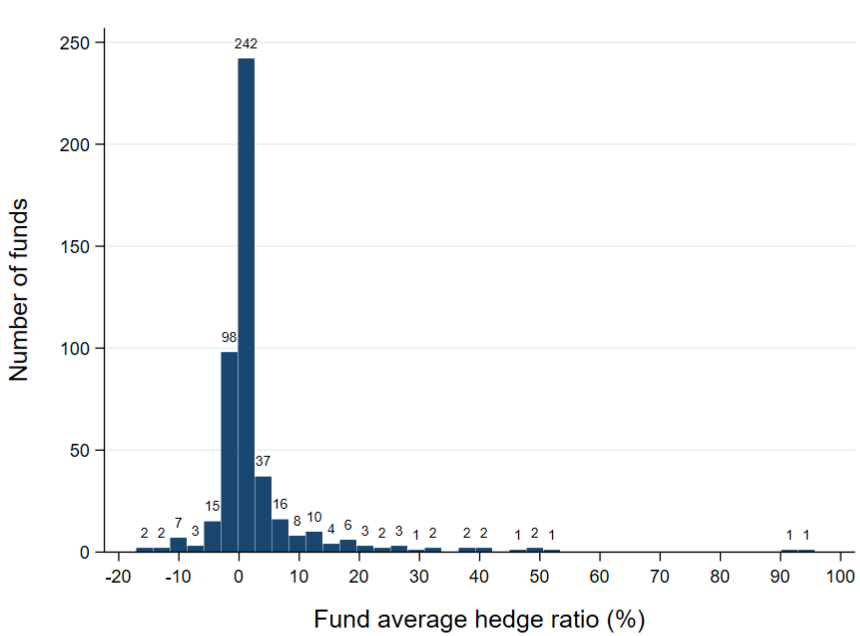
The figure presents an extract of the foreign currency forward contracts held by AB International Value Fund as of May 2019. The extract displays the dealer name (counterparty), the amount and currency the fund has contracted to deliver (Contracts to Deliver), the amount and currency the fund has contracted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

Figure 3: The Time Series of Currency Forward Usage

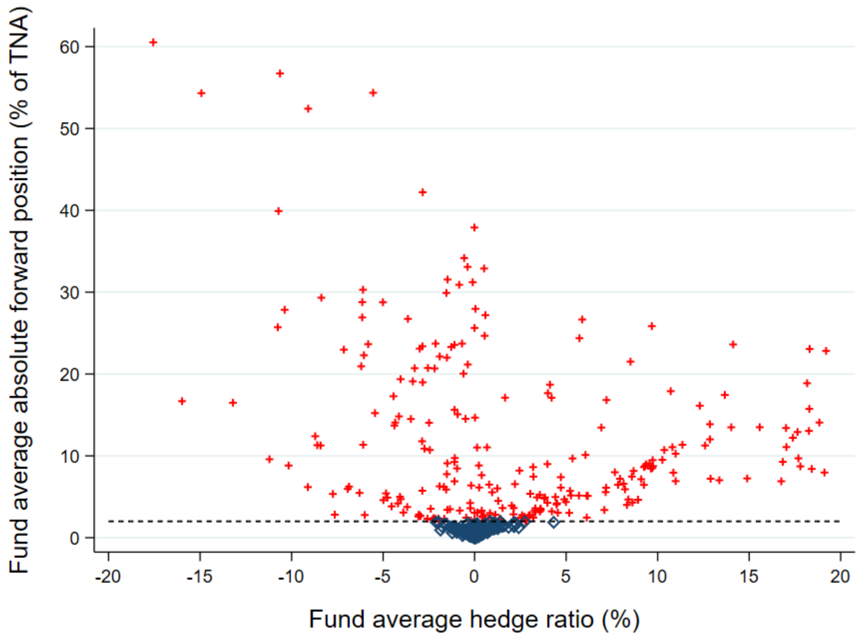


The top graph presents the total number of funds in the sample each year, split between funds that used currency forward contracts during the year (users) and those which did not use currency forward contracts (non-users). The bottom graph presents two time series: (i) the total notional amount of currency forward contracts (expressed as the net short position) relative to the funds' total TNA (dashed blue line) and (ii) the total absolute position in forwards, which sums the absolute notional values of both short and long currency forward contracts vis-a-vis the 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 4: Hedge Ratios and Absolute Currency Forward Positions



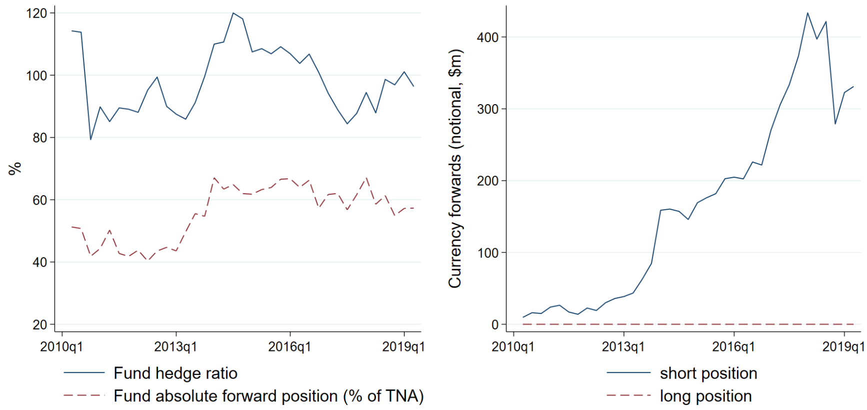
(a)



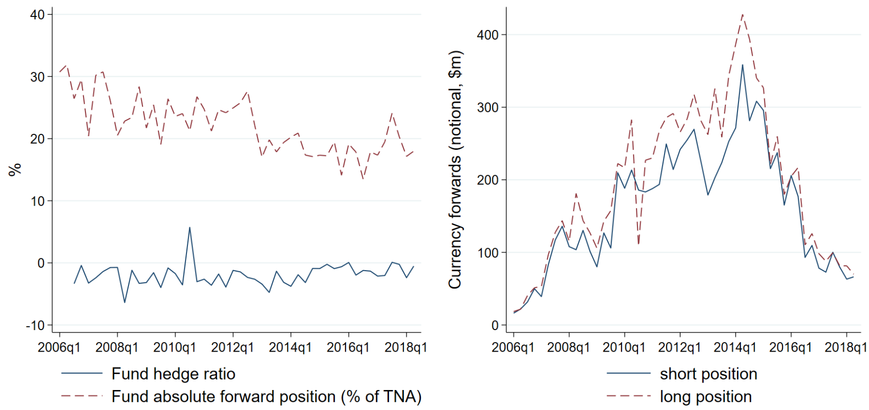
(b)

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

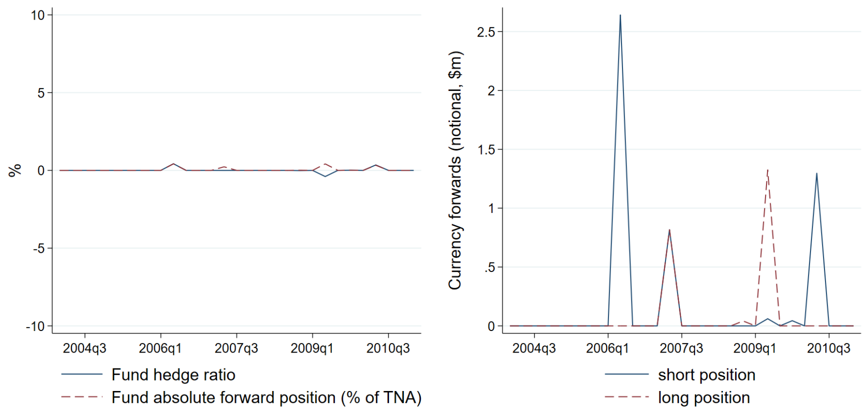
Figure 5: Examples of Currency Management Styles



(a) Exposure Manager: Evermore Global Value Fund



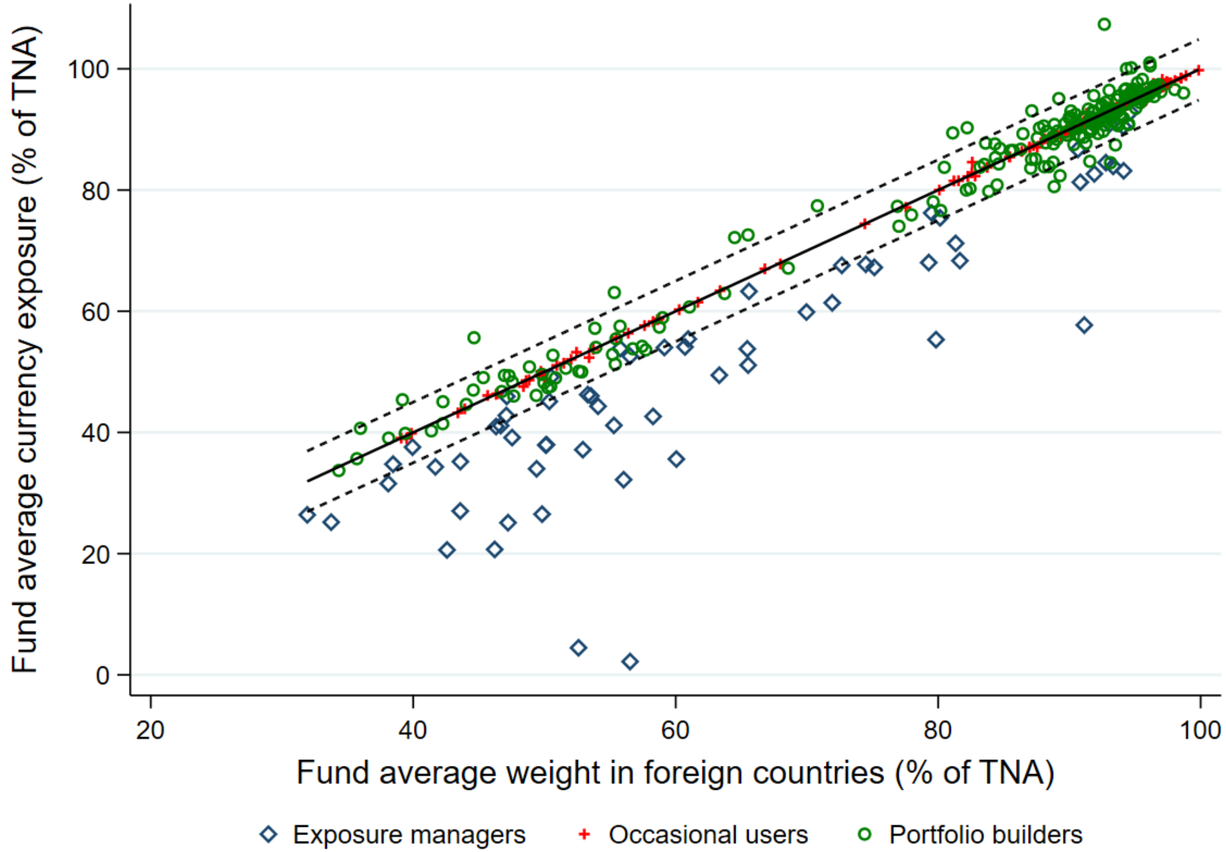
(b) Portfolio Builder: J.P. Morgan International Value Fund



(c) Occasional User: Threadneedle Int. Opportunity Fund

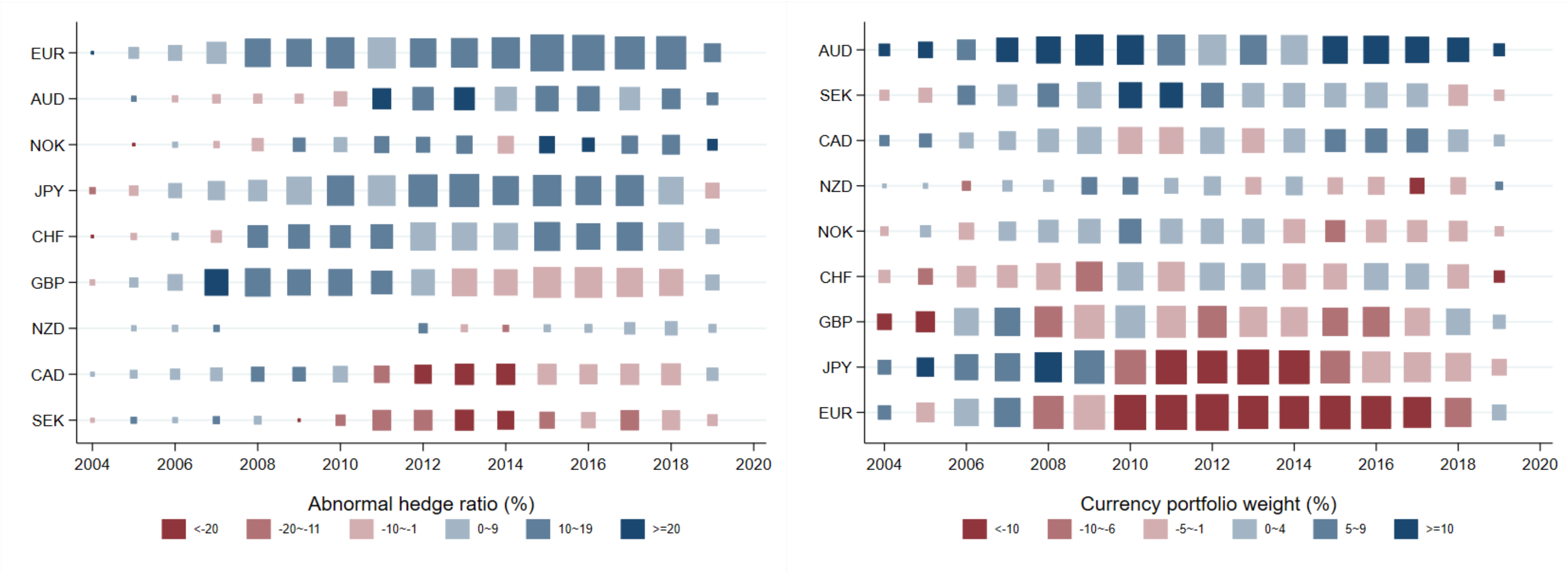
The figure presents the time series of hedge ratios and the total notional dollar values ($million) of long and short currency forward contracts for three funds: Evermore Global Value Fund (top graph, the "Exposure Manager"); J.P. Morgan International Value Fund (middle graph, the "Portfolio Builder");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

Figure 6: Currency Exposure Across Currency Management Styles



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

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



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

Figure 8: Average Return and Standard Deviation of User Funds

The figure presents a scatter plot of user funds' actual average returns (x-axis) plotted against their average standard deviation (y-axis, blue circles) and user funds' potential average returns and standard deviation (red diamonds) under alternative currency management schemes. For portfolio builders we add a G25 currency carry trade portfolio. For exposure managers and occasional users, we overlay the portfolio with the minimum-variance method of Campbell et al. (2010). The solid and dashed lines are fitted quadratic polynomials. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

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

	Users (471 Funds)			Non-Users (808 Funds)			Difference	
	Obs	**Mean**	**Std**	**Obs**	**Mean**	**Std**	**U–NU**	***p*-val**
				Fund Characteristics				
Portfolio weight outside US (%)	17,188	82.2	18.9	23,786	83.0	19.2	−0.82	0.64
Portfolio weight in G9 (%)	17,188	54.1	30.6	23,786	47.0	33.2	7.2	0.00
No. countries invested	17,188	16.8	6.95	23,786	16.0	7.46	0.78	0.01
Fund turnover ratio (annual, %)	17,517	70.4	53.8	22,610	55.2	48.1	15.2	0.00
Fund expense ratio (annual %)	17,573	1.3	0.46	22,749	1.2	0.49	0.07	0.02
Fund management fee (% annual)	16,638	0.80	0.30	21,226	0.79	0.40	0.01	0.15
Dividend yield (%)	18,829	0.91	2.52	25,100	0.83	2.27	0.08	0.00
Fund age (years)	19,107	12.6	8.52	25,594	10.2	8.28	2.4	0.00
Fund TNA ($ millions)	18,320	2,096	10,097	24,473	1,192	3,007	904	0.00
Family TNA ($ millions)	18,901	18,177	51,104	25,228	24,443	44,703	−6,266	0.05
Number of funds in family	19,107	9.1	8.00	25,594	11.9	11.80	−2.8	0.00
Institutional share (% of TNA)	18,597	36.5	38.2	24,863	41.5	42.5	−5.0	0.02
Index funds	19,107	0.08	0.27	25,594	0.10	0.30	−0.02	0.54
				Investment Performance				
Gross return (%)	17,319	2.20	9.38	22,310	2.25	9.28	−0.05	0.25
Net return (%)	18,495	1.85	9.42	24,522	1.93	9.31	−0.07	0.83
Stdev net return (%)	19,107	9.27	2.04	25,581	9.06	2.42	0.20	0.02
Benchmark adj return (%)	18,250	−0.06	2.62	24,207	0.02	2.66	−0.08	0.40
Sharpe ratio	19,099	0.16	0.10	25,540	0.18	0.13	−0.02	0.06
Tracking error (%)	18,993	2.31	1.22	25,257	2.33	1.26	−0.02	0.25

The table presents summary statistics for the international equity mutual funds in the sample. For each fund characteristic, we present the number of fund-quarter observations (Obs), the average (Mean), and the standard deviation (Std). The statistics are split across funds that use currency forward contracts during the sample (Users) and those which do not (Non-Users). The difference between the average fund characteristics for user and non-user funds is calculated and presented in the column headed U-NU. Each p-value is calculated using a permutation test with 1000 resamples. The sample period is from Q1 2004 to Q2 2019. Fund characteristics are defined in Table A.1 of the Online Appendix. Further details on the funds and data sources can be found in Section 2.

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

	Exposure Managers (66 Funds)		Portfolio Builders (202 Funds)		Occasional Users (203 Funds)	
	Mean	Std	Mean	Std	Mean	Std
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
Ratio of forward currencies to equity currencies (%)	34.2	22.6	37.9	31.2	18.1	12.6
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
No. of net forward positions	7,963		37,564		10,088	
No. of net long forward positions	1,147		19,730		6,106	
No. of no underlying positions (NUP)	300		4,274		193	

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

Table 3: Currency Forward Usage by Currency and Management Style

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

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

Table 4: The Determinants of Hedge Ratios Among Exposure Managers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Country weight	0.816***								0.701***	0.580***
	(0.082)								(0.082)	(0.096)
Momentum		−0.084**							−0.139***	−0.113***
		(0.037)							(0.037)	(0.032)
Carry			−0.729***						−0.378***	0.100
			(0.117)						(0.125)	(0.101)
Value				0.068***					−0.018	−0.027
				(0.025)					(0.024)	(0.024)
Bid-ask spread					−0.061***				0.023	−0.015
					(0.022)				(0.019)	(0.019)
Volatility						0.428***			0.472***	0.038
						(0.099)			(0.107)	(0.087)
Equity return							−0.012		−0.001	0.026
							(0.021)		(0.021)	(0.018)
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	27,365
Fund × Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund × Currency FEs	No	No	No	No	No	No	No	No	No	Yes
Adj R^2	0.303	0.267	0.273	0.268	0.268	0.271	0.267	0.286	0.315	0.628

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. All regressions include fund × quarter fixed effects and the regression in the last column also includes fund × currency 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.

Table 5: The Hedging Behaviour of Exposure Managers

	Hedging Style	
	Static	**Dynamic**
Number of funds	32	32
Hedge ratio volatility (ts)	8.8	23.7
Hedge ratio volatility (cs)	22.0	20.6
Excess return (%)	5.22	4.82
Sharpe ratio	0.41	0.36
Avg % correct hedge ratio timing	49.2	51.4
Unhedged portfolio (relative to actual performance)		
Excess return	-0.11^{*}	-0.24^{***}
Sharpe ratio	-0.01^{**}	-0.02^{***}
Full hedge (relative to actual performance)		
Excess return	0.34	0.58^{***}
Sharpe ratio	0.12^{***}	0.10^{***}
Carry trade (relative to actual performance)		
Excess return	0.45^{***}	0.47^{***}
Sharpe ratio	0.08^{***}	0.06^{***}
Minimum-variance (relative to actual performance)		
Excess return	0.42^{**}	0.49^{***}
Sharpe ratio	0.13^{***}	0.10^{***}

The table presents statistics on the hedging behavior of exposure managers, split into two groups (static and dynamic) based on their Hedge ratio volatility (*ts*), which 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. 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. Performance gain relative to funds' own hedging approach is reported for the following approaches: Unhedged portfolio has the impact of funds' own forward positions removed; Full hedge completely eliminates the currency exposure using forwards; Carry trade fully hedges currencies of countries that had lower interest rates compared to the US; Minimum-variance hedge implements dynamic hedge ratios that minimize the portfolio variance. The sample period is from Q1 2004 to Q2 2019. All hedging approaches are implemented using monthly data. Further details on the funds and the hedging approaches can be found in Section 4.

Table 6: The Determinants of Portfolio Weights Among Portfolio Builders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country weight	-0.498^{***}						-0.520^{***}	-1.723^{***}
	(0.069)						(0.071)	(0.153)
Momentum		0.236^{***}					0.270^{***}	0.266^{***}
		(0.034)					(0.037)	(0.035)
Carry			0.240^{***}				0.355^{***}	0.181
			(0.093)				(0.126)	(0.147)
Value				-0.024			0.033	0.029
				(0.026)			(0.026)	(0.028)
Bid-ask spread					0.009		-0.011	-0.027
					(0.015)		(0.021)	(0.022)
EM dummy						-1.037	-4.824^{***}	
						(1.075)	(1.163)	
Observations	32,923	36,411	36,211	35,944	36,211	36,411	32,864	32,499
Fund × Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund × Currency FEs	No	No	No	No	No	No	No	Yes
Adj. R^2	0.146	0.120	0.119	0.118	0.118	0.119	0.151	0.474

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 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. All regressions include fund × quarter fixed effects and the regression in the last column also includes fund × currency 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.

Table 7: The Investment Performance of Portfolio Builders

	SR	Mean	Median	p25	p75
All portfolio builders	0.08	0.95	0.88	−1.15	2.84
G1 to G4 portfolio builders	−0.09	−0.36	0.21	−1.58	1.79
	G1	**G2**	**G3**	**G4**	**G5**
	Currency Portfolios (Actual)				
Sharpe ratio	−0.75	−0.09	−0.13	0.35	0.77
Portfolio return (%)	−4.25	−0.79	0.96	2.69	6.28
Stdev portfolio return (%)	7.00	7.92	7.47	7.74	8.26
Currency portfolio size (% of TNA)	9.79	14.4	15.5	12.3	9.29
Impact on the funds' Sharpe ratio from adopting an alternative currency portfolio					
Δ *Sharpe ratio without currency forwards*	0.01***	0.00	−0.01***	−0.01***	−0.01***
Δ *Sharpe ratio using G9 carry trade*	0.06***	0.05***	0.05***	0.06***	0.05**
Δ *Sharpe ratio using G25 carry trade*	0.14***	0.12***	0.12***	0.12***	0.12**
Δ *Sharpe ratio using G25 combo trade*	0.08***	0.07***	0.07***	0.09***	0.07**

The table presents statistics on the investment performance of portfolio builders. The first row presents aggregate summary statistics across all portfolio builders pertaining to their currency-specific portfolio of currency forward contracts. The values include the average Sharpe ratio (**SR**), mean, median, 25th and 75th percentiles of the return distribution. In the lower panel, funds are split into five equally sized groups based on their sample currency portfolio Sharpe ratio from low (G1) to high (G5). Investment performance is presented for the five groups for their currency portfolio. Performance gain relative to the fund's actual performance is reported when combining funds' fully hedged equity portfolio with a separate currency portfolio with weights of 80%/20%. G9 (G25) carry trade is a long/short portfolio constructed using G9 (G25) currencies. G25 combo trade is an equally weighted portfolio of carry, value, and momentum long/short portfolios constructed using G25 currencies. Significance of Δ *Sharpe ratio* at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. All currency forward trades are implemented using monthly data. Further details on the funds and the currency portfolio approaches can be found in Section 4.

Table 8: The Potential Performance Gains from Using Currency Forwards

		Incremental Performance		
	Actual	**Full Hedge**	**Carry**	**Min-Var**
		2004 to 2019		
Mean excess return (%)	5.69	0.60***	0.77***	0.59***
Std excess return (%)	15.4	−2.56***	−0.96***	−2.77***
Sharpe ratio	0.39	0.14***	0.09***	0.14***
Certainty-equivalent return (%)	1.90	1.73***	1.19***	1.81***
Benchmark-adjusted return (%)	−0.56	0.60***	0.77***	0.59***
Tracking error (%)	5.13	2.26***	0.96***	1.94***
		2004 to 2011		
Mean excess return (%)	7.75	−2.81***	−1.40***	−1.62***
Std excess return (%)	22.6	−4.46***	−1.32***	−4.57***
Sharpe ratio	0.38	−0.05***	−0.04***	0.02**
Certainty-equivalent return (%)	−0.27	−0.06	−0.52***	1.20***
Benchmark-adjusted return (%)	−1.17	−2.81***	−1.40***	−1.62***
Tracking error (%)	6.12	3.40***	0.81***	3.03***
		2012 to 2019		
Mean excess return (%)	5.70	1.42***	1.30***	1.10***
Std excess return (%)	13.5	−2.13***	−0.90***	−2.38***
Sharpe ratio	0.45	0.21***	0.15***	0.19***
Certainty-equivalent return (%)	2.89	2.24***	1.64***	1.99***
Benchmark-adjusted return (%)	−0.25	1.42***	1.30***	1.10***
Tracking error (%)	4.84	2.03***	1.02***	1.74***

The table presents the portfolio performance gains from various approaches to currency management for non-user funds. The full sample includes 732 funds that have at least 12 monthly hedged returns under all approaches. Performance gain relative to the fund's actual performance is reported for the following hedging strategies: Full hedge completely eliminates the currency exposure using forwards; Carry fully hedges currencies of countries that had lower interest rates compared to the US; Minimum-variance hedge implements dynamic hedge ratios that minimize the portfolio variance. Significance of the performance difference at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Results are reported for the full sample and for two sub-samples (Q1 2004 to Q4 2011 and Q1 2012 to Q2 2019). All hedging approaches are implemented using monthly data. Further details on the funds and the hedging approaches can be found in Section 5.

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

Not for publication

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SECTION B: FURTHER ANALYSES
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Table B.2: The Determinants of Exposure Managers' Hedge Ratios
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Table B.3: The Determinants of Portfolio Builders' Portfolio Weights
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Exploring the investment performance of occasional users if a hedging strategy were overlaid to their equity portfolio.

SECTION C: DATA APPENDIX
Full details on how the main dataset was constructed.

Table A.1: Variable Definitions

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 Table 1, and annualized return in Table 8.
Tracking error (%)	Table 1 reports the standard deviation of quarterly benchmark-adjusted returns. Table 8 reports the annualized standard deviation of monthly benchmark-adjusted returns.
Gross Return (%)	Quarterly net return plus 1/4 of the annual expense ratio.
Fund Flow (%)	Quarterly fund flow is $\frac{AUM_t - AUM_{t-1} \times (1+GrossReturn_{t-1})}{AUM_{t-1}}$, where *Gross Return* 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 management fee (% annual)	Management fee/Average Net Assets as reported by *CRSP*.
Dividend yield (%)	The quarterly average of monthly fund distribution of dividends and capital gains as a percentage of Net Asset Value (NAV).

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.
Institutional share (% of TNA)	Proportion of a fund's TNA held in institutional share classes (definition according to *Morningstar*)
Fund forwards as % of TNA	Net forward position in each currency aggregated at the fund level and scaled by TNA.
Absolute value of fund forwards as % of TNA	Absolute value of net forward position in each currency aggregated at the fund level and scaled by TNA.
Fund hedge ratio (%)	Total net forward currency sale positions as a percentage of total investment in foreign currencies.
Fund exposure as % of TNA	Total country weights in foreign currencies as a percentage of TNA plus total currency forward 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.
Cross-currency basis	Difference between the US dollar interest rate and the synthetic dollar interest rate (foreign currency interest rate converted into US dollars using currency forwards) as defined by Du et al. (2018).
CEQ return (%)	Mean (excess return)- $\frac{1}{2}$ $\times$ 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.
Can use forwards	Dummy variable = 1 if a fund states in its prospectus that the fund may use forward currency contracts.
Can speculate	Dummy variable = 1 if a fund states in its prospectus that the fund may use currency forwards for non-hedging purposes as detailed in Section VI of the Online Data Appendix.

Table A.2: Fund Characteristics and the Use of Currency Forwards

	All Users Funds	Exposure Managers	Portfolio Builders	Occasional Users
Portfolio weight in G9 (%)	0.00	−0.03***	0.02***	0.01
	(0.00)	(0.01)	(0.01)	(0.00)
Portfolio weight in non-G9 (%)	−0.01	−0.06***	0.02***	−0.01**
	(0.00)	(0.01)	(0.01)	(0.01)
No. countries invested	0.03***	−0.05*	0.03**	0.07***
	(0.01)	(0.03)	(0.01)	(0.01)
Fund turnover ratio (annual, %)	0.01***	0.01	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Fund expense ratio (annual, %)	0.62***	1.51***	0.42*	0.77***
	(0.20)	(0.51)	(0.25)	(0.26)
Dividend yield (%)	0.22*	0.13	0.18	0.15
	(0.13)	(0.28)	(0.16)	(0.18)
Fund age (years)	0.02**	−0.01	0.04***	0.03**
	(0.01)	(0.02)	(0.01)	(0.01)
Fund TNA ($ millions)	0.23***	0.72***	0.12	0.20**
	(0.06)	(0.15)	(0.08)	(0.08)
Family TNA ($ millions)	0.14***	0.13	0.06	0.30***
	(0.05)	(0.14)	(0.07)	(0.08)
Number of funds in family	−0.05***	−0.10**	−0.03**	−0.09***
	(0.01)	(0.04)	(0.01)	(0.02)
Institutional share (% of TNA)	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Index funds	0.07		0.57*	−0.47
	(0.27)		(0.31)	(0.41)
Can use forwards	2.02***		2.14**	1.42
	(0.75)		(1.03)	(1.06)
Can speculate	0.27**	0.53	−0.10	0.72***
	(0.13)	(0.33)	(0.17)	(0.18)
Observations	1,248	7432	988	987
Pseudo R^2	0.11	0.28	0.08	0.18

The table presents cross-sectional determinants of forward usage from logit regressions. The dependent variable in each regression is a indicator for user type and has the value 0 for non-users. The independent variables are fund characteristics averaged within each fund. 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. Fund characteristics are defined in Table A.1 of the Online Appendix. Further details on the funds and data sources can be found in Section 2.

Table A.3: Flow-Performance Sensitivity

	Exposure Managers		Portfolio Builders	
	Fund Flow	Forward	Fund Flow	Forwards
Negative BM-adjusted return	0.36***	−0.36**	0.34***	−0.10
	(0.14)	(0.16)	(0.07)	(0.07)
Positive BM-adjusted return	0.54***	0.10	0.42***	−0.09**
	(0.16)	(0.08)	(0.15)	(0.04)
Portfolio weight in G9 (%)	−0.07	0.18*	−0.15**	−0.07
	(0.08)	(0.09)	(0.07)	(0.07)
Portfolio weight in non-G9 (%)	−0.14	0.27*	−0.13*	−0.05
	(0.09)	(0.16)	(0.07)	(0.11)
No. countries invested	−0.03	−0.42	0.05	0.12
	(0.12)	(0.26)	(0.06)	(0.11)
Fund expense ratio (annual, %)	−4.86	8.76	−1.64	0.47
	(5.93)	(7.77)	(1.93)	(2.45)
Fund turnover ratio (annual, %)	0.01	−0.01	−0.01	0.01
	(0.03)	(0.02)	(0.01)	(0.01)
Fund TNA ($ millions)	1.21	1.11	0.41	0.82
	(1.25)	(1.86)	(0.56)	(0.83)
Family TNA ($ millions)	−0.85	−0.99	−0.04	1.08
	(1.10)	(1.31)	(0.85)	(1.19)
Observations	1,840	1,854	6,005	6,072
Fund FEs	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
Adj. R^2	0.23	0.57	0.21	0.61

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is quarterly fund flow in columns (1) and (3), and TNA-scaled total absolute forward positions in columns (2) and (4). Negative BM-adjusted return equals min(BM-adjusted return, 0) and Positive BM-adjusted return equals max(0, BM-adjusted return), where BM-adjusted return is fund return minus the return on the index assigned by *Morningstar* based on funds' portfolio holdings. Other fund characteristics are defined in Table A.1 of the Online Appendix. All independent variables are lagged by one quarter and each regression includes fund and quarter fixed effects. Standard errors clustered by fund and quarter are presented in parentheses. Significance of the coefficients at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Further details on the funds and data sources can be found in Section 2.

Table A.4: Cross-Currency Basis (Exposure Managers)

	(1)	**(2)**
Cross-currency basis	-0.588^{***}	-0.366^{***}
	(0.102)	(0.087)
Country weight		0.702^{***}
		(0.103)
Momentum		-0.079
		(0.068)
Carry		0.306
		(0.613)
Value		-0.002
		(0.055)
Bid-ask spread		-0.196
		(0.360)
Volatility		0.337
		(0.261)
Equity return		0.063
		(0.045)
Observations	13,976	13,488
Fund × Quarter FEs	Yes	Yes
Adj R^2	0.416	0.442

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is the hedge ratio of fund i for G9 currency/country j in quarter t. The independent variables include the deviation from the CIP condition (*Cross-currency basis*), 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, and the MSCI equity index return for country j. All independent variables are lagged by one quarter except for the cross-currency basis. All regressions include fund × quarter fixed effects and 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.

Table A.5: Volatility-Adjusted Carry

	(1)	**(2)**
Volatility-adjusted carry	2.321***	4.644***
	(0.840)	(1.111)
Country weight		−0.539***
		(0.070)
Momentum		0.245***
		(0.038)
Value		0.038
		(0.026)
Bid-ask spread		−0.015
		(0.021)
EM dummy		−4.691***
		(1.125)
Observations	32,864	32,864
Fund × Quarter FEs	Yes	Yes
Adj. R^2	0.152	0.152

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is the currency portfolio weight of fund i for currency/country j in quarter t. The independent variables include the forward discount adjusted by the prior three months' volatility of the exchange rate (*Volatility-adjusted carry*), fund i's portfolio's weight in country j, the exchange rate return (*Momentum*), 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. All regressions include fund × quarter fixed effects and 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.

Table A.6: Cross-Currency Basis (Portfolio Builders)

	(1)	**(2)**
Cross-currency basis	0.379***	−0.0314
	(0.085)	(0.075)
Country weight		−0.861***
		(0.104)
Momentum		0.411***
		(0.057)
Carry		0.109
		(0.454)
Value		0.037
		(0.047)
Bid-ask spread		−1.266***
		(0.252)
Observations	21,212	19,524
Fund × Quarter FEs	Yes	Yes
Adj. R^2	0.099	0.153

The table presents coefficient estimates from fixed effects panel regressions. The dependent variable is the currency portfolio weight of fund i for G9 currency/country j in quarter t. The independent variables include the deviation from the CIP condition (*Cross-currency basis*), 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*), and the bid-ask spread. All independent variables are lagged by one quarter except for the cross-currency basis. All regressions include fund × quarter fixed effects and 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.

Table A.7: Top Long-and-Short Currencies of Portfolio Builders

	G1	**G2**	**G3**	**G4**	**G5**
			Top Long Currencies		
1	GBP	AUD	AUD	AUD	AUD
2	AUD	EUR	SEK	SEK	SEK
3	CHF	GBP	INR	SGD	INR
4	EUR	SEK	NOK	CAD	SGD
5	MYR	KRW	NZD	BRL	MXN
			Top Short Currencies		
1	JPY	JPY	EUR	EUR	EUR
2	NOK	CNY	GBP	JPY	GBP
3	CNY	HKD	MXN	GBP	CHF
4	KRW	THB	TRY	CNY	ZAR
5	ILS	PHP	PHP	NZD	JPY

The table presents the most bought and sold currency forwards across five groups of portfolio builders. Funds are split into five equally sized groups based on their sample currency portfolio Sharpe ratio from low (G1) to high (G5). Within each fund group, currencies are ranked by the currency portfolio weight in each currency averaged across funds, and the first currency in the top (bottom) panel has the highest (lowest) average currency portfolio weight. The sample period is from Q1 2004 to Q2 2019. Further details on the funds can be found in Section 4.

Table A.8: The Potential Performance Gains from Using Currency Forwards

		Incremental Performance		
	Actual	**G9 Carry**	**G25 Carry**	**Combo**
		2004 to 2019		
Mean excess return (%)	5.69	-0.61^{***}	0.07	-0.46^{***}
Std excess return (%)	15.4	-4.27^{***}	-4.36^{***}	-4.96^{***}
Sharpe ratio	0.39	0.10^{***}	0.17^{***}	0.15^{***}
Certainty-equivalent return (%)	1.90	1.19^{***}	1.90^{***}	1.58^{***}
Benchmark-adjusted return (%)	−0.56	-0.61^{***}	0.07	-0.46^{***}
Tracking error (%)	5.13	2.41^{***}	2.51^{***}	2.76^{***}
		2004 to 2011		
Mean excess return (%)	7.75	-3.18^{***}	-2.86^{***}	-3.93^{***}
Std excess return (%)	22.6	-6.79^{***}	-7.08^{***}	-7.96^{***}
Sharpe ratio	0.38	-0.03^{***}	−0.01	-0.07^{***}
Certainty-equivalent return (%)	−0.27	0.85^{***}	1.32^{***}	0.67^{**}
Benchmark-adjusted return (%)	−1.17	-3.18^{***}	-2.86^{***}	-3.93^{***}
Tracking error (%)	6.12	3.92^{***}	4.47^{***}	4.87^{***}
		2012 to 2019		
Mean excess return (%)	5.70	−0.03	0.65^{***}	0.28^{***}
Std excess return (%)	13.5	-3.63^{***}	-3.68^{***}	-4.21^{***}
Sharpe ratio	0.45	0.15^{***}	0.23^{***}	0.23^{***}
Certainty-equivalent return (%)	2.89	1.29^{***}	1.98^{***}	1.76^{***}
Benchmark-adjusted return (%)	−0.25	−0.03	0.65^{***}	0.28^{***}
Tracking error (%)	4.84	2.09^{***}	2.08^{***}	2.30^{***}

The table presents the portfolio performance gains from adding a separate currency portfolio for non-user funds. The full sample includes the same 732 funds that we examined in Table 8. Performance gain relative to the fund's actual performance is reported when combining funds' fully hedged equity portfolio with a separate currency portfolio with weights of 80%/20%. G9 (G25) carry trade is a long/short portfolio constructed using G9 (G25) currencies. G25 combo trade is an equally weighted portfolio of carry, value, and momentum long/short portfolios constructed using G25 currencies. Significance of the performance difference at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Results are reported for the full sample and for two sub-samples (Q1 2004 to Q4 2011 and Q1 2012 to Q2 2019). All hedging approaches are implemented using monthly data. Further details on the funds and the hedging approaches can be found in Section 5.

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

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

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

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

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

(a) AB International Value Fund

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

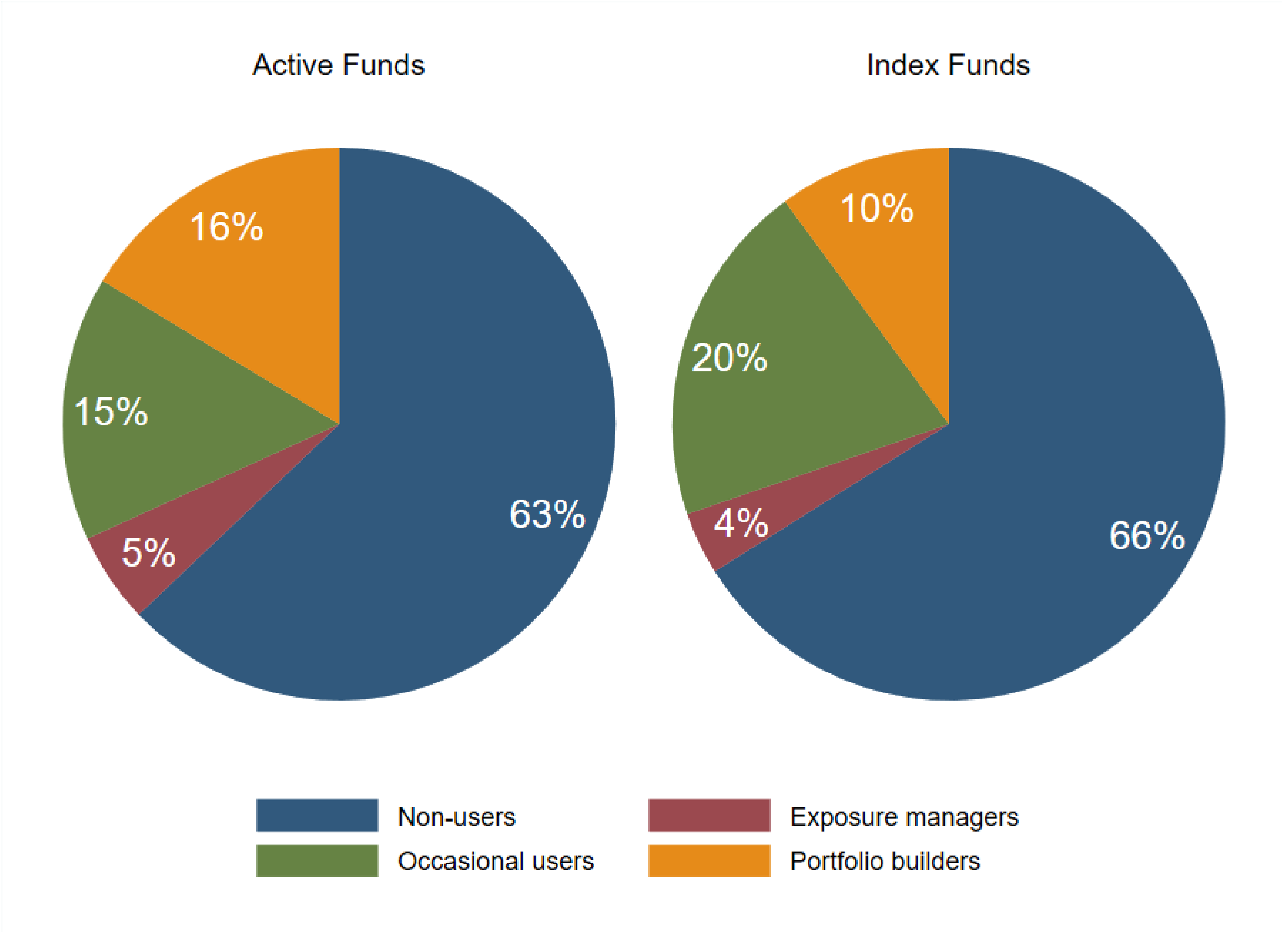
(b) Vanguard Global Equity Fund

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

(c) Goldman Sachs Total Emerging Markets Income Fund

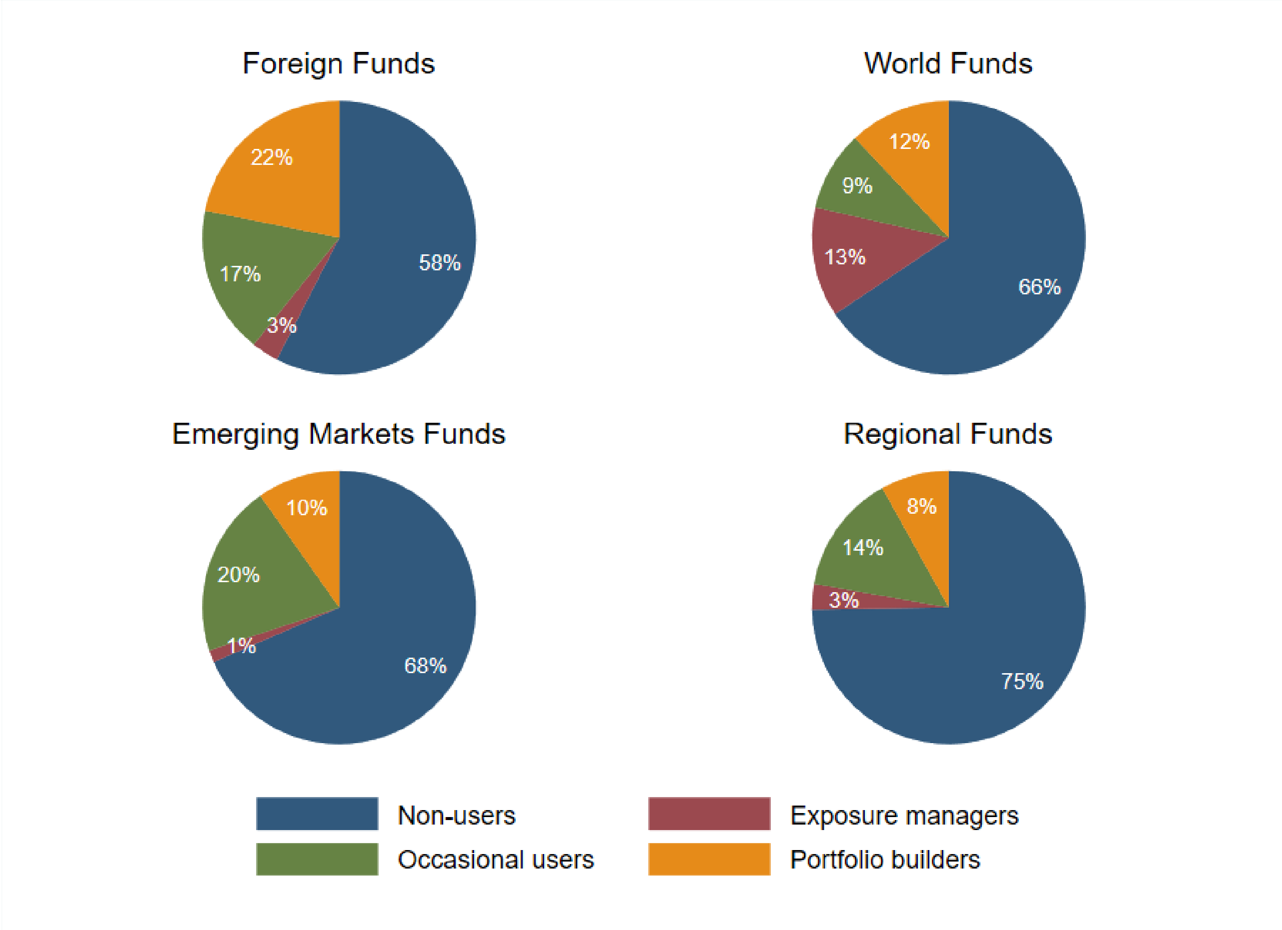
The figure presents extracts from fund reports and prospectuses concerning their potential use of foreign currency forward contracts. Panel A is extracted from the May 2019 N-CSR form of AB International Value Fund, Panel B is extracted from the prospectus (form N-1A) of the Vanguard Global Equity Fund,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

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



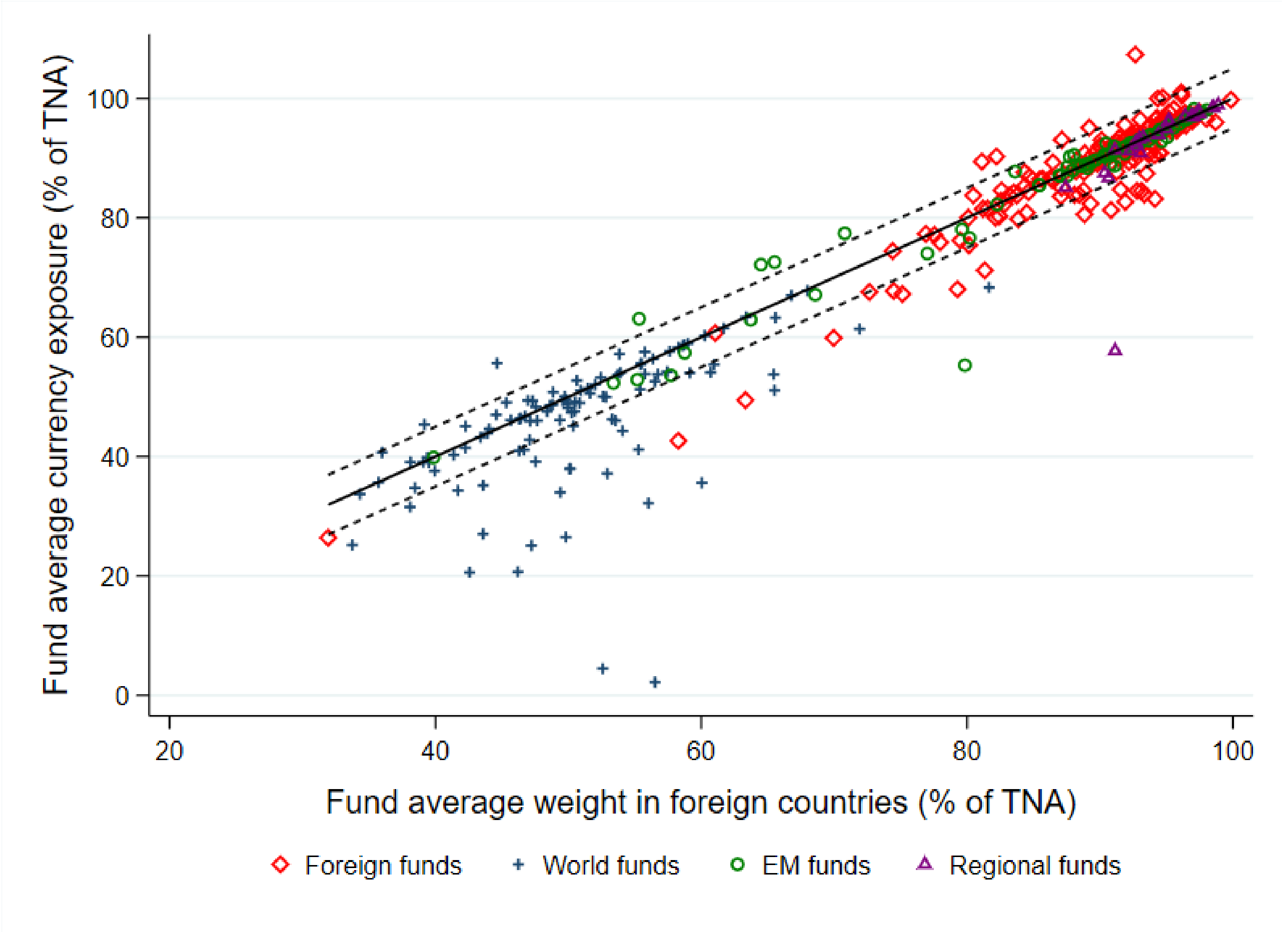
The figure presents pie charts that split the active and passive funds in our sample between users and non-users of currency forward contracts. Within the group of user funds, the funds are split between exposure managers, portfolio builders, and occasional users. The sample period is from Q1 2004 to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

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



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

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



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

Section B: Alternative Categorization Schemes

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

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

As an additional robustness check, we also cluster funds into three groups in a two-step procedure using the k-means machine learning algorithm (**v7**).[45] 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.

[45] 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.

Table B.1: Currency Management Styles

	(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

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

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

	(v1)	**(v2)**	**(v3)**	**(v4)**	**(v5)**	**(v6)**	**(v7)**
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

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. All regressions include fund × quarter fixed effects and 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.

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

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
Country weight	−0.530***	−0.533***	−0.522***	−0.636***	−0.520***	−0.633***	−0.605***
	(0.076)	(0.072)	(0.071)	(0.075)	(0.071)	(0.074)	(0.073)
Momentum	0.279***	0.272***	0.276***	0.289***	0.270***	0.278***	0.260***
	(0.037)	(0.037)	(0.037)	(0.039)	(0.037)	(0.039)	(0.038)
Carry	0.319**	0.362***	0.375***	0.456***	0.355***	0.445***	0.406***
	(0.132)	(0.128)	(0.128)	(0.139)	(0.126)	(0.137)	(0.138)
Value	0.050*	0.040	0.036	0.036	0.033	0.033	0.038
	(0.027)	(0.026)	(0.026)	(0.029)	(0.026)	(0.029)	(0.027)
Bid-ask spread	−0.017	−0.015	−0.017	−0.028	−0.011	−0.024	−0.025
	(0.022)	(0.021)	(0.021)	(0.024)	(0.021)	(0.023)	(0.024)
EM dummy	−4.169***	−4.763***	−4.829***	−5.896***	−4.824***	−5.950***	−5.828***
	(1.211)	(1.180)	(1.172)	(1.217)	(1.163)	(1.211)	(1.217)
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	0.145	0.148	0.149	0.103	0.151	0.105	0.190

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 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. All regressions include fund × quarter fixed effects and 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.

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

	(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

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. All regressions include fund × quarter fixed effects and 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.

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

	(v1)	(v2)	(v3)	(v4)	(v5)	(v6)	(v7)
Country weight	−0.047	0.203**	0.193*	0.128	0.221**	0.140	0.019
	(0.113)	(0.100)	(0.103)	(0.085)	(0.106)	(0.086)	(0.094)
Momentum	0.075	0.063	0.045	0.097	0.061	0.120*	0.097
	(0.078)	(0.087)	(0.089)	(0.068)	(0.090)	(0.069)	(0.074)
Carry	0.067	−0.047	−0.099	−0.148	0.027	−0.111	0.007
	(0.214)	(0.215)	(0.215)	(0.178)	(0.228)	(0.184)	(0.181)
Value	−0.003	0.023	0.037	0.034	0.054	0.043	0.060*
	(0.036)	(0.035)	(0.036)	(0.030)	(0.036)	(0.030)	(0.032)
Bid-ask spread	−0.005	−0.018	0.012	0.007	−0.040	−0.006	−0.004
	(0.027)	(0.031)	(0.031)	(0.026)	(0.032)	(0.027)	(0.026)
EM dummy	−2.96	−0.147	0.337	1.774	0.376	2.104	2.214
	(1.806)	(2.030)	(2.083)	(2.162)	(2.136)	(2.195)	(2.061)
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

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 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. All regressions include fund × quarter fixed effects and 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.

Table B.6: The Potential Performance Gains from Using Currency Forwards

		Incremental Performance		
	Actual	**Full Hedge**	**Carry**	**Min-Var**
		2004 to 2019		
Mean excess return (%)	5.60	0.24	0.45***	0.44***
Std excess return (%)	16.2	−2.92***	−1.02***	−3.16***
Sharpe ratio	0.36	0.12***	0.07***	0.13***
Certainty-equivalent return (%)	1.46	1.59***	0.95***	1.88***
Benchmark-adjusted return (%)	−0.55	0.24	0.45***	0.44***
Tracking error (%)	4.61	2.78***	1.19***	2.32***
		2004 to 2011		
Mean excess return (%)	7.58	−3.10***	−1.70***	−1.67***
Std excess return (%)	22.4	−4.43***	−1.37***	−4.62***
Sharpe ratio	0.36	−0.07***	−0.06***	0.02
Certainty-equivalent return (%)	−0.25	−0.36	−0.76***	1.16***
Benchmark-adjusted return (%)	−1.34	−3.10***	−1.70***	−1.67***
Tracking error (%)	5.44	3.66***	1.08***	3.10***
		2012 to 2019		
Mean excess return (%)	5.89	1.55***	1.35***	1.16***
Std excess return (%)	13.8	−2.41***	−0.97***	−2.68***
Sharpe ratio	0.45	0.23***	0.15***	0.21***
Certainty-equivalent return (%)	2.96	2.49***	1.73***	2.18***
Benchmark-adjusted return (%)	0.14	1.55***	1.35***	1.16***
Tracking error (%)	4.31	2.46***	1.21***	2.08***

The table presents the portfolio performance gains from various approaches to currency management for occasional users. The full sample includes 181 funds that have at least 12 monthly hedged returns under all approaches. Performance gain relative to the fund's actual performance is reported for the following hedging strategies: Full hedge completely eliminates the currency exposure using forwards; Carry fully hedges currencies of countries that had lower interest rates compared to the US; Minimum-variance hedge implements dynamic hedge ratios that minimize the portfolio variance. Significance of the performance difference at the 10%, 5%, and 1% levels of statistical significance are denoted by the superscripts *, **, and ***. The sample period is from Q1 2004 to Q2 2019. Results are reported for the full sample and for two sub-samples (Q1 2004 to Q4 2011 and Q1 2012 to Q2 2019). All hedging approaches are implemented using monthly data. Further details on the funds and the hedging approaches can be found in Section 5.

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.

<u>Step One</u>

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.

Step Two

One major reason why there are still significant inconsistencies remaining is because there are many cases where the computed *crsp_ret* is consistent with *mret*, and the computed *ms_ret* is consistent with *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.